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I'll Be There for You: Disaster Relief and Trust in Supranational Institutions

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Abstract

Declining trust in supranational institutions may undermine the effective management of global challenges requiring cross-border coordination. We estimate the causal effect of supranational financial assistance following major adverse shocks on citizens' trust in supranational institutions. Our empirical setting is the European Union (EU), where the European Union Solidarity Fund (EUSF) – the EU's main instrument for post-disaster support – provides a uniquely suitable empirical setting for identifying the political effects of supranational assistance following major natural disasters. Identification relies on plausibly exogenous variation in exposure to EUSF assistance together with the "impressionable years" hypothesis. Combining individual-level survey data with geocoded information on natural disasters and EUSF interventions over the 2002–2018 period, we find that exposure to EUSF assistance generates a sizable increase in confidence in the EU that remains detectable several years after the intervention. The effect is economically meaningful and substantially stronger in regions characterized by lower-quality local governance and among more risk-averse individuals, consistent with institutional substitution and insurance mechanisms. Finally, using regional macroeconomic data, we provide supporting evidence that EUSF interventions mitigate the economic downturns associated with natural disasters, suggesting that supranational assistance in moments of distress can generate both economic and political returns.

Keywords: European Union, confidence in institutions, European Solidarity Fund, natural disasters, impressionable years.
JEL: D91, H11, H84, I38

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1 Non-technical summary

Many of today's major challenges —- from climate change and migration to geopolitical and economic shocks —- require cooperation across national borders. Yet supranational institutions can perform these functions effectively only if citizens regard them as legitimate and trustworthy. This raises a fundamental question: can supranational institutions earn citizens' trust by providing effective and visible support when it is most needed?

We study this question in the context of the European Union Solidarity Fund (EUSF), the EU's main instrument for providing financial assistance after major natural disasters. The Fund offers an especially useful setting because its interventions are targeted at communities experiencing large and highly salient shocks and are publicly communicated as EU support. Between 2002 and 2018, the EUSF financed 88 interventions across 24 countries and 115 European regions.

Our analysis combines individual-level survey data on confidence in institutions with detailed geographical information on natural disasters and EUSF interventions. The empirical strategy builds on the idea that experiences during the "impressionable years" of early adulthood can have persistent effects on political attitudes. We compare individuals from different birth cohorts and regions who were differentially exposed to natural disasters and EU assistance between ages 18 and 25. Because EUSF assistance is not randomly allocated following disasters, we use the occurrence of natural disasters to isolate plausibly exogenous variation in exposure to EU support. Importantly, our main outcome measures confidence in the EU relative to confidence in national institutions, allowing us to distinguish EU-specific effects from broader changes in trust in the public sector.

We find that exposure to EUSF assistance during early adulthood substantially increases subsequent confidence in the EU. The estimated effect amounts to roughly one-third of a standard deviation and remains detectable several years after exposure. The increase reflects greater confidence in the EU itself, rather than declining confidence in national institutions. A range of falsification exercises also provides no evidence that natural disasters increase confidence in the EU in settings in which EUSF assistance is absent.

We also investigate why EU assistance may generate these political returns. Two patterns stand out. First, the effect is stronger in regions with weaker local government quality, consistent with supranational intervention being particularly valued where domestic institutional capacity is limited. Second, the effect is substantially larger among more risk-averse individuals, consistent with citizens valuing the EU's role in providing insurance and sharing risks across regions.

Finally, the political effects appear to be accompanied by economic benefits. Using regional macroeconomic data, we find that areas receiving EUSF assistance display more resilient trajectories of GDP and disposable income after natural disasters than disaster-hit regions without EU assistance. This evidence is consistent with the idea that citizens respond not only to the symbolic value of European solidarity, but also to improvements in local economic resilience.

Overall, our findings suggest that trust in supranational institutions need not rest solely on ideology, identity, or abstract support for integration. It can also be built through tangible and effective policy delivery. Although our empirical setting is the European Union, the broader lesson extends to other forms of supranational cooperation: as countries increasingly rely on common institutions to address cross-border challenges, what these institutions visibly deliver to citizens may be an important determinant of their political legitimacy.

2 Introduction

Modern democracies increasingly rely on supranational institutions to address global challenges that national governments cannot effectively manage alone. The importance of supranational governance is likely to grow further as countries face increasingly global and interdependent shocks, including the twin green and digital transitions, renewed geopolitical tensions, and the rising frequency of extreme climate-related events. Yet the political sustainability of this institutional architecture ultimately depends on whether citizens perceive supranational institutions as legitimate and trustworthy. This tension is especially salient in Europe, where the authority delegated to the European Union (EU, hereafter) has expanded substantially while confidence in the EU has weakened over recent decades (Figure 1).[1] These trends have raised concerns about the political sustainability of deeper supranational integration. Not surprisingly, European Central Bank President Christine Lagarde recently warned that "in recent decades, we have also seen an imbalance emerge between the authority delegated to supranational governance and its *legitimacy in the eyes of citizens*" (emphasis added; Lagarde, 2023).

Can supranational institutions earn citizens' trust through concrete policy interventions? Despite the centrality of this question, we still know remarkably little about this. In this paper, we study one potentially important mechanism through which supranational institutions may strengthen citizens' confidence: the provision of tangible support in moments of distress. The European Union Solidarity Fund (EUSF), the EU's main instrument for post-disaster support, provides a uniquely suitable empirical setting because it delivers tangible supranational assistance following major natural disasters. Resources are mobilized at the European level and targeted to local communities hit by large adverse shocks. Importantly, interventions are explicitly branded and publicly communicated as EU support, making them relatively easy for citizens to associate with the EU. This makes the EUSF a particularly clean setting for identifying the political effects of supranational assistance following salient adverse shocks.

Identification takes advantage of two sources of variation. First, natural disasters are geographically localized shocks that trigger EUSF interventions in affected regions. Second, a well-established literature in economics, political science, and social psychology shows that prefer-

[1] Voting data consistently show that the average vote share of Eurosceptic parties in national elections increased from 6.9% in 2003 to 28.5% in 2023 (European Commission, 2024).

ences, beliefs, and political attitudes are especially malleable during the "impressionable years" of early adulthood and remain largely stable thereafter (Krosnick and Alwin, 1989). We therefore compare cohorts within the same region and survey wave that were differentially exposed to EUSF assistance during their impressionable years, instrumenting assistance with disaster occurrence to address the potential endogeneity of Fund allocation. Our preferred outcome is *relative* confidence in the EU, defined as confidence in the EU net of confidence in national institutions. This measure allows us to isolate changes in attitudes toward supranational institutions from broader shifts in generalized confidence in the public sector. We support this identification strategy with multiple placebo exercises supporting the exclusion restriction assumption and extensive robustness checks. To implement this design, we combine individual-level survey data on institutional confidence from the Integrated Values Survey (IVS) with geocoded information on natural disasters (taken from the Geocoded Disasters (GDIS) database) and EUSF interventions over the 2002–2018 period.

We find that exposure to EUSF assistance during early adulthood generates a sizable increase in confidence in the EU that remains evident several years after exposure. The effect is driven by higher absolute confidence in the EU rather than by lower confidence in national institutions. The magnitude is economically meaningful, amounting to roughly one-third of the standard deviation of the dependent variable. This effect emerges despite the relatively limited fiscal scale of the EUSF, whose annual expenditures represent only a tiny fraction of EU GDP. This suggests that the political returns to supranational assistance need not be proportional to its fiscal cost. We find no significant effects in a range of placebo exercises, while our results survive a number of sensitivity tests.

We next provide evidence on the mechanisms underlying this relationship. First, the impact of EUSF exposure is substantially stronger in regions characterized by lower-quality local governance, consistent with the idea that EU intervention can partly substitute for weaker domestic institutional capacity. Second, the effect is larger among more risk-averse individuals, suggesting that citizens perceive the EU as providing insurance against adverse shocks. Finally, using regional macroeconomic data and a Local Projection Difference-in-Differences framework (Dube et al., 2025), we provide supporting evidence that disasters followed by EUSF support are associated with more resilient trajectories of GDP and disposable income than disasters without

EU assistance. Taken together, these patterns are consistent with the idea that supranational assistance strengthens political confidence not only symbolically, but also through improved local economic resilience.

Our paper mainly contributes to research on the determinants of political trust. Existing work has highlighted the role of economic growth (Besley et al., 2026; Stevenson and Wolfers, 2011), public-sector performance (Becker et al., 2016), and *information about* institutional effectiveness (Acemoglu et al., 2020; Briscese and Grignani, 2025; Braccioli et al., 2025; Guriev et al., 2020). However, we still know relatively little about how to spur citizens' confidence in *supranational* institutions. Our contribution is to identify one mechanism through which supranational institutions can earn citizens' trust: effective policy delivery following major adverse shocks.

We also contribute to the literature on European integration and Euroscepticism (Becker et al., 2017; Algan et al., 2017; Dustmann et al., 2017). Existing work on EU regional policy provides mixed evidence on the political effects of EU transfers (Becker et al., 2012; Borin et al., 2021; Crescenzi et al., 2020). We differ from this literature by focusing on temporary and highly salient interventions associated with exceptional adverse events rather than on persistent regional redistribution programs. Other studies use experimental designs to examine how priming external threats and common challenges affects voter turnout in European elections (Barone et al., 2025), or how priming common economic interests, shared identity, and the COVID-19 crisis influences altruism, reciprocity, and trust among EU citizens (Aksoy et al., 2025). Both studies focus on short-term effects, whereas we examine a different mechanism and focus on medium- to long-term effects.[2]

The rest of the paper is structured as follows. Section 3 describes the institutional framework. Section 4 presents the data. Section 5 outlines our empirical design and identification strategy. Section 6 reports the main results, while Section 7 sheds light on why the EUSF fosters confi-

[2]To a lesser extent, we also contribute to other strands of literature. First, we add to studies on how aggregate shocks during impressionable years shape persistent preferences and beliefs (Giuliano and Spilimbergo, 2025, 2023; Carreri and Teso, 2023; Bietenbeck et al., 2025; Cotofan et al., 2023; Eichengreen et al., 2021, 2024; Barone et al., 2022) by providing novel evidence that supranational assistance experienced during impressionable years can durably affect confidence in institutions. Second, our results also speak to the recent literature on the macroeconomic effects of natural disasters (Usman et al., 2025; Nguyen et al., 2025; Roth Tran and Wilson, 2024; Eickmeier et al., 2024) by specifically investigating the role of public assistance – an aspect widely recognized as important but still largely understudied. Finally, our paper is related to Andrabi and Das (2017), who study how international relief assistance following the 2005 earthquake in Pakistan affected Muslims' trust in Westerners.

dence in the EU. Section 8 concludes.

3 Institutional framework

The EUSF provides a prominent example of supranational solidarity in response to adverse shocks (e.g. Figure 2). Established in 2002, the Fund provides financial assistance to regions affected by major natural disasters through resources mobilized at the European level. Managed by the Directorate-General for Regional and Urban Policy (DG REGIO), the Fund provides non-repayable financial assistance to eligible applicants, including EU Member States and accession countries. The EUSF targets both *major* natural disasters – defined as events causing damage exceeding €3 billion (a threshold periodically updated for inflation) or 0.6% of national GDP – and *regional* natural disasters, for which the threshold is set at 1.5% of NUTS2 GDP (1% for outermost regions).[3] In addition, the Fund may support regions in neighboring countries affected by major disasters even when no formal damage threshold is met.

