Three Essays in Applied Environmental Economics

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Summary

The first chapter *The Impact of Agri-Environmental Measures on Farms' Costs, Labour and Income*, examines the economic effects of Agri-Environmental Measures (AEMs) implemented under the 2007–2013 programming period using farm-level data from 22 EU countries. While previous studies primarily focus on the environmental benefits of these policies, this chapter explores their broader economic implications, assessing how they influence farm-level costs, labour allocation, and income growth. Using a counterfactual scenario, we find that at the aggregate level, estimates considering all European countries report positive and significant effects on the studied outcomes. However, when examining results in more detail, heterogeneous effects emerge across country groups. The increase in costs is driven by specific expenditure categories that vary across regions. For instance, seed costs rise only in Eastern Europe, while crop protection costs increase only Western Europe, and only crop-specific costs significantly increase in Southern Europe. Regarding labour, we observe an increase in total labour input across all country groups, but unpaid labour (typically family labour) rises more sharply in Southern and Eastern Europe. On the other hand, income-related outcomes show a more homogeneous effect across regions, with farm income growing consistently among treated farms. We provide empirical evidence that challenges the assumption that AEMs are production-neutral. Instead, the results suggest that AEMs can generate income returns and enhance farm productivity, potentially influencing long-term farm investment strategies. This chapter contributes to the policy debate on the structure of AEMs by highlighting the advantages of shifting toward results-based schemes, which directly tie payments to measurable environmental improvements rather than prescribed actions that may create room for strategic investment decisions.

The second chapter *Nudging Toward Climate Adaptation. A Field Experiment on Informational Strategies in Organic Food Markets* shows how informational frictions and cognitive biases influence consumer choices in the organic food market, often leading to suboptimal choices despite pro-environmental preferences. While previous studies highlight the role of nudges to foster sustainable behaviors in climate change mitigation, this chapter shifts the focus to climate adaptation, exploring whether targeted informational interventions can effectively steer consumers toward more climate-resilient food choices. Using a field experiment, we test two messaging strategies—a colloquial and a scientific approach—to assess their ability to reduce information asymmetry and reshape purchasing behavior. We show that while a simple, relatable message

significantly increases purchases of climate-adaptive products, a scientific message is only effective among highly engaged consumers, suggesting that frictions in information processing persist even when knowledge gaps are reduced. These findings indicate that while some barriers can be addressed through clear, accessible communication, deeper cognitive constraints—such as information overload and moral licensing—limit the extent of behavioral change. By showing that the effectiveness of informational strategies depends on pre-existing purchasing habits and motivations, we highlight the importance of targeting messages based on consumer profiles to maximize engagement and drive more effective environmental decision-making.

With the third chapter *The Adverse Impacts of Disasters-In-Name Only*, this dissertation continues to explore information frictions and consumer behavior, this time in the context of disaster mis-naming and its unintended economic consequences. We examine how disaster names that misattribute the geographic scope of destruction can negatively affect local economies, particularly tourism. Leveraging data on tourism flows in Italy, we compare areas that suffered direct earthquake damage with those affected only by the toponym, testing whether mislabeling alone leads to persistent declines in tourist arrivals. Our results show that regions incorrectly associated with disasters experience significant and lasting economic losses, despite the absence of physical damage. Once a disaster toponym enters public discourse, it is difficult to correct the misperception it creates, reinforcing economic downturns over time. Using a counterfactual setting, we identify a new mechanism of perception-driven economic shocks, showing that miscommunication alone can amplify the costs of a disaster beyond its physical effects. This work contributes to the broader literature on information asymmetry and communication strategies, highlighting how inaccurate disaster naming imposes unnecessary economic costs and long-term stigma on unaffected regions.

Keywords: Environmental Economics, Impact Evaluation, Adaptation Strategies, Agriculture, Tourism, Consumer Behavior, Causal Inference, Natural Hazards

General Introduction

During the past decade, the intensification of natural hazards, extreme weather, and environmental degradation has driven the surge in the advancement of empirical economic models and the granularity of available data to quantify their effects on economic outcomes with greater accuracy. Yet the core challenge now is to assess how these shocks not only impose uneven financial burdens across communities but also reveal systemic inefficiencies in market structures, expose gaps in policy design, and information frictions that distort how firms and households adapt their behavior.

Governments can play a crucial role by designing policies that internalize environmental costs, steering economic agents toward more sustainable practices and societal welfare. This is particularly evident in agriculture, where farming practices have a direct impact on ecosystems. While technology has boosted agricultural productivity, intensive farming has also led to soil degradation, water pollution, and biodiversity loss. European farmers are supported through the Common Agricultural Policy (CAP). Since its creation in 1962, the CAP has shaped farming decisions across Europe, originally through price supports and later through direct subsidies. Direct payments, provided annually and originally designed for specific crop types and livestock, were considered coupled payments because they were directly linked to production levels, requiring farmers to maintain agricultural activity to receive financial support. In addition to these direct payments, CAP also included rural development subsidies provided to farms in disadvantaged areas and agri-environmental subsidies (AESs), which aim to promote sustainability. The Agenda 2000 reform introduced the two-pillar structure as we know it nowadays. The first pillar continued to provide direct payments to farmers but began a gradual process of decoupling them from production levels, reducing distortions in agricultural markets. The second pillar focused on rural development support for less-favored rural areas, agri-environmental schemes and farm modernization. This shift aimed to provide farmers with greater flexibility in production choices while ensuring that environmental and social goals were integrated into agricultural policy.
The 2003 Luxembourg reform further advanced this transformation by introducing the Single Farm Payment (SFP), a fully decoupled subsidy granted to farmers regardless of their production levels but conditional on maintaining their land in good agricultural and environmental condition—known as cross-compliance. The shift from coupled to decoupled payments significantly altered the economic dynamics of European agriculture, drawing increased attention to

its economic implications. Unlike coupled payments, which incentivized production and often boosted demand for farm labour, decoupled payments—designed with a stronger environmental focus—provided farmers with a fixed subsidy independent of their output. This transition had profound consequences for farming economic outcomes (Key & Roberts, 2009). As highlighted by Ahearn et al. (2006), the primary concern lies in the impact on productivity: decoupled payments function as general income support, potentially encouraging farmers to allocate more time to off-farm activities. With the increase of environmental awareness, CAP continued to prioritize sustainability by expanding its support for agri-environmental policies. Between 2007 and 2013, the EU allocated nearly €20 billion to AESs, incentivizing farmers to adopt environmentally friendly practices. Since 1993, the AES budget has grown significantly, reaching €3 billion in 2010 and exceeding €5 billion in 2013 (European Commission, 2017). The measures under the 2007–2013 rural development program covered various aspects of sustainable farming, including organic agriculture, landscape management, conservation of pastures and high-nature-value farmlands, integrated production, and extensification strategies aimed at reducing agricultural intensity (Dupraz & Latruffe, 2015).

From this perspective, as more micro-level data on individual farms has become available, research has expanded to evaluate the economic and environmental effects of these policies. The AES, due to their voluntary opt-in nature and implementation at the Member State level, are particularly challenging to assess, leading to mixed results in the literature regarding both their economic and environmental effectiveness (Zimmermann & Britz, 2016). A major challenge in assessing voluntary policies such as AESs is the *windfall effect*, which occurs when farmers receive payments for adopting environmentally friendly practices they would have implemented anyway, even without subsidies (Chabé-Ferret & Subervie, 2013). When a policy successfully induces new sustainable behaviors, it achieves high additionality, meaning that subsidies encourage farmers to shift from conventional to more sustainable practices. However, when a policy suffers from a windfall effect, public funds are spent without generating real environmental improvements, reducing the program's efficiency. Because AES payments are voluntary and uniform across all farmers, there is a high risk of adverse selection—where farmers who already follow environmentally friendly practices are the most likely to apply for subsidies, while those who would need financial support to make real changes may not participate. Advancements in statistical and econometric tools for causal inference in non-experimental studies have enhanced our ability to overcome selection bias and isolate the effects of participating to a policy on specific socio-economic outcomes. As shown in the First Chapter of this dissertation—*The Impact of Agri-Environmental Measures on Farms' Costs, Labour, and Income*, the economic implications of AESs extend beyond individual farms and can be observed at an aggregate level. Understanding whether these policies are attractive enough to incentivize a larger number of farmers is key to ensuring that they generate higher additionality and lower windfall effects. Moreover, evaluating their broader economic impact is crucial for informing the design of future policies that aim to reduce environmental externalities from agriculture while simultaneously adapting productivity to climate change challenges.

However, inefficiencies do not arise only from environmental externalities; behavioral biases and informational frictions also play a crucial role in shaping environmental and economic outcomes. Insights from behavioral economics have challenged the assumption of fully rational agents, revealing that individuals often struggle to make optimal decisions, particularly when confronted with complex environmental trade-offs (**shro**; Handel & Schwartzstein, 2018). For instance, consumers may fail to invest in energy-efficient appliances not because of financial constraints but due to a lack of awareness about long-term operating costs. Studies show that when lifetime energy savings are not clearly communicated, individuals disproportionately prioritize low upfront costs over more sustainable, cost-effective choices (Allcott & Taubinsky, 2015; Andor et al., 2019). The same issue emerges in agriculture and food systems, where eco-friendly practices or sustainable products may be undervalued by consumers due to insufficient information. In these cases, simple interventions such as clearer labeling or additional information can help align individual decision-making with social and environmental objectives. However, when mental gaps or behavioral biases prevent individuals from acting optimally even when information is available, stronger policy measures—such as subsidizing information acquisition, implementing default green choices, or using behavioral nudges—may be necessary to steer consumption and production toward sustainability (La Nauze & Myers, 2023; Sallee, 2014).

Food is at the core of the discussion for what concern sustainable consumption within changing environmental conditions (Ivanovich et al., 2023). In the context of food markets, there is a growing trend toward product differentiation based on process attributes, such as organic certification, free-range poultry, and GMO-free labeling. These goods fall under the category of "credence food", meaning that consumers cannot verify process-related claims, even after lengthy consumption (Ambec & De Donder, 2022; Roe & Sheldon, 2007). Environmentally-conscious consumers exhibit a willingness to pay premium prices for products that are perceived as environmentally friendly. However, they often face challenges in distinguishing between products that offer diverse degrees of environmental benefits due to differences in production procedure (Larson, 2003). When consumers cannot ascertain the environmental performance of products, the price is generally distorted upward to signal the quality and "cleanliness" of a product, typically through labeled packaging. However, such product relying on labels often may also suffer from an increasing phenomena—commonly referred to as *greenwashing*, that only in recent years European Union is trying to regulate—which is the surge in misleading claims about environmental merits that companies are using without supporting evidence and with very different level of transparency[1]. In such cases, even companies that genuinely adhere to cleaner practices may feel compelled to engage in exaggerated environmental claims, as competition incentivizes overstating green credentials rather than focusing on actual sustainability improvements (Hattori & Higashida, 2015). This creates a market failure where consumers, unable to verify claims, base their purchasing decisions on branding rather than true environmental impact. As a result, the

[1] https://environment.ec.europa.eu/topics/circular-economy/green-claims_en

market for sustainable products becomes distorted, with price signaling failing to reflect genuine ecological benefits.

For this reason, the effectiveness of labeling alone in guiding sustainable consumption choices is limited. Behavioral changes among households are crucial to reducing the environmental impact of food consumption, and even small adjustments could significantly reduce environmental stress (Schor, 2005). Fostering these changes requires complementing existing labels with additional information to uncover how certain products—not only labeled as sustainable—may provide additional resilience benefits, such as improved soil health, water retention, and biodiversity conservation. These often-overlooked attributes play a crucial role in preserving natural resources in a context of increasing climate variability and extreme weather events. However, using information-based strategies to nudge shifting consumption behavior does not come without risks, even within a community of already eco-conscious consumers. Indeed, the risk of overloading consumers with additional information may trigger biased beliefs, overconfidence in their green autopilot—namely moral licensing or a boomerang effect—ultimately reducing their likelihood of acting optimally anyway (Bonan et al., 2020; Schwartzstein, 2014). The second chapter *Nudging Toward Climate Adaptation. A Field Experiment on Informational Strategies in Organic Food Markets* provides empirical evidence that these mechanisms exist within organic consumers showing how information-based strategies can serve as effective market-based instruments to promote a form of consumption that goes beyond what us, as consumers—partly by trends, partly by generalised beliefs that associate sustainability with health benefits—and instead fosters a market for resilience-oriented products that directly contribute to agricultural adaptation to climate challenges. We document that providing simple and relatable additional information alongside an existing label—such as organic certification—highlighting the adaptive benefits of a product increases its purchase. However, for some consumers, informational frictions persist due to a moral licensing effect, preventing the full assimilation of the new information into their decision-making process. In line with the existing literature, the findings of this chapter recall that targeted policies are necessary to address heterogeneous consumer responses and ensure broader adoption of climate-resilient consumption choices.

So far, I have discussed cases in which information frictions arise either from a lack of information itself or from biased beliefs and cognitive gaps that hinder proper information acquisition, even when the information is available. But what happens when the information provided is inaccurate or misleading? Misinformation introduces a different kind of market failure, one in which consumers make distorted decisions not due to missing knowledge, but because they rely on inaccurate signals. This story is often connected in the literature to one key player: the media. Media outlets shape how information is framed, amplifying certain narratives while downplaying others, influencing public perception and consumer behavior.

The role of media has gained attention when exploring how individuals react or overreact to the perception of risk of random events such as natural hazards. Gallagher (2014) finds that media coverage of floods can influence insurance take-up even in areas that were not directly affected, simply because they share the same media market as flooded regions. This suggests that media-driven narratives can amplify perceived risk, affecting economic decisions regardless of actual exposure to the hazard. However, a related and much more extensive economic literature examines the effect of media coverage on voting behaviour and political outcomes (e.g., Allcott and Gentzkow (2017), Barnes and Hicks (2018), DellaVigna and Kaplan (2007), and Thaler (2024)). In the absence of clear regulations or guidelines, media outlets—driven by the need to rapidly respond to public demand for information—often simplify or distort details about natural disasters (Dessaint & Matray, 2017). One notable aspect of this simplification is the practice of naming extreme events, which has been widely studied in meteorology and climatology as a communication strategy. The central question in this literature is whether naming extreme events influences public perception and preparedness. However, findings are contradictory: while some studies suggest that naming increases hazard awareness and preparedness, others indicate little to no effect (Charlton-Perez et al., 2019; Kotroni et al., 2021; Lin et al., 2018; Morss et al., 2017; Rainear et al., 2017). More recently, the growing frequency of wildfires and heatwaves has sparked discussions on whether naming these environmental shocks could similarly shape public perception (Metzger et al., 2024). However, most of these studies do not account for the specific content of the names assigned, as they are often proper nouns, much like the well-documented cases of hurricanes and tropical storms[2]. When a disaster is given an inaccurate or misleading name, it can be associated with a broader region rather than the specific area affected. This misnaming can unfairly stigmatize places that were not directly impacted. While often overlooked in economic research, such mislabeling can have real consequences, including changes in tourism patterns, shifts in property values, and disruptions to local businesses due to misplaced fears. A parallel can be drawn with public health crises, such as the COVID-19 pandemic, where media-driven mislabeling—such as referring to the virus as the "Chinese virus"—led to stigmatization, xenophobic reactions, and economic consequences for specific regions (Tanaka et al., 2020). Similarly, misnaming environmental disasters can distort economic resilience and recovery efforts by unfairly discouraging investment and economic activity in unaffected but wrongly associated regions. Understanding the financial consequences of such misnaming is critical, as it highlights a subtle yet powerful channel through which media framing affects economic decision-making and long-term recovery. The third chapter of this dissertation, *The Adverse Impacts of Disasters-In-Name Only*, examines this phenomenon in the context of three earthquakes that occurred in Italy over the past 20 years. It shows that assigning an "inaccurate name" to an event leads to economic losses that compound the direct costs of the disaster itself, even in areas that were not affected. Specifically, we study the impact of a toponym that described a much larger region than was actually impacted by seismic activity. This inaccurate naming creates information frictions between the supply and demand for tourism, as potential visitors struggle to distinguish between affected and unaffected locations. Our findings provide insights

[2]Since 1953, the World Meteorological Organization has assigned these names from predefined alphabetical lists of male and female names.

into how inaccurate disaster toponyms can affect economic sectors that are highly sensitive to risk perception, such as tourism. While our analysis focuses on tourism, this mechanism could extend to other perception-dependent sectors, such as real estate, investment, and insurance. Moreover, we find empirical evidence that the effects of misnaming persist in people's memory, reinforcing the long-term economic consequences of misleading disaster labels.

Outline of the Dissertation

While distinct in their focus, the three chapters presented in this dissertation share a common methodological foundation in applied microeconometrics and causal inference. The empirical analyses combine counterfactual evaluation techniques with rich observational data, leveraging multiple sources of variation—including individual-level data, survey data, administrative records, and experimental interventions—to estimate the causal effects of policies, information, and perceptions on economic outcomes. By integrating foundations of environmental and behavioral economics, this work offers insights on how economic agents respond to external shocks.

Chapter 1: The Impact of Agri-Environmental Measures on Farms' Costs, Labour and Income

The first chapter *The Impact of Agri-Environmental Measures on Farms' Costs, Labour and Income*[3] analyzes the economic impact of Agri-Environmental Measures (AEMs) during the 2007–2013 programming period. Using a counterfactual approach, the study provides causal evidence on the extent to which AEM subsidies influence farm-level economic outcomes across the European Union. The analysis relies on Coarsened Exact Matching (CEM) combined with a Difference-in-Differences (DiD) estimator, which helps account for time-invariant unobserved differences between treated and control farms. Additional robustness checks include Propensity Score Matching (PSM) and Synthetic Difference-in-Differences (SDID), which allow for greater flexibility in modeling policy effects. Results indicate that AEMs lead to higher income and productivity, with treated farms experiencing a 14.7% increase in farm net income and a 9.2% rise in net value added per annual work unit (AWU) at the EU level. These effects are particularly pronounced in Southern and Eastern Europe, where income growth and productivity gains are strongest. Labour allocation also shifts significantly, with total labour input rising by 2.7% across the EU, driven primarily by unpaid family labour in Southern and Eastern Europe, where increases exceed 5%. In contrast, paid labour input increases only at the EU level and in Southern Europe, with a significant 8.2% rise in total wage expenditure (11.7% in Southern Europe, though only marginally significant). Western and Eastern Europe show no major changes,

[3] R&R at *European Review of Agricultural Economics*

while Northern Europe experiences no significant impact. On the cost side, AEM participation increases expenditures on key inputs, but regional heterogeneity emerges. Seed and seedling costs rise by 4.4% at the EU level, with the largest increase in Eastern Europe (+5.7%). Crop protection costs increase slightly at the EU level and in Western Europe, while fertilizer costs remain unchanged across all regions. In terms of livestock-related expenses, treated farms experience significant cost increases in veterinary services, feed for grazing livestock, and home-grown feed, particularly at the EU level and in Western Europe. However, no significant effects are found in Southern, Eastern, or Northern Europe. These findings highlight regional differences in how AEMs affect reinvestment strategies, labour dynamics, and production costs. While AEMs encourage sustainability-driven spending, their impact on economic outcomes varies, indicating that cost adjustments may be farm-specific rather than systematic.

Contributions

The main contribution of this chapter is to provide a large-scale empirical evaluation of the economic impact of Agri-Environmental Measures under CAP Pillar II, shifting the focus from environmental benefits to an extensive number of farm-level economic outcomes. While previous studies have examined the effects of AEMs on specific regions or farm types, this paper extends the analysis to a comprehensive EU-wide setting, using farm-level data and counterfactual methods to estimate causal effects. The study also contributes to the debate on AEM policy design, highlighting the potential implications of transitioning from action-based to results-based schemes. While AEMs are formally designed as compensatory payments, the results suggest they may influence production decisions, potentially affecting investment and labour dynamics. Our findings reinforce the argument put forward by Sckokai and Moro (2009) that farmers frequently reinvest both first and second pillar payments into their operations. Similarly, AEM payments, despite being intended as neutral compensatory measures, may still facilitate strategic investments that enhance farm productivity and profitability, potentially shifting the focus away from purely environmental objectives.

Limitations

The results of our analysis appear to be sensitive to sample size restrictions. To ensure a precise estimation of AEM effects, we include only farms that exclusively participated in AEMs and exclude those that also received other CAP Pillar II payments. While this approach isolates the impact of AEMs, it significantly reduces the number of observed farms, limiting the external validity of our findings. Future research could explore more flexible selection criteria to improve the representativeness of the sample while still addressing confounding effects. Another limitation concerns the absence of a cost-benefit analysis, which prevents us from determining whether AEM payments are proportionate to the additional costs incurred by farmers. While our findings suggest that participating farms experience income growth alongside higher costs and labour use, we do not formally assess whether subsidies fully compensate for these costs or lead to overcompensation. Without a direct comparison between AEM payments and actual economic burdens, it is not possible to conclude whether payments are strictly aligned with the "cost incurred or income foregone" principle or if they provide unintended financial gains to beneficiaries. Finally, our policy discussion does not account for the transaction costs associated with more targeted AEM payments. While we highlight the potential inefficiencies of flat-rate payments, shifting towards a more differentiated payment system—either at the regional or farm level—would likely entail administrative complexities and higher implementation costs. The feasibility of such an approach depends on the extent to which these additional costs would be offset by improved targeting efficiency, a consideration beyond the scope of this paper.

Chapter 2: Nudging Toward Climate Adaptation. A Field Experiment on Informational Strategies in Organic Food Markets

The second chapter *Nudging Toward Climate Adaptation. A Field Experiment on Informational Strategies in Organic Food Markets*[4], examines whether targeted informational interventions can shift consumer preferences toward climate-adaptive food products. The intervention highlights the climate-adaptive and drought-resistant properties of ancient wheat pasta, a product offering environmental benefits beyond standard organic certification but remaining less widely recognized by consumers. Using a randomized field experiment with online purchase data from an Italian organic food brand, the study investigates how different types of messaging affect purchasing decisions among consumers who already buy organic but may substitute a green product with a greener one.

The results show that a colloquial, easy-to-understand message increases the share of "greener" pasta purchased among treated consumers by 13%. The effect persist for at least three months without monetary incentives and it is particularly pronounced among those who previously bought ancient wheat pasta occasionally but preferred modern wheat varieties. In contrast, a scientific and more technical message has a significant impact only on highly environmentally aware consumers with higher educational attainment. A notable finding is the backfire effect among the greenest consumers—those who already had over 50% of their pasta purchases consisting of ancient wheat pasta. Rather than increasing their consumption, they reduce it, suggesting possible moral licensing or psychological resistance to additional pro-environmental pressure. The study also provides insights into how external climate events influence consumer responsiveness. By exploiting geographic variations in drought severity, it finds that consumers living in areas that experienced extreme droughts in 2022 were more likely to react positively to the colloquial message. This suggests that real-world exposure to climate risks can heighten

[4] Under review at *Journal of Environmental Economics and Management*

the salience of adaptation-related information, making consumers more receptive to nudges promoting climate-resilient choices. These findings underscore the potential for more transparent information on the agricultural background of food products to serve as a market-based tool for reducing information asymmetry.

Contributions

This chapter makes several key contributions to the literature on environmental economics, behavioral interventions, and climate adaptation.

First, it advances the research on nudging sustainable consumption by shifting the focus from mitigation to adaptation exploring how targeted information can stimulate demand for climate-resilient products—an essential but often overlooked aspect of sustainability. Second, it expands the literature on information frictions in green markets, showing that eco-labels frequently fail to communicate key differences in environmental benefits. Consumers struggle to distinguish between products with the same certification but varying levels of climate resilience, highlighting the limitations of current labeling systems in guiding adaptive consumption.
Third, this study sheds light on the heterogeneity of green consumer responses to information-based interventions. Not all environmentally conscious consumers react in the same way, raising an important policy question: What makes an informational strategy effective in driving demand for adaptive agricultural practices? The results highlight the need for a more nuanced approach to nudging policies, recognizing that consumer responses to adaptive consumption messages depend not only on their socio-demographic characteristics but also on how the information is framed and presented, which may lead to suboptimal information uptake.
A relatively novel insight in the literature emerging from this work is the role of lived climate experiences in shaping adaptive behavior. The findings suggest that linking consumer behavior to climate shocks offers a powerful avenue to enhance sustainability interventions, as individuals in affected areas appear more responsive to adaptation-focused messages. This opens new perspectives on how localized environmental experiences can serve as a lever for improving the effectiveness of sustainability policies.

Limitations

One limitation of our study is that consumers may perceive climate adaptation as primarily a concern for Alce Nero itself, rather than a collective issue. While our intervention aimed to highlight the benefits of drought-resistant wheat, consumers might view the responsibility for adaptation as falling on agricultural producers rather than themselves. This could reduce the motivational appeal of the message, as adaptation may not directly trigger the same pro-social or environmental engagement mechanisms that typically drive sustainable consumption choices. Additionally, the social spillover effects of adaptation may not be immediately clear to

consumers—saving water in agriculture, for instance, might not be perceived as a benefit that extends to broader societal use. As a result, some individuals may fail to connect their purchasing decisions with larger environmental or food security concerns.
Furthermore, the study was conducted in a specific online organic food market in Italy, which may limit external validity—consumer responses could differ in other retail environments, such as supermarkets, where decision-making is influenced by a wider range of stimuli.

Chapter 3: The Adverse Impacts of Disasters-In-Name Only

The third chapter, *The Adverse Impacts of Disasters-In-Name Only*, explores the economic losses caused by a decline in tourism following an earthquake, particularly in regions unaffected but wrongly associated with the disaster due to inaccurate naming. This overlooked consequence is analyzed through the lens of how media and disaster communication shape perceptions of geographic locations. This work provides empirical evidence that when a natural disaster is labeled with a toponym that encompasses a wider area than the one actually affected, it can trigger significant and lasting economic losses in undamaged regions. Our study focuses on the tourism sector in Italy, analyzing three major earthquakes between 2009 and 2017: the L'Aquila earthquake (2009), the Central Italy earthquake (2016), and the Ischia earthquake (2017). While the actual damage was limited to specific municipalities, the "Central Italy" label, first used by the media and later adopted by official institutions, included a much larger area, encompassing popular but untouched tourist destinations. The results show that in municipalities covered by the toponym but unaffected by the earthquake, tourist arrivals dropped by 12.5% in 2017 and continued to decline in 2018.
To assess whether distance from the disaster zone influenced this effect, we categorize municipalities based on their proximity to the earthquake crater. The findings reveal that tourism declined even in municipalities 41–50 km from the epicenter, confirming that it was the broad toponym—rather than the physical event itself—that deterred visitors. Additionally, we investigate whether tourists' country of origin played a role in their response to the disaster name. The results suggest that international tourists were particularly affected, likely due to their reliance on foreign media, which often provides less detailed geographic information about Italy. International tourist arrivals fell significantly in both 2017 and 2018, while the effect for Italian tourists was strongest in 2017 but diminished over time. Attempts by Italian institutions to introduce a more precise designation—"Amatrice-Visso-Norcia Seismic Sequence"—failed to gain traction, as both media and government reports continued to use the original misleading name. Google search data further confirm that public awareness remained tied to the initial toponym, reinforcing the misperception over time.
Ischia presents a unique case, as the island provides a natural boundary for assessing whether a broad disaster toponym impacts tourism in undamaged areas. As with the Central Italy earthquake, media reports referred to the event as the "Ischia earthquake", despite the damage being

highly localized to a single municipality, Casamicciola Terme. The results show a significant decline in tourist arrivals in undamaged municipalities—approximately 11.5% in 2017—with the effect persisting into 2018. Interestingly, in this case, the media impact appears stronger for domestic tourists, likely because the earthquake received limited international coverage compared to the Central Italy earthquake. By contrast, when the disaster name accurately reflected the affected area, as in the case of the L'Aquila earthquake (2009), the economic impact remained largely confined to the directly damaged locations. The precise geographic designation of the event did not discourage tourist arrivals in nearby unaffected areas, ensuring that the economic repercussions remained proportional to the actual damage.
These findings underscore the importance of accurate disaster naming to avoid unnecessary economic losses.

Contributions

This study contributes to several strands of economic literature by highlighting the role of misnaming extreme natural events in shaping economic outcomes.

First, it expands the literature on belief updating and misperception by showing how the inaccurate naming of disasters can create localized information asymmetries. Specifically, while residents of the affected areas may have accurate knowledge of the actual impact, the broader population—including potential tourists and investors—develops distorted perceptions due to misleading toponyms. This misalignment of beliefs leads to economic stigmatization, where regions wrongly associated with disasters suffer unnecessary economic losses despite experiencing no physical damage.
Second, it contributes to the literature on the economic costs of misinformation in the aftermath of crisis events, particularly in relation to media coverage. While existing research has extensively explored the role of misinformation in shaping political outcomes—such as the spread of fake news—this study shows how misreporting and inaccurate labels can have long-term economic consequences by affecting risk perceptions and market behavior. By doing so, it links misinformation in disaster contexts to broader discussions on the economic repercussions of inaccurate information dissemination.
Third, it extends research on the direct and indirect costs of environmental disasters, identifying additional economic consequences beyond the commonly studied physical destruction and disruption of local economies. By focusing on the role of risk perception, it suggests that economic damage is not only driven by actual destruction but also by the way information about disasters is framed and communicated. Misleading toponyms can trigger avoidance behaviors, deterring economic activity in areas that remain physically unaffected but suffer from negative reputation.
Beyond these theoretical contributions, this study also has significant policy implications. The findings highlight the need for clearer and more precise disaster naming conventions to avoid unnecessary economic harm.

The misattribution of disasters not only hinders the recovery of affected areas that could benefit from the stability of nearby unaffected economies but also disrupts tourism and investment in regions wrongly associated with the catastrophe. Moreover, it underscores the importance of integrating media accuracy and risk communication strategies into disaster preparedness and recovery policies. If misleading toponyms distort public perceptions of risk, they may also affect long-term resilient strategies and governmental responses to future disasters. Ultimately, this research calls for greater attention to the "economics of naming"—words matter and bring costly consequences by shaping long-term economic decisions and market behavior.

Limitations

This study needs to be interpreted in light of its limitations. The primary constraint is the lack of municipal data, particularly in assessing the precise spatial extent of disaster toponyms. Since tourism data on arrivals and overnight stays for Italian municipalities are only available from 2014 onward and are not consistently recorded for all municipalities, we cannot capture a more granular toponym effect, especially for the L'Aquila earthquake, which in turn may have functioned as a toponym itself, extending beyond the city. Similarly, the toponym assigned to the "Emilia earthquake" in 2012 is also inaccurate, as it outlines a broad area within Emilia-Romagna while excluding other affected municipalities in neighboring regions. However, the lack of municipal data for 2012 and 2013 prevents us from including this case in our analysis.

Another limitation concerns the immediate emergency response following the L'Aquila and Central Italy earthquakes. In both cases (albeit to different extents), the Civil Protection Department and local authorities implemented large-scale assistance measures, including the relocation of displaced residents to hotels—typically cater to tourists, along the Abruzzo coast and in other Italian regions. These accommodations were occupied for extended periods until temporary housing solutions were completed. Unfortunately, no detailed data are available to differentiate between displaced residents and tourists, making it impossible to determine whether the decline in tourism observed in certain areas was driven by the toponym effect or by the temporary unavailability of many hospitality facilities due to their use as emergency housing.

A further concern relates to the external validity of our findings. While our study establishes a link between disaster toponyms and economic losses in Italy, it remains unexplored whether similar effects can occur in other countries or for different types of disasters. The broader influence of naming on economic consequences would require cross-country and cross-disaster comparisons, as public perceptions of earthquake frequency, reconstruction timelines, and institutional responses can vary significantly across contexts. Without such comparative analysis, our conclusions remain specific to the Italian context.

Finally, while we attribute the observed decline in tourism to the toponym effect, further research is needed to disentangle it from other potential spillover effects. For instance, official granular seismic maps indicating the vulnerability of each municipality relative to risk zones are publicly available, highlighting the need for further analysis of whether declines in tourist flows were driven solely by misnaming or by broader concerns about earthquake vulnerability.

Chapter 1

The Impact of Agri-Environmental Measures on Farms' Costs, Labour and Income

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Abstract

This study examines the effects of Agri-Environmental Measures on crop and livestock costs, labour inputs, and income growth using FADN farm-level data for the years 2006 and 2013, covering the 2007–2013 programming period in 22 EU countries. Employing a Difference-in-Differences Coarsened Exact Matching model, it finds that while some specific production costs rise on subsidized farms, these increases differ by region. Income growth and labour inputs are consistently higher across all regions. Notably, crop protection costs increase significantly in Western countries, while labour inputs rise in Southern and Eastern countries and at the EU level. Positive and significant effects on productivity outcomes are observed in the EU and Western EU countries.

Keywords: Agri-Environmental Measures, Common Agricultural Policy, Difference-in-Differences, Coarsened Exact Matching

JEL: Q18, Q15, C21

1.1 Introduction

This study aims to address a significant gap in the literature by empirically analyzing the economic impacts of Agri-Environmental Measures (AEMs) under Pillar 2 of the Common Agricultural Policy (CAP) during the 2007-2013 programming period in 22 EU countries.

These measures are designed to promote the conservation of high-nature-value farmland, biodiversity, and agroecosystems by compensating farmers for additional costs or income losses associated with their commitment to AEM requirements. Understanding these economic outcomes is crucial for farmers deciding whether to enroll in these programs. Because empirical studies show that the ecological and economic performance of AEMs varies markedly with local biophysical, institutional, and socio-economic conditions, often producing only "patchy success" across Europe (Uthes & Matzdorf, 2013), continuous evaluation of CAP subsidies is essential to prevent bottlenecks in subsequent programming periods, to redirect funds that generate the greatest environmental additionality, and to embed adaptive learning into policy cycles. These adjustments are more urgent than ever as intensive agricultural practices frequently lead to environmental degradation, including soil erosion, water scarcity, pollution, and the depletion of wildlife habitats. Simultaneously, agriculture is among the sectors most susceptible to the physical risks posed by climate change and extreme weather events, as temperature and precipitation are crucial factors in crop production (Deschênes & Greenstone, 2007). In this perspective, AEMs have a dual purpose: supporting rural development and addressing the increasing demand for environmental services. From a regulatory standpoint, the AEMs are structured so they can be reported to the World Trade Organization as part of Green-Box supports to keep these payments outside the Amber-Box limits. Indeed, Green-Box criteria require that supports (i) do not distort production or prices, (ii) are part of a clearly defined environmental programme, and (iii) are calculated to cover the additional costs incurred and income foregone (Matthews, 2021). Accordingly, Member States are required to include the AEMs in their Rural Development Programmes. Farmers and land managers voluntarily commit to these measures for a minimum of five years, during which they receive annual fixed payments per hectare as compensation for adopting increased environmental practices that exceed basic cross-compliance and mandatory standards[1]. Eligibility for payments under these policies is contingent upon participation in a clearly defined environmental and conservation program.[2].

During the 2007–2013 programming period, Member States (MS) were further required to allocate at least 25% of their Pillar 2 funding to land management and AEMs, reinforcing their role in fostering sustainable agricultural practices while adhering to international trade and environmental commitments. Although widely implemented, the cost-effectiveness of Agri-Environmental

[1]The regulation specifies the maximum payment rates for different land types under AEMs, with payment levels determined by RDPs. While these rates are typically capped, exceeding the ceiling is permissible if properly justified.

[2]These program requirements may include adherence to specific production methods or input use.

Measures is increasingly questioned (Hasler et al., 2022). AEM payments may lack efficiency if they do not adequately compensate farmers for the environmental goods and services they provide through compliance with policy objectives. Alternatively, AEM payments are also inefficient if they target farmers who would achieve the policy goals even without participating in the program, leading to adverse selection and poor policy additionality. These issues are particularly significant in action-based policy designs, where farmers receive payments for adopting specified environmental practices rather than for measurable outcomes (Canessa et al., 2023). To address these issues, results-based AEMs have been proposed as an alternative approach. In results-based schemes, farmers are compensated based on demonstrated ecological improvements (Wuepper & Huber, 2022). By focusing on actual outcomes, these schemes can enhance both environmental impact and cost-efficiency, as they encourage farmers to tailor their land management practices to local ecological conditions that promote biodiversity. This approach is considered more effective than action-based payments because it fosters meaningful environmental improvements and incentivizes farmers to enroll land most likely to achieve these outcomes. Results-based schemes operate on the assumption that achieving additionality requires proper incentives; payments should encourage changes in farming practices that would not occur otherwise. Conversely, action-based payments may lead farmers to focus on areas that already meet, or nearly meet, policy requirements (Bartkowski et al., 2019; Canessa et al., 2023). Despite their advantages, implementing results-based schemes carries certain risks for farmers, such as higher transaction costs or dependence on external factors (e.g., adverse weather conditions), and they involve costly monitoring systems. In contrast, action-based instruments are easier to implement, less costly to monitor, and generally more widely accepted since they often require less drastic changes in farming practices. Payments are standardized for all participants and are not dependent on external risks. A potential solution that combines elements of both systems is a hybrid compensation scheme, which includes a base payment for participation and an additional top-up payment based on achieving the desired outcome ((Burton & Schwarz, 2013)).[3]

We exploit a large-scale sample to assess AEMs' impacts on several economic outcomes of productivity, labour, income and crops and livestock costs with the main purpose of providing a clearer view of the indirect effects of this policy. This study serves as an impact assessment, highlighting opportunities for optimizing policy design through effective resource allocation and tailored implementation strategies.

Using farm-level data from the Farm Accountancy Data Network (FADN) database, covering 22 EU countries, we can observe how the effects of subsidies on different outcomes are distributed geographically across specific country groups. This categorization allows us to understand how

[3] Despite the topic's relevance, a deeper investigation of the pros and cons of different payment schemes is out of the scope of this article. An in-depth treatment of this topic can be found for instance in Burton and Schwarz (2013), Canessa et al. (2023), and Wuepper and Huber (2022).

farmers in particular regions have utilized subsidies, whether to promote labour-intensive sustainable practices, offset higher input costs, or achieve income growth compared to their pre-subsidy levels.

In evaluating the economic impact of policy measures, such as (voluntary) CAP Pillar 2 instruments, inherent difficulties arise due to well-documented potential shortcomings, as highlighted by Canton et al. (2009), Chabé-Ferret (2014), and Chabé-Ferret (2015).

Our analysis faces two main challenges that emerge due to the structure of the policy. First, under the current CAP regulation, AEM eligibility is tied to clearly defined environmental commitments, and the payments are set to cover additional costs incurred or income foregone. In practice, however, a single regional rate is applied, so farms with very different opportunity costs receive the same compensation, leading to over- or under-payment (Uthes & Matzdorf, 2013). Secondly, it is unlikely that farmers following pure maximizing profit behaviour would switch to a different production system if they do not receive any (extra) economic incentive (Mennig & Sauer, 2020). Indeed, voluntary AEM application can introduce adverse selection, as farmers who already meet environmental standards may be more inclined to participate, potentially resulting in limited additional impact, as noted by Arata and Sckokai, 2016 and Chabé-Ferret and Subervie, 2013. However, not all applicants necessarily meet these standards initially. If only compliant farmers applied, any income increase would merely reflect the AEM payment amount. Although this is not directly tested here, Chabé-Ferret and Subervie, 2013 suggest that the extent of additionality varies by program rigor: stricter programs, like organic subsidies, generally show higher impact and less windfall effect, while less stringent ones may attract already-compliant participants.

Our paper overcomes these two challenges using a counterfactual method based on a Difference-in-Differences (DID) with the Coarsened Exact Matching estimator (hereafter CEM) to avoid upward bias and accurately estimate policy impacts (Iacus et al., 2012). Our focus on economic outcomes may be considered of particular interest, as the participation in AEMs is tied to management restrictions for at least five years[4]. Therefore, recipient farmers are not allowed to freely adapt to changing market or production conditions (Garrone et al., 2019). As a result, these economic indicators of farms' performance, represent crucial elements for farmers when deciding to apply for AEMs (Lastra-Bravo et al., 2015). Moreover, this work focuses much attention on the methodological strategy of matching using CEM and counterfactual analysis to isolate the causal impact of the subsidies on several farm economic aspects and to avoid selection bias that distinguishes the structure of the policy.

Although primarily designed to promote sustainable farming practices, agri-environmental policies also have substantial economic impacts on farms, influencing areas such as labour demand, income distribution, and agricultural productivity. In the labour market, for example, we expect

[4]Farmers are obliged to comply with the standard sustainable requirement of measure and they cannot leave the program before five years.

that agri-environmental policies may increase the demand for skilled labour related to sustainable practices, such as integrated resource management, soil conservation, and biodiversity protection. Farms adopting these practices might require additional labour or specialized technical expertise, particularly for operations that involve non-traditional skills, such as organic farming or reducing the use of chemical inputs.

In terms of income distribution, these policies could lead to both positive and negative effects. On one hand, farms receiving subsidies might experience increased revenues, which could raise income levels in rural areas. On the other hand, the uniformity of payments, without adjusting for differences in farm size, productivity, or local conditions, could exacerbate income inequality. Larger, more efficient farms may benefit disproportionately from these subsidies, while smaller farms might struggle to cover the costs of compliance, leading to unequal financial outcomes within the agricultural sector. Regarding agricultural productivity, we expect that the adoption of environmentally friendly practices could initially reduce output in the short term, as farmers adjust their production methods to meet policy requirements. For instance, reducing chemical inputs might result in lower yields at first. However, in the long term, these practices could lead to more resilient farming systems that enhance productivity by improving soil health, water retention, and ecosystem services, which are vital for sustainable agricultural growth.

Thus, agri-environmental policies, while focused on environmental outcomes, are also likely to reshape these key economic areas, creating both opportunities and challenges. A deeper understanding of how these policies impact costs, labour, income, and productivity is crucial for enhancing their design and ensuring they achieve their intended environmental goals without unintended economic consequences.

In line with Mennig and Sauer, 2020 and Dudu and Smeets Kristkova, 2017, our findings suggest that payments are not only covering the extra costs for production and labour inputs but are also providing higher income returns and productivity for receiving farmers. Potential overcompensation revolves around the idea that farmers, driven by the goal of maximizing profits, would implement more sustainable agricultural practices if it proves to be economically advantageous for them. However, a potential issue arises when subsidies are distributed uniformly per hectare without considering the inherent variability among farms. Indeed, if the subsidy criteria fail to consider variations in agricultural setups, soil conditions, or other location-specific factors, it can result in either excessive or insufficient compensation for certain farmers, favouring some over others due to their distinct circumstances.

The scale of our analysis provides a broad overview of the impact of AEM on an extended set of economic indicators influencing farmers' decisions to move towards more sustainable production fronts. It allows us to compare the effect of the policy on specific groups of countries, facilitating the identification of both common trends and significant differences among regions.

The remainder of the paper is organized as follows: Section 1.2 provides a review of previous studies on the direct and indirect impacts of AEMs on farmers by highlighting still uncovered gaps in the literature. Section 1.3 describes the data and variables used in the analysis. Section 1.4 explains the applied methodology. Section 1.5 discusses the main findings related to the specified outcomes. In Section 1.6 we test the robustness of our results, replicating the analysis using the Propensity Score Matching and the Synthetic Difference-in-Differences to corroborate our results. Section 1.7 discusses the implications of our findings and draws some conclusions.

1.2 Previous Studies

The adoption of Agri-Environmental Measures varies widely across countries, with some exhibiting high enrollment rates while others lag significantly (Matthews, 2013). In 2009, AEMs encompassed approximately 20.9% of the agricultural area within the EU-27. By 2013, the area under agri-environmental commitments had expanded to 47 million hectares, representing 26% of the total utilized agricultural area (Arata & Sckokai, 2016). Regional studies highlight the spatial heterogeneity of AEM expenditures across EU countries, showing that political institutions, farmers' political influence, and financial limitations are the main factors affecting participation levels (Bertoni & Olper, 2008). Interestingly, negative externalities have a minor impact on AEM payments; for example, areas with more intensive agriculture and environmental pollution tend to receive lower agro-environmental spending (Baylis et al., 2006). Other studies focusing on the factors influencing farmers' participation in AEMs emphasize the importance of farm-specific characteristics. Motivating factors for participation include prior experience, the accessibility of sustainable practices, and fair cost reimbursement (see, for instance, (Davies & Hodge, 2006; Defrancesco et al., 2008)).

The political reputation of the Common Agricultural Policy has attracted considerable criticism, particularly regarding its centralized nature and its perceived shortcomings in addressing environmental issues. Scepticisms persist around the ability of AEM expenditures to deliver both environmental benefits and economic improvements that are crucial for sustainable and economically stable rural development (Ait Sidhoum, Canessa, & Sauer, 2023; Hasler et al., 2022). Despite substantial financial investments by the EU to promote sustainable farming, research on the overarching economic impacts of participation in AEMs remains limited. Moreover, studies investigating these effects at both the EU and country levels are notably scarce and often yield conflicting findings. The literature examining the influence of CAP Pillar II payments on farms' socio-economic outcomes exhibits, on one hand, a lack of consensus regarding the structure of production functions, estimation methods, and parameterization. On the other hand, it reveals a range of mixed results by farm type, crop focus, region, timing of studies, and the level of aggregation.

