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Climate Protest to Policy

A Time-Series Analysis of the Impact of Protest Events on Policymaking

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ABSTRACT:

As the frequency of natural disasters increases, marked by hotter summers and abnormal ecological changes, climate issues have become impossible to ignore. People are taking to the streets, not only demanding greater awareness but also pushing for meaningful policy changes. This research investigates the relationship between protest events and policymaking within the EU between July 2018 and December 2022 by means of time-series analysis. By building three models with the Poisson regression approach, this thesis looks into how three protest dimensions, the number of events, crowd size and geographical spread, influence policymaking. The findings suggest that protest has a limited impact on policy outcomes and, if any, the impact comes at around 10 months after the event breakout. Future research should explore more comprehensive data over longer periods and incorporate additional control variables to deepen understanding.

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1 Introduction

In recent years, the frequency and intensity of protest events have increased globally, drawing significant attention from scholars, policymakers, and the public alike. These protests range from localised demonstrations to large-scale movements, addressing a multitude of issues, including social justice, environmental concerns, and political reforms. Protests serve as instruments to express public dissatisfaction with social problems (Lohmann, 1993). Political leaders use the ensuing turnout of political actions to update their beliefs about the state of the world (Lohmann, 1993). Through the passage that consists of policy drafting, debating, and roll-called voting, the protest groups are able to eventually materialise their voices into real political outcomes. Therefore, the underlying question that arises from these events is whether and how these protests influence policymaking. Understanding this relationship is crucial as it sheds light on the dynamics of political responsiveness and the mechanisms through which citizens can effect change.

Climate protests are particularly significant within this context due to the urgent and global nature of the climate crisis. Climate change poses a timely and existential threat that transcends national borders, demanding coordinated policy responses at both the national and supranational levels. The rise of radical movements such as Fridays for Future, youth-led voices by Greta Thunberg, and other mobilisations have drawn unprecedented public and political attention to environmental issues (Friberg, 2022; Thunberg, 2019). These protests have succeeded in putting climate change at the forefront of political agendas, compelling governments and international bodies to consider more ambitious environmental policies. However, whether these advancements turn into actual policy or stop at political rhetoric has fundamental meanings in the appeals. The climate protest focus will provide valuable insights into the effectiveness of climate activism in shaping environmental governance and contributing to sustainable policy outcomes.

Focusing on the European Union (EU) region is particularly pertinent for several reasons. The EU, with its diverse member states, represents a unique political and social landscape where policies are often influenced by both national and supranational considerations. The complexity of EU governance, with its multi-layered decision-making processes, provides a rich context for analysing the impact

of protests on policy. Additionally, despite the EU being the forerunner of environmental policy, recent years have seen a surge in climate protest activities across Europe, making it a particularly interesting region to study the relationship between protest events and policymaking. Lastly, despite the significant position of the EU in the sustainable transition, there is limited research considering the EU as a whole in such an investigation. By examining the EU, this research aims to contribute to a broader understanding of how protests function as a mechanism for political change in the EU political systems and cultural contexts.

This thesis explores the temporal relationship between protest events and subsequent policymaking using a time-series analysis approach. By examining the lagged effects of protests on policy changes, this study seeks to identify the extent to which protests serve as a catalyst for policy decisions. To identify the key qualities of protest events that lead to more substantial policy outcomes, the models focus on three aspects: the number of events, the size of participants, and the geographical spread of events. The analysis will cover various lag periods to determine the immediate and delayed impacts of protests, providing a comprehensive understanding of their role in shaping policy outcomes.

In conclusion, this research aims to fill a critical gap in the existing literature by an empirical analysis of the influence of protests on policy within the EU context. It will contribute to the broader discourse on political responsiveness and the potential of movements to effect meaningful policy outcomes in the face of pressing global challenges.

2 Previous Research

To date, the relationship between protest movements and policymaking has garnered significant scholarly attention, highlighting the complex interplay between public demonstrations and political responsiveness. Lohmann (1993) provides a foundational framework, demonstrating how protests can transform public dissatisfaction into political outcomes, emphasising the role of strategic actions and political context in shaping protest effectiveness. Barberá et al. (2019) utilise social media data to examine the dynamic between public issue priorities and legislative agendas, finding that politicians are more likely to follow public priorities, especially those of their supporters, rather than lead them. This study complements the findings of Wlezien and Soroka (2007), who explore the broader opinion-policy nexus, revealing that public preferences do influence policy, though the extent varies across issues and contexts.

Therefore, a couple of works have been done to scope into narrower topics of issue. Amenta et al. (2010) and Giugni (2007) break protests into different family groups for deeper investigation. Amenta et al. (2010) discuss the broader historical and comparative perspective on social movements, exploring the broader conditions under which social movements influence political change and comparing movements like labour and civil rights to highlight the importance of favourable political alignments and strategic mobilisation. Giugni (2007) examines the policy outcomes of the ecology, antinuclear, and peace movements in the United States from 1977 to 1995, finding that while these movements often struggle to achieve immediate legislative success, their long-term impact on public awareness and political agenda-setting is significant. However, in the timely and critical field of climate policy, extensive research has explored exclusively the impact of climate movements, offering a substantial depth of insights.

Agnone (2007) extends his analysis by employing a time-series approach to assess the lagged effects of environmental protests on policy changes in the United States, underscoring the critical role of media in amplifying protest impact. Johnson et al. (2010) highlight the nuanced influence of the U.S. environmental movement on the legislative process. They find that while social movements significantly impact the agenda-setting stage, their influence wanes during the law passage stage unless combined with institutional influence activities. This suggests a critical interaction between diverse tactics within a movement, supporting the notion that both protest and institutional engagement are necessary to secure legislative gains. This aligns

with findings by Olzak and Soule (2009), who also emphasise the importance of institutional tactics over disruptive protests in framing congressional debates favourably towards environmental legislation. They argue that while protests can catalyse agenda-setting, it is the institutional engagements that ultimately push legislation through. Together, these studies provide a comprehensive understanding of how social movements influence political outcomes. Nonetheless, two shortcomings of this literature limit our ability to understand how protest affects policymaking in a wider application.

Firstly, existing empirical studies typically focused on the country level, with a heavy amount focusing on the United States (Giugni, 2007; Agnone, 2007; Johnson et al., 2010; Olzak & Soule, 2009). The prevalence of a quantitative research culture and the availability of comprehensive data in the US may account for this focus. Although some studies have been conducted at the individual European country level, analysing at the EU level sheds light on the foundational complexity of the EU political stance and the intertwined relationship between national and EU-binding policies. Investigating the EU as a whole also offers a clearer picture of how large-scale EU-wide protests influence the development of forerunning EU climate policies.

Secondly, while a few studies have incorporated time-series analysis to account for lag effects, limited work has employed distributed lag analysis to delve deeper into the nature of these effects (Giugni, 2007; Agnone, 2007; Johnson et al., 2010; Olzak & Soule, 2009). Distributed lag analysis can provide detailed insights into the lagged effects, such as answering questions such as how long it takes for a protest to influence policy outcomes, thereby extracting valuable temporal information.

Lastly, previous research predominately focuses on the number of protest events when examining their impact on political outcomes, overlooking the influence of other crucial factors such as crowd size or geographical spread (Giugni, 2007; Agnone, 2007; Johnson et al., 2010; Olzak & Soule, 2009). Expanding the scope of analysis by incorporating models that account for these additional variables allows for a more comprehensive understanding of how different aspects of protest dynamics contribute to polity outcomes.

