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Risk Perceptions as a Multivariate System: Crowding Out, Affect Generalization, and Heterogeneous Belief Updating

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Abstract: Crises rarely arrive alone: pandemics overlap with wars, financial shocks with climate risks, personal hardship with collective upheaval. When one risk becomes salient, does worry about the others recede or spread? We provide a multi-domain, multi-shock field test using the German Socio-Economic Panel (SOEP), which elicits worries across eight domains from 1999 to 2022, and exploit quasi-random survey timing around major societal crises and within-person variation around idiosyncratic personal life events. Risk perceptions are not separable: a shock in one domain moves worries in others, even when the underlying risks are unrelated. The direction depends on the shock's proximity to the individual. Distant societal crises crowd out competing worries (Finite Pool of Worry); proximal personal events amplify worry across domains (Affect Generalization). Combining imputation-based difference-in-differences with latent profile analysis, we find the population splits into qualitatively distinct types: 27% generalize worry, 62% reallocate it, 11% suppress it. Profile membership is organized above all by neuroticism, revealing that personality shapes not only the level of worry, but the structure of belief updating itself. Interdependent worries imply that crises generate externalities in the mental economy of risk perception: displacing concern from persistent risks for some individuals, diffusing pessimism for others.

Keywords: Risk Perception; Finite Pool of Worry; Affect Generalization; Belief Updating; Crisis Response

JEL-Codes: D81; D91; D01

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1 Introduction

Crises impose risks but overlap and rarely occur in isolation. Economic downturns coincide with geopolitical tensions, pandemics overlap with climate emergencies, and personal hardships unfold against broader societal shocks. This raises fundamental questions: Are perceptions of such risks domain-separable, or are they interdependent? When one crisis becomes salient, does worry about other risks decline or increase and does concern spill over across domains?

Risk perceptions are not epiphenomenal. They reflect subjective judgments about the likelihood and impact of risks that shape economic behavior, political preferences, and policy support (Slovic, 1987). While standard economic models treat beliefs about independent risks as separable and often updated in a Bayesian fashion, psychological and behavioral research suggests that "risk perceptions are influenced by association- and affect-driven processes as much or more than by analytic processes" (E. U. Weber, 2006). As Johnson and Tversky (1983) remarked, "one characteristic that distinguishes judgments about risks from other estimates, […] is that they seldom occur in an emotionally neutral context. […] We do not merely revise our subjective probabilities; we are also shaken and disturbed. Our encounters with news about risk […] generate fear, anxiety, and worry." In other words, we experience "risk as feeling" (Loewenstein et al., 2001).

Worry is an aversive emotional perception of risk arising as repetitive unpleasant thoughts (Sweeny & Dooley, 2017). It mentally simulates risks in an uncertain environment and keeps them "top of mind" (Haaland et al., 2024). Worries thus serve as what Damasio (1994) called "lubricants" of reason: they shape how individuals allocate attention (Link et al., 2026; Loewenstein & Wojtowicz, 2025) and motivate, as part of the "springs of action" (Peters & Slovic, 2000), both mitigating reactions during crises and longer-term precautionary behavior (Watkins, 2008). If perceptions of risks are interdependent through an affective channel, worries form a multivariate system in which beliefs across risk domains interact. Such interdependencies create complex dynamics at the micro level, whereby increased worry about one domain prompts behavioral adjustments in others that can result in macro-level externalities—such as adverse shocks to consumer sentiment contributing to business cycle fluctuations (Lagerborg et al., 2023). Understanding whether worries crowd out or reinforce each other across domains is therefore central for models of belief formation, attention allocation and sentiment dynamics.

Two contrasting hypotheses dominate the literature on such interdependencies. According to the Finite Pool of Worry (FPW) hypothesis (E. U. Weber, 2006), individuals possess limited emotional and cognitive capacity to worry about multiple risks simultaneously. When one risk becomes salient, it crowds out worries about other risks, particularly those that are more distant or abstract. In contrast, the Affect Generalization (AG) hypothesis (Johnson & Tversky, 1983) predicts affective spillovers whereby heightened worry in one domain amplifies worries across others, resulting in a generalized sense of being at risk. Despite their opposing predictions, both hypotheses imply that risk perceptions are interdependent and shaped by unrelated risks, thereby challenging the standard framework in which beliefs about independent risks are treated as separable. Yet it remains unclear which mechanism dominates in field settings and whether the type and proximity of shocks systematically determine which mechanism operates.

Empirical evidence on interdependencies remains inconclusive. Existing studies typically focus on single crises, narrow sets of worries, inconsistent measurement, small samples, or aggregate outcomes, making it difficult to draw generalizable conclusions or to assess whether different types of risks operate through distinct mechanisms. Moreover, little is known about multivariate heterogeneity, as population averages may mask fundamentally different patterns across individuals.

This paper contributes to the literature by providing comprehensive evidence on the relationship between individuals' experiences of risks and their effects on domain-specific and non-domain-specific worries. We address three main questions. First, are risk perceptions interdependent? Second, do salient risks crowd out competing worries or generalize them—and does this depend on the type of risk? Third, do individuals differ systematically in how they update their beliefs about risks? By analyzing an extensive set of salient, high-impact adverse events across two decades that differ systematically in the risk domains they affect and are measured using a consistent multi-domain battery of worries within a single longitudinal survey, we directly test the competing predictions of the FPW and AG hypotheses. We further classify risks into societal and personal categories and assess their consequences, thereby highlighting significant nuances. We decompose aggregate effects to identify and characterize latent heterogeneous response profiles—groups of individuals who update their worries in systematically different ways.

Our findings reveal three main results. First, risk perceptions are interdependent: shocks in one domain systematically affect worries in others, even when the underlying objective risks are largely unrelated. Second, societal and personal risks operate through different mechanisms. At the aggregate level, societal crises—such as the Russian invasion of Ukraine, the COVID-19 pandemic, the Global Financial Crisis and others—predominantly induce crowding-out patterns consistent with the FPW hypothesis. When a particular risk becomes salient, worry shifts toward that risk at the expense of other concerns. In contrast, personal life events—such as health crises, unemployment, indebtedness, discrimination experience, among others—tend to generate generalized increases in worries across multiple domains, consistent with the AG hypothesis. This distinction shows that belief updating across risk domains is systematically state-dependent: the proximity of the shock to the individual determines whether worries are reallocated or generalized.

Third, once we move beyond population averages, substantial and structured heterogeneity emerges. We identify six latent profiles. Approximately 27% of individuals exhibit AG-type generalized increases in worry. About 11% exhibit absolute decreases in worry, a pattern that may reflect emotional shutdown, compartmentalization, or resilience. The remaining 62% exhibit relative reallocation patterns, including classic FPW-type crowding-out in which immediate and personal worries increase while more general societal worries decrease. Crucially, these profiles differ systematically along observable characteristics. The most striking predictor is neuroticism—the dispositional tendency to experience negative affect. More neurotic individuals are substantially more likely to belong to profiles characterized by generalized increases in worries, whereas less neurotic individuals are more likely to display crowding-out dynamics or even broad reductions in worry. In this sense, neuroticism does not merely predict higher baseline worry; it predicts the structure of belief updating itself. Further systematic differences emerge along gender, education, income, age, and migration background, indicating that heterogeneity in belief updating is structured rather than random.

Assessing the interdependencies among worries presents empirical challenges because individuals may be exposed to unobserved, time-varying, and correlated shocks that confound identification. We address these challenges by leveraging survey data from the German Socio-Economic Panel (SOEP), a longitudinal dataset covering a wide range of worries and life events from 1999 to 2022. For societal events, we exploit the quasi-random timing of survey interviews to construct repeated cross-sections and compare worry levels around exogenous shocks, following the "unexpected events during survey design" approach (Muñoz et al., 2020). For personal events, we evaluate within-individual variation in worries around idiosyncratic life events using a difference-in-differences panel framework.

To move beyond sample averages, we combine imputation-based differences-in-differences (Borusyak et al., 2024) with stochastic, model-based clustering (Latent Profile Analysis). This data-driven estimation allows us to identify and classify individuals into latent profiles based on their multivariate response patterns across worry dimensions following treatment. The approach yields heterogeneous treatment profiles: distinct and systematic patterns in how worries are reallocated across domains in response to events. This combination allows us to estimate heterogeneous treatment effects across multiple belief domains simultaneously without imposing ex ante strict structure on the form of heterogeneity. To validate this method, we conduct a simulation study showing that LPA outperforms alternative clustering algorithms, including k-means, and reliably recovers both the latent profiles and the treatment effects, even under significant measurement error.

Taken together, this paper makes three central contributions. First, to our knowledge we provide the first multi-domain, multi-shock field test of FPW and AG, systematically comparing cross-domain interdependencies across multiple events and risk domains in field data with a consistent battery of directly elicited worry dimensions. Second, we establish that the type of risk-inducing event—societal versus personal—determines which mechanism dominates, providing a unifying explanation for previously mixed evidence on FPW versus AG effects in risk perceptions. Third, we document that heterogeneity in belief updating is structured and substantively meaningful, identifying latent response profiles that differ qualitatively—not merely quantitatively—and characterizing them along psychological and socioeconomic dimensions.

The remainder of this paper is organized as follows. Section 2 reviews the conceptual foundations and related literature. Section 3 describes the data, including the SOEP sample and the events. Section 4 presents the results for societal events. Section 5 focuses on personal events. Section 6 introduces our latent profile analysis and reports heterogeneous response profiles. Section 7 discusses implications and concludes.

2 Foundations & Related Literature

This section connects several strands of literature that form the basis of this study. This includes (i) conceptual work defining the terminology of “risk”; (ii) research on subjective risk perceptions and behavioral implications; (iii) the “risk-as-feelings” framework, which makes worry a natural object of study; (iv) evidence and theory on interdependencies across risks perceptions including the FPW and AG hypotheses; and, finally, (v) the growing behavioral economics and macroeconomics literature on attention, belief formation, narratives, and heterogeneous agents. We draw these strands together to motivate a central claim: risk perceptions and worries are not domain-separable objects but form an interdependent multivariate system in which shocks can propagate across seemingly unrelated domains as externalities, with implications for theory, measurement, and policy design.

A first conceptual distinction concerns what is meant by the term “risk.” In classical economic usage, risk refers to situations that involve a set of possible outcomes related to states of the world and represented by a known probability distribution. This concept, which Gigerenzer (2023) calls the "dispersion meaning" of risk, involves quantifiable probabilities, distinguishing it from (Knightian) uncertainty. Yet psychological research typically uses “risk” as a narrower concept encompassing uncertain situations that involve potential harm, loss or hazards—what Gigerenzer (2023) calls the “possibility-of-harm meaning” of risk. In other words, “risks threaten things we value” (Fischhoff & Kadvany, 2011). Neuroscientific research demonstrates that this distinction is of relevance as the two concepts of risk activate distinct brain regions (Mohr et al., 2010).

This motivates a second distinction: risks as objective hazards versus subjective perceptions. The psychometric tradition in psychology demonstrates that perceived risk is structured along dimensions such as dread, controllability, familiarity, and catastrophic potential—features that are only partially aligned with actuarial probabilities. In this view, risk perception is a systematic psychological object that reflects how people process hazard attributes (Slovic, 1987). Thus, subjective appraisals and disagreements about “how risky” a crisis is can reflect not only differences in objective information, but also differences in attention, affect, representation, and mental frames.

A large empirical literature documents that subjective risk perceptions strongly predict real behavior, including preventive health actions and compliance with safety recommendations (Vacondio et al., 2021; Wise et al., 2020), consumption and investment decisions (Lagerborg et al., 2023), and policy support

(Börger et al., 2026). This became especially salient during the COVID-19 pandemic, where perceived infection risk and perceived severity shaped protective behavior and support for restrictions (Wise et al., 2020). These findings underline that understanding how risk perceptions form and evolve is central for explaining both private choices and public support for collective action.

A further step is recognizing that risk perception is not a purely cognitive process. Rather, it is often experienced through fear, dread, anxiety, and worry. During Covid-19, for instance, individuals' worries were a particularly close indicator of perceived vulnerability and corresponding protective behaviors (Vacondio et al., 2021). The "risk-as-feelings" framework highlights that emotional reactions to risky situations can diverge from, and dominate, analytic evaluations of probabilities and outcomes (Loewenstein et al., 2001). In this framework, worry is not merely an epiphenomenon: it influences decisions (incidental affect) and is itself shaped by judgments about risks and associated behaviors (integral affect) (Lerner et al., 2003, 2015; E. U. Weber, 2006). Neurological evidence reinforces this point, linking risk perception to activation of brain regions associated with aversive emotion (Mohr et al., 2010). Treating worry as an economic object therefore aligns with modern behavioral models in which affect and cognition jointly determine choice and in which both subjective mental models and objective states govern behavior.

Beyond their implications for well-being, risk perceptions shape public discourse, narratives, private decision-making, and collective action. Understanding their formation and dynamics is therefore central. For instance, economic research has shown how lived experiences and risk-inducing crises—so called "belief-twisting events" like recessions, inflation spikes, or stock market crashes—shape beliefs and perceptions (Giuliano & Spilimbergo, 2025) with persistent consequences—so called "experience effects" (Malmendier, 2021). Experience effects imply systematic divergence from the canonical Bayesian benchmark due to experience- and recency-weighting. A key open question is whether these effects are confined to the same domain as the underlying risk, or across domains—especially when societies and individuals face overlapping crises ("polycrisis"). This question is central for understanding belief dynamics yet remains underexplored.

Two prominent hypotheses structure the debate about how risk perceptions interact across domains. The FPW hypothesis argues that individuals possess limited emotional resources for worry: when worry about one risk rises, worries about other risks fall (E. U. Weber, 2006). FPW has been widely discussed in the context of long-run crises such as climate change: worry for slow-moving and abstract risks may be crowded out by acute crises. Conceptually, FPW implies that worry behaves like a scarce resource, and that the allocation of this resource changes endogenously with the salience of risks constrained by the "worry budget". A competing hypothesis, the AG hypothesis, suggests that worry can spill over from one domain to another, as affective states shape broad judgments and risk appraisals (Johnson & Tversky, 1983). Worry experienced in response to one event can influence perceptions of unrelated risks, leading to a generalized sense of risk and vulnerability. AG is closely related to the affect heuristic (Slovic et al., 2002), which posits that people rely on immediate emotional responses to a situation in order to make judgments or decisions, rather than engaging in systematic, analytical analysis: affect is used as a cue for decisions. Whereas the affect heuristic emphasizes affect as a cue within a judgment, AG captures emotional spillover or contagion: affect triggered by one stimulus transfers to other unrelated domains and behaviors.

Importantly, these hypotheses have distinct implications. Under FPW, the aggregate "worry budget" is constrained and reallocated. Under AG, worry is not constrained but effectively expands. Distinguishing these mechanisms matters for policy. If FPW dominates, crises may systematically displace worry and thereby attention away from long-run collective risks, potentially delaying mitigation and weakening support for protective or insurance policies (Lohse et al., 2012). If AG dominates, crises may instead amplify support for broad protective policies, but also risk inducing generalized pessimism that depresses economic activity and political trust. In either case, interdependent worries imply that shocks generate externalities in the "mental economy" of risk perception.

Both the AG and the FPW hypotheses posit that individuals incorporate new information about risks to update their beliefs. However, both depart in important ways from the benchmark of rational belief updating typically associated with Bayesian learning (e.g., Karni and Vierø 2013). In standard expected utility or Bayesian learning models, beliefs about distinct, independent risks are separable unless explicitly correlated through the objective state space: posterior beliefs in domain A depend only on signals relevant to domain A. In other words, beliefs are updated as a function of all available domain-specific information, and belief formation is separable across independent domains. This structure effectively rules out interference, emotional spillovers, or imperfect perception—an assumption that is arguably more restrictive as a descriptive model than as a normative benchmark. A growing body of empirical evidence challenges this separability view by documenting that perception, attention, and learning are themselves endogenous outcomes shaped by limitations to cognition, motivation, state of mind, and information environments (e.g., Chabris and Simons 2010; Weber et al. 2025).

Crucially, deviations from the separable benchmark need not be interpreted as "irrationality". Both FPW and AG are consistent with decision-theoretical frameworks that relax the assumption of frictionless information processing and allow for cognitive constraints or ambiguity-sensitive belief formation. FPW aligns naturally with models of limited cognition and rational inattention, in which agents allocate scarce mental resources across competing concerns (Bordalo et al., 2022b; Gabaix, 2019; Link et al., 2026; Loewenstein & Wojtowicz, 2025). In these models, mental resources are directed toward risks that are more volatile, more decision-relevant, or associated with larger losses from misperception. When an immediate risk becomes salient, the marginal benefit of attending to that risk rises, inducing a reallocation of mental resources away from other risks. In this sense, FPW is consistent with the boundedly rational view of agents as rational optimizers operating under mental constraints. By contrast, AG resonates with decision-theoretic models that allow for imprecise or non-unique beliefs reflecting uncertainty in beliefs, most prominently the max-min expected utility framework of Gilboa and Schmeidler (1989). In such settings, ambiguity-averse agents evaluate choices under pessimistic, non-additive beliefs as a hedge against uncertainty. From this perspective, a generalized sense of risk reflects a response to ambiguity, rather than cognitive error: generalized worry emerges as a precautionary reaction to the perceived possibility of misalignment of uncertain subjective beliefs in the context of risks and possibly absorbing adverse states.

The implications of FPW and AG extend beyond individual psychology. If worries are interdependent, then public discourse and collective priorities are shaped by an endogenous allocation mechanism across issues. This connects the FPW mechanism directly to political economy research on issue competition and agenda dynamics. Downs' (1972) "issue-attention cycle" emphasizes that public attention is scarce and rotates across issues as crises emerge, peak, and fade. Under an FPW logic, acute crises may displace concern for slower-moving or less immediate risks, generating predictable cycles in political support. Under AG, by contrast, crises may increase pessimism, not simply shifting which issue dominates, but expanding perceived vulnerability across domains. These mechanisms provide micro-foundations for broader swings in societal sentiment and connect to research on narratives cycles (Shiller, 2017, 2019). This link is also consistent with behavioral macroeconomic models of sentiment propagation and belief distortions even absent commensurate changes in economic and political fundamentals (Bordalo et al., 2022a; Lagerborg et al., 2023).

Empirical studies provide some support for FPW-type dynamics. During recessions and periods of financial stress, public concerns for long-run issues such as climate change is often deprioritized as immediate economic worries rise (Gifford, 2011; Scruggs & Benegal, 2012; Whitmarsh, 2011). During COVID-19, Gregersen et al. (2022) find a small but significant decrease in climate worry, and Smirnov and Hsieh (2022) and Smirnov, Hsieh, and Urbina (2025) document decreases in environmentally related social media posts, consistent with crowding-out. However, other studies challenge FPW and argue that observed effects reflect reallocation of attention rather than worry per se (Evensen et al., 2021; Sisco et al., 2023).

At the same time, empirical evidence also supports AG-type spillovers. In their seminal study, Johnson and Tversky (1983) show experimentally that negative emotional stimuli raise perceived higher risk in unrelated domains. Subsequent work documents similar spillovers (Keller et al., 2006) and recent experimental studies find some evidence for affect generalization across crises: Bergquist et al. (2023) in the United States and Rinscheid and Koos (2023) in Germany show that pandemic concern can increase support for climate policy (see also Stefkovics et al. 2024). Fetzer et al. (2021) find that COVID-19 increased health anxiety and broader economic anxiety. Błaszczyk and Dyczek (2025) show that direct war exposure in Ukraine increased climate concern under extreme risk. Moreover, recent behaviorally-motivated macroeconomic studies have shown that negatively affected consumer sentiment, such as due to mass shootings and security concerns (Lagerborg et al., 2023), influence aggregate economic indicators—a spillover effect consistent with AG.

Overall, however, findings remain fragmented across events, domains, and measurement strategies (e.g., relying on indirect proxies such as policy support and social media usage or more immediate elicitation of worries). Most studies focus on single events, examine only few risk dimensions, evaluate aggregate outcomes missing heterogeneous patterns and the multivariate nature of worries, and emphasize societal shocks, leaving open whether results generalize, are comparable and whether personal shocks—often more vivid and emotionally consequential—operate through different mechanisms. There is therefore no systematic and conclusive empirical evidence evaluating cross-domain interdependencies in worries and directly testing FPW versus AG using a multi-domain, multi-shock design in field data.

We contribute to this literature by providing the first multi-domain, multi-shock field test of FPW and AG that systematically compares both societal and personal events using a consistent battery of directly elicited worry dimensions and over two decades of longitudinal data. By leveraging large-scale field data with rich variation in both aggregate and idiosyncratic shocks, we strengthen the external validity of research on cross-domain risk interdependencies. Our contribution challenges the separability benchmark and shows that beliefs about risks behave as components of a multivariate system with endogenous cross-effects. Most centrally, we highlight the relevance of the type of event—societal or personal—for the underlying mechanism and identify latent heterogeneous profiles of worry reallocation and characterize them along psychological and socioeconomic dimensions, moving beyond population averages to show that FPW-type and AG-type responses coexist systematically within the population.[2]

3 Data

The FPW and AG hypotheses structure how worries are updated and generate distinct empirical predictions about the interdependence of risk perceptions. Under both hypotheses, an increase in perceived risk in a given domain should raise worries within that domain. However, they diverge in their predictions regarding worries in other domains. The FPW hypothesis predicts a reallocation within a constrained "worry budget": increases in domain-specific worries should be accompanied by decreases in worries elsewhere.

[2] A natural concern is whether worry merely proxies attention. Indeed, attention and worry are closely related: worries keep risks cognitively salient and influence what individuals attend to. However, several considerations suggest that worry cannot be fully reduced to attention alone. First, attention is valence-neutral, whereas worry is intrinsically affective and aversive. Individuals may attend to risks out of curiosity or strategic interest without experiencing negative affect. Worry reflects a subjective appraisal of risk and vulnerability and is closely linked to precautionary behavior. Second, a pure attention-based account generates different empirical predictions. If shocks merely reallocate attention, we should observe mechanical crowding-out across domains. Yet we observe absolute increases across multiple domains following personal shocks, inconsistent with a pure attention-only mechanism.