The Fund operates under a system of shared management between the EU, which is responsible for financing, oversight, and monitoring, and beneficiary states, which are in charge of implementation. National authorities may in turn delegate execution to ministerial departments and/or regional and local administrations, depending on the country's institutional structure. The disbursement process is relatively rapid: eligible countries must submit an application within 12 weeks of the disaster, the EU generally approves applications within 15 weeks, and implementation must be completed within 18 months after approval. Importantly for our analysis, the institutional design of the Fund implies that financial assistance is both relatively rapid and publicly communicated, with resources typically approved and spent within two years of the disaster. Funds cannot be used freely but must finance specific recovery activities, including restoring infrastructure, providing temporary accommodation and rescue services, securing preventive infrastructure, protecting cultural heritage, and cleaning up affected areas, including natural zones. The Fund financed 88 interventions across 24 countries and 115 NUTS2 regions between 2002 and 2018, with total disbursements amounting to €5.5 billion. Average (median)

[3] EU outermost regions are French Guiana, Guadeloupe, Martinique, Mayotte, Réunion, and Saint-Martin (France); the Azores and Madeira (Portugal); and the Canary Islands (Spain).

assistance amounted to €62.9 million (€13.6 million), corresponding to 3.1% (2.6%) of estimated damages.

Are European citizens aware of the Fund? An important question for our analysis is whether citizens are aware of the Fund and can attribute post-disaster assistance to the EU. Available evidence suggests that many citizens are aware of the Fund and are likely to associate post-disaster assistance with the EU. In both 2017 and 2019, around 60% of Europeans reported being aware of the EUSF – a higher share than for the European Regional Development Fund (ERDF) and the Cohesion Fund (CF), two central pillars of EU Cohesion Policy (Figure 3, Panel A).[4] From 2021 onward – when changes in survey methodology limit comparability with earlier waves – the visibility of the EUSF becomes broadly aligned with that of the ERDF/CF and the European Social Fund (ESF), another major component of Cohesion Policy. In all years, more than 40% of Europeans report being aware of the Fund, a non-negligible share that exceeds awareness of the Next Generation EU program. Figure 3, Panel B, provides complementary evidence on the public visibility of the Fund. The European Commission conducted a media survey covering more than 4,000 news items from major outlets during disaster periods. The survey focuses on seven case-study countries – Austria, Bulgaria, Greece, Italy, Portugal, Romania, and Serbia – and collects information on both the EUSF application process and the implementation of Fund-supported interventions (Bachtler et al., 2019). The evidence indicates that media coverage of the EUSF in connection with natural disasters is far from negligible, suggesting that Fund interventions received substantial public exposure. On average, 11.3% of news articles mention the EUSF. References mainly concern political and policy announcements related to funding applications or approvals, as well as specific projects financed through the Fund. Taken together, these features suggest that EUSF interventions received substantial public visibility and are plausibly associated with the EU by many citizens.

[4]EU Cohesion Policy absorbs nearly one-third of the total EU budget and targets all regions and cities in the European Union with the objective of promoting job creation, business competitiveness, economic growth, sustainable development, and improvements in citizens' quality of life.

4 Data and preliminary descriptive analysis

This section describes the main data sources, the construction of the key variables, and presents descriptive evidence.

4.1 Individual trust in the EU

To study citizens' views about supranational institutions, we rely on individual-level survey data from the Integrated Values Survey (IVS), which harmonizes the European Values Study (EVS) and the World Values Survey (WVS). The IVS provides nationally representative surveys covering institutional attitudes, socio-demographic characteristics, and respondents' region of residence at the NUTS2 level – a key feature given the localized nature of natural disasters and EUSF interventions.[5] The questionnaires elicit respondents' attitudes on a broad range of issues, including confidence in institutions. In particular, respondents are asked the following question: "I am going to name a number of organizations. For each one, could you tell me how much confidence you have in them: is it a great deal of confidence, quite a lot of confidence, not very much confidence or none at all?" This question is asked with respect to the EU as well as a variety of other institutions. Responses are recorded on a four-point Likert scale, coded as 1 = "A great deal", 2 = "Quite a lot", 3 = "Not very much", and 4 = "None at all".

We first construct an indicator increasing in confidence by defining *absolute* confidence in the EU as 4 minus the original response variable, yielding a scale ranging from 0 (minimum confidence) to 3 (maximum confidence). Our preferred outcome measure is *relative* confidence in the EU, defined as absolute confidence in the EU net of absolute confidence in national institutions.[6] This outcome is particularly useful in our setting because natural disasters may affect *generalized* confidence in public institutions. By netting out confidence in national institutions, the relative measure isolates changes in attitudes toward the EU that go beyond contemporaneous shifts in confidence in the public sector more broadly, while also accounting for individual-specific

[5] The IVS harmonizes waves 2 to 5 of the European Values Study (EVS) and waves 2 to 7 of the World Values Survey (WVS). The resulting dataset contains nationally representative samples from 120 countries and covers approximately 664,000 respondents surveyed between 1981 and 2021.

[6] Measured on the same 0–3 scale and computed as the simple average of absolute confidence in the national government and in the national parliament.

reference points. Throughout the paper, unless otherwise specified, we will use the terms "confidence" and "trust" in the EU interchangeably to refer to this *relative* measure, which ranges from -3 to 3.

The IVS also provides information on respondents' age, year of birth, year of interview, region of residence at the NUTS2 level, gender, education, employment status, marital status, and migration background.[7]

4.2 Disasters and EUSF interventions

Data on disaster occurrences – including floods, storms, earthquakes, landslides, droughts, volcanic activity, and extreme temperatures – are drawn from the Geocoded Disasters (GDIS) dataset managed by NASA (Rosvold and Buhaug, 2021), which provides a geocoded extension of a large subset (approximately 90%) of natural disasters recorded in the Emergency Events Database (EM-DAT).[8] The GDIS dataset covers nearly 10,000 disasters worldwide over the 1960–2018 period. For each event, the data report the disaster type, year of occurrence, number of fatalities, estimated economic damages, and detailed geographic information in the form of polygons delineating affected areas. The high geographic resolution of the GDIS data is particularly important because it allows us to exploit the highly localized nature of both natural disasters and EUSF interventions.

We map disasters to NUTS2-2006 regions using a spatial join procedure, defining a region as affected whenever its territory overlaps, even partially, with a disaster polygon. To merge disaster data with the IVS, we collapse the information to the region–year level and define a disaster dummy equal to one if at least one disaster occurs within a given region–year cell. For disaster characteristics, we aggregate economic damages and the number of affected individuals across

[7] In the IVS, geographical units are reported using different classifications depending on the survey wave (e.g., region names, ISO codes, NUTS2-2006, or NUTS2-2016 classifications). To harmonize regional information across waves, we first use waves containing both region names and region codes as crosswalks to assign codes to waves in which only names are available. We then use geographical coordinates in ArcGIS to map all regional identifiers into the NUTS2-2006 classification. When NUTS2-2006 regions correspond to subdivisions of broader classifications (e.g., NUTS2-2016 or ISO regions), we use the larger geographical unit as the reference region.

[8] Additional information on the GDIS dataset is available at https://data.nasa.gov/dataset/geocoded-disasters-gdis-dataset. Disasters are included if they satisfy at least one of the following criteria: (i) ten or more fatalities; (ii) one hundred or more individuals affected; (iii) declaration of a state of emergency; or (iv) a call for international assistance.

all disasters occurring within the same region–year cell.

Data on EUSF interventions are collected from the official Fund website. For each intervention, we observe the affected area, date, amount of aid, and reported damages. Since the data do not provide explicit geolocation at the NUTS2 level, we manually geocode interventions to NUTS2 regions using detailed information from official reports, institutional documentation, and complementary public sources. As with disasters, we collapse intervention data to the region–year level using the same aggregation procedure described above.

After merging the two datasets, we obtain a region–year panel containing information on disaster occurrence, fatalities, and damages from GDIS, as well as EUSF interventions, Fund-reported damages, and aid amounts.

4.3 Other data sources

As part of our analysis of the spatial allocation of EUSF funds, we measure regional quality of government using the widely employed European Quality of Government Index (EQI) developed by Charron et al. (2014). The EQI is available for 2010, 2013, 2017, 2019, 2021, and 2024. We also use region–year data from the European Commission on EU disbursements under the EU regional policy.

When examining transmission channels, we focus on individual risk aversion. Because the IVS does not include a standard measure of risk attitudes, we predict an individual-level indicator of risk aversion using auxiliary regressions estimated on data from the Survey of Health, Ageing and Retirement in Europe (SHARE), which contains a widely used measure of willingness to take financial risks. The prediction model is estimated out of sample and relies exclusively on demographic characteristics observed in both SHARE and the IVS. Appendix C describes the imputation procedure and evaluates the resulting measure.

Finally, we use regional data from the ARDECO database to study both the spatial allocation of EUSF funds and the effects of disasters and EUSF interventions on migration and local macroeconomic conditions. ARDECO is a panel database maintained by the European Commission's Directorate-General for Regional and Urban Policy that provides macroeconomic and demographic variables, including population, net migration, GDP, and employment, at different levels of geographic aggregation (NUTS1, NUTS2, NUTS3, and metropolitan regions).

4.4 Sample construction and descriptive analysis

Our analysis combines individual-level survey data on institutional trust with geocoded information on natural disasters and EUSF interventions at the NUTS2-year level, as well as with region-level indicators of government quality. The resulting dataset covers the 1981–2018 period. Individual risk aversion is imputed using SHARE data. Exposure to disasters and EUSF interventions during the impressionable years (ages 18–25) is assigned to respondents based on their current region of residence and year of birth.

Our main estimation sample includes individuals whose impressionable years potentially overlap with the existence of the EUSF, namely cohorts born in 1984 or later and residing in eligible countries – namely EU Member States and accession countries – which, for simplicity, we refer to throughout the paper as "EU members".[9]

Table 2, Panel A, reports descriptive statistics for the main estimation sample used to analyse the effect of disasters and EUSF interventions on confidence in the EU. The sample includes nearly 30,000 respondents, whose average relative confidence in the EU is positive. More than one-third of respondents experienced at least one disaster during their impressionable years, and 13% were also exposed to EUSF assistance. On average, EUSF aid corresponds to around 3% of the damage reported to the EU.

Figure 4, Panel A, displays the distribution of impressionable ages (18–25) at the time of disaster exposure with a peak around age 21. Panel B reports the number of years elapsed between disaster exposure and the survey interview, allowing us to assess whether our findings reflect short-, medium-, or long-run effects. On average, respondents are interviewed 4.3 years after the disaster; in 75% of cases, the interview takes place within seven years of the event, whereas in only 10% of cases the time lag exceeds ten years. Figure 5 presents the corresponding analysis

[9] Eligibility status changes over time for Albania, Serbia, and Montenegro. However, we exclude observations from these countries in all years, since Serbia and Montenegro became separate states only in 2006 and NUTS2-level regional information is unavailable for Albania. Table 1 reports the full list of eligible countries.

for EUSF interventions.

Table 2, Panel B, reports descriptive statistics at the region–year level. Disasters occur in more than one-third of observations, with substantial variation in both fatalities and estimated damages. The EUSF is activated in approximately 10% of disaster events, and associated aid amounts on average to roughly 3% of reported damages.