To address these shortcomings, this thesis incorporates a time series analysis of the relationship between protest events and policymaking in the EU. It aims to fill the gaps in understanding within the EU's leading environmental policy realm and ultimately seeks to enhance our understanding of the efficacy of climate protests and their role in shaping progressive environmental policies in the EU.

3 Methodology

This section outlines the methodological approach employed to investigate the impact of environmental protests, political representation, media coverage, and air pollution on policymaking.

Recognising the absence of an analytical framework incorporating monthly data with multiple lagging variables, this research extends the Poisson regression framework used by Agnone (2007), Olzak and Soule (2009) and Johnson et al. (2010) by adding additional lagged features. This extension aims to provide a more detailed analysis of the data.

Given that I am working with count data, the Poisson regression model—estimated using maximum likelihood estimation (MLE)—is ideally suited for this analysis due to its effectiveness in handling dependent variables that are counts (Scott Long, 1997). MLE estimates the parameters of a model by maximising the likelihood function, ensuring that the observed data is most probable under the estimated parameters. In the context of Poisson regression, this approach is particularly useful because it facilitates the estimation of the relationship between independent variables and the count-based dependent variable, taking into account the non-negative and discrete nature of the data.

This study incorporates three models to examine three aspects of protest events—the number of events, the accumulated crowd size, and the geographical spread of the events—to identify the key elements that influence a movement's ability to shape policy outcomes. This approach facilitates a detailed understanding of protest dynamics and enables a comparative analysis of each aspect’s impact.

3.1 Dependent and Independent Variables

This research focuses on the relationship, including the lagging effect, between the dependent variable the independent variable. I adhere to the approach established by earlier researchers by considering political, media, and environmental control variables (Giugni, 2007; Agnone, 2007; Johnson et al., 2010; Olzak & Soule, 2009).

3.1.1 Dependent Variables – The Environmental Policy

To measure public policy outcomes, government spending and policy count are two common methods. However, there are two notable shortcomings with expenditure data when analysing climate policy. Firstly, expenditure data lacks sensitivity due to the absence of monthly data, making it less responsive to specific events, which is crucial for the analysis in this research (Burstein & Freudenburg, 1978). Secondly, expenditure data does not adequately capture all legislative activities, particularly when legislation primarily involves regulatory actions, which are significant in the context of climate policy (Burstein & Freudenburg, 1978). Governmental regulation is also crucial for the development of private industry that supports sustainable transitions, even in countries with minimal state intervention. Considering all types of policies acknowledges the decisive role of the state. Therefore, I follow the precedent set by earlier researchers by measuring public policy through the count of policies (Agnone, 2007; Johnson et al., 2010; Olzak & Soule, 2009). However, I am aware that laws vary in significance, with some causing major policy shifts and others being minor or cosmetic. This limitation is acknowledged in the research.

Climate public policy data is sourced from the Climate Policy Radar database, which provides comprehensive climate-related policy data across the world, collected from various submitted documentation to the United Nations Framework Convention on Climate Change. Extracting raw data from a prestigious source, the United Nations, the dataset provides solid references regarding the world's policy trends, which contribute to the dependent variable for the analysis.

3.1.2 Independent Variables - Environmental Protest Activities

Three distinct dimensions of protest activity—number of events, crowd size, and geographical spread—were selected to capture the multifaceted nature of protest dynamics and their potential impact on policymaking. These variables were chosen based on both theoretical and empirical considerations. The number of events reflects the frequency and persistence of protests, often seen as a direct indicator of sustained public pressure, and is widely used in similar research (Giugni, 2007; Agnone, 2007; Johnson et al., 2010; Olzak & Soule, 2009).

While the number of protests is a direct measure of public pressure, it may not fully capture the scale or impact of these protests (Biggs, 2018). Given that protest events often follow a heavy-tailed distribution, with most participants concentrated in a few

large events and most other events remain small, Biggs (2018) suggests that focusing on crowd size when analysing protest data provides a deeper understanding of protest participation. Examining total participation, derived by summing up participants across all events, provides a different representation of protest activity, as it captures the significant contribution of these large events. Thus, accounting for crowd size is a distinctive aspect of quantifying protest, making it a valuable addition.

Agnone (2007) and Beyerlein et al. (2018) highlight the significant geographical bias in visibility and influence of protests. For instance, Agnone (2007) notes that protests occurring closer to major urban centres like New York City are more likely to gain attention, suggesting that the geographical spread of protests can affect their overall impact. Beyerlein et al. (2018) further confirm that events in larger cities tend to receive more focus, while those in smaller towns may be overlooked, potentially influencing a movement's broader perception and effectiveness. Therefore, incorporating geographical spread as a variable captures the movement's support across regions, addressing these biases and providing a different dimension of protest influence.

The selection of these variables is essential for a comprehensive analysis of how different aspects of protest activity might influence policy outcomes. By examining each dimension individually, this research aims to disentangle the specific contributions of each factor, leading to a more nuanced understanding of their roles in the policymaking process.

To glimpse into the protest landscape, this research uses the Armed Conflict Location and Event Data (ACLED) as a source of the dependent variables. ACLED provides extensive information on global political violence and protests, including dates, actors, locations, fatalities, and event types. ACLED researchers compile the dataset from thousands of sources reviewed weekly in various languages, including traditional media, reports, local partner data, and new media.

Since this research focuses on the climate, I singled out climate events from the dataset. These protest events include peaceful rallies and demonstrations as well as more radical ones like blockades and other confrontational or violent actions. The data were aggregated into monthly counts and organised for time-series analysis. Further details are provided in the preprocessing sections.

3.1.3 Control Variables

Political Composition

I controlled for various aspects of democratic politics in the EU, as theories of democratic and political opportunity suggest that partisan politics and elections play significant roles in shaping public policy, social movement development, and outcomes (Jenkins & Perrow, 1977). This research measured political alliances in two ways. First, the percentage of seats held by pro-climate parties in the European Parliament captures the environmental voting tendencies of that year. Second, whether the year was an election year accounts for the behavioural differences of politicians during such periods.

The data was sourced from a Statista dataset, "Seats Won in European Parliament Elections From 1979 to 2024," which consolidates data from the European Parliament. According to an analysis by #votefutureEU, the Green/European Free Alliance, The Left, and The Progressive Alliance of Socialists and Democrats are identified as environmental protectors based on their track record of voting for legislation to protect climate, nature, and air quality. For election years, I incorporated an additional variable to denote European Parliament election years, assigning a value of 1 if the observation year coincided with an election year.

Media Attention

The mass media significantly influences the policy process by contributing to protest efficacy, shaping perceptions of protestors, and guiding public opinion towards policy changes (Lipsky, 1968; Gitlin, 2003). To capture the media's impact, I quantified the monthly number of environmental stories in European media.

However, generating consistent time series data on media coverage is challenging due to limited availability and the multilingual nature of the EU region. I utilised a dataset consolidated by researchers from the University of Colorado, which presents European newspaper coverage of environmental issues from 2004 to 2024. Although this dataset does not include all media outlets in the EU and contains some prominent UK media, which has not been part of the EU since 2021, the geographical proximity and the intertwined relationship between the included media and the EU region make this dataset a good representation of media trends, thus suitable for my investigation.

Environmental Composition

Objective indicators of environmental degradation draw public attention to issues identified by scientists, advocacy groups, and social movement organisations (Dunlap & Mertig, 1991). These indicators also influence the urgency for policy action, which is why they are included in the investigatory model.

To consolidate environmental degradation data, the European Environment Agency (EEA) collects yearly greenhouse gas data from member states. The greenhouse gases encompass a basket of six GHGs as defined by the Kyoto Protocol, namely carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, and sulphur hexafluoride. These pollutants are known to pose significant health risks to humans and have detrimental effects on the environment. I included this variable in the dataset to account for environmental factors.

