

Report

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Key takeaways

Analysis of LISS panel survey data (same individual survey in multiple years):

- Advantages: allows for robust causal identification
- Survey includes both questions that allow us to construct measures of affective polarization and measures of out-group risk aversion
- We can use multiple treatments of economic insecurity: (1) unemployment, (2) individual income decrease, (3) household income decrease

Precarity is different though, these are proxies. I'd love to see bankruptcy, foreclosure, homelessness.

Results:

- Shocks to individuals' economic security increase their affective polarization!
- So far, I was not able to establish that this is because of increased outgroup risk aversion

I wouldn't expect it to be caused by that, I would expect it to be either identical with it, or (more likely) to create a context of identity / in-group "shopping". That could explain why "polarisation" increases more easily where there are ethnic schisms, the creation of mass movements, the weaponising of social media, etc.

Why LISS?

Background:

The LISS (Longitudinal Internet studies for the Social Sciences) is a panel survey that consists of 5,000 households, comprising approx. 7,500 individuals. It is based on a true probability sample of households drawn from the population register by **Statistics Netherlands**.

If it's just one region, the types of precarity I mention above won't likely vary, though they might. **

Panel members complete online questionnaires every month of about 15 to 30 minutes in total. They are paid for each completed questionnaire. One member in the household provides the household data and updates this information at regular time intervals.

The core longitudinal study is repeated yearly and is designed to follow changes in the life course and living conditions of the panel members.

Why is this useful?

This could be super useful for another project I'm working on in the unlikely chance you want to do another paper with me after this one, on the impacts of AI on work & society. I don't suppose the Germans have such a panel? I could possibly bid to start one from 2025. BMAS likes me.

Panel data is among the strongest data types when it comes to causal inference. Panel data allows the researcher to configure a *within*-subject research design that tracks individuals during an extended period of economic volatility.

These kinds of research designs are superior to cross-sectional survey data in which scholars find correlations between measures of survey respondents' economic standing and their political views. With this type of evidence a causal link between the two measures remains unclear: It could be that individuals' economic circumstances shape their attitudes; Yet it is also plausible that an unobservable characteristic—such as people's upbringing, or the influence of their parents—explains their political preferences and their standing in economic context (see Margalit 2013).

These are not mutually exclusive. See also the identity-shopping thing earlier.

** so should this be its own paper, or should we combine this with our world- and europe- wide previous results?

Treatment Variables

I construct four different treatment variables that capture some form of increased economic insecurity.

1. **Unemployment:** An individual is treated in a time period if she is unemployed.
2. **Income decrease:** The LISS includes a variable where individuals assert under which category they fall income-wise. An individual is treated if the indicated income category is lower in a given year compared to the previous year.

Might also want to look at duration of unemployment. Could be real valued or broken into "normal" vs "extended". Though Δincome could be sufficient here.

Again, might want to look for these outcomes over sustained periods of loss not just acute (single period) drops.

3. **Substantial income decrease:** The same variable as before is used, but now an individual is treated when the indicated income category is at least **two levels** lower in a given year compared to the previous year.
4. **Household income decrease:** Because economic (in)security can also depend on the economic situation of other household members (such as one's partner), this variable indicates that an individual is treated if her household income falls by at least 25% as compared to the previous year.

How do you control for someone just moving out of a household, I guess that's the individual income line.

Outcome variables

I construct three different outcome variables that capture affective polarization.

Partisan Affect

This is constructed following [Boxell, Gentzkow, Shapiro \(2022\)](#) and is very similar to the measures by [Gidron et al \(2020\)](#) and [Reiljan \(2020\)](#).

It reflects the extent to which an individual expresses a more favorable attitude toward her own party than toward other parties. This is based on questions about party identification (for defining her own party) and on thermometer scores for all parties.

In particular, we code an individual's party affection based on two questions:

- "Which political party are you an adherent of?"
- "Do you feel more attracted to one of the political parties than to others?"

If an individual indicates a specific party for any of the two questions (the first question being treated as first order), we code her to be a partisan of that party.

For the thermometer scores we use the following question:

- "What do you think of the [party name]?"

Respondents can choose from a 0-10 discrete scale where 0 is "very unsympathetic" and 10 "very sympathetic".

From this, we calculate the thermometer score of respondents for each party.

For a partisan's "ingroup score" we choose the thermometer score of the partisan with respect to her own party. Note, that in a very small number of cases respondents are coded as partisans of more than one party. We then select the party based on the highest thermometer score for a respective individual.

