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Sometimes, a descriptive figure is worth more than a thousand model coefficients: the importance of data description in social research

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ABSTRACT

Many social research questions aim at understanding relationships between different phenomena, and increasingly complex multivariate statistical models are often employed to address these questions. The suitable choice of statistical model must be grounded in the nature of the research aim itself, with simple descriptive analyses forming the starting point for constructing robust statistical models. In this short article, we will demonstrate the importance of data description. Serving as an example study and cautionary tale, we will critically discuss a recently published research finding related to arson attacks on refugees in Germany. Ignoring descriptive figures, this study comes to wrong conclusions due to solely focussing on misspecified, complex statistical models. We therefore highlight how mismatches between descriptive figures and statistical models ask for caution and conclude by reminding the scientific community of the key role of descriptive data analysis at both the outset and conclusion of an analysis.

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Introduction

Much of quantitative social research aims at discovering relationships between different behaviours and phenomena – classical social scientific research studies have, for example, asked how suicide rates vary depending on religiosity (Durkheim, 1897), whether intergroup contact leads to a reduction of discrimination (Allport, 1954), or how participation in associations relate to political behaviour (Putnam, 2000). These relationships are explored via data analytical models which, in the last decades, have become increasingly complex and varied. While this increase in statistical sophistication provides new opportunities, it also comes with challenges. In this short article, we want to remind the research community that the suitability of a statistical model depends on the research question and that 'simple' data descriptions can assist in formulating a robust argument and lead to important insights. They should always form the starting point of any more

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complex analysis as they guide pre-processing and selection steps and remain important at the conclusion for highlighting key findings.

Describing data: why does it matter?

Descriptive statistical analyses describe or summarise features from the data to provide an overview – illustrating how variables are distributed and helping to identify outliers and abnormalities in data (Cooksey, 2020, pp. 61–139; see Gerring, 2012 for a more comprehensive discussion of description). Univariate analysis involves the description of a single variable, including its central tendency, its dispersion, and its shape, using key statistical values like a variable's mean, variance, or quartiles. When multiple variables are of interest, bivariate (or multivariate) descriptive statistics such as cross-tabulations, contingency tables, or quantitative measures of dependence can describe the relationship between them.

The use of descriptive and summary statistics has an extensive history. These statistics depend on fewer assumptions than complex modelling approaches, they are simple to calculate, can easily be visualised, and are straight-forward to communicate. One of the first often-cited instances of descriptive statistics is John Graunt's pioneering analysis of demographic data (Graunt, 1676). In the last century, these summarisation techniques have been advocated for as part of *exploratory data analysis* in the seminal work of Tukey (1977) who presented an idiosyncratic, coherent approach to looking at data and commended data visualisation (see for similar arguments Chatfield, 1985; Cox & Snell, 1981). These ideas were reiterated in Tufte's pioneering work on data visualisation (Tufte, 1983) and had also been illustrated by Francis Anscombe and his famous quartet (Anscombe, 1973).

Despite the fact that these seminal works, which still form part of the teaching canon (see e.g. on Anscombe's quartet Kohler & Kreuter, 2012, p. 280) and the basis of more recent developments in statistical modelling (see e.g. Gelman, 2004), all highlight the importance of understanding one's data, data description is often neglected in research articles. While it is common practice in the social sciences to include a table describing samples and measures, the information provided in this infamous 'Table 1' is rarely discussed (Murphy, 2021). Moreover, although 'Table 1' typically presents univariate descriptives of key variables, bivariate relationships are seldom considered or shown in research papers, despite their importance for gaining a first understanding of relationships and for testing model assumptions. What a sufficient description of data specifically includes depends on the research question and the data at hand. For example, when studying the development of a specific phenomenon over time, a simple line graph can initially visualise trends, patterns, and notable peaks, prompting further investigation into explanatory factors. Neglecting descriptive analyses can lead to wrong conclusions and misspecified models. We will illustrate this with a case example.

Ignoring the descriptive figures: what can go wrong?

During the 2015/2016 New Year's Eve (NYE) celebrations in Cologne, Germany, hundreds of individuals were sexually assaulted and harassed by offenders later described as being of 'North African and Middle Eastern' origin (Shuster, 2016). The event sparked public reactions, and according to Hinz et al. (2023) an increase in violence against refugees in the form of arson attacks.