It is important to acknowledge that this study only considers a limited set of control variables—namely, political context, election year, news coverage, and emissions. While these variables are critical to understanding the factors that influence the number of climate policies passed, other influential factors, such as economic conditions or public sentiment, were not included in this analysis. The exclusion of these variables could potentially overlook additional dynamics that might also impact policy outcomes, suggesting an area for further research to provide a more comprehensive understanding.

3.2 Data Collection

The data spans the period from July 2018 to December 2022 and was sourced from various trustworthy institutions, including think tanks, government databases, environmental organisations, and previous research archives. The data collection process prioritised reliability and validity. Please note that some preprocessing was conducted to transform the raw data into suitable variables. For example, the climate policy radar dataset was quantified to create the "Policy" variable for the framework. Further details are provided in the next section.

The dataset source is summarised as follows:

Table 1: Variable List and Sources

Related Variable	Description	Duration	Source
Dependent Variable			
Policy	Number of pro-	Dec 13, 1999 -	Climate Policy Radar

	environmental policies enacted	May 31, 2023	
Independent Variables			
EnvProtests	n_protest: Count of environmental protest events	July 5, 2018 - June 21, 2024	Armed Conflict Location and Events Dataset (ACLED)
	crowdsize: Accumulated crowd size		
	unique_locations: Unique locations		
Control Variables			
SeatsProClimate	Percentage of seats held by pro-climate parties in the European Parliament	1979 - 2024	Seats won in European Parliament Elections from 1979 to 2024, by party grouping, Statista; European Parliament
ElectionYearDummy	Binary variable indicating if it is an election year		European Parliament
EnvMediaCoverage	Count of media articles on environmental issues	Jan 2004 - May 2024	European Newspaper Coverage of Climate Change or Global Warming, 2004-2024, University of Colorado
AirPollution	Levels of air pollution particles	1990 - 2022	European Environment Agency (EEA) greenhouse gases

In comparing the sample size and data frequency of these studies, it is noteworthy that while research such as Giugni (2007), Agnone (2007), Johnson et al. (2010), and Olzak and Soule (2009) benefited from longer time spans ranging from several decades, these studies predominantly worked with yearly data, resulting in fewer data points. For instance, a dataset covering 30 years with annual data provides only 30 data points. In contrast, my study, covering the period from July 2018 to December 2022, utilises monthly data, resulting in 54 data points. Despite the shorter overall time span, the higher frequency of data collection in my study allows for a more granular analysis of the protest-policy relationship, offering potential insights that might be obscured in studies with fewer data points. This increased number of

observations provides a robust foundation for analysis, making the findings of this study comparable, if not more detailed, than those in earlier research.

3.3 Preprocessing & Exploratory Data Analysis (EDA)

Before implementing the models, I conducted several preprocessing steps to ensure the data's validity and suitability for analysis. I selected the period from July 2018 to December 2022 as it is the only timeframe available for all datasets. With only 54 months of data, I acknowledge the limitation and its potential impact on the research outcomes.

3.3.1 Dataset Preprocessing

Firstly, I transformed the Climate Policy Radar dataset by selecting data points where Geography equals "European Union." Then, I aggregated these records on a monthly basis to create a count dataset representing monthly climate policy activity in the EU.

Secondly, I applied the same process to the ACLED data, but with an additional filter: only records containing the keyword "climate" were included, as the dataset encompasses all types of movement data. These two datasets were then concatenated into one table as dependent and independent variables.

The crowd size information was included in the “tags” column, which is a descriptive string that required some preprocessing. I extracted the number if only one was provided, and averaged the numbers if a range was given in brackets. The numerical text was converted to numeric values (e.g., "dozen" to 12), and range descriptions were also converted to numeric values (e.g., "hundreds" to 500). For the locations data, which indicates how many different locations experienced climate protest events in a given month, the count of distinct location values was calculated and recorded.

Regarding the political control variables, I fetched the raw data from "Seats won in European Parliament Elections from 1979 to 2024, by party grouping" on Statista and transformed it into percentiles. The source data is consolidated from the European Parliament. A dummy variable was added manually to label the years that hosted the European Parliament elections.

I incorporated the "European Newspaper Coverage of Climate Change or Global Warming, 2004-2024" dataset from the University of Colorado to account for the

media effect. One of the challenges of working at the EU level is the difficulty of including every media outlet within the EU to fully capture the media landscape, given the variety of languages and the number of players. However, the consistent representation of selected European media over the time period and the geographic proximity provide a reliable indicator of media changes related to the climate topic.

Lastly, I include air pollution data from the European Environment Agency (EEA). Another challenge arose because the EU encompasses several countries, and due to the nature of pollution data reporting, some countries have not provided their data for the previous year. Consequently, I only have data up to 2022, which sets the end limit for my working dataset.

3.3.2 Time Series Imputation and EDA

After all the data were compiled, missing timestamps were identified and addressed by adding them with a value of zero. This imputation process is crucial for ensuring the time-series analysis is complete and continuous. The missing timestamps represent periods where no protest activity was recorded, and assigning a value of zero accurately reflects this absence in the dataset. This approach does not involve estimating or filling in missing values where data was unavailable, but rather, it ensures that the time series remains consistent and complete for analysis.

The dependent and independent variables are plotted together in Figure 1. The chart displays the counts of protest events and climate policies from 2018 to 2024. Notably, there is a fluctuating pattern in the number of protest events, with peaks occurring intermittently throughout the observed period. In contrast, the introduction of climate policies appears sporadic, with a few noticeable bursts of policy activity. The data suggests a potential correlation where peaks in protest activity often precede or coincide with the introduction of climate policies, implying that public demonstrations might influence policy decisions.

