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ABSTRACT

Can Online Surveys Represent the Entire Population?*

A general concern with the representativeness of online surveys is that they exclude the "offline" population that does not use the internet. We run a large-scale opinion survey with (1) onliners in web mode, (2) offliners in face-to-face mode, and (3) onliners in face-to-face mode. We find marked response differences between onliners and offliners in the mixed-mode setting (1 vs. 2). Response differences between onliners and offliners in the same face-to-face mode (2 vs. 3) disappear when controlling for background characteristics, indicating mode effects rather than unobserved population differences. Differences in background characteristics of onliners in the two modes (1 vs. 3) indicate that mode effects partly reflect sampling differences. In our setting, re-weighting online-survey observations appears a pragmatic solution when aiming at representativeness for the entire population.

JEL Classification: C83, D91, I20

Keywords: online survey, representativeness, mode effects, offliner, public opinion

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1. Introduction

Over the past years, online surveys have become increasingly popular in economics. Online surveys offer several advantages over traditional face-to-face, telephone, or mail surveys for researchers who study people's preferences, opinions, or beliefs. They are easy to implement, offer access to relatively diverse sets of potential study participants, and can usually be implemented at much lower cost than other survey modes. In addition, they facilitate the implementation of attractive methodological tools, such as randomized survey experiments, at a large scale. However, online surveys have a major drawback concerning their external validity: While they cover individuals who use the internet – whom we refer to as "onliners" throughout the paper – they exclude the non-negligible part of the population that does not use the internet – whom we refer to as "offliners." As a consequence, it is unclear whether results from online surveys can be representative for the entire population.[1] For example, the share of offliners in a representative German face-to-face household survey was as high as 22 percent in 2014. While this share has gone down to 17 percent by 2017, the offline population still makes up a substantial part of the population.[2] Since the offline population may differ from the online population in terms of their preferences, beliefs, or sociodemographic characteristics, coverage bias might undermine the generalizability of results from online surveys to the offline population. A common method to circumvent this bias are mixed-mode surveys which complement web-survey data for onliners with face-to-face-survey data for the offline population. In this paper, we assess the extent to which these costly face-to-face complements are necessary to achieve representativeness, and whether response differences across survey modes reflect mode-specific answering behavior or sampling effects.

In particular, we address the question whether online surveys can represent the opinions of the entire population, including the offline population. To this end, we administered the ifo Education Survey 2017, an opinion survey of the German adult population on education policy topics, to three groups of respondents: (1) onliners sampled in the web (online) mode (N=3,699),

[1] Other potential drawbacks of online surveys that have been studied in the literature include non-probability sampling (e.g., Blom et al., 2017) and relatively low response rates (e.g., Jäckle et al., 2010).

[2] These numbers refer to the January to April waves of a regular face-to-face household survey carried out by Kantar Public, the polling firm which carried out the surveys used in our analyses (see section 2 for details). The numbers align well with the data of the digital index collected by Initiative D21 (2018) which quantifies the share of offliners in Germany at 23 percent and 19 percent in 2014 and 2017, respectively.

(2) offliners sampled in the face-to-face mode (N=382), and (3) onliners sampled in the face-to-face mode (N=622). Groups (1) and (2) correspond to a standard mixed-mode survey. For the purposes of this paper, we implemented the extension to group (3) which allows us to test several questions of representativeness. In a comparison of groups (1) and (2), we document systematic response differences between onliners interviewed in the web mode and offliners interviewed in the face-to-face mode.

In this mixed-mode setting, any existing differences between onliners and offliners can either stem from (i) inherent differences between the two groups or from (ii) mode effects that arise because onliners and offliners are sampled and surveyed in different modes. Importantly, the onliners sampled in the face-to-face mode (group (3)) allow us to differentiate between these two potential sources: comparing groups (2) and (3), we can explicitly test for inherent differences between the answers of onliners and offliners while holding the survey mode constant. Similarly, by comparing groups (1) and (3), we can shed light on potential mode effects that arise from surveying onliners in the web mode versus the face-to-face mode. Our setup also allows us to differentiate between two types of mode effects: mode-specific answering behavior such as social desirability bias as opposed to sampling effects that arise because different survey modes may reach different populations even within the group of onliners.