In contrast, the AG hypothesis predicts affective spillovers, whereby heightened worry in one domain leads to stable or rising worries across other domains, reflecting a generalized sense of vulnerability.

Distinguishing between these mechanisms requires observing how multiple worry dimensions co-move in response to plausibly exogenous changes in perceived risk salience. This imposes demanding data requirements. First, we require a broad and stable set of worry dimensions that are measured consistently over time. Consistency ensures comparability across years and across events, while breadth allows us to observe reallocations across domains rather than within a single risk category. Second, because individuals differ in their baseline propensity to worry, longitudinal data are necessary to isolate within-person changes from time-invariant heterogeneity. Third, to test the hypotheses we require shocks that sharply increase the perceived salience of a specific risk, allowing us to observe how worries adjust across domains in response.

Our empirical strategy combines these features. We exploit a long-running panel dataset containing a stable multi-domain worry battery, together with two sets of orthogonal sources of variation in perceived risk: abrupt societal crises that affect large parts of the population simultaneously, and idiosyncratic personal life events that affect only subsets of individuals. Societal shocks generate quasi-experimental variation through the timing of survey interviews around major events, while personal events allow within-person identification based on the onset of individual life shocks. Observing the same individuals reporting the same worry dimensions across multiple crises provides a unique opportunity to study the dynamics of worry reallocation with consistent field data.

This section proceeds as follows. Section 3.1 describes the panel dataset, measurement of worries, and sample restrictions. Section 3.2 explains the selection of societal and personal events that serve as risk-inducing shocks.

3.1 Panel Data Sample

Our analysis uses data from the German Socio-Economic Panel (SOEP), a large-scale longitudinal survey that has collected representative household and individual-level data for Germany since 1984 (Goebel et al., 2019). The SOEP is particularly well suited for studying interdependencies in worries for several reasons.

First, beginning in 1999 the survey has included a stable battery of questions measuring worries across eight domains: environment, peace, migration, crime, the economy, personal finances, unemployment, and health. Respondents are asked: “How concerned are you about the following issues?” and can respond i) “very concerned”, ii) “somewhat concerned”, iii) “not concerned at all”, in addition to a non-response option (“can't / don't want to answer”).[3] The wording and scale of these questions have remained consistent over

[3] The original version of the survey is in German: “Wie ist es mit den folgenden Gebieten - machen Sie sich da Sorgen?“, 1) „Große Sorgen“, 2) „Einige Sorgen“, 3) „Keine Sorgen“, and the opt-out response “Kann / möchte ich nicht beantworten“. We treat the three-point Likert scale as

time, which is crucial because it allows direct comparison of worry allocations across domains, years, and events without changes in measurement. Rohrer et al. (2021) provide an overview of the long-term development of these worries in the SOEP.

Second, we use SOEP version v39, which provides annual data through 2022. Our sample therefore spans the period 1999–2022, covering more than two decades during which Germany experienced several major societal crises. Importantly, SOEP interviews are conducted throughout the year rather than at a single point in time. This staggered fieldwork creates variation in exposure to unexpected events: some respondents are interviewed shortly before an event occurs, while others are interviewed shortly afterward. We exploit this variation in interview timing to implement quasi-experimental comparisons around abrupt salient shocks.

Third, the panel structure of the SOEP allows us to observe the same individuals repeatedly over time. This enables controlling for time-invariant differences in baseline worry levels across respondents. Because individuals vary systematically in their general propensity to worry, exploiting within-person variation is central for identifying reallocations across domains.

Fourth, the SOEP provides extensive background information on respondents, including socioeconomic characteristics, personality traits, and detailed life histories. This data allows us to analyze personal life events as risk-inducing shocks and to examine heterogeneity in responses. Our baseline sample includes individuals aged 18–60 in order to focus on the working-age population and avoid confounding factors related to retirement transitions.

3.2 Event Selection

Our objective is to identify how worries reallocate across domains following abrupt increases in perceived risk salience. To do so, we identify events that generate shifts in perceived risk within a particular domain, allowing us to observe subsequent adjustments in other domains. We distinguish between two types of risk-inducing events: societal crises, which affect large parts of the population simultaneously, and personal life events, which affect individuals idiosyncratically.

3.2.1 Societal crises

Societal crises generate widespread uncertainty and attract intense public attention, thereby reshaping perceptions of risk in collective discourse. To qualify as a societal shock in our analysis, an event must satisfy three criteria. First, it must generate substantial public salience. Second, it must plausibly increase

cardinal and analyze changes in worries. Because all worry variables share the same scale, interpretation in Likert units is meaningful and effect sizes are directly comparable across domains.

perceived risk in a specific domain. Third, it must have an identifiable onset that allows comparisons between observations immediately before and after the event. The identifying variation arises because individuals interviewed shortly before the event serve as a control group for those interviewed shortly afterward. Importantly, we focus on abrupt salience shocks rather than slow-moving structural developments. Gradual processes such as long-run climate change trends do not provide the sharp informational breaks necessary for clean identification. Instead, we identify moments when public attention to a risk increases discontinuously. In this sense, the relevant "shock" is defined not solely by the objective occurrence of the event but by its sudden change in perceived salience. This design follows the logic of the "unexpected events during survey design" approach (Muñoz et al., 2020), which exploits quasi-random interview timing around sudden events to identify effects, and resembles regression discontinuity in time designs and high-frequency event studies. Based on these criteria, we examine five societal events that affect distinct risk domains and are covered by the dataset.

Russian invasion of Ukraine (February 2022): Russia's invasion of Ukraine marked the largest interstate war in Europe in decades and immediately heightened geopolitical uncertainty (Błaszczyk & Dyczek, 2025). In Germany, the invasion triggered major shifts in defense, energy, and foreign policy. Google Trends data show unprecedented search intensity for terms related to war in February 2022 since data collection began in 2004, indicating a sharp salience shock (see Figure 10 in Section 6 of the Supplemental Appendix).

COVID-19 pandemic and first lockdown (March 2020): The introduction of Germany's first nationwide lockdown represents a clear institutional breakpoint that abruptly disrupted economic activity and daily life (Bergquist et al., 2023; Evensen et al., 2021; Fetzer et al., 2021; Gregersen et al., 2022; Rinscheid & Koos, 2023; Sisco et al., 2023; Smirnov et al., 2025; Smirnov & Hsieh, 2022; Stefkovics et al., 2024). Consistent with this interpretation, Google search intensity for terms related to economic crisis surged during this period (see Figure 12 in Section 6 of the Supplemental Appendix).

Climate salience shock (late 2018–early 2019): Climate change typically represents a slow-moving risk. However, the publication of the IPCC Special Report in October 2018 and the rapid rise of the Fridays for Future movement generated a sudden surge in public attention to environmental risks. Media coverage and political debate intensified sharply during this period, creating a distinct salience shock. We identify a salience onset period characterized by heightened media coverage and activism in late 2018 and early 2019.

Domestic security and migration shocks (late 2015): Germany experienced intense public debate about migration during 2015–2016 following the arrival of more than one million refugees and asylum seekers. Two events played a particularly important role in shaping risk perceptions: the November 2015 terrorist attacks in Paris and the following mass sexual assaults during New Year's Eve celebrations in Germany. The coordinated terrorist attacks in Paris, carried out by gunmen and suicide bombers in November 2015, killed 130 people and injured hundreds more. The attacks triggered an immediate and highly visible security response across Europe. The presence of security forces in urban centers became a striking symbol of the perceived security risk and received extensive media coverage across European countries, including Germany. Shortly afterward, the New Year's Eve assaults in multiple German cities in 2015/2016—where large numbers of women reported sexual assaults in public spaces—further intensified debates about public safety, migration, and integration. The events were widely covered in the German media and rapidly became central to political discourse surrounding immigration policy. Google Trends search intensity for terror peaks during this period (see Figure 11 in Section 6 of the Supplemental Appendix).

Global Financial Crisis (September 2008): The collapse of Lehman Brothers marked a sudden and highly visible escalation of the global financial crisis, triggering widespread economic uncertainty (Gifford, 2011; Scruggs & Benegal, 2012; Whitmarsh, 2011). Google Trends data again show a historical peak in search intensity for economic crisis (see Figure 12 in Section 6 of the Supplemental Appendix).

Together, these events span multiple domains—geopolitical conflict, economic uncertainty, environmental risk, domestic security and migration, and financial instability—allowing us to test whether cross-domain worry dynamics generalize across contexts.

3.2.2 Personal life events

Societal shocks provide aggregate variation in perceived risk, but they affect the entire population simultaneously. Personal life events provide complementary variation because they affect only subsets of individuals and occur at different points in time. Moreover, they more immediately affect the individual and are more vivid, thus, their effects may differ from societal shocks.

We build on insights from the threats and stress literature, which has systematically assessed personal life-events. This research expands the traditional risk perception literature, incorporating not only psychological but also physiological aspects with a greater emphasis on health consequences. We focus on 'major stressful life events' that are widely recognized in the literature as substantial threats to well-being (Cohen et al., 2016, 2019). 'Major stressful life events' are considered "threats to one's social status, self-esteem, identity, and physical well-being" (Cohen et al., 2019) that "trigger affective responses (e.g., worry, fear, or anxiety)" (Cohen et al., 2016). Various survey-based and interview-based studies approached the task of systematically constructing impact ratings (so called "stressful life event scales").

Our main personal events include serious health crises of oneself, the spouse or the child, unemployment of oneself and the spouse (due to layoffs or plant closures) and financial risks due to indebtedness. Prior research on stressful life event scales consistently ranks such events among the most consequential disruptions to individual well-being. We also consider discrimination experience, crime in the immediate neighborhood and psychological events including loneliness and loss of purpose.

The combination of societal shocks and personal life crises thus provides two complementary sources of variation that allow us to study both aggregate and individual responses to risk-inducing events. The following sections exploit these events to examine how individuals update their worries in response to newly salient risks.

4 Effects of Societal Events

In this section, we focus on large-scale crises to explore how societal risks reshape worries. We begin by explaining our econometric approach and identification strategy, outlining how repeated cross-sectional observations in the SOEP facilitate a week-by-week (or month-by-month) event study framework. We then present evidence from the events, analyzing whether, and to what extent, these shocks affect different worry domains. Crowding-out patterns typically dominate, consistent with the FPW hypothesis. Finally, we discuss the implications of our findings as well as directions for the next sections of this study.

4.1 Econometric Approach and Identification

A key challenge when studying societal crises is that the entire population is exposed to the event. This precludes the use of standard difference-in-differences approaches with untreated control groups. Instead, we exploit two institutional features of the SOEP survey design. First, SOEP interviews are conducted continuously throughout the year rather than at a single point in time. Respondents are interviewed at different weeks or months, creating variation in exposure to unexpected events in a repeated cross-sectional structure. Individuals interviewed shortly before an event serve as a control group for those interviewed shortly afterward. This approach follows the "unexpected events during survey design" framework (Muñoz et al., 2020), which exploits quasi-random interview timing around abrupt shocks. Second, the panel structure of the SOEP allows us to control for individual fixed effects. This enables identification based on within-person variation while accounting for time-invariant differences in baseline worry levels. Formally, for each worry dimension l we estimate:

$$w_{itl} = \alpha_{il} + \gamma_{tl} + \sum_{t} \delta_{tl} Event_t + \epsilon_{itl}$$

where w_{itl} denotes the reported worry of individual i at time t in domain l; α_{il} represents individual fixed effects capturing persistent differences in worry levels; γ_{tl} captures smooth time effects common to all individuals; $Event_t$ is an event time indicator; δ_{tl} measures the average shift in worry domain l at event time t induced by the event; ϵ_{itl} is an idiosyncratic error term. The coefficients δ_{tl} capture discontinuities in worries around the event. Our estimation focuses on effects within a narrow event window. The main identifying assumption is that, in the absence of the event, worries would evolve smoothly over time. Under this assumption, any discontinuous change around the event can be attributed to the shock. To implement the event studies, we proceed in four steps:

Step 1) Individual fixed effects estimation: We first estimate individual fixed effects regressions for each worry dimension using the full panel period up to the event. This removes time-invariant differences in baseline worry levels across respondents. We store the residuals specific to the event horizon.

Step 2) Sample restrictions: To avoid small-sample fluctuations, we drop event periods within the event horizon with fewer than 20 observations. This restriction mainly affects periods at the beginning and end of survey years. The final number of observations in each period varies from the lower bound up to more than several thousand.

Step 3) Pre-event trend and counterfactual estimation: We test for pre-existing time trends in the pre-event window. If a trend is present, we estimate a time trend and extrapolate it into the post-event period to construct a counterfactual baseline.[4]

Step 4) Event-study estimation: Finally, we estimate flexible event time effects $\widehat{\delta_{tl}}$ by regressing the detrended residuals on time dummy indicators. These coefficients capture deviations from the pre-event trend. Because long-run dynamics cannot be consistently identified in this setting, our analysis focuses on the short-run impact of events on worry allocations.

4.2 Estimation Results

In this section, we present graphical event-study evidence for the five societal shocks (Korting et al., 2023). The below figures plot deviations in worries around the onset of each event relative to the estimated pre-event trend (see Section 2 of the Supplemental Appendix for full regression tables and Section 3 of the Supplemental Appendix for un-detrended estimates).

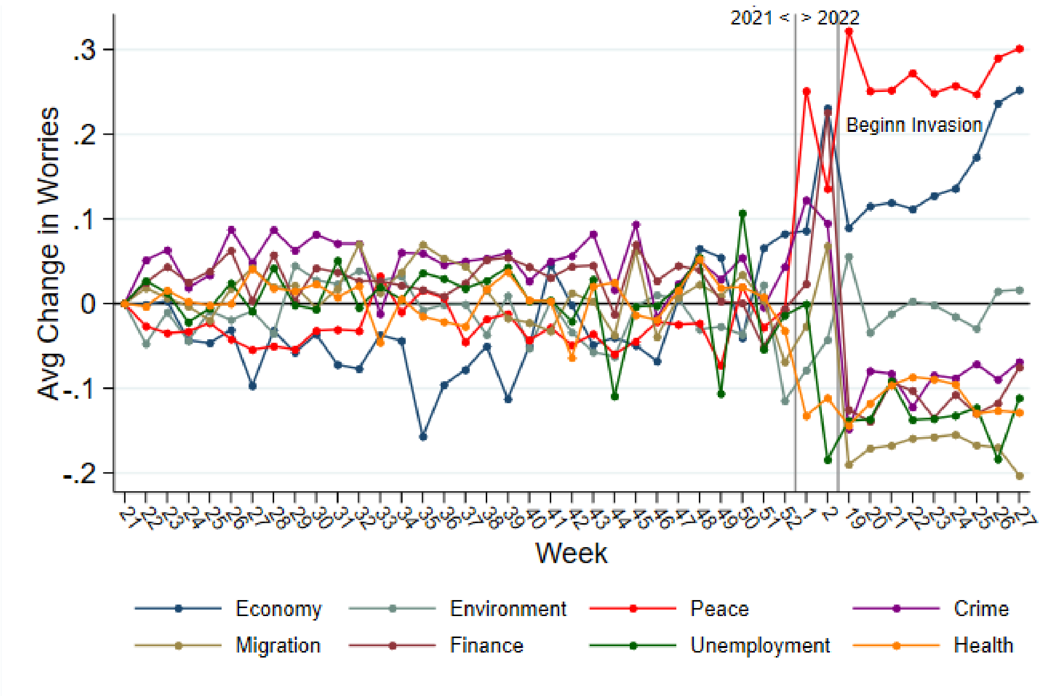
4.2.1 The Russian Invasion of Ukraine (2022)

The Russian invasion of Ukraine in February 2022 produced a sharp increase in geopolitical uncertainty (Figure 1). In the weeks following the invasion we observe a substantial rise in worries about peace and

[4] Detrending can be understood as our assumption about the counterfactual state. Alternatively, we could have instead chosen a reference point close enough to the event, in effect assuming that the current level of the reference point can be extended to the counterfactual state. Given that the dependent variables exhibit relatively large variability, this increases reference point dependence. Using a reference interval somewhat addresses this problem, however, does not account for trends that become relevant in medium to longer time periods. Comparing to the average of some previous year is problematic for the same reasons. Detrending the data allows us to decrease reference point dependence while accounting for smooth time trends. The raw un-detrended data is shown in Section 3 of the Supplemental Appendix. The main conclusions remain unchanged with un-detrended data.

macroeconomic stability. At the same time, concerns about migration, crime, personal finances, unemployment, and health decline relative to their pre-event trend. This pattern suggests a reallocation of worry toward the newly salient geopolitical and macroeconomic threat. In line with the FPW hypothesis, the surge in domain-specific worries crowds out worries in other domains.

Figure 1: The effect of the Russian Invasion of Ukraine (2022) on worries

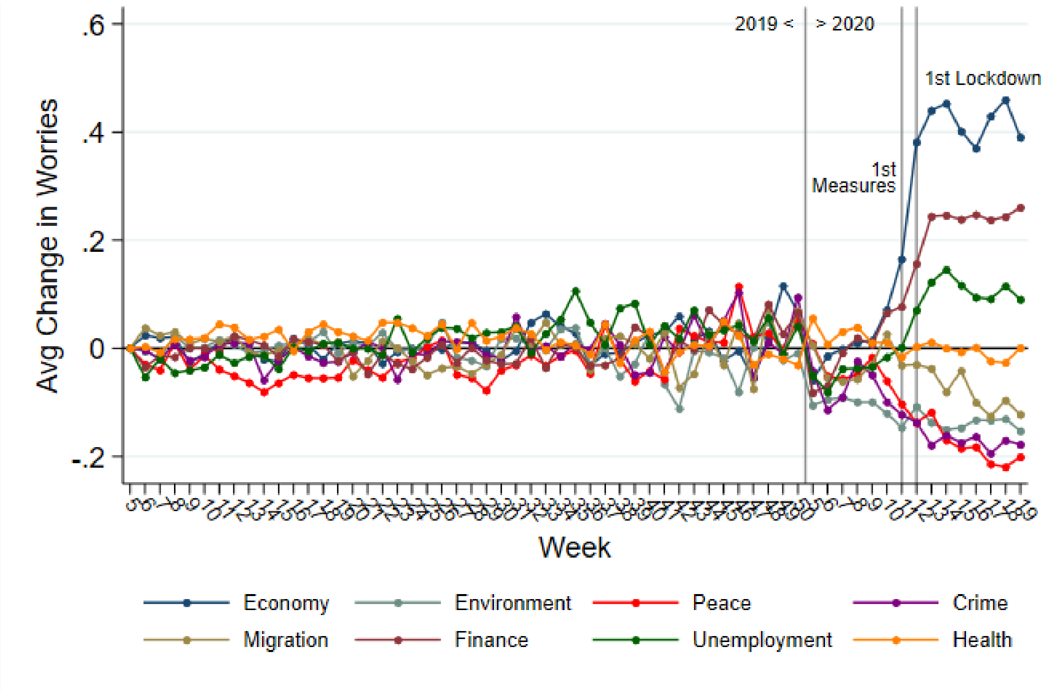


Notes: The figure plots estimated deviations in worry levels across eight domains around the Russian invasion of Ukraine in February 2022. The estimation proceeds in four steps. First, individual fixed effects are estimated for each worry dimension using the full panel period up to the event year, and residuals are stored. Second, event periods with fewer than 20 observations are dropped. Third, pre-event time trends are estimated and extrapolated into the post-event window to construct a counterfactual baseline. Fourth, flexible event-time indicators are regressed on the detrended residuals. Coefficients represent deviations from the pre-event trend. The sharp increase in peace and economy worries accompanied by declines in other domains is consistent with FPW-type crowding-out.

4.2.2 The Covid-19 Pandemic and First Lockdown (March 2020)

The introduction of Germany's first nationwide lockdown in March 2020 represents an abrupt policy shock that affected nearly all aspects of economic and social life (Figure 2). Survey responses around the lockdown reveal a pronounced rise in economic worries, particularly regarding job security, personal finances, and the broader economy (Fetzer et al., 2021). At the same time, worries about environmental issues, peace, migration, and crime decline (Smirnov & Hsieh, 2022), a crowding-out pattern consistent with FPW.

Figure 2: The effect of the Covid-19 Pandemic (2020) on worries

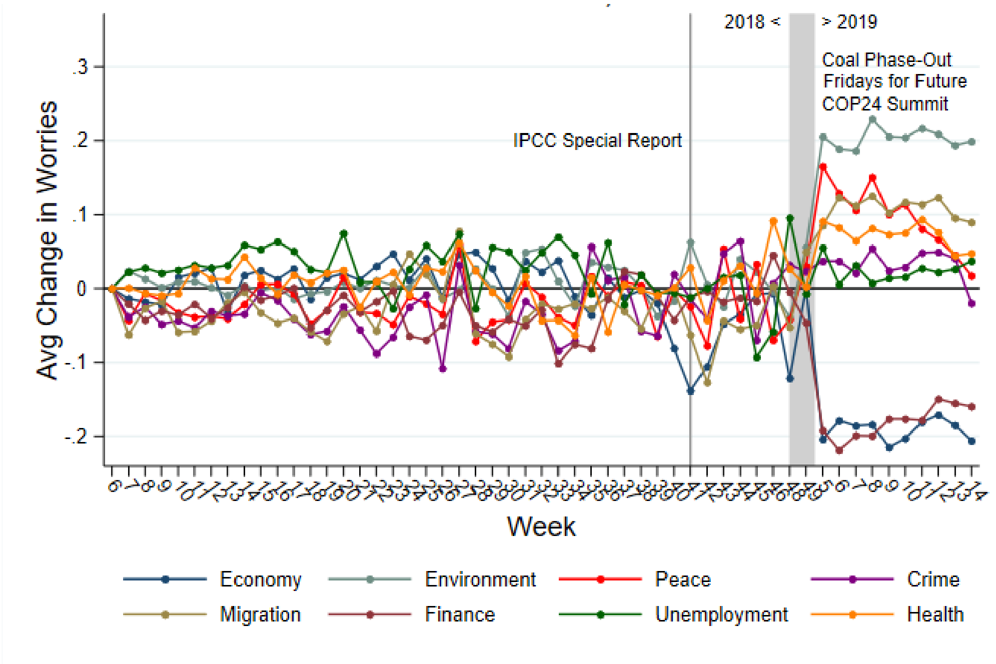


Notes: The figure plots estimated deviations in worry levels across eight domains around Germany's first nationwide lockdown in March 2020. The estimation follows the four-step procedure described in Section 4.2: individual fixed effects estimation, sample restrictions (minimum 20 observations per event period), pre-event trend estimation and counterfactual extrapolation, and flexible event-time regression on detrended residuals. Coefficients represent deviations from the pre-event trend. The pronounced rise in economic worries—particularly regarding job security, personal finances, and the broader economy—accompanied by declines in environmental, peace, migration, and crime worries is consistent with FPW-type crowding-out.