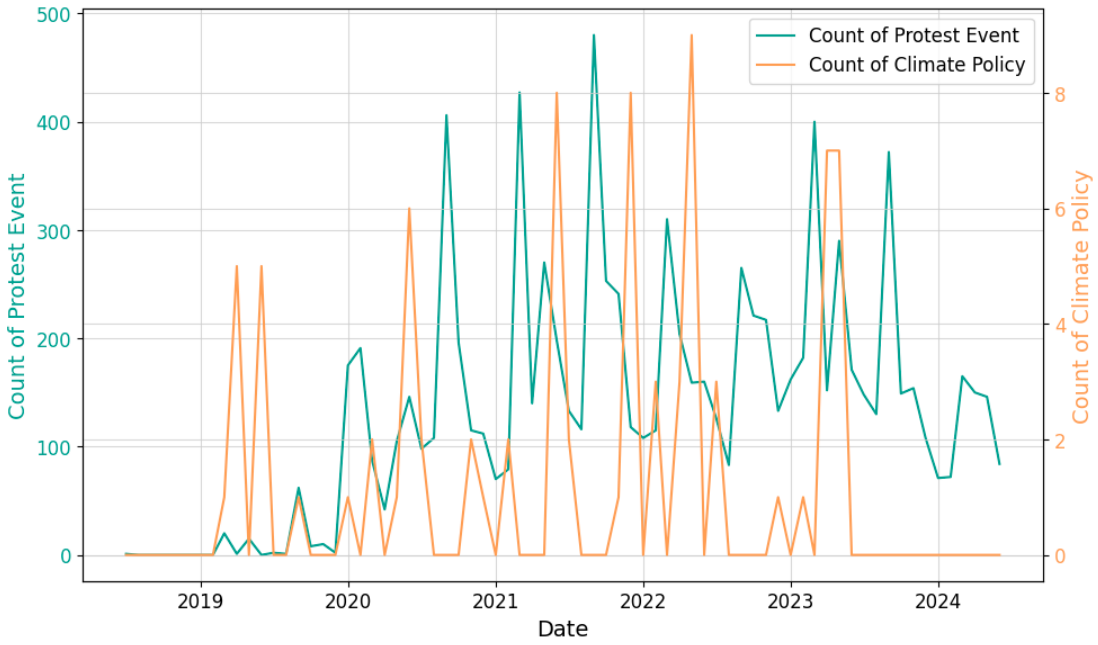


Figure 1: Climate Policy Passed, Protest Activity (Month), 2018 – 2024

However, the irregular nature of policy implementation compared to the more consistent protest events indicates other underlying factors driving policy changes beyond public protests alone. Figure 2 provides a comparison between key independent variables from the three models: the number of protests, unique locations, and crowd size. Notably, in Q3 of 2021, crowd size reached its peak, whereas the number of protests and unique locations did not exhibit the same level of increase. This divergence suggests that while fewer protests occurred in fewer locations during that month, those that did take place may have attracted larger crowds and potentially exerted a different level of influence on policy outcomes. By applying these three models, we can gain deeper insights from various perspectives, allowing for a more nuanced understanding of the dynamics at play.

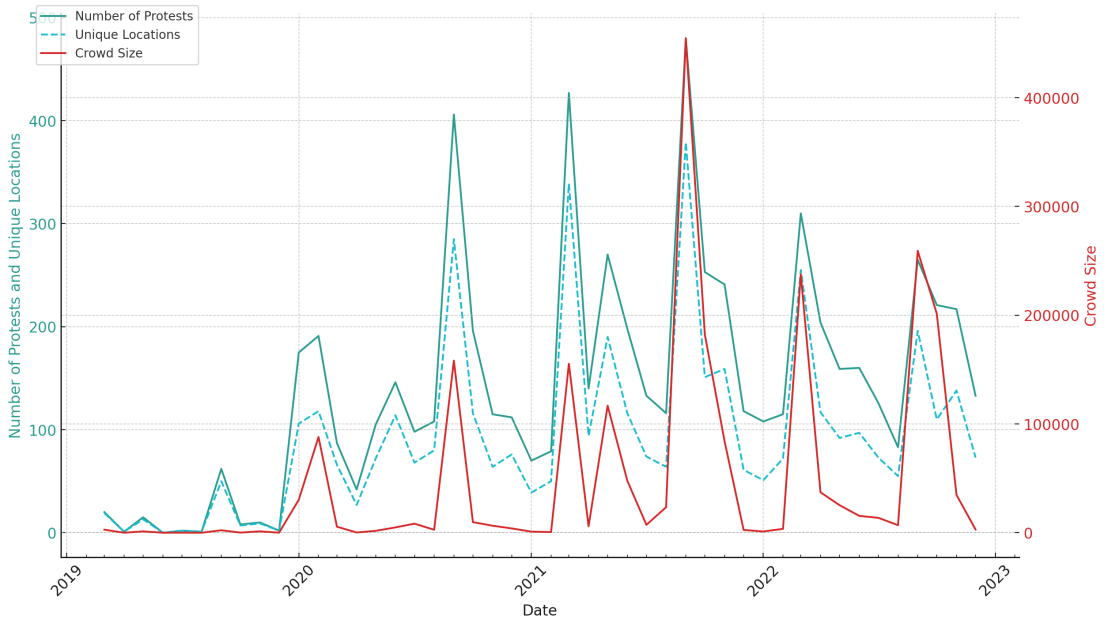


Figure 2: Number of Protest Events, Unique Locations, and Crowd Size (Month), 2019 - 2024

3.3.3 Augmented Dickey-Fuller Test, Stationarity Handling and Standardisation

To assess the potential non-stationarity suggested by the trend observed, the Augmented Dickey-Fuller (ADF) test was conducted (see Table 2) to assess the stationarity of key time series variables in the dataset. `n_protest`, `crowdsize`, `unique_locations`, ` SeatsProClimate`, ` EnvMediaCoverage ` and ` AirPollution` were found to be non-stationary, as their p-values were above 0.05.

Table 2: ADF Test Results

	ADF Statistic	**p-value**
Policy	-7.365	0.000
n_protest	-1.328	0.616
crowdsize	-0.918	0.782
unique_locations	-1.404	0.580
SeatsProClimate	-1.894	0.335
EnvMediaCoverage	-3.035	0.032
AirPollution	-2.015	0.280

To address the stationarity issue, I employed a first-order differencing method to these series (Figure 4), which involves subtracting the current value from the previous value for each observation. This transformation effectively mitigates trends and stabilises

the mean of the series. The resulting differenced dataset demonstrated improved stationarity, as confirmed by visual inspection in Figure 3, facilitating more reliable regression analysis outcomes.

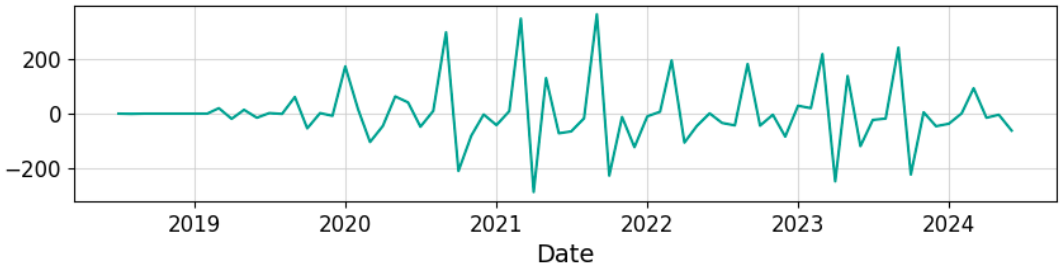


Figure 3: Differenced Count of Protest Event

I also performed standardisation on the independent variables as the datasets include variables measured on distinctively different scales. By converting these variables to a common scale, typically with a mean of zero and a standard deviation of one, standardisation facilitates a fair comparison between them. This process ensures that no single variable unduly influences the model due to its original scale. It is important to note that the outcome variable, which is count data, was not standardised, as Poisson regression relies on the actual counts to model the rate of events.

3.3.4 Breusch-Pagan Test

The Breusch-Pagan test was employed to assess the presence of heteroskedasticity in the residuals of the Poisson regression model. Heteroskedasticity, which occurs when the variance of the residuals is not constant across observations, can lead to inefficient estimates and incorrect inferences if not properly accounted for. The test yielded a Lagrange Multiplier statistic of 13.42 with a corresponding p-value of 0.57, indicating that the null hypothesis of homoskedasticity cannot be rejected. Consequently, there is no strong evidence to suggest that heteroskedasticity is present in the model. Given these results, the assumption of homoskedasticity appears to hold, implying that the standard errors estimated by the model are likely reliable.

3.5 Model

Given the proficiency of Poisson regression in handling count data, and supported by several examples from previous studies, the Poisson regression model is incorporated into this research. To investigate the temporal relationship between variables, I

extended the Poisson regression model by including multiple lagged terms on the count of protest events, enabling it to capture how various lagged values of the independent variables affect current policymaking. Three protest event variables are incorporated into each of the three different models to investigate how different aspects of protest events affect the outcome variable. Please note that in the following equations, these variables will be presented as "Policy," as they will share the same regression approach, but they will be referred to as three distinct models in this thesis.