Our analysis proceeds in three steps. In the first step, we compare groups (1) and (2) to test whether offliners exhibit different answering behavior than onliners in the mixed-mode setting. For 22 out of 79 survey items (28 percent), we find that responses differ significantly (at the 5 percent level) between onliners interviewed in the web mode and offliners interviewed in the face-to-face mode. This number reduces to 9 items (11 percent) when conditioning on respondents' observed background characteristics (age, gender, education, income, region, family status, and employment status). That is, while differences in observed characteristics account for more than half of the onliner-offliner response differences in the mixed-mode survey in our setting, a sizable share of differences remains unexplained.

In the second step, we examine whether these response differences are due to inherent differences in unobserved characteristics between onliners and offliners or due to differences in the web versus face-to-face survey mode. To do so, we draw on group (3), i.e., onliners surveyed in the face-to-face mode, which were asked a subset of eight survey items that we had selected based on prior evidence of relatively large onliner-offliner differences.[3] When comparing the responses of onliners and offliners interviewed in the same face-to-face mode (groups (2) and (3)), we find significant differences for five of the eight items. Intriguingly, all of these differences turn small and statistically insignificant (at the 5 percent level) when conditioning on respondents' observed background characteristics.[4] This suggests that response differences between onliners and offliners in the mixed-mode setting are not due to inherent differences in unobserved characteristics between the two groups but rather reflect survey mode effects.

A comparison of onliners interviewed in the web mode and in the face-to-face mode (groups (1) and (3)) provides additional indication that mode effects are important. For four of the eight items, we find significant differences, independently of whether conditioning on respondents' characteristics or not. Interestingly, these differences all occur for survey items on relatively sensitive topics, namely policies related to the education of refugees and how respondents grade schools.[5] Arguably, such survey items are particularly susceptible to interviewer-demand effects of social desirability, which are more likely to occur in the presence of an interviewer in the face-to-face mode than in the anonymous web mode.

Furthermore, we provide evidence of heterogeneous sample selection across survey modes. Comparing background characteristics of onliners surveyed in the web versus face-to-face mode (groups (1) and (3)), the latter group is significantly older, less likely to be full-time employed, and more likely to be retired or ill, for instance. That is, at least part of the response differences between web and face-to-face surveying stems from the fact that the different survey modes reach different subpopulations even within the group of onliners. Together, our findings suggest that mode effects – i.e., mode-related answering behavior and sampling differences – are an important factor that drives onliner-offliner response differences in mixed-mode settings. In contrast, inherent differences between the answers of onliners and offliners stemming from unobserved characteristics seem to be rather unimportant in our setting.

Building on the result that inherent population differences between onliners and offliners do not drive response differences, the third step of our analysis investigates the extent to which an approach that re-weights the responses of the online survey can recover response patterns of the

[3] Responses differed significantly between groups (1) and (2) on six of the eight selected items without conditioning on respondents' characteristics and four with conditioning (see section 2).

[4] One of the eight differences remains marginally significant at the 10 percent level.

[5] Consistently, we also observe marked differences between groups (1) and (2) for each of these four items.

entire population (onliners *and* offliners) as observed in the mixed-mode setup. To do so, we compare web-mode responses of onliners re-weighted to match the basic characteristics of the entire population (with respect to age, gender, parental status, school degree, federal state, and municipality size) to results of the mixed-mode sample, also weighted to represent the entire population. We find that there are only two of the 79 survey items (2.5 percent) for which the estimated population mean of the re-weighted responses of the onliners differs significantly (at the 5 percent level) from the estimated population mean of the mixed-mode sample. For more than half of the survey items, the difference in the population means estimated by the two approaches is below one percentage point on the binary-coded responses, and it exceeds three percentage points in only four cases.

These results show that re-weighted online samples can produce response patterns that are indistinguishable, statistically and quantitatively, from those of mixed-mode surveys. Interestingly, we observe the single largest difference of 7.7 percentage points between the re-weighted online sample and the mixed-mode sample for the question on whether respondents view themselves as winners of digitalization. This indicates that the re-weighting approach is less suited for questions that are directly related to respondents' offliner status. But overall, our results suggest that re-weighting onliners can be a pragmatic, economic solution in many research contexts to depict preferences, opinions, or beliefs of the entire (online and offline) population.