For the final partisan affect measure, we calculate the distance between the thermometer score for the ingroup party ($like_{ip(i)t}$) and each outgroup party ($like_{ip't}$), weight this distance by the outgroup party's respective vote share in the last parliamentary election, and sum these weighted scores across all parties for each individual.

$$\text{Partisan Affect}_{it} = \sum_{p' \in P_t \setminus p(i)} \frac{v_{p'}}{v_{P_t} - v_{p(i)}} (like_{ip(i)t} - like_{ip't}).$$

Weighted Spread

The major weakness of the above described measure is that it captures affective polarization only among self-declared partisans. In the LISS data, only 36% indicate that they are either an adherent of or attracted to a party.

Therefore, we also construct two additional measures proposed by [Wagner \(2021\)](#).

First, we calculate affective polarization as the weighted average party affect difference compared to each respondent's weighted average party affect.

$$\text{Spread}_{it} = \sqrt{\sum_{p=1}^{P_t} \frac{v_{p_t}}{v_{P_t}} (like_{ipt} - \overline{like}_{it})^2}.$$

where the mean affect is calculated as a weighted mean:

$$\overline{like}_{it} = \sum_{p=1}^{P_t} (v_{p_t} \times like_{ipt}).$$

Weighted Distance

The second measure conceives affective polarization as the average affective distance of other parties from one's most liked party. It captures how much lower on average an individual's affect for other parties is:

$$\text{Distance}_{it} = \sqrt{\sum_{p=1}^{P_t} \frac{v_{p_t}}{v_{P_t}} (like_{ipt} - like_{max,it})^2}.$$

So there's no variables for generalised social trust, or for self opinion? I'm always remembering a talk I saw about Benin that still hasn't gotten published last I checked, but showing people in the same income bracket but who came up to or sank down to that level having not only massive differences in polarisation but also in self confidence vs loathing, presence / absence from work, etc. This seems to be the paper from that talk, not taking time to read whether it includes all that right now https://scholar.google.com/citations?view_op=view_citation&hl=en&user=ar6BDYIAAAAJ&cstart=20&pagesize=80&sortby=pubdate&citation_for_view=ar6BDYIAAAAJ:kzcrU_BdoSEC but that guy (from Princeton) has some amazingly relevant recent work https://scholar.google.com/citations?hl=en&user=ar6BDYIAAAAJ&view_op=list_works&sortby=pubdate

Method

We employ the matching estimator designed by Imai, Kim, and Wang (2021). In particular, we construct a matched set of treatment and control units based on pre-treatment control observations and outcome variable trends from units in the same time period that have an identical treatment history up to four years before treatment. We use covariate balancing propensity score weighting to construct the matched set. We allow for treatment reversal as units can become employed again or increase their income after having experienced an economic shock. We then employ a difference-in-differences estimator to estimate the average treatment effect for the treated (ATT). For pre-treatment control observations we use respondents' age, education, number of children, whether they have a partner, and monthly income in the year before treatment (to avoid post-treatment bias).

The advantage of this method compared to other methods for analyzing panel data (such as recent estimators proposed for the study of staggered policy adoptions) is that it allows respondents to be treated at any point in time, and respondents to switch their treatment status multiple times over time.

Results

The following plots show the average treatment effect for the treated at the time of treatment and the next four years.

I have the feeling you should explain this to me in more depth if you have time.

I'd really like to see whether individual vs. neighbourhood effects are more important on these shocks too. I guess households kind of approximate that.

This is very cool.