3.5.1 Dynamic Regression Model

The dynamic regression model captures the relationship between the dependent variable and multiple lagged values of the independent variables. This model is particularly suitable for understanding how past values of the independent variables affect current policymaking. The general form of the dynamic regression model used in this study is:

Equation 1: General Form for Analysing the Impact of Environmental Protests on Policy Outcomes

$$Policy_t = \beta_0 + \sum_{i=1}^{p} \beta_i \text{EnvProtests}_{t-i} + \gamma_1 \text{SeatsProClimate}_t + \gamma_2 \text{ElectionYearDummy}_t + \gamma_3 \text{EnvMediaCoverage}_t + \gamma_4 \text{AirPollution}_t + \epsilon_t$$

Specific Variables:

- $Policy_t$: Policymaking at time t
- EnvProtests_{t-i}: Environmental protest variables at lag i
- SeatsProClimate_t: Percentage of seats held by pro-climate parties in the European Parliament at time t
- $\text{ElectionYearDummy}_t$: Dummy variable indicating if it is an election year at time t
- $\text{EnvMediaCoverage}_t$: Count of environmental media coverage at time t
- AirPollution_t: Air pollution particles at time t
- β_i: Coefficients for lagged environmental protest events
- $\gamma_1, \gamma_2, \gamma_3, \gamma_4$: Coefficients for control variables
- ϵ_t: Error term at time t

In this study, the decision to include multiple lagged terms for the environmental protest variables while using contemporaneous values for other control variables (SeatsProClimate, ElectionYearDummy, EnvMediaCoverage, and AirPollution) is based on the need to capture the temporal dynamics unique to protest events. Previous studies, such as Johnson et al. (2010), often utilised annual data to examine contemporaneous relationships for variables like political coalitions, election years, media coverage, and environmental factors while relying on protest data from the preceding year. Unlike the control variables, which likely have more immediate effects on policy decisions due to their direct involvement in the legislative process, the influence of protests may not be instantaneous.

To serve the purpose of this research, I follow previous studies by incorporating contemporaneous control variables and lagged independent terms. By extending the environmental protest data to include multiple monthly lags, this approach aims to capture these delayed effects more accurately, providing a more nuanced understanding of how protests influence policy over time. This method enhances the ability to discern patterns that might be overlooked in models relying solely on contemporaneous relationships, aligning this study with existing research while also pushing the boundaries of temporal analysis in the context of monthly data.

Incorporating lagged independent variables into the dynamic Poisson regression model also helps address the issue of reverse causality—the possibility that policy changes could influence public opinion or protest activity, rather than the other way around. By using lagged terms, the model ensures that the influence of protest activities on policy outcomes is analysed based on events that occurred prior to the observed policy changes, thus minimising the risk of reverse causality. Previous research has also explored this issue, and no evidence has been found to support the notion that policy changes significantly drive subsequent public opinion shifts or protest activities (Page & Shapiro, 1983; Olzak & Soule, 2009). This temporal separation in the model design strengthens the validity of the causal inferences drawn from the analysis.

3.5.2 Model Selection

Three models are set up, and each incorporates different aspects of protest activity: the number of events, the accumulated crowd size, and the geographical spread of protests. These models will allow for a cross-comparison of how each dimension of protest activity contributes to influencing policy outcomes. This methodical approach

ensures that each aspect of protest activity is analysed independently, providing a more nuanced understanding of its specific impact on policymaking.

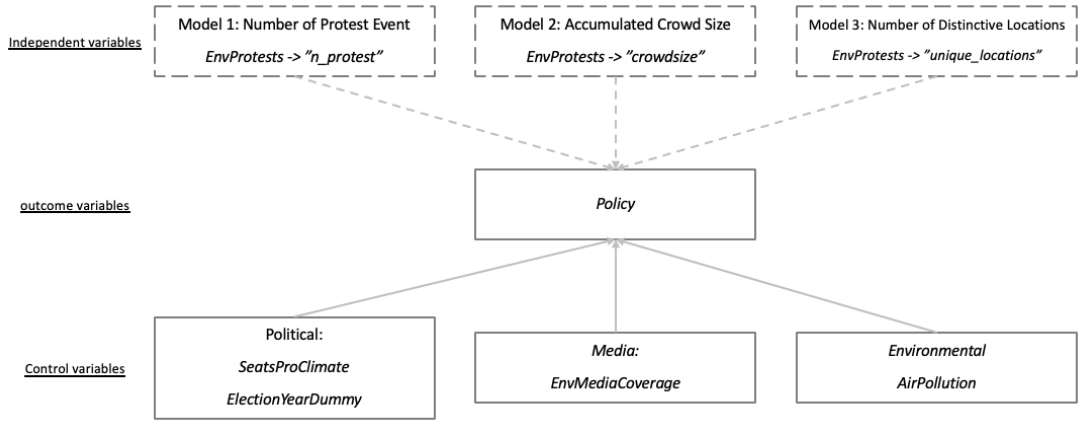


Figure 4: Three Models of Environmental Movement Outcomes

All models will be estimated using Poisson regression to obtain the independent variables coefficients, which are interpreted to understand the temporal effects of environmental protests, political representation, media coverage, and air pollution on policymaking. Significant coefficients will indicate the presence and magnitude of these effects, providing valuable insights into the dynamics of policy formation in response to environmental and political factors.

4 Results and Analysis

This section presents the results of three models, encompassing the relationship between independent variables, namely the number of protest events, the accumulated crowd size of the protest events, and the geographical spread of protest events, together with the four other control variables, and the outcome variable, which is climate policy passed.

The dynamic Poisson regression was conducted to examine the effect of various lagged protest factors (EnvProtests_{t-i}) on the number of climate policies ($Policy_t$). Choosing the number of lagged variables in this analysis is important and tricky, given the limited data available, with only 54 months in the dataset, from July 2018 to December 2022. Including too many lagged variables necessitates trimming off too many earlier data points that do not have lagged variables available for analysis. Including too few might limit the temporal insights that we can get from the investigation.

From the model point of view, more lagged terms also affect the degree of freedom (DF) of the model. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are run on all three models, resulting (16, 16), (17, 1), (16, 3) to Number of Events, Crowd Size and Locations, respectively. Given that the optimal lags of both AIC and BIC to each model are too many or too little that will fundamentally impact the validity of the analyses, I opted for 12 lags to capture a yearly coverage and a DF that is too low. Taking into account the removed initial data point for differencing, this allows me to retain 41 active data points for the analyses.

However, it is important to acknowledge that this decision introduces some limitations. The compromising choice to use 12 lags, while aimed at capturing a full year's worth of data, may still impose constraints on the model's ability to fully account for the complexities of the relationships between protest activities and policy outcomes. The relatively low degrees of freedom resulting from this choice, combined with the sample size, may limit the model's robustness and the generalisability of the findings. These factors should be considered when interpreting the results.

4.1 Model Results

4.1.1 Model Analysis

Model 1: Number of Events

The first model examines the relationship between environmental protests and the number of environmental policy passes. The results reveal a significant positive effect at the 10th lag, indicating that protest events from 10 months prior have a meaningful impact on the current number of protests. However, all other lagged variables and control variables do not show a statistically significant influence on the number of protests.