Our analysis speaks to the growing literature in economics that employs online surveys to study preferences, opinions, and beliefs (e.g., Kuziemko et al., 2015; Armantier et al, 2016; Alesina et al., 2018; Haaland and Roth, 2018; Roth and Wohlfart, 2018). While deriving statements that are representative for the entire population is central to many of these studies (for instance, in political-economy frameworks such as the median voter model), it is unclear to what extent representativeness can be achieved using pure online surveys. Our finding that inherent population differences do not drive onliner-offliner response differences justifies the widespread approach to re-weight onliners so that they match population characteristics.

Our paper also contributes to the literature on mode effects in surveys. A general finding from this literature is that the offline population differs from the online population along various dimensions, such as age, gender, race, education, income, health, and political engagement (e.g., Couper, 2000; Couper et al., 2007; Schonlau et al., 2009; Eckman, 2015).[6,7] A common approach to circumvent potential coverage bias due to these differences are mixed-mode surveys. Consequently, several studies within this methodological literature discuss the comparability of data collected in mixed-mode settings, because each mode may produce different response patterns or sampling effects (e.g., Jäckle et al., 2010; Ye et al., 2011; Bosnjak, 2017). Our unique setting which scrutinizes onliners sampled in both the web mode and the face-to-face mode and offliners sampled in the face-to-face mode allows us to add to the mode-effects literature in several ways. First, we provide new survey evidence on systematic response differences between onliners sampled in the web mode and offliners sampled in the face-to-face mode, which contributes to the literature on mixed-mode surveys. Second, we explicitly test whether onliners and offliners inherently differ in their response patterns when interviewed in the same face-to-face mode, thereby adding to the literature on coverage bias. Third, we add to the literature on mode comparability by investigating how onliners sampled in the web mode differ in their responses from onliners sampled in the face-to-face mode. Finally, we compare response patterns between web-sampled onliners, re-weighted to represent the entire population, and the weighted mixed-mode sample, thereby adding to the literature on the representativeness of online surveys. This last comparison offers guidance for a cost-effective mode choice for surveyors who aim to derive representative conclusions for the entire population.

The remainder of the paper proceeds as follows. Section 2 introduces our data source, the ifo Education Survey 2017. Section 3 presents differences between onliners and offliners in the mixed-mode setting. Section 4 introduces our conceptual framework to differentiate between inherent population differences and mode effects and presents our main results. Section 5 shows that re-weighting online samples can be a pragmatic alternative to mixed-mode surveys. Section 6 concludes.

[6] For the country we study, Germany, the offline population has been found to be older, more likely to be female, less educated, more likely to live in a single household, and less likely to be politically interested (Bosnjak et al., 2013; Blom et al., 2017). These patterns are largely consistent with our findings (see section 4.2).

[7] A related strand of literature compares economic experiments conducted online versus in laboratories (see Anderhub et al., 2001; Chesney et al., 2009; Horton et al., 2011; Amir et al., 2012; Hergueux and Jacquemet, 2015; Arechar et al., 2018).

2. Data Source: The ifo Education Survey 2017

Our analysis is based on data from the 2017 wave of the ifo Education Survey, an annual opinion survey on education policy that we have been conducting in Germany since 2014.[8] The 2017 survey was carried out between April and July 2017 by Kantar Public, a renowned German polling firm. Kantar Public administered stratified sampling in three steps. First, they recruited 3,699 respondents who use the internet via an online panel and interviewed them in web mode (group (1): onliners sampled in web mode). Second, they recruited 382 persons who do not use the internet and interviewed them in face-to-face mode as part of a household survey at their homes (group (2): offliners sampled in face-to-face mode). These two groups are the standard respondents of the mixed-mode ifo Education Survey. For the sake of this paper, Kantar Public sampled a third group: 622 persons who use the internet were recruited at their homes and interviewed in face-to-face mode (group (3): onliners sampled in face-to-face mode).[9] This third group allows us to investigate the reasons behind onliner-offliner response differences between groups (1) and (2) (see our conceptual framework in section 4.1 for greater detail).