Previous studies mostly focus on AEMs' role in enhancing greener farming practices (i.e. crop diversity, lower cattle livestock densities, lower purchasing of farm chemicals) (Bertoni et al., 2020; Chabé-Ferret & Subervie, 2013; Pufahl & Weiss, 2009). Other studies investigating the impact of AEMs on a range of environmental factors, including greenhouse gas emissions (Peerlings & Polman, 2008), the effects of fertilizers on soil quality (Marconi et al., 2015; Richards et al., 2015), water quality, and biodiversity (Jones et al., 2017). The limited environmental impact resulting from the policy uptake suggests a reduced effort exerted by recipient farms toward environmental contributions, coupled with the high adoption level among already green farms (Ait Sidhoum, Mennig, & Sauer, 2023; Chabé-Ferret, 2015). This spurs the need to further explore mechanisms that may disproportionately compensate farmers for minimal environmental effort. As suggested by Arata and Sckokai, 2016, the impact of AEMs in promoting more eco-friendly practices is higher when the share of agri-environmental payments on farm income is sufficiently large. This prompts a discourse on the role of AEMs' subsidies on farms' income as potential returns in terms of environmentally sustainable practices. Therefore, tailoring the implementation of AEMs based on the income composition of different farms can enhance the overall effectiveness of these environmental conservation initiatives. Recent findings show that the average change in eco-efficiency scores, which measure the ratio of farm income to pesticide, fertilizer, and energy usage, shows little variation between participants and non-participants in AEMs, casting doubts on the effectiveness of current implementations (Ait Sidhoum, Canessa, & Sauer, 2023; Baráth et al., 2024).

The literature lacks a comprehensive analysis of the subsidies' impact on various economic outcomes to underscore the need for AEMs to be more attractive to land managers, especially in productive agricultural regions where the payments were lower compared to those in protected areas, as highlighted in the case study of Germany (Früh-Müller et al., 2019). The role of labour in the agricultural sector is often overlooked in climate discourse, yet it is crucial for achieving a more equitable distribution of direct payments for sustainable farming practices. Emphasizing the socio-economic dimensions of agriculture is essential not only for achieving environmental goals but also for driving economic and social sustainability by transitioning agricultural labour towards greener standards. The disbursement of CAP Pillar II payments typically fosters job creation, extending beyond traditional farming sectors such as tourism, food processing, and related industries. However, the actual impact on employment largely depends on how Member States and regions implement these policies. When the allocation of resources from Pillar II is strategically focused and integrated, such as linking training with grant support, the employment effects can be significant. Conversely, when these resources are thinly spread, the impacts tend to be minimal and can be overshadowed by market dynamics and other external factors (Runge et al., 2022). Despite the crucial role that Agri-Environmental Measures might have on labour input allocation and income returns, only a limited number of studies have empirically measured these effects. Pufahl and Weiss, 2009 note that AEMs programs generally did not have significant effects on off-farm labour. On-farm labour increased only moderately, indicating that while there might be some shift, it is not very pronounced. Petrick and Zier, 2011 find a small positive effect of agri-environmental subsidies on farm labour use as they keep labour-intensive technologies in production or induce them. Dupraz and Latruffe, 2015 show similar results, where AEMs positively impacted external farm labour such as hired and contract labour when they targeted farm conversion or the maintenance of organic farming. It remains unclear whether rural employment has a role in shaping sustainable farming practices in more recent programming periods after receiving the AEMs subsidies.

Concerning income returns, Arata and Sckokai, 2016 show that the impact of adopting Agri-Environmental Measures on farmers' earnings is influenced by both the amount of payments and the costs associated with compliance. In regions where compliance costs are minimal, a modest payment may be sufficient to offset income losses. Conversely, in areas with higher compliance expenses, a higher payment level would be necessary. Thus, only a few papers assess the effect of CAP Pillar-II measures on a broad range of production costs, and they inspect especially fertilizers expenditures and crop protection (see (Arata & Sckokai, 2016; Pufahl & Weiss, 2009), among the few exceptions). According to Matthews, 2013, while in specific landscapes the AEM is a promising instrument for enhancing sustainable agricultural practices, more efforts are needed to attract intensive farmers and those in intensively farmed regions to participate. A major issue facing policymakers is the lack of conclusive evidence of the impact of CAP support on the wider rural economy and farm productivity (Dudu & Smeets Kristkova, 2017). Although Agri-Environmental Measures generally negatively impact productivity as they impose constraints on input use (such as fertilizers, pesticides, and land), some studies report farmers' increase in labour productivity and income revenues. Dudu and Smeets Kristkova (2017) and Arata and Sckokai (2016) report heterogeneous effects of AEMs' participation on farmers' income, considering different EU countries, and in particular negative effects for Spain and positive effects for Germany. Cristina and Dario (2018) and Schroeder et al. (2015) find non-significant or modest effects on income. Blazy et al. (2015) and Udagawa et al. (2014), considering French and English farms, find a negative effect of receiving AEM subsidies on income.

From a methodological perspective, the use of a counterfactual method combined with a matching estimator is a valuable method to isolate the causal effect of receiving subsidies and overcome possible self-selection bias ((Michalek et al., 2012)). The most frequent matching estimator employed to analyze the effects of agricultural policy measures on farms' performances, is propensity score matching (PSM) ((Chabé-Ferret & Subervie, 2013; Pufahl & Weiss, 2009; Udagawa et al., 2014)). A recent study by Bertoni et al., 2020 utilizes a CEM matching estimator to evaluate the environmental effects of farms participating in Agri-Environmental Measures from 2007 to 2013, offering a comparative analysis with PSM and revealing significant variations in the magnitude of estimated treatment effects. A key takeaway from the literature on AEMs' impact on farm production choices and performance, is the crucial role of the empirical strategy in delivering stable results due to the complexity and variability of agricultural systems.

1.3 Data

The FADN database includes yearly data encompassing farm-specific technical attributes and economic outcomes from each Member State. These farms represent the broader EU farm population, specifically, those exceeding a designated economic threshold, often referred to as commercial farms[5]. Although this threshold varies among MSs, the overarching criterion is to include farms generating an income adequate to sustain the farmers' households. To ensure the sample's representativeness, the EU commercial farm population is categorized based on region, specialization type, and economic size. Farmers within the FADN sample are then selected from each stratum. Our farm-level data encompasses 22 EU countries for the years 2006 and 2013, strategically selected to thoroughly represent the 2007-2013 programming period.

The DID-matching procedure is particularly demanding in terms of sample size because both farms participating in the policy and those used as control groups have to be observed before and after the implementation of the program. The FADN database is organized as a rotating panel, which does not ensure continuity in the observations over long periods. To balance these needs, we focus on two data points: 2006 (the final year of the 2000–2006 programming period) and 2013 (the final year of the 2007–2013 period). We then restrict our analysis to the subset of farms present in both years.[6] We selected 2013 as our treatment year because AEM payments are multi-year commitments whose effects build up as contracts mature. By focusing on the final year of the 2007–2013 programming period, we capture the full, cumulative impact of participation, reflecting the long-term benefits of these measures. Moreover, 2013 has the largest number of beneficiary farms in our sample, which maximizes statistical power and enhances the robustness of our analysis.[7]

The constraints imposed by our estimation strategy led to the exclusion of six EU countries, which therefore are not considered in the analysis. Specifically, Bulgaria, Romania and Croatia are excluded because, due to their entry into the EU in 2007, they do not present data for the year 2006, a requirement that is essential for our DID estimates. Finland, Denmark, and Luxembourg are also excluded as they do not present available data that fits the requirements imposed by our empirical strategy. Due to the difficulty of working with a representative sample at the country level or, even more challenging, at the programming level (e.g., NUTS 2), the data have been aggregated at two different territorial levels: the whole EU level and the country-groups level.

[5] Our sample of participating farms pertains solely to this FADN subset (3 million commercial farms), which is stratified to be representative of commercial farms at EU level, by Member State, by NUTS 2 region, by economic-size class, and by type of farming. Farms below each Member State's minimum economic-size threshold are not included within the FADN.

[6] To avoid confounding from the use of 2006, which may not fully exclude continued AEM participation into the next period, we use model specifications ensuring control farms do not receive AEM subsidies during 2007-2013. We also account for prior subsidy receipts in our CEM matching. This is fully addressed in Section 1.5.

[7] While AEM commitments are generally five years long, we acknowledge the possibility of "carry-over" effects, where payments initiated during the 2000-2006 programming period may extend into the 2007-2013 period. However, given the structure of our dataset and our focus on 2013 outcomes, any such effects are unlikely to significantly influence our results, as they are expected to taper off by the end of the commitment period.

The country groups are as follows: Northern Europe (Sweden, Lithuania, Latvia, and Estonia); Western Europe (Ireland, UK, France, Belgium, Netherlands, Germany, and Austria); Central and Eastern Europe (Czech Republic, Slovakia, Slovenia, Hungary, and Poland); and Southern Europe (Portugal, Spain, Italy, Greece, Cyprus, and Malta).

Table 1.1 shows descriptive statistics of farms' compliance with the AEMs available in our dataset after applying sample restrictions and the average AEM payments per hectare in 2013.

Table 1.1: Descriptive statistics of AEM-payments recipience

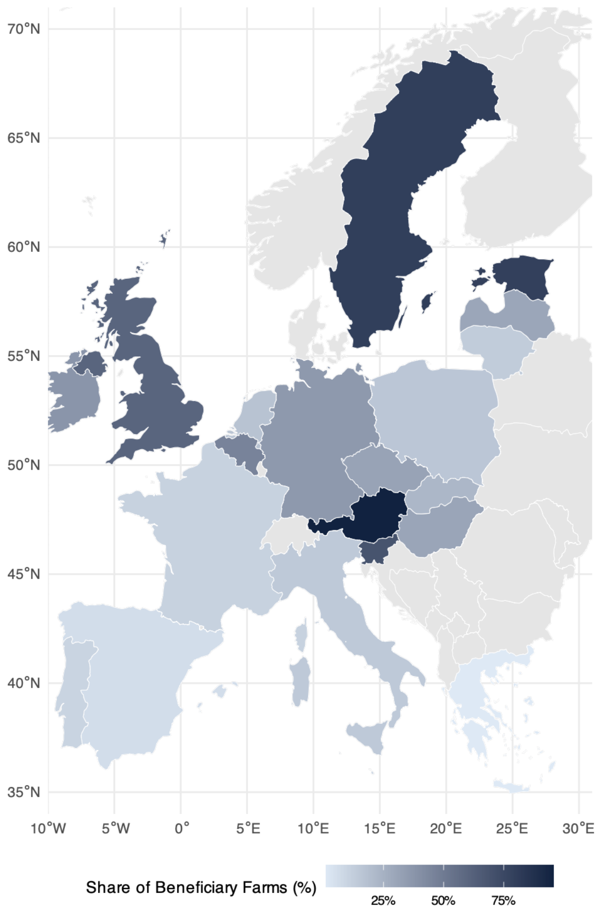
Country-groups	Country	Beneficiaries (1)	Non-Beneficiaries (2)	Average AEM payment per ha UAA [€ /ha] (3)
Western	AUT	452	20	226.55
	BEL	209	245	64.75
	DEU	962	1700	87.41
	FRA	252	2046	149.74
	GBR	590	384	59.35
	IRE	69	113	114.57
	NED	137	651	136.38
Southern	CYP	23	36	275.12
	ESP	220	3374	108.20
	ITA	420	2418	225.03
	GRC	15	1444	259.92
	MLT	5	41	285.88
	PRT	43	387	208.53
Northern	EST	92	24	61.06
	LTU	19	121	19.72
	LVA	47	109	57.38
	SWE	241	60	124.16
Eastern	CZE	80	174	81.64
	HUN	292	657	231.73
	POL	303	1613	98.72
	SVK	23	78	140.22
	SVN	27	12	197.99
Total EU		4521	15707	137.17

Notes: Numbers include individual farms in our sample. Column (3) includes the average payment per ha in 2013 indicating the "level" of adoption corresponding to our sample (total payment/total UAA)

Among the 22 countries, the highest proportion of farms receiving AEM payments in the FADN sample was observed in Austria, Sweden and Estonia (96%, 80%, 79%, respectively), the lowest proportion in Greece, Spain, Portugal (1%, 6% and 10%, respectively). As FADN reports only the total amount of money transferred, but not the area committed, the payments received are divided by the total UAA per farm. On average, farms participating in AEMs received 137.17 € /ha payments. The lowest values can be found in Northern countries especially Lithuania, Latvia and Estonia (19.72, 57.38 and 61.06 € /ha, respectively). In Western countries, the lowest value is received by English farmers (59.35 € /ha). The highest values are observed in Malta, Cyprus and Greece (285.88, 275.12 and 259.92 € /ha, respectively). The total share of beneficiary farms in the whole EU is 22% of the total sample.

The heterogeneity of the policy take-up can be better visualized in Figure 1.1. The map shows the share of beneficiary farms on the total number of farms (beneficiary and non-beneficiary) at the country level in our sample.

FIGURE 1.1: Share of farmers receiving AEM payments across EU countries



Source: based on FADN 2013; six countries (Bulgaria, Romania, Croatia joined in 2007 and lack 2006 baseline data; Finland, Denmark, Luxembourg missing key variables) omitted.

The map illustrates the heterogeneous pattern of compliance rates versus average payments across country groups. Despite having a substantial share of beneficiary farms (almost 34% over the total farms), Western European countries have a relatively lower average payment per hectare compared to other regions (€ 119.82). Southern European countries receive the highest average payment per hectare among all regions (€ 227.11) however, they have the smallest share of beneficiary farms (9%). On the contrary, Northern European countries receive the lowest average payment per hectare (€ 65.58), despite having the largest share of beneficiary farms (56%). Eastern European countries receive a moderately high average payment per hectare (€ 150) and a moderately low share of participation (22%)

1.3.1 Definition of the participation variable

Our treatment variable is a dummy variable that takes the value of one if a farmer receives only the AEM subsidies[8] in 2013 and zero if it does not receive any payments at all from the CAP Pillar-II measure in that year.[9] According to the regulation on Agri-environmental commitments should last between 5 and 7 years. In our sample, 2013 is the year with the highest number of active beneficiaries, so we assume that most participants were still under contract at that point and that 2013 best captures the end-of-cycle "peak" of policy exposure. We retain as treated farms those receiving only AEM subsidies, while farms in the control group do not receive any subsidy at all from any measure of the RDP in that year (e.g. investments measure, LFA, AEM). Our restriction rule, even if it forces us to cut a high number of observations, allows retaining a reliable result on the causal effect of AEMs on our outcomes, by avoiding other potential confounding impacts which could instead affect the results if the same farms participate also to other rural development measures.

1.3.2 Definition of the outcome variables

The outcome variables are calculated as the percentage difference between the logarithm of the outcome variable after the treatment (2013) and the logarithm of the outcome variable in the pre-treatment (2006)[10]. Our outcome variables of interest capture four key economic dimensions, each shedding light on distinct aspects of farm performance.

The Crops and Livestock Costs represent the input expenses farms incur for crop production and livestock maintenance. These costs, which often rise to meet the commitments of Agri-Environmental Measures, act as indicators of cost fluctuations driven by subsidy implementation. Specifically, we consider the following components: costs for seeds and seedlings (€)[11], fertilizers (€)[12], crop protection (€), and other crop-specific costs (€)[13]. For livestock, we assess specific

[8]The variable used to define our treatment, (SE621), representing environmental subsidies, is composed of three components. Agri-environment and animal welfare payments, organic farming subsidies and Natura 2000 payments excluding forestry. However, checking on our sample, neither treated, nor control units have ever received payments regarding organic farming specifically. Thus, the sum of our Agri-Environmental payments includes, in our specific case, the sum of Agri-environment and animal welfare payments (the most prominent part of payments) and Natura 2000. In our estimates, we account for the presence of organic farms within both the treated and control groups, as their inclusion could potentially bias the results (see Section 1.5).

[9]In Section 1.5 we account for control units that received subsidies during the years between 2007 and 2012.

[10]The growth rates, representing the logarithmic differences, quantify the compound percentage change within the two data points. We excluded outliers outside the 1st and 99th percentiles. All monetary outcomes are expressed in nominal terms (in Section .1 are reported the same calculations in real values).

[11]Relating to agricultural and horticultural crops.

[12]Including purchased fertilizers and soil improvers.

[13]This category includes costs for soil analysis, purchasing standing crops, and the storage and marketing of crops.

livestock costs (€)[14], feed for grazing livestock (€), feed for pigs and poultry (€), and other livestock-specific costs (€)[15].

Labour Outcomes provide insights into the utilization and costs of farm labour, both before and after receiving subsidies. These variables include total labour input (measured in annual work units—AWU), wages paid (€)[16], unpaid labour input (AWU)[17], and paid labour input (AWU)[18].

Income Outcomes measure the financial performance of farms, capturing how income levels are influenced by AEM participation. These include gross farm income, farm net income, per worker farm net value added (€/AWU), and overall farm net value added.

Productivity evaluates the efficiency of resource use on farms. Key metrics include total factor productivity, the total output-to-total input ratio, and farm net value added per hectare. Table 1.2 shows the summary statistics of our outcome variables within the sample (before computing matching).

TABLE 1.2: Summary statistics: outcome variables pre-matching (Total EU sample) as defined in our specification model

	Treated			Controls			Total		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Crops and Livestock costs outcomes:									
Seeds and seedlings (€)	.336	0.690	3,709	.271	0.712	11,539	.286	.707	15,248
Fertilisers (€)	.426	0.620	3,915	.419	0.726	13,643	.421	.703	17,558
Crop protection	.302	0.671	3,718	.263	0.824	13,028	.272	.793	16,746
Other crop specific costs (€)	.224	1.254	2,599	.111	1.234	6,484	.143	1.241	9,083
Specific livestock costs / Livestock unit (€)	.502	0.835	2,717	.403	0.905	6,117	.434	.885	8,834
Feed for grazing livestock (€)	.559	0.705	2,048	.404	0.692	4,710	.451	.699	6, 758
Feed for grazing livestock home-grown (€)	.526	0.974	1,635	.317	0.981	3,384	.385	.983	5,019
Feed for pigs and poultry (€)	.375	0.679	963	.343	0.760	2,104	.353	.736	3,067
Feed for pigs and poultry home-grown (€)	.335	0.891	715	.3	0.917	1,269	.313	.908	1,984
Other livestock specific costs (€)	.192	0.745	2,532	.233	0.881	5,649	.221	.841	8,181
Labour outcomes:									
Wages paid (€)	.328	0.950	1,912	.219	0.919	6,177	.245	.927	8,089
Total labour input (AWU)	-.019	0.355	4,456	-.04	0.404	15,380	-.036	.394	19,836
Unpaid labour input (AWU)	-.047	0.318	4,236	-.078	0.359	15,148	-.071	.35	19,384
Paid labour input (AWU)	.136	0.926	1,910	.068	0.915	6,182	.084	.918	8,092
Income outcomes:									
Gross Farm Income (€)	.189	0.594	4,379	.046	0.698	15,043	.078	.679	19,422
Farm Net Value Added (€)	.213	0.758	4,138	.064	0.851	14,184	.098	.833	18,322
Farm Net Income (€)	.209	0.936	3,558	.037	1.000	12,766	.074	.989	16,324
Per Worker Farm Net Value Added (€/AWU)	.223	0.758	4,134	.097	0.866	14,188	.126	.844	18,322
Productivity outcomes:									
Total Factor Productivity	-.019	0.908	4,202	-.112	1.035	14,393	-.091	1.009	18,595
Total Output/Total Input Ratio	.032	0.359	4,518	-.065	0.504	15,702	-.043	.477	20,220
Farm Net Value Added/Ha (€/Ha)	.166	0.863	4,183	.011	1.019	14,107	.046	.988	18,290

Notes: All the outcome variables reported are expressed as the percentage difference between the logarithm of the outcome variable after the treatment (2013) and the logarithm of the outcome variable in the pre-treatment (2006).

The summary statistics present a descriptive snapshot of our economic outcomes within the treated, control groups and for the total sample at the EU level before computing matching.

[14]Specific livestock costs per total livestock unit (LU).

[15]This includes veterinary fees, reproduction costs, milk tests, and occasional purchases of animal products (e.g., milk).

[16]Encompassing wages and social security charges (and insurance) of wage earners.

[17]Referring to unpaid labour, generally expressed as family work units (FWU), equivalent to family AWU.

[18]One AWU represents the full-time equivalent employment, calculated as the total hours worked divided by the average annual hours for full-time jobs in the country.

Crops and livestock costs outcomes reveal that the treated groups have, on average, higher increases in costs compared to the control groups. Regarding labour outcomes, the treated group showed a smaller reduction in the average unpaid labour input and an average increase in paid labour input than the controls. Concerning income outcomes, summary statistics report the treated groups showing a higher average increase in gross farm income, farm net value added, and farm net income compared to the control groups. Treated groups in our sample have a smaller reduction in productivity measures, and in some cases, even improvements compared to the control groups (see subsection .1.2 for country-groups descriptive statistics).

1.3.3 Definition of control variables

Following Buysse et al., 2016, we considered the path dependency as a structural characteristic of some Pillar II measures, namely the tendency of a farmer who applied in time t to a measure, to apply for the same measure also in year t + n as well. The key point of our identification strategy hinges on exact matching based on observable farm-specific characteristics. More importantly, we provide robust estimates by matching treated and control units considering subsidies received in the previous programming period, averaging over the years 2004-2006 (see Mean AEM 2004-2006 variable in Table 1.3). This approach enables us to isolate and assess the specific effects of receiving subsidies during the 2007-2013 programming period. Following Bertoni et al., 2020 and Buysse et al., 2016, we select the control group by matching it with the treated group based on the following observable farm characteristics at the baseline year 2006, which represents the pre-treatment data time-point. Economic size (ESU)[19], total utilised agricultural area (UAA)[20], rented UAA (ha), total output (€), total crops output/ha[21], total output crops & crop production (€), total subsidies (excluding investments), total inputs (hrs)[22], total assets, gross farm income, total labour inputs (AWU)[23], average AEM payments in previous programming period 2004-2006 (€)[24], altitude[25] and type of farming[26]. Table 1.3 shows descriptive statistics of control variables before computing the CEM-matching.

[19]European size unit Economic size of holding expressed in 1000 € of standard output, is a standard gross margin of EUR 1200 that is used to express the economic size of an agricultural holding or farm. See https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:european_size_unit_(ESU)

[20]Utilised agricultural area (UAA)

[21]The variable is calculated as [sales + farm use + farmhouse consumption + (closing valuation - opening valuation)]/ha (excluding area leased out for a short period and area out of production) this formula provides a comprehensive view of the overall productivity and economic value of the cultivated land, considering not only the revenue from sales but also the various ways the crop is utilized on the farm and the changes in crop value over time.

[22]Time worked in hours by total labour input on holding.

[23]Total labour input of holding expressed in annual work units = full-time person equivalents.

[24]The average AEM subsidies in previous programming periods have been averaged over the 2004-2006 period, considering the same measures for which the treated effect is estimated.

[25]Altitude allows controlling for the fact that a farm is located in a plain, hill or mountain setting.

[26]Eight farm types used: field crops, horticulture, wine, other permanent crops, milk, other grazing livestock, granivores, mixed.

Table 1.3: Summary statistics: control variables (Total EU sample)

	Mean	*SD*
Economic Size (ESU)	170.571	383.38
Total Labour Input (AWU)	2.73	6.57
Total Utilised Agricultural Area (ha)	76.8	199.07
Rented UAA (ha)	49.7	179.4
Total Output (€)	163576.51	366004.37
Total crop output (€/ha)	13557.56	88072.95
Total Output Crops and Cost Production (€)	90900.15	253219.2
Total Inputs (€)	148471.2	368553.3
Gross Farm Income (€)	89255.5	184125.3
Farm Net Value Added (€)	69308.9	154064.4
Total Assets (€)	604481.24	1062886.8
Total Subsidies - Excluding on Investments (€)	24110.53	57720.16
Altitude	1.37	0.69
Mean AEM 2004-2006 (€)	1576.2	6736.5
Type of farming	*Shares*	
Field crops	0.34	
Horticulture	0.09	
Wine	0.07	
Other permanent crops	0.1	
Milk	0.11	
Other grazing livestock	0.09	
Granivores	0.06	
Mixed	0.11	
Organic		
Non-organic	0.94	
Organic	0.03	
Mixed	0.02	
obs:	20,228	

Notes: The mean AEM 2004–2006 represents the average subsidies from the Agri-environmental Measure received during the previous programming period (2004–2006). For the variables *Type of Farming* and *Organic*, which are categorical, we reported the percentage distribution relative to the total sample. The *Organic* variable is based on the FADN original variable `A_CL_140_C`, where 1 indicates that the holding does not use organic production methods, 2 means the holding applies organic methods exclusively for all products, and 3 denotes a combination of organic and conventional methods. For simplicity, we renamed these categories as 'Non-organic,' 'Organic,' and 'Mixed.' Although the original variable includes a fourth category for holdings converting to organic, no observations in our sample fall under this category, so it was excluded from the table.

1.4 Empirical Strategy

To evaluate the effect of AEMs, we use a Difference-in-Differences approach with matching to compare variations in the outcome variables between the treated and the selected controls in a pre-treatment and post-treatment period, as in previous contributions (Arata & Sckokai, 2016; Chabé-Ferret & Subervie, 2013; Pufahl & Weiss, 2009). This combination allows us to address the key challenge of adverse selection bias, which is common in voluntary programs like AEMs, where farmers whose practices already comply with policy requirements are more likely to participate (Canton et al., 2009; Gómez-Limón et al., 2019). As noted by Pufahl and Weiss, 2009, treated and control groups often differ in characteristics beyond their participation status, which introduces bias if outcomes are compared directly. Therefore, matching methods are employed to compare treated farms with non-participants who share similar observable characteristics, allowing to estimate what would have happened to participants had they not participated in the program. DID is a widely used method for estimating causal effects by comparing changes in outcomes over time between treated and control groups, controlling for time-invariant unobservable factors.

However, because participation in AEMs is not random and may suffer from selection bias, we employ the exact matching (CEM), to address observable differences between treated and control farms, ensuring balance in pre-treatment covariates that might concur in biasing the treatment status.

CEM is part of a class of matching methods known as monotonic imbalance bounding, which allows us to control the level of imbalance between treated and control units ex-ante (Iacus et al., 2012). CEM has several advantages. First, balance is achieved by grouping observations into strata based on coarsened covariates, preventing the need for ex-post adjustments as in other methods like Propensity Score Matching (PSM). Second, traditional matching methods often violate the axiom of simple random sampling, which assumes every individual has the same probability of being treated (Abadie & Imbens, 2006). Exact matching requires matching on all pre-treatment covariates, but this is rarely feasible with continuous variables and limited data, leading to significant loss of observations. Instead, CEM operates on a stratified sampling framework, improving upon traditional random sampling and allowing for more flexibility in matching continuous variables while retaining more observations. Third, it efficiently handles missing data by matching on the missingness history, making it robust even with rotating datasets like FADN (Iacus et al., 2012, 2019). The formal structure of CEM begins by coarsening the covariates used for matching into strata. Observations that fall into the same stratum are matched, while strata that do not contain both treated and control units are dropped.

Mathematically, the outcome Y_i for a unit i is given by:

$$Y_i = T_i Y(1) + (1 - T_i) Y(0) \tag{1.1}$$

Where: $T_i = 1$ if the unit is treated, and $T_i = 0$ otherwise. $Y(1)$ and $Y(0)$ are the potential outcomes with and without treatment, respectively.

Since we cannot observe both potential outcomes for a single unit, CEM matches treated and control units based on coarsened covariates, then calculates the treatment effect by comparing outcomes within the same stratum. After matching with CEM, we apply a conditional DID estimator to further control for unobserved heterogeneity. This estimator compares the change in outcomes before and after treatment for both treated and control groups, accounting for time-invariant unobservable factors (Mennig & Sauer, 2020). The conditional DID estimator is expressed as:

$$E[Y(1) - Y(0)|T = 1, X] - E[Y(0) - Y(0)|T = 0, X] \tag{1.2}$$

Where: $Y(1)$ and $Y(0)$ are the outcomes for treated and control groups, respectively. $T = 1$ indicates treatment, and $T = 0$ indicates no treatment. X represents the covariates used in the matching.

This formula measures the Average Treatment Effect on the Treated (ATT), controlling for both observable and unobservable factors that could otherwise bias the results.

The average effect of participation in AEM programs is estimated by comparing the changes in individual outcomes between participants and their matched counterparts between 2006 and 2013. The impact of treatment is estimated by computing mean differences across both groups following Pufahl and Weiss, 2009:

$$ATT = \frac{1}{N_1}\left(\sum_{i=1}^{N_1} \Delta Y_i^1 - \sum_{i=1}^{N_1} \Delta Y_i^0\right) \tag{1.3}$$

In this context, the ATT measures the difference in Y (e.g., income, costs, labour) between farms that obtained the subsidies and a comparable group of farms that did not, isolating the effect of AEM participation.

This theoretical framework allows matching on a comprehensive set of control variables along with three critical pre-treatment outcomes—Total Labour Input, Farm Net Value Added, and Gross Farm Income—thereby enhancing the precision of our estimates and developing a robust counterfactual scenario. Matching on pre-treatment outcomes is crucial when treated and control farms may differ systematically, as in voluntary AEM enrolment. Flat per-hectare payments and self-selection mean that farmers with low compliance costs can join without materially changing their practices, creating adverse-selection concerns noted in earlier AEM studies (Gailhard & Bojnec, 2015; Gómez-Limón et al., 2019). Aligning baseline outcomes helps ensure comparability despite this risk. As supported by Zeldow and Hatfield, 2021, leveraging pre-treatment outcomes in our matching process provides a valuable alternative for estimating causal effects. This foundational assumption is aligned with methodologies like lagged dependent variables regression and synthetic control (Abadie et al., 2010), and addresses the challenges posed by adverse selection and other unobservable factors (Stuart, 2010). Furthermore, to isolate the effects of the current AEM subsidies during the analyzed period (2007-2013), we also consider average payments received during the previous programming period (2004-2006). Although this strategy clarifies the impact of AEMs, it might introduce additional biases, as the effects of earlier subsidies could influence outcome variables without direct observation (Lindner & McConnell, 2019).

This comprehensive approach aims to bring us closer to capturing the impact of subsidies on the analysed farms' economic outcomes[27]. A diagnostic of our matching, before and after computing

[27] A key limitation of our strategy is that the two-point panel (2006–2013) prevents a formal test of the parallel-trends assumption and may miss intervening shocks or modelling year-by-year dynamics. Our outcomes are defined as the logarithmic growth between these two years, which captures the accumulated, compound percentage change over the full seven-year horizon. Crucially, this specification does not rely on an assumption that all policy effects

CEM, is presented in Table 1.4 showing a reduced mean difference between treated and control groups after matching (Iacus et al., 2012). After applying CEM weights to the selected covariates, the values indicate a substantial reduction in the mean difference between treated and control units. The p-values and t-values exhibit no statistically significant difference between the treated and control units after computing CEM. In contrast, before matching, the t-test exhibited a significant statistical difference between the treated and control units, as shown in Table .1.1.

TABLE 1.4: Balance Diagnostic before and after CEM matching: control variables (Total EU sample)

	After Matching		Before Matching	After Matching	
	Treated	Control	Control	(t-test)	(p-value)
Economic Size (ESU)	131.16	126.93	159.71	0.84	0.4022
Total Labour Input (AWU)	1.91	1.93	2.47	0.92	0.356
Total Utilised Agricultural Area (ha)	72.94	59.87	59.73	0.91	0.364
Rented UAA (ha)	40.22	35.08	36.95	0.70	0.487
Total Output (€/farm)	125275.6	117401.2	150058.9	0.69	0.489
Total crop output (€/ha)	56066.44	52649.28	88908.49	0.82	0.410
Total Output Crops and Cost Production (€/farm)	1813.97	2736.10	17297.77	0.65	0.518
Total Inputs (€)	116829.10	102245.93	129961.6	0.84	0.460
Gross Farm Income (€)	71747.26	66349.04	81328.06	0.74	0.460
Farm Net Value Added (€)	52958.77	50837.64	63876.47	0.91	0.364
Total Assets (€)	643006.8	533763.5	527748.3	-0.44	0.657
Total Subsidies - Excluding on Investments	26403.7	20107.6	18004.25	0.91	0.364
Altitude	1.37	1.37	1.36	0.00	1.000
Type of farming	4.10	4.10	3.52	0.00	1.000
Mean AEM 2004-2006	3180.2	790.44	471.04	0.91	0.364

Notes: The table reports 2006 sample means of each covariate for treated and control farms before and after CEM matching. Columns "Treated" and "Control" under "After Matching" show the post-match means; the "Control" column under "Before Matching" shows the pre-match control mean. The final two columns report the post-match t-statistic and p-value for the difference between treated and control means. After matching, all p-values exceed 0.10, indicating no statistically significant differences remain.

After running the CEM matching on the selected covariates, the following equation shows the empirical model used to estimate the treatment effects:

$$log(y_{it}) - log(y_{it-1}) = \alpha + w[\beta_1 AEM_i] + \varepsilon_{it}. \tag{1.4}$$

Our Y_{it} is assessed using a first difference estimation between the growth rate of the logarithm of the outcome variable in the last year of the treatment (2013) and the logarithm of the outcome variable in the pre-treatment scenario (2006); indeed, we exploit the variation in outcome growth rates before and after the treatment. Estimates are calculated with weights assigned through the

materialize instantaneously in 2013; rather, it reflects the total effect of AEM participation regardless of whether a given farm entered in 2007 or as late as 2012. To reduce possible resulting risks of selection and time-varying bias, we implement several empirical "safeguards". (i) using rich covariate matching, including prior AEM exposure (2004–2006); (ii) exclusion of ever-treated farms from the control group; (iii) robustness checks using alternative estimators; (iv) re-estimation of monetary outcomes in real euros. (v) Exclusion from our sample organic farms as they have stricter requirements to fulfil and different production technologies. (vi) Balancing diagnostics across our matched set of covariates. (vii) Adding country as a CEM covariate allowing the comparison into a within-country estimates. The stability of estimates across these exercises reported in Section 1.6 indicates that our main results are unlikely to be driven solely by the constraints of the two-period design.

exact matching, and standard errors are clustered at the EU and country-group levels. AEM_i is the binary treatment variable indicating the policy weighed using CEM-weight w and ε_{it} is a random error term.

1.5 Results

This section presents the estimated average treatment effect on the treated, evaluating how receiving AEM subsidies influences growth rates in various outcomes—including crop and livestock costs, labour, income, and productivity—among treated farms compared to non-beneficiaries across different country groups. The results reported in Table 1.5 provide insights concerning the impact of AEMs on production costs. Compared to untreated farms, those receiving financial support experience a significant increase in costs for seeds and seedlings, which are likely due to the effort needed to align with sustainable objectives. When considering costs for seeds and seedlings in the whole sample (i.e., EU level), the results in column 1 suggest that AEMs lead farms complying with the policy to increase these costs by 4.4% more than farms in the control group. When disentangling the effect for the different EU regions, only the results for the Eastern Europe sample align with those at the EU level, showing a significant increase in costs for treated farms that is 5.7% higher than those in the control group. The results for the Western, Southern and Northern Europe groups are not statistically significant. When considering fertilizer costs, the results do not show any significant increase in costs for treated farms with respect to the counterfactual. Instead, the estimated coefficients exhibit a negative sign for all the analyzed country groups, but in none of the cases is the difference statistically significant.

Our results regarding crop protection costs provide evidence of a modest significant increase for farms at both the overall EU (column 1) and Western countries (column 2) levels. South, East, and North EU regions do not show any significant change in crop protection costs due to the policy uptake with respect to non-recipient farms. Concerning other crop-specific costs, our results suggest that AEMs lead to a significant increase for farms complying with the policy at the Total EU (column 1) and South EU (column 3) levels with respect to farms in the control group, while the Western, Eastern, and Northern EU countries exhibit no significant impact. The magnitude of the effect is particularly relevant for Southern European farms, where our estimation suggests an average increase in other crop-specific costs that is 29% higher in treated farms with respect to non-treated ones.

Moving to livestock costs, our estimates provide evidence of a significant increase in recipient farms with respect to the counterfactual at the Total EU (column 1) and Western EU (column 2) levels for specific livestock costs (e.g. veterinary costs), feed for grazing livestock costs and feed for grazing livestock home-grown. The magnitude of the estimated effects is particularly relevant at the Total EU level, which suggests an increase of around 12% and 11% in the first two livestock cost categories, which rises at around 20% when considering costs for feed for grazing livestock home-grown. In contrast, no significant effects are observed for these cost categories in Southern, Eastern, and Northern EU countries.

When considering the other three livestock categories, the results are less clear-cut. Evidence at the Total EU level (column 1) suggests that participation in AEMs leads only to a significant increase in feed for pigs and poultry pigs costs for recipient farms with respect to the counterfactual. The last two livestock cost categories (feed for pigs and poultry home-grown and Other livestock-specific costs) do not highlight a significant difference between treated and untreated farms. The results for the different country groups in these last three livestock cost categories suggest heterogeneous effects, which in most cases are not statistically significant. Except for a positive and significant effect for feed for pigs and poultry home-grown costs in the West EU sample (+14% higher costs compared to controls), the other significant differences in the estimated effect for Southern countries suggest a reduction in costs due to the policy compliance in treated farms with respect to the control group. However, we do not consider these results reliable due to the very low number of observations, which can impair the validity of the considered estimates.

Table 1.5: ATT on crops and livestock costs at EU level and country-group level

	Total EU	West EU	South EU	East EU	North EU
			Crops costs		
Seeds and seedlings (€)	0.044***	0.001	-0.032	0.057***	0.030
	(0.013)	(0.017)	(0.044)	(0.028)	(0.073)
Obs.	14,309	5,721	4,429	2,494	436
Fertiliser (€)	-0.019	-0.015	-0.027	-0.001	0.013
	(0.013)	(0.014)	(0.039)	(0.030)	(0.087)
Obs.	15,885	6,287	6,223	2,579	369
Crop protection (€)	0.028*	0.053***	-0.030	0.011	0.083
	(0.015)	(0.014)	(0.050)	(0.030)	(0.098)
Obs.	15,135	5,960	5,588	2,746	347
Other crop specific costs (€)	0.096***	0.013	0.290***	0.066	0.076
	(0.031)	(0.036)	(0.106)	(0.109)	(0.197)
Obs.	8,014	3,816	2,629	1,061	295
			Livestock Costs		
Specific livestock costs/Livestock unit (€/Livestock unit)	0.123***	0.066***	-0.131	-0.063	0.100
	(0.021)	(0.023)	(0.093)	(0.051)	(0.142)
Obs.	9,989	4,520	1,838	1,608	239
Feed for grazing livestock (€)	0.112***	0.040*	-0.098	-0.092	0.037
	(0.019)	(0.022)	(0.060)	(0.062)	(0.102)
Obs.	7,546	3,513	1,640	977	174
Feed for grazing livestock home-grown (€)	0.199***	0.099***	-0.042	-0.101	0.196
	(0.031)	(0.045)	(0.084)	(0.069)	(0.123)
Obs.	5,659	2,503	1,022	966	172
Feed for pigs & poultry (€)	0.071***	0.026	-0.649*	0.023	-0.151
	(0.028)	(0.035)	(0.376)	(0.050)	(0.192)
Obs.	3,688	1,499	172	1,125	105
Feed for pigs&poultry home-grown (€)	0.054	0.142***	-1.293*	-0.090	-0.226
	(0.039)	(0.061)	(0.650)	(0.065)	(0.265)
Obs.	2,421	914	32	999	86
Other livestock specific costs (€)	-0.057	-0.002	-0.013	-0.083	-0.438***
	(0.020)	(0.020)	(0.098)	(0.055)	(0.170)
Obs.	9,358	4,328	1,562	1,534	228

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Estimates include matched farms and are weighted with CEM weights. Robust standard errors indicated in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

As shown in Table 1.6, the results concerning labour outcomes reveal substantial disparities in paid wages and paid labour across the entire EU and its country groups. We observe a significant impact of AEMs subsidies on paid wages, only at the EU level and in Southern countries. At the EU level, treated farms have an 8.2% higher total paid wage expenditure, including wages and employer-paid social security and insurance contributions, compared to farms without AEMs subsidies. In Southern countries, this difference is even more pronounced, with treated farms having an 11.7% higher total wage expenditure than non-recipient farms, although this effect is only marginally significant at the 10% level.

Regarding total labour input measured in Annual Work Units (AWU), there is a notable increase across all EU regions, except for the Northern countries. At the EU level, the AEMs' uptake leads farms to increase the full-time person-hours dedicated to agricultural activities by 2.7% more than other farms not receiving AEMs subsidies. This increase is 1.6% in Western countries, 6.9% in Southern countries and 5.1% in Northern countries; all effects are statistically significant at 1% level.

The analysis shows some regional differences in unpaid labour (AWU) across the EU, with significant increases in farms receiving AEMs subsidies in Southern and Eastern countries with respect to the counterfactual but no changes in Western and Northern countries. This highlights the uneven expenditure of AEMs, which support unpaid, mainly family labour, more in Southern and Eastern EU regions than paid labour. Finally, the results suggest that AEMs subsidies lead to an increase in paid labour input in recipient farms with respect to the control group at the Total EU and Southern EU levels, although in the last case, the effect is only marginally statistically significant (10% level).

Table 1.6: ATT on labour outcomes at EU level and country-group level

	Total EU	West EU	South EU	East EU	North EU
Wages paid (€)	0.082***	0.047	0.117*	0.010	-0.253
	(0.029)	(0.041)	(0.068)	(0.073)	(0.159)
Obs.	6,261	2,538	2,550	1,076	128
Total labour Input (AWU)	0.027***	0.016***	0.069***	0.051***	-0.043
	(0.007)	(0.007)	(0.020)	(0.017)	(0.042)
Obs.	18,041	6,780	7,202	2,895	467
Unpaid labour Input (Family AWU)	0.023***	-0.001	0.053***	0.039***	-0.005
	(0.006)	(0.006)	(0.018)	(0.016)	(0.035)
Obs.	17,905	6,758	7,204	2,757	452
Paid labour Input (AWU)	0.057***	0.047	0.126*	0.084	-0.081
	(0.029)	(0.039)	(0.069)	(0.073)	(0.168)
Obs.	6,261	2,537	2,549	1,047	129

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Estimates include matched farms and are weighted with CEM weights. Wages paid regressed using real deflated values, the coefficient is 0.062**. Robust standard errors are included in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

The results on income growth rates show greater consistency across different groups, except for Northern countries (probably due to the lower number of observations), as detailed in Table 1.7. When considering the Total EU sample (column 1), farms receiving AEM subsidies exhibit an increase in growth rates for gross income, net value added (€), net income and per worker net value added (AWU) of about 12%, 13%, 15% and 9% compared to untreated farms. It is worth noting that the magnitude of the estimated effects is particularly high in the Southern countries sample (column 3)[28].

Table 1.7: ATT on farms' income at EU and country-group level

	Total EU	West EU	South EU	East EU	North EU
Gross Farm Income (€)	0.123***	0.060***	0.227***	0.137***	0.018
	(0.012)	(0.013)	(0.034)	(0.031)	(0.082)
Obs.	17,596	6,579	7,109	2,811	411
Farm Net Value Added (€)	0.129***	0.078***	0.231***	0.189***	-0.071
	(0.015)	(0.018)	(0.040)	(0.043)	(0.102)
Obs.	16,505	6,206	6,678	2,607	357
Farm Net Income (€)	0.147***	0.076***	0.243***	0.212***	-0.074
	(0.019)	(0.026)	(0.046)	(0.049)	(0.124)
Obs.	14,883	5,221	6,264	2,429	302
Farm Net Value Added(€/AWU)	0.092***	0.066***	0.160***	0.143***	-0.002
	(0.016)	(0.018)	(0.042)	(0.042)	(0.092)
Obs.	16,487	6,195	6,686	2,603	355

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Estimates include matched farms and are weighted with cem weights. Robust standard errors in parenteses. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

We perform the same computation of the income growth rates by removing the subsidies and taxes components from the outcome variables Gross Farm Income and Farm Net Income (respectively SE600 and SE405). Overall, the results presented in Table .1.3 are in line with those in Table 1.7, especially when considering Farm Net Income. The estimated coefficients of Gross Farm Income are lower in magnitude than those presented in Table 1.7, especially in the case of the Total EU sample (column 1), while the effect for the Eastern EU group, though positive, is no longer statistically significant.