Figure 6, Panel A, plots the evolution of disasters and EUSF interventions over time. Beginning around 2000, the number of reported disasters increases sharply, a pattern likely reflecting improvements in reporting quality rather than changes in underlying climate-related hazards (Delforge et al., 2025). This consideration further motivates our focus on the post-2000 period. Panel B shows substantial geographic variation in disasters and EUSF interventions across regions and countries, generating rich variation in exposure to EU disaster assistance across cohorts and locations.

5 Empirical strategy

5.1 Where do EUSF funds go?

We start by investigating the spatial allocation of EUSF support. To this end, we build a region–year panel covering the 2002–2018 period and define an intervention dummy equal to one if a region receives at least one EUSF intervention in a given year and zero otherwise. We construct an analogous disaster dummy equal to one if a region experiences at least one disaster in that year. Importantly, there are no instances of EUSF intervention in the absence of a disaster, satisfying the one-sided non-compliance condition that we exploit below. In Table 3, Columns 1–4, we regress the intervention dummy on the disaster dummy under alternative combinations of fixed effects. As expected given the institutional design of the Fund, disaster occurrence strongly increases the probability of receiving EUSF support. For example, the specification in Column 4 indicates that the probability of receiving EUSF support increases by nearly 12 percentage points following a disaster – more than three times the mean of the dependent variable and approximately 60% of its standard deviation (see Table 2, Panel B).

We next examine whether, conditional on disaster occurrence, EUSF interventions are randomly allocated across regions. In the next three columns, we use the same region–year panel, restricted to region–year observations experiencing at least one disaster, and regress the intervention dummy on a set of time-varying regional characteristics: government quality (Column 5), logged GDP per capita (Column 6), and logged per capita EU disbursements under the EU regional policy (Column 7). We find that, following a disaster, EUSF interventions are more likely in regions characterized by lower-quality local government and lower GDP per capita, while other EU financial support is balanced between disaster-affected regions receiving and not receiving EUSF assistance. The latter finding suggests that EUSF assistance does not systematically substitute for other sources of EU funding.

5.2 The IV identification strategy

The findings on the allocation of EUSF funds have important implications for our empirical strategy. Unlike settings in which the treatment underlying an impressionable-years design can plausibly be regarded as exogenous, we cannot simply regress the outcome of interest (trust in the EU) on the treatment (exposure to EUSF assistance during early adulthood) and interpret the resulting coefficient as causal. EUSF interventions are not randomly allocated across regions experiencing disasters. In particular, the OLS estimate would be downward biased if lower government quality and poorer local economic conditions are associated with lower trust in the EU (as suggested, for example, by Karahasan and Pinar (2024) and Mayne and Katsanidou (2023), respectively). Moreover, other observed or unobserved factors may jointly affect EUSF allocation and subsequent trust in the EU.

To address these concerns, we isolate the exogenous component of EUSF exposure by instrumenting intervention with disaster occurrence. Identification comes from comparing individuals belonging to different cohorts within the same region, and individuals belonging to different regions within the same cohort that were differentially exposed to disasters and EUSF interventions during their impressionable years. Specifically, we estimate Two-Stage Least Squares (TSLS) regressions of the following form:

First stage:

$$EUSF_{icr} = \alpha_1 Disaster_{icr} + \alpha_2 X_{icrts} + \theta_{rt} + \iota_c + \kappa_s + \mu_{icrts} \tag{1}$$

Second stage:

$$y_{icrts} = \beta_1 \widehat{EUSF}_{icr} + \beta_2 X_{icrts} + \delta_{rt} + \zeta_c + \eta_s + \epsilon_{icrts}. \tag{2}$$

Here, y_{icrts} is the relative confidence in the EU (or the absolute confidence in the EU/national institutions in some exercises) for individual i belonging to cohort c, interviewed in region r, year t, and survey s (EVS or WVS); $EUSF_{icr}$ is a binary indicator for exposure to the EUSF aid during impressionable ages; $Disaster_{icr}$ is a binary indicator for exposure to a disaster during impressionable ages; disaster and intervention experiences are attributed to respondents based on their NUTS2 region of residence at the time of the interview; $\widehat{EUSF}_{icr}$ is the predicted value of $EUSF_{icr}$ according to Equation 1; in X_{icrts} we control for gender, while θ_{rt} and δ_{rt} are region–year of interview fixed effects, ι_c and ζ_c are cohort fixed effects, κ_s and η_s are survey fixed effects. Note that unlike most studies building on the impressionable years hypothesis, which typically include time-invariant spatial fixed effects at the level of the shock (e.g., country or region), we adopt a more demanding specification by controlling for region–time of interview fixed effects. This ensures that concurrent time-varying local economic shocks that could affect the outcome (e.g. economic downturns, see Algan et al., 2017 and Dijkstra et al., 2020) are controlled for. μ_i and ϵ_i are the usual error terms. Standard errors are clustered at the NUTS2 level.[10]

Our empirical strategy requires two further clarifications. First, one might argue that instrumenting $EUSF_{icr}$ is redundant because our specification includes region–time fixed effects that would absorb the non-random spatial allocation of EUSF. This argument, however, overlooks the timing of the relevant variation. In Equation 2, δ_{rt} absorb shocks at the region-*year of interview* level, whereas the potential confounders highlighted in Table 3, such as government quality and GDP per capita, are measured at the region-*year of disaster* level. Because different cohorts within the same region–year of interview cell were exposed to these conditions at different stages of life, region–year of disaster characteristics are not absorbed by region–year of interview fixed effects and may remain correlated with both EUSF exposure during early adulthood and subsequent trust in the EU. The two dates are, on average, 4.3 years apart, with

[10]We cannot include age fixed effects because they are perfectly collinear with cohort and year fixed effects.

substantial heterogeneity across respondents (Figure 4, Panel A). One might argue that government quality and GDP per capita are sufficiently persistent for the distinction between the year of interview and the year of disaster to be largely immaterial. This is not the case in our data: over a four-year period, the average absolute value of the percentage change in these variables is 25.0% for government quality and 8.5% for GDP per capita. Moreover, other potential confounders may display substantially less persistence, further reinforcing the relevance of distinguishing between the two dates in our empirical design. Second, because of one-sided non-compliance (see Section 4), the TSLS coefficient can be interpreted as an ATT rather than a LATE (Bloom, 1984; Angrist and Pischke, 2009). This makes the estimated effect more directly relevant to the population actually exposed to EUSF assistance than a conventional LATE defined for an instrument-specific complier population.

Figure 7 uses the 2018 IVS survey to illustrate the cross-cohort and cross-regional variation in exposure to disasters and interventions, which is the source of identification in our empirical strategy. Cohort fixed effects account for year-of-birth specific factors, which may matter if different generations are exposed to disasters with varying probabilities – an outcome potentially driven by climate change – and display different confidence in the EU.

As to the IV strategy, a potential concern is that disasters could influence confidence in the EU through channels other than the activation of the EUSF. Although the exclusion restriction cannot be tested directly, several features of the research design make this concern less compelling. First, an important feature of our design is the use of relative confidence in the EU as the main outcome. Since this measure nets out confidence in national institutions, the exclusion restriction does not require disasters to have no effect on generalized trust in public institutions. Put differently, the identifying assumption is not that disasters leave institutional attitudes unaffected, but that they do not alter attitudes toward the EU differently from attitudes toward national institutions except through EUSF exposure. This is a weaker and more plausible condition, especially once we condition on region–year and cohort fixed effects. Second, the rich set of fixed effects and control variables included in Equation 2, which are consistent with the literature based on the impressionable years hypothesis, helps absorb several potential channels through which disasters may directly affect political attitudes.[11] Third, in a set of falsification

[11]In some robustness exercises, we further enrich the set of controls, providing additional support for this point.

tests, we document that in the absence of the EUSF, experiencing a disaster between ages 18 and 25 does not affect future confidence in the EU (Table 6). Taken together, the structure of the empirical design and the evidence from placebo exercises are consistent with the interpretation that the estimated effects primarily reflect exposure to EUSF interventions rather than disaster occurrence per se.

A remaining concern with the exogeneity of $Disaster_{icr}$ is that individuals may be aware that certain regions are more prone to disasters and could self-select into (or out of) these regions based on risk aversion or other characteristics correlated with both the key regressor and the outcome. Although it is well known that some regions are indeed more exposed to natural hazards, this source of bias is controlled for by the inclusion of region fixed effects. By contrast, the timing of a disaster – determining which cohorts are affected and which are not – is inherently unpredictable.

6 Results

6.1 Main results

We begin by examining whether exposure to EU disaster assistance during early adulthood shapes subsequent confidence in the EU. Table 4 presents our baseline results. Column 1 reports the OLS estimate of the effect of EUSF intervention on relative confidence in the EU. The estimated coefficient is small and statistically indistinguishable from zero. Column 2 reports the TSLS estimate based on Equations 1 and 2. Consistent with the institutional design of the Fund, disaster occurrence strongly predicts exposure to EUSF assistance. Once we account for the non-random allocation of EUSF interventions, a sizable and statistically significant relationship emerges between exposure to EU disaster assistance and subsequent confidence in the EU, consistent with the expected direction of bias discussed in Section 5. We estimate a sizable and statistically significant increase in trust in the EU associated with early-adulthood exposure to EUSF assistance, amounting to nearly one-third of a standard deviation of the outcome variable. The magnitude of the estimated effect is notable given the relatively limited fiscal scale of the intervention: over the 2002–2018 period, average annual EUSF disbursements amounted to only

0.002% of EU GDP in 2018. Table 4 also reports the reduced-form estimates (Column 3), which we later use in robustness and falsification exercises. Consistent with the TSLS estimates, the reduced-form specification indicates that disasters occurring during the impressionable years increase subsequent confidence in the EU in contexts where they trigger EUSF interventions. These findings suggest that tangible forms of supranational assistance can generate durable political support for supranational institutions.

In Table 5, Column 1 reproduces our baseline specification, while Columns 2 and 3 re-estimate the model using, respectively, absolute confidence in the EU and absolute confidence in national institutions as dependent variables. Both the TSLS and reduced-form estimates indicate that, importantly, the effect operates through higher confidence in the EU itself rather than through lower trust in national institutions. This exercise also speaks to the main identification concern. If disasters primarily affected generalized institutional trust, we would expect changes in confidence in national institutions as well. Instead, the estimated effect is driven by higher confidence in the EU, while confidence in national institutions is essentially unaffected.

In the remainder of the paper, we therefore focus on the relative measure, which isolates attitudes toward supranational institutions from broader fluctuations in generalized institutional trust.

6.2 Robustness checks.

Placebo exercises. We start by corroborating our findings through a series of falsification exercises. These provide indirect evidence supporting the identifying assumption that, absent EUSF intervention, natural disasters do not affect confidence in the EU or other supranational institutions, providing support for the exclusion restriction underlying our IV strategy.

First, we find no evidence that natural disasters affected confidence in the EU *before* the introduction of the EUSF. In Table 6, Panel B, Column 1, we re-estimate the reduced-form specification using individuals born in 1976 or earlier – the last cohort whose impressionable years occurred entirely prior to the establishment of the EUSF – and find no significant effect. However, because disaster reporting quality before 2000 was substantially poorer (see Figure 6), the statistical power of this exercise may be limited. To address this concern, Column 2 instead focuses on the post-EUSF period while restricting the sample to individuals living in European countries that were *not eligible* for EUSF support – namely, countries that were neither EU Member States nor accession countries (see Table 1). Even in this case, we again find no evidence that disasters affect confidence in the EU. Both exercises provide no evidence of an effect of disasters on confidence in the EU in settings in which EUSF assistance is absent, providing further support for the exclusion restriction.