Unemployment

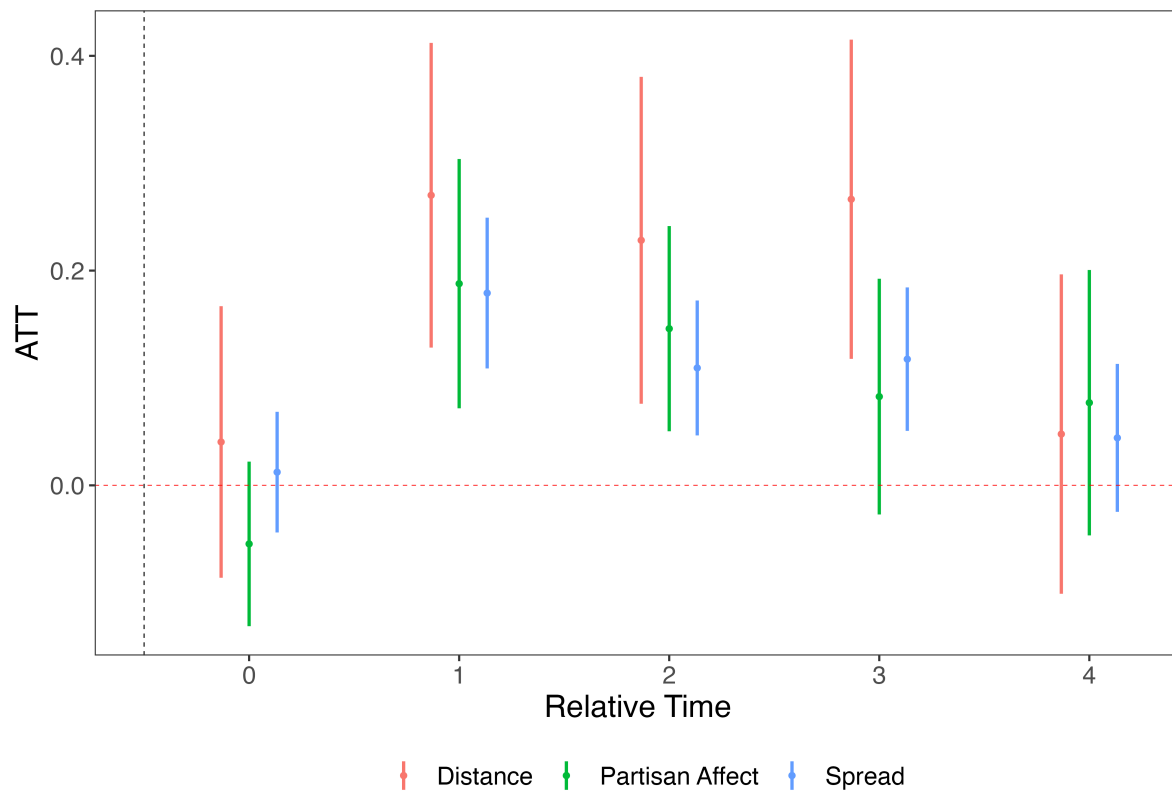


Figure 1: Effect of unemployment

Is this saying that the impact declines with time, or is lower when the “shock” is spread out over more time?