Table 3: Results of Three Models Assessing Climate Protest Effect on Policy Passed in the EU

	Model 1: Number of Events	**Model 2: Crowd Size**	**Model 3: Locations**
Variable		**Coefficient (Std Error)**	
SeatsProClimate	0.1328	-1.0940	0.0815
	(0.616)	(0.743)	(0.620)

ElectionYearDummy	-1.6460	-1.3065	-1.6476
	(1.021)	(1.032)	(1.020)
EnvMediaCoverage	-0.0003	0.0004	-0.0003
	(0.000)	(0.000)	(0.000)
AirPollution	8.709e-10	-4.676e-10	3.861e-10
	(3.67e-09)	(3.66e-09)	(3.48e-09)
EnvProtests Lag 1	0.0004	1.695e-06	0.0016
	(0.002)	(2.64e-06)	(0.002)
EnvProtests Lag 2	-0.0032	3.284e-06	-0.0028
	(0.002)	(2.75e-06)	(0.003)
EnvProtests Lag 3	-0.0006	7.684e-06*	0.0018
	(0.003)	(3.25e-06)	(0.004)
EnvProtests Lag 4	-0.0047	3.813e-06	-0.0041
	(0.003)	(3.51e-06)	(0.005)
EnvProtests Lag 5	-0.0007	1.008e-05*	0.0003
	(0.003)	(3.99e-06)	(0.005)
EnvProtests Lag 6	-0.0031	4.573e-06	-0.0044
	(0.003)	(4.28e-06)	(0.005)
EnvProtests Lag 7	-0.0031	1.41e-05**	-0.0056
	(0.003)	(4.94e-06)	(0.005)
EnvProtests Lag 8	0.0033	1.517e-05**	0.0032
	(0.003)	(4.94e-06)	(0.005)
EnvProtests Lag 9	0.0045	1.755e-05***	0.0029
	(0.004)	(5.31e-06)	(0.005)
EnvProtests Lag 10	0.0076*	2.256e-05***	0.0073
	(0.004)	(5.55e-06)	(0.005)
EnvProtests Lag 11	0.0030	1.541e-05**	0.0018
	(0.003)	(5.5e-06)	(0.004)
EnvProtests Lag 12	0.0031	1.91e-05***	0.0030
	(0.002)	(5.54e-06)	(0.003)

***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$

To get an overall picture of the coefficients, the coefficient plot provides valuable insights into the temporal dynamics of protest event impacts on the number of subsequent events. Statistical significance is established at the 10^{th} lag, where a positive coefficient suggests that protests from 10 months prior have a notable impact on current protest activity.

There also appears to be a clustering of coefficients around the 10th lag, particularly between the 8th and 12th lags, which could suggest a broader pattern of influence. Specifically, the coefficients near the 10th lag show a more pronounced and consistent pattern. This clustering might indicate a temporal "build-up" effect, where the influence of protests gradually accumulates and peaks around the 10th month. However, it is important to note that, while the 10th lag is statistically significant, the effect size remains relatively small, with a coefficient of 0.0076. This suggests that although the timing of protests plays a role, the impact on policymaking is marginal.

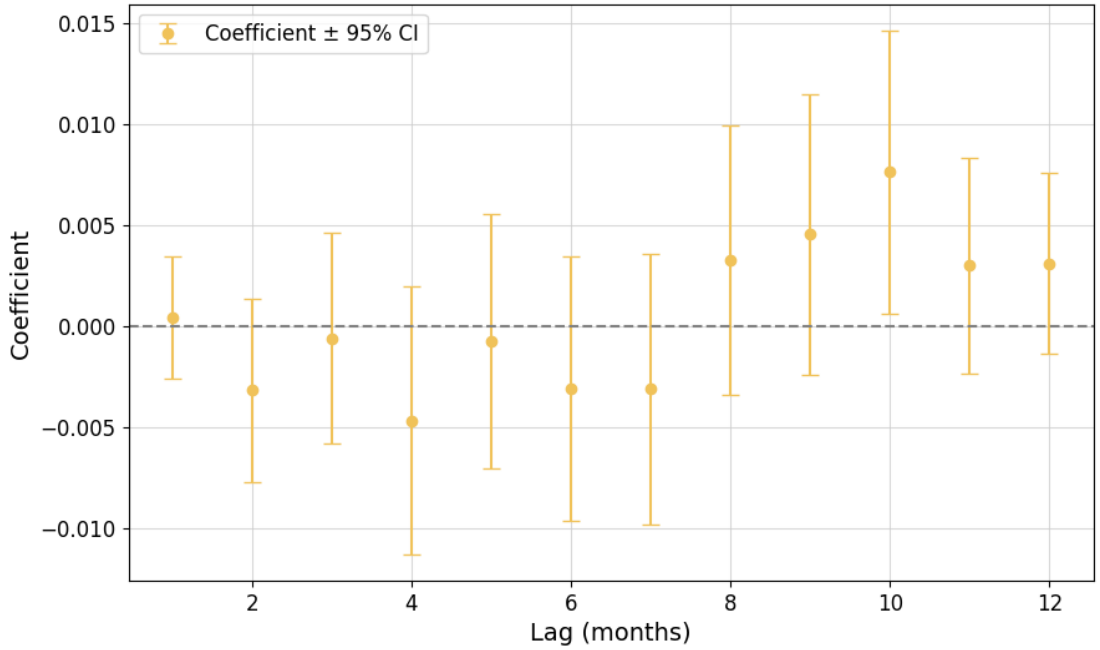


Figure 5: Coefficient Plot, Model 1: Number of Protests Lagged Terms Over 12 Months

Model 2: Crowd Size

The second model, focusing on crowd size, reveals several significant findings. Yet all control variables appear non-significant. Several lagged terms of protest crowd size are more pronounced in this model. A significant positive appears at crowd size with lag 3, 5, 7, 8, 9, 10, 11, and 12. However, all of the significant terms show a marginal effect on policymaking.

The coefficient plot for the Crowd Size model reveals a significant, positive, and increasing impact of environmental protests over time, with the most substantial effects occurring 10 to 12 months after the initial protest events. Despite small coefficients, it indicates that the influence of crowd size on policymaking is not immediate but instead builds and intensifies over the course of a year.

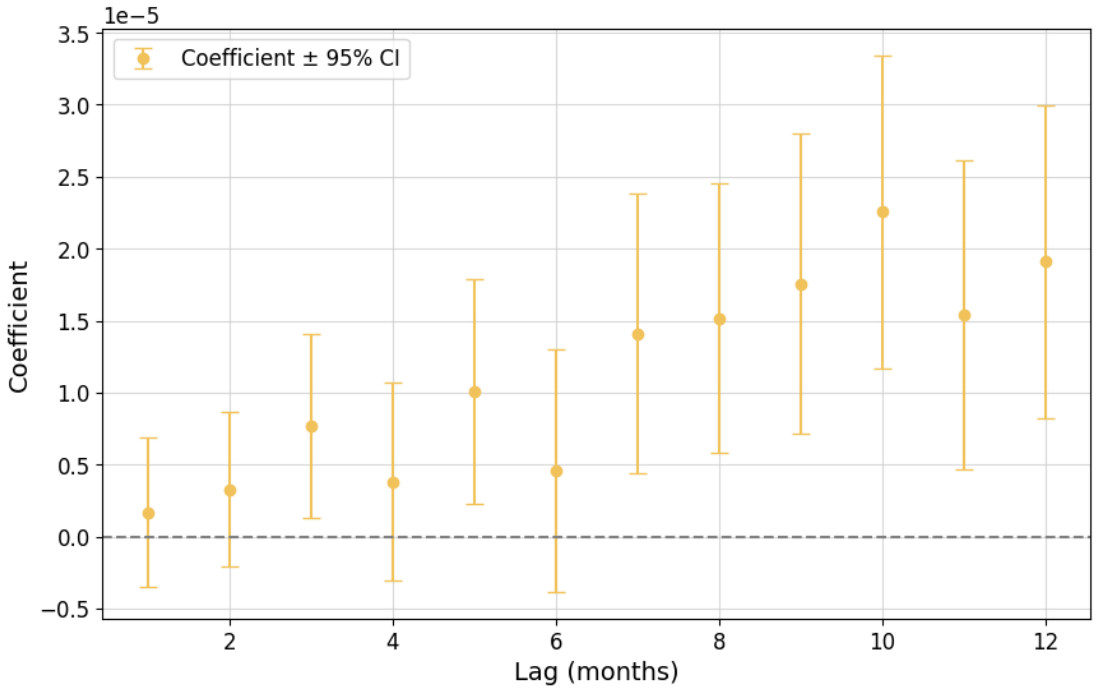


Figure 6: Coefficient Plot, Model 2: Accumulated Protest Crowd Size Lagged Terms Over 12 Months

Model 3: Locations

The third model examines how the geographical spread of protests affects policymaking. The results indicate that all variables, including every lag term and control variables, are non-significant, suggesting that the geographical spread of protests does not have a substantial impact on policy outcomes. However, the coefficient plot reveals an interesting pattern: there is a noticeable peak at the 10th lag, similar to the patterns observed in the other two models. Although this peak is not statistically significant, it suggests a potential delayed effect where the influence of geographically spread protests might become more pronounced around the 10-month

mark.