As noted above, our CEM estimator already adjusts for past participation by including each farm's average AEM payments over 2004–2006. However, if a control unit received AEM funds at any point between 2007 and 2012, it could dilute our estimated effect downward. Although we cannot track all treated units across all years, we can monitor our control group from 2007 to 2012 to identify any changes in treatment status. Since these programs are multi-annual, a lasting economic effect is expected to increase with the duration of participation. However, too rigorous management prescriptions or lack of policy coordination could lead to farms exiting

[28]For the Northern EU regions, the limited number of observations prevents the reliable identification of the effect.

treatment at any time (Uthes & Matzdorf, 2013). Notably, 2,482 farms classified as control units in 2013, received payments during some previous years. To assess whether this could significantly affect the results, we re-estimated the analysis for the Total EU sample, excluding these control units. The findings remain robust, with an overall increase in magnitude, as shown in Table .1.2.

1.5.1 Potential mechanisms

We explore potential mechanisms behind our results estimating the effect of AEM payments on productivity outcomes such as Total Factor Productivity (TFP), the Total Output/Total Input ratio, and Farm Net Value Added per hectare.

Our results present compelling evidence of higher income growth in participant farms compared to control units, which hold not only at the Total EU level but also in most of the cases for the considered country groups (except for North EU). Conversely, crops and livestock cost increases are found especially for the Total EU case, and less so for the other groups. A potential catalyst for these results may rely on enhanced productivity as an indirect effect of AEMs, if the additional income and stability allow farmers to invest in more efficient practices or adopt technological advancements. The literature highlights instances of misallocation and overcompensation with AEMs, particularly for arable land farms, as detailed by Mennig and Sauer (2020). In contrast, dairy farms participating in AEMs often see reduced productivity. These payments do not account for farm-specific characteristics and changing market conditions, potentially discouraging some farmers from participating[29]. At the same time, AEM payments provide a stable source of income, contrasting with the volatility of commodity prices and yield variations, which makes these payments especially attractive in less productive regions with limited alternative income opportunities (Uthes & Matzdorf, 2013; Wilson & Hart, 2000).

To investigate this issue further, we estimate the TFP following Levinsohn and Petrin, 2003's approach. The TFP measures the efficiency with which inputs (e.g., labour and capital) are combined to produce output, accounting for unobservable factors such as technology and managerial effectiveness. Accurately measuring TFP allows the analysis to detect whether the additional income and policy compliance requirements from AEM subsidies are leading to genuine productivity improvements rather than just financial gains due to overcompensation. In estimating production functions, a major challenge is the connection between unobservable productivity shocks and the levels of inputs used by firms. When firms experience positive productivity shocks, they tend to increase output and, consequently, require more inputs. Conversely, negative shocks cause firms to reduce output and input usage. This relationship can lead to biased estimates when using ordinary least squares (OLS) methods (Petrin et al., 2004). Levinsohn and Petrin (2003) suggests using intermediate inputs (like electricity or materials) as proxies, as these

[29] Depreciation of capital assets is included in the variables Farm Net Value Added and Total Inputs see https://fadn.pl/wp-content/uploads/2012/12/RICC-882-rev9.2-Definitions-of-Variables.pdf for definitions of variables used in FADN data

are typically reported consistently, even for firms that do not report investment. This approach helps avoid the issues related to zero investment reports and may better reflect productivity shocks since intermediate inputs can be adjusted more easily than investments. As suggested by Van Beveren (2012) in the computation of the TFP, it is assumed that unobserved productivity indicated as ω_{it} is plant-specific but time-invariant, labour is the only freely variable input and capital is quasi-fixed. As a result, estimation considers labour, capital and materials of firm i in period t. We adopt the approach of Petrin et al. (2004) to estimate TFP as follows:[30]

$$Y_{it} = \beta_0 + \beta_k K_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_i + u_{it}^q \tag{1.5}$$

Where Y_{it} is our dependent variable that indicates the Farm Net value added expressed in € and calculated at the farm level[31]. β_0 is the intercept term, $\beta_k K_{it}$ is the Average Farm Capital (SE510 FADN-database) (see (Baldoni et al., 2017)), $\beta_l l_{it}$ are free inputs determined by the firm in which we include Total labour Inputs and (SE010) and Energy (SE345) expressed in € and indicates Motor fuels and lubricants, electricity, heating fuels. $\beta_m m_{it}$ is Machinery (SE455 FADN-database) as a proxy for materials inputs (Comin et al., 2023; Van Beveren, 2012).

The results in Table 1.8 suggest that, overall, AEM payments lead to higher productivity growth in recipient farms than those in the control group. Considering our three productivity outcomes the estimated coefficients are always positive (except for the Output/Input ratio in the East EU group), but not always statistically significant. Significant productivity growth in farms complying with the policy is evident at the Total EU, Western EU and Southern EU levels, although in the latter case, the estimated TFP coefficient is not statistically significant. When considering the results at the EU level, farms benefiting from AEM payments show, on average, an increase in productivity that is about 8% higher than in the non-treated farms. The estimated coefficients are smaller in magnitude in the West EU sample, but higher in the South EU one (except for TFP). Southern and Eastern countries the show highest estimated coefficients concerning Farm Net Value Added per hectare (+17% and +12% respectively higher than controls).

In summary, farmers receiving subsidies, both at the EU level and in Western and Southern countries, demonstrate an improved output capacity despite facing increased costs and employing more labour-intensive production practices. CAP-II Pillar payments may affect the aggregate

[30] All terms in the TFP estimation are expressed in logarithmic form. Using logarithmic transformations allows for the interpretation of coefficients as elasticities, enabling a clearer understanding of how proportional changes in inputs affect output while addressing distributional issues. Moreover, this approach helps mitigate the influence of price variations in 2006 and 2013 time points, as the logarithmic difference filters out some of the aggregate price fluctuations.

[31] The levpet STATA command allows for the flexible specification of inputs and proxies in the production function. It assumes a Cobb–Douglas production technology, and users specify inputs such as labour, capital, and the intermediate input to be used as a proxy. The estimation process involves two stages. In the first stage, the command estimates the coefficients for the freely variable input(s) and constructs a nonparametric proxy function using a third-order polynomial. In the second stage, the command identifies the coefficients for capital and other state variables (like intermediate inputs) by using a combination of polynomial approximations and assumptions on productivity following a Markov process. Users can choose whether to specify the dependent variable as value added or gross revenue, which affects the estimation approach (Petrin et al., 2004).

TFP growth due to several farms entering and exiting agriculture or moving from one type of farming or specialization to another (Baldoni et al., 2017). As suggested by Dudu and Ferrari, 2018 AEM payments can stimulate land-augmenting technical change and output, resulting in additional productivity growth.

While we find positive results at the Total EU level, disaggregated analyses reveal more nuanced effects across country groups, likely influenced by regional characteristics, implementation differences, or farm-type variations, in line with findings by Rizov et al., 2013 and Sidhoum et al., 2024. Several studies, employing different levels of aggregation and modeling approaches, provide mixed support for these findings. For example, Bokusheva et al., 2012 observed productivity improvements in Swiss dairy farms under environmental policies, but stricter regulations led to declines in crop farms. Similarly, Mary, 2013 found no significant productivity gains in French crop farms, attributing this to policy design limitations, while Biagini et al., 2023 reported positive effects on TFP for highly productive cereal farms but less impact on low-productivity farms. Counterfactual studies by Baráth et al., 2020 and Mennig and Sauer, 2020 found mixed effects on productivity, with evidence of overcompensation and reduced productivity in specific farm types, such as arable and dairy farms. Although our aggregate findings do not explicitly distinguish between farm types, they suggest that the observed positive effects may be driven by specific farm characteristics, as highlighted in previous disaggregated analyses.

Table 1.8: ATT on farms' productivity at EU and country-group level

	Total EU	West EU	South EU	East EU	North EU
Total Factor Productivity	0.0971***	0.0806***	0.0330	0.0427	0.0619
	(0.0183)	(0.0214)	(0.0480)	(0.0502)	(0.118)
Obs.	16,742	6,495	6,806	2,657	368
Output/Input ratio	0.0747***	0.0215***	0.134***	-0.0040	0.0106
	(0.0077)	(0.0064)	(0.0257)	(0.0219)	(0.0363)
Obs.	18,492	7,033	7,416	2,956	476
Farm Net Value Added per hectare	0.0851***	0.0428*	0.174***	0.122***	0.0363
	(0.0180)	(0.0206)	(0.0482)	(0.0465)	(0.110)
Obs.	16,393	6,478	6,721	2,601	368

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Estimates include matched farms and are weighted with cem weights. Robust standard errors in parenteses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

While we applied matching between treated and control units based on the 2006 type of farming, a potential driver of increased productivity in treated units could be a change in farming type over time. However, the share of farms that changed their farming type is similar in both groups (20% for treated and 18% for control). Table .1.4 presents the share of farms switching to each farming category within the treated and control groups. As shown, no significant differences are observed that could influence our results.

1.6 Validation tests and Robustness

We corroborate our estimates by replicating the analysis employing alternative methodologies for both matching and modelling. Concerning matching, we replicate our estimates using the Propensity Score Matching (PSM) technique to prove comparability between the treatment and control groups in our estimates as previously demonstrated by Rosenbaum and Rubin, 1983. Instead of conditioning on the observable covariates that fall within the same stratum for both treated and control groups (as in CEM), we condition on the propensity score, defined as the conditional probability of participation for farm i, given a set $X = x_i$ of farm characteristics (Mennig & Sauer, 2020):

$$p(X) \equiv \Pr(P_i = 1 \mid X = x_i) \tag{1.6}$$

In our analysis, the PSM allows us to match treated farms with control farms that have similar propensity scores, thus creating comparable groups for the analysis. After performing the PSM, we further apply a conditional DID estimator to account for unobserved time-invariant heterogeneity, ensuring a robust estimate of the treatment effect. This approach compares the change in outcomes before and after treatment for both treated and control groups, accounting for unobserved factors that remain constant over time (Mennig & Sauer, 2020). In our case, we use the nearest neighbour matching with the commonly used caliper value of 0.1 times the standard deviation of the propensity score and the common support, dropping treatment observations whose score is higher than the maximum or less than the minimum score of the controls. According to Fullerton et al. (2016) exact matching methods exhibit efficacy across various balance metrics, albeit at the expense of excluding a considerable number of observations. As extensively described by Bertoni et al., 2020 in their comparative analysis between CEM and PSM estimates, the latter exhibits high variability in the results depending on how the PSM is specified. Conversely, the CEM prevents this risk as it matches observations that are very close to each other according to the covariates specification. We replicate the estimates for two key variables of each economic outcome, allowing for a comparative evaluation with the results obtained through CEM. Figure 2 shows the extent of balancing between the two samples before and after having performed matching. The use of PSM, in the majority of the estimated ATTs, does not change the sign of our results but produces differences in magnitude due to the loss of further observations as shown in Table .1.5. Compared to PSM, the CEM estimator effectively reduces the imbalance between treated and control groups without further reducing the number of observations. Unlike CEM, matched observations in PSM are often significantly different in terms of individual characteristics, despite having similar probabilities of receiving treatment.

To further validate our estimates, we replicate the analysis using the Synthetic Difference-in-Differences (SDID) method as proposed by Arkhangelsky et al. (2021a). This technique integrates the core principles of both traditional difference-in-differences and synthetic control (SC) methods, capturing the causal effect of a binary intervention. The SDID method aims to assess the effect of a policy or an intervention (denoted as W_{it}) on a specific group, without assuming consistent trends across all treated and untreated units (Clarke, Pailañir, et al., 2023). It calculates the average treatment effect on the treated using a two-way fixed effect regression model as follows:

$$\tau_{b\text{sdid}}, \mu, b\alpha, b\beta_b = \text{argmin}_{\tau,\mu,\alpha,\beta} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau\right)^2 \omega_{\text{sdid}i} \lambda_{\text{sdid}t} \right) \tag{1.7}$$

In this model, unit weights ($\omega_{\text{sdid}i}$) are chosen so that, prior to the intervention, the weighted control group closely mirrors the pre-intervention evolution of the treated units. Time weights ($\lambda_{\text{sdid}t}$) are adjusted to emphasize similarities between pre- and post-treatment periods, ensuring a consistent baseline for comparing post-treatment outcomes to pre-treatment averages across all controls. This approach considers both shared temporal factors (captured by time-fixed effects β_t) and farm-specific factors (captured by unit-fixed effects α_i)(Clarke, Pailañir, et al., 2023). Unlike DID, which applies equal weights across all periods and units, and SC, which optimizes unit-specific weights without incorporating time variability or unit-fixed effects, SDID allows for adjusting covariates as a preliminary step, thus isolating covariate shifts from the outcome Y_{it}. In our setting $W_{it} = 1$ if the farm received subsidies in 2013. The SDID approach builds on both synthetic control and difference-in-differences by reweighting observations to correct for remaining imbalances. Unlike DID alone, it relaxes the strict parallel-trends assumption, and unlike synthetic control by itself, it automatically balances on key covariates before measuring the policy effect (Arkhangelsky et al., 2021a). Under SDID, control farms are first weighted (unit-weights) so that their single pre-treatment outcome and covariates match each treated farm, and time periods are also weighted to lessen the influence of unusual market swings. In our two-year setup (2006 vs. 2013), however, there is only one pre-treatment observation to weight, so the time-weighting simply places equal emphasis on both years; the real gain comes from the unit-weights ensuring a clean baseline comparison. As shown in Table .1.6, repeating this SDID analysis on the full EU sample yields coefficients with the same sign and magnitude as our main results.[32] This procedure absorbs any farm-level differences , but it does not adjust for time-varying price shocks, such as inflation or commodity-price shifts, that might occur after 2006. To rule out the possibility that these differences in price changes confound our main CEM-DID results, we re-estimated all cost, income, and productivity outcomes in real (deflated) euros using Eurostat's 2005 = 100 indices. The real-euro ATT estimates remain in line with our results, albeit slightly lower in magnitude, identical in both sign and significance to the nominal

[32] Under SDID, "Other livestock-specific costs" remains significant, while "Total Labour Input" loses significance and "Paid Labour Input" becomes marginally significant.

estimates, confirming the economic impact of our main results (see Table .1.10, Table .1.11 and Table .1.12). These results support the validity of our findings and enable more robust inferences about the causal links between subsidies and farms' economic outcomes.

1.6.1 Robustness of Results

To assess the robustness of our results, we conducted several additional analyses using different matching estimators and sub-samples.

A potential concern is that aggregating organic and non-organic farms might bias our findings, as these two farm types use different production technologies, and organic farms face additional certification requirements. As shown in Table 1.3, 94% of the sample consists of non-organic farms. Therefore, we replicated the analysis for the Total EU sample, focusing exclusively on farms that were non-organic in both 2006 and 2013, resulting in a sample of 19,066 out of 20,228 farms.

Table .1.7 reveals that most outcomes show minimal differences between analyses with and without organic farms, indicating that our results are not substantially biased by this factor. Overall, excluding organic farms increases the power of our estimates while maintaining the same direction of effects. Notably, the presence of organic farms tends to increase some cost-related effects, particularly for "Other Crop Specific Costs" and "Feed for Grazing Livestock Home-Grown". Additionally, "Wages Paid" decreases slightly from 0.08 with organic farms to 0.07 without them. The impact on farm net income is also marginally lower with organic farms included, likely due to differing costs to meet organic requirements.

In our empirical model, CEM is performed before estimation to enhance comparability between treated and control units, rather than in the regression itself. This approach ensures that the covariates are used exclusively in the matching process, reducing concerns about potential multicollinearity that could undermine the reliability of the estimates. Nevertheless, we verified whether the covariates used for matching might exhibit multicollinearity, as they are potentially related to farm size and economic scale. Indeed, variables such as Total Output, Total Inputs, Gross Farm Income, and Farm Net Value Added showed strong positive correlations with Economic Size (ESU), each with a correlation coefficient above 0.7. To address this, we re-estimated the model without including these variables in the CEM matching. As shown in Table .1.8 the results hold robust.

The voluntary opt-in nature of AEM instruments, along with the number of EU agri-environmental programs and the extent of agricultural land covered, varies significantly across Member States. This variation reflects the spatial heterogeneity in program uptake across Europe (Glebe & Salhofer, 2007; Zimmermann & Britz, 2016). Given these differences, accounting for MS is relevant in our analysis. Due to the limited number of observations for individual countries, we opted to use more aggregated subsamples based on country groups as shown in our Section 1.5. Nevertheless, including the country variable as a CEM matching covariate could further strengthen the credibility of the results by ensuring comparisons are made within the same Member State rather than across different country groups. We replicated the estimates with this adjustment, and the results, presented in Table .1.9 remain consistent overall, though the magnitude of the effect on paid labour input increased.

1.7 Concluding remarks

This paper investigates the impact of CAP Pillar II's Agri-Environmental Measures on participant farmers compared to non-participants. These measures provide subsidies to farmers adopting sustainable farming practices, which are typically associated with higher production costs and reduced profitability compared to conventional methods. The analysis evaluates the economic effects of this policy in a counterfactual framework.

We offer a comprehensive assessment of how AEM subsidies influence various socio-economic outcomes, including costs, labour, income, and productivity, shaping farmers' decisions to adopt greener agri-food practices and their capacity to comply with policy requirements. The analysis distinguishes the effects of AEMs across different EU regions. While labour, income, and productivity outcomes generally show positive and relatively uniform impacts across country groups, the costs incurred by recipient farms reveal significant regional variability. From an aggregate perspective, we provide empirical evidence showing that these subsidies may offset higher costs and be channeled into strategic investments in labour inputs or productivity enhancements. Our results also highlight the potential of AEMs to boost farm income. The spatial pattern of beneficiary uptake (Figure 1.1) and the contrasting magnitudes in costs, income and productivity gains reveal that AEMs operate both as cost-compensation tools and as possible investment levers. In high-adoption countries, where participation exceeds 60% and average payments per hectare are among the highest in Europe, farms report only modest increases in core inputs like seeds and crop protection, alongside targeted spending on specific crops and livestock costs. By contrast, in southern and eastern regions where uptake hovers around 30–50% but per-hectare payments remain generous, enrolled farms face substantially higher "other" crop and livestock costs yet achieve disproportionately larger jumps in net income (e.g. +24.3% in the South) and in value-added per unit of labour (+16.0%). These patterns suggest that AEM funds are not merely back-filling extra production expenses but are leveraged as seed capital for infrastructure upgrades and expanded labour capacity to manage more complex, sustainable rotations.

As suggested in previous studies, sustainable farming encourages labour-intensive practices and the efficient use of local resources, such as diversified crop rotations, to maintain soil fertility, manage weed and disease pressures, and enhance nutrient availability. Our findings reveal significant positive ATTs on total and unpaid labour inputs, indicating that subsidized farms may be channelling AEM payments more effectively into labour resources compared to non-beneficiary farms. This reallocation likely helps optimize sustainable production methods and meet the higher labour demands associated with sustainable farming practices. Our results on unpaid labour inputs partially align with Eurostat's 2020 data, which indicates that nearly six out of ten farms (approximately 57%) in the EU are managed by family members, and family labour constitutes at least half of the workforce on 36% of farms.[33] This phenomenon relates to unpaid labour inputs, as family members contribute substantially to agricultural activities without direct monetary compensation. The prevailing use of family labour is particularly pronounced in Southern Europe, highlighting a regional difference that aligns with our results where we observe a significant increase in unpaid labour in the South and East of the EU. Baldoni et al. (2017) suggests that mitigation actions that increase environmental performance are somehow self-financing and sustainable in economic terms. This occurs because the best technologies imply both higher productivity and lower emissions, which might be part of a potential long-term mechanism explaining our results concerning income and productivity growth rates between 2006 and 2013.

The surge in costs for seeds and seedlings, particularly prominent at the EU level and in Eastern countries, suggests farmers' efforts to align with sustainable objectives. However, this trend is not uniform, as evidenced by the lack of significant increases in expenses for crop protection across different regions. Livestock costs, while significantly increasing in the Total EU and West EU, show no such effect in South, East, and North EU countries, emphasizing regional disparities. These patterns challenge the expectation that AEMs, designed to compensate for income losses or higher costs, would uniformly address challenges across diverse agricultural landscapes. Our results highlight that AEMs can improve both farmers' productivity and income. As highlighted by Mennig and Sauer (2020), while AEMs are intended to be neutral in terms of trade and production, they may inadvertently overcompensate arable land farms. Our findings can contribute to the policy debate on the structure of AEM payment schemes. In an action-based framework, overcompensation is viewed as a policy inefficiency, whereas results-based schemes incentivize changes in farmers' behavior by offering adequate payments for achieving outcomes that ensure policy additionality. All types of agricultural programs that affect farmers' income can significantly influence their investment decisions, thus, they are not fully production-neutral, as evidenced by the dependency of organic farms on direct payments shown by Offermann et al., 2009. Farmers often utilize both first and second pillar payments for reinvestment in their operations and similarly AEM payments, despite their intention to be neutral, still enable farmers to make strategic investments that enhance their overall productivity and profitability (Sckokai & Moro, 2009). This element highlights the need to consider both the economic and environmental objectives in policy design to ensure that subsidies effectively support sustainable agricultural practices while also promoting economic viability for farmers.

[33] https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20231024-2

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.1

.1.1 List of Tables

TABLE .1.1: Comparison of Covariates Before CEM Matching: t-Statistics and p-Values (EU Sample)

	t-test	p-value
Economic Size (ESU)	-7.528	0.000
Total Labour Input (AWU)	-10.572	0.000
Total Utilised Agricultural Area (ha)	-23.116	0.000
Rented UAA (ha)	-19.146	0.000
Total Output (€/farm)	-9.836	0.000
Total crop output (€/ha)	-2.220	0.027
Total Output Crops and Cost Production(€/farm)	9.891	0.000
Total Inputs (€)	-13.398	0.000
Gross Farm Income (€)	-11.471	0.000
Farm Net Value Added (€)	-9.388	0.000
Total Assets (€)	-19.311	0.000
Total Subsidies - Excluding on Investments	-28.637	0.000
Altitude	3.59	0.000
Type of farming	14.98	0.000
Mean AEM 2004-2006	-45.697	0.000

Notes: The table shows t-statistics and p-values for the difference in covariates between treated and control groups before computing CEM matching.

Table .1.2: ATT without biased controls (EU Sample)

Outcome	ATT	Standard Error
Crops and Livestock Costs		
Seeds and Seedlings	0.079***	(0.014)
Fertiliser	-0.007	(0.013)
Crop Protection	0.035**	(0.015)
Other Crop Specific Costs	0.126***	(0.032)
Specific Livestock Costs / Livestock Unit	0.131***	(0.021)
Feed for Grazing Livestock	0.119***	(0.019)
Feed for Grazing Livestock Home-Grown	0.214***	(0.032)
Feed for Pigs & Poultry	0.096***	(0.028)
Feed for Pigs & Poultry Home-Grown	0.128***	(0.039)
Other Livestock Specific Costs	-0.066***	(0.021)
Labour		
Total Labour Input (AWU)	0.026***	(0.007)
Wages Paid	0.087***	(0.029)
Unpaid Labour Input (AWU)	0.037***	(0.006)
Paid Labour Input (AWU)	0.052*	(0.029)
Income		
Gross Farm Income	0.126***	(0.012)
Farm Net Value Added	0.125***	(0.016)
Farm Net Income	0.144***	(0.020)
Farm Net Value Added (AWU)	0.090***	(0.016)
Productivity		
Total Factor Productivity	0.067***	(0.019)
Input/Output Ratio	0.071***	(0.008)
Farm Net Value Added per Hectare	0.126***	(0.019)

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table .1.3: ATT on farms' income (without balance subsidies and taxes outcomes)

	Total EU	West EU	South EU	East EU	North EU
Farm Net Income	0.148***	0.0542**	0.239***	0.225***	-0.0203
	(0.0186)	(0.0248)	(0.0455)	(0.0475)	(0.124)
Gross Farm Income	0.0164***	0.0517***	0.182***	0.0336	0.0279
	(0.0165)	(0.0181)	(0.0439)	(0.0437)	(0.131)

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Estimates include matched farms and are weighted with cem weights. Robust standard errors in parenteses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table .1.4: Shares of Treated and Control Farms Switching to Each Category

Category	**Treated (%)**	**Control (%)**
1. Field crops	42.5	41.8
2. Horticulture	1.9	4.5
3. Wine	4.2	6.2
4. Other permanent crops	3.8	7.3
5. Milk	6.5	8.0
6. Other grazing livestock	9.6	9.7
7. Granivores	4.3	3.0
8. Mixed	27.2	19.5

Table .1.5: ATT using DiD PSM (Total EU sample)

Outcome	ATT	Standard Error	Obs.
Crops Costs			
Seeds and Seedlings	0.0414**	(0.0204)	4,360
Fertilisers	-0.0415**	(0.0181)	4,358
Labour			
Wages	0.182***	(0.0411)	2,040
Paid Labour Input (AWU)	0.0766*	(0.0407)	2,046
Income			
Farm Net Value Added	0.102***	(0.0304)	3,872
Farm Net Income	0.0179	(0.0217)	4,596
Productivity			
Total Factor Productivity	0.0183	(0.0247)	4,658
Input/Output Ratio	-0.0279***	(0.0102)	4,936

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table .1.6: ATT using the Synthetic DiD (Total EU sample)

Outcome	ATT	Standard Error
Crops and Livestock Costs		
Seeds and Seedlings	0.058***	(0.0147)
Fertiliser	-0.003	(0.012)
Crop Protection	0.030***	(0.010)
Other Crop Specific Costs	0.105***	(0.033)
Specific Livestock Costs / Livestock Unit	0.1***	(0.016)
Feed for Grazing Livestock	0.14***	(0.017)
Feed for Grazing Livestock Home-Grown	0.20***	(0.034)
Feed for Pigs & Poultry	0.03*	(0.02)
Feed for Pigs & Poultry Home-Grown	0.02	(0.04)
Other Livestock Specific Costs	-0.043**	(0.019)
Labour		
Total Labour Input (AWU)	0.06	(0.07)
Wages Paid	0.073***	(0.021)
Unpaid Labour Input (AWU)	0.02***	(0.006)
Paid Labour Input (AWU)	0.039*	(0.021)
Income		
Gross Farm Income	0.104***	(0.010)
Farm Net Value Added	0.111***	(0.014)
Farm Net Income	0.136***	(0.017)
Farm Net Value Added (AWU)	0.103***	(0.014)
Productivity		
Total Factor Productivity	0.087***	(0.014)
Input/Output Ratio	0.088***	(0.005)
Farm Net Value Added per Hectare	0.125***	(0.015)

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE .1.7: ATT without organic or mixed holdings (Total EU sample)

Outcome	ATT	Standard Error
Crops and Livestock Costs		
Seeds and Seedlings	0.040***	(0.009)
Fertiliser	-0.015*	(0.009)
Crop Protection	0.029***	(0.010)
Other Crop Specific Costs	0.073***	(0.023)
Specific Livestock Costs / Livestock Unit	0.125***	(0.015)
Feed for Grazing Livestock	0.119***	(0.013)
Feed for Grazing Livestock Home-Grown	0.190***	(0.022)
Feed for Pigs & Poultry	0.052***	(0.019)
Feed for Pigs & Poultry Home-Grown	0.038	(0.028)
Other Livestock Specific Costs	-0.059***	(0.015)
Labour		
Total Labour Input (AWU)	0.022***	(0.022)
Wages Paid	0.070***	(0.005)
Unpaid Labour Input (AWU)	0.029***	(0.004)
Paid Labour Input (AWU)	0.050**	(0.021)
Income		
Gross Farm Income	0.122***	(0.008)
Farm Net Value Added	0.129***	(0.011)
Farm Net Income	0.163***	(0.014)
Farm Net Value Added (AWU)	0.103***	(0.011)
Productivity		
Total Factor Productivity	0.088***	(0.013)
Input/Output Ratio	0.064***	(0.005)
Farm Net Value Added per Hectare	0.128***	(0.013)

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Estimates include matched farms and are weighted with cem weights. Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE .1.8: ATT without highly correlated covariates (Total EU sample)

Outcome	ATT	Standard Error
Crops and Livestock Costs		
Seeds and Seedlings	0.043***	(0.013)
Fertiliser	-0.017	(0.012)
Crop Protection	0.026*	(0.014)
Other Crop Specific Costs	0.088***	(0.030)
Specific Livestock Costs / Livestock Unit	0.114***	(0.020)
Feed for Grazing Livestock	0.109***	(0.018)
Feed for Grazing Livestock Home-Grown	0.205***	(0.029)
Feed for Pigs & Poultry	0.077***	(0.027)
Feed for Pigs & Poultry Home-Grown	0.074*	(0.038)
Other Livestock Specific Costs	-0.064***	(0.020)
Labour		
Total Labour Input (AWU)	0.028***	(0.006)
Wages Paid	0.077***	(0.028)
Unpaid Labour Input (AWU)	0.028***	(0.006)
Paid Labour Input (AWU)	0.084***	(0.027)
Income		
Gross Farm Income	0.123***	(0.011)
Farm Net Value Added	0.125***	(0.015)
Farm Net Income	0.141***	(0.019)
Farm Net Value Added (AWU)	0.084***	(0.015)
Productivity		
Total Factor Productivity	0.068***	(0.018)
Input/Output Ratio	0.059***	(0.007)
Farm Net Value Added per Hectare	0.124***	(0.017)

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Estimates include matched farms and are weighted with cem weights. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE .1.9: ATT with *Country* included as covariate (Total EU sample)

Crops and Livestock Costs		
Outcome	ATT	Standard Error
Seeds and Seedlings	0.045***	(0.014)
Fertiliser	-0.019	(0.013)
Crop Protection	0.028*	(0.015)
Other Crop Specific Costs	0.096***	(0.031)
Specific Livestock Costs / Livestock Unit	0.123***	(0.021)
Feed for Grazing Livestock	0.112***	(0.019)
Feed for Grazing Livestock Home-Grown	0.199***	(0.030)
Feed for Pigs & Poultry	0.071**	(0.028)
Feed for Pigs & Poultry Home-Grown	0.054	(0.039)
Other Livestock Specific Costs	-0.057***	(0.020)
Labour		
Total Labour Input (AWU)	0.027***	(0.007)
Wages Paid	0.080***	(0.029)
Unpaid Labour Input (AWU)	0.023***	(0.006)
Paid Labour Input (AWU)	0.086***	(0.029)
Income		
Gross Farm Income	0.123***	(0.012)
Farm Net Value Added	0.130***	(0.015)
Farm Net Income	0.147***	(0.019)
Farm Net Value Added (AWU)	0.092***	(0.016)
Productivity		
Total Factor Productivity	0.076***	(0.018)
Input/Output Ratio	0.059***	(0.008)
Farm Net Value Added per Hectare	0.128***	(0.018)

Notes: ATT estimates on log-differences (2006–2013) of each outcome. Estimates include matched farms and are weighted with cem weights. Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table .1.10: ATT on costs outcomes in nominal and real (deflated) values (Total EU sample)

Outcome	Nominal	Real (Deflated)
	Crops costs	
Seeds and seedlings (€)	0.044***	0.040***
	(0.013)	(0.013)
Fertiliser (€)	−0.019	−0.025**
	(0.013)	(0.013)
Crop protection (€)	0.028*	0.019
	(0.015)	(0.015)
Other crop specific costs (€)	0.096***	0.089***
	(0.031)	(0.031)
	Livestock costs	
Specific livestock costs / Livestock unit (€/LU)	0.123***	0.108***
	(0.021)	(0.021)
Feed for grazing livestock (€)	0.112***	0.106***
	(0.019)	(0.019)
Feed for grazing livestock home-grown (€)	0.199***	0.204***
	(0.031)	(0.030)
Feed for pigs & poultry (€)	0.071***	0.060**
	(0.028)	(0.027)
Feed for pigs & poultry home-grown (€)	0.054	0.070*
	(0.039)	(0.039)
Other livestock specific costs (€)	−0.057	−0.071***
	(0.020)	(0.020)

Notes: ATT estimates on log-differences (2006–2013) of each outcome, with robust standard errors in parentheses. Real values are computed using Eurostat price indices of the means of agricultural production (input), base 2005 = 100. Price indices cover 2006–2012, and 2013 values are proxied by 2012 indices. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table .1.11: ATT on income outcomes in nominal and real (deflated) values (Total EU sample)

Outcome	Nominal	Real (Deflated)
Gross Farm Income (€)	0.123***	0.109***
	(0.012)	(0.012)
Farm Net Value Added (€)	0.129***	0.109***
	(0.015)	(0.015)
Farm Net Income (€)	0.147***	0.130***
	(0.019)	(0.019)
FNVA (€/AWU)	0.092***	0.056***
	(0.016)	(0.016)

Notes: ATT estimates on log-differences (2006–2013) of each outcome, with robust standard errors in parentheses. Real values are computed using Eurostat price indices of agricultural products (output) and of the means of agricultural production (input), base 2005 = 100. *FNVA per annual work unit*: numerator SE415 deflated by output-side index, full-time person equivalents (SE010). Price indices cover 2006–2012, and 2013 values are proxied by 2012 indices. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table .1.12: ATT on productivity outcomes in nominal and real (deflated) values (Total EU sample)

Outcome	Nominal	Real (Deflated)
Total Factor Productivity	0.097***	0.085***
	(0.018)	(0.018)
Input/Output ratio	0.074***	0.063***
	(0.007)	(0.008)
FNVA (€/ha)	0.085***	0.083***
	(0.015)	(0.018)

Notes: ATT estimates on log-differences (2006–2013) of each outcome, with robust standard errors in parentheses. Real outcomes are constructed as follows: (a) *TFP*: inputs (energy SE345, machinery SE455, capital SE510) and output (SE415) are first deflated into constant 2005 € using the appropriate input-side (for SE345, SE455, SE510) or output-side index (for SE415); (b) *Input/Output ratio* (SE132): directly re-scaled by the ratio of output-to-input price indices (so that the ratio is in real terms); (c) *FNVA per hectare*: numerator SE415 deflated by output-side index, area (SE025) in hectares. Price indices are from Eurostat (base 2005 = 100), cover 2006–2012, with 2013 proxied by the 2012 index. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

.2 Additional Tables

TABLE B1: Descriptive statistics West EU (pre-matching)

	Treated			Controls			Total		
	mean	sd	N	mean	sd	N	mean	sd	N
Crops and Livestock costs outcomes:									
Seeds and seedlings	.334	0.636	2249	.302	0.614	4202	.313	.622	6451
Fertiliser	.416	0.511	2382	.377	0.559	4594	.39	.543	6976
Crop protection	.261	0.532	2224	.176	0.566	4632	.203	.557	6856
Other crop specific costs	.168	1.104	1799	.091	1.015	2765	.121	1.052	4564
Specific livestock costs / Livestock unit	.557	0.719	1816	.508	0.721	2479	.529	.721	4295
Feed for grazing livestock	.652	0.683	1389	.6	0.598	1913	.622	.635	3302
Feed for grazing livestock home-grown	.602	1.040	1014	.453	1.103	1373	.516	1.079	2387
Feed for pigs and poultry	.415	0.667	607	.41	0.654	830	.412	.659	1437
Feed for pigs and poultry home-grown	.34	0.917	438	.156	0.969	372	.256	.945	810
Other livestock specific costs	.129	0.595	1693	.135	0.618	2380	.132	.608	4073
Labour outcomes:									
Wages paid	.341	0.995	1179	.262	0.889	2472	.287	.925	3651
Total labour input (AWU)	-.006	0.286	2627	-.01	0.298	5047	-.009	.294	7674
Unpaid labour input (AWU)	-.048	0.254	2562	-.044	0.247	5035	-.045	.249	7597
Paid labour input (AWU)	.21	0.967	1180	.129	0.861	2471	.155	.897	3651
Income outcomes:									
Gross Farm Income	.159	0.482	2607	.095	0.527	4910	.117	.512	7517
Farm Net Value Added	.152	0.626	2487	.097	0.672	4653	.116	.657	7140
Farm Net Income	.181	0.872	2144	.12	0.934	3845	.142	.913	5989
Farm Net Value Added(AWU)	.156	0.635	2483	.099	0.670	4657	.119	.658	7140
Productivity outcomes:									
Total Factor Productivity	-.025	0.771	2529	-.076	0.829	4749	-.058	.81	7278
Input/Output Ratio	.048	0.255	2671	.016	0.265	5155	.027	.262	7826
Farm Net Value Added/Ha	.121	0.718	2530	.044	0.821	4706	.071	.787	7236

TABLE B2: Descriptive statistics South EU (pre-matching)

	Treated			Controls			Total		
	mean	sd	N	mean	sd	N	mean	sd	N
Crops and Livestock costs outcomes:									
Seeds and seedlings	.17	0.924	494	.202	0.866	4736	.199	.871	5230
Fertiliser	.34	0.896	596	.407	0.862	6441	.401	.865	7037
Crop protection	.259	0.953	550	.316	1.077	5787	.311	1.067	6337
Other crop specific costs	.339	1.576	235	.056	1.386	2614	.079	1.405	2849
Specific livestock costs / Livestock unit	.065	1.099	194	.069	1.116	2222	.069	1.114	2416
Feed for grazing livestock	-.038	0.672	175	.098	0.629	1832	.086	.634	2007
Feed for grazing livestock home-grown	-.074	0.855	142	-.06	0.829	1061	-.062	.832	1203
Feed for pigs and poultry	.258	1.488	21	.301	1.050	359	.299	1.076	380
Feed for pigs and poultry home-grown	-.914	1.846	9	.492	1.382	55	.294	1.521	64
Other livestock specific costs	.358	1.102	170	.258	1.120	1912	.266	1.118	2082
Labour outcomes:									
Wages paid	.215	0.921	263	.13	0.941	2677	.137	.939	2940
Total labour input (AWU)	-.005	0.446	712	-.059	0.477	7546	-.055	.474	8258
Unpaid labour input (AWU)	-.057	0.416	703	-.107	0.437	7530	-.103	.435	8233
Paid labour input (AWU)	.138	0.959	265	.069	0.954	2675	.075	.955	2940
Income outcomes:									
Gross Farm Income	.108	0.736	714	-.086	0.788	7409	-.069	.785	8123
Farm Net Value Added	.126	0.954	692	-.068	0.927	6996	-.051	.931	7688
Farm Net Income	.096	1.052	634	-.121	1.017	6588	-.102	1.022	7222
Farm Net Value Added(AWU)	.113	0.932	689	-.016	0.963	6999	-.004	.961	7688
Productivity outcomes:									
Total Factor Productivity	-.146	1.068	694	-.174	1.121	7065	-.172	1.116	7759
Input/Output Ratio	.002	0.546	726	-.154	0.636	7688	-.14	.63	8414
Farm Net Value Added/Ha	.051	1.064	696	-.123	1.126	6855	-.107	1.121	7551

Table B3: Descriptive statistics East EU (pre-matching)

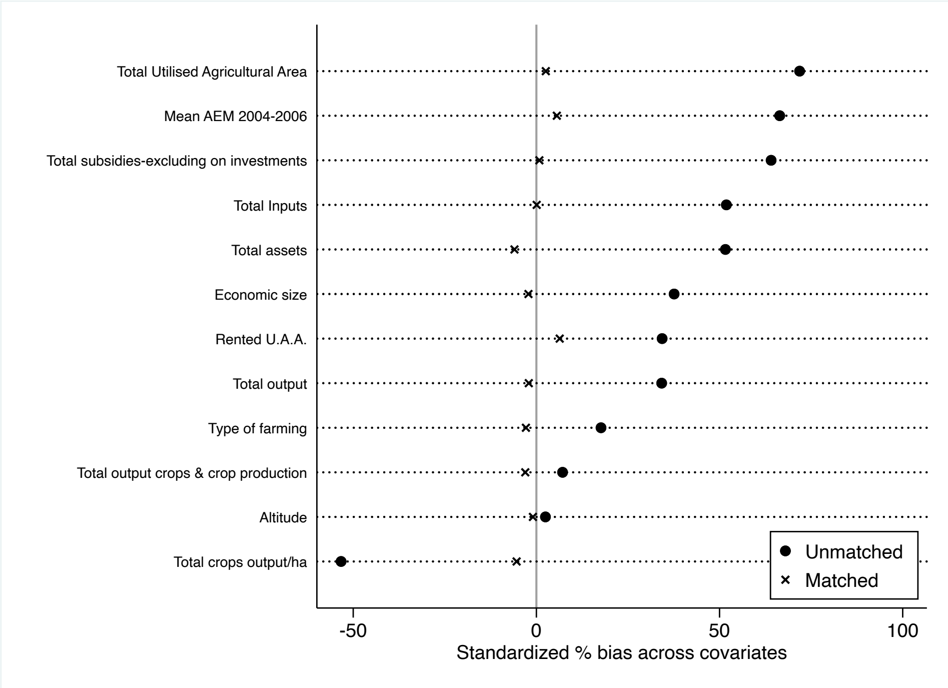
	Treated			Controls			Total		
	mean	sd	N	mean	sd	N	mean	sd	N
Crops and Livestock costs outcomes:									
Seeds and seedlings	.399	0.562	596	.344	0.548	2322	.355	.551	2918
Fertiliser	.534	0.612	615	.515	0.611	2353	.519	.611	2968
Crop protection	.309	0.612	640	.303	0.611	2399	.304	.611	3039
Other crop specific costs	.385	1.489	255	.231	1.382	950	.264	1.406	1205
Specific livestock costs / Livestock unit	.664	0.882	429	.711	0.866	1292	.699	.87	1721
Feed for grazing livestock	.552	0.788	270	.623	0.792	853	.606	.791	1123
Feed for grazing livestock home-grown	.482	0.894	265	.573	0.878	844	.552	.882	1109
Feed for pigs and poultry	.367	0.648	264	.332	0.694	854	.34	.683	1118
Feed for pigs and poultry home-grown	.328	0.839	208	.374	0.813	794	.365	.818	1002
Other livestock specific costs	.252	0.862	411	.334	0.896	1228	.313	.888	1639
Labour outcomes:									
Wages paid	.24	0.872	340	.271	0.917	857	.262	.904	1197
Total labour input (AWU)	-.039	0.397	705	-.052	0.372	2490	-.049	.378	3195
Unpaid labour input (AWU)	-.006	0.337	582	-.049	0.331	2328	-.04	.333	2910
Paid labour input (AWU)	-.106	0.864	339	-.12	0.905	858	-.116	.893	1197
Income outcomes:									
Gross Farm Income	.385	0.665	678	.291	0.654	2436	.311	.657	3114
Farm Net Value Added	.484	0.844	626	.366	0.864	2263	.391	.861	2889
Farm Net Income	.469	0.959	541	.347	0.947	2091	.372	.951	2632
Farm Net Value Added(AWU)	.509	0.850	630	.413	0.860	2259	.434	.858	2889
Productivity outcomes:									
Total Factor Productivity	.155	1.057	644	.15	1.013	2295	.151	1.023	2939
Input/Output Ratio	.006	0.451	723	.028	0.370	2533	.023	.389	3256
Farm Net Value Added/Ha	.399	1.009	622	.32	0.941	2264	.337	.957	2886

Table B4: Descriptive statistics North EU (pre-matching)

	Treated			Controls			Total		
	mean	sd	N	mean	sd	N	mean	sd	N
Crops and Livestock costs outcomes:									
Seeds and seedlings	.442	0.746	363	.322	0.752	290	.389	.751	653
Fertiliser	.417	0.750	319	.684	0.889	262	.538	.826	581
Crop protection	.558	0.825	279	.676	0.889	239	.613	.856	518
Other crop specific costs	.311	1.471	301	.757	1.534	166	.469	1.507	467
Specific livestock costs / Livestock unit	.341	0.977	264	.307	0.961	142	.329	.971	406
Feed for grazing livestock	.488	0.666	221	.43	0.560	107	.469	.633	328
Feed for grazing livestock home-grown	.605	0.791	217	.364	0.614	105	.527	.745	322
Feed for pigs and poultry	.013	0.718	72	-.012	1.249	64	.001	1	136
Feed for pigs and poultry home-grown	.229	1.167	64	.277	1.423	46	.249	1.274	110
Other livestock specific costs	.404	1.131	258	.771	1.039	133	.529	1.113	391
Labour outcomes:									
Wages paid	.704	0.760	131	.772	0.824	170	.742	.796	301
Total labour input (AWU)	-.078	0.429	393	-.003	0.473	318	-.045	.451	711
Unpaid labour input (AWU)	-.1	0.384	359	-.089	0.353	295	-.095	.37	654
Paid labour input (AWU)	.177	0.824	133	.089	0.850	171	.127	.839	304
Income outcomes:									
Gross Farm Income	.279	0.738	373	.386	0.839	301	.327	.786	674
Farm Net Value Added	.35	0.909	329	.363	1.008	278	.356	.955	607
Farm Net Income	.26	1.129	246	.218	1.195	239	.24	1.161	485
Farm Net Value Added(AWU)	.405	0.911	331	.332	0.873	276	.372	.894	607
Productivity outcomes:									
Total Factor Productivity	-.018	1.099	335	-.192	1.184	284	-.098	1.141	619
Input/Output Ratio	.026	0.330	398	.027	0.375	326	.026	.351	724
Farm Net Value Added/Ha	.309	0.999	335	.25	1.252	282	.282	1.121	617

.3 List of Figures

Figure 2: PSM balancing diagnostic



Chapter 2

Nudging Toward Climate Adaptation. A Field Experiment on Informational Strategies in Organic Food Markets

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Abstract

We conduct a field experiment to test whether informational messages can nudge organic consumers toward purchasing "greener" products that support climate change adaptation. Leveraging data from a large Italian online shop of organic products, we use pasta as a case study to examine consumer responses to information about an ancient durum wheat variety with superior drought tolerance compared to modern wheat. We test two types of messages that frame climate adaptation as achievable through everyday choices: a colloquial information that adopt a relatable tone and a science-based message that presents evidence with visual elements. We find that the colloquial message increases the market share of "greener" pasta by 13%, while the science-based message is effective only among highly environmentally conscious consumers. Effects persist for at least three months and are stronger among women, younger individuals, and those with higher education. The effect of colloquial messaging is amplified among consumers

previously experiencing severe or extreme drought conditions. We observe a backfire effect among the greenest consumers, i.e. those who were already predominantly purchasing ancient pasta.