In their article, Hinz et al. (2023) provide a fine-grained county-level analysis of the geographic and temporal patterns of arson attacks from 2015 to 2017. They provide spatial and temporal descriptions of arson attacks in Germany and, for their multivariate analysis, use *two-level binary random intercept models* to analyse *discrete-time event history data*. These models estimate the time until the occurrence of an event (arson attacks) and account for the hierarchical structure of the data, where events are nested within larger units (regions or time periods), allowing for variability at both levels. This approach is suitable for the present event history data, which records the timing of attacks. As part of a comprehensive analysis, Hinz et al. (2023) also assess the effect of the NYE sexual assaults and how they triggered more arson attacks in the weeks following NYE. They claim to find a temporary increase and base this claim on their random intercept models. We argue that the interpretation of NYE is highly sensitive to how the timeframe of comparison is operationalised. While their model reveals a significant and positive coefficient (see Figure 1, panel A), the descriptive figure visualising the biweekly number of attacks over time raises doubts: descriptively, no increase in arson attacks is noticeable after NYE (see Figure 1, panel B). Instead, we see that the number of arson attacks remains stable for the two weeks after NYE, then decreases, before it then increases in the six weeks after the event (before the number then again drops).[1]

Hinz et al. (2023) do not discuss the mismatch between descriptive finding and statistical model, base their claim of an increase of violence solely on the positive and significant model coefficient, and ignore Murphy's (2021) proposed reservation: 'Any result that is established based on a complex data analysis that cannot be shown to be at least plausible based on the types of simple statistics [. . .] should be treated as suspect and interpreted with the utmost caution' (p. 467).

We argue that the mismatch between the descriptive figure and the model result is due to a model misspecification. In their models, NYE is modelled as a binary variable (including a slight decay expressing a shrinking impact of NYE over eight weeks; however, this neither affects their results nor our argument). With this approach, the two weeks following NYE are compared to all other weeks in the time frame of 2015–2017.[2] Given the diffusion of violence in Germany and the temporal development of the refugee crisis, such a comparison must lead to a positive NYE effect as more attacks occurred in the weeks surrounding NYE than in the timeframe 2015–2017 on average. However, such a specification does not test a potential NYE effect but simply highlights that NYE fell within the peak time of violence in Germany.

Further exposing the misspecification of Hinz et al. (2023), we show that choosing any other date during that peak time also leads to positive effects. For example, if we select 6 November 2015 as an arbitrary, placebo key date (four 2-week time frames before NYE) but otherwise run the same model as Hinz et al. (2023), we also find a similarly strong, positive, and significant effect (see Figure 1, panel C).

To correctly detect a potential NYE effect, we shorten the time frame of comparison. Comparing the two months after NYE with the two months before, we are not able to identify a significant NYE effect, both with and without further control variables (see