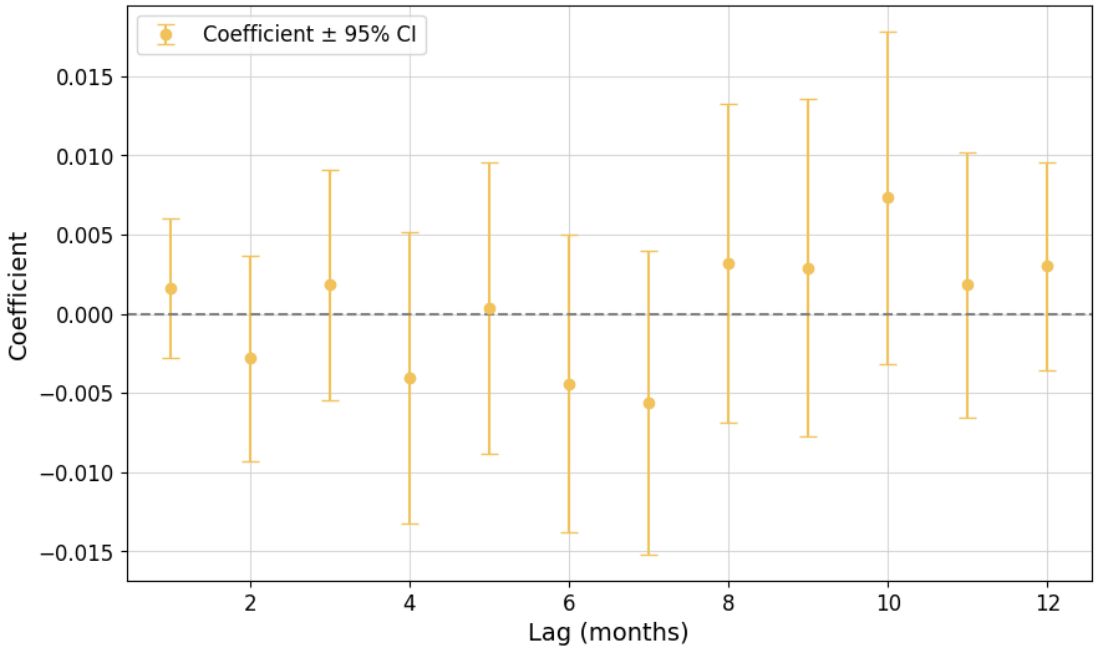


Figure 7: Coefficient Plot, Model 2: Distinct Locations of Protests Lagged Terms Over 12 Months

4.1.2 Cross-analysis

The cross-analysis of the three models, Number of Events, Crowd Size, and Locations, reveals patterns in the impact of various predictors on protest dynamics. All control variables show an insignificant effect across all models, suggesting that these three factors, political, media and environmental, might not be evident in determining the effect on the number of policies passed.

Regarding the three protest event variables, the highest coefficient appears at the 10th lag for all three models, although it is only statistically significant in the Number of Events and Crowd Size models. All three models exhibit a distinctive clustering pattern around the 10^{th} lag, suggesting a feeling of a "normal distribution" effect, where the coefficients near the 10^{th} lag are relatively closer to each other in magnitude compared to those further away. However, even though a couple of significant variables are present, they only show a marginal effect on policymaking. In essence, while some patterns are observable, they are not robust enough to draw strong conclusions or characterise as distinctive trends. This suggests that the protest variables do not strongly influence the outcomes measured. The analysis instead points to the possibility that other factors not included in these models might play a more critical role in influencing protest dynamics.

Table 4: Results That are Significant on Three Models

	Model 1: Number of Events	Model 2: Crowd Size	Model 3: Locations
Variable	**Coefficient (Std Error)**		
SeatsProClimate	No	No	No
ElectionYearDummy	No	No	No
EnvMediaCoverage	No	No	No
AirPollution	No	No	No
EnvProtests	Appears at Lag 10	Appears at Lag 2, 3, 5, 7, 8, 9, 10, 11, and 12	No

4.2 Robustness Checks

To ensure the reliability of the findings, robustness checks were performed by re-estimating the model using a Negative Binomial regression and testing different lag structures. The Negative Binomial regression was employed to address potential overdispersion in the data, where the variance of the dependent variable exceeded its mean, violating the assumptions of the Poisson model. The results, see Appendix 1, from the Negative Binomial regression were consistent with those of the Poisson model, indicating that the findings are robust to overdispersion and that the initial analysis is reliable.

Additionally, the model was re-estimated using alternative lag structures of 7 and 15 months, compared to the original 12-month lags. This was done to ensure that the results were not overly sensitive to the specific choice of lag length. The findings remained consistent across these different lag structures, further supporting the robustness of the results. These checks confirm the stability of the relationship between the independent and dependent variables, though the lack of significant predictors suggests that further investigation with additional variables or models may be necessary.

5 Finding and Discussion

The analysis of the three models—Number of Events, Crowd Size, and Locations—provides insights into the nuanced and complex relationship between environmental protests and climate policy enactment, particularly focusing on how different aspects of protest events influence outcomes.

The results unfold under three key characteristics: they are investigated within the realm of environmental issues, within the geopolitical complexity of the EU, and through an extensive examination of detailed temporal effects on a monthly level. While the analysis offers some insights, it also highlights the challenges in drawing strong conclusions from the available data.

Firstly, the analysis indicates that the number and crowd size of protest events have minimal, if any, effect on policy outcomes. Even though some variables, such as crowd size and the number of events at the 10^{th} lag, show significant effects, these impacts are modest, suggesting that the direct influence of protests on policy is limited. In comparison, the geographical spread of protests does not appear to impact the passage of climate policies. The overall findings are consistent with research conducted in the U.S. by Olzak and Soule (2009), which also found that pro-environmental protests had little to no influence on the enactment of pro-environmental laws. This points to a broader issue: while protests are often seen as a critical tool for social change, their ability to directly influence policy, particularly in the area of climate action, may be less substantial than commonly assumed.

Secondly, media coverage and environmental degradation show no significant influence on policy outcomes, echoing the findings of Olzak and Soule (2009) and Johnson et al. (2010). The political factors, specifically the composition of parliament and whether it is an election year, differ from the U.S. research. While the election year factor consistently shows influence in the models of Olzak and Soule (2009) and Johnson et al. (2010), it does not have a significant impact in this study. This discrepancy may be due to different political mechanisms underlying the U.S. and EU systems, where the political eagerness in driving policy outcomes during election years appears to be less pronounced in the EU. Regarding the parliamentary composition, a similar model conducted by Olzak and Soule (2009) suggests no effect, but when other factors are included, as in Johnson et al., it becomes influential. This suggests the need for further study, including more interactive terms and variables, to allow for a more detailed comparative investigation.