In the remaining columns, we replace the dependent variable and show that neither EUSF interventions (Panel A) nor disasters (Panel B) affect trust in two other major supranational organizations: the United Nations (UN) (Column 3) and the North Atlantic Treaty Organization (NATO) (Column 4). This pattern suggests that the estimated effects are specific to attitudes toward the EU rather than to supranational institutions more generally.[12]

Alternative empirical specifications. We next assess the robustness of the baseline estimates to alternative specifications and fixed-effects structures commonly used in the impressionable years literature, where no canonical empirical specification has emerged. In Table 7, Panel A, Column 1 augments the baseline specification with region-specific age trends. Column 2 replaces cohort fixed effects with age fixed effects and includes region-specific cohort trends. In Column 3, we further control for additional individual characteristics measured at the time of the interview, namely education, employment status, marital status, and migration background.[13] Across specifications, the estimated effects remain broadly stable in magnitude and statistical significance, with the exception of Column 2, where the coefficient is somewhat larger, although qualitatively similar to the baseline result. Panel B presents the corresponding reduced-form estimates. Overall, the results suggest that the estimated relationship between EUSF exposure and trust in the EU is not driven by a specific choice of controls or fixed-effects structure.

[12]Consistent with the construction of our main outcome variable, these falsification outcomes are defined relative to confidence in national institutions.

[13]In Column 2, cohort and age fixed effects cannot be included simultaneously because of perfect collinearity induced by the inclusion of time fixed effects. Additional controls in Column 3 are excluded from the baseline specification because they may themselves be affected by treatment (Angrist and Pischke, 2009).

Migration and measurement error. We now examine whether our estimates are sensitive to biases arising from migration and geographic aggregation. A first concern is that disaster and intervention exposure are assigned based on respondents' current NUTS2 region of residence rather than on their region of residence during the impressionable years. This could threaten the exogeneity of the instrument if the resulting measurement error is correlated with the true value of $Disaster_{icr}$. Such a correlation could arise if disasters induce both in- and out-migration.

To address this concern, we adopt a different empirical framework: the Local Projections Difference-in-Differences (LP-DiD) model proposed by Dube et al. (2025), which has recently emerged as a framework particularly well suited to studying dynamic effects in settings with multiple non-absorbing treatments such as natural disasters (Usman et al., 2025; Nguyen et al., 2025; Roth Tran and Wilson, 2024; Eickmeier et al., 2024). The analysis combines net migration data from the ARDECO database with information on natural disasters from GDIS. The resulting NUTS2-year panel spans the period 1990–2018. Intuitively, we compare the evolution of the net migration rate – defined as net migration divided by the population – in regions affected by a disaster with that in unaffected regions. Additional technical details on the LP-DiD framework and the construction of clean control groups are provided in Appendix A. Figure 8 shows that, in our sample, disasters do not affect migration, providing strong reassurance that disaster-induced spatial sorting is unlikely to threaten the exogeneity of our instrument. This finding is also consistent with the mixed evidence in the existing literature on the effects of natural disasters on migration.[14]

A second concern is that assigning disaster and intervention exposure based on respondents' region of residence at the time of the interview may generate classical measurement error even if migration itself is unrelated to disaster occurrence. To assess the sensitivity of our estimates to this issue, we re-estimate the regressions assigning greater weight to individuals and regions for which treatment misclassification is likely to be less severe. In Table 7, Column 4, we assign greater weight to respondents interviewed in regions with higher historical net out-migration rates, under the assumption that individuals currently residing in such regions are more likely to have spent their impressionable years there. In Column 5, we assign greater weight to respon-

[14]For example, Boustan et al. (2020) find that natural disasters increase *outmigration*, whereas Henkel et al. (2022) document an increase in *immigration* driven by individuals seeking to benefit from post-disaster interventions.

dents whose age at the time of the interview is closer to the end of the impressionable-years window (age 25), since treatment misclassification is less likely when less time has elapsed since exposure. In both cases, we obtain modestly larger TSLS and reduced-form estimates, consistent with attenuation bias in the baseline results.

A final concern arises from assigning disasters to NUTS2 regions whenever disaster polygons overlap multiple regions. To assess the importance of this source of geographic aggregation, we re-estimate the regressions assigning greater weight to smaller regions, where geographic misclassification is likely to be less severe. This geographic reweighting exercise leaves the estimates essentially unchanged (Column 6), while the corresponding reduced-form estimates point to the same conclusion.[15]

Supporting the impressionable years assumption. Finally, We assess whether the estimated effects are specific to exposure during the impressionable years of early adulthood. The first three columns of Table 8, Panel A, show that EUSF interventions experienced at stages of life other than ages 18–25 do not significantly affect confidence in the EU later in life. The estimated effect is statistically indistinguishable from zero when the impressionable period is alternatively defined as ages 10–17 (Column 1, where the first stage is absent), 26–33 (Column 2), or 34–41 (Column 3). These findings suggest that the malleability of political attitudes declines both before and after early adulthood. In these exercises, individuals exposed between ages 18 and 25 are excluded from the estimation sample. We also show that the results are not sensitive to modest changes in the definition of the impressionable years window. The TSLS estimates remain quantitatively similar when the age window is slightly shifted to 17–24 (Column 4) or 19–26 (Column 5). Panel B replicates the same exercises using the reduced-form specification and yields results broadly consistent with the TSLS evidence.[16] Overall, these findings suggest that the estimated effects are tightly linked to exposure during the impressionable years rather than to exposure at other stages of the life cycle.

[15] Technical details on the weighting schemes are reported in Appendix B.

[16] Analogously to our main estimation sample, each regression is restricted to individuals whose impressionable years potentially overlap with the period in which the EUSF was in place. Accordingly, Columns 1–5 include cohorts born in 1992 or later, 1976 or later, 1968 or later, 1985 or later, and 1983 or later, respectively.

7 Transmission channels

We now investigate the mechanisms through which supranational assistance may shape political trust. We focus on two complementary channels: institutional substitution and insurance against adverse shocks. We then provide supporting evidence on the macroeconomic consequences of EUSF interventions.

7.1 Institutional substitution?

One possible mechanism is that EUSF interventions are perceived as more effective or more reliable than locally managed post-disaster support.[17] Under this interpretation, the effect of EUSF assistance should be stronger in regions characterized by weaker local institutional capacity. To test this implication, Columns 1 and 2 of Table 9 estimate our baseline models separately for respondents living in regions with above- and below-median government quality, as measured by the EQI. The 2SLS estimates indicate a positive effect for individuals residing in regions with lower-quality institutions, whereas inference for high-quality regions is limited by a weak first stage. The reduced-form estimates point in the same direction, suggesting that the effect is stronger where local institutional quality is lower. Taken together, these findings are consistent with the view that EUSF interventions can partly compensate for weaker local institutional capacity in the aftermath of natural disasters.

7.2 Insurance mechanism?

Next, we test whether citizens perceive the Fund as a form of insurance against adverse shocks. Under this interpretation, the impact of EUSF interventions should be stronger among more risk-averse individuals.

Because the IVS does not include a standard measure of risk attitudes, we predict an individual-level indicator of risk aversion using auxiliary regressions estimated on data from SHARE,

[17] As discussed in Section 3, EUSF resources are generally disbursed within two years after a disaster, whereas anecdotal evidence suggests that nationally managed reconstruction processes often take substantially longer.

which contains a widely used measure of willingness to take financial risks. The imputation procedure and its validation are described in Appendix C. We then re-estimate our baseline model on two subsamples, distinguishing between treated individuals classified as risk averse and those classified as non-risk-averse.[18]

Both the TSLS and reduced-form estimates, reported in Columns 3 and 4 of Table 9, indicate a substantially larger effect among respondents classified as risk averse.[19]

These findings are consistent with the interpretation that citizens perceive the EU as providing insurance and interregional risk sharing in the aftermath of adverse shocks.

7.3 Economic downturn mitigation?

Finally, we examine whether the EUSF helps shield local economies from the adverse macroeconomic consequences of natural disasters. To address this question, we resort again to the LP-DiD approach (Dube et al., 2025). We merge ARDECO data with GDIS information to obtain a NUTS2-year panel over the 1980–2018 period that includes key macroeconomic variables – such as GDP and disposable income – together with indicators of disaster occurrence. The empirical analysis compares the path of GDP and disposable income in regions hit by a disaster relative to unaffected areas, distinguishing between disasters without or with EUSF intervention. Additional technical details on the LP-DiD framework and the construction of clean control groups are reported in Appendix A.

Figure 9 reports the estimated effects for GDP (Panel A) and disposable income (Panel B). Shaded areas represent 95% confidence intervals. Turning first to GDP, we observe no meaningful differences between the two treatment regimes in the year of the disaster. Over time, the trajectories of regions receiving EUSF assistance diverge from those of regions affected by

[18] By construction, the imputed risk-aversion indicator is defined only for individuals exposed to a disaster during their impressionable years (i.e., treated individuals). We therefore split the treated sample according to predicted risk aversion while using the same group of untreated individuals – namely, respondents not exposed to disasters during their impressionable years – as the control group in both regressions.

[19] We cannot impute risk aversion for Ireland and the UK because they are not covered by SHARE. Replicating our baseline analysis after excluding these two countries yields a 2SLS coefficient of 0.248 (0.088) and a reduced-form estimate of 0.072 (0.026), both statistically significant at the 1% level. These estimates are very similar to the baseline results reported in Table 4.

disasters without EU support, suggesting greater economic resilience in the presence of EUSF interventions.[20]

A similar pattern emerges when considering disposable income, with regions receiving EUSF assistance displaying stronger economic recovery following natural disasters. Overall, the LP-DiD estimates are consistent with the idea that EUSF interventions mitigate the adverse effects of natural disasters on local economic activity. These patterns may help explain the positive relationship between EUSF exposure and trust in the EU documented above, in line with the broader literature emphasizing the role of public-sector performance in shaping institutional trust (Besley et al., 2026).

A final consideration concerns timing. The divergence between the two trajectories is broadly consistent with the institutional timing of EUSF disbursements, which typically occur within two years of the disaster, as well as with the structure of our individual-level sample, in which respondents are generally surveyed several years after exposure to EUSF interventions (Figure 5). Taken together, these patterns are consistent with the idea that improved local economic resilience may contribute to the positive relationship between EUSF exposure and trust in the EU documented above.

8 Conclusions

The European Union is one of the most ambitious experiments in supranational governance in the world, created to address challenges that individual member states cannot effectively manage on their own. Yet the Union currently faces a tension between growing demand for supranational coordination (Draghi, 2024; Letta, 2024) and weakening public trust. This tension raises concerns about whether the EU can sustain the public trust needed to support deeper supranational integration.

In this paper, we show that EU assistance following natural disasters helps strengthen citizens' confidence in the EU. The evidence is consistent with two complementary mechanisms. First,

[20]These findings are broadly consistent with Usman et al. (2025), who document adverse effects of disasters on GDP, and with Henkel et al. (2022), who find that post-disaster aid exerts positive countercyclical effects.

supranational assistance appears to be particularly valuable where local institutional capacity is weaker, suggesting a substitution role for EU intervention. Second, the effects are stronger among more risk-averse individuals, consistent with citizens valuing the insurance dimension of supranational assistance. We also provide supporting evidence consistent with the idea that EUSF interventions improve local economic resilience following natural disasters. More generally, our findings suggest that political support for the EU may depend not only on ideology or attitudes toward integration, but also on whether the EU delivers effective policies that citizens can plausibly associate with the EU. Our findings therefore suggest that effective policy delivery can generate political as well as economic returns.