4.2.3 Climate Salience Shock and Fridays for Future (late 2018–2019)

The global climate debate intensified propelled by the Intergovernmental Panel on Climate Change (IPCC) Special Report 2018 and the subsequent Fridays for Future protests, mobilizing global youth and drawing significant public attention to environmental and climate issues. We identify a definable "onset" period in late 2018 and early 2019 where environmental concerns increased sharply, climate activism surged and warnings about the possible consequences of climate change, including imminent dangers to vulnerable populations, threats to land habitability, the security of essential resources like water, and climate-induced migration intensified (Figure 3). In Germany, these developments converged with the government's decision to implement a coal phase-out, marking a significant policy shift. During this period, environmental worries rose sharply, along with modest increases in concerns about peace and migration (possibly due to discourses linking climate change to geopolitical instability). Notably, we observe a parallel decline in economic and financial worries. During the European Parliament elections in 2019, climate change and environmental protection dominated other topics, leading to considerable gains for green parties. The debate functioned as a significant cultural and political shock, although its impact was somewhat short-lived due to the advent of the COVID-19 pandemic.

Figure 3: The effect of the climate debate and Fridays For Futures demonstrations (2018-2019) on worries

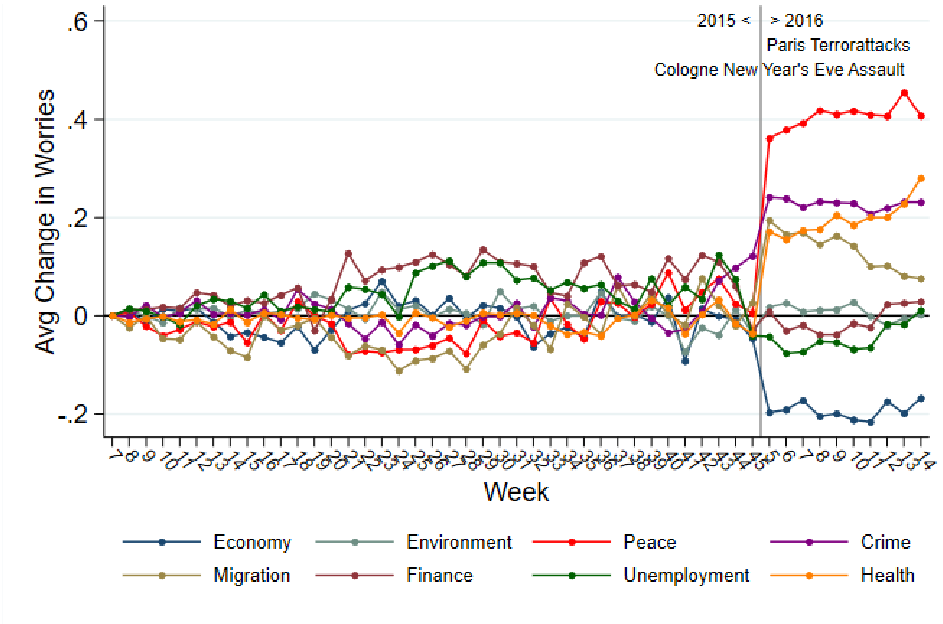


Notes: The figure plots estimated deviations in worry levels across eight domains around the climate salience shock of late 2018–2019, identified by the IPCC Special Report (October 2018) and the subsequent rise of the Fridays for Future movement. The estimation follows the four-step procedure described in Section 4.2. Coefficients represent deviations from the pre-event trend. The sharp rise in environmental worries accompanied by modest increases in peace and migration worries and a parallel decline in economic and financial worries is consistent with FPW-type reallocation, whereby environmental risk crowded out economic concerns during this period.

4.2.4 The Paris Terror Attacks and the subsequent New Year's Eve Sexual Assaults in Germany (late 2015)

Germany experienced intense public debate about migration during 2015–2016 following the arrival of more than one million refugees (the so-called "refugee crisis"). Public opinion in Germany varied widely, ranging from a welcoming attitude to xenophobic sentiments. Two events in particular, the November 2015 terrorist attacks in Paris and the New Year's Eve assaults across Germany, particularly in Cologne, shaped risk perceptions. Around these events we observe simultaneous increases in worries related to peace, crime, personal health, and migration (Figure 4). Economic worries decline during the same period. This pattern suggests that the perception and narrative of migration became increasingly framed through a security lens, shifting attention away from economic concerns. The shift had wide-reaching policy implications, prompting intensifying scrutiny of integration policies.

Figure 4: The effect of the Paris Terrorattacks and the subsequent New Year's Eve Assault (2015) on worries

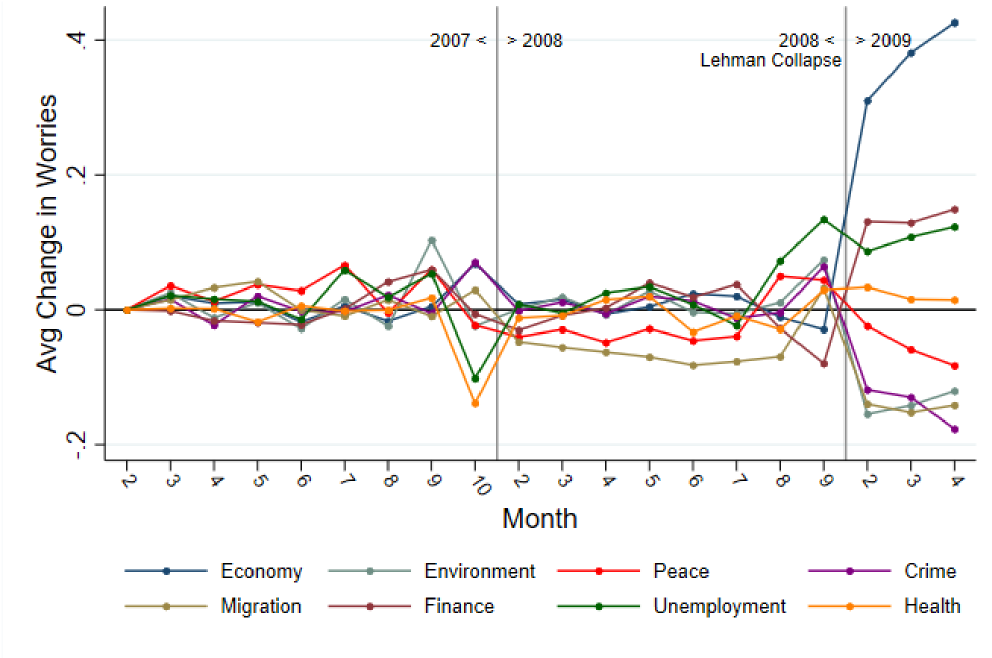


Notes: The figure plots estimated deviations in worry levels across eight domains around the November 2015 Paris terror attacks and the subsequent New Year's Eve sexual assaults in Cologne (2015/2016). The estimation follows the four-step procedure described in Section 4.2. Coefficients represent deviations from the pre-event trend. The simultaneous increases in worries related to peace, crime, and migration, accompanied by a decline in economic worries, suggest that the public narrative surrounding migration was increasingly framed through a security lens, redirecting attention away from economic concerns. This pattern is consistent with FPW-type reallocation within a broadened security domain.

4.2.5 The Global Financial Crisis (2007-2009), with Lehman Brothers' Collapse

The collapse of Lehman Brothers in September 2008 marked the most visible escalation of the global financial crisis. Around this event, economic worries related to the macroeconomy, personal finances, and job security rise sharply (Figure 5). Simultaneously, worries about crime, the environment, and migration decline (Gifford, 2011; Scruggs & Benegal, 2012; Whitmarsh, 2011). This pattern again aligns with the FPW hypothesis: the emergence of a major economic threat crowds out other risks.

Figure 5: The effect of the Financial Crisis (2007-2009) on worries



Notes: The figure plots estimated deviations in worry levels across eight domains around the collapse of Lehman Brothers in September 2008. The estimation follows the four-step procedure described in Section 4.2. Coefficients represent deviations from the pre-event trend. The sharp rise in economic worries—related to the macroeconomy, personal finances, and job security—accompanied by declines in crime, environmental, and migration worries is consistent with FPW-type crowding-out. The emergence of a major economic risk temporarily displaced attention from other risk domains.

4.3 Summary and Implications

Across societal events, we observe recurring evidence that newly salient risks tend to crowd-out other worries. This pattern provides support for the FPW hypothesis (Weber, 2006). These findings have broader implications for public policy. Salient crises absorb a disproportionate share of emotional and cognitive resources, shape how the public perceives multifaceted issues, and reduce worry for other important yet non-domain-specific challenges. For example, the COVID-19 pandemic shifted public perception away from environmental concerns, while security shocks redirected worry away from the economy toward migration and crime. Policymakers therefore face an inherent trade-off when attempting to mobilize political support for multiple risks simultaneously.

At the same time, personal events may differ in their mechanism and the aggregate event-study results may mask substantial heterogeneity in individual responses. Some individuals may experience strong spillovers across domains while others compartmentalize risks. The next sections address these limitations by examining personal events (Section 5), which provide individual-level variation in exposure to risk shocks, and heterogeneous responses (Section 6).

5 Effects of Personal Events

Societal events affect the entire population and provide valuable insights into how large-scale crises reshape public attention. On the other hand, personal life events, such as severe illness, constitute substantial disruptions to an individual's life circumstances, are important stressors in the psychological and health literature (Cohen et al., 2016, 2019), and allow a more direct examination of how individuals update their worries in response to immediate and vivid risks. These events represent salient risks to personal well-being and therefore provide natural tests of how individuals adjust their perceptions of risk.

The analysis of personal events deviates from the existing research literature on interdependences of risk perceptions that mostly focuses on societal risks. Unlike societal shocks, personal events are idiosyncratic, affect only subsets of individuals and occur at different points in time across the population. This creates individual-level variation in exposure that allows us to compare individuals experiencing a life shock with those who do not using a more conventional microeconometric estimation strategy.

This section proceeds as follows. Section 5.1 outlines the empirical specification. Section 5.2 presents the results and highlights that personal events differ in their effects on worries, causing on average a generalized sense of risk and worry across domains, which is in line with the prediction from AG (Johnson & Tversky, 1983).

5.1 Econometric Strategy

To estimate the effects of personal life events on worry allocations, we exploit the longitudinal structure of the SOEP and implement a difference-in-differences framework centered on the onset of each life event. Our empirical specification compares changes in worries around the occurrence of the event between treated and untreated individuals:

$$\Delta w_{itl} = w_{itl} - w_{i(t-2)l} = \gamma_{tl} + \delta_l Event_{it} + X + \epsilon_{itl}$$

where Δw_{itl} denotes the change, $(w_{itl} - w_{i(t-2)l})$, in worry domain l for individual i; γ_{tl} capture common time shocks on the year level[5]; $Event_{it}$ is an indicator equal to one if individual i experiences the life event in period t; δ_l is the target vector of responses and measures how worries change following the life event[6]; X is a set of control variables from the baseline period; ϵ_{itl} is an error term.

Because life events develop their strongest impact immediately and may trigger broader long-run adjustments in life circumstances, we focus on the first post-event period, capturing the immediate impact while

[5] Using month-year fixed effects instead of year fixed effects does not meaningfully alter the estimation results.

[6] Interpretationally, δ_l is the conventional difference-in-differences estimand: the differential change in worries from two years before the event to the event year for treated individuals relative to individuals who are never treated or not yet treated.

minimizing potential post-treatment channels and attrition effects. Dropping all post-treatment periods, besides the first, addresses further the bad control problem associated with staggered events. Using a linear regression-based framework suits our empirical setting with an unbalanced panel. We consider changes in worries over two periods to address potential anticipation effects while balancing sample size considerations. Conceptually, this setup shares features with recent local-projection approaches that accommodate staggered events (Dube et al., 2025), while remaining grounded in a linear regression panel framework.

Moreover, although for some events the parallel trends assumption is more plausible than for others—for instance, unemployment due to layoffs and plant closures is a standard event used in health and labor economics (Marcus, 2013), and indirect events, such as health issues of household members, provide plausibly exogenous variation—the main argument of our empirical strategy is to provide consistent findings from a broad range of events, thereby not relying on individual events.

We add the lagged level of the dependent variable as a control which helps for several reasons. Firstly, there may be a mechanical ceiling and floor effect arising from the three-point worry scale. On a 3-point scale, someone already at the top cannot increase much further, and someone already at the bottom cannot decrease much further. The lagged level partly absorbs that mechanical restriction. Second, it helps with mean reversion. Extreme answers at baseline may drift back somewhat even without treatment. In the end, it makes individuals more comparable in terms of where they started. Standard errors are clustered at the individual-level to account for possible serial correlation and heteroscedasticity in our panel data.

5.2 Estimation Results

Table 1 reports estimated effects of personal life events on changes in worries across the eight domains (results without control variables are shown in Table 7 in Section 4 of the Supplemental Appendix). The results reveal a pattern that differs markedly from the crowding-out dynamics observed for societal shocks in Section 4.

Consider first the personal health crisis treatment[7], which provides a large sample of treated individuals (N_{treat} = 8,809). As expected, the largest effect appears in the health domain itself ($\hat{\delta}$=0.289, $\delta^{\widehat{stand}}$=0.419)[8]. However, the health shock also produces statistically significant increases in all seven remaining worry dimensions. All coefficients are positive and significant at the one percent level. This broad-

[7] A health crisis is defined as experiencing at least half a year of health problems, becoming chronically ill, or being severely limited in daily life due to one's health.

[8] $\hat{\delta}$ is the estimated average effect of the event on the worry dimension on the original three-point Likert scale. $\delta^{\widehat{stand}}$ is the estimated average effect in standard deviation units.

based pattern is consistent with the AG hypothesis: the experience of a health crisis elevates perceived vulnerability across domains, not only within the directly affected domain.

Similar patterns emerge for other personal events. Unemployment shocks produce the largest effects on personal economic worries—finances ($\hat{\delta}$=0.356, $\widehat{\delta^{stand}}$=0.5) and job security ($\hat{\delta}$=0.322, $\widehat{\delta^{stand}}$=0.46)—but also significantly increase in health worries ($\hat{\delta}$=0.104, $\widehat{\delta^{stand}}$=0.15) and macroeconomic concerns ($\hat{\delta}$=0.094, $\widehat{\delta^{stand}}$=0.14). Indebtedness generates substantial increases in financial worries ($\hat{\delta}$=0.36, $\widehat{\delta^{stand}}$=0.51) alongside significant effects on unemployment ($\hat{\delta}$=0.156, $\widehat{\delta^{stand}}$=0.22), health ($\hat{\delta}$=0.129, $\widehat{\delta^{stand}}$=0.187), crime ($\hat{\delta}$=0.059, $\widehat{\delta^{stand}}$=0.086), the economy ($\hat{\delta}$=0.113, $\widehat{\delta^{stand}}$=0.174), and migration ($\hat{\delta}$=0.08, $\widehat{\delta^{stand}}$=0.106). When unemployment and indebtedness co-occur, the effects amplify, with particularly large increases in financial ($\hat{\delta}$=0.73, $\widehat{\delta^{stand}}$=1.04), unemployment ($\hat{\delta}$=0.41, $\widehat{\delta^{stand}}$=0.59), health ($\hat{\delta}$=0.342, $\widehat{\delta^{stand}}$=0.5), broader economic ($\hat{\delta}$=0.284, $\widehat{\delta^{stand}}$=0.43), migration ($\hat{\delta}$=0.269, $\widehat{\delta^{stand}}$=0.357) and peace ($\hat{\delta}$=0.198, $\widehat{\delta^{stand}}$=0.29) worries—i.e. broad spillovers across nearly all domains.

Social and psychological events exhibit especially pronounced cross-domain effects. Discrimination experience produces significant increases across all eight worry dimensions, with notably large effects on finances ($\hat{\delta}$=0.249, $\widehat{\delta^{stand}}$=0.353), unemployment ($\hat{\delta}$=0.264, $\widehat{\delta^{stand}}$=0.377), health ($\hat{\delta}$=0.258, $\widehat{\delta^{stand}}$=0.374), and crime ($\hat{\delta}$=0.177, $\widehat{\delta^{stand}}$=0.256). Loneliness similarly generates broad increases, with the strongest effects on finances ($\hat{\delta}$=0.272, $\widehat{\delta^{stand}}$=0.386), unemployment ($\hat{\delta}$=0.191, $\widehat{\delta^{stand}}$=0.272), and health ($\hat{\delta}$=0.249, $\widehat{\delta^{stand}}$=0.36). Loss of purpose shows a comparable pattern, with large effects on finances ($\hat{\delta}$=0.328, $\widehat{\delta^{stand}}$=0.469), unemployment ($\hat{\delta}$=0.267, $\widehat{\delta^{stand}}$=0.381), and health ($\hat{\delta}$=0.281, $\widehat{\delta^{stand}}$=0.407). These events, which represent threats to social identity and psychological well-being rather than concrete material losses, nevertheless produce substantial increases in worries across material and societal domains—a finding that underscores the affective rather than purely informational channel through which personal shocks propagate.

Indirect events affecting household members show more moderate but still significant cross-domain effects. A spouse's health crisis increases the respondent's own health worries ($\hat{\delta}$=0.171, $\widehat{\delta^{stand}}$=0.248) and produces smaller but significant spillovers to finances ($\hat{\delta}$=0.045, $\widehat{\delta^{stand}}$=0.064), unemployment ($\hat{\delta}$=0.028, $\widehat{\delta^{stand}}$=0.04), the economy ($\hat{\delta}$=0.029, $\widehat{\delta^{stand}}$=0.045), migration ($\hat{\delta}$=0.016, $\widehat{\delta^{stand}}$=0.021), and the environment ($\hat{\delta}$=0.014, $\widehat{\delta^{stand}}$=0.022). A child's health crisis produces a similar pattern with comparable effect sizes for finances ($\hat{\delta}$=0.113, $\widehat{\delta^{stand}}$=0.161) and health ($\hat{\delta}$=0.117, $\widehat{\delta^{stand}}$=0.17).

Table 1: Regression Table Personal Events

	Personal Worries			**Societal Worries**				
Event	*Finance*	*Unemp.*	*Health*	*Crime*	*Economy*	*Migr.*	*Environ.*	*Peace*
Panel A: Direct personal events								
Health crisis	0.072***	0.044***	0.289***	0.023***	0.046***	0.023***	0.032***	0.022***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
	N = 66,794; $N_{treated}$ = 8,809							
Unemployment	0.355***	0.322***	0.104***	0.041	0.094***	0.065**	-0.022	-0.008
	(0.032)	(0.043)	(0.032)	(0.032)	(0.031)	(0.032)	(0.028)	(0.033)
	N = 154,062; $N_{treated}$ = 361							
Debt	0.360***	0.156***	0.129***	0.059***	0.113***	0.080***	0.008	0.025*
	(0.014)	(0.014)	(0.014)	(0.014)	(0.012)	(0.014)	(0.013)	(0.014)
	N = 10,158; $N_{treated}$ = 3,542							
Unemp. + Debt	0.730***	0.410***	0.342***	0.025	0.284***	0.269***	0.087	0.198*
	(0.084)	(0.136)	(0.096)	(0.101)	(0.101)	(0.087)	(0.067)	(0.113)
	N = 6,199; $N_{treated}$ = 39							
Discrimination	0.249***	0.264***	0.258***	0.177***	0.131***	0.059	0.090**	0.103***
	(0.035)	(0.044)	(0.039)	(0.036)	(0.037)	(0.043)	(0.036)	(0.036)
	N = 112,522; $N_{treated}$ = 328							
Crime in neighb.	0.175***	0.158***	0.141***	0.316***	0.147***	0.249***	0.024*	0.107***
	(0.014)	(0.015)	(0.014)	(0.014)	(0.013)	(0.015)	(0.013)	(0.014)
	N = 10,472; $N_{treated}$ = 2,850							
Panel B: Indirect and psychological events								
Loneliness	0.272***	0.191***	0.249***	0.078***	0.167***	0.072***	0.037**	0.055***
	(0.017)	(0.019)	(0.018)	(0.017)	(0.018)	(0.018)	(0.016)	(0.016)
	N = 25,166; $N_{treated}$ = 1,267							
Loss of purpose	0.328***	0.267***	0.281***	0.069***	0.111***	0.047**	-0.002	-0.018
	(0.019)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
	N = 18,046; $N_{treated}$ = 1,226							
Health spouse	0.045***	0.028***	0.171***	0.011	0.029***	0.016**	0.014**	0.000
	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
	N = 57,134; $N_{treated}$ = 10,842							
Health child	0.113***	0.057**	0.117***	0.032	0.059***	0.042*	0.023	0.038*
	(0.022)	(0.022)	(0.022)	(0.023)	(0.021)	(0.023)	(0.020)	(0.021)
	N = 9,763; $N_{treated}$ = 802							

Notes: Each row reports estimated coefficients from separate regressions of changes in worries on an event indicator. The dependent variable is the change in each worry domain. All specifications include year fixed effects, the lagged level of the dependent variable, and controls for age, partner status, sex, German-born status, migration background, and federal state. Standard errors clustered at the individual level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Treatment definitions: Health = experiencing at least half a year of health problems, becoming chronically ill, or being severely limited in daily life; Unemployment = becoming unemployed due to layoffs or plant closures; Debt = reporting financial difficulties due to indebtedness; Unemploy + Debt = experiencing both unemployment and indebtedness; Discrimination = reporting an experience of discrimination; Crime in neighb. = reporting increased crime in the immediate neighborhood; Loneliness = reporting feelings of loneliness; Loss of purpose = reporting a sense of loss of purpose; Health spouse = spouse experiencing a serious health crisis; Child health = child experiencing a serious health crisis.