Income Decrease

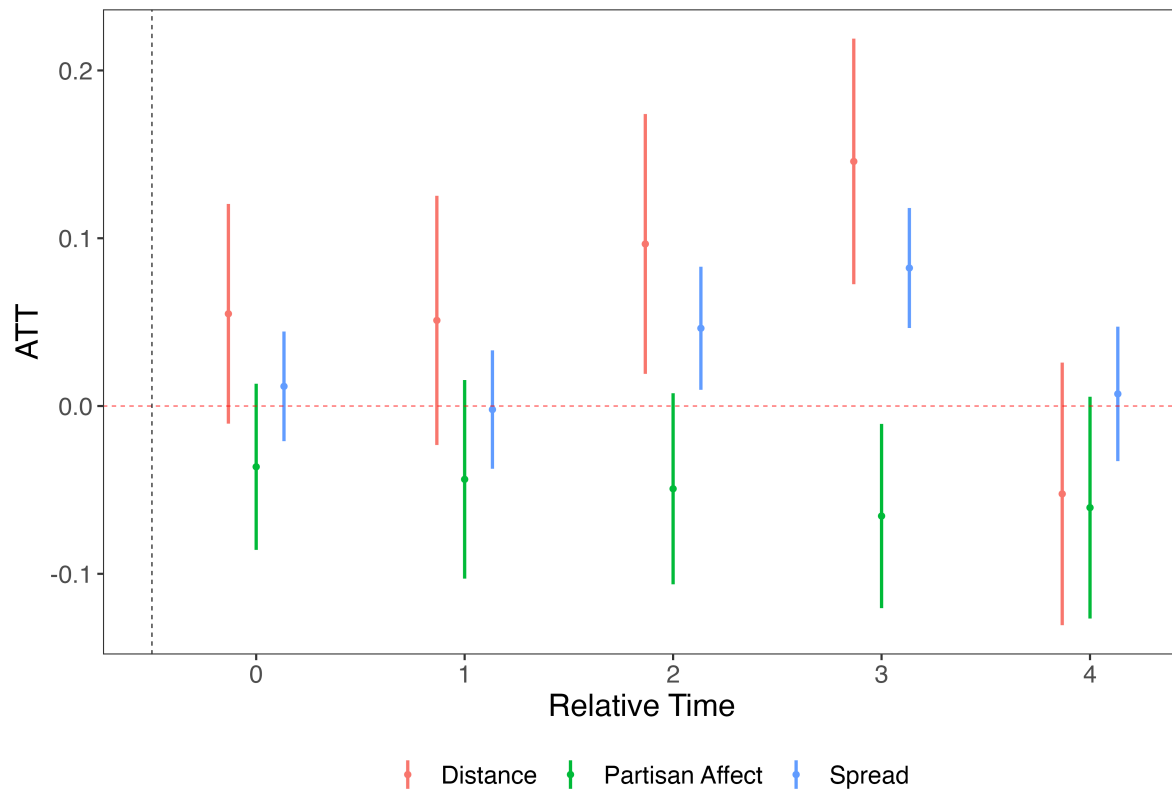


Figure 2: Effect of income decrease

oooooh this might be that self loathing I talked about a few pages ago!

Drastic Income Decrease (at least two points)

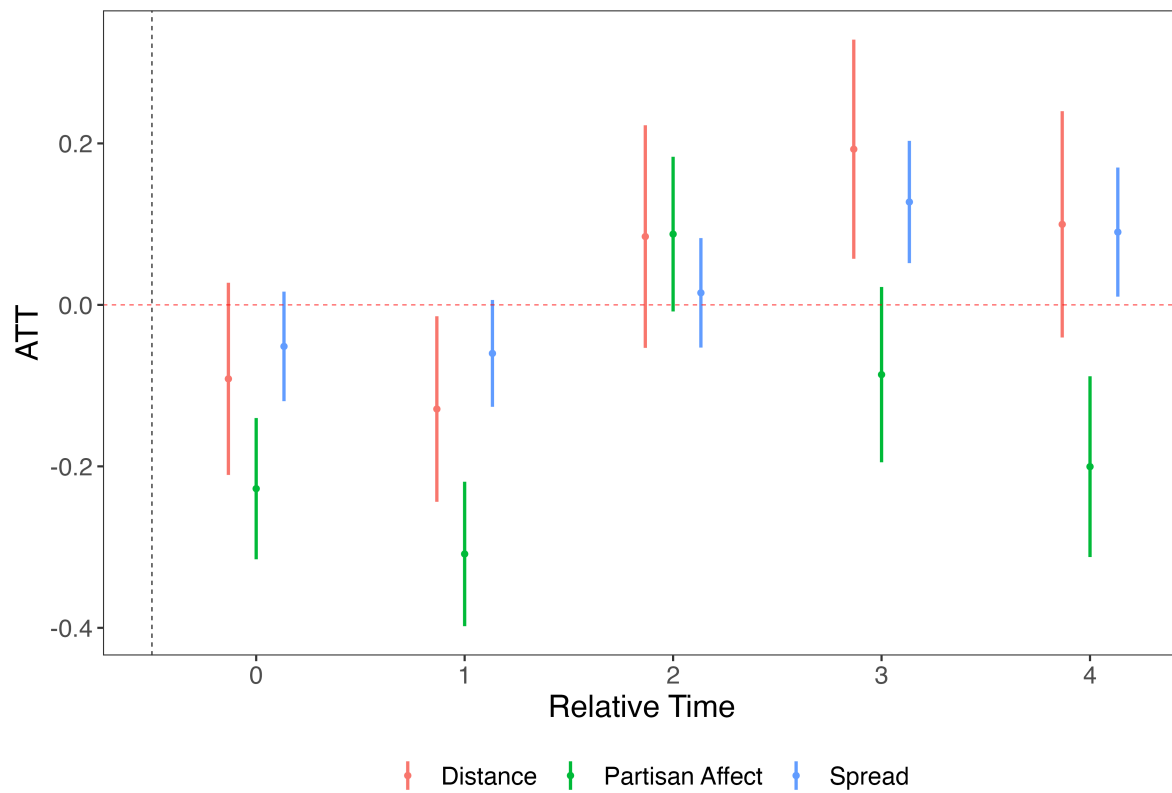


Figure 3: Effect of drastic income decrease

This is interesting, but kind of relates to some of Vishali's results where certain kinds of threats seem to bind communities together. Still, it looks really noisy so I don't want to over interpret. Why would partisan affect go up at 2, is there some data cluster dragging it?