While our empirical setting is the EU, the broader question we address extends beyond it. As cross-border externalities become increasingly important, countries may increasingly create supranational institutional arrangements to address specific cross-border challenges. In such settings, understanding how such institutions build citizens' trust may become an increasingly important research and policy question.

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Tables and Figures

Tables

Table 1: List of EUSF eligible and non-eligible countries

Eligible countries		Non-eligible countries
Austria	Latvia	Albania
Belgium	Lithuania	Belarus
Bulgaria	Luxembourg	Bosnia and Herzegovina
Croatia	Malta	Iceland
Czech Republic	Netherlands	Macedonia
Denmark	Poland	Norway
Estonia	Portugal	Switzerland
Finland	Romania	
France	Slovakia	
Germany	Slovenia	
Greece	Spain	
Hungary	Sweden	
Ireland	United Kingdom	
Italy		

Note: The Table displays the full list of EUSF eligible and non-eligible European countries used in the empirical analysis. Eligible countries are EU member states or official accession candidates. Most of the analysis focuses on eligible countries, which are often referred to simply as "EU members" throughout the paper. Non-eligible countries are included in falsification tests.

Table 2: Summary statistics

	Panel A: Individual level statistics – estimation sample					
Variable	Obs.	Mean	Sd.	Min	Max	Source
Relative confidence in EU	14,817	0.396	0.855	-3	3	IVS
Absolute confidence in EU	14,936	1.50	0.824	0	3	IVS
Confidence in national insts.	15,513	1.10	0.753	0	3	IVS
Impressionable at disaster	29,072	0.368	0.482	0	1	IVS-EMDAT
Impressionable at intervention	29,072	0.126	0.332	0	1	IVS-EU
Gender	15,878	0.535	0.499	0	1	IVS
Unemployed	15,393	0.088	0.284	0	1	IVS
Marital status (in couple)	15,642	0.228	0.420	0	1	IVS
Years of schooling	13,887	14.75	3.94	0	22	IVS
Migrant	29,072	0.036	0.186	0	1	IVS
Age	14,548	23.679	4.420	15	34	IVS
	Panel B: Region–year level statistics					
Variable	Obs.	Mean	Sd.	Min	Max	Source
Disaster dummy	4,097	0.361	0.480	0	1	EMDAT
Total deaths	1,181	691.48	2,891.58	1	20,090	EMDAT
Total damage (thousand US$)	520	2,022,557	3,354,350	81	22,200,000	EMDAT
EUSF intervention dummy	1,478	0.099	0.299	0	1	EUSF
EUSF aid (million euros)	147	36.71	103.17	0.24	762.45	EUSF
Relief (aid/damage)	147	0.0323	0.0096	0.0031	0.0561	EUSF
GDP (2015 euros)	4,097	57,859.10	84,077.07	1,540.40	714,880.10	ARDECO
Net disposable income (2015 euros)	3,468	32,243.53	46,914.16	973.08	372,817.20	ARDECO

Note: The Table reports summary statistics at the individual level (Panel A) and the regional level (Panel B). Panel A refers to our main estimation sample, consisting of individuals in EU member countries whose impressionable years occurred after the introduction of the EUSF (i.e., cohorts born after 1983). Panel B presents statistics for regions in EU member countries over the period 2002–2018 (i.e., following the establishment of the EUSF). Summary statistics for the disaster dummy, GDP, and net disposable income refer to the full sample of EU regions during this period. Statistics for total deaths, economic damage, and the EUSF intervention dummy refer to the subsample of region–years affected by disasters. Lastly, statistics for EUSF aid and relief refer to the subsample of region–years that received an EUSF intervention.

Table 3: Disasters and EUSF interventions

	EUSF intervention						
Disaster	0.099***	0.104***	0.109***	0.115***			
	(0.009)	(0.009)	(0.009)	(0.010)			
Gov. quality					-0.024**		
					(0.010)		
GDP p. c.						-0.035***	
						(0.012)	
Other EU funds							0.008
							(0.008)
N	4,097	4,097	4,097	4,097	1,200	1,478	1,201
region fe		✓		✓			
year fe			✓	✓	✓	✓	✓
sample	all	all	all	all	Disaster	Disaster	Disaster

Note: The Table reports estimated coefficients for explanatory variables of interventions from a model run on a region–year of disaster panel (2002-2018). The dependent variable is a dummy indicating whether an EUSF intervention occurred in a given region–year. Columns 1–4 include all region–year observations and use as the main regressor a dummy for the occurrence of a disaster in the same region–year. Columns 5-7 restrict the sample to region–years with at least one disaster and use, as regressor, the EQI indicator of regional government quality (Column 5; for years 2002-2009, EQI is set to its 2010 value; for years 2011, 2012, 2014, 2015, 2016, 2018 EQI is imputed using interpolation), the log of regional GDP per capita at constant prices (Column 6), and the average amount of other European funds received by the region in the three preceding the disaster year (Column 7). Standard errors in parentheses clustered at regional level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: Effect of exposure to disaster or EUSF intervention in impressionable years on confidence in EU

	Relative confidence in EU		
	OLS	TSLS	RF
EUSF	-0.003	0.249***	
	(0.025)	(0.088)	
Disaster			0.071***
			(0.026)
First stage		0.286***	
		(0.068)	
F-test		17.48	
gender	✓	✓	✓
region–year fe	✓	✓	✓
cohort fe	✓	✓	✓
survey fe	✓	✓	✓
Stndrd. Coeff.	-0.002	0.294	0.088
N	13,642	13,642	13,642

Note: The Table reports estimated coefficients from our main regression model corresponding to equations 1 and 2. The dependent variable is relative confidence in the EU, computed as the difference between absolute confidence in the EU and average confidence in national institutions (i.e., parliament and government). Column 1 presents estimates from the baseline OLS specification, where the key explanatory variable is a dummy indicating exposure to an EUSF intervention during the impressionable years (ages 18–25). Column 2 reports the structural equation from the two-stage least squares (TSLS) model, in which exposure to EUSF intervention is instrumented using a dummy for exposure to a natural disaster during the same impressionable age window. The corresponding first-stage coefficient and F-statistic are reported in the panel below. Column 3 shows the reduced-form estimate, regressing relative confidence in the EU directly on the disaster exposure dummy. All regressions include gender, region–year, cohort, and survey (EVS or WVS) fixed effects. Standard errors in parentheses clustered at regional level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: Effect of exposure during impressionable years on institutional confidence

	Relative confidence in EU	Absolute confidence in EU	Absolute confidence in national institutions
Panel A: IV estimates			
EUSF	0.249***	0.213**	-0.036
	(0.088)	(0.103)	(0.085)
Stndrd. Coeff.	0.294	0.260	-0.048
F-test	17.48	17.48	17.48
N	13,642	13,642	13,642
Panel B: Reduced-form estimates			
Disaster	0.071***	0.061**	-0.010
	(0.026)	(0.024)	(0.026)
Stndrd. Coeff.	0.088	0.075	-0.014
N	13,642	13,642	13,642
gender	✓	✓	✓
region–year fe	✓	✓	✓
cohort fe	✓	✓	✓
survey fe	✓	✓	✓

Note: The Table reports estimated coefficients from TSLS second-stage regressions (Panel A) and OLS reduced-form regressions (Panel B). In Panel A, the key explanatory variable is a dummy indicating exposure to an EUSF intervention during the impressionable years (ages 18–25), instrumented with a dummy for exposure to a natural disaster during the same age window. In Panel B, the disaster exposure dummy is used directly as the regressor. In Column 1, the dependent variable is relative confidence in the EU, computed as the difference between absolute confidence in the EU and average confidence in national institutions. In Column 2, the dependent variable is absolute confidence in the EU, while in Column 3 it is average confidence in national institutions (i.e., parliament and government). All regressions include gender, region–year, cohort, and survey (EVS or WVS) fixed effects. Standard errors in parentheses clustered at regional level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 6: Placebo tests

	Relative conf. in EU		Relative conf. in UN	Relative conf. in NATO
	EU-members	non-EU-members	EU-members	EU-members
	pre	post	post	post
Panel A: IV estimates				
EUSF			0.156	0.168
			(0.096)	(0.150)
F-test			17.13	6.56
N			13,084	4,632
Panel B: Reduced-form estimates				
Disaster	-0.016	0.031	0.044	0.046
	(0.010)	(0.053)	(0.027)	(0.048)
N	91,823	3,399	13,084	4,632
gender	✓	✓	✓	✓
region–year fe	✓	✓	✓	✓
cohort fe	✓	✓	✓	✓
survey fe	✓	✓	✓	✓

Note: The Table reports estimated coefficients from TSLS second-stage regressions (Panel A) and OLS reduced-form regressions (Panel B). In Panel A, the key explanatory variable is a dummy indicating exposure to an EUSF intervention during the impressionable years (ages 18–25), instrumented with a dummy for exposure to a natural disaster during the same age window. In Panel B, the disaster exposure dummy is used directly as the regressor. In Column 1, the dependent variable is relative confidence in the EU, computed as the difference between absolute confidence in the EU – the dependent variable in Column 2 – and average confidence in national institutions (i.e., parliament and government) – dependent variable in Column 3. Column 1 refers to individuals in EU member countries whose impressionable years occurred before the introduction of the EUSF (i.e., cohorts born before 1977). Column 2 includes individuals in non-member countries whose impressionable years occurred after the EUSF was established (cohorts born after 1983). Finally, Columns 3 and 4 refer to individuals in member countries with impressionable years occurring after the introduction of the EUSF. All regressions include gender, region–year, cohort, and survey (EVS or WVS) fixed effects. Standard errors in parentheses clustered at regional level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 7: Robustness checks: specification and measurement error

	Relative confidence in EU					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV estimates						
EUSF	0.287**	0.420**	0.244***	0.263***	0.267***	0.255***
	(0.129)	(0.194)	(0.093)	(0.074)	(0.089)	(0.094)
F-test	14.50	8.97	16.55	22.06	17.32	16.67
N	13,642	13,642	11,660	13,627	13,591	13,547
Panel B: Reduced-form estimates						
Disaster	0.065**	0.089***	0.070**	0.093***	0.077***	0.069***
	(0.026)	(0.030)	(0.028)	(0.026)	(0.026)	(0.027)
N	13,642	13,642	11,660	13,627	13,591	13,547
gender	✓	✓	✓	✓	✓	✓
region–year fe	✓	✓	✓	✓	✓	✓
cohort fe	✓		✓	✓	✓	✓
survey fe	✓	✓	✓	✓	✓	✓
region-specific age trends	✓					
age fe		✓				
region-specific cohort trends		✓				
individual controls			✓			
weight: migration rates				✓		
weight: inverse dist. impr. ages					✓	
weight: inverse land area						✓

Note: The Table reports estimated coefficients from TSLS second-stage regressions (Panel A) and OLS reduced-form regressions (Panel B). In Panel A, the key explanatory variable is a dummy indicating exposure to an EUSF intervention during the impressionable years (ages 18–25), instrumented with a dummy for exposure to a natural disaster during the same age window. In Panel B, the disaster exposure dummy is used directly as the regressor. The dependent variable is relative confidence in the EU, computed as the difference between absolute confidence in the EU and average confidence in national institutions (i.e., parliament and government). All regressions include gender, region–year, cohort and survey (EVS or WVS) fixed effects. Column 1 includes region-specific age trends. Column 2 replaces cohort fixed effects with age fixed effects and adds region-specific cohort trends. Column 3 adds individual-level controls: dummies for marital status, unemployment, and migrant status, as well as a continuous variable for years of schooling. Columns 4 to 6 present weighted regressions. Specifically, weights correspond to regional net out-migration rates (Column 4), the inverse of the individual's distance—in years—from the impressionable age window (Column 5), and the inverse of regional land area (Column 6). Standard errors in parentheses clustered at regional level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 8: Robustness: alternative impressionable age definitions