Two regularities stand out across all personal events. First, the cross-domain effects are overwhelmingly positive: personal shocks almost never reduce worries in unrelated domains, in stark contrast to the crowding-out observed for societal events. Second, there is a tendency for personal events to affect personal worries—finances, employment, and health—more strongly than societal worries—crime, the economy, migration, the environment, and peace. The environmental and peace worry dimensions are particularly resistant to cross-domain spillovers: they show often small or nonsignificant effects across most personal events, suggesting that they may be less responsive to personal disruptions than other worry domains.

Taken together, these results indicate that personal life events produce generalized increases in perceived risk that extend well beyond the immediate domain of the event. This pattern is consistent with the AG hypothesis: individuals experiencing personal shocks perceive a heightened sense of vulnerability that is not confined to the specific risk they have encountered. The contrast with the FPW-type crowding-out observed for societal events in Section 4 is striking and suggests that different types of risk-inducing events operate through systematically different mechanisms. We explore this distinction further—and the heterogeneity within it—in Section 6.

6 Heterogeneous Profiles

The previous sections have focused on average responses to risks. However, average effects may conceal substantial heterogeneity in how individuals update their worries. Different individuals may rely on different mechanisms or cognitive strategies when processing risk-related information. Some may compartmentalize and reallocate worry toward the most salient risk, while others may experience generalized emotional spillovers that elevate worries across domains. Furthermore, additional nuanced patterns may emerge.

To investigate this possibility, we examine whether the population exhibits distinct updating profiles in response to risk shocks. Rather than imposing a single behavioral model on all individuals, we allow the data to identify and characterize latent profiles with different patterns of worry updating. We build on and combine recent insights from difference-in-differences methodology and idiosyncratic, time-varying personal events with stochastic, model-based clustering to identify and classify profiles.

This section makes three key contributions. First, we empirically identify heterogeneous treatment profiles. Our findings suggest that the population is composed of different belief updating types. Individuals vary significantly in their responses and the interdependence of their risk perceptions: some experience FPW, some AG, and some other patterns. We also estimate each profile's share in the population. Second, we characterize these profiles, showing that they differ along socioeconomic and psychological dimensions. Finally, to identify and characterize such multivariate, heterogeneous treatment profiles we combine imputation-based difference-in-differences-estimation with stochastic, model-based clustering. We provide supporting evidence for this approach by designing a simulation study (see Section 1 of the Supplemental Appendix).

The remainder of this section is structured as follows. Subsection 6.1 details the econometric strategy for identifying individual-level treatment effects and outlines how we use latent profile analysis to capture heterogeneity in multiple domains, and subsection 6.2 presents our empirical findings.

6.1 Econometric Approach

Our core objective is to estimate how an event affects multiple dependent variables simultaneously, while allowing for heterogeneous treatment effects across latent subpopulations. We formalize this via the following baseline model for each worry dimension l:

$$\Delta w_{itlp} = \beta_{tl} + \delta_{lp} D_{it} + \epsilon_{itl}$$

where Δw_{itlp} is again the change, $(w_{itlp} - w_{i(t-2)lp})$, in worry level of individual i at time t in domain l; β_{tl} is a time fixed effect; D_{it} indicates treatment (the onset of a personal shock); and ϵ_{itl} is an idiosyncratic error. The model has a key modification differentiating it from the standard homogenous-effect model from the previous section: δ_{lp} is the treatment effect for worry dimension l, which varies by latent profile membership $p \in \{1, \ldots, P\}$. Neither profiles nor profile memberships are observed; they must be inferred from the data.

We estimate profiles in three steps: (1) impute individual-level treatment effects using the Borusyak, Jaravel, and Spiess (2024) (BJS) estimator; (2) recover latent profiles from the joint distribution of individual treatment effects using a Gaussian finite mixture model (Latent Profile Analysis)[9]; and (3) characterize profiles by incorporating observed covariates into the structural model. We describe each step in turn.

Step 1) Imputation of individual treatment effects: We use the BJS imputation estimator, which is designed for staggered difference-in-differences settings, and exploit the SOEP's panel data structure and the onset of a personal life event as a treatment. The BJS approach avoids "forbidden comparisons" that arise in two-way fixed effects regressions with heterogeneous treatment timing (Goodman-Bacon, 2021) and accommodates unbalanced panels without discarding observations (Bellégo et al., 2025).

For each worry dimension l, using only never-treated or not-yet-treated individuals, we regress the change in worries, Δw_{itl}, on control variables, year fixed effects, and federal state fixed effects, accounting for aggregate time and regional differences. By working in changes, we absorb time-invariant individual heterogeneity without estimating individual fixed effects, reducing data requirements and Nickell bias concerns (Angrist & Pischke, 2009). From this regression, we predict $\widehat{\Delta w_{itl}}^{control}$ for each treated individual—an estimate of how Δw_{itl} would have evolved had the individual remained untreated. This is the individual's

[9] Essentially, this step recovers weights for aggregating the individual treatment effects.

imputed counterfactual outcome. The non-consistently estimated individual-level treatment effect for dimension l is then:

$$\widehat{\delta_{\iota lp}} = \Delta w_{itlp}^{actual} - \widehat{\Delta w_{\iota tl}}^{control}$$

Each individual's treatment effect profile is represented by the L-dimensional vector $\widehat{\boldsymbol{\delta}_{\iota p}} = \left(\widehat{\delta_{\iota 1p}}, \widehat{\delta_{\iota 2p}}, \dots, \widehat{\delta_{\iota Lp}}\right)$. Like before, we focus on the first post-treatment period only, as this captures the immediate impact while minimizing confounding from long-run adjustments, post-treatment channels, and attrition.

Two points make personal events well suited to study heterogeneous effects: i) simultaneous control and treatment groups are defined, enabling application of BJS difference-in-differences methodology, and ii) a high confidence in the impact of an event on each treated individual, reducing noise in profile estimation. We treat each event as a plausibly exogenous disruption to individuals' day-to-day experience of risks and threats. Identification relies on three standard assumptions: parallel trends (treated individuals in each profile would have followed the same counterfactual trend as control individuals), no anticipation (individuals do not systematically alter worries prior to the event), and SUTVA (no cross-individual spillovers). Because these are personal events, we can safely assume that other individuals in the sample are mostly not affected. Like before, we consider changes in worries over two periods to address potential anticipation effects.

Step 2) Latent profile estimation: To uncover latent heterogeneity in the multivariate treatment effect vectors, we estimate a Gaussian finite mixture model—specifically, Latent Profile Analysis (LPA). LPA is a person-centered data reduction method that groups individuals who have similar patterns across multiple dependent variables. LPA posits that the population consists of P unobserved subgroups (latent profiles), each characterized by a distinct mean treatment effect vector. The overall distribution of observed treatment effects is modeled as a mixture of P multivariate normal distributions:

$$f\left(\widehat{\boldsymbol{\delta}_{\iota p}}\right) = \sum_{p=1}^{P} \pi_{ip} \cdot \phi\left(\widehat{\boldsymbol{\delta}_{\iota p}};\ \boldsymbol{\delta}_p, \boldsymbol{\Sigma}_p\right),$$

where π_{ip} is the mixing proportion, ϕ is the multivariate normal distribution, $\boldsymbol{\delta}_p$ is the profile-specific mean treatment effect vector, and $\boldsymbol{\Sigma_p}$ is the profile-specific (diagonal) variance-covariance matrix. The diagonal restriction on $\boldsymbol{\Sigma}_p$ imposes conditional independence: within each profile, interdependencies between worry dimensions are fully captured by profile membership (Tein et al., 2013). Thus, LPA serves as a stochastic clustering method such that variability within the profiles is minimized and the between-profile variability is maximized. The model is estimated by maximum likelihood using the EM algorithm with 50 sets of random starting values to guard against local maxima (Masyn, 2013).[10] We select the number of

[10] We use the gsem command in Stata with the default maximum number of iterations and convergence criterion.

profiles P using the Akaike and Bayesian information criteria. Moreover, we additionally require that each profile contain at least five percent of the sample (to address problems of under-identification associated with observation size) and that profiles mostly differ qualitatively, not merely quantitatively, in their treatment effect patterns.

Step 3) Profile characterization: To characterize the identified profiles, we extend the structural model by incorporating observed covariates x_i from the baseline period as predictors of profile membership through a multinomial logit regression:

$$\Pr(c_i = p|x_i) = \frac{\exp(\gamma_{0p} + \gamma_{1p}x_i)}{\sum_{j=1}^{P} \exp(\gamma_{0j} + \gamma_{1j}x_i)}$$

We estimate average partial effects (APE) for each covariate on the probability of belonging to each profile. Covariates include the Big Five personality traits, age cohort dummies, gender, migration background, partnership status, university degree, and household net income brackets. This characterization serves also as a construct validity check: if the profiles are substantively meaningful, they should differ systematically along theoretically relevant dimensions.

A potential concern is that the individual-level treatment effects $\hat{\boldsymbol{\tau}}_i$ are not consistently estimated—they contain idiosyncratic imputation error: $\widehat{\delta_{il}} = \delta_{lp} + u_{il}$, where u_{il} reflects both imputation noise and residual individual variation. However, the Gaussian mixture structure of LPA provides a natural solution to this problem. Under the assumption that imputation errors $\boldsymbol{u}_i$ are independent of profile membership c_i and have mean zero, the measurement error is absorbed into the within-profile variance-covariance matrix $\boldsymbol{\Sigma}_p$. The profile-specific means $\boldsymbol{\delta}_p$ remain unbiased and consistently estimated as the number of treated individuals grows, because symmetric mean-zero errors inflate the dispersion of the mixture components without shifting their locations (McLachlan & Peel, 2000). Intuitively, the measurement error makes each profile's distribution wider but does not move its center. This property distinguishes LPA from deterministic clustering algorithms such as k-means, which assign individuals to the nearest centroid and are therefore directly distorted by noise in individual estimates. LPA's probabilistic assignment, by contrast, effectively downweighs noisy observations by assigning them more diffuse probabilities across profiles. This stochastic clustering property makes the approach particularly well suited to settings such as ours where individual-level estimates may be noisy but the underlying group structure remains.

To validate the procedure, we conduct a Monte Carlo simulation in which we control the data-generating process (see Section 1 of the Supplemental Appendix). We estimate individual-level treatment effect vectors from a known synthetic mixture distribution plus measurement error of varying magnitude, and apply both LPA and k-means clustering. The results demonstrate that LPA reliably recovers the true profile means and mixing proportions even under substantial measurement error (average absolute deviation from true values:

0.057 for LPA vs. 7.90 for k-means when the noise-to-signal ratio is moderate). k-means, by contrast, produces severely biased profile estimates because it deterministically assigns noisy observations to incorrect clusters. The simulation reinforces our analytical argument for using model-based clustering in settings with imputed treatment effects.

This approach is complementary to the causal machine learning literature for heterogeneous treatment effects (e.g., Chernozhukov et al. 2025), which search for heterogeneity as a function of observed covariates. We instead identify heterogeneity in the multivariate structure of treatment effects without pre-specifying which covariates matter, then characterize the profiles ex post. This is advantageous when the object of interest is the joint pattern across multiple outcomes rather than a scalar treatment effect.

6.2 Estimation Results

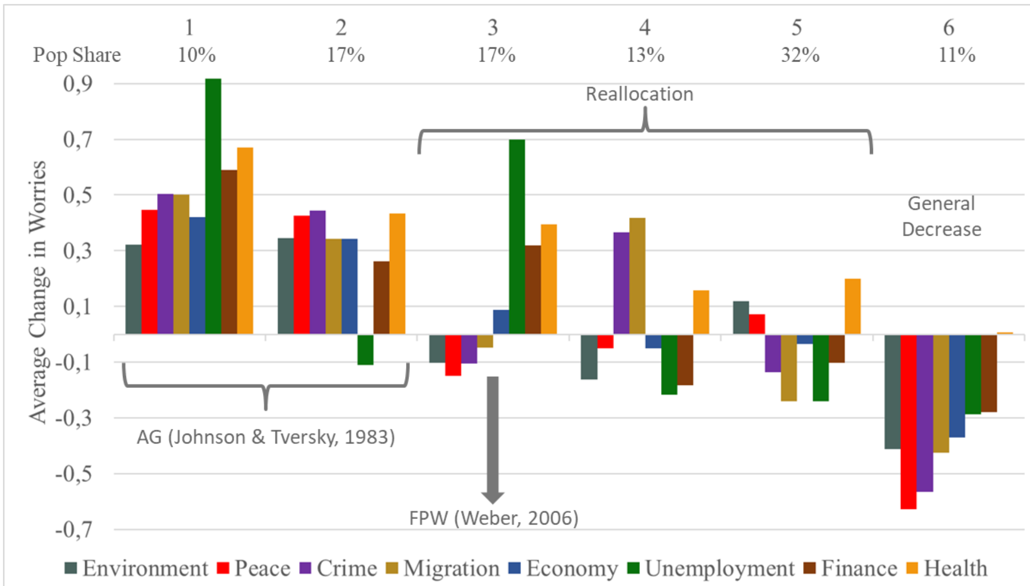
We present the main findings from the health crisis treatment, which serves as our primary illustration. A health crisis is defined as experiencing at least half a year of health problems, becoming chronically ill, or being severely limited in daily life due to one's health. We restrict the sample to individuals aged 18–60 to focus on the working-age population. An alternative treatment definition is examined in Section 5 of the Supplemental Appendix. The patterns are consistent.

Based on the information criteria and our decision rules as described in Section 6.2, we identify six profiles in Figure 6. We label and interpret these as follows.

Profiles 1 and 2 — Affect Generalization: These profiles exhibit a generalized increase in worries across domains. The response pattern closely resembles the AG hypothesis (Johnson & Tversky, 1983): the experience of a health crisis elevates perceived vulnerability broadly, not only within the health domain. Profiles 1 and 2 differ in one important respect: profile 2 shows a relative decline in unemployment worries, whereas profile 1 does not. This divergence may reflect differences in labor market attachment or economic security. Together, these two profiles account for approximately 27 percent of the treated population, indicating that affect generalization is a prevalent response pattern

Profiles 3, 4, and 5 — Relative Reallocation: The profiles exhibit relative changes in worries, with increases in some domains accompanied by decreases in others. Profile 3 (approximately 17 percent) most closely resembles the standard interpretation of the FPW hypothesis (E. U. Weber, 2006): immediate and personal worries—health and economic—increase, while more general societal worries—environment, peace, crime, migration—decrease. Profiles 4 and 5 represent contrasting reallocation patterns. Profile 4 (approximately 13 percent) shows increases in crime and migration worries alongside the health worry increase, reflecting a more closed or security-oriented response. Profile 5 (approximately 32 percent) shows the inverse: increases in environmental and peace worries, reflecting what might be described as a more open orientation—concern that extends to collective, long-term risks. These two profiles are interpretive mirror images that differ not only in which worries increase but, as we show below, in the sociodemographic and psychological characteristics of their members.

Figure 6: Health Crisis - Treatment Profiles



Notes: The figure displays estimated profile-specific average treatment effects from the Latent Profile Analysis for the health crisis event. Each cluster of bars represents one latent profile; bars indicate the average change in the respective worry dimension attributable to the health crisis, estimated relative to the imputed counterfactual from never-treated and not-yet-treated individuals following Borusyak et al. (2024). Individual-level treatment effects are computed as the difference between observed and imputed changes in each worry dimension. Latent profiles are identified using a finite mixture of multivariate normals with profile-varying, diagonal covariance matrices, estimated via the EM algorithm with 50 sets of random starting values. Profile enumeration is based on AIC, BIC, and the requirement that each profile comprises at least 5% of the treated sample. Population shares (shown above each profile) are estimated mixing proportions. The treatment group consists of individuals aged 18–60 experiencing at least half a year of health problems, onset of chronic illness, or severe limitation in daily life due to health issues (N = 7,486). All specifications use changes over two periods with year–month and federal state fixed effects. Profile labels reflect qualitative interpretation: Profiles 1 and 2 exhibit generalized increases in worries consistent with AG (Johnson & Tversky, 1983); Profiles 3, 4 and 5 display relative reallocation patterns; Profile 3 shows domain-specific increases alongside decreases in non-domain worries consistent with the FPW (E. U. Weber, 2006); Profile 6 exhibits broad decreases in worries ("General Decrease").

Profile 6 — General Decrease. This profile is characterized by an absolute decrease in worries across nearly all domains, excluding health. It represents approximately 11 percent of treated individuals. This pattern is notable because it implies that the experience of a health crisis does not uniformly increase expressed concern; for a minority, the response is instead one of dampening or suppression. Possible interpretations include emotional shutdown, avoidant coping, or genuine resilience. The low neuroticism score associated with this profile (discussed below) is consistent with lower affective reactivity and a greater capacity for suppression or emotional regulation.

Importantly, the profiles also differ in their health worry response—the primary risk dimension of this treatment. A clear gradient emerges from left to right across the profiles, with the largest health worry increases in profiles 1 and 2 (AG) and the smallest in profile 6 (General Decrease).

We use the structural model to characterize the identified profiles in Table 2. Variables included are the Big 5 personality traits, and dummies for age cohorts, children, sex, migration background, relationship status, education represented by university degree, and income brackets. The SOEP elicits the Big 5—consisting of neuroticism, extraversion, agreeableness, openness, and conscientiousness—from a standard 15-question battery on seven-point Likert scales.

Table 2: Health Crisis - Profile Characteristics

Health Crisis / APE	Profile					
N(Treat) = 7,486	1	2	3	4	5	6
Neuroticism	2.21	2.35	1.91	0.47	-4.25	-2.69
Extraversion	0.01	1.40	-0.28	1.28	-1.72	-0.70
Agreeableness	0.15	1.01	0.29	-1.98	2.05	-1.51
Openness	-0.28	0.54	-0.76	-1.96	3.08	-0.62
Conscientiousness	1.67	1.11	-0.44	1.91	-2.65	-1.60
Age (Ref: 18-29)						
30-39	-0.05	0.65	1.44	6.37	-4.40	-4.01
40-49	0.03	3.99	4.48	0.95	-4.85	-4.59
50-60	0.14	7.12	-2.36	4.74	-3.13	-6.51
Children	2.12	-2.09	1.17	-0.37	-0.27	-0.56
Female	-3.76	5.10	-6.29	-0.09	7.89	-2.85
Partner	-0.37	-0.72	-0.49	1.53	-0.23	0.28
Migrant	4.92	1.06	5.23	-6.11	-7.83	2.72
University Degree	-5.88	-6.16	0.71	-9.65	19.15	1.82
Mon HH Net Income						
1500€-3000€	-1.99	-2.41	-4.44	7.92	1.32	-0.39
3000€-4500€	-5.58	-3.30	-5.45	9.76	6.22	-1.66
>4500€	-4.95	-3.37	-5.22	1.35	9.24	2.95

Notes: The table reports average partial effects (APEs) from the multinomial logistic structural model of the Latent Profile Analysis, estimated in percentage points. Each entry gives the change in the predicted probability of belonging to a given profile associated with a unit change in the covariate (or a discrete change for binary and categorical variables). For example, holding a university degree is associated with a 19.15 percentage point higher probability of belonging to Profile 5 relative to not holding a university degree. The Big Five personality traits (neuroticism, extraversion, agreeableness, openness, conscientiousness) are measured on seven-point scales. Age cohort reference category: 18–29. Income reference category: below €1,500 monthly household net income. Children indicates the presence of children in the household; Female is an indicator for female respondents; Migrant indicates migration background; Partner indicates cohabitation with a partner. The treatment group comprises individuals experiencing a health crisis, defined as at least half a year of health problems, onset of chronic illness, or severe limitation in daily life. N(Treated) = 7,486.

The most robust finding is a pronounced gradient along neuroticism—the dispositional tendency to experience negative emotions. From profiles 1 and 2 (Affect Generalization) to profile 6 (General Decrease), neuroticism decreases monotonically. The finding implies that neuroticism does not merely predict higher baseline worry but shapes the qualitative structure of how individuals update their worries in response to crises. More neurotic individuals are substantially more likely to generalize a domain-specific shock into a broader sense of vulnerability, while less neurotic individuals are more likely to compartmentalize, reallocate, or even suppress worry. This result provides a psychologically grounded microfoundation for heterogeneous belief updating and connects personality to the economics of risk perception and belief formation with implications for subsequent or “downstream” behaviors.

Profile 5 ranks higher on openness to experience, while profile 4 ranks lower. This pattern is consistent with the substantive interpretation of these profiles: openness is associated with intellectual curiosity, aesthetic sensitivity, and receptiveness to novel ideas and perspectives—traits that may predispose individuals to attend to collective, abstract risks such as environmental degradation, climate change, peace and geopolitical instability. Conversely, lower openness is associated with preference for familiarity and conventional values, which may predispose individuals toward domestic security-oriented concerns such as crime and migration. More broadly, profiles 4 and 5 represent mirror images across the Big Five: they differ in nearly all personality dimensions, suggesting that personality constellations—not single traits—organize worry reallocation patterns.

A systematic gender gap emerges across profiles. Women are overrepresented in profiles 2 and 5—the affect-generalization and open-reallocation profiles—and underrepresented in profiles 1, 3 and 6. The difference between profiles 1 and 2, which are both AG-type but differ in unemployment worry and gender composition, may additionally reflect the influence of differential labor market exposure and traditional gender roles.

A large education and income gap emerges between the profiles. Individuals in profile 5 are substantially more likely to hold a university degree and to earn higher household incomes (above 4500€), whereas profile 4 consists disproportionately of individuals without university degrees and medium income brackets (1500€-4500€). Profile 3—the classic FPW pattern in which economic worries take precedence—is associated with lower income, consistent with research showing that economic concerns dominate when financial resources are scarce (Scruggs & Benegal, 2012). The AG profiles (1 and 2) tend to contain respondents without higher education degrees that belong to lower-income brackets. More generally, we observe patterns consistent with diminishing marginal utility of money: higher income is associated with lower economic worry responses in times of crisis, vice versa.

Younger individuals tend to be more represented in profiles 5 and 6, whereas middle aged individuals are more likely to be profile 3 and 4, older individuals are more likely to be in profile 2. People with migration backgrounds are less likely to belong to profiles with environmental and peace-oriented reallocation and more likely to belong to profiles emphasizing economic and personal concerns. These patterns, suggest that life-course position and social identity also shape how worry is allocated during a crisis.