Household income decrease (25%)

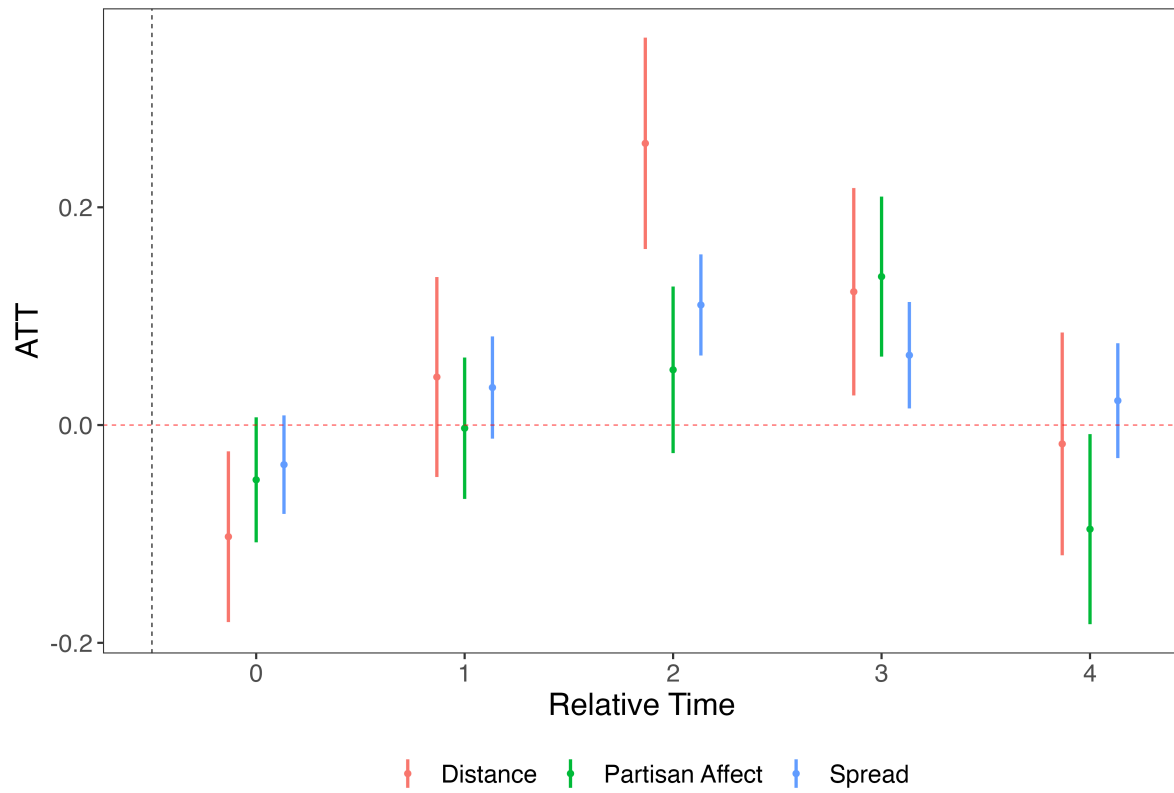


Figure 4: Effect of household income decrease

Mechanism

Our theory predicts that affective polarization decreases because people seek lower-risk in-group interactions and shy away from more risky out-group interactions when the economic environment favors risk aversion (see [Bryson et al., 2020](#)).

As mentioned above, one advantage of the LISS data is that apart from containing questions that allow us to measure affective polarization it also contains questions that we can use to operationalize aversion to out-group interaction.

In particular, we construct the following two measures:

Generalized trust

Generalized trust is measured on a 10 point scale:

- “Generally speaking, would you say that most people can be trusted, or that you can’t be too careful in dealing with people? Please indicate a score of 0 to 10.”

Aversion to outgroup interaction

Next, we construct a measure that captures individuals’ aversion to outgroup interaction. This is constructed by conducting a principal component analysis (PCA) - a dimension-reduction technique that projects high-dimensional data onto a low-dimensional space and parametrically assigns differential weights to each question - to systematically uncover a latent dimension of aversion to outgroup interaction. We use multiple questions that should capture one’s aversion:

- “Generally speaking, would you say that most people can be trusted, or that you can’t be too careful in dealing with people? Please indicate a score of 0 to 10.”
- “I feel little concern for others”: 1 (very inaccurate)-5 (very accurate)
- “I am interested in people”: 1 (very inaccurate)-5 (very accurate)
- “I feel comfortable around people”: 1 (very inaccurate)-5 (very accurate)
- “I insult people”: 1 (very inaccurate)-5 (very accurate)
- “I sympathize with others’ feelings”: 1 (very inaccurate)-5 (very accurate)
- “I am not interested in other peoples’ problems”: 1 (very inaccurate)-5 (very accurate)
- “I talk to a lot of different people at parties”: 1 (very inaccurate)-5 (very accurate)
- “I am not really interested in others”: 1 (very inaccurate)-5 (very accurate)