2.1 Introduction

Over the past two decades, experimental research has highlighted the effectiveness of non-pecuniary, information-based strategies in influencing individuals toward welfare-enhancing and policy-relevant consumption behaviors (Allcott & Rogers, 2014; Allcott et al., 2022; Duflo & Saez, 2003). These strategies have been shown to successfully promote environmentally conscious actions, including energy and water conservation (Bonan et al., 2020; d'Adda et al., 2022; Ferraro & Price, 2013; Gillingham & Tsvetanov, 2018), forest protection (Higgins et al., 2020; Voors et al., 2011), resource reuse, and waste reduction (Bretter et al., 2023; Essl et al., 2021). A relevant application is in the organic food market, where nudging strategies, such as *green* labels, have significantly influenced consumer behavior by shifting preferences from conventional products to healthier and more sustainable alternatives (Duckworth et al., 2022; Rousseau & Vranken, 2013).

Organic consumers often associate private health benefits with pro-social environmental behavior (Van Doorn & Verhoef, 2011; Van Horen et al., 2018; Zanoli & Naspetti, 2002). However, even within the organic sector, there is substantial variation in the externalities these products generate. While organic food contributes to climate change mitigation by reducing greenhouse gas emissions, eliminating the use of synthetic pesticides, and lowering potential health risks (Muller et al., 2017; van Der Werf et al., 2020), they might also support the adaptation of agro-ecosystems to environmental extremes, such as drought and temperature fluctuations, through practices that enhance resilience (Reganold & Wachter, 2016). These adaptive benefits, while socially valuable, are often overlooked by consumers due to significant information asymmetry. Consumers may lack the necessary knowledge to distinguish products that not only meet standards for climate change mitigation but also offer critical climate-adaptive benefits. This lack of awareness could arise from frictions, like the time and effort required to evaluate product characteristics, or mental gaps, including cognitive biases that distort how information is processed and prioritized (Handel & Schwartzstein, 2018).

This paper investigates how informational messages can reduce these asymmetries, shifting consumer behavior from standard organic "green" products toward more climate-adaptive, "greener" consumption choices. Specifically, we focus on informational strategies highlighting the superior adaptive benefits of organic pasta made from an ancient wheat variety over organic pasta made from modern wheat. Pasta is a particularly relevant case for this study, as it is a staple food with significant potential to contribute to climate change adaptation. Our goal is to align available information with consumer decisions, promoting more informed choices that support broader environmental objectives.

Providing environmentally conscious consumers, who already purchase organic food, with information about the benefits of climate-adaptive products has the potential to drive the rapidly growing organic food market toward more socially optimal choices (Bonroy & Constantatos, 2008;

Pieper et al., 2020; Rana & Paul, 2020; Swift et al., 2004; Willer & Lernoud, 2017). However, addressing the informational gap presents significant challenges. Supplying additional information on "new" environmental challenges, such as adaptation, risks overwhelming consumers who are already environmentally engaged. Behavioral research highlights phenomena such as *moral licensing* (Lasarov et al., 2022) and *boomerang effects* (Bonan et al., 2020), where individuals justify avoiding further pro-environmental actions by considering their current efforts, such as purchasing green products, as sufficient. This behavior can reduce the effectiveness of informational campaigns promoting sustainable behaviors[1]. As a consequence, tailored communication strategies are critical to encourage a greener consumption (Allcott & Taubinsky, 2015; T. Li et al., 2018; McCluskey & Loureiro, 2003).

Despite the potential of information-based strategies and nudges to shape sustainable behaviors (Andor et al., 2022; Dannenberg & Weingärtner, 2023; Giaccherini et al., 2021; Hainmueller et al., 2015; Lohmann et al., 2022; Perino & Schwirplies, 2022), empirical evidence on effective communication approaches for fostering climate-adaptive food consumption remains limited.

Our study aims to address this gap by leveraging a field experiment conducted in collaboration with Alce Nero S.p.A., a leading brand in the Italian organic food market, using detailed individual-level data on daily online purchases. The experiment combines two treatments — two distinct informational messages — and a control group with three discount levels on pasta products, designed to incentivize participation and simulate real-world price variations. The experiment follows a three-phase structure. In the pre-intervention phase, we collect baseline data to understand individual purchasing behavior. During the intervention phase, participants are recruited via email, randomly assigned to one of three discounts on pasta products, and exposed to one of two informational messages or placed in the control group. Finally, in the post-intervention phase, we analyze purchasing data to evaluate the persistence of treatment effects over time. Our final sample comprises 872 individuals.

Adopting the 2022 drought occurred in Europe to remind the relevance of climate change adaptation [2], we examine whether the two informational messages can encourage a shift in preferences from organic pasta made from modern durum wheat to pasta made from the ancient wheat variety *Cappelli* (hereafter *modern* and *ancient* wheat, respectively). The first message uses a straightforward, colloquial tone designed to resonate with a broad audience, while the second adopts a scientific, evidence-based tone. Both messages convey the same information: the superior tolerance of the *ancient* wheat to severe drought compared to *modern* durum wheat, as measured using unique on-farm agronomic data provided by Alce Nero wheat suppliers.[3]

[1] Evidence from Dorner (2019) suggests these effects are especially likely among consumers with strong pro-environmental attitudes, such as those in the organic market.

[2] The drought has been documented through Copernicus, the European Union's Earth Observation Programme. For further details, see: https://edo.jrc.ec.europa.eu/documents/news/GDO-EDODroughtNews202207_Europe.pdf

[3] Rizza et al. (2012) identify significant differences in water use efficiency between the ancient durum wheat cultivar *Cappelli* and a modern cultivar, attributing these differences to physiological traits such as improved

Our findings show that the colloquial message increased the share of *ancient* wheat pasta purchases by 13 percent (6.3 p.p.) compared to the control group, despite an 18% price premium over pasta made from *modern* wheat. This represents a significant shift from green to greener consumption, as consumers substantially increased their share of drought-resistant *ancient* wheat pasta compared to their typical organic purchasing patterns. The effect persisted for at least three months post-intervention, without additional discounts. In contrast, the scientific message had no overall impact, despite being effective among consumers with high environmental sensitivity, trust in scientific information, and awareness of climate change.

Heterogeneous effects analysis revealed that the main impact of the colloquial message was primarily driven by women, younger individuals, and those with higher education. However, a significant reduction in the consumption of pasta made from *ancient* wheat emerged among consumers who predominantly purchased that pasta during the pre-intervention phase. We also show that the impact of the colloquial message is amplified when consumers have been exposed to moderate and severe drought, as measured by Standardized Precipitation Evapotranspiration Index (SPEI).

Additionally, the results confirm findings from the literature suggesting that offering a higher discount to appeal to green consumers does not encourage additional pro-environmental behavior compared to using an informational strategy alone (Schwartz et al., 2020).

Overall, our research contributes to the environmental economics literature on how to nudge individual behaviors to improve environmental outcomes and promote sustainable development (Alpizar et al., 2008; Frederiks et al., 2015; Gillingham et al., 2013). While prior studies have focused on reducing the negative externalities of food consumption through climate mitigation strategies (e.g., Bryngelsson et al. (2016), Kurz (2018), and Lohmann et al. (2022)), we extend this work by exploring the role of food choices in promoting climate adaptation. This perspective is increasingly important as the accelerating impacts of climate change and rising food demand necessitate strategies that enhance resilience in both agricultural production and consumer behavior. A key challenge we address is how to motivate environmentally engaged consumers to sustain additional changes, particularly in contributing to agro-ecosystem adaptation.

We also contribute to the literature examining the impacts of climatic shocks and the adaptive capacity of widely cultivated agricultural species, such as wheat (Wing et al., 2021). Using a case study approach, we analyze the productivity differences between two key wheat cultivars, highlighting how these differences were shaped by the severe drought that affected Europe in 2022. By combining insights on consumer behavior with agricultural adaptation, our research provides an additional perspective on the intersection of climate resilience and sustainable agri-food systems.

photosynthetic efficiency and reduced transpiration rates, which make *Cappelli* better adapted to drought-prone environments.

The remainder of the paper is as follows. Section 2.2 presents the motivation and the conceptual framework. Section 2.3 describes the implementation of the experiment presenting the design, data and empirical strategy. Section 2.4 presents the main findings together with potential mechanisms and heterogeneous effects, while Section 2.5 provides additional results. Section 2.6 discusses the implications of our findings and concludes.

2.2 Background

2.2.1 *Motivation*

The increasing frequency of climate extremes, particularly drought, presents substantial challenges for agro-ecosystems worldwide (Mbow et al., 2017). In this context, organic farming has emerged as a pivotal strategy for achieving emission reduction targets. While the environmental impacts of organic farming vary depending on crop type and local practices, organic systems consistently demonstrate key adaptive advantages, such as natural pest control and enhanced water efficiency (Clark & Tilman, 2017). These attributes are particularly relevant for mitigating the adverse effects of extreme temperatures and prolonged droughts, thereby strengthening agricultural resilience in the face of climate change (Bengtsson et al., 2005; Gattinger et al., 2012; Ponisio et al., 2015). Despite its environmental benefits, organic agriculture faces critical scalability and productivity constraints that may undermine its long-term contribution to food security (Chiriaco et al., 2022; European Parliament and Council, 2021; Meemken & Qaim, 2018). As a consequence, enhancing the production and consumption of organic food as part of a broader strategy for climate change mitigation and adaptation remains a key challenge.

A significant barrier to this goal is the issue of consumer trust in organic products, which is often driven by external information such as labels. Organic products are indeed *credence goods*, whose perceived quality depends on external information such as labels or recommendations, rather than on attributes directly observed by consumers (Bonroy & Constantatos, 2008; Roe & Sheldon, 2007). However, labels often fail to convey key aspects of the production process and its environmental impact, especially in the online market, where the spread of unreliable and heterogeneous information frequently leads to *greenwashing*, which can undermine consumer trust and decision-making (Testa et al., 2015). Nevertheless, the online channel has emerged as a rapidly expanding segment of the organic market, reflecting broader European trends.[4] For instance, in Italy, the number of online organic retailers grew from 49 in 2001 to 375 in 2018, underscoring the increasing confidence in e-commerce as a viable channel for organic sales.[5] The

[4]In 2019, online food sales accounted for approximately 10% of the market in Spain and 14% in the UK. In Italy, a survey conducted on a nationally representative sample of 3,792 consumers showed that 27% of respondents reported a 50% increase in their online organic spending over the past five years, while 40% purchased organic products online at least once a week.

[5]Survey conducted by ISMEA and MIPAAF, available at: https://www.sinab.it/pubblicazioni/il-mercato-italiano-online-dei-prodotti-agroalimentari-biologici.

COVID-19 pandemic further accelerated this trend, with consumer demand for organic products doubling over the last decade and continuing to grow steadily (Shaw et al., 2022)[6].

Information played a crucial role in driving consumer preferences toward organic products, particularly when it highlights health-related or nutritional benefits, reinforcing the perception of organic food as a healthier alternative to conventional options (Fresacher & Johnson, 2023; Shi et al., 2018). A confirmation of this role related to our experiment arises from the observed change in consumers' behavior following an information shock about the health-related attributes of the pasta made from the *ancient* wheat. To show this, we leverage an episode of *Report*, a prominent Italian TV current affairs program that aired in 2020 and discussed the superior nutritional traits of *ancient* wheat, using both comprehensible language and scientific evidence. Using raw data from Alce Nero's online sales, Figure 2.1 presents a reduced-form event study, where $t = 0$ marks the *Report* episode date (October 19$^{\text{th}}$, 2020). The figure shows a significant increase in purchases of pasta made from the *ancient* wheat immediately after the broadcast.

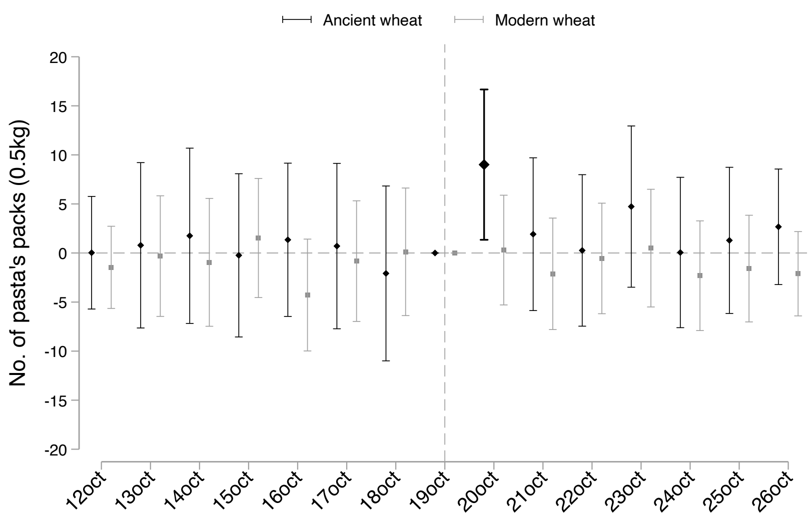


FIGURE 2.1: Event study on pasta purchases after *Report* TV program. The period $t = [-7, -1]$ represents the week before the event, and $t = [+1, +7]$ denotes the week after the event. The outcome variables include the average number of packages of either *ancient* durum or *modern* durum pasta. The estimation sample includes 192 consumers who bought pasta within the time frame of the *Report* broadcast. Standard errors are clustered at the individual level. Confidence intervals are at 95%.

However, the *ancient* wheat possess properties that extend beyond its nutritional and health benefits, as it is highly resilient to water scarcity, making it an ideal substitute to enhance adaptation while supporting the food supply. Unlike other wheat varieties, the adaptation of *ancient* wheat to heat and drought stress includes enhanced water use efficiency through mechanisms such as minimizing water loss (e.g., stomatal closure, increased thickness of the leaf cuticle) and optimizing water uptake (e.g., developing a deeper or more extensive root system) (Aprile et al.,

[6]Report SINAB, 2019, accessible at: https://www.ismeamercati.it/flex/cm/pages/ServeBLOB.php/L/IT/IDPagina/6022.

2013; Giusti et al., 2017). The severe drought that occurred in Europe in 2022 (Montanari et al., 2023), where many wheat-producing areas were severely affected, provides a clear example of its potential[7].

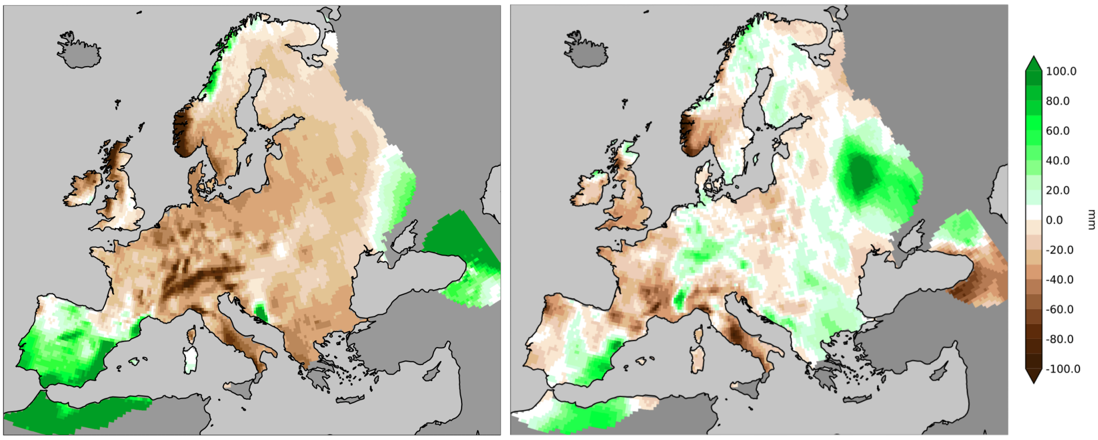


FIGURE 2.2: Anomalies in total precipitation on wet days during the wheat growing season of 2022. The figure displays anomalies in total precipitation on wet days during March (left) and April (right) of 2022, with respect to the reference period 1991-2020. These months cover a significant portion of the wheat growing season. The values have been processed by the Copernicus service of the European Union using high-resolution meteorological data from E-OBS. Source: https://climate.copernicus.eu/esotc/2022/drought

The exceptional severity and extensive coverage of the drought are visible from Figure 2.2, which displays the monthly anomalies in total precipitation on wet days compared to the 1991-2020 period for March and April 2022, corresponding to a significant portion of the wheat growing season. Using Alce Nero's production data, Figure 2.3 provides a graphical comparison of the average annual yield of both *modern* and *ancient* organic wheat during the 2022 drought and in previous years[8]. It emerges that *ancient* wheat maintains its productivity while *modern* wheat suffers a large yield reduction when water availability is reduced. These figures highlight the large resilience potential of *ancient* wheat.[9]

[7] Agronomic studies have shown that the *ancient* wheat exhibits remarkable resilience to extreme temperatures and drought conditions, employing efficient water use strategies like reduced water loss and improved water absorption capabilities (Rizza et al., 2012; Sabella et al., 2020)

[8] The production of *ancient* wheat within Alce Nero's consortium is mainly centered in the southern regions of Italy, such as Apulia and Sicily.

[9] Although other pasta varieties, like those made of chickpeas, might offer additional ecological benefits, the absence of analogous data within our dataset necessitated their exclusion from our analysis, thus allowing for a direct comparison between the two chosen wheat varieties, each known for its distinct environmental benefits.

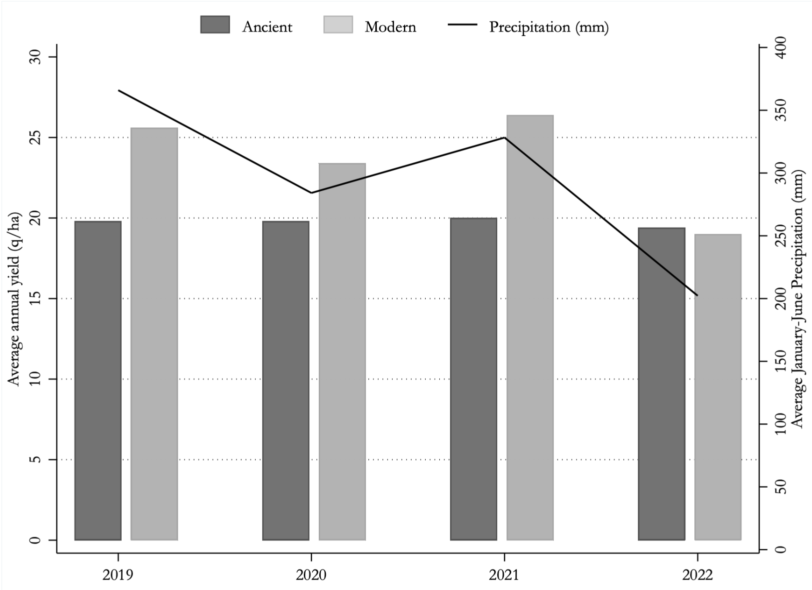


FIGURE 2.3: Annual yields and precipitation patterns, by type of wheat. The figure displays the average yearly yield of *modern* and *ancient* wheat using data from Alce Nero's organic farmers. Yield data are paired with average annual precipitation (January-June) data collected from the Gridded Agro-Meteorological dataset overseen by Mars Agri-4-Cast. Source: own elaboration.

Following the observed consumer response to health-related information during the *Report* broadcast, we leverage the 2022 drought to highlight the climate-adaptive features of *ancient* wheat. We hypothesize that a similar response could be triggered by shifting the focus of informational treatments from nutritional benefits to social benefits related to climate change adaptation. Organic consumers, who already demonstrate an established interest in sustainable consumption, represent a natural pool of potential "first movers" within a market segment focused on organic adaptive-based, *greener* food products (McFadden & Huffman, 2017).

2.2.2 *Conceptual framework and hypothesis*

The main outcome variable of our analysis is the share of packs of pasta made from *ancient* wheat purchased by a consumer relative to her total pasta purchases on the online Alce Nero shop. This outcome allows us to assess the impact of two informational messages in terms of substitution from "green" organic pasta to a "greener" organic pasta.

The design assumes that online organic consumers maximize their utility by evaluating various product characteristics and giving weight to environmentally related features alongside traditional attributes like price (Ambec & De Donder, 2022; Hainmueller et al., 2015; Roe & Sheldon, 2007). While health is often cited as the primary motivation for purchasing organic food, research shows that health concerns are closely tied to ecological values and pro-social environmental behavior (Van Doorn & Verhoef, 2011; Zanoli & Naspetti, 2002).

We therefore examine an online organic food market consisting of a mass unit n of consumers, denoted $i = 1, ..., n$. The consumer i utility is:

$$U_i = U(x_i, z_i, G(z_i); \tau, \theta) \tag{2.1}$$

where x is a numeraire private good which includes online organic products other than z. The pasta category z includes two substitute goods: pasta made from *ancient* wheat, denoted as z^1, and pasta derived from *modern* wheat, denoted as z^0. The consumption of these goods contributes differently to the provision of a positive externality G, that is the agro-ecosystem adaptation to droughts and rainfall variability (Khan & Munira, 2021). The parameter τ represents consumers' preference for G, while θ represents a vector of other taste parameters that characterize heterogeneous preferences or motivations. These may include dietary or health-related considerations that are relevant among consumers of organic food, as well as preferences for environmental attributes (e.g. mitigation), other than G, that are already associated with and recognized by organic food consumers (Y. Li & van't Veld, 2015).
Under a budget m_i and prices for the online organic products, the budget constraint is $m_i = x_i + p^{z^0} z_i^0 + p^{z^1} z_i^1$ with $p^{z^1} > p^{z^0}$, being pasta made from *ancient* wheat more expensive than *modern* wheat pasta. Consumer i maximizes utility by selecting the optimal levels of consumption: $x_i^*; z_i^{*,0}; z_i^{*,1}$. Without information on the contribution of z^0 and z^1 to G, consumers distribute their pasta purchases conditionally only to θ and relative prices. Thus, assuming that all the n households are not, *a priori*, aware of the distinct contributions of z^0 and z^1 to G, their observed pre-information consumption behavior does not reveal the true individual preferences τ for their marginal contribution to G.

Upon introducing an informative message D which makes it evident that $G(z^0) < G(z^1)$[10], we expect that true consumers' preferences for G will emerge revealing three consumer types (Larson, 2003). First, those who purchase organic pasta but are not interested in the provision of G; we conventionally label these consumers as *green* and their share of *ancient* wheat pasta over the total pasta purchased is zero.[11] Second, the *greener* refers to consumers for whom $0 < z_i^1/z_i < 0.5$. Finally, the *greenest*, for whom $z_i^1/z_i \geq 0.5$. The treatment effect of the provided information on the market share of greener pasta depends on both the proportion of organic consumer types within the mass of organic online consumers n and the effectiveness of the information in driving consumers to reveal their underlying preferences τ.

As recently confirmed by Dannenberg and Weingärtner (2023), nudging an adaptation-based consumption with information that complements green labeling is a compelling strategy to induce consumers to enhance a pro-social environmental behavior but introduces additional complexity compared to standard green consumption. First, environmentally friendly behaviors, such

[10]Note that consumers are just aware of their contribution to G, without having information on the overall G provided by the other $n-1$ consumers

[11]Formally, for these consumers the marginal utility of G is lower than the excess unit price to be paid for z^1.

as buying organic food, can lead committed individuals to see these actions as progress, encouraging further efforts, while less committed ones may view them as sufficient proof of their dedication, justifying reduced engagement (Mullen & Monin, 2016). In such cases, the intended message promoting the contribution to climate change adaptation may backfire, leading to a rebound effect that undermines pro-social environmental behavior (Bhanot, 2017; Byrne et al., 2018; d'Adda et al., 2024; Hertwich, 2005). Second, consumers must not only understand a product's environmental impact but also its added value under abnormal climatic conditions. This requires conveying specific and detailed information in a way that avoids information overload and maintains clarity. In a context where communication often aims to inform and entertain simultaneously, frequently sacrificing thoroughness and accuracy, science plays a crucial role in closing knowledge gaps on climate resilience by providing accurate and reliable information. Its impact might largely depend on consumers' trust in scientific sources, which shapes their willingness to engage with and act upon the information (Andre et al., 2024; Brewer & Ley, 2013; Gundersen et al., 2022; Vecina et al., 2024). However, even when consumers are exposed to trustworthy information, cognitive biases, and motivational barriers can undermine its effectiveness. For instance, motivated reasoning can lead consumers to favor information that aligns with their preexisting beliefs while dismissing conflicting evidence (Thaler, 2024).

In light of the limited empirical evidence regarding the effectiveness of different informational strategies in promoting adaptive consumption, we evaluate the efficacy of two distinct approaches: a colloquial message D^c and a scientific-based D^s message. Since online organic consumers already exhibit a high level of trust in the labeled products they purchase (Roe & Sheldon, 2007), we expect that providing easily understandable information D^c about the superior environmental benefits of a subset of organic products – such as pasta made from *ancient* wheat – will be sufficient to allow true *greener* and *greenest* consumers to increase their demand for *ancient* wheat pasta. Our first hypothesis is thus:

H1: Easily understandable and colloquial information on greener products drives their substitution over similar green products. This hypothesis is verified for an increase of the proportion of z^1 over z, conditional to receiving the "colloquial" information D^c. This implies that the majority of n is at least a *greener* or a *greenest* consumer and an easy-to-convey information is efficient in letting them reveal their true preferences τ for G.

Due to the limited public awareness of the positive externality consumers are expected to contribute to—agro-ecosystem adaptation—tangible, detailed science-based information may prove more effective in eliciting consumers' true preferences for G. Therefore, we test the following second hypothesis.

H2: Scientifically-based information is more effective than a easy-to-convey information in shifting demand from green to greener products. This hypothesis is verified when the treatment effect for consumers who receive scientific information D^s, is positive and larger than the treatment effect estimated from the group who received the colloquial treatment D^c.

Details about the specific content of the two informational messages are provided in the following section.

2.3 Methods and data

2.3.1 Experimental design

Our field experiment, conducted over eight weeks and three days from January 24th to March 31st, 2023, was structured into three key phases outlined in Figure 2.4: *i*) the baseline phase (pre-intervention), during which daily individual purchase data was collected from January 1st, 2022, to January 23rd, 2023; *ii*) the intervention phase, conducted from January 24th to March 31st, 2023, during which participants were recruited via email to assess consumer preferences for Alce Nero's organic product range, specifically in the context of the challenges climate change poses to farmers; and *iii*) the post-intervention phase, aimed at assessing the enduring effects of the treatments by tracking individual purchasing patterns.[12] During the intervention phase, Alce Nero sent two reminder emails to participants who had not yet responded: the first one week after the experiment began and the second after one month.

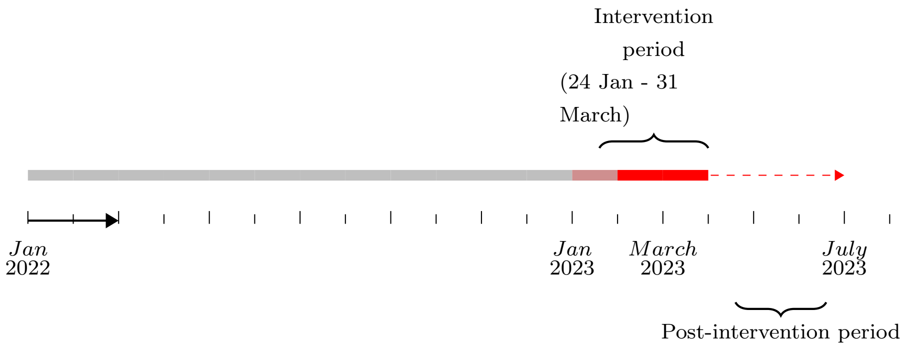


FIGURE 2.4: Timeline of the experiment.

In detail, the experiment follows a 3-by-3 design, randomly assigning participants to different combinations of informational messages (colloquial, scientific, and a control group receiving no message) and three levels of discounts on pasta products (5%, 10%, or 20%). The discounts were strategically designed to incentivize survey participation. At the start of the intervention period, participants received email invitations to complete an online survey. As a reward, they were offered conditional, single-use discounts on pasta purchases, redeemable only after completing the survey. Since all survey questions were compulsory and the discount was revealed only upon completion, this rules out the possibility that observed effects were confounded by prior

[12]The study was pre-registered at the American Economic Association RCT Registry on July 28th: https://doi.org/10.1257/rct.11784-1.0

awareness of the discount.[13] By incorporating three distinct discount levels, the design allowed for an investigation of potential nonlinearities in demand, providing insights into how varying price incentives shape consumer purchasing behavior and responsiveness. The survey and associated discount offer were extended to all eligible participants, including those in both treatment and control groups, ensuring a comprehensive approach to participant engagement.

Since Alce Nero lacked prior demographic information about its customers, the randomization process was carefully stratified based on historical online purchasing behavior using data between January 2020 and December 2022. Key randomization variables included the type of pasta previously purchased (categorized as *ancient*, *modern*, or both), total expenditure on pasta, purchasing tendencies during discount events, and geographic characteristics such as municipal income levels and regional distribution. We identified potential participants from an initial pool of roughly 20,000 customers, narrowing it down to a sample of 4,727 individuals who had consented to be contacted by third parties and had purchased at least one pack of pasta in 2022.[14]

Each consumer was randomly assigned to one of three groups: control (1,588 participants), colloquial (1,558 participants), or scientific (1,581 participants). Discount assignments were distributed unevenly to ensure sufficient representation and statistical power: 25% of participants received a 5% discount, 50% received a 10% discount, and 25% received a 20% discount.[15]

From the initial sample of 4,727 customers, 1,225 completed the survey, resulting in a 25% response rate. Among these, 872 individuals purchased at least one pack of pasta during the experiment, distributed as follows: 292 in the control group, 294 in the scientific treatment group, and 286 in the colloquial treatment group. The primary reason for attrition was participants

[13] This design choice ensures that both groups shared the same baseline awareness of Alce Nero's established focus on environmental sustainability. As a result, any observed differences in behavior or survey responses between the treatment groups are unlikely to reflect a broader sensitivity to climate change but instead can be attributed to the specific information provided with the treatment messages. Importantly, both invitation emails do not introduce any technical details about adaptation, drought tolerance or specific wheat variety, neither do they directly mention substituting pasta made from *modern* wheat with pasta made from *ancient* wheat, nor do they prescribe specific consumer actions. This framing minimizes the risk that the treatment effects observed are confounded by the recruitment process. Nevertheless, as the emails sent to the treatment and control groups differed by a single sentence in the treatment email: *"You will discover which product best fits a planet that is becoming increasingly arid."*(see Figure C1 in Section .1), further in the text, we test empirically whether this element might have produced some selection issues.

[14] The year 2022 was chosen for the baseline period due to the significant impact of severe droughts on wheat production in Italy, providing valuable insights into Alce Nero's agricultural practices and the comparison of yields between *ancient* and *modern* wheat varieties under challenging weather conditions. This approach allowed for a thorough examination of purchase patterns throughout the year, including the impact of seasonal trends and promotional events on consumer behavior, and highlighted the increase in online shopping during weekends.

[15] The sample sizes were determined through a power analysis using pre-existing data, including the average price of pasta (€2.20) and discounted prices ranging from 5% to 25%. This approach ensured balanced representation across experimental groups and optimized statistical power to detect meaningful differences. Figure .2.2 in Section .1 displays the distribution of the randomized sample across treatment groups and Italian regions. Table .1.1 in Section .1 provides the baseline characteristics, confirming that the treatment groups are balanced. We repeat the same balancing of baseline characteristics for survey respondents (n = 1,225), showing balancing across treatments (see Table D4).

declining to complete the survey or make purchases.[16] We examine the distribution of baseline characteristics to ensure balance across treatment groups (see Figure .2.1 in Section .1).

2.3.2 Survey and Treatments

The survey collected detailed information on participants' socio-demographic characteristics, including age, gender, education, and occupation, along with their motivations for purchasing organic food. It specifically examined environmental concerns and purchasing habits associated with organic products, excluding factors like taste or health, which were assumed to remain stable and unaffected by the treatment messages displayed on the survey's front page.

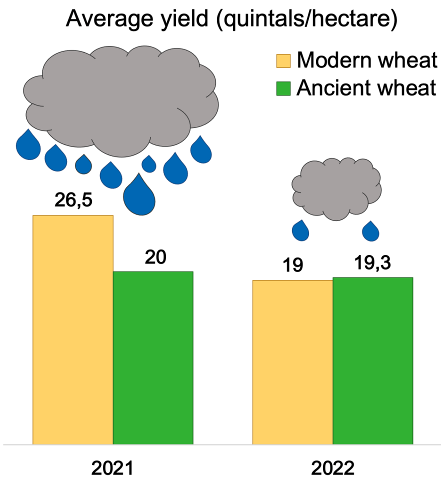
The treatment messages, D^c (colloquial) and D^s (scientific), were presented at the beginning of the survey to the two treatment groups. Both texts conveyed the same claim: ancient Cappelli durum wheat is resilient to drought-related water scarcity and therefore represents an effective climate-adaptation option for agriculture.[17] Their only intentional difference lies in style, in particular, the cognitive load induced by wording, length, and the presence (or absence) of a supporting graph. Participants in the treatment groups were randomly exposed to one of the following scripts:

> **Colloquial treatment**: *"As an Alce Nero consumer, you are already contributing significantly to environmental protection. However, the challenge of climate change calls for further efforts to change our habits. The weather and environmental conditions are changing rapidly, with drought periods becoming more intense and prolonged, especially in Italy. Last year, this resulted in decreased water availability for both domestic use and agricultural production across many regions. As the impacts of the climate crisis become increasingly difficult to overlook, we must adapt to these changes.*
> *How can we do this?*
> *One approach is producing and consuming foods that are more resilient to water shortages. For instance, pasta made from Cappelli durum wheat, an ancient Italian variety, has been shown to be more drought-tolerant than other types of durum wheat. By choosing Cappelli pasta, you encourage Alce Nero farmers to cultivate it, thereby supporting the adaptation of Italian agriculture to the changing climate."*

[16] According to our power analysis, this sample size was adequate. The most conservative estimate, based on the pre-intervention average pasta price (€2.20) and a maximum price differential of €0.55 (25% discount), with conventional significance levels ($\alpha = 0.05$) and power ($\beta = 0.80$), required a minimum of 64 individuals per treatment cell. Descriptive statistics confirm no significant baseline differences across groups, ensuring that the randomization process was successful and internal validity upheld (see Table .1.2 in Section .1).

[17] In this work, we adopt the concept of resilience as articulated by Holling et al. (1973), described as the capacity of a system to absorb shocks and preserve its essential functions. Our experiment draws on this capacity of the ancient Cappelli durum wheat under reduced water availability, whereas the modern cultivar does not.

Scientific treatment: *"As an Alce Nero consumer, you are already contributing significantly to environmental protection. However, the challenge of climate change calls for further efforts to change our habits. The National Research Council reports a significant decline in rainfall from January to May 2022, with 46% less precipitation than the average of the last 30 years. This has led to reduced water availability for domestic use and agricultural production. The series of increasingly severe droughts necessitates our adaptation to the changing climate. One way to do this is by producing and consuming foods more resilient to water scarcity. Pasta made from Cappelli durum wheat, an ancient Italian variety, exhibits this resilience. As the graph below illustrates, despite lower rainfall levels, its yield has remained steady compared to the previous year, while yields of other modern durum wheat have dropped by 16-20% due to the scarcity of rainfall affecting its yield. By choosing Cappelli pasta, you encourage Alce Nero farmers to cultivate it, thereby supporting the adaptation of Italian agriculture to the changing climate."*



Both messages framed climate adaptation as a practical and achievable goal tied to consumers' everyday actions. The colloquial message uses a relatable language to minimize information avoidance, indeed, it highlights the resilience of ancient wheat without making direct claims about yields. By linking drought conditions to the resiliency of the ancient wheat Cappelli, excluding visual elements to avoid cognitive overload (Boon-Falleur et al., 2022; Brick et al., 2023; T. Li et al., 2018), the colloquial treatment seeks to deliver a clear yet engaging message to foster intrinsic motivation toward an adaptive behavior.

The scientific message demands more time and attention from readers: it presents evidence-based content and an accompanying graph to enhance credibility, increasing cognitive load while aiming at a more selective, detail-oriented audience. Indeed, the text is richer in technical details, presents percentages, a bar chart, and a clear reference to evidence from the Italian National Research Council (CNR), signaling scientific rigor. The data show that although the ancient Cappelli durum wheat usually yields slightly less in ordinary years, during the recent drought it kept its yield steady, whereas modern durum varieties dropped by 16–20%. The graph is therefore an essential part of the call to action: it makes the decline in modern wheat yields salient, exposing their adaptation gap and the stronger resilience of ancient wheat. Because individuals are sensitive to losses when they can compare with a reference point (Tversky & Kahneman, 1974), such as a yield drop in our case, highlighting this decline can shift risk perception and motivate adaptive behavior, even when final yields come out similar (O'Donoghue & Sprenger, 2018). Thus, adapting to climate uncertainty is framed as a way to avoid losses, and resilience becomes a valued trait for consumers precisely because it prevents such drops during drought conditions, even if in "normal" years the expected yields are lower. The use of the graph aligns with evidence-based communication strategies, as visual elements are shown to improve the clarity and persuasiveness of complex information (Fischhoff, 2013; Franconeri et al., 2021).

To measure comprehension of the treatment messages, we incorporated a validation question designed to encourage respondents to internalize the content if they had not already done so.[18] These questions are presented under the respective informational message in Section .3.

Beyond the treatment, the survey sought to identify participants' primary motivations for purchasing organic food by asking them to select one of three options: environmental concern, health, or taste.[19] Additionally, participants were asked to gauge their awareness of climate change by responding to the extent to which they felt it impacted their daily lives.[20]

Our survey also explored participants' reliance on and trust in various sources of information on environmental issues. Since organic food is a credence good, whose quality cannot be directly verified by consumers and must instead rely on subjective beliefs, trust in information channels plays a critical role in shaping decision-making (McCluskey & Loureiro, 2003). Participants were asked to rate their trust in sources ranging from scientific outlets to informal ones like family, friends, media, and institutions, including local governments and environmental organizations, which may not always offer verified information.[21] Finally, the survey explored participants' broader purchasing habits to determine whether the online consumers in the experiment also bought organic products at conventional supermarkets and how frequently. This inquiry provided insights into whether the online demographic reflected broader trends in organic product consumption across different retail environments.[22]

Alce Nero products, widely available in major supermarket chains and specialty stores, have seen significant growth in e-commerce sales, now exceeding 2% of total sales over the past three years.[23] This positions Alce Nero as a mainstream player in the Italian organic food sector rather than a niche brand, further emphasizing the relevance of the surveyed consumer base.

[18] *Colloquial* treatment check question: *"In your opinion, durum wheat Cappelli: i) reduces its productivity due to drought; ii) Tolerates drought better that other durum wheat varieties; iii) like all organic durum wheat varieties, handles drought periods well". Scientific* treatment check question: *"According to researchers, the drought that is affecting Italy with increasing frequency: i) has led to a reduction in durum wheat Cappelli productivity by up to 20%; ii) Some durum wheat varieties may tolerate it well".*

[19] *"What is your main motivation for buying organic products?" a) They are healthier. b) They are better for the environment. c) They taste better.*

[20] *"To what extent do you believe climate change is affecting your everyday life?" 1) Not at all. 2) Significantly.*

[21] *"What is your level of trust in the following sources of information on environmental issues?" 1) not at all; 2) it is reliable: a) Local government; b) Environmental organizations; c) Social media; d) Friends or relatives; e) Newspapers and TV; f) Scientists and academics.*

[22] *"How often do you buy organic products at the supermarket?" a) At least once a week; b) At least once a month; c) A few times a year; d) Never.*

[23] Source: https://www.efanews.eu/resources/originals/91d019fec2815056382251ae68943d34.pdf

2.3.3 Data and descriptive statistics

Table 2.3.1 provides an overview of the key outcome variables. As explained in section subsection 2.2.2, our primary variable of interest is the proportion of pasta packs made from *ancient* wheat relative to total pasta purchases. Additionally, we consider the total number of packets purchased as a complementary measure to analyze market demand and assess own-price elasticity.[24]

During the experiment, the share of *ancient* wheat pasta increased most notably in the colloquial treatment group, with smaller changes observed in the scientific group and control group. Similarly, the quantity of *ancient* wheat pasta purchased rose significantly during the intervention. In post-intervention, the outcomes returned to pre-intervention levels, although the group treated with the colloquial message retained slightly higher shares of *ancient* wheat pasta.

TABLE 2.3.1: Descriptive statistics. Numbers refer to the mean and the standard deviation (in parentheses) of the observations for the period January 2022-July 2023 (Obs. 3,713, 1,158, and 1,007, respectively).

	Control	Colloquial	Scientific	Total
	Share of *ancient* wheat pasta packs			
Pre	0.48	0.46	0.49	0.48
	(0.41)	(0.41)	(0.41)	(0.41)
Exp	0.49	0.53	0.49	0.50
	(0.41)	(0.41)	(0.41)	(0.41)
Post	0.48	0.49	0.47	0.48
	(0.42)	(0.41)	(0.43)	(0.42)
	Number of *ancient* wheat pasta packs			
Pre	3.84	4.06	3.94	3.94
	(7.56)	(7.17)	(7.68)	(7.47)
Exp	5.18	5.41	5.03	5.20
	(8.74)	(7.76)	(7.29)	(7.97)
Post	4.02	3.74	3.51	3.76
	(7.06)	(6.82)	(7.20)	(7.03)
	Number of *modern* wheat pasta packs			
Pre	3.26	3.71	3.49	3.48
	(6.24)	(6.54)	(6.62)	(6.47)
Exp	4.80	4.19	4.69	4.56
	(8.54)	(6.93)	(8.06)	(7.89)
Post	3.08	3.32	2.96	3.12
	(4.98)	(6.54)	(6.01)	(5.88)

Table .1.3 in Section .1 displays summary statistics for the variables used in the empirical analysis. The final sample is composed of 57% women, with the largest age group being 45–65 years (40%), followed by 35–44 years (30%). Half of the respondents have attained secondary education, and 70% are employed. Notably, 40% of participants frequently purchase organic food

[24]The average unit price (€/pack) for the two types of pasta is €2.28 (s.d. 0.27) for the *ancient* variety and €1.95 (s.d. 0.71) for the *modern* variety.

in supermarkets (at least weekly), and 43% cite health benefits as their primary motivation for choosing organic. Furthermore, 39% recognize climate change as a pressing issue impacting their daily lives.

The geographic distribution of our participants across the country is mixed, as depicted in the map in Appendix Figure .2.3. It shows that the Lombardy region accounts for 20% of the sample, with Lazio and Emilia-Romagna following at 14% and 12%, respectively. There is a noticeable underrepresentation of Southern regions compared to Northern ones, highlighting a regional difference in online purchasing behaviors observed during the experiment.

Table .1.3 in Section .1 also reports the balance tests conducted for the entire sample of survey respondents. The results indicate that while most survey-collected variables are balanced between the treatment and control groups, certain characteristics exhibit imbalances.[25] Any concern about the influence of imbalances between treated and control users on the results should be alleviated by the use of individual fixed effects in the empirical analysis.

2.3.4 Estimation strategy

We identify the causal impact of the treatment on the share of total pasta made from *ancient* wheat purchased by individuals in a difference-in-differences setting as follows:

$$Y_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 Exp_t + \beta_3 (Treat_i \times Exp_t) + \gamma_d + \zeta_i + \epsilon_{it} \tag{2.2}$$

where Y_{it} denotes the outcome, the share of pasta packs made from *ancient* wheat relative to the total pasta purchased at the individual level. $Treat_i$ is a binary indicator set to 1 for individuals receiving either colloquial, D^c, or scientific, D^s, messaging, Exp_t is a dummy variable indicating the duration of the experiment. The coefficient β_3 captures the impact of the treatment (colloquial or scientific) during the experimental phase, γ_d and ζ_i account for day-of-the-week and individual-specific fixed effects, respectively. In addition, we employ two distinct model specifications: *i*) the first incorporates fixed effects for day-of-the-week (γ_d) and individual-specific discount dummies (ζ_s); *ii*) the second specification builds upon the first by adding a set of variables that capture individual characteristics such as age class, gender, educational attainment, and occupation type X_i. Lastly, to investigate the diverse characteristics of our sample and explore the mechanisms potentially influencing our principal findings, we use a triple interaction model ($Treat_i \times Exp_t \times \theta_i$) where θ_i denotes individual socio-demographic characteristics, individual motivations, and preferences to buy organic products, awareness of climate issues, confidence in scientific evidence, as well as the correct answer to the control question verifying

[25] The demographic and attitudinal imbalances reflect post-randomization survey responses and are thus unrelated to the randomization process itself. These differences may arise due to variations in response rates or survey participation behaviors.

their understanding of the information presented.[26] In all specifications, we cluster standard errors at the individual (treatment) level (Bertrand et al., 2004).