Table 3 reports the estimated population shares. The AG profiles (1 and 2) together account for approximately 27 percent of the treated population. The three relative reallocation profiles (3, 4, and 5) together account for approximately 62 percent. The General Decrease profile (6) accounts for approximately 11 percent. Using the alternative treatment definition as shown in Section 5 of the Supplemental Appendix, we find broadly consistent patterns and population shares. The six-profile structure, the neuroticism gradient, and the key sociodemographic patterns replicate consistently. The stability of these results supports the interpretation that the profiles reflect persistent individual differences in worry-updating strategies.

Table 3: Health Crisis - Population Shares

Health Crisis	Profile					
N(Treat) = 7,486	1	2	3	4	5	6
Population Share	10%	17%	17%	13%	32%	11%

Notes: The table reports estimated population shares (mixing proportions) from the multinomial logistic structural model of the Latent Profile Analysis. Shares represent the predicted probability of belonging to each profile, averaged over all treated individuals, and sum to 100%. The treatment group comprises individuals aged 18–60 experiencing a health crisis, defined as at least half a year of health problems, onset of chronic illness, or severe limitation in daily life due to health problems (N = 7,486). Profile enumeration is based on AIC, BIC, and the requirement that each profile comprises at least 5% of the treated sample.

7 Discussion & Conclusion

This paper studies whether risk perceptions are domain-separable or interdependent. We provide field evidence that worries form a connected multivariate system in which shocks in one domain affect worries in others, even when the underlying objective risks are largely unrelated. This conclusion emerges consistently across our analyses and constitutes the central contribution of the paper.

Our findings clarify an important ambiguity in the literature surrounding the FPW and AG hypotheses. Existing work has often treated these as competing explanations, implicitly suggesting that one should dominate the other. Our evidence points to a more nuanced conclusion: both mechanisms are empirically relevant, but they characterize different settings and different individuals. At the aggregate level, societal crises tend to generate crowding-out patterns consistent with FPW. Across all societal events we examine—the Russian invasion of Ukraine, the COVID-19 pandemic, the climate salience shock, the Paris terror attacks, and the Global Financial Crisis—newly salient risks absorb a disproportionate share of worry at the expense of competing concerns. By contrast, personal life events—health crises, unemployment, indebtedness, discrimination, and others—induce broader increases in worries across domains, consistent with AG. Thus, the relevant question is not which mechanism but under which conditions and for whom each mechanism dominates.

This asymmetry between worry responses also permits an informal decomposition of the channels through which personal shocks propagate across domains. A personal health crisis, for example, provides the individual with direct private information about personal vulnerability but conveys usually little information about the state of the economy, the environment, or geopolitical risks. If worry updating were purely informational—driven by Bayesian processing of domain-specific signals—we should observe effects only in the health domain and perhaps in closely related domains (personal finances, if health affects earnings capacity). Yet we observe significant increases across other domains, including those for which no informational channel is plausible. This pattern isolates the affective channel: the component of cross-domain updating that cannot be explained by informational spillovers and must reflect affect-driven generalization. The fact that effects are larger for personal worries (where informational and affective channels reinforce each other) than for societal worries (where only the affective channel operates) is consistent with this decomposition. This finding strengthens the claim that affect, not merely information, drives the interdependence of risk perceptions.

This logic—comparing a shock's effect across domains where an informational channel is and is not plausible—has recently received attention in the macroeconomic-expectations literature (Bordalo et al., 2026). Taubinsky et al. (2026) link Danish consumer-expectations surveys to administrative records and show that inflation forecasts co-move strongly and negatively with idiosyncratic household income and adverse health shocks, even though these shocks are essentially uninformative about aggregate inflation; they establish formally that this pattern violates the Bayesian rational-expectations benchmark and attribute it to affect-cued recall. A central distinction in this work is between domain-specific (DS) experiences, which carry information about the variable being assessed, and non-domain-specific (NDS) experiences, which do not but are retrieved through shared affective valence. Our results are the worry-battery analogue of this finding: a personal shock that carries no information about macroeconomic, environmental, or geopolitical risk nonetheless raises worries across all of these domains. Affect Generalization can thus be understood as the worry-system counterpart of NDS-driven belief formation, in which an adverse experience is generalized into a broad sense of vulnerability.

An alternative theoretical framework that may help organize the divergence between societal and personal events is Construal Level Theory (CLT) (Trope & Liberman, 2003, 2010). CLT posits that the psychological distance of an event (its temporal, spatial, social, and hypothetical remoteness) determines the level of abstraction at which it is mentally represented. Psychologically distant events are processed through abstract representations, whereas proximal events engage concrete, vivid, and affectively charged processing. This distinction maps onto the contrast between societal and personal crises. Societal crises are typically experienced at a distance: they are mediated through news coverage, involve abstract statistical risks, and affect diffuse populations. Under CLT, such distal processing favors analytic evaluation; conditions under which individuals engage in prioritization, reallocating limited attention resources toward the most salient and decision-relevant risk—a dynamic which may be reinforced by news cycles. This mode of processing (the individual as a constrained attention optimizer) aligns with attention-driven reallocation, resonating with the "Finite Pool of Attention" interpretation proposed by Sisco et al. (2023). Personal life events, by contrast, are psychologically proximal: they are concrete, vivid, emotionally immediate, and directly threatening to one's identity and well-being. This activates affect-driven evaluation, in which risk perceptions are more intense, less category-specific, and more likely to generalize across domains. This pattern aligns with the AG hypothesis: the individual does not compartmentalize the risk but instead experiences a general vulnerability. CLT thus generates a testable prediction: societal shocks, processed at a distance, should predominantly produce crowding-out reallocation, while personal shocks, processed proximally, should predominantly produce AG-type generalization. Our empirical design provides evidence consistent with this prediction. In this framing, the distinction between FPW and AG is not a contradiction but may reflect how psychological distance modulates the channel through which risk information is processed: analytic and attention-based for distal threats, affective and generalized for proximal ones. Further clarifying the cognitive mechanisms of interdependencies in risk perceptions through experimental manipulation of psychological distance constitutes a promising avenue for future research.

A central result of the paper is that heterogeneity is structured and substantively meaningful. Our latent profile analysis identifies distinct response types that differ qualitatively in how worries are reallocated after adverse events. These profiles are stable and are replicable. Approximately 27 percent of individuals exhibit AG-type generalized increases in worry. About 11 percent exhibit absolute decreases in worry—a pattern we discuss further below. The remaining 62 percent exhibit variations of relative reallocation, including classic FPW-type crowding-out in which immediate and personal worries rise while more general societal worries decline. These profiles imply that interdependent risk perceptions are qualitatively heterogeneous, not merely quantitatively so. An important predictor of these latent profiles is neuroticism. Individuals scoring higher on neuroticism are substantially more likely to belong to profiles characterized by generalized increases in worries, whereas less neurotic individuals are more likely to display crowding-out dynamics or even broad reductions. This finding moves the literature beyond documenting that average effects differ across settings. It suggests that stable psychological traits help determine the mechanism through which shocks are translated into broader systems of belief. Neuroticism, in this sense, does not merely predict higher baseline worry; it predicts the structure of updating itself. This provides a psychologically grounded microfoundation for heterogeneous belief updating and links personality to the economics of risk perception, attention, and expectations formation.

These results have several implications. First, they challenge descriptive models in which beliefs about independent risks are updated separately and according to narrowly domain-specific information. Our evidence suggests that risk perceptions are better understood as elements of a multivariate belief system connected through affective and attentional channels.

Second, the coexistence of FPW and AG within the population indicates that theory must account for multiple updating regimes rather than a single representative mechanism, which would miss diverging behaviors. FPW can be interpreted as a reallocation constrained cognitive capacity, consistent with bounded rationality and rational inattention frameworks, in which individuals shift limited processing capacity toward the most salient risk (Bordalo et al., 2022b; Gabaix, 2019; Link et al., 2026; Loewenstein & Wojtowicz, 2025). When an immediate risk surges to prominence, the marginal benefit of monitoring that risk rises, inducing a reallocation of finite cognitive and emotional resources away from other less urgent concerns. AG, by contrast, resonates with ambiguity-aversion models in which agents hold multiple priors over uncertain states and evaluate choices under pessimistic, non-additive beliefs (Gilboa & Schmeidler, 1989). In such settings, encountering a stark new threat can trigger worst-case thinking across seemingly unrelated domains. Our results suggest that the psychological marker of neuroticism is correlated with response patterns resembling this maxmin behavior and, thus, with ambiguity aversion. Future research should test this link directly.

The profile characterized by broad declines in worry deserves additional attention. This pattern indicates that adverse experiences do not always heighten expressed concern; for some individuals, the response may instead take the form of compartmentalization, emotional dampening, or defensive suppression. One interpretation draws on Terror Management Theory (Greenberg et al., 1986): when confronted with existential threats, some individuals engage in worldview affirmation that manifests as reduced expressed worry. Another connects to clinical coping frameworks (Lazarus & Folkman, 1984), which suggest that avoidant coping may suppress worry expression without resolving the underlying risk appraisal. The low neuroticism of this profile is consistent with both interpretations. Future research should attempt to distinguish healthy resilience from avoidant coping, as the welfare implications differ substantially.

Third, as worries about different risks are interdependent, crises generate externalities in the mental economy of risk perception. A highly salient shock can redirect worry away from other issues even when fundamentals in those domains have not improved. This helps explain why long-run collective problems such as climate change, public health preparedness, or institutional reform may lose salience when war, inflation, terrorism, or migration dominate the agenda. Our evidence provides micro-foundations for the concept of "issue-attention cycles" (Downs, 1972): public risk perceptions rarely operate in isolation, and keystone events may reshape public perceptions although underlying risks remain unchanged. For example, the IPCC Special Report and the subsequent Fridays for Future movement led to a broad shift toward environmental worry and support for climate policies, with sweeping gains for green parties in European elections in 2019. The COVID-19 pandemic and subsequent low growth perspectives reversed this dynamic, with significant vote share losses for green parties in later elections. In both cases, the crowding-out effect led to a narrow public focus on the most immediately salient concerns, neglecting other potentially important long-term issues, despite the unchanged underlying risk of climate change.

From a political-economic perspective, externalities resulting from interdependent worries imply social inefficiencies. Self-interested policymakers may be incentivized to follow changing sentiments or actively shape public narratives for policy support, thereby neglecting longer-term societal goals and increasing policy uncertainty. Conversely, policymakers may overemphasize more immediate but fundamentally less relevant risks if addressing them appears to gather voter support. These dynamics likely lead to both oversupply and undersupply of worry and policy support across distinct risks—a misallocation. Thus, individual-level reallocation of emotional resources may collectively lead to suboptimal policy choices and coordination failures.

These results suggest that long-term strategic planning may benefit from entrenching societal goals into law to insulate them from temporary fluctuations in public salience, perception and support. Moreover, crisis communication cannot be designed for a representative citizen alone. For individuals prone to crowding-out, policy communication may need to actively preserve awareness of slower-moving but socially important risks. For individuals prone to affect generalization, communication that heightens salience may amplify insecurity beyond the originating crisis. A more effective strategy may therefore require differentiated messaging that both sustains attention to neglected risks and limits unnecessary spillovers into generalized pessimism. Our findings also strengthen the case for adopting nudge-type policies (Thaler & Sunstein, 2008) that are typically less salient and more subtle, reducing the risk of triggering unintended cross-domain worry reallocation.

Fourth, the presence of heterogeneous agents with divergent belief-updating regimes has important ramifications for economic modeling. Traditional representative-agent frameworks typically assume homogeneous expectations or symmetrical Bayesian updating. Yet recent research in heterogeneous-agent macroeconomics demonstrates that mixing agents with different belief-formation rules can induce systemic risks, coordination failures, multiple equilibria, and feedback loops (Angeletos & La'O, 2013; Boehl & Hommes, 2025). Our study provides a behavioral basis for this research: if, in response to a shock, a sufficiently large fraction of the population develops generalized concern and pessimism—leading to precautionary saving, deprioritized consumption, and reduced investment—negative macroeconomic feedback effects beyond standard expectations may arise (Lagerborg et al., 2023). This channel may be state-dependent and hold particularly in already uncertain and fragile market environments. If policymakers attempt to stimulate demand post-crisis, generalized-worry agents may remain reluctant to consume despite accommodative policies, potentially prolonging a recession. Incorporating cross-domain risk reallocations into macro frameworks could thus deepen the understanding of how subjective mental states propagate through the real economy.

A related implication concerns economic forecasting and nowcasting. Increasingly, high-frequency qualitative survey and social media data on beliefs, expectations, and sentiments are leveraged to nowcast current and forecast future economic developments. Our findings suggest that such sentiment measures may be contaminated by cross-domain spillovers: a non-domain-specific shock—such as a terror attack, geopolitical crisis or a personal event—could move economic sentiment even though economic fundamentals remain unchanged. Controlling for more complete mental profiles, could reduce errors resulting from such spillovers and improve forecasting accuracy.

Several limitations should be acknowledged. First, although our design identifies how shocks affect multiple worries, it does not fully resolve the precise cognitive pathway. Second, while the SOEP provides unusually rich longitudinal data and a stable battery of worry measures, our evidence comes from one country context. Cultural, institutional, and media environments may moderate how crowding-out and spillover manifest in other countries. Third, the worry variables are measured on a three-point Likert scale, which constrains the granularity of observed changes. While we address ceiling and floor effects through our estimation strategy, richer measurement scales would strengthen future analyses. This, however, also relates to a more fundamental debate of how risk perceptions and worries should be measured. Fourth, for some personal events the identification assumptions are more plausible than for others, though we address this concern by providing consistent findings across a broad range of events rather than relying on any single shock.

These limitations point to several promising avenues. Firstly, future research should aim to pin down the mechanisms behind FPW- and AG-type responses more precisely, potentially through experimental designs that manipulate psychological distance and affect independently. Secondly, replicating these analyses cross-nationally would help determine how culture, institutions, and media systems shape the propagation of worries across domains. Thirdly, combining panel survey data with physiological measures could illuminate whether latent profiles have a biological basis, building on neuroeconomic research showing distinct brain activation for uncertainty and losses (Mohr et al., 2010). Finally, extending our methodological approach—combining causal inference with person-centered clustering—to other settings with multiple dependent variables and heterogeneous treatment effects represents a broader contribution to empirical methodology.

In sum, this paper shows that risk perceptions are interdependent and that this interdependence is both systematic and heterogeneous. Shocks in one domain influence worries in others, but they do not do so uniformly across individuals. At the aggregate level, societal crises crowd out competing worries and personal shocks generate broader spillovers; however, beneath averages lie latent updating profiles that differ predictably along socioeconomic and psychological dimensions. Among these, neuroticism emerges as a key organizing trait: more neurotic individuals generalize risks and become pessimistic, whereas less neurotic individuals crowd out or experience a total reduction in worries. The broader implication is that belief formation under risk is neither fully separable nor homogeneous. Understanding how people perceive one risk therefore requires understanding how they perceive many risks at once and how this joint system differs across people.

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- Data availability: The data analyzed in this study are from the German Socio-Economic Panel (SOEP), provided by the DIW Berlin (German Institute for Economic Research). These data are subject to data-protection restrictions and were accessed under a data distribution contract; they are therefore not publicly available and cannot be shared by the authors. The SOEP data are available from the SOEP Research Data Center at DIW Berlin upon conclusion of a standard data distribution contract.
- Human-participation: This study is a secondary analysis of de-identified survey data from the SOEP. SOEP participants provide informed consent at the point of data collection, and the data were accessed under a standard data distribution contract with DIW Berlin.
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Supplemental Appendix: Risk Perceptions as a Multivariate System: Crowding Out, Affect Generalization, and Heterogeneous Belief Updating

1 Simulation

Our empirical strategy in Section 6 combines imputation-based individual-level treatment effects (Borusyak, Jaravel, and Spiess, 2024) with Latent Profile Analysis (LPA) to identify heterogeneous response profiles across multiple worry dimensions. A key concern is whether this approach can reliably recover latent profiles when the individual-level treatment effect estimates that serve as inputs to the clustering step are themselves inconsistently estimated and therefore subject to measurement error. To assess the performance of our method under controlled conditions, we design a Monte Carlo simulation in which the data-generating process (DGP) is fully known, allowing us to benchmark the accuracy of profile recovery against the true parameters.

We generate synthetic data that mirror the structure of our empirical application. The DGP produces a sample of n treated individuals, each characterized by a vector of $L = 8$ outcome variables (corresponding to eight worry dimensions). The population consists of $P = 5$ latent profiles with known mixing proportions. Each profile p is defined by a distinct vector of true average treatment effects, $\delta_p = (\delta_{1p}, \ldots, \delta_{8p})$, which governs the profile-specific mean shift in each outcome dimension. The five profiles are designed to capture qualitatively distinct treatment patterns: generalized increases, generalized decreases, and domain-specific reallocation with opposite signs across dimensions. The true treatment effects range from -30 to $+10$ across profiles and dimensions, generating substantial cross-profile heterogeneity.

For each individual i belonging to profile p, the observed treatment effect estimate is generated as

$$\hat{\tau}_{ilp} = \delta_{lp} + \gamma_{tl} + u_{il}, \;\; u_{il} \sim N(0, \sigma^2)$$

where u_{il} is an independently drawn noise term. This noise represents idiosyncratic differences. The noise is drawn independently across individuals and dimensions, consistent with the local independence assumption maintained in LPA. Relative to the range of true treatment effects (40 units), the noise standard deviation is varied to generate different signal-to-noise ratios. Moreover, estimation error inherent in imputed individual-level treatment effects, which are not consistently estimated on a per-individual basis is introduced by the estimator (Borusyak, Jaravel, and Spiess, 2024). The sample size of treated and untreated individuals is set to 10,000, allocated equally between treated and untreated individuals and across the five profiles.

After using the imputation estimator, we compare two clustering methods applied to the noisy individual-level treatment effect estimates for identifying latent profiles and, thus, the aggregation weights. The first is k-Means clustering, a widely used deterministic algorithm that partitions observations into k clusters by minimizing within-cluster sum of squared Euclidean distances. k-Means assigns each observation to a single cluster based on proximity to the nearest centroid. The second is Latent Profile Analysis (LPA), the model-based probabilistic clustering method used in our main analysis (Section 6). LPA models the joint distribution of treatment effect estimates as a finite mixture of multivariate normal distributions with profile-varying diagonal covariance matrices. Unlike k-Means, LPA provides probabilistic profile assignments and accounts for within-profile variability through explicit distributional assumptions.

Both methods are applied to the same noisy treatment effect matrix. We evaluate performance along three criteria: (i) whether the true profile-specific treatment effect vectors are accurately recovered, measured by the mean absolute deviation (MAD) between estimated and true profile means; (ii) whether profiles are correctly identified in terms of their qualitative patterns; and (iii) whether sign errors occur in the estimated profile-level average treatment effects.

Table 1 reports the true and estimated average treatment effects by profile and dimension for both methods. LPA recovers the true treatment effects with striking precision. Across all 40 profile–dimension combinations (5 profiles × 8 dimensions), the mean absolute deviation between the LPA estimates and the true values is 0.06—effectively negligible relative to the scale of the treatment effects. All five profiles are correctly identified, and no sign errors occur. This result demonstrates that LPA's probabilistic framework, which models within-profile variance explicitly, is highly robust to measurement error of the magnitude present in our setting.

By contrast, k-Means performs poorly. The mean absolute deviation is 7.90—roughly 130 times larger than for LPA. Critically, k-Means fails to recover the qualitative structure of profiles: the estimated cluster centroids bear little resemblance to the true treatment effect patterns. The fundamental problem is that k-Means, as a distance-based algorithm using hard assignments, is vulnerable to noise: individual observations contaminated by estimation error are deterministically assigned to the nearest centroid, which biases the centroids themselves. This bias cascades through the algorithm, producing centroids that reflect noise patterns rather than the true latent structure. LPA avoids this problem through soft, probabilistic assignments that account for the dispersion of observations around each profile's mean, effectively averaging out idiosyncratic noise.

Figure 1, 2 and 3 visualize the true and estimated profile-specific treatment effects. Whereas the LPA estimates are virtually indistinguishable from the true DGP, the k-Means estimates show severe distortions, including reversed signs and collapsed profile distinctions.