- “I feel others’ emotions”: 1 (very inaccurate)-5 (very accurate)
- “I am quiet around strangers”: 1 (very inaccurate)-5 (very accurate)
- “Which values act as a guiding principle in your life and which values are less important to you? - Open-minded”: 1 extremely unimportant - 7 extremely important
- “Please indicate to what extent you generally feel connected to other people”: 1 not connected (circle) - 7 very connected (circle)

We reduce each respondents answers to these questions to one dimension via PCA (explains 35% variation). Higher values denote lower risk aversion towards out group. Lower values denote higher risk aversion towards out group.

We use the same matching DiD estimator as above.

Unemployment

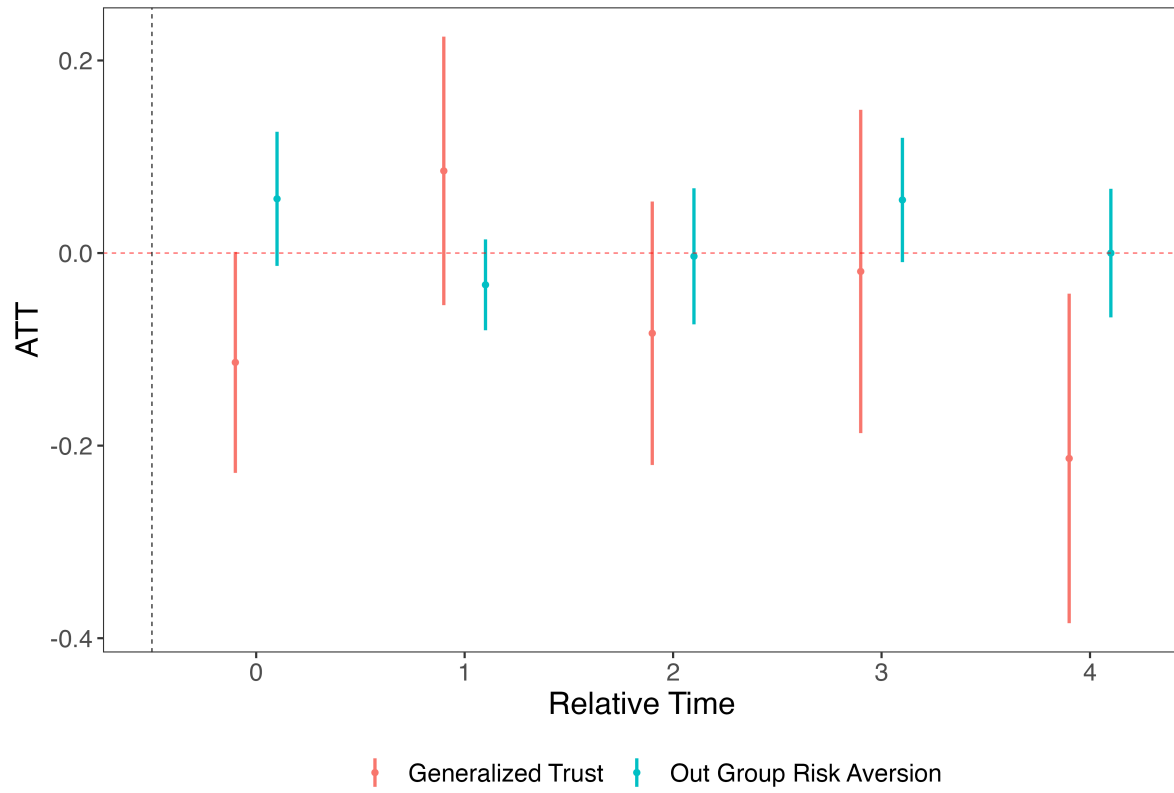


Figure 5: Effect of unemployment

Income decrease

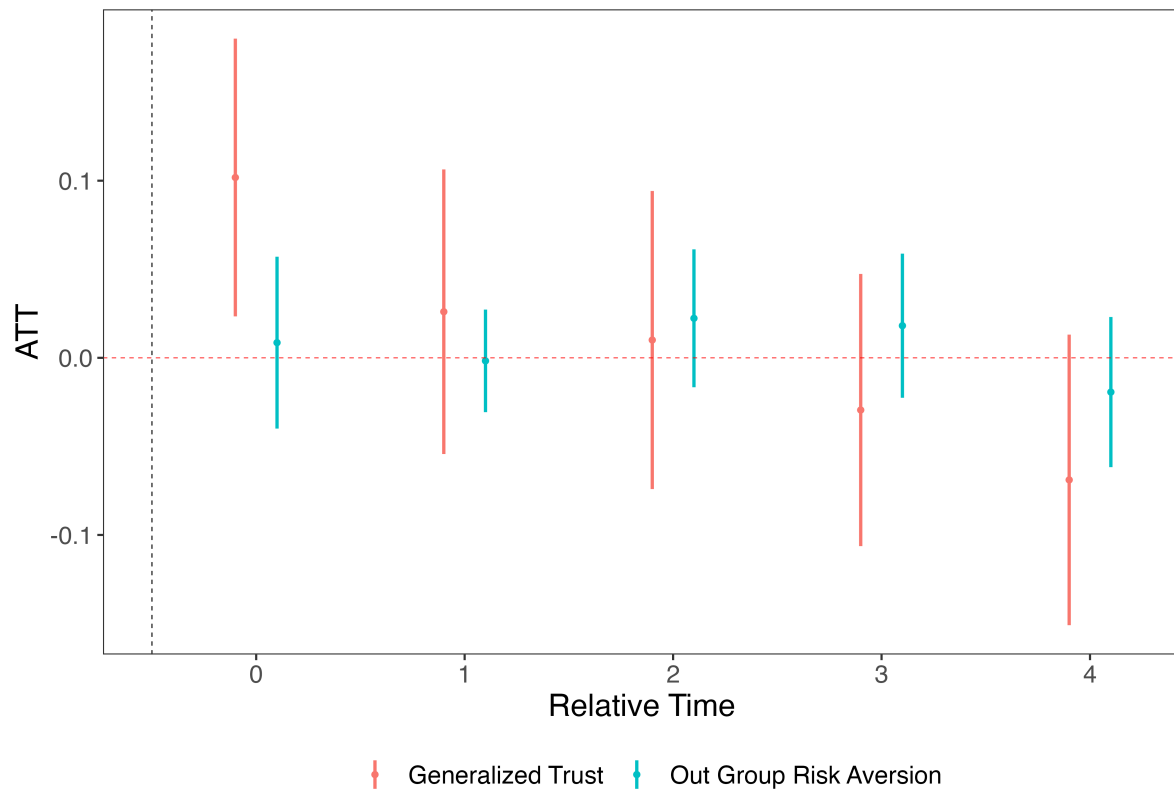


Figure 6: Effect of income decrease