	Relative confidence in EU				
Impressionable ages:	10–17	26–33	34–41	17–24	19–26
Panel A: IV estimates					
EUSF	3.785	0.126	-0.025	0.191**	0.147*
	(4.922)	(0.106)	(0.066)	(0.087)	(0.083)
F-test	0.90	20.92	41.85	12.69	8.77
N	1,373	15,374	35,935	12,324	14,995
Panel B: Reduced-form estimates					
Disaster	-0.153	0.036	-0.007	0.060**	0.042*
	(0.142)	(0.029)	(0.019)	(0.027)	(0.023)
N	1,373	15,374	35,935	12,324	14,995
gender	✓	✓	✓	✓	✓
region–year fe	✓	✓	✓	✓	✓
cohort fe	✓	✓	✓	✓	✓
survey fe	✓	✓	✓	✓	✓

Note: The Table reports estimated coefficients from TSLS second-stage regressions (Panel A) and OLS reduced-form regressions (Panel B). In Panel A, the key explanatory variable is a dummy indicating exposure to an EUSF intervention in a different age-at-exposure bin, instrumented with a dummy for exposure to a natural disaster during the same age window. In Panel B, the disaster exposure dummy is used directly as the regressor. The regression samples include all individuals whose impressionable period occurs after the introduction of the EUSF. In the first three columns individuals aged 18-25 at the time of disasters are excluded from the estimation sample. Columns 1–5 include cohorts born in 1992 or later, 1976 or later, 1968 or later, 1985 or later, and 1983 or later, respectively. The dependent variable is relative confidence in the EU, computed as the difference between absolute confidence in the EU and average confidence in national institutions (i.e., parliament and government). All regressions include gender, region–year, cohort and survey (EVS or WVS) fixed effects. Standard errors in parentheses clustered at regional level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

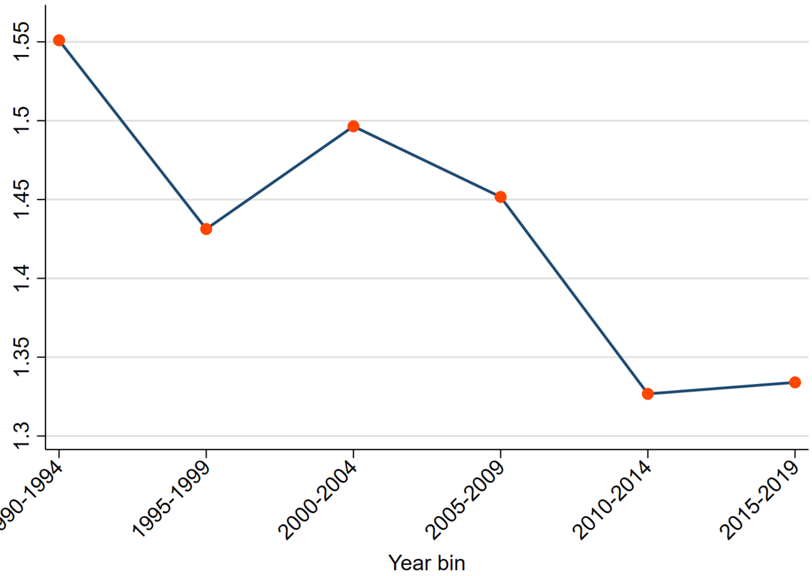
Table 9: Transmission channels: government quality and risk aversion

	Relative confidence in EU			
	Regional government quality		Individual risk aversion	
	High	Low	High	Low
Panel A: IV estimates				
EUSF	0.415	0.217***	0.353**	0.173
	(0.450)	(0.071)	(0.140)	(0.112)
F-test	2.38	29.94	17.21	12.14
N	5,318	7,876	8,608	8,191
Panel B: Reduced-form estimates				
Disaster	0.040	0.096***	0.116***	0.045
	(0.040)	(0.031)	(0.038)	(0.032)
N	5,318	7,876	8,608	8,191
gender	✓	✓	✓	✓
region–year fe	✓	✓	✓	✓
cohort fe	✓	✓	✓	✓
survey fe	✓	✓	✓	✓

Note: The Table reports estimated coefficients from TSLS second-stage regressions (Panel A) and OLS reduced-form regressions (Panel B). The dependent variable is relative confidence in the EU, computed as the difference between absolute confidence in the EU and average confidence in national institutions (i.e., parliament and government). In Panel A, the key explanatory variable is a dummy indicating exposure to an EUSF intervention during the impressionable years (ages 18–25), instrumented with a dummy for exposure to a natural disaster during the same age window. In Panel B, the disaster exposure dummy is used directly as the regressor. Columns 1 and 2 split the sample based on whether a region's institutional quality is above or below the median, respectively. Columns 3 and 4 split the sample based on whether individual risk aversion is above or below the median. All regressions include gender, region–year, cohort, and survey (EVS or WVS) fixed effects. Standard errors in parentheses clustered at regional level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figures

Figure 1: Absolute confidence in EU over time



Note: The Figure shows the evolution of absolute confidence in the European Union sourced from the IVS database, computed as a weighted average within 5-year bins using IVS survey weights.

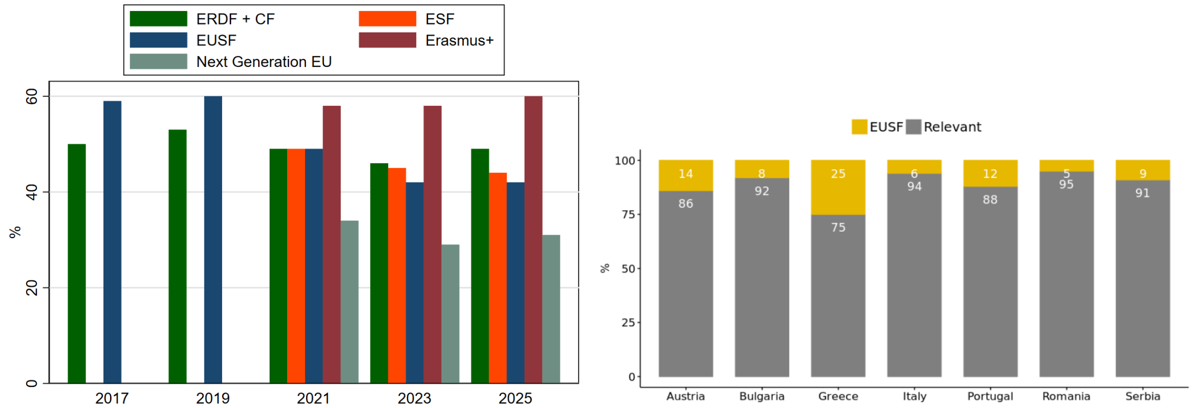
Figure 2: Spreading information about the EUSF

Note: The Figure shows a tweet posted by Ursula von der Leyen, President of the European Commission, on 27 August 2024, to share information about one of the EUSF interventions.

Figure 3: EUSF visibility

Panel A: Citizens' awareness

Panel B: EUSF media visibility

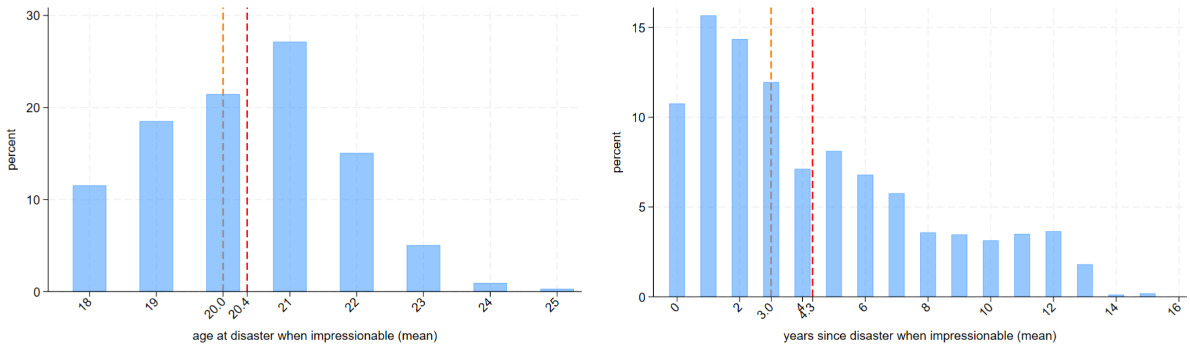


Note: In Panel A, citizens's awareness is measured as the percentage of citizens who have heard of a particular fund. ERDF + CF refers to having heard at least one fund between ERDF and CF; source: "Flash Eurobarometer: Citizens' awareness and perceptions of EU regional policy", various years. Panel B reports the prevalence of EUSF articles as proportion of relevant articles related to natural disasters; source Bachtler et al. (2018).

Figure 4: Mean age at and years since disaster during impressionable years

Panel A: Age at impr. disaster

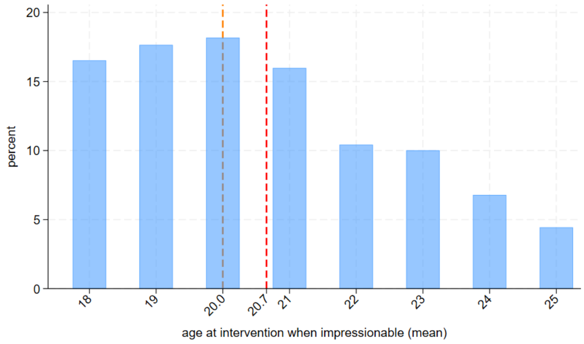
Panel B: Years since impr. disaster



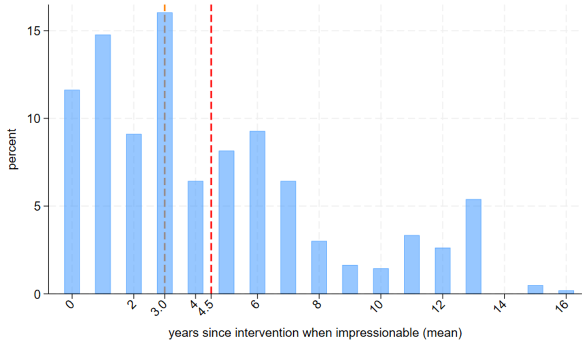
Note: The Figure reports, in the Panel A, the distribution of the mean age at disaster during impressionable years; when respondents experience multiple disasters, we compute the average exposure age and round it to the nearest integer; Panel B shows the distribution of the average number of years since disaster(s) occurred during impressionable years. The sample includes individuals in EU member states born after 1983; that is, those whose impressionable years took place after the introduction of the EUSF. The normal (bold) dashed vertical line represents the median (mean).