Figure 1: True DGP

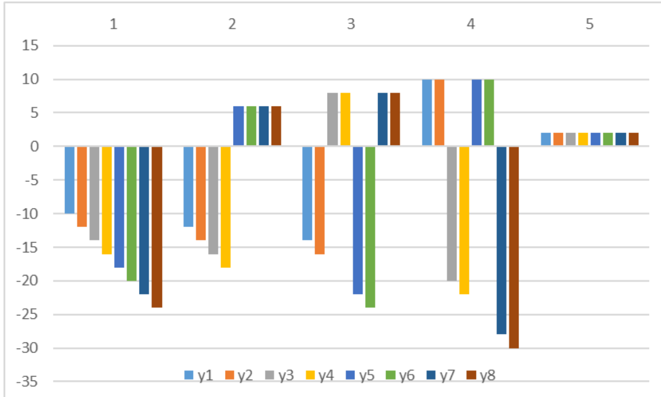


Figure 2: LPA

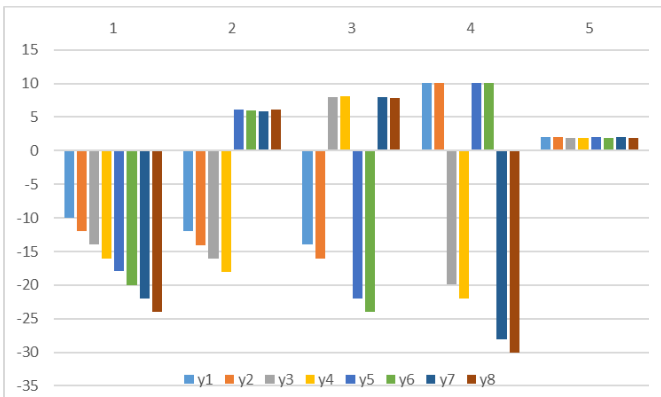


Figure 3: k-Means

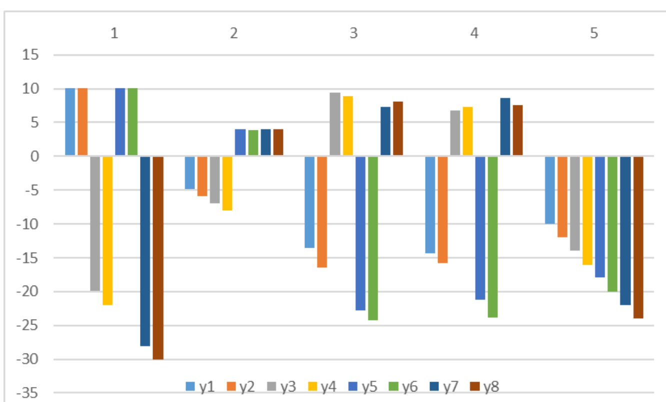


Table 1: Simulation Results

Profile – Variable	True ATE	kMeans ATE	LPA ATE
1			
y1	-10	10.05	-9.96
y2	-12	10.06	-11.91
y3	-14	-19.93	-14.00
y4	-16	-22.04	-16.06
y5	-18	10.02	-17.91
y6	-20	10.06	-19.96
y7	-22	-28.01	-22.01
y8	-24	-30.06	-24.02
2			
y1	-12	-4.89	-11.97
y2	-14	-5.94	-14.12
y3	-16	-6.95	-15.99
y4	-18	-7.97	-18.03
y5	6	4.06	6.14
y6	6	3.93	6.02
y7	6	3.96	5.92
y8	6	3.96	6.07
3			
y1	-14	-13.56	-13.95
y2	-16	-16.42	-16.09
y3	8	9.39	8.02
y4	8	8.84	8.09
y5	-22	-22.78	-22.00
y6	-24	-24.29	-24.04
y7	8	7.34	7.99
y8	8	8.11	7.85
4			
y1	10	-14.32	10.05
y2	10	-15.76	10.06
y3	-20	6.73	-19.93
y4	-22	7.37	-22.04
y5	10	-21.27	10.02
y6	10	-23.80	10.06
y7	-28	8.59	-28.01
y8	-30	7.61	-30.06
5			
y1	2	-9.96	2.03
y2	2	-11.91	2.06
y3	2	-14.00	1.89
y4	2	-16.06	1.87
y5	2	-17.91	2.02
y6	2	-19.96	1.88
y7	2	-22.01	2.04
y8	2	-24.02	1.89

The simulation results provide strong support for the use of LPA as the clustering method in our empirical application. The key insight is that individual-level treatment effects estimated via the imputation approach of BJS are inherently noisy—each individual's estimate includes an idiosyncratic error component that cannot be separated from the true treatment effect on a per-person basis. Any clustering method applied to these estimates must therefore be robust to measurement error. LPA achieves this robustness through its probabilistic, model-based framework: by explicitly modeling within-profile variance, it treats the noise as a nuisance parameter to be estimated rather than a source of misclassification. The multivariate normal assumption within each profile provides a natural mechanism for averaging out idiosyncratic estimation error when recovering profile-level means.

We note the following qualification. The simulation fixes the number of profiles at the true value for both methods. In our empirical application, profile enumeration is determined by information criteria (AIC, BIC) combined with the requirement that each profile comprises at least 5% of the sample. The simulation therefore evaluates recovery conditional on correct enumeration.

In summary, the simulation demonstrates that the combination of imputed individual-level treatment effects with LPA-based clustering is a reliable method for identifying heterogeneous, multivariate response profiles in the presence of estimation noise. The method recovers both the qualitative structure and the quantitative magnitudes of profile-specific treatment effects, substantially outperforming the most commonly used alternative.

2 Regression Tables: Societal Events

Table 2: The Russian Invasion of Ukraine (2022) — Event-Study Coefficients

	Finance	Unemp.	Health	Crime	Econ.	Migr.	Envir.	Peace
2021								
w=21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
w=22	0.02	0.03	-0.00	0.05**	-0.00	0.02	-0.05**	-0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=23	0.04**	0.01	0.02	0.06***	0.00	0.01	-0.01	-0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=24	0.03	-0.02	0.00	0.02	-0.04*	-0.00	-0.04**	-0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=25	0.04*	-0.01	-0.00	0.03	-0.05**	-0.02	-0.01	-0.02
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=26	0.06***	0.02	-0.00	0.09***	-0.03	0.02	-0.02	-0.04*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=27	0.00	-0.01	0.04**	0.05**	-0.10***	0.04**	-0.01	-0.05***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=28	0.06**	0.04	0.02	0.09***	-0.03	0.02	-0.04	-0.05**
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
w=29	0.00	-0.00	0.01	0.06**	-0.06**	0.02	0.04*	-0.05**
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
w=30	0.04	-0.01	0.02	0.08***	-0.04	-0.01	0.03	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=31	0.04	0.05*	0.01	0.07***	-0.07***	0.02	0.02	-0.03

	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=32	0.03	-0.00	0.02	0.07***	-0.08***	0.07**	0.04	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=33	0.03	0.02	-0.05	-0.01	-0.04	0.01	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=34	0.02	0.01	0.01	0.06**	-0.04	0.04	0.03	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
w=35	0.02	0.04	-0.02	0.06**	-0.16***	0.07**	-0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=36	0.01	0.03	-0.02	0.05*	-0.10***	0.05*	-0.00	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=37	0.02	0.02	-0.03	0.05*	-0.08***	0.04*	-0.00	-0.05*
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
w=38	0.05**	0.03	0.02	0.05**	-0.05*	0.02	-0.04	-0.02
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
w=39	0.05**	0.04	0.04	0.06**	-0.11***	-0.02	0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=40	0.04	0.00	0.00	0.03	-0.05*	-0.02	-0.05*	-0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=41	0.03	0.00	0.00	0.05	0.05	-0.03	0.00	-0.03
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
w=42	0.04	-0.02	-0.06**	0.06*	-0.00	0.01	-0.03	-0.05
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=43	0.05	0.03	0.02	0.08**	-0.05	0.00	-0.06*	-0.04
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=44	-0.01	-0.11***	0.02	0.02	-0.04	-0.04	-0.06*	-0.06
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=45	0.07**	-0.00	-0.01	0.09**	-0.05	0.06	-0.00	-0.04
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=46	0.03	-0.00	-0.02	-0.02	-0.07**	-0.04	0.01	-0.02
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=47	0.04	0.02	0.02	0.02	0.01	0.01	0.01	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=48	0.04	0.05*	0.05**	0.05*	0.07**	0.02	-0.03	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=49	0.00	-0.11**	0.02	0.03	0.05	0.01	-0.03	-0.07*
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=50	0.00	0.11**	0.02	0.05	-0.04	0.03	-0.04	0.02
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
w=51	-0.05	-0.05	0.01	-0.00	0.07	0.00	0.02	-0.03
	(0.04)	(0.06)	(0.04)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
w=52	-0.01	-0.01	-0.03	0.04	0.08	-0.07	-0.11	-0.01
	(0.05)	(0.09)	(0.04)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
2022								
w=1	0.02	-0.00	-0.13**	0.12**	0.09	-0.03	-0.08	0.25***
	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
w=2	0.23**	-0.18*	-0.11	0.09	0.23**	0.07	-0.04	0.14
	(0.10)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.09)	(0.10)
w=19	-0.13*	-0.14	-0.14**	-0.15**	0.09	-0.19***	0.06	0.32***
	(0.07)	(0.10)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
w=20	-0.14***	-0.14***	-0.12***	-0.08***	0.12***	-0.17***	-0.03	0.25***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=21	-0.09***	-0.09***	-0.10***	-0.08***	0.12***	-0.17***	-0.01	0.25***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=22	-0.10***	-0.14***	-0.09***	-0.12***	0.11***	-0.16***	0.00	0.27***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=23	-0.13***	-0.14***	-0.09***	-0.08***	0.13***	-0.16***	-0.00	0.25***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=24	-0.11***	-0.13***	-0.10***	-0.09***	0.14***	-0.15***	-0.02	0.26***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=25	-0.13***	-0.12***	-0.13***	-0.07***	0.17***	-0.17***	-0.03	0.25***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=26	-0.12***	-0.18***	-0.13***	-0.09***	0.24***	-0.17***	0.01	0.29***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=27	-0.08***	-0.11***	-0.13***	-0.07***	0.25***	-0.20***	0.02	0.30***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	22664	13409	22687	21123	21164	21132	21190	21183

Notes: Each column reports coefficients from a separate OLS regression of detrended residuals (after absorbing individual fixed effects and a pre-event time trend) on week dummies. The base period is week 21 (2021). Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: The Covid-19 Pandemic and First Lockdown (2020) — Event-Study Coefficients

	Finance	Unemp.	Health	Crime	Econ.	Migr.	Envir.	Peace
2019								
w=5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
w=6	-0.03	-0.05	0.00	-0.00	0.02	0.04	-0.01	-0.03
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=7	-0.01	-0.02	-0.01	-0.02	0.02	0.02	-0.02	-0.04
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=8	-0.02	-0.05	0.02	0.01	0.02	0.03	0.02	0.01
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=9	0.00	-0.04	0.02	-0.02	-0.03	0.01	-0.00	-0.04
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=10	-0.00	-0.04	0.02	-0.02	-0.01	0.02	0.00	-0.01
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=11	-0.01	-0.01	0.04	0.01	0.01	0.01	0.02	-0.04
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=12	0.02	-0.03	0.04	0.01	0.02	0.02	0.01	-0.05
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=13	0.02	-0.02	0.02	0.01	-0.00	-0.01	-0.01	-0.06*
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=14	0.01	-0.01	0.02	-0.06*	-0.02	-0.01	-0.00	-0.08**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=15	-0.01	-0.04	0.03	-0.02	-0.02	-0.00	0.01	-0.06*
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=16	0.02	0.00	-0.00	0.00	0.02	0.00	0.01	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
w=17	0.01	-0.01	0.03	-0.01	0.01	0.02	0.01	-0.05
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
w=18	0.01	0.01	0.04	-0.03	-0.02	0.01	0.03	-0.06
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
w=19	-0.02	0.01	0.03	-0.02	0.01	0.01	-0.01	-0.05
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
w=20	-0.01	-0.00	0.02	-0.01	0.01	-0.05	0.01	-0.02
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
w=21	-0.05	-0.00	0.01	0.01	0.01	-0.02	0.00	-0.04
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
w=22	-0.01	-0.01	0.05	0.00	-0.03	0.01	0.03	-0.05
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=23	-0.03	0.05	0.05	-0.06	-0.01	0.00	-0.00	-0.03
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=24	-0.04	-0.01	0.04	-0.01	-0.00	-0.02	-0.00	-0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=25	-0.02	0.02	0.02	-0.01	-0.00	-0.05	0.00	0.00
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=26	0.01	0.04	0.04	0.01	-0.00	-0.04	0.05	0.01
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=27	-0.03	0.04	-0.00	0.01	0.01	-0.03	-0.02	-0.05
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=28	0.00	0.02	0.05	0.01	0.01	-0.05	-0.02	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=29	-0.02	0.03	0.01	-0.01	-0.00	-0.03	-0.03	-0.08**
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
w=30	-0.03	0.03	0.02	-0.02	-0.02	-0.01	0.02	-0.04
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
w=31	-0.03	0.04	0.04	0.06	-0.00	0.04	0.02	-0.03
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
w=32	0.02	-0.01	0.03	-0.00	0.05	0.01	0.00	-0.01
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=33	-0.04	0.03	-0.00	0.00	0.06	0.05	-0.00	-0.03
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=34	0.01	0.05	0.01	-0.01	0.04	0.01	0.04	-0.01
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=35	0.00	0.11**	0.01	0.01	0.03	0.01	0.04	-0.00
	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=36	-0.03	0.05	-0.01	-0.00	-0.03	-0.04	-0.03	-0.05

	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
w=37	-0.03	0.01	0.04	0.05	-0.01	0.02	0.00	0.04
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
w=38	-0.02	0.07	-0.03	0.01	-0.01	0.02	-0.05	-0.02
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
w=39	0.04	0.08	0.01	-0.05	0.01	0.01	-0.03	-0.06
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
w=40	0.02	0.01	0.03	-0.04	0.03	-0.02	0.03	-0.04
	(0.04)	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
w=41	-0.04	0.04	-0.04	0.02	0.03	0.03	-0.07	-0.06
	(0.04)	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
w=42	0.01	0.02	-0.01	-0.01	0.06	-0.07	-0.11**	0.04
	(0.04)	(0.06)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)
w=43	-0.00	0.07	0.01	0.06	0.02	-0.05	-0.00	0.02
	(0.04)	(0.06)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)
w=44	0.07	0.03	0.00	0.00	0.03	0.03	-0.01	0.01
	(0.05)	(0.07)	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
w=45	0.04	0.03	0.05	0.05	-0.02	-0.03	-0.02	0.01
	(0.05)	(0.06)	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
w=46	0.03	0.04	0.02	0.10*	-0.00	0.05	-0.08	0.11*
	(0.05)	(0.07)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
w=47	0.02	0.01	-0.03	-0.05	-0.05	-0.07	0.00	0.02
	(0.05)	(0.09)	(0.05)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)
w=48	0.08*	0.06	-0.01	0.01	0.02	0.07	0.05	0.03
	(0.05)	(0.09)	(0.05)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
w=49	0.03	-0.01	-0.02	-0.01	0.12	-0.01	-0.02	-0.00
	(0.05)	(0.10)	(0.05)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)
w=50	0.07	0.04	-0.03	0.09	0.07	0.07	-0.01	0.05
	(0.05)	(0.09)	(0.04)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)
2020								
w=5	-0.08**	-0.05	0.06	-0.04	-0.06	0.00	-0.11***	0.01
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=6	-0.07**	-0.08*	0.01	-0.11***	-0.01	-0.05	-0.09***	-0.05
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=7	-0.01	-0.04	0.03	-0.09***	-0.00	-0.06*	-0.09***	-0.06*
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=8	0.02	-0.04	0.04	-0.02	0.01	-0.06*	-0.10***	-0.05
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=9	0.01	-0.03	0.01	-0.05	0.01	-0.03	-0.10***	-0.02
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=10	0.07**	-0.02	0.01	-0.10***	0.07**	0.03	-0.12***	-0.06*
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=11	0.08**	0.00	-0.02	-0.12***	0.16***	-0.03	-0.15***	-0.10***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=12	0.16***	0.07*	0.00	-0.14***	0.38***	-0.03	-0.11***	-0.14***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=13	0.24***	0.12***	0.01	-0.18***	0.44***	-0.04	-0.14***	-0.12***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=14	0.25***	0.15***	-0.00	-0.16***	0.45***	-0.08**	-0.15***	-0.17***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=15	0.24***	0.12***	-0.01	-0.17***	0.40***	-0.04	-0.15***	-0.19***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=16	0.25***	0.09**	0.00	-0.16***	0.37***	-0.10***	-0.13***	-0.18***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=17	0.24***	0.09**	-0.02	-0.19***	0.43***	-0.13***	-0.13***	-0.21***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
w=18	0.24***	0.12***	-0.03	-0.17***	0.46***	-0.10***	-0.13***	-0.22***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
w=19	0.26***	0.09**	0.00	-0.18***	0.39***	-0.12***	-0.15***	-0.20***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
N	44747	26533	44749	41674	41634	41631	41692	41694

Notes: Each column reports coefficients from a separate OLS regression of residuals (after absorbing individual fixed effects, with dimension-specific pre-event detrending where applicable) on week dummies. The base period is week 5 (2019). Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Climate Salience Shock and Fridays for Future (2018–2019) — Event-Study Coefficients

	Finance	Unemp.	Health	Crime	Econ.	Migr.	Envir.	Peace
2018								
w=6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
w=7	-0.02	0.02	0.00	-0.04**	-0.01	-0.06***	0.02	-0.04**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=8	-0.04**	0.03	-0.01	-0.03	-0.02	-0.03	0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=9	-0.03*	0.02	-0.01	-0.05***	-0.02	-0.02	0.00	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=10	-0.04*	0.02	-0.01	-0.04**	0.01	-0.06***	0.01	-0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=11	-0.02	0.03	0.03	-0.05***	0.02	-0.06***	0.01	-0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=12	-0.04**	0.03	0.01	-0.03	0.03	-0.04**	0.00	-0.04*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=13	-0.03	0.03	0.01	-0.04*	-0.03	-0.02	-0.01	-0.04*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=14	0.00	0.06**	0.04**	-0.03*	0.02	-0.00	0.00	-0.02
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=15	-0.02	0.05**	0.01	-0.01	0.02	-0.03	-0.00	0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=16	-0.01	0.06**	-0.01	-0.02	0.01	-0.05**	0.00	0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=17	0.00	0.05**	0.02	-0.04**	0.03	-0.04*	-0.01	-0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=18	-0.05**	0.03	0.01	-0.06***	-0.01	-0.06***	-0.01	-0.05**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=19	-0.03	0.02	0.02	-0.06***	0.01	-0.07***	-0.00	-0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=20	-0.01	0.07***	0.02	-0.02	0.02	-0.03	0.01	0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=21	-0.03	0.01	-0.03	-0.06**	0.01	-0.02	0.00	-0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=22	-0.02	0.01	0.01	-0.09***	0.03	-0.06**	0.01	-0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=23	-0.00	-0.03	0.02	-0.07***	0.05*	0.01	0.00	-0.05*
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
w=24	-0.06**	0.03	-0.01	-0.03	0.01	0.05*	0.00	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=25	-0.07***	0.06*	0.03	-0.01	0.04	0.02	0.03	-0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
w=26	-0.05*	0.04	0.02	-0.11***	-0.01	-0.01	-0.01	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=27	-0.00	0.07*	0.06	0.03	0.05	0.08*	-0.00	0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=28	-0.05	-0.03	0.02	-0.06*	0.05	-0.06*	0.03	-0.07**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=29	-0.06**	0.06*	-0.01	-0.06**	0.03	-0.08***	-0.00	-0.05*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
w=30	-0.04*	0.05*	-0.02	-0.08***	-0.02	-0.09***	-0.04*	-0.04*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=31	-0.05*	0.02	0.02	-0.02	0.04	-0.04	0.05**	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
w=32	-0.03	0.05	-0.04*	-0.04	0.02	-0.02	0.05**	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
w=33	-0.10***	0.07**	-0.04	-0.08***	0.04	-0.03	0.01	-0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=34	-0.08**	0.05	-0.06**	-0.07**	-0.01	-0.02	-0.02	-0.05
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=35	-0.08**	-0.01	0.01	0.06*	-0.04	-0.03	0.04	0.02
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=36	-0.01	0.06	-0.06	0.01	0.01	-0.01	0.03	-0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=37	0.02	-0.02	0.01	0.02	-0.01	-0.03	0.02	0.01

	(0.03)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=38	0.02	0.02	-0.00	-0.06	-0.00	-0.05	0.00	0.00
	(0.03)	(0.06)	(0.03)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
w=39	-0.01	-0.01	-0.01	-0.06	-0.02	-0.01	-0.04	-0.06
	(0.03)	(0.05)	(0.03)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
w=40	-0.04	-0.01	0.00	0.02	-0.08*	-0.00	-0.02	-0.00
	(0.03)	(0.05)	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
w=41	-0.01	-0.01	0.03	-0.01	-0.14**	-0.06	0.06	-0.02
	(0.03)	(0.06)	(0.03)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)
w=42	-0.00	0.00	-0.04	-0.04	-0.11**	-0.13**	0.01	-0.08
	(0.03)	(0.06)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
w=43	-0.02	0.01	0.01	0.05	-0.05	-0.04	-0.02	0.05
	(0.03)	(0.06)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
w=44	-0.01	0.02	0.03	0.06	-0.04	-0.06	0.04	-0.04
	(0.03)	(0.06)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
w=45	-0.02	-0.09	-0.01	-0.07	-0.01	-0.05	0.02	0.03
	(0.03)	(0.07)	(0.03)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
w=46	0.04	-0.06	0.09***	0.01	-0.01	0.00	-0.00	-0.07
	(0.03)	(0.07)	(0.03)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
w=48	-0.00	0.10	0.03	0.03	-0.12**	-0.05	-0.04	-0.04
	(0.03)	(0.06)	(0.03)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
w=49	-0.05	-0.01	0.00	0.02	0.00	0.05	0.06	0.03
	(0.03)	(0.08)	(0.03)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
2019								
w=5	-0.19***	0.05	0.09***	0.04	-0.20***	0.09**	0.21***	0.16***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
w=6	-0.22***	0.01	0.08***	0.04*	-0.18***	0.12***	0.19***	0.13***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=7	-0.20***	0.03	0.06***	0.02	-0.19***	0.11***	0.19***	0.11***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=8	-0.20***	0.01	0.08***	0.05***	-0.18***	0.12***	0.23***	0.15***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=9	-0.18***	0.01	0.07***	0.02	-0.21***	0.10***	0.21***	0.10***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=10	-0.18***	0.02	0.08***	0.03	-0.20***	0.12***	0.20***	0.11***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=11	-0.18***	0.03	0.09***	0.05**	-0.18***	0.11***	0.22***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=12	-0.15***	0.02	0.08***	0.05**	-0.17***	0.12***	0.21***	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=13	-0.16***	0.03	0.04**	0.04**	-0.18***	0.10***	0.19***	0.04**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=14	-0.16***	0.04	0.05**	-0.02	-0.21***	0.09***	0.20***	0.02
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	37924	21848	37952	35878	35836	35838	35882	35884

Notes: Each column reports coefficients from a separate OLS regression of detrended residuals (after absorbing individual fixed effects and dimension-specific pre-event trends) on week dummies. The base period is week 6 (2018). Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Paris Terror Attacks and New Year's Eve Assaults (2015–2016) — Event-Study Coefficients