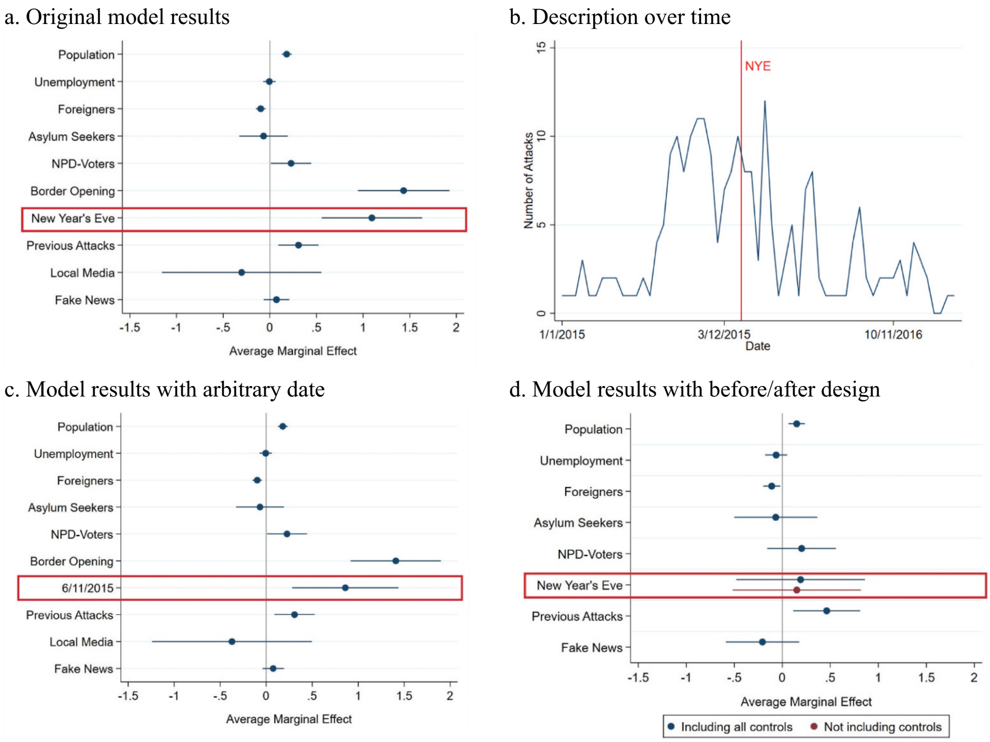

Figure 1. Misspecified models lead to a mismatch of descriptive results and model results. (a) Original results of two-level binary random intercept models to discrete-time event history data as reported by Hinz et al. (2023). Average marginal effects, point estimates with 95% confidence intervals. (b) Number of arson attacks over time across Germany as reported by Hinz et al. (2023). Red line highlights NYE. (c) Results of two-level binary random intercept models with arbitrary date instead of NYE as independent variable. Average marginal effects, point estimates with 95% confidence intervals. Result table can be found in the supplementary material (Table S2). (d) Results of two-level binary random intercept models with restricted time frame (comparing two months before NYE with two months after NYE). Average marginal effects, point estimates with 95% confidence intervals. Result table can be found in the supplementary material (Table S3).

Figure 1, panel D). Only if we broaden the timeframe to include at least 30 weeks (i.e. seven and a half months) before and after the event, we obtain a significant effect (see Table S4 in the supplementary material).

These analyses shed more light on the problem in the statistical model, but the descriptive figure has already told the story: there is no striking increase in arson attacks on refugee accommodations after NYE.[3] The correctly specified model (i.e. Figure 1, panel D) matches the descriptive finding.

Conclusion

Data description is a necessary beginning and an end to a convincing narrative: it should form the starting point of any data analysis and relied upon when making conclusions. Albeit data description is not a substitute for attempting to model complex social reality with appropriate statistical models, we need to be reminded that descriptive figures can make shortcomings, violations of assumptions, and misspecifications of these more complex statistical models evident.

Notes

1. Hinz et al. (2023) find a significant NYE effect for Germany as a whole, and their separate analyses show that this effect can be found in West Germany only. We recreate all analyses for East and West Germany separately and these analyses can be found in the supplementary material. Descriptively, the pattern for both East and West Germany is no different to the countrywide one: the number of arson attacks has decreased after NYE, and it does not increase again until six weeks after the incident.
2. We want to mention that we find the data setup of Hinz et al. (2023) unsuitable for testing an effect of NYE. Hinz et al. (2023) divide time into two-week intervals starting 1/1/2015. Therefore, time frame 27 starts on 31/12/2015. Their dummy variable highlights timeframe 28 as being the one after NYE. While this is technically true, it also means that January 1st up to January 13th are not considered to have occurred after NYE.
3. An increase in arson attacks can be found under specific assumption: five arson attacks on refugee homes in Germany occurred in the last week of the year 2015, five attacks in the week after NYE, nine in the second week after, eight in the third week after, and four in the fourth week after (Frey, 2023; Schwitter & Liebe, 2023). Given the small number of cases and the variability of the number of arson attacks over time, interpretation must be done with caution, and we refrain from interpreting this as a striking increase in attacks (note also the differentiation between attacks on unoccupied and on occupied refugee shelters made by Frey, 2023). While it is possible to argue that there was a short-term increase of arson attacks after NYE, the analytical strategy of Hinz et al. (2023) does not allow for this conclusion to be drawn.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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