Onliners sampled in the web mode (group (1)) completed the survey autonomously on their own digital devices. Respondents sampled face-to-face (groups (2) and (3)) were provided tablet computers to complete the survey at their homes in the presence of the interviewer. Upon request, the interview was conducted by the interviewers who read the questions aloud and entered the respondents' answers. Expectably, the share of respondents who opted into this interview mode differs markedly between onliners and offliners: While 79 percent of the offliners in group (2) requested assistance, the share is only 36 percent among the onliners in group (3).[10]

The ifo Education Survey 2017 comprised 79 substantive questions on education policy covering different areas such as preferences for education spending, general education policies,

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[8] For substantive research papers using data from the ifo Education Survey, see, for instance, West et al. (2016), Lergetporer and Woessmann (2018), and Lergetporer et al. (2018a, 2018b).

[9] To differentiate between persons who do and do not use the internet, internet usage was elicited at the very beginning of the household interview. Persons who stated not to use the internet for private or professional reasons were classified as persons who do not use the internet.

[10] By providing respondents in the face-to-face mode with tablet computers, we intended to make the web mode and the face-to-face mode as comparable as possible. Thus, the face-to-face mode comprises both persons who complete the survey autonomously in the presence of an interviewer and those who were interviewed by the interviewer directly. The fact that most people who do not use the internet refuse to complete the survey autonomously on the tablet computer provides an interesting methodological insight: It appears practicably infeasible to survey most offliners in the web mode, even if they were provided with the necessary devices.

tertiary and vocational education policies, political voting behavior, educational aspirations, educational inequality, and digitalization. At the end, the survey elicited a host of respondents' background characteristics. While groups (1) and (2) answered all survey items, respondents in group (3) received a shortened questionnaire that comprised eight substantive questions.[11] To focus this part of the analysis on items with substantive onliner-offliner response differences, we had selected these eight questions based on the observation that they had produced large and significant differences between onliners and offliners in earlier waves of the mixed-mode ifo Education Survey.[12] Median completion time was 17 minutes for onliners sampled in the web mode, 20 minutes for offliners sampled face-to-face, and three minutes for onliners sampled face-to-face. In general, respondents provided answers to the opinion questions on five-point scales. Here, we dichotomize responses to ease exposition in our analysis and to document majority support in the population.[13]

To reflect representativeness of the German adult population, we employ survey weights so that our sample matches the characteristics of the entire population with respect to age, gender, parental status, school degree, federal state, and municipality size. In this paper, we use two different sets of weights: The first set is calculated using the mixed-mode sample (i.e., onliners sampled in the web mode and offliners sampled face-to-face) and the second set is calculated using only the onliners sampled in the web mode. These two sets of weights allow us to explore whether re-weighting the online sample can recover response patterns of the mixed-mode sample (see section 5).

[11] For efficiency reasons, several questions were only posed to randomly selected subgroups of onliners sampled in the web mode and offliners sampled in the face-to-face mode so that each respondent of these two groups answered a total of 34 substantive questions. Importantly, all offliners sampled in the face-to-face mode answered each of the eight selected questions in order to maximize power for the comparative analysis of these survey items.

[12] These questions were on preferences for free preschool, increased school spending, increased teacher salaries, whether education policy is important for personal voting decisions, preferences towards governmental subsidies for refugees' training costs, and grading of schools in Germany, in the respondent's federal state, and in her local area. Previous waves of the ifo Education Survey were sampled as mixed-mode surveys that included onliners surveyed in the web mode (group (1)) and offliners surveyed face-to-face (group (2)). Results from previous survey waves are available upon request.

[13] The five-point scales for most survey items are 1 = "strongly favor," 2 = "somewhat favor," 3 = "neither favor nor oppose," 4 = "somewhat oppose," and 5 = "strongly oppose." The corresponding dummy is coded 1 if the respondent selected one of the first two categories and 0 otherwise. The same coding is used in the remaining cases where categories range from 1 = "strongly increase" to 5 = "strongly decrease" or from 1 = "strongly agree" to 5 = "strongly disagree."

3. Onliner-Offliner Differences in the Mixed-Mode Setting

We start our analysis by documenting onliner-offliner response differences in the mixed-mode setting, i.e., between onliners sampled in the web mode and offliners sampled in the face-to-face mode. Table 1 shows results from regressions of binary survey responses on an "Offliner" dummy which is coded 1 if the respondent is an offliner and 0 otherwise. Each entry in the table corresponds to a separate regression. Column (1) shows regression coefficients without conditioning on background characteristics, column (2) reports results after conditioning on a set of basic controls, and column (3) includes our full set of controls (see table notes for a list of included control variables).