	Finance	Unemp.	Health	Crime	Econ.	Migr.	Envir.	Peace
2015								
w=7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
w=8	0.01	0.01	-0.01	-0.00	0.01	-0.02	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
w=9	0.01	0.01	-0.01	0.02	-0.01	-0.00	-0.00	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=10	0.02	-0.00	-0.00	-0.00	0.01	-0.05***	-0.01	-0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=11	0.01	-0.02	-0.01	0.01	0.01	-0.05***	0.02	-0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=12	0.05***	0.02	-0.01	0.03*	0.02	-0.01	0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=13	0.04**	0.03	-0.02	0.00	-0.01	-0.04**	0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=14	0.02	0.03	0.01	0.01	-0.04*	-0.07***	-0.00	-0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=15	0.03	0.02	-0.01	0.00	-0.03*	-0.08***	0.01	-0.05***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=16	0.03	0.04	0.01	0.01	-0.04**	-0.00	0.00	0.00
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=17	0.04*	0.01	0.00	-0.01	-0.06**	-0.03	0.01	-0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=18	0.06**	0.02	-0.01	0.05**	-0.02	-0.02	0.01	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=19	-0.03	0.01	-0.01	0.02	-0.07***	-0.00	0.04*	0.00
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
w=20	0.03	0.01	0.00	0.01	-0.03	-0.04*	0.03	-0.02
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
w=21	0.13***	0.06**	-0.00	-0.02	0.01	-0.08***	0.01	-0.08***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=22	0.07***	0.05*	-0.00	-0.05**	0.02	-0.06**	-0.01	-0.07***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=23	0.09***	0.04	0.00	-0.01	0.07***	-0.07***	0.05**	-0.08***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=24	0.10***	-0.00	-0.04	-0.06***	0.02	-0.11***	0.01	-0.07***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=25	0.11***	0.09***	0.01	-0.02	0.03	-0.09***	0.02	-0.07***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=26	0.12***	0.10***	-0.00	-0.04*	0.00	-0.09***	-0.00	-0.06***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=27	0.10***	0.11***	-0.02	-0.02	0.04	-0.07***	0.01	-0.05*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
w=28	0.08***	0.08***	-0.01	-0.02	-0.01	-0.11***	0.00	-0.08***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
w=29	0.13***	0.11***	0.01	-0.00	0.02	-0.06**	-0.02	-0.01
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
w=30	0.11***	0.11***	0.00	-0.00	0.02	-0.04	0.05**	-0.04*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=31	0.11***	0.07**	0.01	0.03	-0.00	0.02	0.01	-0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
w=32	0.10***	0.08**	0.00	-0.02	-0.06**	-0.02	0.02	-0.06*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=33	0.05*	0.05	-0.02	0.04	-0.04	-0.07**	-0.01	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=34	0.04	0.07**	-0.04	0.03	-0.02	0.02	-0.00	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=35	0.11***	0.06	-0.03	0.00	-0.04	-0.00	0.00	-0.05
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
w=36	0.12***	0.06*	-0.04	0.00	0.05	-0.04	0.05	0.03
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
w=37	0.06**	0.03	-0.01	0.08***	-0.00	0.06*	-0.01	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=38	0.06**	0.01	0.00	0.03	0.00	-0.00	-0.01	-0.00

	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w=39	0.05*	0.08**	0.03	-0.01	-0.01	0.04	0.02	0.02
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
w=40	0.12***	0.02	0.02	-0.03	0.04	0.00	0.00	0.09**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=41	0.07**	0.06	-0.04	-0.03	-0.09**	-0.02	-0.07**	0.01
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=42	0.12***	0.03	0.00	0.01	0.01	0.08*	-0.02	0.05
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
w=43	0.11***	0.12***	0.03	0.07*	-0.00	0.02	-0.04	0.08*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
w=44	0.06	0.07	-0.02	0.10**	-0.01	-0.02	0.01	0.02
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
w=45	-0.03	-0.04	-0.04	0.12**	-0.05	0.03	-0.03	0.01
	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
2016								
w=5	0.01	-0.04	0.17***	0.24***	-0.20***	0.19***	0.02	0.36***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=6	-0.03*	-0.08***	0.15***	0.24***	-0.19***	0.16***	0.03*	0.38***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=7	-0.02	-0.07***	0.17***	0.22***	-0.17***	0.17***	0.01	0.39***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
w=8	-0.04**	-0.05**	0.18***	0.23***	-0.20***	0.14***	0.01	0.42***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
w=9	-0.04**	-0.05**	0.20***	0.23***	-0.20***	0.16***	0.01	0.41***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
w=10	-0.02	-0.07***	0.18***	0.23***	-0.21***	0.14***	0.03*	0.42***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=11	-0.02	-0.07***	0.20***	0.21***	-0.22***	0.10***	-0.00	0.41***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=12	0.02	-0.02	0.20***	0.22***	-0.17***	0.10***	-0.02	0.41***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=13	0.03	-0.02	0.23***	0.23***	-0.20***	0.08***	-0.01	0.45***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w=14	0.03	0.01	0.28***	0.23***	-0.17***	0.08***	0.00	0.41***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	37839	22482	37759	36635	36701	36601	36635	36645

Notes: Each column reports coefficients from a separate OLS regression of residuals (after absorbing individual fixed effects, with dimension-specific pre-event detrending where applicable) on week dummies. The base period is week 7 (2015). Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: The Global Financial Crisis (2007–2009) — Event-Study Coefficients

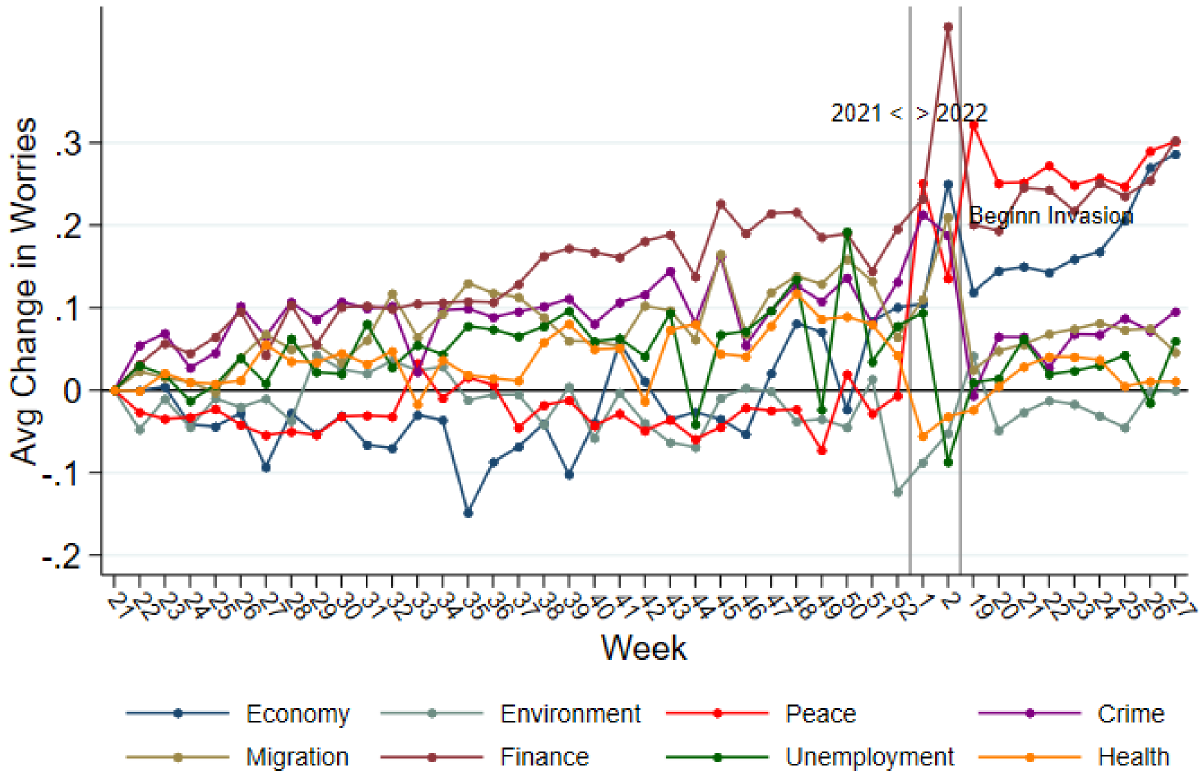
	Finance	Unemp.	Health	Crime	Econ.	Migr.	Envir.	Peace
2007								
m=2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
m=3	-0.00	0.02*	0.00	0.02*	0.02**	0.01*	0.03***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
m=4	-0.02	0.02	0.00	-0.02**	0.01	0.03***	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
m=5	-0.02	0.01	-0.02	0.02	0.01	0.04***	0.01	0.04***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
m=6	-0.02	-0.01	0.01	-0.00	-0.02	-0.00	-0.03*	0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
m=7	0.00	0.06***	-0.00	-0.00	0.01	-0.01	0.02	0.07***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
m=8	0.04**	0.02	-0.00	0.02	-0.02	0.01	-0.02	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
m=9	0.06**	0.05*	0.02	-0.01	0.01	-0.01	0.10***	0.06**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
m=10	-0.01	-0.10	-0.14***	0.07	0.07	0.03	-0.02	-0.02
	(0.06)	(0.07)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)
2008								
m=2	-0.03***	0.01	-0.01	-0.00	0.01	-0.05***	0.00	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
m=3	-0.01	-0.00	-0.01	0.01	0.02*	-0.06***	0.02**	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
m=4	0.00	0.03*	0.02	-0.01	-0.01	-0.06***	-0.01	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
m=5	0.04***	0.03*	0.02	0.02	0.00	-0.07***	0.03**	-0.03**
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
m=6	0.02	0.01	-0.03**	0.01	0.02	-0.08***	-0.00	-0.05***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
m=7	0.04**	-0.02	-0.01	-0.01	0.02	-0.08***	-0.01	-0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
m=8	-0.03	0.07**	-0.03	-0.00	-0.01	-0.07***	0.01	0.05**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
m=9	-0.08	0.13	0.03	0.06	-0.03	0.03	0.07	0.04
	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
2009								
m=2	0.13***	0.09***	0.03***	-0.12***	0.31***	-0.14***	-0.15***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
m=3	0.13***	0.11***	0.02*	-0.13***	0.38***	-0.15***	-0.14***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
m=4	0.15***	0.12***	0.01	-0.18***	0.43***	-0.14***	-0.12***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	54100	30264	54126	54092	54107	53995	54113	54109

Notes: Each column reports coefficients from a separate OLS regression of residuals (after absorbing individual fixed effects, with dimension-specific pre-event detrending where applicable) on month dummies. The base period is month 2 (2007). Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

3 Societal Events Un-detrended

3.1 The Russian Invasion of Ukraine (2022)

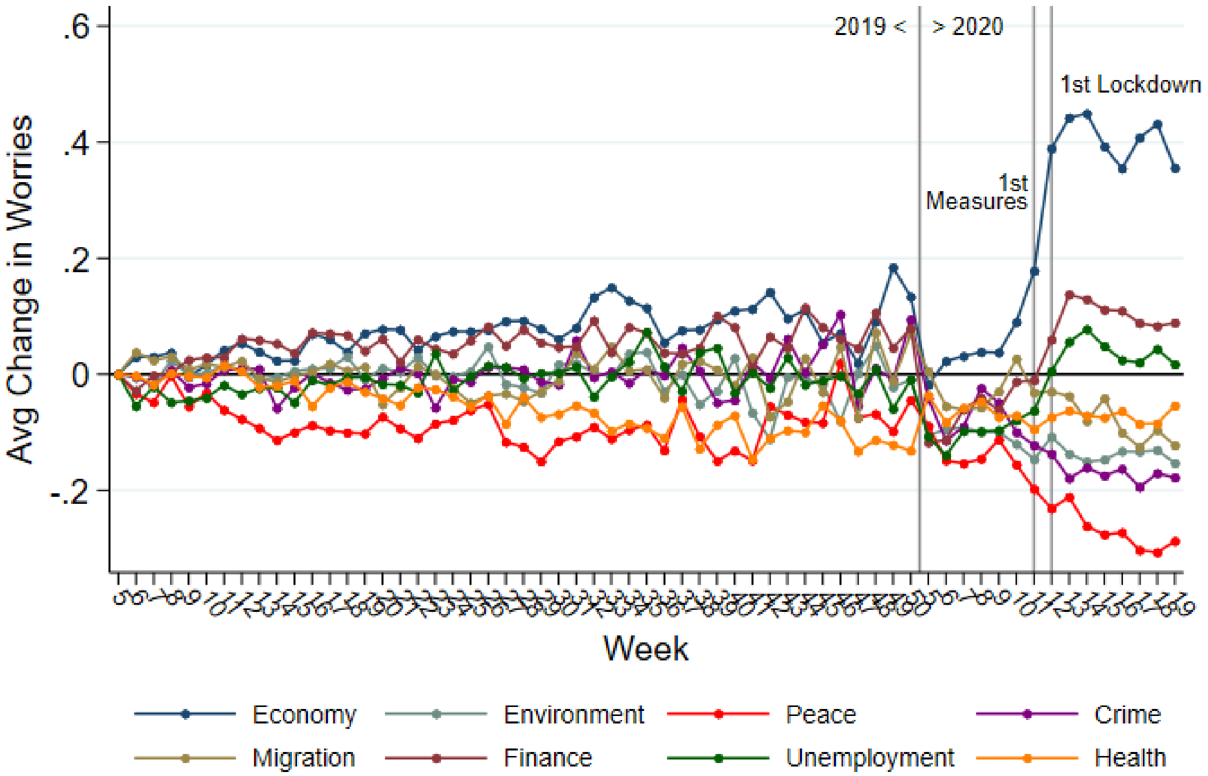
Figure 4: The Russian Invasion of Ukraine (2022)



Notes: The figure plots estimated deviations in worry levels across eight domains around the Russian invasion of Ukraine in February 2022. The estimation proceeds in three steps. First, individual fixed effects are estimated for each worry dimension using the full panel period up to the event year, and residuals are stored. We do not estimate pre-event time trends that are extrapolated in the main specification into the post-event window to construct a counterfactual baseline. Second, event periods with fewer than 20 observations are dropped. Third, flexible event-time indicators are regressed on the un-detrended residuals.

3.2 The Covid-19 Pandemic and First Lockdown (March 2020)

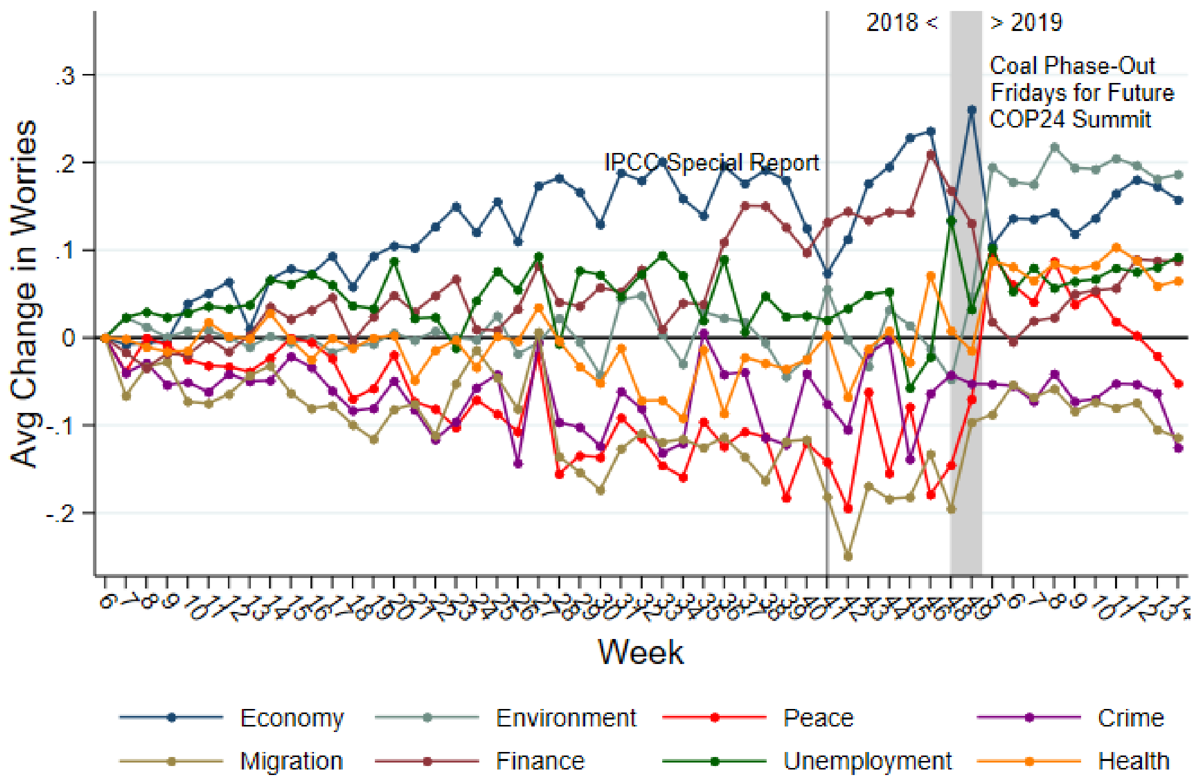
Figure 5: The Covid-19 Pandemic and First Lockdown (March 2020)



Notes: The figure plots estimated deviations in worry levels across eight domains around Germany's first nationwide lockdown in March 2020. The estimation proceeds in three steps. First, individual fixed effects are estimated for each worry dimension using the full panel period up to the event year, and residuals are stored. We do not estimate pre-event time trends that are extrapolated in the main specification into the post-event window to construct a counterfactual baseline. Second, event periods with fewer than 20 observations are dropped. Third, flexible event-time indicators are regressed on the un-detrended residuals.

3.3 Climate Salience Shock and Fridays for Future (late 2018–2019)

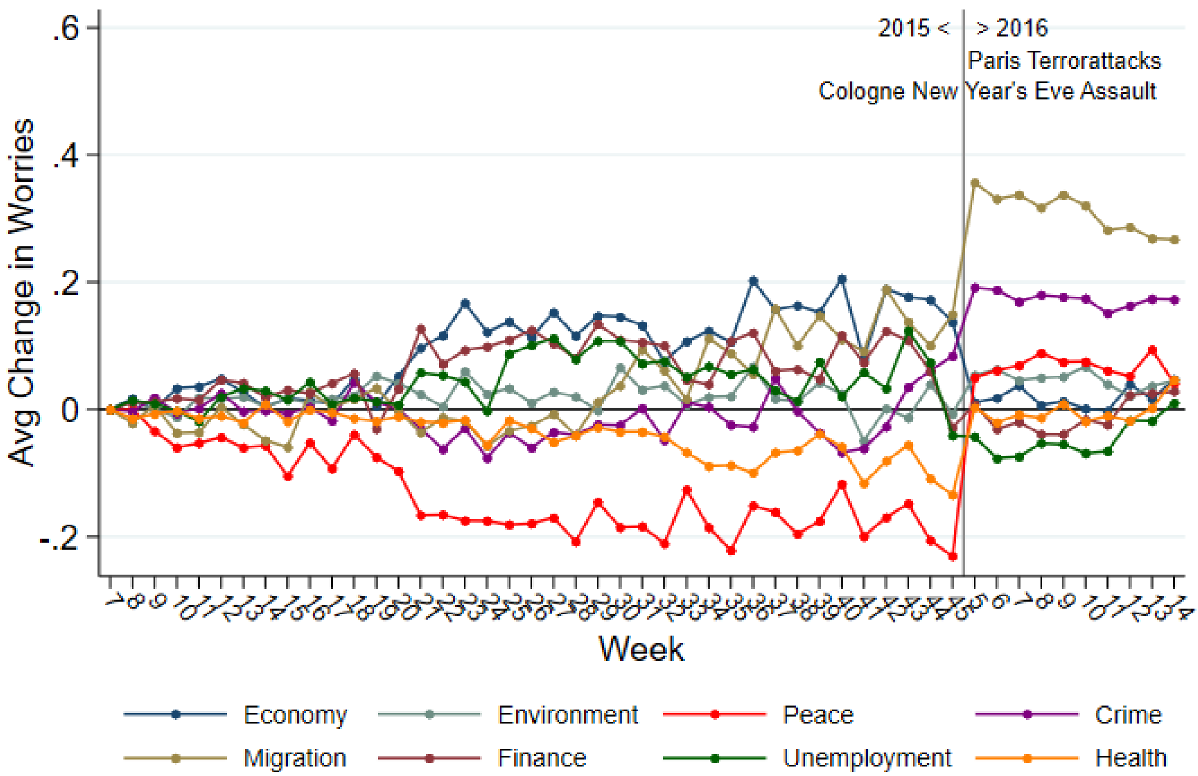
Figure 6: Climate Salience Shock and Fridays for Future (late 2018–2019)



Notes: The figure plots estimated deviations in worry levels across eight domains around the climate salience shock of late 2018–2019, identified by the IPCC Special Report (October 2018) and the subsequent rise of the Fridays for Future movement. The estimation proceeds in three steps. First, individual fixed effects are estimated for each worry dimension using the full panel period up to the event year, and residuals are stored. We do not estimate pre-event time trends that are extrapolated in the main specification into the post-event window to construct a counterfactual baseline. Second, event periods with fewer than 20 observations are dropped. Third, flexible event-time indicators are regressed on the un-detrended residuals.