Figure 5: Mean age at and years since intervention during impressionable years

Panel A: Age at impr. intervention



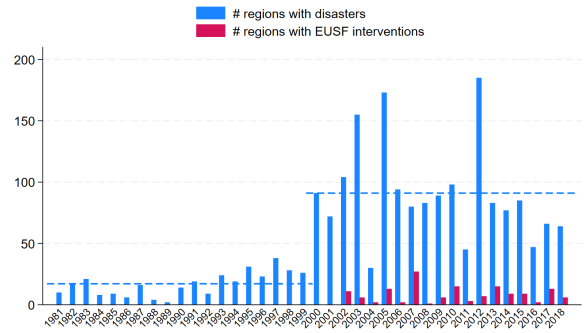
Panel B: Years since impr. intervention



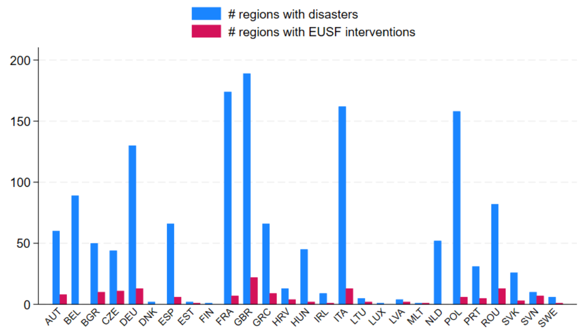
Note: The Figure reports, in the Panel A, the distribution of the mean age at EUSF intervention during impressionable years; when respondents experience multiple disasters, we compute the average exposure age and round it to the nearest integer; Panel B shows the distribution of the average number of years since intervention(s) occurred during impressionable years. The sample includes individuals in EU member states born after 1983; that is, those whose impressionable years took place after the introduction of the EUSF. The normal (bold) dashed vertical line represents the median (mean).

Figure 6: Regions with disasters and intervention

Panel A: Over time



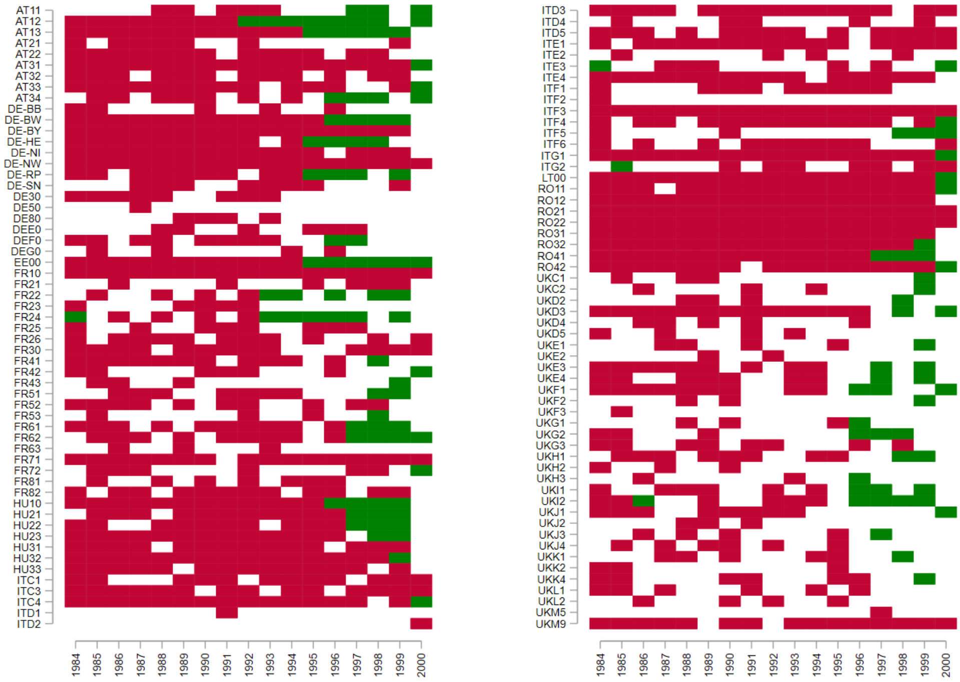
Panel B: Across EU-member states



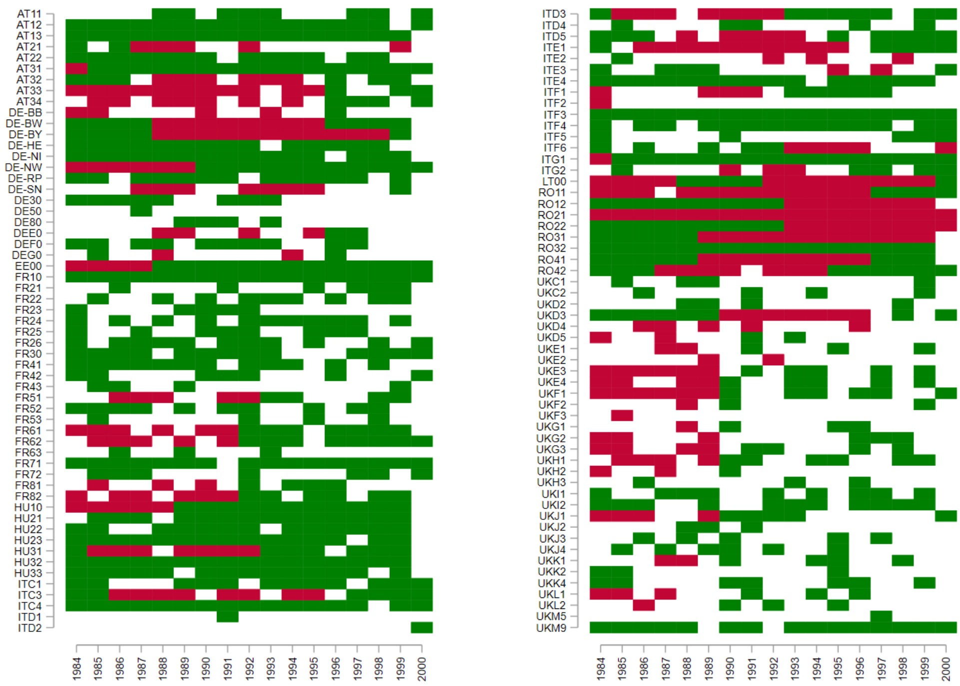
Note: The Figure displays the number of regions experiencing disasters (in blue) and EUSF interventions (in red), over time (Panel A) and across EU member states (Panel B). Panel A covers regions in EU member states from 1981 to 2018, while Panel B refers to the period 2002–2018, corresponding to the years in which the EUSF was active.

Figure 7: Cohort and regional variation in disaster and EUSF exposure — 2018 wave

Panel A: Disasters

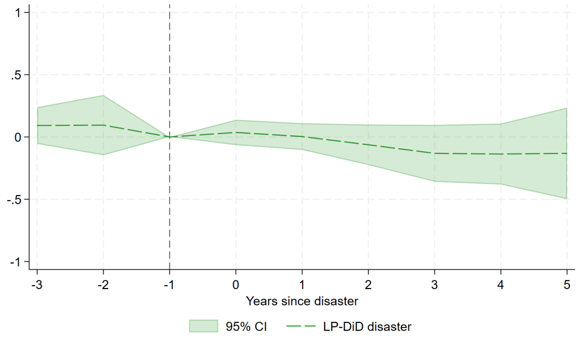


Panel B: Interventions



Note: The Figure shows, for each region in the sample (vertical axis), the birth cohorts (horizontal axis) that were exposed (in red) or not exposed (in green) to disasters (Panel A) or interventions (Panel B) during their impressionable years. The information refers to individuals interviewed in the 2018 wave of the IVS survey.

Figure 8: Effect of disaster on net migration rate

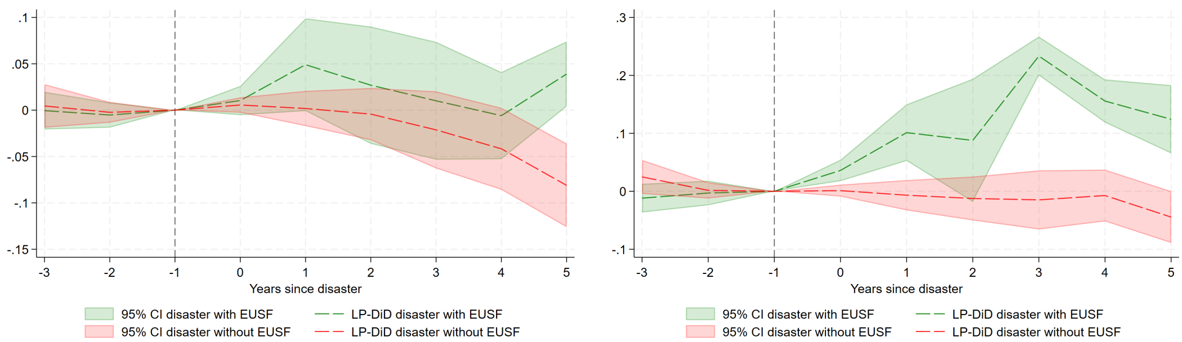


Note: The Figure presents event study plots showing the dynamic effects of disasters on net migration rate. The sample includes all regions in EU member states during the period 2002–2018, when the EUSF was in place. Event studies are estimated using the Local Projection Difference-in-Differences (LP-DiD) method proposed by Dube et al. (2025), which accounts for multiple treatment events (equation A1).

Figure 9: Effect of disaster with and without EUSF intervention

Panel A: GDP constant prices

Panel B: Net disposable income



Note: The Figure presents event study plots showing the dynamic effects of disasters on regional GDP (Panel A) and net disposable income (Panel B), both measured in constant 2015 euros. The analysis distinguishes between disasters that received EUSF intervention (green) and those that did not (red), which are simultaneously included in the regressions as separate treatments. The sample includes all regions in EU member states during the period 2002–2018, when the EUSF was in place. Event studies are estimated using the Local Projection Difference-in-Differences (LP-DiD) method proposed by Dube et al. (2025), which accounts for multiple treatment events. To ensure comparability across events, we impose a common support condition on the distribution of the deaths-to-population ratio between disasters with and without EUSF interventions. This ratio – calculated as disaster-related deaths divided by 2001 population – is also included as a control variable in the regressions (equation A2).

Appendix

A Details on the LP-DiD Framework

To examine whether the disasters affect migration and whether EUSF helps shield local economies from the adverse macroeconomic consequences of disasters, we adopt the Local Projections Difference-in-Differences (LP-DiD) approach proposed by Dube et al. (2025), which is particularly well suited to studying dynamic effects in settings with multiple non-absorbing treatments such as natural disasters (Usman et al., 2025; Nguyen et al., 2025; Roth Tran and Wilson, 2024; Eickmeier et al., 2024).The LP-DiD framework has increasingly served as a bridge between empirical macroeconomics and policy evaluation (Jordà and Taylor, 2025). It offers several desirable properties. First, it overcomes the well-known limitations of the two-way fixed-effects estimator in settings with staggered treatment timing and dynamic, heterogeneous treatment effects across cohorts. Second, it provides a transparent definition of treatment and control groups. Third, it is particularly well suited for multiple non-absorbing treatments – a common feature of natural disaster shocks. Finally, many estimators proposed in the "new" difference-in-differences literature can be interpreted as special cases of the LP-DiD framework (see Roth et al., 2023, and De Chaisemartin and d'Haultfoeuille, 2023, for recent surveys).

The analysis is conducted using ARDECO data merged with GDIS information (see Section 4). The resulting NUTS2-year panel spans the 1990–2018 period and includes net migration rate (net migration divided by the population), key macroeconomic variables – such as GDP and disposable income – together with indicators of disaster occurrence and related characteristics, including fatalities and estimated damages.