We find that responses to 22 of the 79 survey items (28 percent) differ significantly (at the 5 percent level) between onliners and offliners when not conditioning on respondents' background characteristics (see bottom of column (1)). Using our full set of controls in column (3), this reduces to 9 items (11 percent). Thus, more than half of the significant response differences between onliners and offliners can be accounted for by differences in observed characteristics. But this also implies that a significant share of the raw onliner-offliner differences is not due to differences in observed characteristics.

Grouping survey items by topic allows us to identify topic areas for which onliner-offliner differences are particularly pronounced. For questions on education spending, five out of 15 items (33 percent) are significantly different, which reduces to one (7 percent) when including controls in column (3). For questions on general education policies, six out of 19 items (32 percent) differ between onliners and offliners, and conditioning on respondents' characteristics leaves four differences (21 percent) significant. The number of significant differences is one out of eight items (12.5 percent) for tertiary and vocational education policies, four out of nine items (44 percent) for political voting behavior, and two out of four items (50 percent) for questions on educational aspirations. No significant differences remain in these three groups after adding the control variables. For items related to educational inequality, one of three (33 percent) differs significantly and remains significant when adding controls. Finally, responses to three out of 19 items (14 percent) on digitalization are statistically significantly different between onliners and offliners without and with conditioning on respondents' characteristics.

In summary, responses of onliners sampled in the web mode and offliners sampled face-to-face differ markedly, but a substantial share of these differences can be accounted for by differences in respondents' observed background characteristics. Notably, the differences remaining after conditioning on these characteristics are prevalent in a wide range of topics and do not seem to be driven by response differences within one specific subject area of our education survey. As onliners are recruited and interviewed in a different mode than offliners, the sources of remaining response differences are unclear a priori. They can be either due to unobserved population differences between the online population and the offline population or due to mode effects such as mode-related answering behavior or sampling. Below, we analyze the additional sample of onliners sampled in the face-to-face mode to investigate the empirical relevance of these alternative explanations.

4. Distinguishing Population Differences from Mode Effects

4.1 Conceptual and Empirical Framework

The analysis so far reveals significant response differences between onliners interviewed in the web mode and offliners interviewed in the face-to-face mode. Part of these response differences can be accounted for by observed characteristics such as age, gender, education, income, region, family status, and employment status. This is intuitive given that the online and offline populations differ along numerous dimensions (see below) that might plausibly affect opinions on education policy. However, even after conditioning on a wide range of observed factors, important differences between onliners and offliners remain. Our survey design allows us to investigate two possible sources of these remaining response differences: differences in unobserved characteristics and mode effects. On the first potential source, it is possible that onliners and offliners do not only differ in observed characteristics, but also in unobserved and inherent attributes that might be correlated with opinions on education policy. If this was the case, observed response differences between onliners and offliners would raise important concerns about coverage bias in web surveys and would make it impossible to draw conclusions from web surveys that are valid for the entire population (comprising onliners and offliners).

The second potential source of onliner-offliner response differences, mode effects, are those that are solely attributable to differences in the modes of how onliners and offliners are surveyed (i.e., web versus face-to-face). Mode effects can come in different forms, such as mode-related answering behavior and mode-specific sampling effects. The former means that different modes trigger different answers to the same question by the same person, e.g., because of social desirability or satisficing effects (see Jäckle et al. (2010) for a discussion). The latter can arise because different modes might recruit different types of respondents. For instance, our respondents surveyed in the web mode are recruited via an online panel, whereas respondents in the face-to-face mode are recruited at their homes. These two recruitment channels likely attract respondents who differ in their characteristics.

To shed light on these potential sources of onliner-offliner response differences, the following analysis compares the basic mixed-mode sample with our additional sample of onliners surveyed in the face-to-face mode. This sample, which was specifically drawn for this analysis, allows us to hold the mode between onliners and offliners constant and therefore to explicitly test for inherent population differences. It also allows us to shed light on the prevalence of mode effects by holding the onliner status constant and comparing onliners interviewed in the web mode versus face-to-face.