2.4 Results and mechanisms

2.4.1 Main results

We verify *H1* and *H2*[27] by estimating whether the colloquial and scientific information exerts a significant influence on consumer purchasing decisions. Our baseline model specification includes individual and day-of-week fixed effects. However, Table .1.4 in Section .1 presents alternative specifications that control for a rich set of individual characteristics, with very similar results. Moreover, to ensure the robustness of our results, we account for multiple hypothesis testing by calculating FDR sharpened q-values which are reported below estimation tables and figures.

Table 2.4.1: ATE on the shares of *ancient* wheat pasta purchased. Estimates include 872 individuals who bought pasta after receiving treatment (292 controls, 294 scientific treatment, and 286 colloquial treatment) out of the 1,225 respondents to the survey. Standard errors, in parentheses, are clustered at the individual level. FDR sharpened q-values in squared brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Treatment	
	Colloquial	Scientific
	(1)	(2)
Treat × Exp	0.063**	0.007
	(0.026)	(0.025)
	[0.03]	[0.63]
Obs.	2,433	2,430
Individual FE	Yes	Yes
Day-of-week FE	Yes	Yes

Table 2.4.1 reports the main estimation results for both colloquial (column 1) and scientific treatments (column 2) on the share of pasta made from *ancient* wheat. Individuals who received the colloquial treatment exhibited an increase in their purchase of *ancient* wheat pasta by 6.3 p.p., equivalent to a +13% increase.

This gain occurs despite the price premium associated with the *ancient* wheat pasta. Conversely, the scientific treatment effect shows a positive but statistically insignificant impact of 0.7 p.p., which contradicts our second hypothesis (*H2*). These results indicate that only the colloquial

[26] To address the risk of false positives associated with analyzing treatment effects across multiple subgroups, we apply FDR sharpened two-stage q-values, as outlined by Benjamini et al. (2006) and further discussed by Anderson (2008).

[27] *H1*: Easily understandable information on greener products drives their substitution over similar green products; *H2*: Detailed scientific-based information is more effective than shorter, colloquial one in shifting demand from green to greener products.

message effectively conveyed the additional environmental value of the greener product, successfully shifting consumer preferences.[28] The scientific message, which provided a detailed and more complex explanation of the relationship between drought conditions and the adaptive yield of *ancient* wheat, failed to influence purchasing decisions.

An important test to conduct is whether our main results regarding the effect of the informational strategy on the drought resistance characteristics of *ancient* durum wheat persist over time in the absence of a discount to incentivize purchase. To do this, we exploit the fact that our consumer data collection continued for about three months (13 weeks) after the end of the experiment. By estimating the impact of the informational messages in the period following the experiment (thus excluding the actual experimental period), we can determine if consumers have somehow "consolidated" a change in purchasing preferences through the message to which they were exposed. The results of this estimation are reported in Table 2.4.2.[29]

Table 2.4.2: Persistence of the ATE on the share of *ancient* wheat pasta purchased. Estimates include 759 individuals who bought pasta in the post-intervention period out of the 872 individuals who received treatment. Standard errors, in brackets, are clustered at the individual level.

	Treatment	
	Colloquial (1)	Scientific (2)
Treat × Post	0.069**	0.018
	(0.035)	(0.036)
Obs.	2,081	2,079
Individual FE	Yes	Yes
Day-of-week FE	Yes	Yes

The estimated coefficient for the medium-term effect is 0.069, approximately 10% higher than the one observed in the short-term effect, while still exhibiting the same significance. Also, in this case, we find no significant effects for consumers exposed to the scientific treatment. Even though we lack data to observe purchases beyond 13 weeks after the experiment's conclusion, this result allows us to conclude that the effect of the colloquial message was effective, not limited to the short term.

[28] Through the lenses of a randomised encouragement design, a regression on the full sample of 4,727 individuals shows that the single sentence that differ in the treated invitation emails, does not affect the probability of responding to the survey (see Table D2). Moreover, within the 1,225 survey respondents, pre-treatment purchasing variables remain balanced across treatments (Table D4). Socio-demographic and attitudinal traits show the same pattern we observe in final sample (see Table D5), where the vast majority are balanced, and few variables exhibit imbalances as these were not used for randomization (see Table .1.3). Finally, we replicated our main analysis on the entire set of 1,225 survey respondents, using alternative specifications that control for all individual characteristics, showing that results are robust when non-purchasers are retained in the sample (see Table D3).

[29] We estimate Equation 2.2, capturing the impact of the treatment during the post-intervention phase through the interaction term $Treat_i \times Post_t$.

2.4.2 Mechanisms

As highlighted in subsection 2.2.2, the magnitude and direction of the treatment effect of our messages are expected to be influenced by the effectiveness of the information itself and the real distribution of consumers' preferences for contributing to G. In this section, we investigate the mechanisms that may drive our main findings.

Our initial analysis focuses on the differing effectiveness of the two informational messages. While our first hypothesis (*H1*) is confirmed, the results indicate that the scientific treatment fails to significantly increase the share of *ancient* wheat pasta purchased by treated individuals. To better understand this outcome, we analyze how the scientific treatment performs among subgroups of consumers with specific characteristics.

Firstly, excessively complicated information may divert consumers' attention (T. Li et al., 2018; McCluskey & Loureiro, 2003). Therefore, we control for whether correctly answering the check question at the end of the informational message explains any potential diversion. In Figure 2.5, we observe that treated consumers who answered the check question correctly exhibit a positive and significant effect in both treatments[30] The effect size of the scientific treatment closely aligns with the main estimate observed for the colloquial treatment. This suggests that the primary factor differentiating the impact of the two treatments is the level of message comprehension, likely influenced by the additional time and cognitive effort required to engage with the longer and more complex scientific content.

[30] In the validation question, 42% of participants in the colloquial group and 63% in the scientific group responded correctly. The correct answers were: "It tolerates drought better than other durum wheat varieties" for the colloquial group and "Some durum wheat varieties might tolerate it well" for the scientific group.

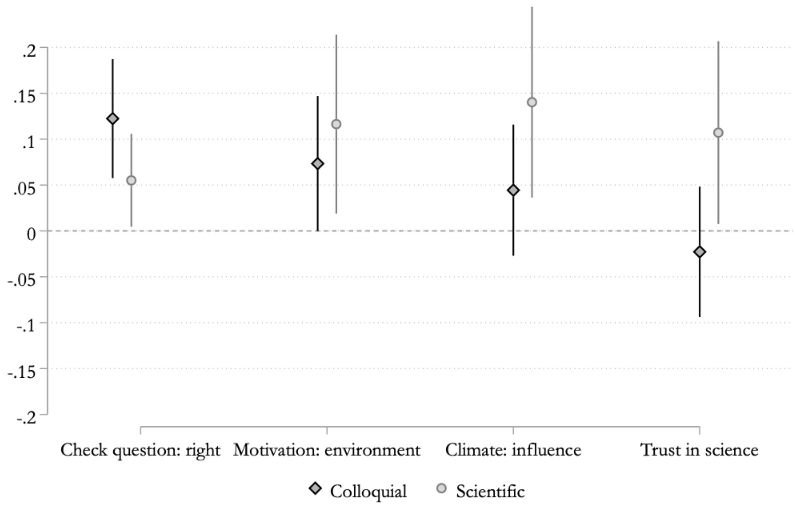


FIGURE 2.5: ATE on the share of *ancient* wheat pasta purchased conditional on: right answer, environmental motivation, climate awareness, and trust in science. Estimates include: 1) *Check question: right* 2,002 and 1,718 observations, 2) *Motivation: environment*, 3) *Climate influence daily life*, and 4) *Trust in science* to 2,430 and 2,443 observations for the scientific treatment, respectively. Standard errors are clustered at the individual level. Confidence intervals at 95%. FDR sharpened q-values for the treatments are as follows: i) colloquial: 0.003, 0.229, 0.224, and 0.356, respectively ii) scientific: 0.059, 0.021, 0.041, and 0.059, respectively.

Secondly, we argue that the distribution of preferences for *modern* wheat pasta type features, such as health, taste, or non-adaptive environmental motivations, could crowd out the effectiveness of the provided information. Indeed, as shown in Figure 2.5, individuals who prioritize environmental concerns as their primary motivation for purchasing organic products, rather than health or taste, exhibit a significantly positive effect.

Another factor shaping consumer preferences in response to our scientific message is their perception of the effects of climate change. Figure 2.5 corroborates our expectation that consumers with heightened sensitivity to climate change were significantly influenced by the scientific treatment, resulting in an increased share of *ancient* wheat pasta purchases. Similarly, trust in scientific sources, positively and significantly influenced the effectiveness of the scientific treatment. This aligns with our hypothesis that consumers who place high trust in scientific information are more receptive to evidence-based messages, enabling them to adjust their behavior towards more sustainable consumption, such as switching from green to greener products. In contrast, the colloquial treatment shows a no-significant result for consumers with higher trust in scientific sources. One plausible yet speculative explanation for this outcome is a cognitive dissonance effect, wherein consumers who trust science may react negatively to messages they perceive as oversimplified or superficial, thereby reducing their willingness to engage in the promoted behavior. This mismatch between message tone and consumer expectations might have diminished the credibility of the colloquial treatment, leading to a counterproductive effect among this subgroup. This highlights the importance of tailoring communication strategies to align with the audience's informational preferences and trust dynamics.

A third mechanism to explore is the role played by the pre-intervention individual consumption habits. Summary statistics showed that a significant portion of the sample already purchased a non-zero amount of *ancient* wheat pasta, that means they could be classified as *greener* or *greenest* consumers. As outlined in subsection 2.2.2, we assume that pre-information purchasing behavior primarily reflected preferences for the attributes of *ancient* wheat pasta, rather than individual preferences for contributing to agro-ecosystem adaptation G, as consumers were not yet aware of this contribution. On the other hand, organic consumers who are already purchasing a large share of *ancient* wheat pasta and perceive themselves as highly engaged in pro-social environmental behavior could react adversely to information that conveys the message to contribute more to the environment. As recently assessed by (Lasarov et al., 2022), a moral licensing, which leads to deviations from previously adopted norms, is likely among this type of consumer. In this context, Figure 2.6 reports the effect of both the messages when conditioning the estimates on pre-intervention consumers' types: *green*, *greener*, and *greenest*. After receiving the informational messages, pre-intervention *green* consumers, those who never purchased *ancient* wheat, display the largest treatment effects, although the scientific one is only marginally significant. According to our hypothesis, this means that a fraction of these consumers were *greener* or *greenest* consumers needing information to reveal their "true" preferences τ for contributing to G. The pre-intervention group of *greener* consumers follow a similar pattern. On the opposite, we have the pre-intervention group of *greenest*, those who were used to purchase more than 50% of *ancient* wheat pasta. These consumers reduced their share of *ancient* wheat pasta, confirming the hypothesis of a potential backfire. As further empirical confirmation of that, we find that pre-information *greenest* consumers, with the environment as their primary motivation to buy organic food, are those reducing the share of *ancient* wheat pasta the most. Results are reported in Table .1.5.

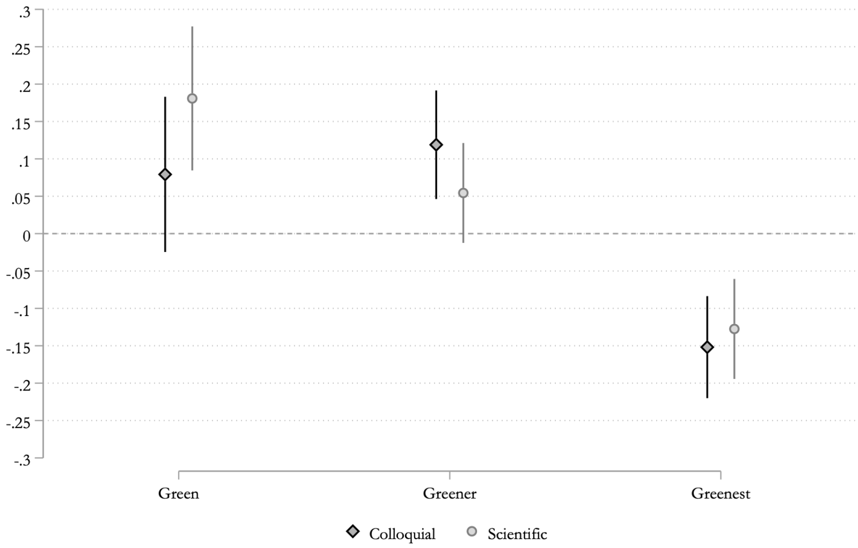


FIGURE 2.6: ATE on the share of *ancient* wheat pasta purchased conditional on pre-intervention purchase category: green, greener, and greenest. Estimates include 2,430 and 2,443 observations for the scientific and colloquial treatment, respectively. Standard errors are clustered at the individual level. Confidence intervals at 95%. FDR sharpened q-values for the treatments are as follows: i) colloquial: 0.224, 0.01, and 0.001, respectively; ii) scientific: 0.003, 0.124, and 0.003, respectively.

2.4.3 Heterogeneous effects

In this section, we test whether our colloquial and scientific treatments exert differential effects by exploiting the individual socio-economic characteristics collected from the survey. We focus on four important dimensions: gender, age classes, educational level, and employment status. We graphically present these results in Figure 2.7.

Firstly, although the effect of the scientific message nearly doubles the one of the colloquial message, both treatments have a larger impact on females. When analyzing the effects across different age groups, the treatment effects are positive and slightly more pronounced for younger consumers (aged 25-34), and comparable for middle-aged consumers (aged 35-44 and 45-64). Across all these age groups, there are minimal differences in the magnitude of effects between the colloquial and scientific treatments. However, we observe negative coefficients for older individuals (aged 65 and above), which are larger for the scientific treatment. We also observe differential treatment effects across educational levels: both colloquial and scientific treatments have a positive effect on consumers with tertiary education, while they exhibit negative and less significant effects on consumers with primary or secondary educational attainment. Additionally, we find no significant differences in the effects of either treatment among consumers, regardless of whether they are homemakers, employed, or unemployed.

Our finding of stronger positive effects among females, younger individuals, and those with higher educational attainment aligns with the notion that these demographic groups demonstrate greater environmental motivation and sensitivity to climate risks (Berger, 2019; Laroche et al., 2001; Piao & Managi, 2023; Shahsavar et al., 2020). Furthermore, the large negative impact observed among consumers over 65 years old, particularly those exposed to the scientific treatment, is likely attributable to their limited familiarity with digital tools and, potentially, a shorter time horizon to fully benefit from mid- to long-term environmental impacts. Consequently, their motivation to change established dietary habits in support of climate change adaptation is lower.

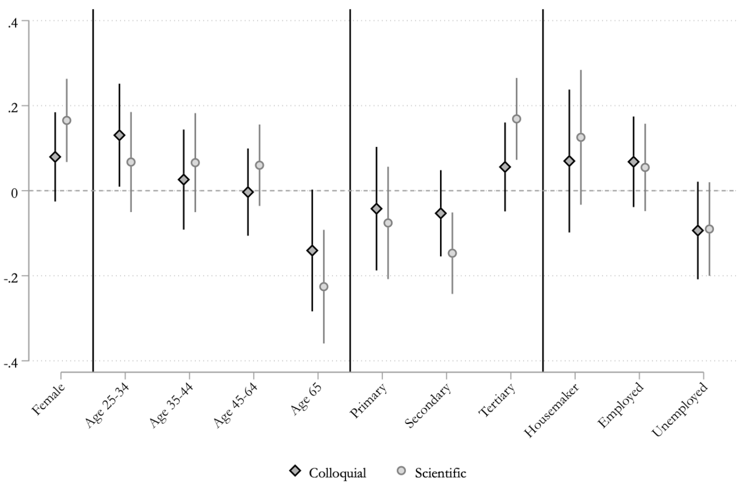


FIGURE 2.7: ATE on the the share of *ancient* wheat pasta purchased conditional on individual characteristics. Estimates include 2,430 and 2,443 observations for the scientific and colloquial treatment, respectively. Standard errors are clustered at the individual level. Confidence intervals at 95%. FDR sharpened q-values for the treatments are as follows: i) colloquial: 0.224, 0.121, 0.372, 0.494, 0.154, 0.366, 0.356, 0.356, 0.356, 0.289, and 0.224, respectively; ii) scientific: 0.005, 0.202, 0.202, 0.202, 0.005, 0.202, 0.009, 0.005, 0.126, 0.216, and 0.124, respectively.

2.5 Additional results

Habits of purchasing organic food at supermarket. Using the information gathered in our survey, we present estimates of the differential effects on consumers who have different purchasing habits for the same products at the supermarket.

To capture this information, survey participants responded to the following question: *"How often do you buy organic products at the supermarket?"*; response options included: *a) at least once a week, b) at least once a month, c) a few times a year, d) never.* We report our results graphically in Figure 2.8. From these results, a fairly consistent pattern of outcomes emerges. The only consumers who exhibit a significant treatment effect are those who purchase organic products rather frequently at the supermarket (at least once a month), especially for the colloquial treatment, while for others, we do not observe marked differences. Although our experiment focuses on consumers who purchase products online from a specific brand, this evidence suggests that its external validity does not appear to be very limited because the effect is driven by individuals who purchase the same products – widely available across the national distribution network – also from regular supermarkets, selecting them from the shelves.

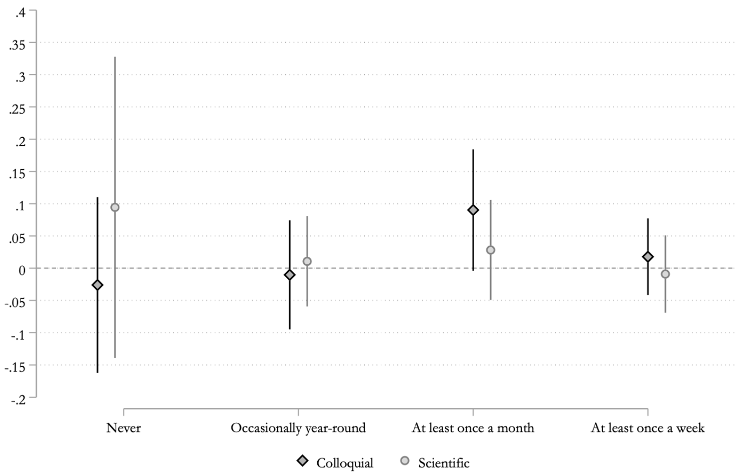


Figure 2.8: ATE on the share of *ancient* wheat pasta purchased conditional on habits of purchasing organic food at supermarket. Estimates include 2,430 and 2,443 observations for the scientific and colloquial treatment, respectively. Standard errors are clustered at the individual level. Confidence intervals at 95%. FDR sharpened q-values for the treatments are as follow: i) colloquial: 0.229, 0.224, 0.098, and 0.356, respectively; ii) scientific: 0.243, 0.202, 0.087, and 0.243, respectively.

Spillover effects. An additional aspect to analyze is whether consumers exposed to the two informational messages have extended their preference change to other food products made from *ancient* wheat. In fact, it is possible to produce various products from *ancient* wheat besides pasta, from biscuits and rice cakes to simple flour. In other words, we are testing whether the treatment effect for pasta may have spilled over into other products. The results of these estimations are reported in Table 2.5.1, where we do not observe any significant effect among additional products to pasta. The absence of significant effects in both treatments demonstrates that consumers did not gather additional information thoroughly. We therefore conclude that our informational strategy had significant effects only on the product mentioned in the treatment messages.

TABLE 2.5.1: Spillover effects – ATE on the share of other products made from *ancient* cultivar besides pasta. Estimates include 688 individuals who purchased a product made from *ancient* cultivar during the experiment. Standard errors, in brackets, are clustered at the individual level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

	Treatment	
	Colloquial (1)	Scientific (2)
Treat × Exp	-0.033	-0.003
	(0.029)	(0.029)
Obs.	1,822	1,927
Individual FE	Yes	Yes
Day of Week FE	Yes	Yes

Role of severe drought in 2022. Our main estimate shows that the colloquial message uniquely succeeds in encouraging *green* consumers to choose *greener* products. In this section, we focus on this message to evaluate its differential effects in areas affected by the severe drought that hit Italy in 2022. Our testable assumption is that consumers are more sensitive to the treatment message in areas more impacted by the drought. In the absence of informational frictions, all consumers would be perfectly informed about the ongoing increase in drought risk, and we would not expect heterogeneous effects among consumers living in differently affected areas. However, previous evidence (Clayton et al., 2015; Lee et al., 2015) suggest that it is unlikely that individuals are fully aware of the climate risk unless directly exposed to this risk. To explore this margin, we estimate our model by conditioning the colloquial treatment on the classification of drought severity at the provincial level. To capture the exposure to drought, we use the SPEI, a state-of-the-science drought indicator.[31] Since SPEI is expressed in standard deviations, it allows for full comparability over time and across regions. Negative SPEI values indicate dry conditions, and according to a standard classification, SPEI values in the range of -1.5 to -3 s.d. signal moderate to extremely severe drought. Table .1.6 reports the distribution of individuals for each examined SPEI category, including controls, treated groups with the colloquial message, and the total sample. In 2022, 3% of the total sample experienced extreme drought events ($SPEI \leq -3$), 4% of individuals receiving the colloquial treatment, and 2% of individuals receiving the scientific treatment faced the same extreme events. Meanwhile, 1% of individuals in our sample experienced severe drought ($SPEI \leq -2.5$).

[31]SPEI integrates the effects of temperature on drought conditions, making it a more comprehensive tool compared to the Standardized Precipitation Index (SPI), which only considers precipitation. We used the SPEI computed over a one-month accumulation period. SPEI values were sourced from ISPRA, the Italian National Institute for Environmental Protection and Research. We extracted SPEI values for each month from raster files available from ISPRA, interpolated them with provincial shapefiles gathered from ISTAT (National Institute of Statistics) to obtain average SPEI values for each province. For additional details, see https://groupware.sinanet.isprambiente.it/bigbang-data/library/bigbang_70/ascii_grid/spei.

Table 2.5.2 shows the effects of the colloquial message considering these levels of drought. The effects are large and significant only in columns 3 and 4, corresponding to drought levels classified as "severe" and "extreme", respectively.[32] For more moderate levels of drought exposure, we observe non-significant and substantially smaller coefficients. These results support our hypothesis of heterogeneous effects based on the level of actual exposure to climate impacts, while also suggesting a low perception of climate risks among the consumers involved.

TABLE 2.5.2: ATE of Colloquial Treatment on the shares of *ancient* wheat pasta purchased. Estimates include 872 individuals. Standard errors, in brackets, are clustered at the individual level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

	Colloquial Treatment			
	(1)	(2)	(3)	(4)
Treat×Exp	0.125**	0.054**	0.042**	0.049***
	(0.061)	(0.024)	(0.018)	(0.018)
Treat×Exp× (SPEI<-1.5)	-0.079			
	(0.059)			
Treat×Exp× (SPEI<-2)		0.002		
		(0.037)		
Treat×Exp× (SPEI<-2.5)			0.343**	
			(0.151)	
Treat×Exp× (SPEI<-3)				0.296*
				(0.173)
Obs.	2,443	2,443	2,443	2,443
Day of Week FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes

Role of discount and prices. Here we discuss the potential effects of our treatments in terms of market demand. As outcome variables, we focus on the quantity of packs of *modern* and *ancient* wheat pasta purchased at each shopping session.[33]

Working with units purchased allows us to estimate the own-price elasticity for the two pasta products. We remind that the *ancient* wheat pasta requires, on average, an 18% price premium to be paid[34]. Own-price elasticities are reported in Table 2.5.3.

[32] We replicated the same estimates for the scientific treatment, and the results are mirroring the main findings, showing no significant results.

[33] The use of these outcome variables expands the observations for our 872 individuals.

[34] We estimate price elasticities by exploiting variation in absolute prices of pasta across time and formats. The price differential between ancient and modern wheat pasta remains constant within each format and over time. Randomized discounts induce exogenous shifts in absolute prices, preserving the price gap between pasta types and formats. This structure ensures that price variation is exogenous to treatment assignment and comparable across groups. Residual price variation after controlling for discount and format fixed effect overlap between treated and control groups.

TABLE 2.5.3: Own-price elasticities (log quantity of packs). Estimates include 872 individuals who bought pasta after receiving treatment (292 controls, 294 scientific treatment, and 286 colloquial treatment) out of the 1,225 respondents to the survey. Standard errors, in brackets, are clustered at the individual level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Ancient wheat		Modern wheat	
	Colloquial (1)	Scientific (2)	Colloquial (3)	Scientific (4)
Log Price	-0.758***	-0.799***	-0.325***	-0.246***
	(0.202)	(0.196)	(0.202)	(0.055)
Treat × Exp × Log Price	0.111***	-0.004	-0.002	0.015
	(0.023)	(0.026)	(0.024)	(0.024)
Obs.	4,306	4,259	4,526	4,557
Individual FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes

The effect of an increase in price is always negative, and the demand is inelastic. The marginal effect of being treated with the colloquial information is positive for the *ancient* wheat pasta. This means that consumers reduce their consumption less than the control group. On the other hand, both treatments do not induce any significant differences in the own-price elasticities of *modern* wheat pasta with respect to the control group.

A second result concerns the heterogeneous role of the pasta discount offered to consumers to participate in the experiment. Figure 2.9 shows the marginal effect of the colloquial treatment on the number of packs of *ancient* and *modern* wheat pasta.

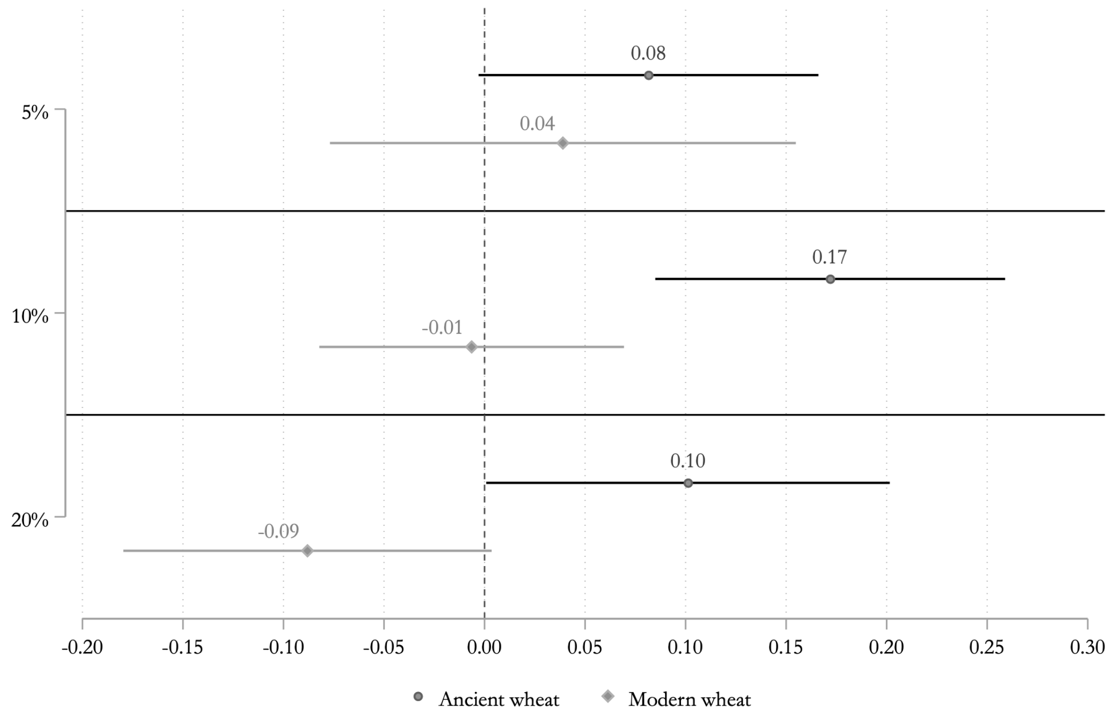


FIGURE 2.9: ATE on the log number of packs with the colloquial treatment, by pasta discount value. Estimates include 4,306 observations. Standard errors are clustered at the individual level. Confidence intervals at 95%.

The 5% discount is so minimal that it brings the paid price close to the undiscounted price, leading us to expect a negligible effect from this discount. Conversely, we expect that larger discounts, when combined with information, would increase the average treatment effect. While the point estimates suggest a non-linear pattern, the confidence intervals overlap across discount levels, and we cannot reject the hypothesis that the treatment effect is constant. Therefore, we interpret the apparent concavity with caution. These findings align with previous evidence in the literature, which suggests that offering higher discounts to appeal to green consumers does not foster additional pro-environmental behavior beyond what can be achieved with an information-based strategy alone (Schwartz et al., 2020).

2.6 Discussion and conclusions

We conducted a field experiment targeting online consumers of a leading Italian organic food brand. Our findings show that non-pecuniary strategies can shift the preferences of already environmentally engaged consumers from "green" to "greener" products — specifically, toward those offering less-recognized but critical environmental benefits, such as agro-ecosystem adaptation to climate change. Consumers exposed to informational messages highlighting the superior drought tolerance and climate-adaptive traits of an ancient wheat variety increased their purchases of the corresponding organic pasta, relative to organic pasta made from modern wheat, despite a price premium. This shift proved durable, persisting for at least three months post-intervention.

Our study contributes to the literature on nudging sustainable food consumption by focusing on climate adaptation, a dimension that has been largely overlooked compared to mitigation. While most existing research examines the impact of information or eco-labels related to greenhouse gas emissions, water use, or biodiversity conservation, we show that consumers are also willing to reward farmers' efforts to adapt to climate change with their purchasing choices. This finding points to an untapped niche in the sustainable food market, which is particularly relevant for firms and policymakers as climate extremes such as droughts become increasingly frequent.

Targeting already environmentally conscious consumers, as we do in this paper, offers a promising strategy to internalize the positive externalities associated with climate-adaptive products. Given the ongoing expansion of the organic market, this segment represents a natural base for deeper engagement. When these consumers are confronted with the total cost of food production under climate stress, they may revise their understanding of what sustainable consumption truly means, thus shifting from general green behaviors (e.g., buying organic) toward more targeted, high-impact choices that support agro-ecosystem resilience. By showing that informational strategies alone can effectively drive consumer demand toward climate-adaptive food, we identify a cost-effective strategy that complements or substitutes pecuniary tools or other labels. Moreover, our findings underscore the importance of expanding the vocabulary of sustainable food labeling and marketing to include adaptation benefits, an aspect largely underrepresented in the current discourse. The study also sheds light on the mechanisms driving this behavioral shift. First, consumer attention and comprehension of environmental messages play a critical role. For some, standard organic labels suffice to reveal preferences for sustainability. For others, such labels leave gaps that targeted messages can fill. A colloquial message about ancient wheat's adaptive properties proved effective across a wide group of consumers. In contrast, a technical, science-based message was only effective among individuals with strong environmental concern, trust in science, and direct experience of climate change. These heterogeneous effects highlight how prior beliefs, cultural background, and personal experiences shape consumers' responsiveness to the provided information.

Two additional findings are worth to be highlighted. First, we observe a backfire effect among the most engaged consumers — those already purchasing large shares of the "greener" product, the ancient wheat pasta, before the intervention. For them, an additional pro-environmental request of effort, may lead to disengagement, possibly due to moral licensing. This calls for careful message framing: adaptation should be presented not as an added duty but as a natural extension of existing sustainable behaviors. Second, and critically, we confirm that preferences can be shifted toward more environmental-friendly products without any price manipulation, suggesting that even small-scale informational nudges can have meaningful market effects. In line with research on climate change communication (Clayton et al., 2015; Lee et al., 2015), our findings emphasize the importance of tailoring messages to consumers' lived experiences — particularly with localized climate stressors such as severe droughts. Public engagement with adaptation efforts will be more effective when messages are made personally relevant and contextually grounded.

Our insights contribute to the current debate on how to internalize the externalities of food production in a context of climate stress. The *State of Food and Agriculture 2023* emphasizes the need to account for the "true" cost of food — including environmental, health, and social externalities — as a priority for global policy actors such as the FAO and the United Nations.[35] Projected yield losses underscore the urgency of fostering demand for adaptation: the *Wheat Initiative* predicts a 7% global wheat yield decline for every additional degree of warming (Tuberosa et al., 2021) and Wing et al. (2021), estimate 3–12% global crop losses by mid-century under high-warming scenarios, with potential losses exceeding 25% by 2100 in the absence of adaptation. In this context, our study provides evidence that consumer behavior can be aligned with adaptation objectives through low-cost, information-based interventions. This offers a promising leverage for firms, policymakers, and sustainability advocates to promote climate resilience in food systems.

[35] See the full report at: https://www.fao.org/documents/card/en/c/cc7724en

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.1

.1.1 Check questions

We employ multiple-choice check questions as follows:

> **Colloquial**: *"In your opinion, does durum wheat Cappelli: a) Reduce its productivity due to drought, b) Tolerate drought better than other durum wheat varieties, c) Like all organic durum wheat varieties, handle drought periods well?"*
>
> **Scientific**: *"According to researchers, the drought affecting Italy with increasing frequency: a) Has led to a reduction in Cappelli durum wheat's productivity by up to 20%. b) Some durum wheat varieties may tolerate it well."*

The correct answers are *b* for both treatments. We observe that 42% and 63% of consumers answer correctly, respectively for the colloquial and scientific message.

.1.2 Additional Tables

Table .1.1: Descriptive statistics and Balance for the experiment (initial sample). Column 1 presents the descriptive statistics for the entire sample of 4,727 individuals, each of whom bought at least one pack of pasta in 2022 (individuals are 1,588, 1,558 and 1,581 for the control, colloquial and scientific group, respectively). Column 2 reveals the mean differences between the Treatment groups and the Control group. Column 3 highlights the mean differences between the Scientific and Colloquial Treatment groups. In all cases, the t-tests did not indicate any significant differences, similar to the results from the joint F-tests for all characteristics reported at the end of columns 2 and 3. Columns 2 and 3 have robust standard errors in parenthesis.

	Sample mean	Treatment - Control Difference	Scientific - Colloquial Treatment Difference
Purchase only *ancient* wheat (0-1)	0.291	0.022	-0.015
	(0.454)	(0.014)	(0.016)
Purchase only *modern* wheat (0-1)	0.277	-0.001	0.021
	(0.448)	(0.014)	(0.016)
Purchase both wheats (0-1)	0.411	-0.014	-0.009
	(0.492)	(0.015)	(0.018)
Pasta total purchases (euro)	33.570	-1.238	0.096
	(51.079)	(1.573)	(1.823)
Number of purchases	2.379	-0.074	0.005
	(2.150)	(0.067)	(0.075)
Purchases only during discount event (0-1)	0.150	-0.007	-0.003
	(0.357)	(0.011)	(0.013)
Income pc (thousands euro)	21.286	-0.122	0.097
	(3.974)	(0.123)	(0.141)
Q.ty ancient > q.ty modern (0-1)			
Fusilli pasta	0.088	-0.004	0.009
	(0.283)	(0.009)	(0.010)
Penne pasta	0.130	-0.005	-0.001
	(0.337)	(0.010)	(0.012)
Spaghetti pasta	0.124	-0.007	-0.000
	(0.329)	(0.010)	(0.012)
F-Test p-value		0.599	0.933
Observations	4,727	3,146	3,169

TABLE .1.2: Descriptive statistics and T-tests of baseline characteristics (final sample). Columns 1, 2, and 3 presents mean and standard deviation (in parenthesis). Columns 4 and 5 reveal the mean differences between the Colloquial and Control groups and the Scientific and Control groups, respectively. In all cases, the t-tests did not indicate any significant differences.

	Control	Colloquial	Scientific	Colloquial - Control Difference	Scientific - Control Difference
Purchase only *ancient* wheat (0-1)	0.216	0.207	0.235	-0.009	0.019
	(0.412)	(0.405)	(0.425)	(0.034)	(0.035)
Purchase only *modern* wheat (0-1)	0.195	0.203	0.187	0.008	-0.008
	(0.397)	(0.403)	(0.391)	(0.033)	(0.033)
Purchase both wheats (0-1)	0.586	0.591	0.575	0.005	-0.011
	(0.493)	(0.493)	(0.495)	(0.041)	(0.041)
Pasta total purchases (euro)	57.173	60.266	57.719	3.093	0.546
	(66.277)	(66.160)	(68.446)	(5.509)	(5.566)
Number of purchases	3.870	3.797	3.745	-0.073	-0.125
	(3.043)	(2.880)	(2.762)	(0.247)	(0.240)
Purchases only during discount event	0.086	0.091	0.068	0.005	-0.018
	(0.280)	(0.288)	(0.252)	(0.024)	(0.022)
Income pc (thousands euro)	21.367	21.294	21.197	-0.073	-0.170
	(4.024)	(4.017)	(3.880)	(0.143)	(0.140)
Q.ty ancient > q.ty modern					
Fusilli pasta	0.127	0.157	0.139	0.031	0.013
	(0.333)	(0.365)	(0.347)	(0.029)	(0.028)
Penne pasta	0.223	0.224	0.218	0.001	-0.005
	(0.417)	(0.418)	(0.413)	(0.035)	(0.034)
Spaghetti pasta	0.202	0.220	0.163	0.018	-0.039
	(0.402)	(0.415)	(0.370)	(0.034)	(0.032)
Observations	292	286	294	578	586

Table .1.3: Descriptive statistics and T-tests of individual characteristics. Columns 1, 2, and 3 present mean and standard deviation (in parentheses) for 872 individuals who bought pasta after receiving treatment out of the 1,225 respondents to the survey. Columns 4 and 5 reveal the mean differences between the Colloquial and Control groups and the Scientific and Control groups, respectively.

	Control	Colloquial	Scientific	Colloquial - Control Difference	Scientific - Control Difference
Female	0.538	0.612	0.568	0.074*	0.030
	(0.499)	(0.488)	(0.496)	(0.041)	(0.041)
Age: 25-34	0.192	0.143	0.167	-0.048	-0.025
	(0.394)	(0.351)	(0.373)	(0.031)	(0.032)
Age: 35-44	0.257	0.276	0.293	0.019	0.036
	(0.438)	(0.448)	(0.456)	(0.037)	(0.037)
Age: 45-64	0.411	0.385	0.330	-0.026	-0.081**
	(0.493)	(0.487)	(0.471)	(0.041)	(0.040)
Age: 65+	0.140	0.196	0.211	0.055*	0.070**
	(0.348)	(0.398)	(0.409)	(0.031)	(0.031)
Education level:					
Primary	0.233	0.084	0.092	-0.149***	-0.141***
	(0.423)	(0.278)	(0.289)	(0.030)	(0.030)
Secondary	0.438	0.584	0.582	0.146***	0.143***
	(0.497)	(0.494)	(0.494)	(0.041)	(0.041)
Tertiary	0.329	0.332	0.327	0.003	-0.002
	(0.471)	(0.472)	(0.470)	(0.039)	(0.039)
Type of occupation:					
Houseworker	0.045	0.059	0.058	0.015	0.013
	(0.207)	(0.237)	(0.234)	(0.018)	(0.018)
Self-employed/Manager/Employee	0.699	0.682	0.673	-0.017	-0.025
	(0.460)	(0.467)	(0.470)	(0.039)	(0.038)
Unemployed/Retired	0.257	0.259	0.269	0.002	0.012
	(0.438)	(0.439)	(0.444)	(0.036)	(0.036)
Habits of purchasing organic food at supermarket:					
Never	0.065	0.059	0.061	-0.006	-0.004
	(0.247)	(0.237)	(0.240)	(0.020)	(0.020)
Occasionally year-round	0.349	0.269	0.354	-0.080**	0.004
	(0.478)	(0.444)	(0.479)	(0.038)	(0.040)
At least once a week	0.418	0.430	0.405	0.012	-0.013
	(0.494)	(0.496)	(0.492)	(0.041)	(0.041)
At least once a month	0.168	0.241	0.180	0.073**	0.012
	(0.374)	(0.429)	(0.385)	(0.033)	(0.031)
Motivation:					
Environment	0.486	0.350	0.255	-0.137***	-0.231***
	(0.501)	(0.478)	(0.437)	(0.041)	(0.039)
Taste	0.199	0.206	0.255	0.008	0.056
	(0.400)	(0.405)	(0.437)	(0.033)	(0.035)
Health	0.315	0.444	0.490	0.129***	0.175***
	(0.465)	(0.498)	(0.501)	(0.040)	(0.040)
Climate influences daily life: Yes	0.274	0.497	0.429	0.223***	0.155***
	(0.447)	(0.501)	(0.496)	(0.039)	(0.039)
Trust in science: Yes	0.637	0.413	0.415	-0.224***	-0.222***
	(0.482)	(0.493)	(0.494)	(0.041)	(0.040)
Pre-intervention purchase category:					
Green	0.140	0.126	0.136	-0.015	-0.004
	(0.348)	(0.332)	(0.343)	(0.028)	(0.029)
Greener	0.384	0.437	0.391	0.054	0.008
	(0.487)	(0.497)	(0.489)	(0.041)	(0.040)
Greenest	0.476	0.437	0.473	-0.039	-0.003
	(0.500)	(0.497)	(0.500)	(0.041)	(0.041)
Discount:					
5%	0.236	0.234	0.248	-0.002	0.012
	(0.426)	(0.424)	(0.433)	(0.035)	(0.035)
10%	0.538	0.486	0.503	-0.052	-0.034
	(0.499)	(0.501)	(0.501)	(0.042)	(0.041)
20%	0.226	0.280	0.248	0.054	0.022
	(0.419)	(0.450)	(0.433)	(0.036)	(0.035)
Check questions: Right	-	0.42	0.63		
		(0.49)	(0.48)		
Observations	292	286	294	578	586

TABLE .1.4: ATE on shares of *ancient* wheat pasta purchased. Estimates include 872 individuals who bought pasta after receiving treatment (292 controls, 294 scientific treatment, and 286 colloquial treatment) out of the 1,225 respondents to the survey. Omitted category for age: 65+, Gender: Male, Occupation: Housemaker, Study: Compulsory education level, Buy organic in supermarkets: Never. Robust standard errors in parentheses are clustered at the individual level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Colloquial			Scientific		
Exp × Treat	0.063**	0.061*	0.068**	0.007	-0.007	-0.013
	(0.026)	(0.033)	(0.032)	(0.025)	(0.030)	(0.030)
Age: 25-34			0.033			0.099*
			(0.066)			(0.058)
Age: 35-44			0.026			0.092**
			(0.049)			(0.045)
Age: 45-64			0.039			0.195***
			(0.046)			(0.043)
Female			0.101***			0.095***
			(0.034)			(0.031)
Secondary			-0.029			-0.001
			(0.045)			(0.045)
Tertiary			0.009			0.022
			(0.047)			(0.046)
Employed			-0.002			-0.139*
			(0.083)			(0.075)
Unemployed			0.037			-0.134*
			(0.085)			(0.079)
Occasionally year-round			0.005			0.006
			(0.062)			(0.059)
At least once a week			-0.013			-0.032
			(0.062)			(0.059)
At least once a month			0.010			-0.057
			(0.066)			(0.064)
Obs.	2,443	2,443	2,443	2,430	2,430	2,430
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Discount FE	No	Yes	Yes	No	Yes	Yes
Individual FE	Yes	No	No	Yes	No	No

TABLE .1.5: ATE on share of *ancient* wheat pasta purchased for the pre-intervention *greenest*: environmental motivation. Estimates include 199 e 204 individuals who received, respectively, the colloquial and scientific treatment among those classified as *greenest*. Standard errors, in brackets, are clustered at the individual level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Treatment	
	Colloquial (1)	Scientific (2)
Treat × Exp	-0.280***	-0.256***
	(0.009)	(0.057)
Obs.	870	1,032
Individual FE	Yes	Yes
Day of Week FE	Yes	Yes

Table .1.6: Summary statistics of conditional exposure to different SPEI thresholds (from <-1.5 to <-3), by type of treatment and control group. N refers to the number of individuals.