Drastic income decrease

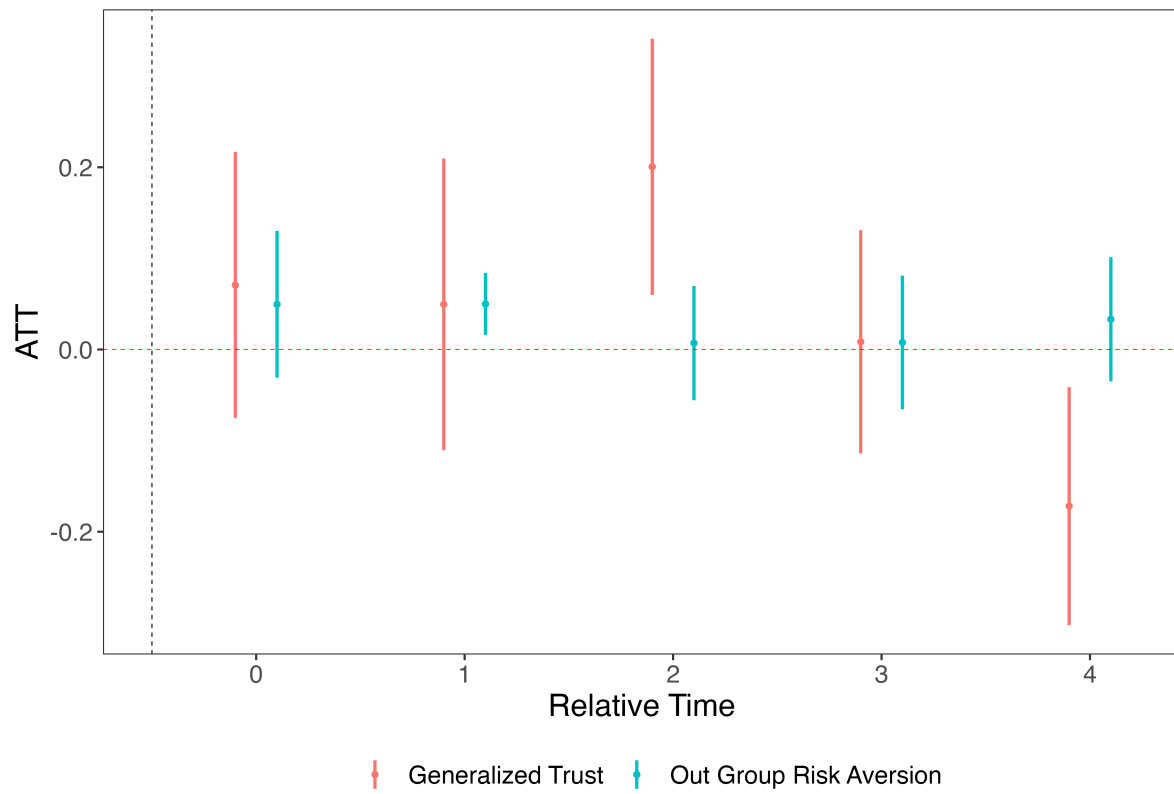


Figure 7: Effect of drastic income decrease

Household income decrease

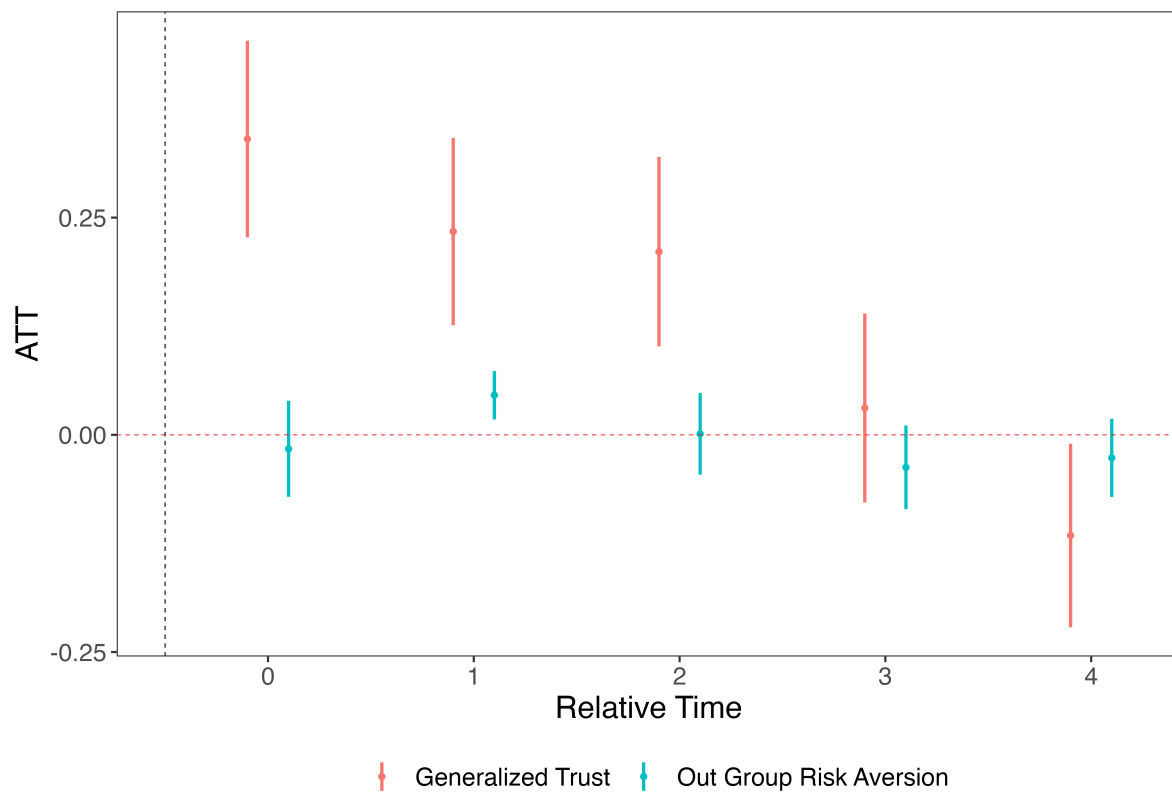


Figure 8: Effect of household income decrease

Evidently, economic insecurity does not significantly change people's risk aversion towards the outgroup in these models. The results are oftentimes insignificant and sometimes even contrary to our expectations.