The weak influence of protest-related variables on policy outcomes suggests that other factors, possibly including economic or institutional forces, may be more decisive in shaping climate policy. This finding is particularly important for activists, policymakers and future researchers alike, as it suggests that protest alone may not be sufficient to drive significant policy changes. Instead, a multifaceted approach, possibly combining protest with strategic advocacy, lobbying, and coalition-building, might be necessary to influence policy more effectively.

Lastly, albeit limited, the positive significant effects observed in several lags within the Number of Events and Crowd Size model suggest that the number and size of protest crowds may have marginal impacts on policy creation. Furthermore, all three models exhibit a pattern of clustering at coefficients around the 10^{th} lag, even though not all coefficients are statistically significant. This indicates a potential pattern where protests occurring within this time frame (8th to 12th months) might be more impactful. This somehow "normal distribution" effect could imply that the influence of protests is more concentrated during this period, potentially due to the time required for policymakers to respond to public demands and incorporate them into legislative processes. These findings resonate with the hypothesis that sustained public pressure from environmental movements can eventually lead to policy changes, albeit with some delay (Lohmann, 1993; Wlezien & Soroka, 2007).

5.1 Future Research

Future research should aim to address the limitations of this study by expanding the dataset to include more observations over a longer period. Increasing the sample size will enhance the statistical power of the analyses, providing more reliable and generalisable results. Additionally, incorporating other relevant variables, such as economic indicators, political events, and media coverage, could offer deeper insights into the factors influencing the relationship between protests and climate policymaking.

Including variables related to the quality of the protest, such as whether it is institutional (e.g., organised by established environmental organisations) or grassroots in nature, as well as the presence of leadership and the degree of public engagement, could provide a more nuanced understanding of how different quality of protests influence policy outcomes. Interaction terms can also be added to capture complex dynamics between independent variables, as shown in similar research by Johnson et

al. (2010), which yielded insightful results. However, determining the appropriate interaction terms can be challenging when dealing with multiple lag terms, presenting an opportunity for future research to explore.

By examining other qualitative aspects alongside quantitative data, future research could better capture the complexities of protest dynamics and their effectiveness in driving climate policy changes. Moreover, comparative studies across different countries or regions could reveal how varying political and cultural contexts affect the impact of environmental protests, offering a broader perspective on the global efficacy of such movements. This expanded approach would help in identifying the conditions under which protests are most likely to succeed in influencing policy, thereby informing both activists and policymakers in their efforts to address climate change.

6 Conclusions

Despite numerous studies on the relationship between protest events and policymaking in the US and other countries, comprehensive research at the EU level has been lacking. Given the EU's leadership in climate policy, this study sought to explore the temporal impact of protest activities on the passage of climate policies within the EU's complex geopolitical landscape.

To examine these temporal effects, three models—Number of Events, Crowd Size, and Locations—were developed to assess how different aspects of protest events impact policymaking. The study utilised multiple dynamic Poisson regressions to explore how these three aspects of protest events come into play. Additionally, political, media, and environmental factors were included as control variables. The analysis covered 54 months of data from July 2018 to December 2022, with lag terms set up to 12 months, allowing for a detailed exploration of how past protests influenced policymaking over time.

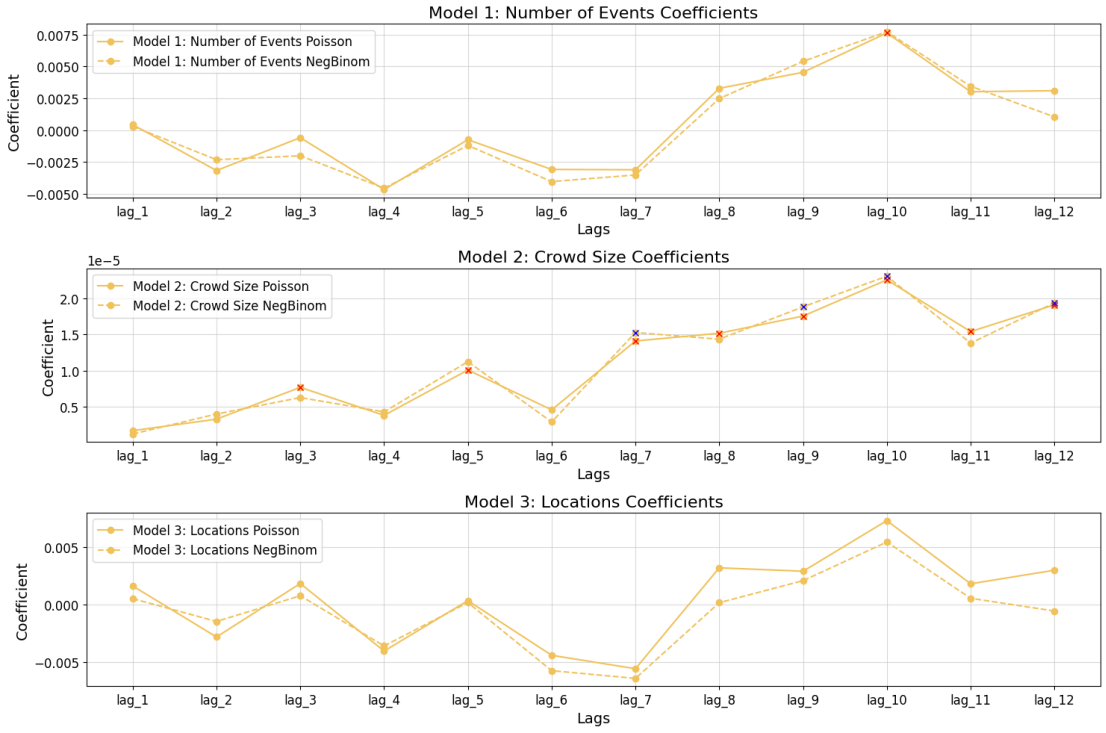
The results revealed that the number and the crowd size of events have an incremental impact on policymaking. In contrast, the geographical spread of events has no direct impact on policy outcomes. Additionally, all three models indicated a notable pattern at the 10-month mark, with the effects showing a pattern resembling a normal distribution around this point. Alas, the non-significant and marginal coefficients do not provide solid ground for the conclusion and, therefore, are left for future investigation.

However, this study faced limitations, particularly the small sample size, which constrained the statistical power and robustness of the findings. Data collection challenges in a multi-language environment and varying data availability across EU countries further complicated the research. Future research should aim to expand the dataset and include additional relevant variables to gain a more comprehensive understanding of the factors influencing the relationship between protests and policymaking.

In conclusion, while this study leads to the rejection of most hypotheses regarding the relationship between protests and policy outcomes, it contributes methodologically by investigating the monthly temporal dynamics. The findings also highlight the complexity of these social phenomena, underscoring the need for further research to build on these results and to inform more effective policy responses.

Appendix 1 Robustness Checks

The visual summary illustrates the coefficients of the Poisson and Negative Binomial models for three key variables: the number of events, crowd size, and unique locations across different lags. Significant points, marked with "x," indicate where the coefficients are statistically significant at the 5% level. The models show generally consistent trends across lags, with some variations in the magnitude and significance of the coefficients, particularly in the crowd size model. These results underscore the robustness of the findings across different model specifications and highlight areas where the relationship between the independent variables and the dependent variable is most pronounced.



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