When examining the impact of disasters on migration, our LP-DiD specification is as follows:

$$y_{rt+h} - y_{rt-1} = \beta^h D_{rt} + \mu_t^h + \epsilon_{rt}^h, \tag{A1}$$

where y_{rt} denotes net migration rate in region r and year t; D_{rt} is an indicator variable for the occurrence of a disaster in region r and year t; μ_t^h control for horizon-specific time fixed effects; and $h = 0, 1, \ldots, 5$ denotes the time horizon (in years) following the treatment. The dependent variable is the change in the outcome from the pre-disaster period to horizon h, which can be interpreted as an approximation of the cumulative change. The coefficient of interest β^h captures the dynamic evolution of the outcome following disasters relative to unaffected regions. The model is estimated using years from 2002 onwards.

Our LP-DiD specification for examining the macroeconomic impact of disasters/interventions is slightly different and reads as follows:

$$y_{rt+h} - y_{rt-1} = \beta^h D_{rt} + \gamma^h I_{rt} + \delta^h Damage_{rt} + \mu_t^h + \epsilon_{rt}^h, \tag{A2}$$

where y_{rt} denotes GDP or disposable income, measured in logs and expressed in constant 2015 prices, in region r and year t; D_{rt} and I_{rt} are indicator variables for the occurrence of a disaster without and with EUSF intervention, respectively, in region r and year t; $Damage_{rt}$ is the deaths-to-population ratio that captures disaster intensity; μ_t^h control for horizon-specific time fixed effects; and $h = 0, 1, \ldots, 5$ denotes the time horizon (in years) following the two possible treatments – namely, a disaster with or without EUSF intervention. As above, the dependent variable is the change in the log outcome from the pre-disaster period to horizon h, which can be interpreted as an approximation of the cumulative percentage change. The coefficients of interest β^h and γ^h capture the dynamic evolution of outcomes following disasters with and without EUSF support relative to unaffected regions. To improve comparability across disasters with and without EUSF support, we impose a common-support condition based on disaster intensity.[21] Unlike the previous empirical exercise that focuses on a single treatment like most of the existing literature, our primary interest lies in estimating the *difference* between experiencing a disaster without EUSF support and experiencing the same disaster with EUSF assistance. The model is estimated using years from 2002 onwards.

In both equations A1 and A2, to establish clean treatment and control groups for estimation, we model treatments as non-absorbing and "one-off" events, and assume that their dynamic effects stabilize within three years. By "one-off" treatment, we refer to settings – such as natural disasters – in which treatment can reasonably be defined as lasting only one period (i.e., the year of the disaster), even though its effects may be dynamic and persistent over time. In both equations A1 and A2, the set of clean control regions is defined separately for each horizon. In equation A2, the set of clean control regions is common to both treatment types (disaster and disaster with intervention).

For post-treatment estimates, the control group includes regions that did not experience any disasters from three periods before the event up to h periods afterward. For pre-treatment estimates, the control group consists of regions without disasters during the $(3 + h)$ periods preceding the event. This sample-selection procedure excludes observations affected by repeated or overlapping extreme events that could otherwise contaminate the estimates.[22]

[21] For each disaster, we compute the deaths-to-population ratio as the number of disaster-related fatalities divided by the region's population in 2001. We then calculate the 10th and 90th percentiles of this ratio separately for disasters with and without EUSF intervention. A disaster satisfies the common-support condition if its ratio exceeds the maximum of the two 10th percentiles and falls below the minimum of the two 90th percentiles.

[22] For additional details on the specification of clean-control conditions in LP-DiD models with non-absorbing and one-off treatments, see https://github.com/danielegirardi/lpdid/blob/main/lpdid_oneoff_nonabs_example.do.

B Weighting schemes

This appendix provides additional details on the weighting schemes used in the robustness exercises discussed in Section 6. The first weighting scheme assigns greater weight to respondents interviewed in regions with higher historical net out-migration rates (Table 7, Column 4). Region-level weights are constructed as follows:

$$w_r = \frac{migr\,rate_r - min(migr\,rate)}{max(migr\,rate) - min(migr\,rate)}$$

where $migr\,rate_r$ denotes the average 1990–2018 ratio between net out-migration (outflows minus inflows) and the population in region r, while $max(migr\,rate)$ and $min(migr\,rate)$ denote the maximum and minimum migration rates across regions, respectively. The underlying intuition is that respondents currently residing in regions with persistent net out-migration are more likely to have spent their impressionable years in the same region, whereas respondents living in highly attractive regions are more likely to have migrated from elsewhere.

In the second weighting scheme (Table 7, Column 5) individual-level weights are defined as:

$$w_i = 1 - \frac{age - 25}{108 - 25}, \quad \text{with} \quad w_i = 1 \quad \text{if} \quad age \leq 25$$

where 108 corresponds to the maximum age observed in the sample. The intuition is that the more time has elapsed since age 25, the more likely it is that an individual experienced the relevant event in a region different from the current one.

Finally, in Table 7, Column 6, region-level weights are computed as:

$$w_r = 1 - \frac{surface_r - min(surface)}{max(surface) - min(surface)}$$

where $surface_r$ denotes the surface area of region r, while $max(surface)$ and $min(surface)$ denote the maximum and minimum regional surface areas in the sample. The underlying intuition is that the smaller the region, the less severe potential geographic aggregation error is likely to be.

C Predicting the individual-level indicator of risk aversion

This appendix describes the two-stage procedure used to predict an individual-level indicator of risk aversion.

First stage. We use data from the Survey of Health, Ageing and Retirement in Europe (SHARE), which contains self-reported information on financial risk attitudes for individuals aged 50 and above in several European countries. Specifically, we use waves 1 to 9 (2004–2022), which include the following widely used question on willingness to take financial risks (e.g., Banks et al., 2020): "When people invest their savings they can choose between assets that give low return with little risk to lose money, for instance a bank account or a safe bond, or assets with a high return but also a higher risk of losing, for instance stocks and shares. Which of the statements on the card comes closest to the amount of financial risk that you are willing to take when you save or make investments?" Possible responses are coded as follows: 1 = "Take substantial financial risks expecting to earn substantial returns"; 2 = "Take above average financial risks expecting to earn above average returns"; 3 = "Take average financial risks expecting to earn average returns"; and 4 = "Not willing to take any financial risks." We define a binary indicator of risk aversion equal to one for respondents choosing option 4 and zero otherwise. Under this definition, 76% of respondents are classified as risk averse.

To evaluate the predictive performance of the imputation procedure, we randomly split the SHARE sample into a training sample (approximately 75% of the observations, corresponding to more than 115,000 individuals) and a testing sample (the remaining 25%). Using the training sample, we estimate a linear probability model in which the risk-aversion indicator is regressed on age, age squared, a female dummy, and a constant. We use a linear probability model because the objective is prediction using a parsimonious and fully transparent specification. All regressors are interacted with country dummies, thereby allowing the relationship between demographics and risk aversion to vary flexibly across countries.

The estimated coefficients are then used to predict the probability of being risk averse in the testing sample. We classify an individual as risk averse whenever the predicted probability exceeds the sample mean of the dependent variable in the training sample. Using the sample sample rather than 0.5 accounts for the unbalanced distribution of the dependent variable. To ensure that the results are not driven by a particular random split of the data, we repeat the entire training–testing procedure 10 times.

Table A1 reports the country-specific average estimated coefficients across the 10 iterations. Women are systematically more likely to be classified as risk averse, while the relationship between age and risk aversion tend to follow an inverted U-shape.

Table A2 summarizes the predictive performance of the model across the ten iterations. On average, sensitivity (the proportion of true positives among true positives plus false negatives) equals 0.614, while specificity (the proportion of true negatives among true negatives and false positives) equals 0.694. Both measures display very limited variation across iterations, indicating that the imputation procedure is highly stable.

The model achieves moderate predictive accuracy. This is unsurprising given that we deliberately adopt a parsimonious and fully transparent prediction model based exclusively on demographic characteristics that are observed both in SHARE and in the IVS. More flexible prediction

Table A1: Risk aversion imputation coefficients, by country

Country	β_{male}	β_{female}	β_{age}	β_{age^2}
Austria	0.196	0.341	0.009	-0.002
Belgium	0.791	0.908	-0.009	0.011
Bulgaria	0.031	0.053	0.022	-0.014
Croatia	-0.027	0.079	0.014	-0.005
Czech Republic	0.083	0.189	0.010	-0.002
Denmark	-0.645	-0.455	0.018	-0.002
Estonia	-0.826	-0.771	0.044	-0.027
Finland	-0.025	0.152	0.006	0.002
France	0.420	0.506	0.000	0.005
Germany	0.395	0.544	0.001	0.004
Greece	0.442	0.557	0.005	-0.000
Hungary	0.605	0.685	-0.004	0.009
Italy	0.466	0.579	0.003	0.002
Latvia	-0.275	-0.196	0.029	-0.018
Lithuania	-0.677	-0.618	0.035	-0.020
Luxembourg	0.152	0.262	0.012	-0.005
Malta	0.657	0.714	-0.000	0.003
Netherlands	-0.657	-0.498	0.031	-0.016
Poland	0.481	0.537	0.006	-0.001
Portugal	0.646	0.714	0.005	-0.002
Romania	0.318	0.377	0.012	-0.006
Slovakia	0.575	0.646	-0.004	0.009
Slovenia	0.294	0.355	0.010	-0.003
Spain	0.058	0.115	0.020	-0.012
Sweden	0.249	0.396	-0.005	0.011
Average	**0.149**	**0.247**	**0.011**	**-0.003**

methods could likely improve classification accuracy. However, our objective is not to maximize predictive performance, but to construct an interpretable measure of ex-ante risk attitudes that can be consistently applied to the IVS sample. Importantly, any remaining misclassification mechanically reduces the distinction between the predicted risk-averse and non-risk-averse groups. Consequently, the heterogeneity estimates reported in the main text should be interpreted as conservative.

Table A2: Predicted *versus* actual risk aversion

Iteration	True positive	True negative	False positive	False negative	Total	Sensitivity	Specificity
1	16,675	5,999	2,522	10,785	35,981	0.607	0.704
2	16,989	5,927	2,607	10,753	36,276	0.612	0.695
3	16,927	5,833	2,646	10,452	35,858	0.618	0.688
4	17,005	5,910	2,673	10,774	36,362	0.612	0.689
5	17,153	6,001	2,597	10,586	36,337	0.618	0.698
6	16,942	5,970	2,684	10,837	36,433	0.610	0.690
7	16,754	5,931	2,594	10,663	35,942	0.611	0.696
8	16,877	5,965	2,566	10,670	36,078	0.613	0.699
9	17,217	6,048	2,675	10,722	36,662	0.616	0.693
10	17,028	6,147	2,729	10,544	36,448	0.618	0.693
Average	**16,957**	**5,973**	**2,629**	**10,679**	**36,238**	**0.614**	**0.694**

Second stage. In the second stage, we use the estimated coefficients to predict respondents' risk aversion *at the time of disaster exposure* in the IVS sample.

To provide an external validation of the imputation procedure, we exploit an IVS question available for a small subsample of approximately 2,500 respondents: "Adventure and taking risks are important to this person; to have an exciting life." Responses are measured on a six-point scale and provide a proxy for the inverse of risk aversion. Reassuringly, regressing this variable on the predicted risk-aversion indicator yields a negative and statistically significant coefficient equal to -0.172* (0.0634), indicating that individuals classified as risk averse by our procedure are significantly less likely to report positive attitudes toward risk-taking.

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