Group	N (1)	Mean (2)	s.d. (3)	Min. (4)	Max. (5)
Control					
$SPEI$ <-1.5	292	0.884	0.321	0	1
$SPEI$ <-2	292	0.401	0.491	0	1
$SPEI$ <-2.5	292	0.044	0.207	0	1
$SPEI$ <-3	292	0.027	0.164	0	1
Numeric					
$SPEI$ <-1.5	294	0.878	0.328	0	1
$SPEI$ <-2	294	0.469	0.500	0	1
$SPEI$ <-2.5	294	0.051	0.220	0	1
$SPEI$ <-3	294	0.037	0.190	0	1
Colloquial					
$SPEI$ <-1.5	286	0.881	0.324	0	1
$SPEI$ <-2	286	0.430	0.496	0	1
$SPEI$ <-2.5	286	0.035	0.184	0	1
$SPEI$ <-3	286	0.021	0.144	0	1
Total					
$SPEI$ <-1.5	580	0.879	0.326	0	1
$SPEI$ <-2	580	0.450	0.498	0	1
$SPEI$ <-2.5	580	0.043	0.203	0	1
$SPEI$ <-3	580	0.029	0.169	0	1

.2 List of Figures

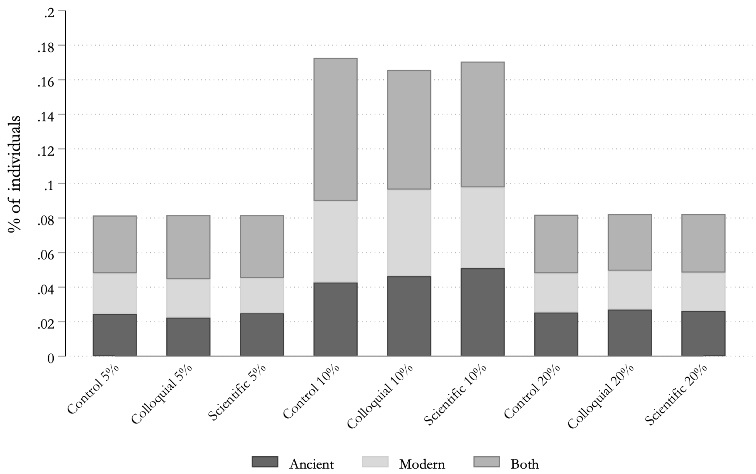


FIGURE .2.1: Sample distribution across treatment groups based on 4,727 individuals (initial sample).

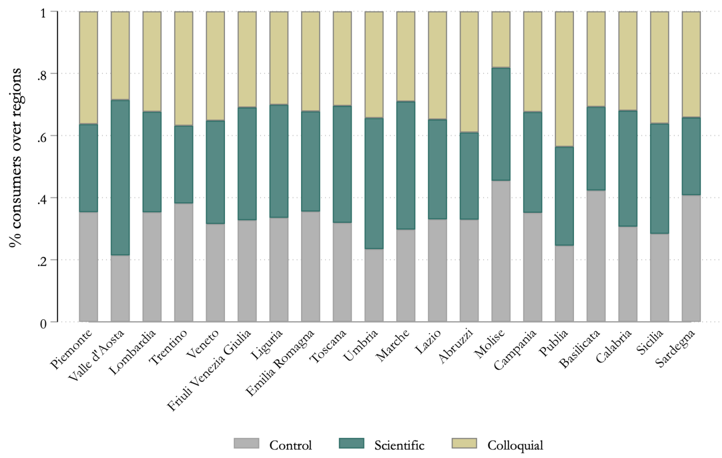


FIGURE .2.2: Randomized sample distribution over Italian regions. Numbers refer to the randomization sample of 4,727 individuals (initial sample).

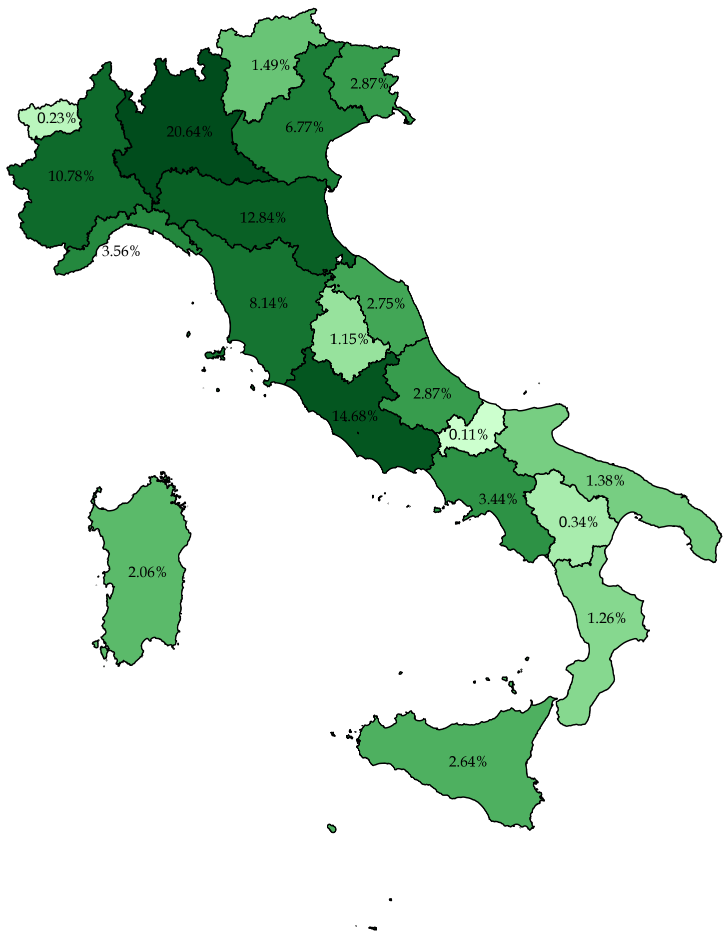


FIGURE .2.3: Regional distribution of our final sample. Numbers refer to the 872 individuals who participate at the experiment.

.3 Field experiment

On January 24^{th}, 2023, randomized individuals received an email from Alce Nero informing them about an initiative to adapt product offerings to climate change challenges that farmers are facing by inviting them to participate in a survey. In return, they will receive a gift: a discount code valid for all pasta products until March 31^{st}, 2023 (activated upon completion of the survey). Treated customers are invited to participate in the survey to discover which product is suitable for a planet facing increasing aridity.

FIGURE C1: E-mail for colloquial and scientific groups

The translated text of the e-mail for treated groups to inform customers about the opportunity to participate in a survey is:

Hi Cecilia,
as Alce Nero, we strive every day to adapt our range of organic products to the new challenges that climate change poses to our farmers. By answering this short questionnaire, you will discover which product best fits a planet that is becoming increasingly arid and help us improve our offerings. At the end, you will receive a gift we have reserved for you as a token of our appreciation for your contribution.
Thank you for your availability.
The Alce Nero Team
GO TO SURVEY

The translated text of the e-mail to invite control group to answer to the short survey is:

Hi Cecilia,
as Alce Nero, we strive every day to adapt our range of organic products to the new challenges that climate change poses to our farmers. By answering this short questionnaire, you will help us improve our offerings. At the end, you will receive a gift we have reserved for you as a token of our appreciation for your contribution.
Thank you for your availability.
The Alce Nero Team
GO TO SURVEY

Figure C2: Colloquial Treatment and check questions

Prepararsi ad un pianeta più arido? Adattiamo i nostri acquisti!

* Indica una domanda obbligatoria

Email *

Il tuo indirizzo email

SIAMO PRONTI AD ADATTARE I NOSTRI ACQUISTI AD UN PIANETA PIÙ CALDO E ARIDO?

Come consumatore di prodotti bio Alce Nero stai già facendo molto per proteggere l'ambiente, tuttavia la sfida del cambiamento climatico richiede ulteriori sforzi per cambiare le nostre abitudini.

I periodi di siccità stanno diventando sempre più intensi e prolungati. Lo scorso anno questo ha comportato in molte regioni italiane una riduzione della disponibilità di acqua per uso domestico e per la produzione agricola.

Mentre gli effetti della crisi climatica diventano sempre più difficili da ignorare, dobbiamo adattarci all'ambiente che cambia.
Come? Ad esempio, producendo e consumando alimenti più resistenti alla scarsità d'acqua.
I dati di produzione della filiera di Alce Nero hanno messo in luce come, nel 2022, il grano duro Cappelli abbia tollerato meglio la siccità rispetto ad altre varietà, ottimizzando l'utilizzo dell'acqua piovana durante la campagna agraria.

Scegliendo la pasta Cappelli puoi incentivare gli agricoltori di Alce Nero a coltivare il grano duro Cappelli, favorendo così la capacità dell'agricoltura italiana di adattarsi al clima che cambia.

In base a quanto letto sopra, secondo te, la varietà di grano duro Cappelli:

- ○ Ha ridotto la sua produttività a causa della siccità
- ○ Tollera la siccità meglio di altre varietà di grano duro
- ○ Come tutte le varietà di grano duro biologico, tollera bene i periodi di siccità

FIGURE C3: Scientific Treatment and check questions

alcenero.com

alce nero

Prepararsi ad un pianeta più arido? Adattiamo i nostri acquisti!

* Indica una domanda obbligatoria

Email *

Il tuo indirizzo email

SIAMO PRONTI AD ADATTARE I NOSTRI ACQUISTI AD UN PIANETA PIÙ CALDO E ARIDO?

Come consumatore Alce Nero stai già facendo molto per proteggere l'ambiente, tuttavia la sfida del cambiamento climatico richiede ulteriori sforzi per cambiare le nostre abitudini. Secondo il Consiglio Nazionale delle Ricerche, da Gennaio a Maggio 2022 è caduta il 46% di pioggia in meno rispetto alla media degli ultimi 30 anni, riducendo la disponibilità di acqua per uso domestico e per la produzione agricola.

Il susseguirsi di siccità sempre più severe ci impone di adattarci al clima che cambia, ad esempio producendo e consumando alimenti che siano più resistenti alla scarsità di acqua.

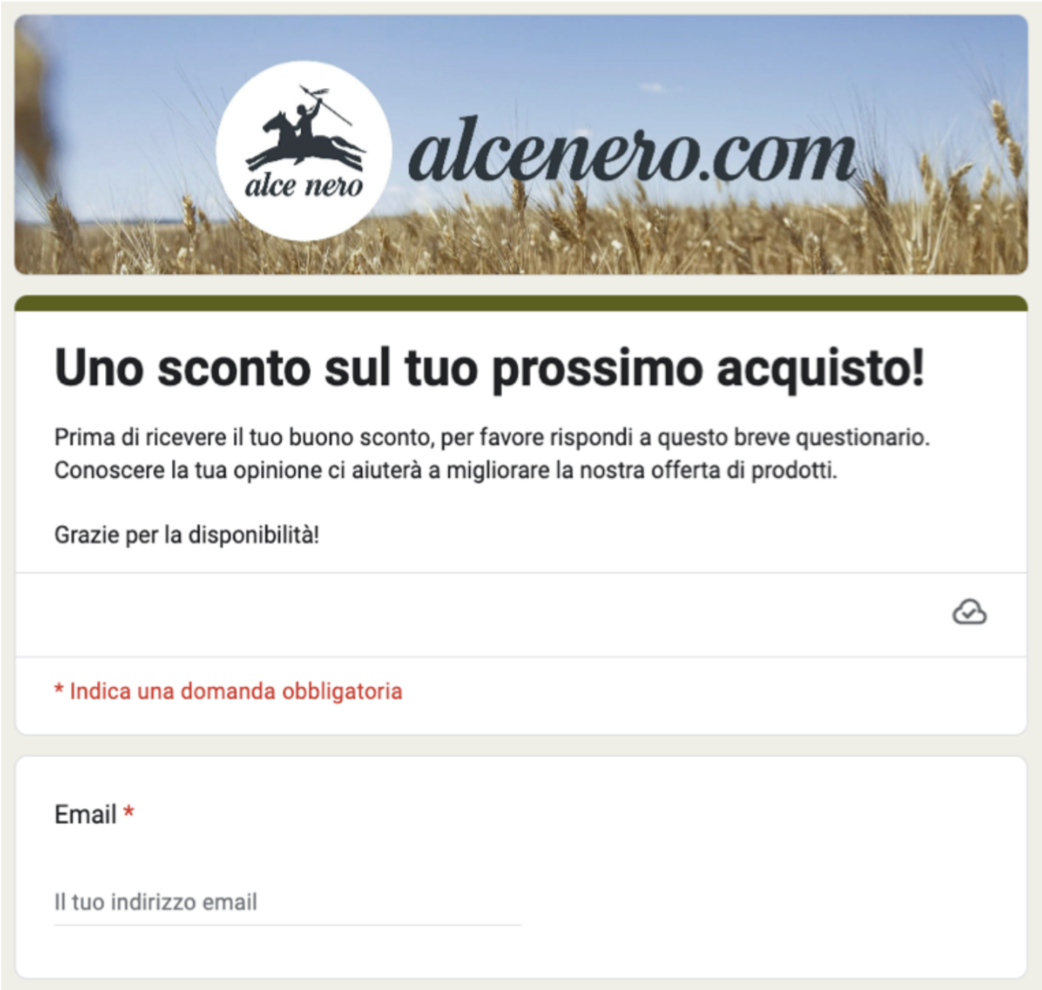
La pasta di grano duro Cappelli, un'antica varietà italiana, possiede questa caratteristica. Come evidenziato dal grafico sotto la sua resa è stata costante rispetto all'anno scorso, mentre altri grani duri hanno subito un calo del 16-20%.

Scegliendo la pasta Cappelli puoi incentivare gli agricoltori di Alce Nero a coltivarla, favorendo così la capacità dell'agricoltura italiana di adattarsi al clima che cambia.

Secondo i ricercatori, la siccità che colpisce l'Italia con frequenza crescente:

- ◯ Ha portato a una riduzione della produttività del grano duro Cappelli fino al 20%.
- ◯ Alcune varietà di grano duro potrebbero tollerarla bene.

Figure C4: Control group



.3.1 Survey

Before receiving your voucher, please answer these last questions.

How old are you?

a) 15-24
b) 25-34
c) 35-44
d) 45-64
e) +65

In which gender do you identify?

a) Female
b) Male

Which is your education level?

a) Primary Education
b) Secondary Education
c) Tertiary Education

Which is your occupation?

a) Housemaker
b) Employed
c) Unemployed

What is your main motivation for buying organic products?

a) They are healthier
b) They are better for the environment
c) They are better-tasting

How often do you buy organic products at the supermarket?

a) At least once a week
b) At least once a month
c) A few times a year
d) Never

What is your level of trust in the following sources of information on environmental issues?

a) Local government
    1) not at all
    2) it is reliable
b) Environmental organizations
    1) not at all
    2) it is reliable
c) Social media
    1) not at all
    2) it is reliable
d) Friends or relatives
    1) not at all
    2) it is reliable
e) Newspapers and TV
    1) not at all
    2) it is reliable
f) Scientists and academics
    1) not at all
    2) it is reliable

To what extent do you believe climate change is affecting your everyday life?

1) not at all
2) significantly

.4

Table D1: Average treatment effect on the share of ancient wheat pasta purchased, comparing colloquial versus scientific message framings. Estimates include 580 individuals who bought pasta after receiving treatment (294 scientific treatment, and 286 colloquial treatment) out of the 1,225 respondents to the survey. Standard errors, in parentheses, are clustered at the individual level. Individual characteristics include respondents' age, gender, educational attainment, occupational status, and whether they purchase organic food at supermarkets.
$^{**}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)
Exp × Colloquial	0.051^{**}	0.063^{**}	0.072^{**}
	(0.025)	(0.031)	(0.030)
Observations	2399	2399	2399
Day of Week FE	Yes	Yes	Yes
Discount FE	No	Yes	Yes
Individual FE	Yes	No	No
Individual characteristics	No	No	Yes

Table D2: Average treatment effects on the probability of survey participation. Columns (1)–(2) report Control vs Treat (both messages combined). Sample comprises 1,225 respondents out of 4,727 randomized invitees. Standard errors (in parentheses) are clustered at the individual level. Historical controls include total pasta sales, mean regional quantity of ancient-wheat pasta, and regional fixed effects.
$^{**}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1) Control *VS* Treat	(2) Control *VS* Treat
Treat	0.001	0.004
	[0.013]	[0.013]
Observations	4727	4727
Historical char.	No	Yes

Table D3: ATE on Share of *ancient* wheat pasta purchased for the sample of 1225 survey respondents. Omitted category for: age= 65+, Gender: Male, Occupation=Housemaker, Study=Compulsory education level, Buy organic in supermarkets: Never. Robust standard errors in parentheses are clustered at the individual level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Colloquial			Scientific		
Exp × Treat	0.058**	0.065**	0.068**	-0.013	-0.005	-0.006
	[0.027]	[0.031]	[0.031]	[0.027]	[0.030]	[0.030]
Age: 25-34			0.019			0.098**
			[0.047]			[0.045]
Age: 35-44			-0.000			0.048
			[0.040]			[0.038]
Age: 45-64			0.026			0.136***
			[0.038]			[0.036]
Female			0.068**			0.053**
			[0.028]			[0.026]
Secondary			0.008			-0.001
			[0.038]			[0.037]
Tertiary			0.022			0.044
			[0.039]			[0.038]
Self-employed/Manager/Employee			0.008			-0.094
			[0.062]			[0.061]
Unemployed/Retired			0.037			-0.075
			[0.065]			[0.066]
Occasionally year-round			0.032			0.034
			[0.049]			[0.051]
At least once a week			0.037			0.001
			[0.048]			[0.050]
At least once a month			0.033			-0.038
			[0.053]			[0.054]
Observations	3250	3271	3271	3268	3289	3289
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Discount FE	No	Yes	Yes	No	Yes	Yes
Individual FE	Yes	No	No	Yes	No	No

TABLE D4: Descriptive statistics and T-tests of baseline characteristics (1225 individuals who answer at the survey). Columns 1, 2, and 3 presents mean and standard deviation (in parenthesis). Columns 4 and 5 reveal the mean differences between the Colloquial and Control groups and the Scientific and Control groups, respectively. In all cases, the t-tests did not indicate any significant differences.

	Control	Colloquial	Scientific	Colloquial - Control Difference	Scientific - Control Difference
Purchase only *ancient* wheat (0-1)	0.21	0.20	0.24	-0.006	0.034
	(0.41)	(0.40)	(0.43)	(0.028)	(0.029)
Purchase only *modern* wheat (0-1)	0.23	0.26	0.21	0.029	-0.019
	(0.42)	(0.44)	(0.41)	(0.030)	(0.029)
Purchase both wheats (0-1)	0.52	0.52	0.52	0.001	0.005
	(0.50)	(0.50)	(0.50)	(0.035)	(0.035)
Pasta total purchases (euro)	48.99	49.72	47.25	0.732	-1.745
	(64.84)	(62.56)	(68.06)	-4.479	(4.626)
Number of purchases	3.91	3.90	3.87	-0.010	-0.047
	(2.99)	(2.90)	(2.90)	(0.207)	(0.205)
Purchases only during discount event	0.09	0.07	0.07	-0.012	-0.013
	(0.28)	(0.26)	(0.26)	(0.019)	(0.019)
Income pc (thousands euro)	21.50	21.30	21.51	-0.199	0.012
	(3.67)	(3.66)	(3.77)	(0.258)	(0.259)
Q.ty ancient > q.ty modern					
Fusilli pasta	0.11	0.14	0.12	0.026	0.009
	(0.31)	(0.34)	(0.32)	(0.023)	(0.022)
Penne pasta	0.18	0.19	0.17	0.003	-0.011
	(0.39)	(0.39)	(0.38)	(0.027)	(0.027)
Spaghetti pasta	0.18	0.18	0.14	-0.002	-0.038
	(0.38)	(0.38)	(0.35)	(0.027)	(0.026)
Observations	411	399	415	810	826

Table D5: Descriptive statistics and T-tests of individual characteristics. Columns 1, 2, and 3 present the mean and standard deviation (in parentheses) for 1,225 respondents to the survey. Columns 4 and 5 reveal the mean differences between the Colloquial and Control groups and the Scientific and Control groups, respectively.

	Control	Colloquial	Scientific	Colloquial - Control Difference	Scientific - Control Difference
Female	0.550	0.619	0.564	0.069**	0.014
	(0.498)	(0.486)	(0.497)	(0.035)	(0.035)
Age: 25-34	0.175	0.148	0.152	-0.027	-0.023
	(0.381)	(0.355)	(0.359)	(0.026)	(0.026)
Age: 35-44	0.260	0.291	0.289	0.030	0.029
	(0.439)	(0.455)	(0.454)	(0.031)	(0.031)
Age: 45-64	0.401	0.378	0.357	-0.023	-0.045
	(0.491)	(0.486)	(0.480)	(0.034)	(0.034)
Age: 65+	0.163	0.183	0.202	0.020	0.039
	(0.370)	(0.387)	(0.402)	(0.027)	(0.027)
Education level:					
Primary	0.243	0.085	0.089	-0.158***	-0.154***
	(0.430)	(0.280)	(0.285)	(0.026)	(0.025)
Secondary	0.431	0.546	0.540	0.116***	0.109***
	(0.496)	(0.498)	(0.499)	(0.035)	(0.035)
Tertiary	0.326	0.368	0.371	0.042	0.045
	(0.469)	(0.483)	(0.484)	(0.033)	(0.033)
Type of occupation:					
Houseworker	0.039	0.060	0.051	0.021	0.012
	(0.194)	(0.238)	(0.219)	(0.015)	(0.014)
Self-employed/Manager/Employee	0.698	0.662	0.684	-0.037	-0.014
	(0.460)	(0.474)	(0.465)	(0.033)	(0.032)
Unemployed/Retired	0.263	0.278	0.265	0.015	0.002
	(0.441)	(0.449)	(0.442)	(0.031)	(0.031)
Habits of purchasing organic food at supermarket:					
Never	0.073	0.065	0.060	-0.008	-0.013
	(0.260)	(0.247)	(0.238)	(0.018)	(0.017)
Occasionally year-round	0.350	0.286	0.335	-0.065**	-0.015
	(0.478)	(0.452)	(0.473)	(0.033)	(0.033)
At least once a week	0.404	0.421	0.431	0.017	0.027
	(0.491)	(0.494)	(0.496)	(0.035)	(0.034)
At least once a month	0.173	0.228	0.173	0.055**	0.001
	(0.378)	(0.420)	(0.379)	(0.028)	(0.026)
Motivation:					
Environment	0.496	0.333	0.205	-0.163***	-0.292***
	(0.501)	(0.472)	(0.404)	(0.034)	(0.032)
Taste	0.197	0.193	0.234	-0.004	0.037
	(0.398)	(0.395)	(0.424)	(0.028)	(0.029)
Health	0.307	0.474	0.561	0.167***	0.255***
	(0.462)	(0.500)	(0.497)	(0.034)	(0.033)
Climate influences daily life: Yes	0.246	0.481	0.431	0.235***	0.186***
	(0.431)	(0.500)	(0.496)	(0.033)	(0.032)
Trust in science: Yes	0.608	0.409	0.390	-0.200***	-0.218***
	(0.489)	(0.492)	(0.488)	(0.034)	(0.034)
Pre-intervention purchase category:					
Green	0.178	0.180	0.149	0.003	-0.028
	(0.383)	(0.385)	(0.357)	(0.027)	(0.026)
Greener	0.375	0.414	0.388	0.039	0.013
	(0.485)	(0.493)	(0.488)	(0.034)	(0.034)
Greenest	0.448	0.406	0.463	-0.042	0.015
	(0.498)	(0.492)	(0.499)	(0.035)	(0.035)
Discount:					
5%	0.236	0.223	0.236	-0.013	0.000
	(0.425)	(0.417)	(0.425)	(0.030)	(0.030)
10%	0.528	0.509	0.537	-0.019	0.009
	(0.500)	(0.501)	(0.499)	(0.035)	(0.035)
20%	0.236	0.268	0.227	0.032	-0.010
	(0.425)	(0.444)	(0.419)	(0.031)	(0.029)
Check question: Right		0.41	0.61		
		(0.49)	(0.49)		
Observations	411	399	415	810	826

Chapter 3

The Adverse Impacts of Disasters In-Name-Only

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Abstract

Disasters caused by natural hazards, such as earthquakes or hurricanes, have many adverse consequences associated with the physical damage they cause. Here, we show that the very name given to a disaster can also lead to adverse consequences. We argue that the name used for a disaster is significant, and is distinct from the physical event itself. Specifically, we show that the toponyms (place names) used to refer to disaster events by the media and the authorities have consequences if these toponyms do not accurately align with the disaster-affected region. Examples of inaccurate disaster toponyms abound, but the costs of these inaccurate toponyms have yet to be recognized. When a disaster damages area A and not area B, but the toponym adopted for that disaster encompasses both A and B, we show that B experiences a decline in tourism that is unrelated to the hazard event that hit only area A. We also show that once B's name has been tarnished, it becomes difficult to clear its name. Our examples are three recent Italian earthquakes for which we quantify the impact on tourism of the earthquakes themselves and of the toponyms they were given. Once an area is defined as affected, even when it was not, this designation leads to a statistically significant and economically material decline in tourism – in our examples, this amounts to an unnecessary 10-15 percent decline in tourist arrivals that endures for several years following the event. We end by making some observations about how disasters should be named.

3.1 What's in a name?

Disasters caused by natural hazards, such as earthquakes or hurricanes, have many adverse consequences that can last even years after the event itself. These arise because disasters hurt and even kill people, and because they destroy infrastructure and homes. All of this is well documented. This article aims to show that the very name given to a disaster can also lead to adverse consequences after that event. We argue that the name used to describe a phenomenon, such as a disaster, is significant and distinct from the physical event itself. Words matter; giving an event a 'bad name' quite literally leads to adverse outcomes.

Shakespeare's answer to Juliet's rhetorical question about Romeo's family name (in their eponymous play): 'What's in a name?' was that names are unimportant. "That which we call a rose/ By any other name would smell as sweet." The evidence we provide below suggests otherwise. We find that names do matter. Specifically, we show that the toponyms (place names) used to refer to disaster events by the media (and governments) have consequences if these toponyms do not accurately align with the region that was directly damaged by the disaster event. A toponym that becomes a 'household name' and that includes regions that were not affected by the physical hazard itself, leads to adverse consequences for these 'wrongly' included regions. In the cases we document, these regions suffer from declines in tourist arrivals even though they were unaffected by the original shock.

Though examples of inaccurate disaster toponyms abound, the costs of these inaccurate toponyms have yet to be recognized. Misleading toponyms include catastrophic events that have had global repercussions, such as the Great East Japan Earthquake (in 2011) or the Indian Ocean Tsunami (in 2004); or, more recently, catastrophes such as the Türkiye-Syria earthquake (in 2022) and the Valencia Flood (in 2024). In all of these cases, the toponym used to define the event covered a vastly different area from the one directly affected by the tsunami, the earthquake, or the flood.

When a disaster damages area A and not area B, but the toponym adopted for that disaster encompasses both A and B, we show that B experiences a decline in tourism that is unrelated to the hazard event that hit area A, only because the toponym gave it a 'bad name.' This is surprising not only because economists rarely think that a name (i.e., a nominal object) can have real consequences, but because once a name is repeated frequently enough it becomes established and is perceived to describe facts. It then becomes exceedingly difficult to change this perceived reality. Once B's name has been tarnished, it becomes difficult to clear its name.

Our case studies are from Italy. We focus on three earthquakes that occurred between 2009 and 2017 and investigate the impact of the earthquakes themselves and of the toponyms they were given on tourism, testing the hypothesis that the toponym exerted its own impact independent from the earthquake.[1] In one case, the toponym used was fairly accurate (the L'Aquila

[1] This hypothesis was first suggested in (Baiocchetti, 2020).

Earthquake of 2009), but in the other two (the Central Italy Earthquake of 2016 and the Ischia Earthquake of 2017), the toponym described a much bigger region than was directly impacted by these seismic events.[2] For the latter two cases, we show that area A (affected by the earthquake) experienced a large reduction in both domestic and international tourism, but that area B (affected only by the toponym) experienced a reduction in tourism as well.

Previously, several empirical studies investigated the effects of naming extreme weather events such as storms, heat waves, and droughts. Their focus was either on the act of naming an event or on the gender of that name. Rainear et al. (2017) analyzed storms in the U.S. and found that naming winter storms affected neither people's perceptions of their severity nor of their susceptibility to the storms' impact. Nor did naming an event affect the perceived credibility of media reports about it. In contrast, Kotroni et al. (2021) studied storm naming in the Eastern Mediterranean and found that naming did influence people's preparedness. Neither of these investigates the names in themselves, but only whether an event received an explicit name (i.e. a proper noun).

In contrast, two other sets of studies did examine the implications of the names themselves. The first focused on gendered naming conventions. A contentious Jung et al. (2014) paper argued that female-named hurricanes in the U.S. were deadlier, hypothesizing that this was because people were less cautious when female-named hurricanes were forecasted to arrive since they viewed female-named storms as more benign than male-named ones. However, a long series of published rebuttals cast doubt on this empirical claim (Bakkensen & Larson, 2014; Christensen & Christensen, 2014; Maley, 2014; Malter, 2014). A more recent paper casts further doubt on the plausibility of the Jung et al. (2014) argument. (Dinh et al., 2023) examined the implications of referring to hurricanes by their gendered names in news coverage, and found that the choice of adjectives and verbs in the description of female-named hurricanes was more negative than for male ones.

Possibly, the only group of studies that is relevant to our work investigates the effects of naming infectious diseases and epidemics. Fukuda et al. (2015) describes how the World Health Organization in collaboration with the World Organisation for Animal Health, the Food and Agriculture Organization of the United Nations, and the International Classification of Diseases (ICD) developed a set of best practices for naming new infectious diseases, with the explicit aim to minimize the potential negative effects of these names.

It has long been argued that the choice of a disease's name can affect people's perceptions and attitudes about the risk it poses, and can also lead to discrimination and stigmatization associated with the labeling of diseases based on geographical locations or nationalities. This last concern has been the focus of a small literature on naming practices for what was called the

[2] The L'Aquila and Central Italy earthquakes were the highest mortality events in Italy since 1980 - in each about 300 people were killed. The Ischia earthquake was much smaller but is the only other event for which we have data and which led to widely reported impacts. The Emilia earthquake of 2012 led to higher mortality than Ischia, and its toponym is also inaccurate, but the required tourism data for 2013 are unavailable.

'Wuhan Virus' or the 'China Virus'; before the ICD settled on the name Corona Virus Disease 2019 (COVID-19) in February 2020.[3] Masters-Waage et al. (2020) and C. Xu and Liu (2021) empirically investigated the effects of using different labels for COVID-19. Masters-Waage et al. (2020) found no evidence to support the hypothesis that different naming conventions of COVID-19 affected people's risk perceptions and attitudes towards Chinese people. C. Xu and Liu (2021) also found that labeling COVID-19 as the 'China virus' did not increase the perception that Chinese immigrants are a threat.[4] They also found that the branding of COVID-19 as "Chinese" did not appear to reduce the extent to which Americans blamed their own federal government for the mismanagement of the pandemic; this branding did not work to deflect blame to China, as was in no doubt intended by very prominent proponents of the 'China' label.

In the next section, we describe how toponyms for earthquakes have been determined in Italy and how people reacted to these toponyms. Maybe unsurprisingly, we also document how toponym-only-affected areas occasionally recognized the significance of their 'wrongful' inclusion in the toponyms. In Section 3.3, we describe our data and empirical methodology, while in Section 3.4 we examine each of the three above-mentioned earthquake events. Section 3.5 concludes with a discussion about the importance of naming conventions, and some policy suggestions for the use of toponyms for the naming of disasters.

3.2 Earthquakes, misnaming and the media

3.2.1 Choosing earthquake toponyms in Italy

No organization or institution in Italy is officially responsible for assigning names to disaster events. Instead, the toponyms that are eventually used to identify these events typically spread through the media. These geographical labels may start to spread from journalists covering the news of the event or from statements by official bodies, such as the National Institute of Geophysics and Volcanology (INGV), which oversees seismic monitoring. Drawing on INGV archive data[5], Table 3.2.1 examines the names attributed to major earthquakes in Italy since 1900 and the types of regions they refer to.

[3] Oddly, the same considerations about stigmatization have not been followed with other viral diseases, like Ebola or Marburg, as both are still officially named after places. In fact, Ebola provides us with an inaccurate toponym that is still used by the World Health Organisation: The West Africa Ebola Outbreak of 2013-2016. In 2013, Ebola spread widely in three very small West African countries — Sierra Leone, Liberia, and Guinea — and a few cases were eventually also diagnosed in Italy, Mali, Nigeria, Senegal, Spain, the United Kingdom, and the United States. See: https://www.who.int/emergencies/situations/ebola-outbreak-2014-2016-West-Africa.

[4] They do find that Chinese immigrants were perceived more negatively, weakly, in a subsample of liberal respondents of their survey.

[5] Source: https://ingvterremoti.com/i-terremoti-in-italia/ (in Italian).

Two key observations emerge. First, when compared to the past, historical names of regions, or names based on topographical or environmental features are now less commonly used, with administrative region names (particularly NUTS-2 and NUTS-3 levels[6]) becoming more prevalent. When historical or geo-physical region names are used—such as "Friuli" in 1976 and "Emilia" in 2012—they often partially overlap with the administrative region's name. Second, with the exception of urban areas, the scale used to identify affected locations has broadened over time. This shift culminated in 2016 with the use of a macro-regional toponym (NUTS-1) for the first time, as in the case of "Central Italy."

Table 3.2.1: Prevailing name of the major earthquakes that occurred in Italy after 1900

Year	**Earthquake name**	**Type of Region**
1905	Calabria	NUTS-2 Administrative region
1908	Messina	Municipality and NUTS-3 administrative region
1915	Marsica	Historical and geographical region (the land of ancient Marsi)
1919	Mugello	Topographical region (a valley)
1920	Garfagnana	Historical and geographical region (a mountain valley)
1930	Irpinia e Vulture	Historical and geographical, and topographical (mountain) regions (respectively)
1962	Irpinia	Historical and geographical region (land of ancient Irpini)
1968	Belice	Topographical region (a valley)
1976	Friuli	Historical and geographical region (partly identifying a NUTS-2 administrative region)
1980	Irpinia	Historical and geographical region (land of ancient Irpini)
1997	Umbria e Marche	Two NUTS-2 administrative regions
2009	L'Aquila	Municipality and NUTS-3 region
2012	Emilia	Historical and geographical region (partly identifying a NUTS-2 administrative region)
2016	Centro Italia	NUTS-1 region
2017	Ischia	Municipality and physical region (an island)

Notes: See Gavinelli, Goldstein, et al., 2022 for a comprehensive explanation of historical, geographical, physical, and administrative regions in Italy. Source: own elaboration based on web archives.

The event referred to as the "Central Italy" earthquake encompasses a series of seismic shocks, with their main epicenters recorded in the following locations: the municipality of Accumoli (NUTS-3 region of Rieti, NUTS-2 Lazio region) on August 24, 2016; the municipality of Visso (NUTS-3 Macerata, NUTS-2 Marche) on October 26, 2016; the municipality of Norcia (NUTS-3 Perugia, NUTS-2 Umbria) on October 30, 2016; and the municipality of Capitignano (NUTS-3 L'Aquila, NUTS-2 Abruzzo) on January 18, 2017. The toponym "Central Italy" broadly encompasses all these areas,[7] but it also includes many other areas within Central Italy that were unaffected by the earthquake. No toponym precisely identifies all these areas; perhaps the

[6] NUTS are the Nomenclature of Territorial Units for Statistics adopted by the European Commission and used throughout the European Union. NUTS-1 are the macro-regions, of which Italy has five (north-west, north-east, central, south, and the islands); NUTS-2 are typically referred to as Regions (e.g., Abruzzo), of which Italy has 21, NUTS-3 are sometimes referred to as Provinces (e.g., L'Aquila), of which Italy has 67. The smallest layer are the municipalities (comuni), of which Italy has 7904 (e.g., L'Aquila City is a municipality).

[7] Abruzzo is classified as part of Southern Italy by the Italian National Institute of Statistics (ISTAT), but it is considered part of Central Italy in geophysical terms.

closest equivalent is "Alta Sabina", a historical-geographical region, yet it would exclude the municipalities located in the Marche region. In any case, already after the first tremor, when obviously no one knew that others would follow and where, the area affected was referred to as Central Italy in the press, as shown in Figure 3.2.1. Taking into consideration the titles on the front pages of the major Italian newspapers[8] on the day after the event (August 25, 2016), the following toponyms appear to identify the area that was hit: Central Italy (NUTS-1, 7 times); Lazio, Marche and Umbria (NUTS-2, twice); Lazio, Marche, Umbria and Abruzzo (NUTS-2, twice); Appennino (the mountain range that runs from the north to the south of the country, twice); Amatrice, Arquata and Accumoli (municipalities, twice); Lazio and Marche (NUTS-2, once); Amatrice and Accumoli (municipalities, once); Amatrice (a municipality, once).

FIGURE 3.2.1: Front page of the best-selling newspaper in Italy the day after the August 24, 2016 earthquake.


GIOVEDÌ 25 AGOSTO 2016

www.corriere.it

EURO 1,50 | ANNO 141 - N. 202

CORRIERE DELLA SERA

140

FONDATO NEL 1876

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Come effettuare i versamenti

Il territorio

La linea rossa e la scossa anomala in superficie

G. Caprara, Meldolesi Rovelli alle pagine 12-13

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24 AGOSTO 2016

Morti e paesi cancellati

Sisma devasta il Centro Italia, oltre 150 vittime. Trappola in un albergo

Un terremoto del sesto grado della scala Richter si è abbattuto sul Centro Italia, tra Lazio, Marche, Umbria e Abruzzo. Morti, sfollati, distruzione: interi paesi cancellati.

In press releases and on its website, the INGV adopted the toponym Central Italy to identify the affected area.[9] The three municipalities where fatalities were recorded were Accumoli, Amatrice, and Arquata. The three are located in a valley called Alta Valle del Tronto, an alternative toponym that could have defined better the heavily affected area. Alternative toponyms can also be suggested with reference to the other main events of the sequence. The aftershocks occurred between October 26 and October 30, 2016, and mostly hit the municipalities of Ussita, Visso, Sant'Angelo sul Nera and Norcia, all of which are part of the Monti Sibillini National Park.

[8]We considered: Il Corriere della Sera (the best-selling Italian newspaper, reported in Figure 3.2.1), La Repubblica, La Stampa, Il Sole 24 Ore, Il Messaggero, Il Giornale, Il Foglio, Il Fatto Quotidiano, Il Manifesto, Libero, L'Unità, Il Tempo, Avvenire, L'Osservatore Romano, Il Mattino, Il Tirreno, and La Gazzetta del Mezzogiorno

[9]See https://ingv.it/stampa-e-urp/stampa/note-stampa/3025-sequenza-sismica-in-italia-centrale-aggiornamento-12-settembre-ore-11-00 (in italian).

It also represents an alternative and more geographically concise toponym. The municipalities mostly affected by the last relevant shock that occurred on January 16, 2017, were Capitignano, Montereale and Campotosto, all of which are also located in the Alta Valle dell'Aterno area.

A similar reasoning can be applied to the Ischia case, where an earthquake was recorded on August 21, 2017. The toponym refers both to the entire island and to one of the six municipalities it is divided into. The epicenter was located in the municipality of Casamicciola Terme, where the only two fatalities were recorded. Minor damages were also reported in the bordering municipality of Lacco Ameno. We analyzed again the titles of the main Italian newspapers (listed in footnote 8) on the day following the event and found that they all refer to the area as Ischia; only one newspaper mentions Casamicciola Terme, in addition to Ischia, in its subtitle. The front page of Il Corriere della Sera, the best-selling Italian newspaper, is shown in Figure 3.2.2. As with the previous example, referring to the area as Ischia is not incorrect if referring to the island, though it can be misleading: Ischia is also the name of a municipality (the most populous of the six) that was not affected by the earthquake and, anyway, the island was affected only partly, since four municipalities out of six municipalities on the island were not damaged at all (including the municipality of Ischia).

FIGURE 3.2.2: Front page of Il Corriere della Sera, the best-selling newspaper in Italy, the day after the August 21, 2017 earthquake.

Quotidiano

Tiratura: 410.224
Diffusione: 316.808

MARTEDÌ 22 AGOSTO 2017 www.corriere.it In Italia EURO 1,50 ANNO 142 - N. 197

CORRIERE DELLA SERA

FONDATO NEL 1876

Aveva 86 anni
Addio a Guido Rossi il giurista anti crisi
di **Paola Pica** e **Giangiacomo Schiavi**
a pagina 12

Il ritratto
Il sacerdote laico amante delle regole
di **Ferruccio de Bortoli**
a pagina 13

STOSA

Comunità islamiche

LA REAZIONE CHE ANCORA NON C'È

di **Sabino Cassese**

C'è un grande assente nelle vicende — tra loro intrecciate — degli attentati terroristici islamici e del controllo statale dell'immigrazione: le comunità islamiche. Eppure i cittadini di origine o fede musulmana, che rappresentano circa il 7 per cento della popolazione dell'Europa (complessivamente, 49 milioni di persone, secondo stime recenti), sono danneggiati due volte dal terrorismo. Gli attentati producono, innanzitutto, negli Stati, una reazione di diffidenza nei confronti delle comunità islamiche già stabilite, una diffidenza che non agevola il dialogo interreligioso, la pacifica convivenza, l'integrazione. L'altra è una reazione di chiusura degli Stati a danno dei migranti appartenenti alla medesima comunità, che sarebbero interessati a entrare nei nostri Paesi. È noto, infatti, che gli immigrati non si muovono alla cieca, hanno sempre in tasca il numero telefonico di un parente, un

Il terremoto Panico e gente per le strade, frazioni isolate. Va giù una palazzina abitata. Requisito un traghetto per i soccorsi

Scossa a Ischia, crolli e vittime

Sisma di magnitudo 4: un morto, se ne temono altri. Bimbi tra le macerie, si scava per salvarli

Una scossa di terremoto di magnitudo 4 ha colpito ieri sera alle 20.57 l'isola di Ischia. L'epicentro in mare a 10 km di profondità.

● Una donna è morta per la caduta dei calcinacci della chiesa di Santa Maria del Suffragio, a Casamicciola, la località più colpita dove ci sono feriti e vari crolli. Collassate almeno sei case. In macerie una palazzina. Almeno dieci i dispersi. I feriti sarebbero ventisei, due gravissimi. Tre bambini rimasti sotto le macerie, uno di soli sette mesi. Durante la notte sono stati estratti vivi un uomo e una donna.

● Tanta la paura: popolazioni e turisti in strada. Isolati molti alberghi dell'isola. Evacuato l'ospedale Rizzoli per le crepe sui muri. Requisito un traghetto per i soccorsi. Lesionato anche il palazzo del Comune di Casamicciola.

● I testimoni hanno detto di aver sentito un boato proveniente dal mare».

alle pagine 2 e 3 **Carioti, Martucci, Sensini**

Crolli dopo la scossa di terremoto di magnitudo 4 a Lacco Ameno, nell'isola di Ischia davanti a Napoli.

STORIE & VOLTI

LE TESTIMONIANZE
«I turisti in fuga con le valigie»
di **A. Pasqualetto** a pagina 3
La paura nelle parole dei turisti in fuga dall'isola.

IL MAGISTRATO
«Paghiamo il conto delle case abusive»
di **Alfio Sciacca** a pagina 5
Il magistrato Aldo De Chiara: «Queste le conseguenze dell'abusivismo».

LA GEOLOGA
Perché tanti danni? Quell'area è friabile
di **Leonard Berberi** a pagina 5
L'intervento di Micla Pennetta, docente di Geologia.

For the L'Aquila earthquake, in contrast, the toponym is more geographically accurate. It refers to the earthquake that occurred on April 6, 2009, whose epicenter was located in the municipality of L'Aquila. The toponym refers to both the municipality and its province (NUTS-3 region),[10] most of which was affected by the shock. This event garnered significant media attention: Italy had not experienced an earthquake of such magnitude for decades, and it struck a regional capital not far from Rome. Its resonance may have also stemmed from the politicization of the event by the then Prime Minister, Silvio Berlusconi (Alexander, 2018; Özerdem & Rufini, 2013). Apart from the heavily affected provincial capital (72,696 inhabitants as of January 1, 2009), all other affected municipalities in the province had populations of fewer than 5,000. The media's attention focused almost exclusively on the city of L'Aquila, the most severely affected in terms of both casualties and building collapses (Galli & Camassi, 2009). Since the L'Aquila toponym coincides quite precisely with the heavily hit area (the so-called earthquake crater), we do not discuss it in the next subsection.

3.2.2 Adversely affected undamaged areas - in the media

A discontent regarding the names for the Central Italy and the Ischia earthquakes emerged not long after these events. Protests came from both local institutions and tourism operators who were located in the regions described by the toponym, but which experienced no damage.