3.4 The Paris Terror Attacks and the subsequent New Year's Eve Sexual Assaults in Germany (late 2015)

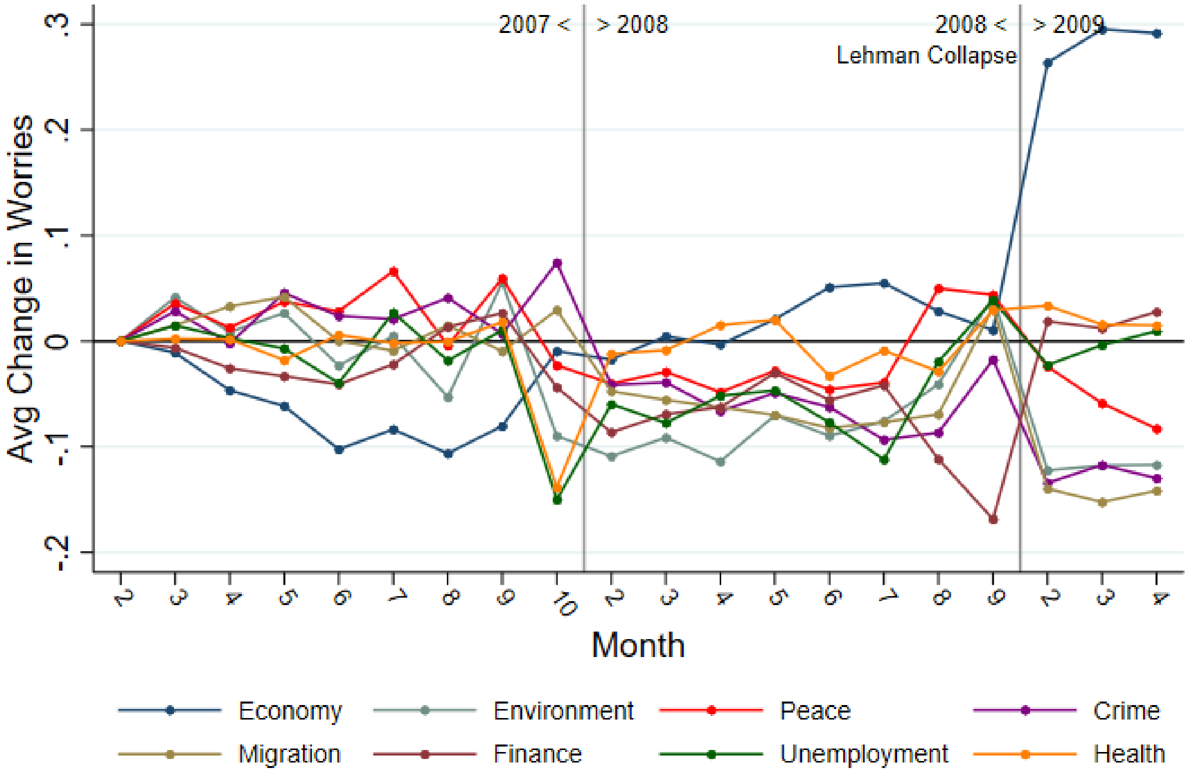
Figure 7: The Paris Terror Attacks and the subsequent New Year's Eve Sexual Assaults in Germany (late 2015)



Notes: The figure plots estimated deviations in worry levels across eight domains around the November 2015 Paris terror attacks and the subsequent New Year's Eve sexual assaults in Cologne (2015/2016). The estimation proceeds in three steps. First, individual fixed effects are estimated for each worry dimension using the full panel period up to the event year, and residuals are stored. We do not estimate pre-event time trends that are extrapolated in the main specification into the post-event window to construct a counterfactual baseline. Second, event periods with fewer than 20 observations are dropped. Third, flexible event-time indicators are regressed on the un-detrended residuals.

3.5 The Global Financial Crisis (2007-2009), with Lehman Brothers' Collapse

Figure 8: The Global Financial Crisis (2007-2009), with Lehman Brothers' Collapse



Notes: The figure plots estimated deviations in worry levels across eight domains around the collapse of Lehman Brothers in September 2008. The estimation proceeds in three steps. First, individual fixed effects are estimated for each worry dimension using the full panel period up to the event year, and residuals are stored. We do not estimate pre-event time trends that are extrapolated in the main specification into the post-event window to construct a counterfactual baseline. Second, event periods with fewer than 20 observations are dropped. Third, flexible event-time indicators are regressed on the un-detrended residuals.

4 Regression Tables: Robustness Personal Events (no controls)

Table 7: Regression Tables: Robustness Personal Events (no controls)

	Personal Worries			Societal Worries				
Event	*Finance*	*Unemp.*	*Health*	*Crime*	*Economy*	*Migr.*	*Environ.*	*Peace*
Panel A: Direct personal events								
Health crisis	0.065***	0.035***	0.294***	0.037***	0.052***	0.030***	0.041***	0.036***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
	N = 66,794; N_treated = 8,809							
Unemployment	0.379***	0.342***	0.106***	0.046	0.095***	0.071**	-0.032	-0.007
	(0.032)	(0.043)	(0.032)	(0.032)	(0.031)	(0.032)	(0.028)	(0.033)
	N = 154,064; N_treated = 361							
Debt	0.368***	0.168***	0.126***	0.056***	0.111***	0.077***	0.005	0.027**
	(0.014)	(0.014)	(0.013)	(0.014)	(0.012)	(0.014)	(0.012)	(0.013)
	N = 10,158; N_treated = 3,542							
Unemp. + Debt	0.744***	0.421***	0.325***	0.026	0.288***	0.274***	0.089	0.208*
	(0.084)	(0.136)	(0.095)	(0.102)	(0.102)	(0.087)	(0.070)	(0.113)
	N = 6,199; N_treated = 39							
Discrimination	0.298***	0.302***	0.248***	0.164***	0.096***	-0.002	0.056	0.092***
	(0.034)	(0.043)	(0.038)	(0.035)	(0.037)	(0.043)	(0.035)	(0.035)
	N = 112,522; N_treated = 328							
Crime in neighb.	0.178***	0.160***	0.149***	0.319***	0.149***	0.245***	0.027**	0.116***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.015)	(0.013)	(0.013)
	N = 10,472; N_treated = 2,850							
Panel B: Indirect and psychological events								
Loneliness	0.279***	0.193***	0.244***	0.077***	0.172***	0.067***	0.038**	0.062***
	(0.017)	(0.019)	(0.018)	(0.017)	(0.018)	(0.018)	(0.016)	(0.016)
	N = 25,168; N_treated = 1,267							
Loss of purpose	0.317***	0.259***	0.268***	0.065***	0.106***	0.040**	0.001	-0.023
	(0.019)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
	N = 18,046; N_treated = 1,226							
Health spouse	0.048***	0.028***	0.173***	0.015**	0.029***	0.019***	0.020***	0.007
	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
	N = 57,134; $N_{treated}$ *= 10,842*							
Health child	0.125***	0.067***	0.119***	0.041*	0.062***	0.055**	0.008	0.033
	(0.022)	(0.022)	(0.022)	(0.023)	(0.021)	(0.023)	(0.020)	(0.021)
	N = 9,763; $N_{treated}$ *= 802*							

Notes: Each row reports estimated coefficients from separate regressions of changes in worries on an event indicator. The dependent variable is the change in each worry domain. All specifications include year fixed effects, the lagged level of the dependent variable, but no controls. Standard errors clustered at the individual level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Treatment definitions: Health = experiencing at least half a year of health problems, becoming chronically ill, or being severely limited in daily life; Unemployment = becoming unemployed due to layoffs or plant closures; Debt = reporting financial difficulties due to indebtedness; Unemploy + Debt = experiencing both unemployment and indebtedness; Discrimination = reporting an experience of discrimination; Crime in neighb. = reporting increased crime in the immediate neighborhood; Loneliness = reporting feelings of loneliness; Loss of purpose = reporting a sense of loss of purpose; Health spouse = spouse experiencing a serious health crisis; Child health = child experiencing a serious health crisis.

5 Alternative Profile Estimate

We re-estimate the latent profile analysis using an alternative treatment definition for health crises using the methodology introduced in Section 6.1. The objective is to assess whether the patterns documented for the main health-crisis treatment in Section 6.2 can be recovered using a different treatment definition. Here the treatment group consists of individuals reporting a large change in self-rated health status: specifically, treated individuals must have reported high health status in the pre-period and a steep drop in the post-period. The control group is restricted to those reporting continuously high health status. This specification isolates abrupt, individually salient health deteriorations and complements the definition used in the main analysis.

Figure 9 reports the identified profiles. The six-profile structure replicates closely. We again observe a general-decrease profile (profile 1, approximately 8 percent of the treated population), two AG-type profiles characterized by broad increases in worries across domains (profiles 5 and 6, together approximately 39 percent), and three reallocation profiles, including a profile that conforms to the standard FPW pattern of crowding out (profiles 2, 3, and 4, together approximately 53 percent). The monotone neuroticism gradient running from profile 1 to profiles 5 and 6 is preserved. Profile characterizations in Table 8 likewise replicate the main results: the gender gap, the education–income divergence between profiles 2 and 3, and the openness contrast between these two profiles all emerge as in Section 6.2. Population shares are reported in Table 9. The robustness of these patterns to an alternative operationalization of the treatment strengthens the interpretation that the profiles reflect stable individual differences in worry-updating strategies rather than features of any particular health-crisis definition.

Figure 9: Health Crisis - Treatment Profiles

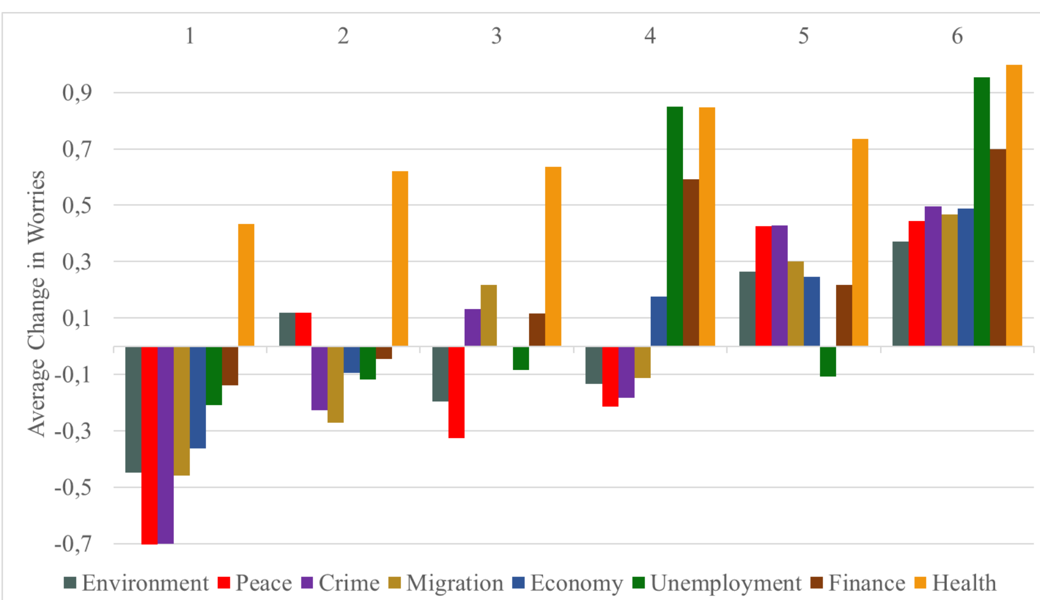


Table 8: Health Crisis - Profile Characteristics

Health Crisis	Profile					
	1	2	3	4	5	6
Neuroticism	-1,95	-2,74	-1,18	1,34	2,28	2,25
Extraversion	-0,20	-1,89	0,97	-1,20	2,02	0,31
Agreeableness	-0,84	1,85	-2,50	0,40	0,93	0,15
Openness	-0,99	2,15	-2,36	-0,29	1,40	0,09
Conscientiousness	-0,69	-2,95	0,91	-0,19	0,52	2,40
Age						
30-39	-2,90	-0,22	4,76	-1,51	-1,22	1,09
40-49	-4,89	-4,87	6,79	-1,12	1,94	2,15
50-60	-5,95	-4,01	6,16	-7,58	8,47	2,91
Children	0,67	-1,38	-1,30	1,73	0,10	0,18
Female	-0,55	2,79	-2,98	-5,30	7,44	-1,40
Migrant	0,09	-10,37	-0,61	3,98	0,75	6,17
Partner	1,22	0,28	-2,03	-1,29	0,43	1,40
University Degree	0,93	19,47	-3,83	0,99	-9,67	-7,89
HH Net Income						
1500€-3000€	0,88	-0,34	0,38	-1,39	3,44	-2,97
3000€-4500€	0,14	1,54	3,12	-0,70	4,10	-8,20
>4500€	2,54	2,77	1,28	-2,92	3,59	-7,27

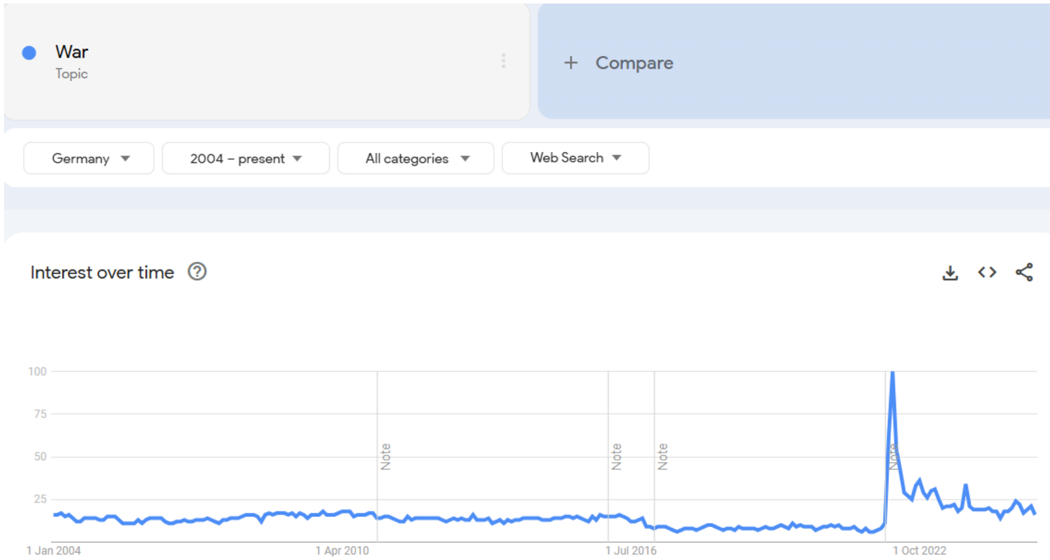
Table 9: Health Crisis - Population Shares

Health Crisis	Profile					
	1	2	3	4	5	6
Population Share	7,58	21,97	18,05	13,03	25,00	14,38

6 Google Trends Data

Our identification strategy for societal events relies on the assumption that each event represents a sudden and substantial increase in the public salience of a specific risk domain. To provide independent evidence supporting this assumption, we present Google Trends data for search terms associated with the societal events. Google Trends measures the relative popularity of search queries over time, normalized to a scale of 0 to 100 where 100 represents the peak search intensity within the selected time frame and geography. While Google Trends captures information-seeking behavior rather than worry per se, sharp spikes in search intensity around the event dates provide external validation that these events constituted significant salience shocks in public attention. All data refer to web searches in Germany from 2004 to the present.

Figure 10: Google Trends – "War" (Topic), Germany, 2004–present

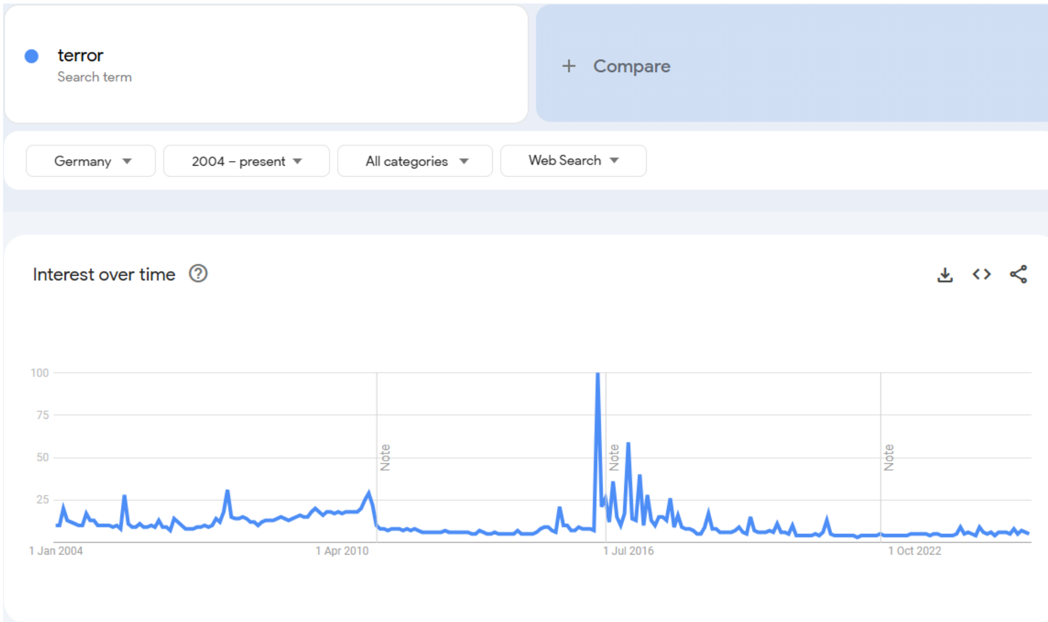


Notes: Source: Google Trends (trends.google.com). The figure displays the relative search interest for the topic "War" in Germany from January 2004 to the present. Values are normalized such that 100 represents the peak search intensity within the displayed period. The vertical axis measures relative search interest; the horizontal axis shows time.

Figure 10 presents Google Trends data for the topic "War" in Germany. Search interest remains at a uniformly low level throughout the entire observation period from 2004 to early 2022, fluctuating between approximately 5 and 25 on the normalized index. In February 2022, coinciding with Russia's invasion of Ukraine, search intensity surges abruptly to the maximum value of 100—an unprecedented spike that dwarfs any prior fluctuation in the series. The increase is not only large in magnitude but also sharp in timing: it occurs within a single month and is followed by a gradual but sustained decline, with search interest remaining elevated relative to pre-invasion levels for several months. This pattern confirms that the invasion constituted a discrete and historically exceptional salience shock to war-related concerns in Germany, consistent with our treatment of February 2022 as the onset of a geopolitical risk shock in Section 4.

Figure 11 shows Google Trends data for the search term "terror" in Germany. Search interest fluctuates at low levels (approximately 10–25) from 2004 through mid-2015. In November and December 2015, coinciding with the coordinated terrorist attacks and the mass sexual assaults on New Year's Eve in Germany, search intensity rises sharply to the series maximum of 100. This represents the highest level of terror-related search activity in Germany since the beginning of Google Trends data collection in 2004. This pattern confirms that the period in late 2015 was characterized by an exceptional and sustained increase in public attention to terrorism and security risks in Germany, supporting our identification of the salience shock to security-related concerns.

Figure 11: Google Trends – "terror" (Search term), Germany, 2004–present

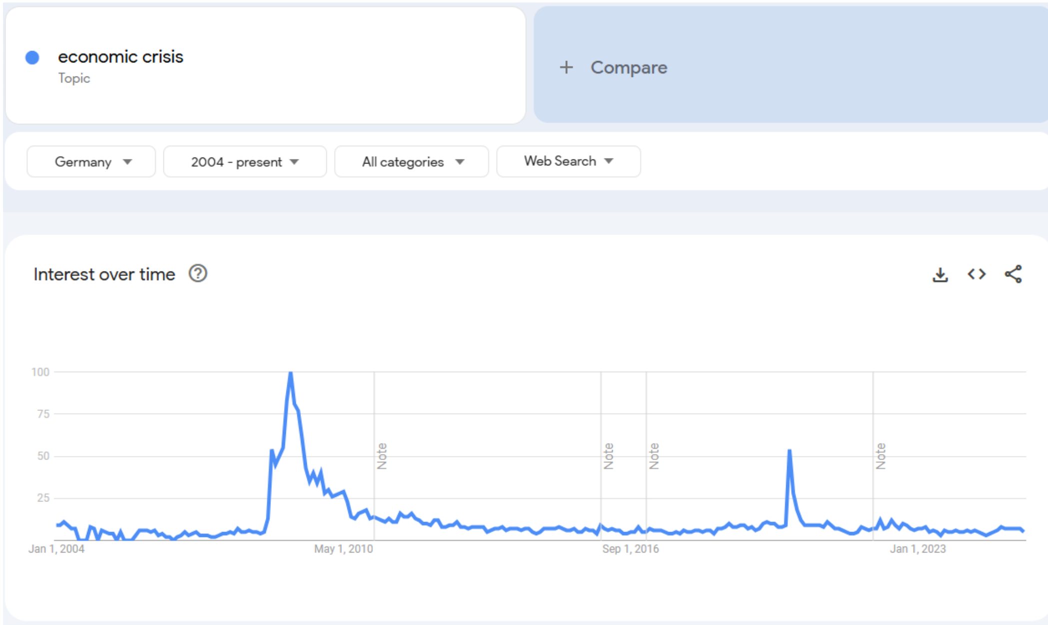


Notes: Source: Google Trends (trends.google.com). The figure displays the relative search interest for the search term "terror" in Germany from January 2004 to the present. Values are normalized such that 100 represents the peak search intensity within the displayed period.

Figure 12 presents Google Trends data for the topic "economic crisis" in Germany. Two distinct episodes of heightened search activity are visible, each corresponding to one of our societal events. The first and largest spike occurs in late 2008 and early 2009, coinciding with the collapse of Lehman Brothers in September 2008 and the subsequent intensification of the global financial crisis. Search intensity rises from a low baseline to the series maximum of 100, reflecting the unprecedented nature of the economic shock and its salience in public discourse. Interest declines gradually over the course of 2009 and 2010, returning to a low baseline by 2011.

The second notable spike occurs in early 2020, coinciding with the onset of the COVID-19 pandemic and Germany's first nationwide lockdown in March 2020. Search interest rises to approximately 50 on the normalized scale—substantially above baseline levels though below the 2008–2009 peak. This is consistent with the economic disruption caused by the pandemic, which, while severe, was perceived as qualitatively different from a financial system crisis. The presence of two clearly delineated spikes in a single series provides compelling evidence that both the global financial crisis and the COVID-19 lockdown represented major economic salience shocks, supporting their inclusion as distinct societal events in our analysis.

Figure 12: Google Trends – "Economic crisis" (Topic), Germany, 2004–present



Notes: Source: Google Trends (trends.google.com). The figure displays the relative search interest for the topic "economic crisis" in Germany from January 2004 to the present. Values are normalized such that 100 represents the peak search intensity within the displayed period. The first peak corresponds to the global financial crisis (2008–2009); the second to the COVID-19 pandemic (2020).

Taken together, the Google Trends evidence confirms that the societal events in our analysis were associated with sharp, historically exceptional increases in public attention to the corresponding risk domain. The spikes are temporally precise, large in magnitude relative to baseline search activity, and concentrated around the event dates used in our empirical strategy. This external validation supports the identifying assumption underlying our event-study design: that these events represent discrete salience shocks that plausibly shifted perceived risk within specific domains, allowing us to examine how worries adjust across domains in response.