In January 2017, a few months after the events, the newspaper Il Sole 24 Ore dedicated a report to the economic consequences of the Central Italy earthquakes in areas that were perceived to have been damaged, but were in reality not directly impacted by the earthquakes themselves. They deduced that:

> The damage caused by the earthquake [...] is not limited to the dramatic destruction of buildings [...]. There are less visible but deeply impactful damages that [...] risk exacting a steep toll on one of the most lucrative industries in these regions: tourism. [...] In this quadrilateral area encompassing northern Lazio, Abruzzo, Marche, and Umbria, there are treasures like Valnerina (from Amatrice to Norcia), struck by the earthquake and now grappling with a 90% or total drop in tourist arrivals. Meanwhile, world-famous destinations in Umbria—such as Assisi, Spoleto, and Gubbio—though far from the earthquake's epicenter, have experienced declines ranging from 30% (in November) to 50% (in December). [11]

In May 2017, the newspaper Il Corriere della Sera dedicated an article to the "virtual earthquake", observing that:

> Not just collapsed houses. Among the rubble, there are also empty rooms—rooms that are fully functional. They once hosted tourists, who have now vanished due to

[10] Italian provinces (NUTS-3 regions) are almost always named after their capital.

[11] Source: https://www.infodata.ilsole24ore.com/2017/01/20/la-mappa-costi-economici-delle-aree-piu-colpite-dal-terremoto-del-centro-italia/. The quoted text has been translated from Italian by the authors.

> fear, often unjustified. [...] Even those who were untouched by the disaster have suffered. “I consider Assisi to be the epicenter of a virtual earthquake,” explains Eugenio Guarducci, the city’s Tourism Councilor. “There was no rubble here. No displaced residents. But the economic consequences, unfortunately, have been very real: from October 2016 to March 2017, we observed a 50% drop in arrivals compared to the same period the previous year. And all of this happened because the media spoke vaguely about the earthquake in the province of Perugia [...]".[12]

The protests by the above-mentioned Tourism Councilor of Assisi prompted the INGV to officially change the name assigned to the seismic sequence from "Central Italy Earthquake" to "Amatrice, Norcia, and Visso Seismic Sequence".[13] This, though, happened almost one year after the events. The INGV agreed to change their communication of seismic events from that moment on by providing the name of the municipality where the epicenter is located, instead of a greater administrative unit.[14] Nonetheless, their choice of the new name is unclear, as the first significant tremor was recorded in the municipality of Accumoli, not Amatrice.

However, years after this announcement, we observed that INGV indeed adopts the criterion of indicating the municipality closest to the epicenter in the public technical database where all seismic events are listed.[15] However, on the more public-facing pages of the institutional website, this criterion does not seem to be consistently followed. This is evident, for instance, on the page that lists the major seismic sequences that have occurred in Italy in recent years, all of which caused little damage.[16] Considering those that took place after the date when the Institute announced it would improve its communication, the toponymic references vary, pointing to entire NUTS-2 administrative regions (such as "Molise 2018"), physical regions ("Tuscany-Emilia Apennines 2023"), entire NUTS-3 administrative regions ("Province of Florence 2022"), and municipalities (as in "Umbertide 2023").

At the time, protests came also from tourist operators. One of them, interviewed in Assisi almost one year after the events, explicitly blamed the media for using an inaccurate toponym to identify the seismically-affected area:

> "Tourists no longer come; I’ve lost 70 percent of my business because of your labels," exclaims Paola, [...]. Labels? "The newspapers and television called it the ’Central

[12] Source: https://viaggi.corriere.it/eventi/danni-terremoto-turismo/. The quoted text has been translated from Italian by the authors.

[13] See: https://www.ansa.it/lazio/notizie/2017/02/14/terremoto-centro-italia-cambia-nome_e2765d90-a36f-4262-afe1-ff3ec5ef66c3.html (in Italian). Other official bodies, such as the Chamber of Commerce of Perugia, also emphasized the need for better communication to avoid identifying the entire region with the area affected by the earthquake: see https://www.pg.camcom.gov.it/P42A4495C6858S0/In-Umbria-flussi-turistici-in-caduta-dopo-il-terremoto.html (in Italian).

[14] Source: https://ingv.it/stampa-e-urp/stampa/note-stampa/3083-ingv-il-sito-web-del-centro-nazionale-terremoti-migliora-l-informazione-degli-eventi-sismici.

[15] See: https://terremoti.ingv.it/

[16] See: https://ingvterremoti.com/terremoti-in-italia/

> Italy Earthquake', lumping everyone together... People got scared and now go on vacation elsewhere." [17].

Similar dissatisfaction was also expressed in Ischia. A few months after the earthquake, the president of Federalberghi Ischia (a trade association of hotel owners) said that:

> The Italian market (of tourists) has been the most problematic following the seismic event, as it was heavily influenced by the negative portrayal of the island by Italian media in the initial days. The media often disseminated false information, failing to respect and accurately represent the areas of the island most affected by the disaster. Ischia must prioritize investing in better communication strategies [...].[18]

The association also launched a social media campaign called "ischiavivapiuchemai" (translatable as: Ischia more alive than ever) to explain that:

> Ischia is not a crater; the earthquake [...] affected only two out of six municipalities. In the others, absolutely nothing happened. [...] It is therefore urgent to immediately restart the economy through transparent and comprehensive information for tourists and residents to avoid hasty departures and unwarranted panic, which risk compromising the season of an island that depends on tourism.[19]

Through an analysis of Google Trends data, we document distinct search patterns for keywords related to the Ischia earthquake. Figure .2.1 in the Appendix compares web searches for "terremoto Casamicciola" ("Casamicciola earthquake," referring to the municipality at the epicenter) and "terremoto Ischia" ("Ischia earthquake," referring to the entire island). Overall, significantly more people searched for "Ischia earthquake," indicating that the earthquake was immediately associated with the island's toponym. However, "Casamicciola earthquake" garnered greater search interest within the NUTS-2 region of Campania, which was directly affected by the event. Conversely, the term "Ischia earthquake" exhibited higher search interest across other Italian regions. The maps illustrate that more precise geographical awareness was concentrated in the area where the earthquake occurred.

We conducted a similar descriptive analysis for the Central Italy earthquake, specifically comparing web searches for "Central Italy earthquake," the epicenter, and the most affected location for each of the four shocks associated with that earthquake. Figure .2.2 in the Appendix shows

[17] Source: https://www.repubblica.it/venerdi/reportage/2017/07/05/news/turisti_addio_il_nuovo_crollo_di_assisi_vers_brev 170032915/. The quoted text has been translated from Italian by the authors.

[18] Source: https://ansabrasil.com.br/campania/notizie/2017/11/01/turismo-in-calo-a-ischia-dopo-terremoto_737c5e94-93d3-43c6-8df8-2e241e8be6ee.html. The quoted text has been translated from Italian by the authors.

[19] Source: https://www.sassilive.it/economia/lavoro/terremoto-ischia-federalberghi-aderisce-a-campagna-la-bellezza-non-teme-fatalita/. The quoted text has been translated from Italian by the authors.

that, at the time of the first earthquake in August 2016, the municipality most affected by the event (Amatrice) was predominantly associated with the earthquake, as the vast majority of users searched for "Amatrice earthquake." This trend reversed for the shocks of October 2016 and January 2017, where "Central Italy earthquake" became the most searched term. A similar pattern applies to the second and third shocks, which occurred in late October 2016. Figure .2.3 shows that while the epicenter and the most affected municipality of the October 30 shock (Norcia) were the most searched on the day of the earthquake, "Central Italy earthquake" became the most searched term in the following months and at the time of the final shock. Conversely, when the last earthquake occurred on January 18, 2017, "Central Italy" was the toponym most associated with the earthquake, surpassing searches for the epicenter and the most affected municipality of that shock (see Figure .2.4 in the Appendix). Overall, the descriptive evidence shows that the name "Central Italy earthquake" gained increasing prominence in describing the seismic sequence, eventually becoming the official term used by the media and institutions like INGV to identify the sequence.

In the following sections, we test whether the perceptions reported in the listed quotations find support in empirical analysis, and compare them to the 2009 toponym-accurate L'Aquila earthquake.

3.3 Data and method

3.3.1 Data and sample description

The ideal setting to answer our research question - what's in a name? - would require data on tourist flows at the most granular administrative level (i.e., municipalities) over a long time span. Data on tourist arrivals and overnight stays for Italian municipalities are available from 2014 onward, so we can use this data to analyse only the Central Italy and Ischia earthquakes. We constructed two other datasets at the NUTS-3 and tourist district levels to extend the analysis to the earlier L'Aquila earthquake, as well.

For the municipal-level dataset, we measure tourist flows – tourist arrivals by place of origin (domestic or international) - from 2014 to 2018, collecting data from the Italian National Institute of Statistics (ISTAT) and regional statistical offices.[20] In addition, we collect data on several relevant characteristics of each municipality in our sample, including income per capita, the population size in logarithmic form, the share of foreigners, municipal peripherality with respect

[20]Data on tourist flows in Italy are collected by provincial and regional offices and subsequently submitted to ISTAT. For more details, refer to https://siqual.istat.it/SIQual/lang.do?language=UK. Considering that ISTAT provides data on tourist flows for only 2,872 out of 7,901 municipalities within the time frame of our analysis, we contacted all Italian regional statistical offices to supplement the ISTAT municipal database with data from as many missing municipalities as possible.

to socio-economic centers, and tourism classification.[21] Table .1.1 in the Appendix reports a detailed description of the variables included in our analysis, as well as their data sources. Our final sample comprises 3,362 out of 7,904 municipalities. Figure 3.3.1 illustrates the geographical coverage of our sample.

FIGURE 3.3.1: Municipalities in the dataset

For the L'Aquila earthquake, we sourced data on tourist flows at the NUTS-3 and district levels from ISTAT; these data correspond to the Italian provinces, while tourist districts, which are used for statistical purposes to monitor tourism flows, are defined based on geographic and administrative divisions. These districts typically group contiguous municipalities sharing similar tourism characteristics, such as coastal areas, mountain regions, or towns of similar cultural interest.[22] Tourist districts are more disaggregated than provinces, covering smaller areas. In 2009, the year of the occurrence of the L'Aquila earthquake, Italy had 111 provinces and 542 tourist districts.

We measure monthly tourist arrivals for 107 out of the 111 provinces from January 2008 to March 2010, i.e., up to one year after the earthquake.[23] For tourist districts, we observe annual

[21] See the next section for a detailed explanation of the rationale and relevance behind the inclusion of each variable in our analysis.

[22] Individual municipalities can also constitute independent tourist districts. For instance, the municipality of L'Aquila is also considered a tourist district on its own. The surrounding municipalities within the same Province of L'Aquila are grouped into another tourist district called "Other Municipalities L'Aquila".

[23] We exclude from the analysis four provinces due to missing data: Barletta-Andria-Trani, Fermo, Monza e della Brianza, and Sud Sardegna.

tourist flows from 2004 to 2011 for 474 units.[24] Table 3.3.1 provides descriptive statistics for all variables in our datasets, categorized by earthquake. For each earthquake, we provide separate statistics for units located within the crater (the area directly damaged by the earthquake) and for unaffected units inside and outside the geographical area defined by the toponym[25].

TABLE 3.3.1: Descriptive statistics

Central Italy earthquake (Municipal-level data, 2014-2018)	**Crater**		**Unaffected-Toponym**		**Unaffected-Control group**	
Variable	Mean	St. dev	Mean	St. dev	Mean	St.dev
Total arrivals	4,876.5	14,004.4	16,630.6	44,724.5	37,953.3	243,718.1
Arrivals - Italians	5,727.1	13,595	13,204.4	30,829.3	19,427.7	86,030.8
Arrivals - Internationals	1,126.5	2,979.4	4,760.7	19,313.8	20,490.3	174,115.6
Total overnight stays	16,962.1	45,452.4	58,864.2	150,572.3	131,564.2	706,864.7
Overnight stays - Italians	17,545.6	39,696.2	48,456.8	122,086.9	65,921.3	269,821.1
Overnight stays - Internationals	6,118.3	15,258.0	15,125.9	46,818.6	72,404.1	499,065.2
Population (log)	7.5	1.3	8.3	1.4	8.5	1.3
Share of foreigners	0.08	0.03	0.08	0.04	0.07	0.04
Income per capita	16,444.3	2,048.1	17,204.8	2600.5	19,295.4	3,903.8
Periphery score	3.6	1.0	3.7	1.0	3.5	1.1
Tourism category	8.5	2.8	7.6	3.2	7.1	3.1
Ischia earthquake (Municipal-level data, 2014-2018)	**Crater**		**Unaffected-Toponym**		**Unaffected-Control group**	
Variable	Mean	St. dev	Mean	St. dev	Mean	St.dev
Total arrivals	68,049.4	4,872.0	124,810.1	95,259.4	33,732.3	222,493.1
Arrivals - Italians	56,340.4	5,540.1	95,881.4	74,135.9	18,112.9	79,587.0
Arrivals - Internationals	11,709	1,510.1	28,928.7	23,180.2	17,819.9	159,680.7
Total overnight stays	403,881.4	32,978.9	741,480.5	556,257.4	116,686.2	645,651.4
Overnight stays - Italians	327,565.8	38,560.4	532,257.4	398,803.2	61,609.5	250,435.6
Overnight stays - Internationals	76,315.6	13,443.0	209,223.1	179,179.1	62,640.8	457,686.5
Population (log)	9.0	0.1	9.3	0.6	8.4	1.3
Share of foreigners	0.06	0.01	0.07	0.02	0.07	0.04
Income per capita	18,196.5	536.1	17,393.0	1,191.3	18,908.5	3,798.9
Periphery score	5	0	5	0	3.6	1.1
Tourism category	9	0	5.5	2.7	7.2	3.1
L'Aquila earthquake (Provincial-level data, 01.2008-03.2010)	**Crater-Toponym**		**Unaffected-Bordering provinces**		**Unaffected-Control group**	
Variable	Mean	St. dev	Mean	St. dev	Mean	St. dev
Total arrivals	35,492.6	17,387.8	21,480.7	21,881.1	74,837.6	131,531.3
Arrivals - Italians	33,345.8	17,315.6	17,181.7	17,895.4	42,198.3	58,335.3
Arrivals - Internationals	2,146.8	1,307.4	4,299.0	6,143.3	32,639.2	84,180.7
Total overnight stays	121,547	63,685.7	92,995.8	180,203	286,742	604,883.8
Overnight stays - Italians	113,515.2	62,514.7	76,365.9	157,077.5	161,157.7	311,183.2
Overnight stays - Foreigners	8,031.8	4,529.1	16,629.9	27,252.5	125,584.3	354,973.5
L'Aquila earthquake (Tourist district-level data, 2004-2011)	**Crater-Toponym**		**Unaffected-Bordering tourist districts**		**Unaffected-Control group**	
Variable	Mean	St. dev	Mean	St. dev	Mean	St. dev
Total arrivals	74,789.2	24,341.7	80,019.7	45,648.3	177,612	354,193
Arrivals - Italians	64,909.5	20,330.4	67,998.5	38,399.1	103,392.6	161,258.9
Arrivals - Internationals	9,879.7	4,031.8	12,021.2	8,610.7	74,219.5	230,498.1
Total overnight stays	189,466.1	30,969.5	307,377.5	243,446.9	710,832.3	1,351,669
Overnight stays - Italians	159,715.1	22,076.7	250,048.2	199,783	417,646.6	715,788.6
Overnight stays - Foreigners	29,751	9,550.7	57,329.3	52,833.6	293,185.7	821,740.1

3.3.2 Method

We perform our analysis by implementing the (Imai et al., 2023) non-parametric generalization of the Difference-in-Differences (DiD) estimator. Imai et al. (2023) introduces a matching method

[24]We exclude 17 tourist districts from our analysis due to missing data. For the remaining tourist districts, we aggregated 92 of them into groups of two to four geographically contiguous districts, as ISTAT began reporting aggregate data from a certain year onwards. For example, ISTAT provided separate data for the tourist districts of "Rivisondoli" and "Other Municipalities L'Aquila" from 2004 to 2007, but combined them into a single district ("Rivisondoli and Other Municipalities L'Aquila") from 2008 onwards.

[25]We define as "untouched by the earthquake" municipalities that do not appear in the official list of directly affected ("crater") municipalities and exhibit no reported structural damage or casualties. The full crater list is obtained from official Civil Protection sources.

specifically designed for time-series cross-sectional data, offering a flexible approach to estimate both the short- and long-term average treatment effects on the treated (ATT), even with a limited number of pre-treatment time points. We first describe the methodology with specific reference to our municipal dataset, followed by its application to the datasets at the NUTS-3 and tourist district levels.

For each unit (municipality) $i = 1, ..., N$ and year $t = 2014, ..., 2018$ we observe our outcome variables of interest - tourist arrivals and overnight stays - Y_{it}, a vector of time-varying covariates Z_{it}, a vector of time-invariant municipal characteristics V_i, and a treatment dummy variable X_{it}. According to the primary hypothesis underlying our analysis, inaccurate descriptions of the geographical areas affected by earthquakes (toponyms) can negatively impact tourist arrivals in municipalities that did not experience any direct damage. Consequently, we expect to observe a negative impact on tourist arrivals in toponym areas outside the crater zone for the Central Italy and Ischia earthquakes. Conversely, the impact of the L'Aquila earthquake is expected to be limited to L'Aquila itself, with no significant effects on the surrounding areas. For our municipal dataset, we create a set of treatment variables X_{it} to estimate the effects of interest separately:

i) Two dummy variables identifying municipalities located in the crater of Central Italy or Ischia, respectively. These allow us to estimate the effect of the two earthquakes on tourist arrivals.

ii) A dummy variable identifying municipalities within the geographical area of Central Italy but not hit by the Central Italy earthquake.[26] This allows us to estimate the effect of the Central Italy earthquake toponym for municipalities beyond the crater.

iii) A dummy variable for municipalities located in the island of Ischia but not affected by the Ischia earthquake. This allows us to estimate the effect of the Ischia earthquake toponym for municipalities beyond the crater.

Additionally, we set the number of pre-treatment and post-treatment periods - lags L and leads F, respectively - exploiting all the time points in our municipal dataset. Specifically, we set $L = 2$ and $F = 2$ for the Central Italy earthquake, and $L = 3$ and $F = 1$ for the Ischia earthquake. Following (Imai et al., 2023), we estimate the ATT as:

$$\begin{aligned}\delta(F, L) = E\Big\{ & Y_{i,t+F}(X_{it} = 1, X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^{L}) \\ & -Y_{i,t+F}(X_{it} = 0, X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^{L}) | X_{it} = 1, X_{i,t-1} = 0\Big\}\end{aligned} \tag{3.1}$$

[26] We adopted several geographical specifications for what we define as Central Italy, resulting in treatment variables taking the value of 1 for narrower or wider areas. See the next section for a detailed explanation of the geographical coverage of each treatment variable.

where $Y_{i,t+F}(X_{it} = 1, X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^{L})$ is the potential outcome in case of treatment, and $Y_{i,t+F}(X_{it} = 0, X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^{L})$ is the potential outcome in absence of treatment. $\{X_{i,t-l}\}_{l=2}^{L}$ represents the realized history. Applying this methodology involves three stages:

1. For each treated unit we apply a matching method to create a matched set, M_{it}, of control units. This is particularly important in our context due to the high degree of heterogeneity in outcomes and covariate histories between the treated and control groups.[27] We first perform an exact matching based on municipalities' time-invariant characteristics V_i, i.e. the tourism category and the periphery score. By implementing this exact matching, we restrict the comparison to municipalities with the same degree of tourist attractiveness, as the variation in tourism activity is largely influenced by the presence and quality of specific local natural and cultural features (Faber & Gaubert, 2019). We then refine each matched set M_{it} by computing the Mahalanobis distance, i.e. given a control unit in M_{it}, we calculate the standardized distance using the time-varying covariates Zit and then average it over the pre-treatment periods considered. Refining the matched set with income per capita and the population is particularly relevant, as areas with higher wages and population size tend to generate larger multipliers (Moretti, 2010). Additionally, a higher share of foreigners can attract more international tourists (Kuznetsov & Sabel, 2006). This refinement method allows us to account for past outcomes and time-varying covariates without relying on strict parametric assumptions. The algorithm matches each treated unit with the 5 most similar control units based on the Mahalanobis distance, assigning equal weight to each unit in the refined matched set M_{it}.

2. After refining the matched set, we estimate the counterfactual post-treatment outcome for the treated units by calculating the weighted average of the control units in the refined matched set.

3. Lastly, we implement the DiD estimator to calculate the treatment effect for each treated unit by computing the difference between the actual and counterfactual changes in outcomes. Following equation 3.1, we then derive the ATT by averaging the treatment effect across all treated observations[28].

We use datasets at the NUTS-3 and tourist district levels to apply the same methodology to the L'Aquila earthquake. In this case, we create two treatment variables. The first identifies the province/tourist district of L'Aquila, allowing us to estimate the earthquake's impact on tourist arrivals. The second identifies provinces/tourist districts bordering L'Aquila, to determine

[27] For example, in the year preceding the Central Italy earthquake, municipalities within the affected area (the crater) had significantly fewer tourist arrivals on average compared to the control group (5,526.8 vs. 33,545.9), as well as a smaller population (4,895.9 vs. 13,826.8).

[28] Standard errors are computed using a block-bootstrap approach built for matching analysis in time-series cross-sectional settings (Otsu & Rai, 2017).

whether tourist arrivals in the surrounding areas were also affected. We set $L = 14$ and $F = 12$ for the monthly provincial data, and $L = 5$ and $F = 2$ for the tourist district data. We decided to corroborate our analysis using both data sources for two main reasons. First, we do not have the same territorial granularity as municipal-level data. In the case of provincial data, the province of L'Aquila also includes the areas surrounding the crater, possibly introducing a downward bias in our estimates. Tourist districts are smaller areas, allowing us to better capture the effect of interest. Second, we do not have any Z_{it} for the monthly provincial data, so we create a matched set only with the outcome history for both datasets. Nonetheless, we have enough pre-treatment periods to robustly estimate the ATT using these data sources.

One advantage of this methodology compared to regression methods is that it allows for assessment of the covariate balance between treated and matched control observations, making it possible to evaluate whether the treated and matched control groups are comparable with respect to observed confounders. Additionally, the identifying assumptions of this method - limited carryover effects, the absence of interference, and the parallel trend assumption[29] - are milder than most common methods, such as the DiD estimator, linear regressions with fixed effects, and dynamic models (Imai et al., 2023; Y. Xu, 2024).

3.4 Results

We begin this section by presenting the results for the Central Italy earthquake, followed by a discussion of the findings for the Ischia earthquake, and conclude with the estimates for the L'Aquila earthquake.

3.4.1 Central Italy earthquake

For the Central Italy earthquake, we have data for 114 out of 138 municipalities belonging to the earthquake's crater.[30] Table 3.4.1 presents the earthquake's impact on tourist arrivals and overnight stays for those municipalities. We report the ATT for each post-treatment year—2016, 2017, and 2018. Overall, the estimates indicate a negative impact on tourist arrivals, statistically significant at the 5% level in 2016 and at the 1% level in the following years. Estimates for overnight stays show a similar trend, with a negative statistically significant impact in 2017 (5% level) and 2018 (1% level). The lack of statistical significance in 2016 is likely due to the timing

[29] The assumption of limited carryover effects makes the post-treatment potential outcome not dependent on previous earthquakes. This assumption is satisfied as the affected areas did not experience any huge earthquakes in the previous years (Cerqua et al., 2023). The absence of interference is met as untreated municipalities are not affected by the earthquake occurring in the treated ones. To avoid any estimation bias, we exclude from the control group the municipalities within the crater when specifying the treatment variable as in (ii) and (iii). The same applies to the provincial and tourist district level datasets. The parallel trend assumption is given after conditioning on M_{it} and the treatment and outcome history.

[30] see https://sisma2016data.it/report-page/ for reports containing the full list of municipalities included in the crater.

of the earthquake, a seismic sequence comprising four major tremors occurring from late August 2016 through early 2017. The first tremor struck near the end of the summer season, after most tourist inflows had already been recorded.

Table 3.4.1: Impact of the Central Italy earthquake on tourist arrivals and overnight stays

Total arrivals		
t (2016)	t+1 (2017)	t+2 (2018)
-569.4**	-2,211.0***	-1,466.7***
(231.6)	(678.4)	(564.0)
Total overnight stays		
t (2016)	t+1 (2017)	t+2 (2018)
-1,907.8	-5,999.0**	-6,247.5***
(1,297.1)	(3,107.2)	(2,115.2)

Notes: Treated municipalities are those located in the crater of the Central Italy earthquake. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

As discussed in previous sections, "Central Italy" encompasses a much broader geographical area than the crater itself. To examine whether the earthquake's toponym influenced tourist inflows in municipalities unaffected by the earthquake, we assign treatment to municipalities located within the same NUTS-3 regions as the crater in the estimates presented in Table 3.4.2.[31] Figure 3.4.1 provides a graphical representation of the municipalities classified as treated and Figure 3.4.2 shows the covariate balancing. The balancing remains stable across the two pre-treatment time points and fully within the (-1, 1) range of standardized mean differences. The imbalance level for the lagged values of our primary dependent variable, tourist arrivals, remains consistent throughout the pre-treatment period, supporting the plausibility of the parallel trend assumption for the proposed estimator.

The results in Table 3.4.2 indicate that municipalities untouched by the earthquake but within the Central Italy toponym experienced a statistically significant reduction in tourist arrivals at the 1% level for 2016, 2017, and 2018. The same pattern of Table 3.4.1, but at the 1% level of significance, is observed for overnight stays. When considering the mean number of arrivals in 2015, the year prior to the earthquake, the substantial decline observed in 2017 corresponds to approximately 40% fewer tourists for municipalities in the crater area and 12.5% fewer for unaffected municipalities within the toponym area but not in the crater. Based on official ISTAT statistics for the average daily expenditure of tourists (both domestic and international)[32] in 2017, we estimate that the observed reduction in tourist arrivals in 2017 corresponds to an economic

[31]For this analysis, municipalities within the Central Italy earthquake's crater are excluded from the control group.

[32]The average national daily expenditure per trip was €94 in 2017 and €91 in 2018.

loss of approximately €590,000 in each municipality unaffected by the earthquake but located in Central Italy for that year, rising to around €810,000 in 2018.

Table 3.4.2: Impact of the Central Italy earthquake's toponym on tourist arrivals and overnight stays

	Total arrivals	
t (2016)	t+1 (2017)	t+2 (2018)
-499.9***	-2,128.2***	-1,263.5***
(187.3)	(352.2)	(437.4)
	Total overnight stays	
t (2016)	t+1 (2017)	t+2 (2018)
-757.1	-6,317.3***	-8,903.8***
(916.6)	(1,502.8)	(2,187.5)

Notes: Treated municipalities are those unaffected by the earthquake but inside the geographical area of the toponym. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Figure 3.4.1: Unaffected municipalities within the geographical area of the toponym

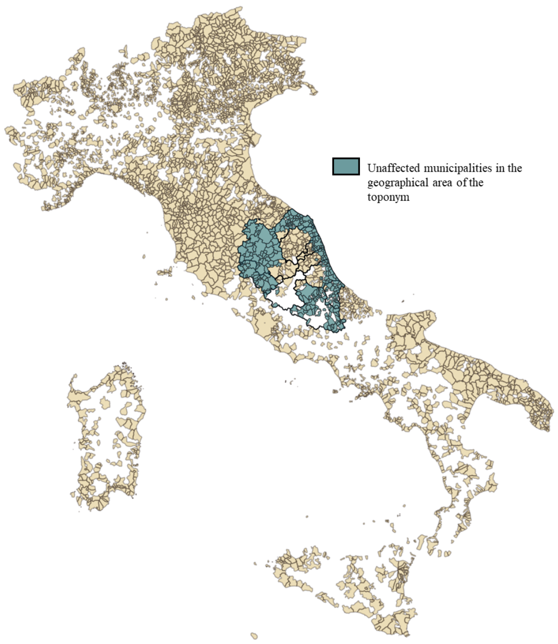
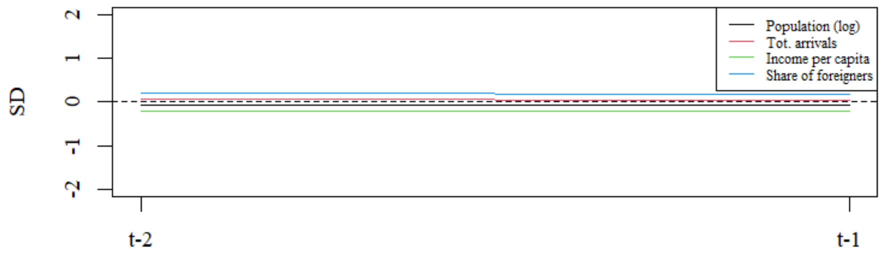


FIGURE 3.4.2: Covariate balancing for the Central Italy earthquake



We replicate the estimation by expanding the definition of treated municipalities to include a broader geographical area than that depicted in Figure 3.4.1. Specifically, we consider as treated those municipalities unaffected by the earthquake but located within the same NUTS-2 regions as the crater area[33], as illustrated in Figure .2.5 in the Appendix. Results, reported in Table .1.2 in the Appendix, are in line with the ones of Table 3.4.2.[34][35]

We also investigate whether (i) the distance from the crater and (ii) tourists' place of origin influence the observed decline in tourist arrivals. Regarding (i) the distance from the crater, in the case of the Central Italy earthquake, the statistically significant reduction in tourist arrivals and overnight stays may be associated with unaffected municipalities located closer to the crater, rather than with the toponym itself. Table .1.3 in the Appendix reports the results of estimations conducted for municipalities grouped by their distance from the crater's border. Specifically, we estimate effects for municipalities within 10km, between 11km and 20km, between 21km and 30km, between 31km and 40km, and between 41km and 50km from the border. In these analyses, municipalities within the crater and those outside the treated group but located within 50km of the border are excluded from the control group. Figure .2.6 in the Appendix provides a visual representation of these distance-based groupings. Results in Table .1.3 in the Appendix indicate

[33] We exclude Rome from the analysis.

[34] Two municipalities, Foligno and Narni, which are formally outside the list of municipalities within the crater, experienced damage from the earthquake. According to the Modified Mercalli Intensity (MMI) scale (Wood & Neumann, 1931), they recorded intensities of VI (Narni) and VII (Foligno), corresponding to light to moderate damage in well-constructed ordinary structures. We exclude these municipalities from the analysis and re-calculate the estimates reported in Table 3.4.2 and Table .1.2. Results do not change.

[35] Even though we are interested in analyzing the short-term effect on tourist arrivals, we repeated the estimates for both the municipalities within the crater and those included in the toponym, adding a post-treatment year, i.e. 2019. The main reason for not including 2019 in the main estimates is that we lose 70 municipalities due to missing data. The reduction in arrivals remains statistically significant even for 2019, both for municipalities within the crater (point estimate: -1,156.3; standard error: 552.4) and for municipalities not affected by the earthquake but located in the geographical area of the toponym (for the municipalities reported in Figure 3.4.1: point estimate: -1,444.9; standard error: 495.3; for the municipalities reported in Figure .2.5: point estimate: -1,696.5; standard error: 899.5).

that the negative effect on tourist arrivals persists even for municipalities situated 41-50km away from the crater[36].

Regarding tourists' place of origin, media outlets vary in the scope and depth of their earthquake coverage (Quarantelli, 1990), potentially shaping perceptions of the crater's size — an effect that may be even more pronounced in international news reporting since both the reporting media and its audience may be less informed about Italian geography. Table .1.4 in the Appendix shows that the reduction in tourist arrivals and overnight stays in unaffected municipalities within the toponym is statistically significant both for Italian and international tourists. Notably, for international tourists, the decline in arrivals is significant at the 5% level in 2016 and at the 1% level in both 2017 and 2018. For Italian tourists, the reduction is significant at the 1% level in 2017, only at the 10% level in 2018, and not significant in 2016.

Lastly, we provide evidence of the robustness of our estimates using as an alternative estimator the Synthetic Difference in Differences (SDID) (Arkhangelsky et al., 2021b). The SDID combines features of Synthetic Control (Abadie & Gardeazabal, 2003; Abadie et al., 2010) and the Difference in Differences, estimating the ATT through a two-way fixed effect regression with optimally chosen unit and time weights.[37] When applying the SDID method, we include only our time-varying covariates, as conditioning on time-invariant covariates is not allowed (Clarke, Pailanir, et al., 2023). Table .1.11 in the Appendix shows that results align closely with our main estimates in Table 3.4.1 and Table 3.4.2. Furthermore, although having a highly skewed dependent variable is not a primary concern for our empirical strategy, we also re-estimate the model using the logarithm of tourist arrivals as the outcome variable. These results, also presented in Table .1.11 in the Appendix, further confirm our findings.

3.4.2 Ischia earthquake

We have data for all 6 municipalities on Ischia Island. One of those municipalities, Casamicciola Terme, represents the crater. Following the approach used for the Central Italy earthquake, we conduct separate estimations for the crater and the other municipalities on the island to identify both the direct earthquake effect and the toponym effect. Table 3.4.3 presents the estimated impact of the earthquake on tourist arrivals and overnight stays for the crater. The results indicate a significant decline in both tourist arrivals and overnight stays, with estimates significant at the 1% level for each post-treatment year.

[36] Although we do not observe direct indicators of infrastructure disruptions at the municipal level, the segmentation by distance from the crater provides a reasonable proxy: municipalities 41–50 km away are unlikely to have suffered meaningful logistical barriers. The statistically significant reduction in tourist flows at these distances makes it improbable that infrastructure damage alone drives the observed decline and strengthens the interpretation of a toponym-driven effect

[37] See (Arkhangelsky et al., 2021b) and (Clarke, Pailanir, et al., 2023) for a detailed description of the method.

Table 3.4.3: Impact of the Ischia earthquake on tourist arrivals and overnight stays

Total arrivals	
t (2017)	t+1 (2018)
-14,493.6***	-14,958.0***
(3,006.0)	(2,811.4)
Total overnight stays	
t (2017)	t+1 (2018)
-58,989.8***	-67,054.2***
(13,176.6)	(7,105.5)

Notes: The treated municipality is Casamicciola Terme, crater of the Ischia earthquake. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

We then estimate the effect on tourist arrivals and overnight stays for unaffected municipalities located on the island. Figure 3.4.3 shows that the pre-treatment balancing of covariates falls within the standardized mean difference range of (-1, 1). Table 3.4.4 shows that the toponym effect also leads to a significant decline in tourist arrivals and overnight stays in the case of the Ischia earthquake. Using the mean number of arrivals in the year before the earthquake as a reference, the observed decline in 2017 corresponds to approximately an 11.5% reduction in tourists among unaffected municipalities within the toponym. The reduction in tourist arrivals is statistically significant at the 5% level for both 2017 and 2018. For overnight stays, the decline is significant at the 5% level in 2017 and at the 10% level in 2018.[38] Based on our results, the estimated decrease in total overnight stays in 2017 corresponds to an economic loss of approximately €6.5 million in each municipality located in the island but untouched by the earthquake for that year[39].

Although standard errors for the point estimates in 2018 are of similar magnitude to the coefficients, they are reported as statistically significant due to the point estimates not being perfectly centered within the confidence intervals, which tend to skew toward negative values. For instance, the 95% confidence interval for total arrivals is (-35,028.9, -1,861.6). This outcome is primarily driven by the high heterogeneity in arrivals across treated units.[40]

[38] Although Casamicciola Terme is the only municipality where significant damage occurred in the inhabited area and the area damaged by the earthquake is very limited, as specified by the Italian Civil Protection (see https://emergenze.protezionecivile.gov.it/en/seismic/ischia-earthquake-2017/), a small portion of the territory within the municipality of Lacco Ameno reported minor damage to local infrastructure. We repeat estimates in Table 3.4.4 excluding Lacco Ameno. The results, reported in Table .1.5 in the Appendix, do not change.

[39] Calculation based on official Istat statistics.

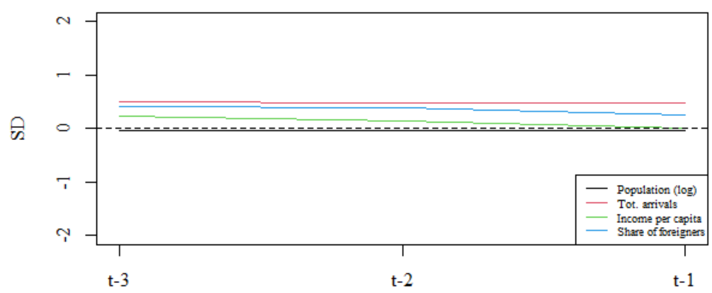
[40] In the year before the earthquake, the five unaffected municipalities on the island had a mean number of arrivals of 108,622.2, with a standard deviation of 105,826.7. The municipality of Barano d'Ischia recorded the lowest number of arrivals, 18,708, while the municipality of Ischia reported the highest, at 235,484.

TABLE 3.4.4: Impact of the Ischia earthquake's toponym on tourist arrivals and overnight stays

Total arrivals	
t (2017)	t+1 (2018)
-12,540.5**	-8,575.1**
(5,568.3)	(8,572.5)
Total overnight stays	
t (2017)	t+1 (2018)
-69,193.3**	-20,620.2*
(29,762.1)	(24,825.9)

Notes: Treated municipalities are those unaffected by the earthquake but inside the geographical area of the toponym. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

FIGURE 3.4.3: Covariate balancing for the Ischia earthquake



We further examine the toponym effect by disaggregating the estimates based on tourists' place of origin. Table .1.6 presents separate results for Italian and international tourists. Notably, only Italian tourists exhibit a significant reduction in arrivals and overnight stays. This pattern may be attributed to the limited media coverage of the Ischia earthquake in international outlets as this was a more minor earthquake. Unlike the Central Italy earthquake, which garnered widespread attention from both media and institutions due to its severity and high number of fatalities, the Ischia earthquake received less coverage due to its lower intensity and more localized impact. Interestingly, estimates divided by tourist place of origin reflect anecdotal evidence reported in Section 2.2 in which the president of Federalberghi Ischia states that "the Italian market of tourist has been the most problematic [...] as it was heavily influenced by the negative portrayal of the island by the Italian media." (see subsection 3.2.2).

To assess the robustness of our estimates, we performed the same additional analyses as those conducted for the Central Italy earthquake.[41] In the case of the Ischia earthquake, when applying

[41] As with the Central Italy earthquake, we also repeated the estimates by adding 2019. In this case, as well, tourist arrivals decreased both for Casamicciola Terme and for the other municipalities on the island.

the SDID estimator, we use placebo standard errors instead of block-bootstrapped ones because a small number of treated units can render the estimated variance and confidence intervals less reliable (Arkhangelsky et al., 2021b; Clarke, Pailanir, et al., 2023). Additionally, while our main estimates remain robust even when a single unit is treated, we further analyze the effect on tourist arrivals for Casamicciola Terme (the municipality in the crater) using the Synthetic Control method, which is specifically designed for such cases. The results, reported in Table .1.12 in the Appendix, are consistent with our main findings.[42]

3.4.3 L'Aquila earthquake

For the L'Aquila earthquake, we present estimates at the tourist district level in the main text, complemented by additional estimates at the provincial level provided in the Appendix. Table 3.4.5 reports the impact of the earthquake on tourist arrivals and overnight stays in the tourist district of L'Aquila, which includes only the municipality of L'Aquila. The earthquake led to a statistically significant reduction at the 1% level in both tourist arrivals and overnight stays in each post-treatment year. While the city of L'Aquila became the primary symbol of the earthquake in media and institutional narratives due to the extensive damage and the tragic loss of hundreds of lives, the tourist district of L'Aquila does not encompass other municipalities within the province of L'Aquila that also sustained damage from the earthquake[43]. These additional municipalities form part of both the crater and the toponym of the earthquake. Table .1.7 in the Appendix shows estimates including the tourist district "Other municipalities of L'Aquila" as treated. The results are consistent with those reported in Table 3.4.5.

TABLE 3.4.5: Impact of the L'Aquila earthquake on tourist arrivals and overnight stays - tourist district of L'Aquila

Total arrivals		
t (2009)	t+1 (2010)	t+2 (2011)
-55,783.0***	-43,831.4***	-35,108.8***
(2,143.3)	(3,550.8)	(4,156.3)
Total overnight stays		
t (2009)	t+1 (2010)	t+2 (2011)
-46,560.0***	-55,314.0***	-88,171.6***
(6,185.7)	(6,445.7)	(9,764.5)

Notes: Estimates refer to tourist district-level data. The treated unit is the tourist district of L'Aquila, representing both the crater and the toponym of the earthquake. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Among our case studies, the L'Aquila earthquake is the only instance where some municipalities were affected—albeit mildly—by the earthquake but were not included within the geographical area defined by the earthquake's toponym. Specifically, 18 municipalities in the province of

[42] Consistent with our main estimates, the 95% confidence interval for total arrivals in logarithmic form at t+1 is (-0.78, 0.03)

[43] Out of 108 municipalities in the province of L'Aquila, only 35 were unaffected by the earthquake.

Teramo, 29 in the province of Pescara, 2 in the province of Chieti, and 14 in the province of Rieti sustained light damage. These municipalities are all part of tourist districts bordering the district of L'Aquila. To test whether these bordering areas experienced a decline in tourist arrivals despite not being part of the earthquake's toponym, we assign them treatment status. For this analysis, we exclude tourist districts within the province of L'Aquila from the control group. Table 3.4.6 shows that when the crater is fully aligned with the earthquake's toponym, bordering areas, even when they did sustain some damage from the earthquake, do not experience a decline in tourist inflows. A narrowly defined toponym can thus shield mildly affected areas from the adverse indirect impact of the earthquake, as long as these areas are excluded from the toponym.

Table 3.4.6: Impact of the L'Aquila earthquake on tourist arrivals and overnight stays - tourist districts bordering the crater

	Total arrivals	
t (2009)	t+1 (2010)	t+2 (2011)
-2,474.7	-998.4	166.1
(3,453.7)	(4,665.7)	(5,957.9)
	Total overnight stays	
t (2009)	t+1 (2010)	t+2 (2011)
-1,490.4	-11,131.1	-20,695
(14,511.6)	(23,187.4)	(24,041.5)

Notes: Estimates refer to tourist district-level data. Treated units are those tourist districts bordering the one of L'Aquila. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

This finding remains consistent when we conduct our analysis using monthly data at the provincial level. Table .1.8 and Table .1.9 in the Appendix present the estimates for the province of L'Aquila and its bordering provinces, respectively.[44] While the province of L'Aquila shows a significant decline in tourist arrivals across all post-treatment time points, no significant reductions are observed for bordering provinces, even in the immediate months following the event.[45] This lack of a significant effect for bordering provinces is consistent for both Italian and international tourists, as shown in Table .1.10 in the Appendix.

To further assess the robustness of our estimates for the L'Aquila earthquake, we replicate the additional analyses performed for the Ischia earthquake, including the SDID estimator and the Synthetic Control method. The results, detailed in Table .1.13 in the Appendix, remain consistent with our main estimates.

[44] The province of Rome is excluded from the analysis.

[45] We repeated the estimation by extending the post-treatment time points to the last available year for tourist districts, which is 2013. By doing so, we included 2 additional years for the tourist districts and 36 additional months for the provincial data. In both cases, the geographical areas neighboring the crater never experience a significant reduction in tourist arrivals.

3.5 Conclusion

Inaccurate toponyms for disasters matter. Once an area was defined as affected, even when it was not, the designation led to a statistically significant and economically material decline in tourism that appears easily preventable. In our examples, this amounts to a 10-15 percent decline in tourist arrivals that endures for several years following the event[46].

We focused on tourism, but this is most likely not the only economic sector that is adversely affected by these toponym errors. Many other economic sectors are also affected by perceptions of economic actors about the availability of services and infrastructure, about current safety, and about future risk in locations where economic activity occurs. For example, disasters also affect supply chains; see (Carvalho et al., 2020). While we do not have the granular data required to show it, it is likely that suppliers located in inaccurate-toponym-affected areas also see declines in the demand for their products and services. All else equal, their customers further down the chain are likely to prefer suppliers from areas that are perceived as less risk-prone to disruptions that might severe these supply links and thus disrupt their own businesses.

Investment is often also dependent on the perceptions of future risks, both because the profitability of this future investment depends on this future risk, and because there may be risk of damage to physical assets. Future risk is very often assessed based on the most salient risks from the recent past - a classic example of the availability heuristic of (Tversky & Kahneman, 1973). As such, investors may be scared off by these disasters, even though these disasters are, unknowingly, in-name-only (e.g., Dessaint and Matray (2017)). Other sectors, such as local hospitality or tertiary education can also be vulnerable to this misnaming (Basile, 2024).

To make matters worse, it is difficult to change a name, once it has been born and used by the media and in official communications. One month after the fourth earthquake in the 'Central Italy' sequence described earlier, the INGV decided to rename the Central Italy earthquake with a new and supposedly more geographically precise name: the "Amatrice-Visso-Norcia Seismic Sequence."[47] The new name lacks a clear rationale, but in any case, it did not catch on.[48] The Central Italy toponym had already stuck and, even within government, reports still refer to the earthquake as the "Central Italy earthquake."[49]

[46] The key limitation of our analysis in tourist outcomes lies in two areas. First, although spillovers from multi-destination trips could, in principle, induce indirect declines in neighboring areas (e.g. if tourists skip Central Italy crater but visit another mountain site), ISTAT (2017) data show that only about 10% of mountain-area vacations combine multiple destinations in Central Italy or L'Aquila, and over 97% of Ischia stays occur exclusively on the island (average length 5.6 nights), indicating that such "itinerary-incomplete" effects are quantitatively small. Second, while our model specification does not implement a formal spatial-econometric model to mitigate residual spatial autocorrelation in tourists' destination patterns, we recognize that a once more granular destination-choice data are available, it would further strengthen the robustness of our estimates.

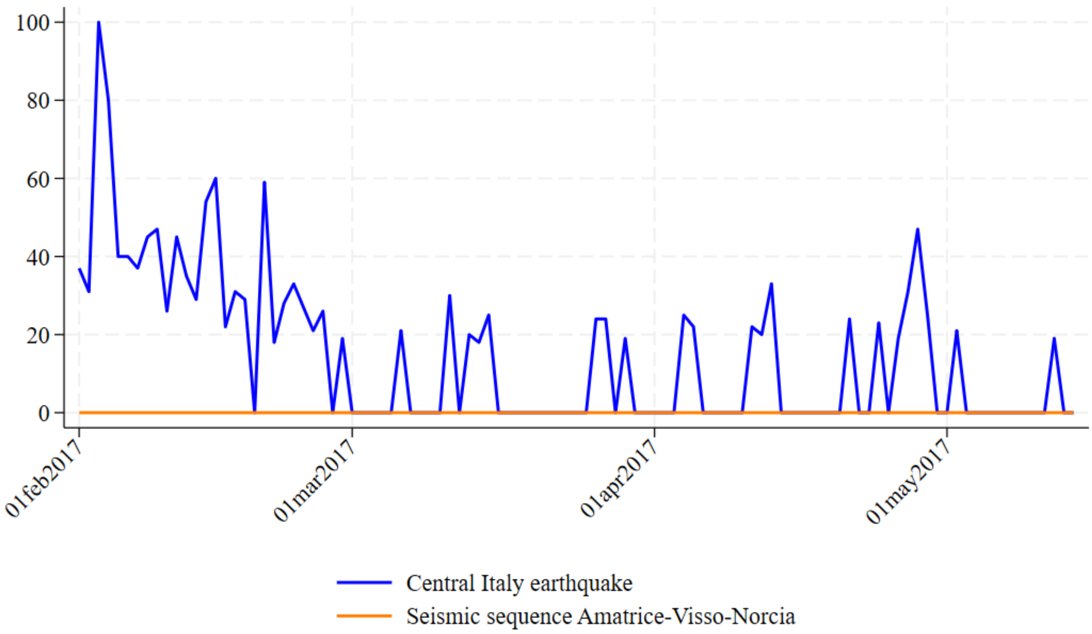
[47] See https://www.ansa.it/sito/notizie/cronaca/2017/02/14/terremoto-del-centro-italia-cambia-nome-in-sequenza-amatrice-norcia-visso_e26406b6-7928-4e09-819c-3639b6ed4c1c.html (in Italian).

[48] The new name includes the municipality most affected by the first earthquake (Amatrice) along with the epicenters of the earthquakes that occurred in late October (Visso and Norcia), but not the 2017 event.

[49] see the official reports on the reconstruction at the following page https://sisma2016data.it/report-page/ (in Italian).

The name continued to haunt not only government reports, but also people's memories of the events. Figure 3.5.2 shows Google searches for the old and new earthquake names after the new name had been changed. Despite the official INGV name change, it had no discernible impact on the public, as people continued to search exclusively for the previous Central Italy name.

FIGURE 3.5.1: Comparison of Google searches for "Central Italy Earthquake" and its new official name



Notes: Data from Google Trends. The Y-axis ranges from 0 to 100 and represents the search interest relative to the highest point on the graph within the considered time frame. A value of 100 indicates the highest search frequency for the term, 50 represents half of the searches, while a score of 0 means that there was insufficient data detected for the term.

The INGV practice of misidentifying toponyms has not abated over time, unfortunately. In 2023, a small earthquake occurred in the province of Florence (NUTS-3), according to the INGV; though the impacted area was much smaller. The image below is taken from Corriere della Sera the day after the earthquake. Worryingly, the newspaper enlarged the toponym even more, and called it Central Italy once again.[50]

FIGURE 3.5.2: Front page of Il Corriere della Sera, the best-selling newspaper in Italy, the day after the "Province of Florence 2023" earthquake.

Spetterà agli esperti militari valutare i rapporti di forza, gli equilibri sul terreno, nel momento in cui l'inverno rallenterà l'offensiva ucraina. Ciò che appare al momento plausibile è che — a meno di clamorose e poco probabili novità sul fronte diplomatico — la guerra russo-ucraina continuerà anche nel prossimo anno. Ciò obbliga a interrogarsi sulla saldezza futura del fronte occidentale, sulla capacità delle democrazie americana ed europee di continuare a sostenere la resistenza ucraina all'invasione. Se quel sostegno venisse meno si aprirebbe la strada alla vittoria russa.

Negli Stati Uniti, una parte dei repubblicani è favorevole ad abbandonare l'Ucraina al suo destino e Joe Biden potrebbe essere in grave difficoltà se le elezioni del novembre 2024 si tenessero con la guerra ancora in atto. L'Europa non è da meno.

La stanchezza dell'opinione pubblica è palpabile e registrata dai sondaggi. La principale causa è che il prolungarsi del conflitto ha fatto evaporare, per molti europei, la drammaticità, e il senso di pericolo, che tutti avevano avvertito nelle sue fasi iniziali.

L'assuefazione del pubblico amplia la libertà di manovra delle forze — assai visibili in Francia, in Germania, in Italia — che sono sempre state schierate con Putin. O per una autentica vicinanza al regime russo o, più semplicemente, per antiamericanismo.

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IL PRECEDENTE DI «SOPHIA» NEL 2015

Divisioni, porti di arrivo: i nodi della missione navale

di **Francesca Basso**

I controlli in mare e la missione navale. Nel 2015 l'operazione «Sophia». Tutti i limiti.

a pagina 6

CAOS E ALLARME A PORTO EMPEDOCLE

I profughi in cerca di cibo, invaso il paese di Camilleri

di **Marco Imarisio**

Scappano dal centro migranti stracolmo. Cercano cibo. È caos a Porto Empedocle.

a pagina 5

GIANNELLI

di **Paola Di Caro** e **Marco Galluzzo**

Emergenza migranti, il governo decide per la linea dura. Il periodo di permanenza nei Centri per il rimpatrio (Cpr) verrà prolungato a diciotto mesi. La premier Giorgia Meloni: il governo è unito. E poi l'affondo contro l'opposizione: dispiace constatare che parte delle forze politiche italiane ed europee agiscano contro. Vertice romano tra i ministri dell'Interno italiano Matteo Piantedosi e francese Gérald Darmanin. Parigi aiuterà l'Italia a tenere sotto controllo la sua frontiera. «Ma non accoglieremo nuovi migranti» spiega Darmanin.

alle pagine 2 e 3

di **Claudia Voltattorni**

I provvedimenti

- Guida con il cellulare **multa fino a 1.697 euro**
- Parcheggio nei posti per disabili **990 euro**
- Guida in stato di ebbrezza **ritiro patente fino a 3 anni**

CdS

Approvato dal governo il nuovo codice della strada: multe fino a 1.700 euro per chi usa il telefonino. Ora la legge in Parlamento.

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Processo Chiesti 7 anni e mezzo per l'ex factotum dell'attrice

Gina Lollobrigida, morta a gennaio a 95 anni, in una foto di dieci anni fa con il suo assistente Andrea Piazzolla

Caso Lollobrigida: «L'eredità è sparita»

di **Ilaria Sacchettoni**

Case, gioielli, contanti e automobili. Tutto ciò che Gina Lollobrigida aveva accumulato nella vita «è sparito» tra il 2013 e il 2018. L'accusa del pm è di circonvenzione di incapace e sotto processo c'è il factotum Andrea Piazzolla. Per lui chiesti oltre sette anni di carcere.

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Decreto Mattarella: i migranti grande potenziale

Scuola, «rimandati» con il 6 in condotta Istituti tecnici in 4 anni

L'EPICENTRO NEL MUGELLO

Terremoto di 4.9 Paura e sfollati nel centro Italia

di **Alfio Sciacca** e **Paolo Virtuani**

Una potente scossa di magnitudo 4.9 ha fatto tremare il Mugello. Il violento terremoto all'alba di ieri si è sentito fino a Firenze, ma lo sciame sismico ha colpito anche la Romagna. Tanta paura e numerosi sfollati nei paesi dell'Appennino Tosco-Emiliano. «Si è attivata una faglia di alcuni chilometri» spiega l'esperto. «La placca Adriatica si sta muovendo».

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di **Riccardo Bruno** e **Valentina Santarpia**

Il sì in Consiglio dei ministri alla riforma della scuola voluta dal ministro Valditara. Con un voto inferiore al sei in condotta sarà automatica la bocciatura o la non ammissione all'esame di Stato. E ancora, il comportamento in classe sarà determinante per ottenere il massimo dei crediti scolastici, che influiranno sul voto finale. E per chi è sospeso scatta l'obbligo di lavori socialmente utili. I voti al comportamento anche alle medie. Saranno riformati gli istituti tecnici che dureranno 4 anni. E Mattarella inaugura l'anno scolastico a Forlì: «I figli di migranti grande potenziale per il Paese».

a pagina 9

One obvious conclusion from our finding is that using toponyms that describe, using a broad brush, a large area as affected by a disaster is unwise and unnecessarily costly. The failure of the Amatrice-Visso-Norcia Seismic Sequence as a replacement name suggests two more insights. It is retroactively difficult to change a name, once it has been used, and long and complicated names are unpopular. This last name has been suggested for its geographic accuracy (though it fails even based on this metric). We are not sure why geographic accuracy should be a deciding criterion. Our investigation suggests that a short and quickly-introduced toponym that describes only areas affected by the event should be preferred. It does not seem necessary for it to encompass all areas affected by the earthquake, and as such does not need to be geographically accurate. A name is good enough if it does not cause easily preventable loss from disasters in-name-only.

[50] A 2018 earthquake in the region of Molise (NUTS-2) offers another example. The earthquake caused some damage in 21 municipalities out of the 136 municipalities that constitute the region. Nonetheless, both on INGV and the Corriere della Sera (August 17, 2018), adopted a toponym for the earthquake based on the entire region (Molise).

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.1.1 List of Tables

TABLE .1.1: Description of variables in our datasets

Variable	Description	Municipalities; years	Provinces; months	Tourist Districts; years	Data source
Total arrivals	Number of guests, both Italian and international, accommodated in lodging facilities	3,362; 2014-2018	107; 01.2008-03.2010	474; 2004-2011	ISTAT
Arrivals - Italians	Number of Italian guests accommodated in lodging facilities	3,052; 2014-2018	107; 01.2008-03.2010	474; 2004-2011	ISTAT
Arrivals - Internationals	Number of international guests accommodated in lodging facilities	3,044; 2014-2018	107; 01.2008-03.2010	474; 2004-2011	ISTAT
Total overnight stays	Number of nights spent by guests, both Italian and international, in lodging facilities	3,362; 2014-2018	107; 01.2008-03.2010	474; 2004-2011	ISTAT
Overnight stays - Italians	Number of nights spent by Italian guests in lodging facilities	3,052; 2014-2018	107; 01.2008-03.2010	474; 2004-2011	ISTAT
Overnight stays - Internationals	Number of nights spent by international guests in lodging facilities	3,044; 2014-2018	107; 01.2008-03.2010	474; 2004-2011	ISTAT
Population (log)	Municipal resident population in logarithmic form	3,362; 2014-2018			ISTAT
Share of foreigners	Percentage of foreign-born municipal population over total population	3,362; 2014-2018			ISTAT
Income per capita	Average income earned per person	3,362; 2014-2018			Ministry of Economy and Finance
Periphery score	Municipal peripherality with respect to socio-economic focal centers. See this link for more information (in italian)	3,362; Time-invariant			ISTAT
Tourism category	Variable with 11 categories describing the municipality's potential for tourism. See this link for more information (in italian)	3,362; Time-invariant			ISTAT

TABLE .1.2: Impact of the Central Italy earthquake's toponym on tourist arrivals and overnight stays - wider definition of the area

Total arrivals		
t (2016)	t+1 (2017)	t+2 (2018)
-413.1	-2,040.6***	-1,338.3*
(355.5)	(500.2)	(730.9)
Total overnight stays		
t (2016)	t+1 (2017)	t+2 (2018)
-2,545.2	-7,337.4***	-10,085.7***
(1,935.3)	(2,661.9)	(3,799.3)

Notes: Treated municipalities are those unaffected by the earthquake but inside the geographical area of the toponym. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Table .1.3: Impact of the Central Italy earthquake's toponym on tourist arrivals and overnight stays - distance to the crater

Total arrivals			
Distance to the crater	t (2016)	t+1 (2017)	t+2 (2018)
0-10km	-215.5	-2,025.7***	-1,467.6**
	(213.3)	(503.5)	(592.8)
11-20km	-189.4	-1,538.5**	-261.7
	(377.0)	(622.4)	(920.2)
21-30km	-156.9	-1,887.9*	-169.3
	(650.2)	(1,026.4)	(1,280.7)
31-40km	-118.4	-1,090.7*	-1,305.4**
(excluding Rome)	(480.4)	(624.4)	(724.3)
31-40km	4,245.4	2,266.1	12,394.2
(including Rome)	(4,599.3)	(8,096.9)	(20,553.3)
41-50km	-602.3	-1,540.7***	-931.0
	(500.2)	(533.4)	(893.7)
Total overnight stays			
Distance to the crater	t (2016)	t+1 (2017)	t+2 (2018)
0-10km	1,580.4	-5,132.9**	-9,560.8**
	(1,155.4)	(2,272.7)	(3,717.3)
11-20km	-2,990.7	-6,924.3**	-10,870.0**
	(2,450.8)	(3,634.3)	(4,687.0)
21-30km	-671.7	-5,777.2**	-1,357.5
	(1,362.7)	(2,592.6)	(2,692.4)
31-40km	-55.1	926.7	-4,711.3
(excluding Rome)	(2,116.7)	(3,603.5)	(3,943.2)
31-40km	6,521.9	27,094.0	49,938.9
(including Rome)	(7,249.5)	(36,501.1)	(70,998.3)
41-50km	2,071.4	-4,873.0**	-4,618.2**
	(4,360.0)	(2,706.4)	(2,352.4)

Notes: Treated municipalities are those unaffected by the earthquake but inside the geographical area of the toponym. Municipalities are divided by their distance to the crater. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Table .1.4: Impact of the Central Italy earthquake's toponym on tourist arrivals and overnight stays by tourists' place of origin

Arrivals - Italians		
t (2016)	t+1 (2017)	t+2 (2018)
-272.7	-1,535.1***	-587.5*
(181.8)	(315.7)	(346.9)
Arrivals - Internationals		
t (2016)	t+1 (2017)	t+2 (2018)
-235.8**	-783.1***	-725.1***
(102.1)	(131.7)	(171.5)
Overnight stays - Italians		
t (2016)	t+1 (2017)	t+2 (2018)
-396.8	-4,293.5***	-6,024.7***
(889.9)	(1,365.3)	(2,068.0)
Overnight stays - Internationals		
t (2016)	t+1 (2017)	t+2 (2018)
-1,109.5**	-2,855.9***	-3,553.8***
(503.7)	(672.0)	(742.1)

Notes: Treated municipalities are those unaffected by the earthquake but inside the geographical area of the toponym. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Table .1.5: Impact of the Ischia earthquake's toponym on tourist arrivals and overnight stays - Municipality of Lacco Ameno excluded from the analysis

Total arrivals	
t (2017)	t+1 (2018)
-11,806.7**	-7,984.9**
(6,610.0)	(10,435.8)
Total overnight stays	
t (2017)	t+1 (2018)
-65,954.5**	-29,832.7**
(37,713.6)	(31,252.4)

Notes: Treated municipalities are those unaffected by the earthquake but inside the geographical area of the toponym. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Table .1.6: Impact of the Ischia earthquake's toponym on tourist arrivals and overnight stays by tourists' place of origin

Arrivals - Italians	
t (2017)	t+1 (2018)
-11,754.1**	-6,725.1**
(4,689.5)	(4,632.6)
Arrivals - Internationals	
t (2017)	t+1 (2018)
-507.5	874.2
(1,644.4)	(2,390.8)
Overnight stays - Italians	
t (2017)	t+1 (2018)
-58,731.0**	-11,945.2
(22,978.1)	(15,547.2)
Overnight stays - Internationals	
t (2017)	t+1 (2018)
-2,686.5	-376.6
(10,735.2)	(14,745.2)

Notes: Treated municipalities are those unaffected by the earthquake but inside the geographical area of the toponym. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Table .1.7: Impact of the L'Aquila earthquake on tourist arrivals and overnight stays - tourist districts included in the province of L'Aquila

Total arrivals		
t (2009)	t+1 (2010)	t+2 (2011)
-40,573.0***	-39,018.5***	-32,022.8**
(13,768.8)	(10,982.3)	(15,303.3)
Total overnight stays		
t (2009)	t+1 (2010)	t+2 (2011)
-9,911.2	-56,280.4***	-80,914.1***
(27,333.1)	(15,580.0)	(19,293.4)

Notes: Estimates refer to tourist district-level data. Treated units are the tourist districts included in the province of L'Aquila, representing both the crater and the toponym of the earthquake. Specifically, they are two tourist districts: L'Aquila; Rivisondoli and other municipalities of L'Aquila. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Table .1.8: Impact of the L'Aquila earthquake on tourist arrivals and overnight stays - province of L'Aquila

Total arrivals	
Time	ATT
t (03.2009)	-24,878.6***
	(2,417.0)
t+1 (04.2009)	-49,772.8***
	(8,222.2)
t+2 (05.2009)	-52,534.6***
	(12037.9)
t+3 (06.2009)	-34,777.0***
	(8,512.3)
t+4 (07.2009)	-39,985.8***
	(8687.7)
t+5 (08.2009)	-33,673.8***
	(12,951.8)
t+6 (09.2009)	-47,762.0***
	(10,603.6)
t+7 (10.2009)	-47,657.6***
	(10,416.6)
t+8 (11.2009)	-34,692.2***
	(10154.8)
t+9 (12.2009)	-21,799.2***
	(1629.3)
t+10 (01.2010)	-6,869.0***
	(2481.8)
t+11 (02.2010)	-2,717.2**
	(1,091.7)
t+12 (03.2010)	-28,325.8***
	(2,050.1)
Total overnight stays	
Time	ATT
t (03.2009)	-58,373.2***
	(4,187.4)
t+1 (04.2009)	-139,607.6***
	(6,644.3)
t+2 (05.2009)	-141,218.0***
	(9,660.1)
t+3 (06.2009)	-114,886.6***
	(12,726.6)
t+4 (07.2009)	-90,038.8**
	(37,356.4)
t+5 (08.2009)	-24,516.2
	(40,741.8)
t+6 (09.2009)	-95,034.0***
	(16,669.6)
t+7 (10.2009)	-129,775.2***
	(11,233.2)
t+8 (11.2009)	-111,256.2***
	(4,453.2)
t+9 (12.2009)	-54,894.8***
	(4,454.7)
t+10 (01.2010)	3,953.0
	(8,812.7)
t+11 (02.2010)	4,190.2
	(6,750.7)
t+12 (03.2010)	-68,794.8***
	(6,188.9)

Notes: Estimates refer to provincial-level data. The treated unit is the province of L'Aquila, representing both the crater and the toponym of the earthquake. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Table .1.9: Impact of the L'Aquila earthquake on tourist arrivals and overnight stays - provinces bordering the crater

Total arrivals	
Time	ATT
t (03.2009)	681.6
	(3,517.9)
t+1 (04.2009)	-4,148.8
	(10,103.1)
t+2 (05.2009)	-6,395.9
	(17,099.2)
t+3 (06.2009)	-2,249.5
	(18,141.8)
t+4 (07.2009)	-4,364.7
	(26,955.7)
t+5 (08.2009)	-3,483.1
	(34,529.9)
t+6 (09.2009)	-4,119.9
	(13,724.2)
t+7 (10.2009)	-1,986.7
	(6,998.3)
t+8 (11.2009)	-925.2
	(1,287.8)
t+9 (12.2009)	-702.7
	(1,334.6)
t+10 (01.2010)	205.9
	(2,082.3)
t+11 (02.2010)	-21.7
	(831.7)
t+12 (03.2010)	842.8
	(3,497.8)
Total overnight stays	
Time	ATT
t (03.2009)	-1,634.5
	(9,000.3)
t+1 (04.2009)	-9,172.1
	(25,657.4)
t+2 (05.2009)	-12,892.6
	(52,386.2)
t+3 (06.2009)	-8,589.3
	(129,840.5)
t+4 (07.2009)	-170,63.8
	(251,311.2)
t+5 (08.2009)	-42,036.9
	(343,406.6)
t+6 (09.2009)	-17,719.7
	(103,271.6)
t+7 (10.2009)	5,145.2
	(21,981.4)
t+8 (11.2009)	9,045.4
	(6,244.8)
t+9 (12.2009)	9,204.1
	(6,347.9)
t+10 (01.2010)	8,840.4
	(6,565.4)
t+11 (02.2010)	7,677.1
	(5,308.0)
t+12 (03.2010)	6,667.9
	(7,127.1)

Notes: Estimates refer to provincial-level data. Treated units are those provinces bordering the one of L'Aquila. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Table .1.10: Impact of the L'Aquila earthquake on tourist arrivals and overnight stays by tourists' place of origin - provinces bordering the crater

	Arrivals - Italians	**Arrivals - Internationals**
Time	ATT	ATT
t (03.2009)	-428.7	1,642.3
	(1,383.9)	(2,408.8)
t+1 (04.2009)	-2,517.6	-4.8
	(4,309.4)	(4,153.3)
t+2 (05.2009)	-3,819.9	-576.9
	(9,080.6)	(5,159.0)
t+3 (06.2009)	-1,290.0	-968.0
	(13,309.6)	(3,938.4)
t+4 (07.2009)	-1,642.2	-1,926.6
	(19,005.6)	(5,713.4)
t+5 (08.2009)	-218.1	-2,465.2
	26,900.5	(5,207.2)
t+6 (09.2009)	-1,750.3	-2,005.7
	(7,411.1)	(5,048.2)
t+7 (10.2009)	-543.0	-1,313.9
	(3,660.2)	(3,010.7)
t+8 (11.2009)	-324.9	-817.8
	(1,006.1)	(858.0)
t+9 (12.2009)	57.3	-736.4
	(1,218.9)	(894.5)
t+10 (01.2010)	361.5	-549.5
	(1,346.3)	(811.9)
t+11 (02.2010)	32.5	-254.8
	(636.0)	(289.1)
t+12 (03.2010)	-513.7	1,609.1
	(1,362.0)	(2,344.9)
	Overnight stays - Italians	**Overnight stays - Internationals**
Time	ATT	ATT
t (03.2009)	-2,991.3	3,179.1
	(4,417,7)	(4,444.3)
t+1 (04.2009)	-8,717.0	387.4
	(15,684.1)	(10,183.8)
t+2 (05.2009)	-10,004.7	-1,816.5
	(33,629,0)	(15,793.9)
t+3 (06.2009)	-4,674.8	-771.3
	(96,103.6)	(20,957.0)
t+4 (07.2009)	-4,866.3	-4,515.0
	(184,865.6)	(38,089.0)
t+5 (08.2009)	-31,392.1	-11,415.9
	(274,089.3)	(34,055.1)
t+6 (09.2009)	-7,309.8	-3,912.0
	(68,181.2)	(22,511.1)
t+7 (10.2009)	-9,205.1	-143.3
	(11,393.3)	(8,158.2)
t+8 (11.2009)	9,577.0	-27.0
	(4,971.4)	(1,716.8)
t+9 (12.2009)	9,565.0	57.7
	4,983.3	(1,927.7)
t+10 (01.2010)	8,745.6	301.6
	4,559.7	(1,641.3)
t+11 (02.2010)	6,862.1	423.6
	(3,825.7)	(751.8)
t+12 (03.2010)	2,912.3	3,578.8
	(4,412.1)	(4,377.6)

Notes: Estimates refer to provincial-level data. Treated units are those provinces bordering the one of L'Aquila. ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses.

Table .1.11: Central Italy earthquake and toponym - additional estimates

Alternative outcome: Logarithm of Arrivals - Crater		
t (2016)	t+1 (2017)	t+2 (2018)
-0.07	-0.49***	-0.37***
(0.06)	(0.11)	(0.12)
Alternative outcome: Logarithm of Arrivals - Unaffected (Toponym)		
t (2016)	t+1 (2017)	t+2 (2018)
-0.03	-0.20***	-0.14***
(0.03)	(0.04)	(0.05)
Alternative estimator: Synthetic Difference in Differences - Crater		
t (2016)	t+1 (2017)	t+2 (2018)
-547.2**	-2,812.8***	-2,313.8***
(265.1)	(728.6)	(608.9)
Alternative estimator: Synthetic Difference in Differences - Unaffected (Toponym)		
t (2016)	t+1 (2017)	t+2 (2018)
-727.3***	-3,282.7***	-2,709.5***
(230.8)	(467.8)	(514.7)

Notes: ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses. Time-varying covariates are included following Kranz, 2022.

Table .1.12: Ischia earthquake and toponym - additional estimates

Alternative outcome: Logarithm of Arrivals - Crater	
t (2017)	t+1 (2018)
-0.19***	-0.19***
(0.05)	(0.03)
Alternative outcome: Logarithm of Arrivals - Unaffected (Toponym)	
t (2017)	t+1 (2018)
-0.20**	-0.14**
(0.11)	(0.17)
Alternative estimator: Synthetic Difference in Differences - Crater	
t (2017)	t+1 (2018)
-11,876.9***	-12,182.9**
(3,273.3)	(5,868.7)
Alternative estimator: Synthetic Control - Crater	
t (2017)	t+1 (2018)
-20,264*	-48,956.8**
(10,673.4)	(16,160.2)
Alternative estimator: Synthetic Difference in Differences - Unaffected (Toponym)	
t (2017)	t+1 (2018)
-11,149.6***	-6,950.5*
(2,425.3)	(3,672.1)

Notes: ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses in the estimation with the alternative outcome. When performing the estimation with the Synthetic Difference in Differences (and the synthetic control method), as the number of treated units is small and estimated variance and confidence intervals may be unreliable (Arkhangelsky et al., 2021b; Clarke, Pailanir, et al., 2023), we report placebo standard errors in parentheses. Time-varying covariates are included following Kranz (2022).

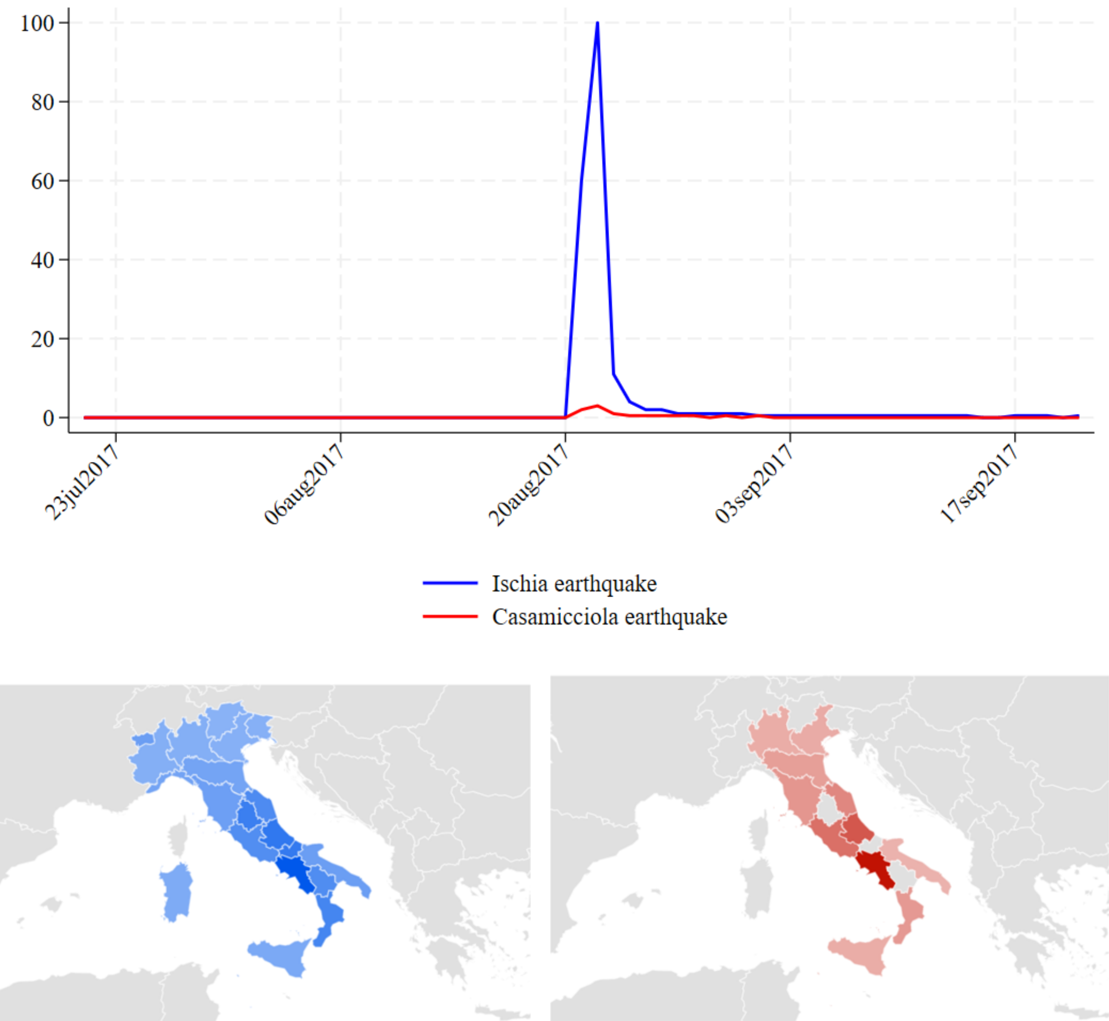
Table .1.13: L'Aquila earthquake and bordering units -additional estimates

Alternative outcome: Logarithm of Arrivals - Crater		
t (2009)	t+1 (2010)	t+2 (2011)
-0.93***	-0.66***	-0.48***
(0.02)	(0.04)	(0.05)
Alternative outcome: Logarithm of Arrivals - Unaffected (Bordering units)		
t (2009)	t+1 (2010)	t+2 (2011)
0.01	0.03	0.06
(0.06)	(0.12)	(0.12)
Alternative estimator: Synthetic Difference in Differences - Crater		
t (2009)	t+1 (2010)	t+2 (2011)
-58,651.3***	-50,627.2***	-45,563.2**
(17,243.3)	(18,998.1)	(21,615.3)
Alternative estimator: Synthetic Control - Crater		
t (2009)	t+1 (2010)	t+2 (2011)
-61,717.4***	-58,033.8***	-56,232.0***
(18,061.2)	(17,619.6)	(20,342.7)
Alternative estimator: Synthetic Difference in Differences - Unaffected (Bordering units)		
t (2009)	t+1 (2010)	t+2 (2011)
-7,107.2	-4,756.7	-7,489.9
(8,150.7)	(15,218.9)	(18,664.1)

Notes: ***, **, * denote significance at the 1, 5, and 10% level, respectively. Block-bootstrapped standard errors are reported in parentheses in the estimation with the alternative outcome. When performing the estimation with the Synthetic Difference in Differences (and the synthetic control method), as the number of treated units is small and estimated variance and confidence intervals may be unreliable (Arkhangelsky et al., 2021b; Clarke, Pailanir, et al., 2023), we report placebo standard errors in parentheses.

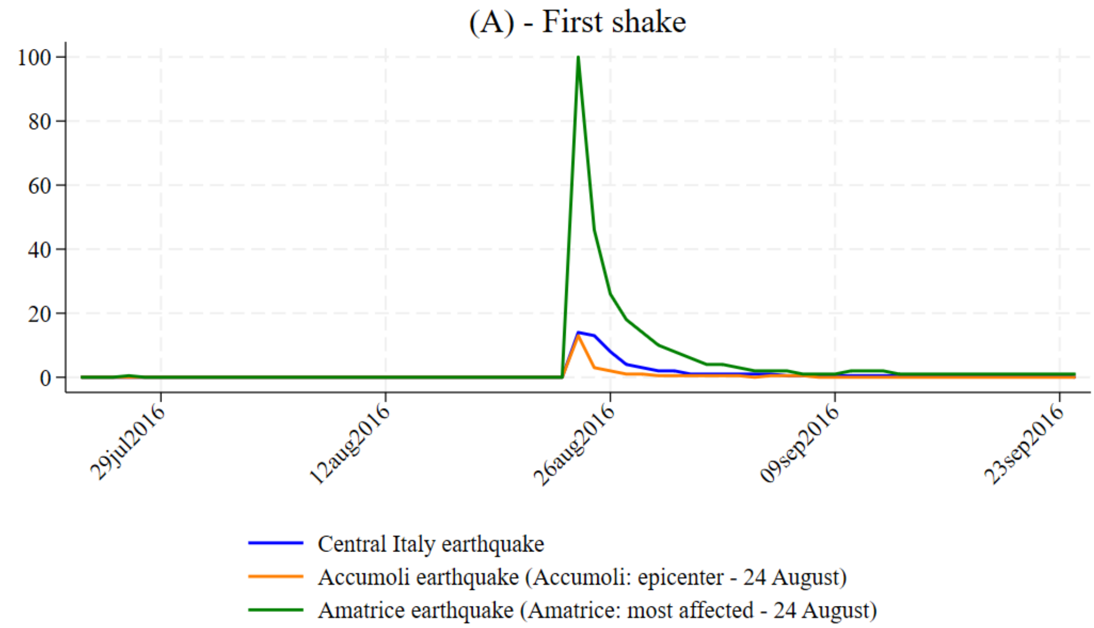
.2 List of Figures

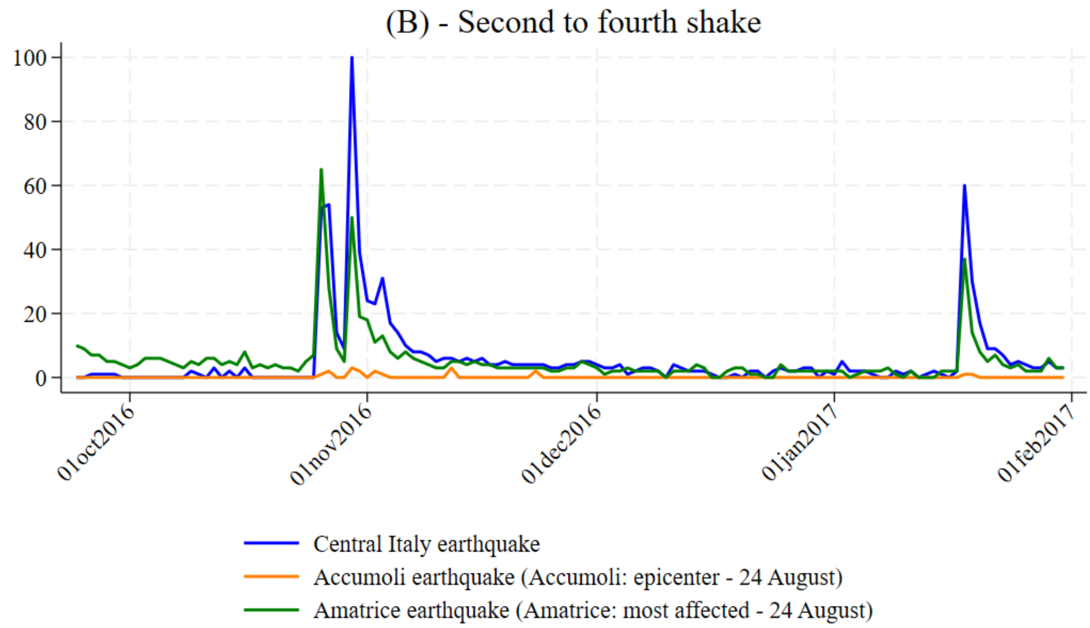
FIGURE .2.1: Comparison of web searches for "Ischia Earthquake" and "Casamicciola Earthquake" on Google Trends



Notes: The Y-axis ranges from 0 to 100 and represents the search interest relative to the highest point on the graph within the considered time frame. A value of 100 indicates the highest search frequency for the term, 50 represents half of the searches, while a score of 0 means that there was insufficient data detected for the term.

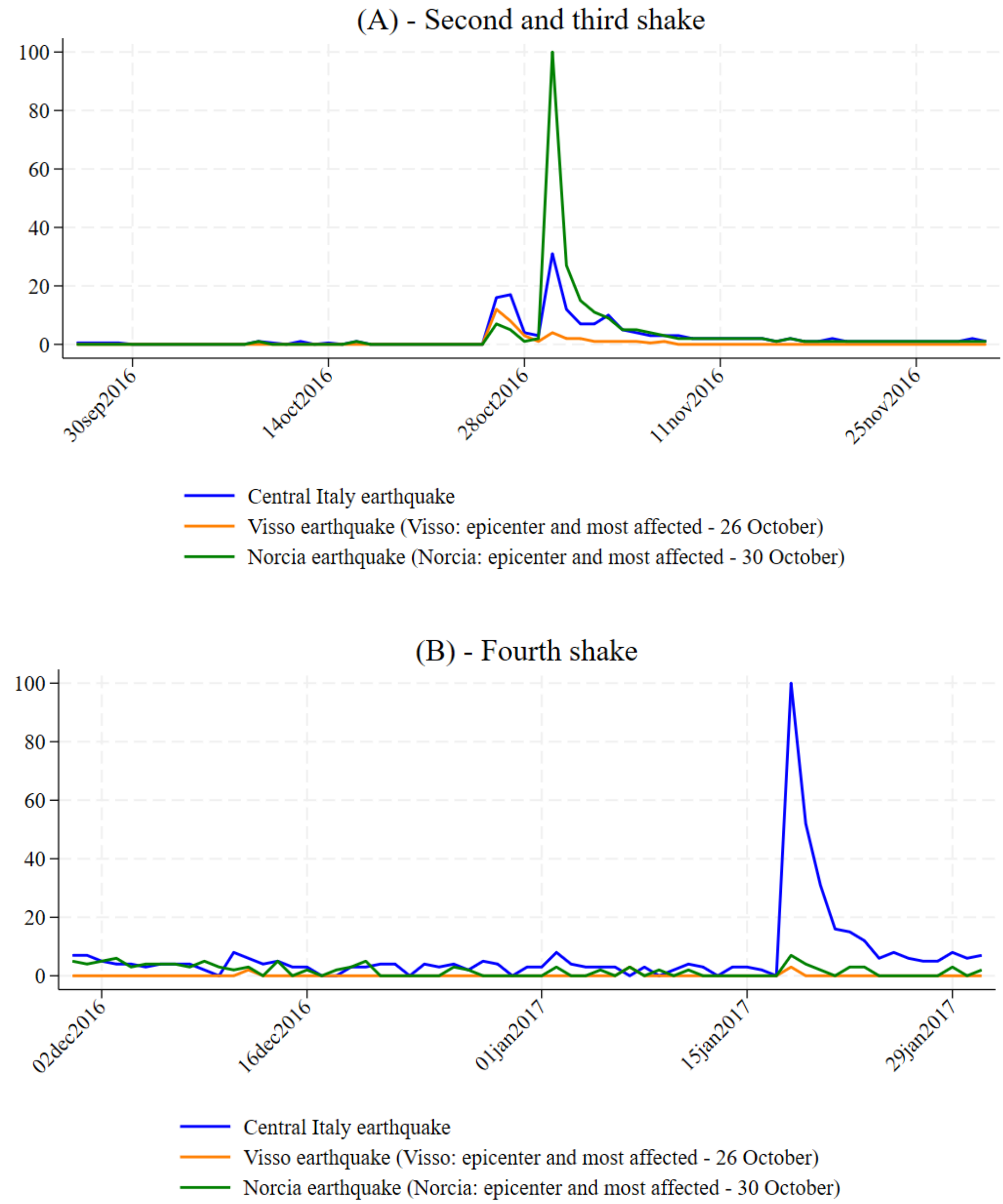
Figure .2.2: Comparison of web searches for "Central Italy Earthquake", "Amatrice Earthquake" and "Accumoli Earthquake" on Google Trends





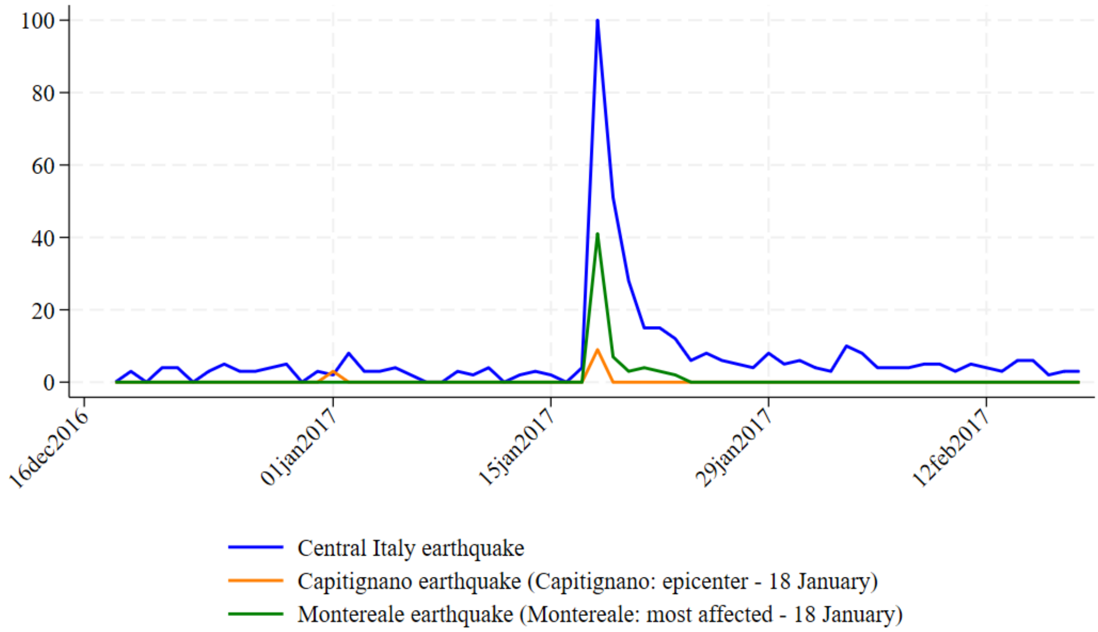
Notes: The Y-axis ranges from 0 to 100 and represents the search interest relative to the highest point on the graph within the considered time frame. A value of 100 indicates the highest search frequency for the term, 50 represents half of the searches, while a score of 0 means that there was insufficient data detected for the term.

Figure .2.3: Comparison of web searches for "Central Italy Earthquake", "Visso Earthquake" and "Norcia Earthquake" on Google Trends



Notes: The Y-axis ranges from 0 to 100 and represents the search interest relative to the highest point on the graph within the considered time frame. A value of 100 indicates the highest search frequency for the term, 50 represents half of the searches, while a score of 0 means that there was insufficient data detected for the term.

FIGURE .2.4: Comparison of web searches for "Central Italy Earthquake", "Capitignano Earthquake" and "Montereale Earthquake" on Google Trends



Notes: The Y-axis ranges from 0 to 100 and represents the search interest relative to the highest point on the graph within the considered time frame. A value of 100 indicates the highest search frequency for the term, 50 represents half of the searches, while a score of 0 means that there was insufficient data detected for the term.

FIGURE .2.5: Unaffected municipalities within the geographical area of the toponym - wider definition of the area

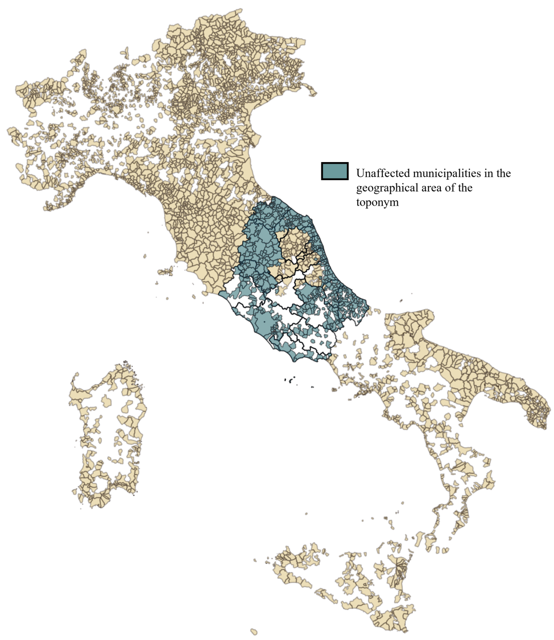


Figure .2.6: Unaffected municipalities within the geographical area of the toponym - distance to the crater