To test whether response differences between offliners and onliners in the mixed-mode survey can be attributed to inherent differences in unobserved characteristics or mode effects, we thus compare three groups of respondents: (1) onliners interviewed in the web mode, (2) offliners interviewed in the face-to-face mode, and (3) onliners interviewed in the face-to-face mode. In particular, we estimate the following type of regressions:

$$y_i = \alpha_0 + \alpha_1 Offliner_i + \alpha_2 Onliner_i^{face\text{-}to\text{-}face} + \gamma' X_i + \varepsilon_i \tag{1}$$

where y_i is the outcome variable of interest, i.e., a dummy indicating respondent i's answer to a given survey item, $Offliner_i$ is a dummy equal to 1 if the respondent belongs to the offline population (and is thus interviewed in the face-to-face mode), and $Onliner_i^{face\text{-}to\text{-}face}$ is a dummy variable equal to 1 if the respondent belongs to the online population and is interviewed in the face-to face mode. X_i is a vector of control variables.

In this specification, α_1 is an estimate of the response difference between offliners interviewed in the face-to-face mode and onliners interviewed in the web mode. The second coefficient of interest, α_2, captures the difference between onliners interviewed in the face-to-face mode and onliners interviewed in the web mode. The latter coefficient indicates whether mode effects are present in the online population. A comparison between α_1 and α_2 shows whether there are inherent differences between onliners and offliners (both interviewed in the face-to-face mode). We perform this analysis for all eight substantive questions which were posed to the three groups of respondents.

4.2 Differences in Background Characteristics across Onliner-Offliner Status and Modes

To describe the populations sampled in the three groups, Table 2 reports background characteristics for each group of respondents. The characteristics of offliners differ from those of onliners in almost all dimensions, independent of whether they are compared to those onliners sampled in the web mode (column (4)) or to those onliners sampled in the face-to-face mode (column (5)). Offliners are older, less educated, more likely to be female, less likely to be full-time employed, have lower income, and are more likely to live alone and in smaller cities.

Notably, the sample of onliners interviewed in the web mode also differs significantly from the sample of onliners interviewed face-to-face in a number of background characteristics (column (6)). Among others, the onliners sampled in the face-to-face mode are older, less educated, more likely to be self-employed, and more likely to be retired or ill than the onliners sampled in the web mode. These differences are not surprising and plausibly reflect sampling differences: participants in face-to-face interviews need to be encountered at home by the interviewers in order to be sampled, which is not the case for onliners sampled in the web mode. The existence of sampling differences underscores the importance of controlling for background characteristics in the regression analysis.

4.3 Differences in Survey Responses: Inherent Population Differences versus Mode Effects

Next, we turn to the question of whether the systematic differences in response behavior between onliners interviewed in the web mode and offliners interviewed face-to-face can be attributed to inherent differences between the offline and the online population or to mode effects. To this end, we run regressions based on equation (1) that compare responses to our set of eight questions between the three groups of respondents. The upper panel of Table 3 presents results without control variables and the lower panel includes our full set of control variables (see table notes for a list of the control variables).

The coefficients on the *Offliner* dummy resemble our earlier results on onliner-offliner differences (see section 3). Without control variables, six of the eight opinion survey items indicate a significant difference between onliners interviewed in the web mode and offliners interviewed face-to-face. Even after conditioning on observed differences in background characteristics, four of the eight differences (50 percent) remain statistically significant. It is not surprising that this share of significant differences is larger than the one reported in Table 1 because we had selected these eight survey items for the present analysis based on the particularly strong differences between onliners and offliners they showed in earlier surveys.

Intriguingly, the coefficients on the *Onliner face-to-face* dummy also show significant differences between onliners interviewed in the web mode and onliners interviewed face-to-face for four of the eight items, independent of whether controls for observed background characteristics are included or not. Interestingly, these four items differ between the onliners sampled in the web mode and both of the face-to-face samples. A likely reason for these systematic differences across modes is social desirability bias: The four items cover relatively sensitive topics, namely subsidizing refugee training costs and grading the quality of schools. As a consequence, respondents might give more "socially desirable" answers when surveyed in the presence of an interviewer in the face-to-face mode compared to answering them anonymously in the web mode (see Roberts (2007) for discussion).

Comparing responses between onliners and offliners who are surveyed in the same face-to-face mode, we find significant unconditional differences (at the 5 percent level) for five of the eight items. Intriguingly, all of these differences turn small and statistically insignificant after conditioning on respondents' background characteristics (see lower panel of Table 3).[14] That is, onliner-offliner differences disappear when we hold the survey mode and respondents' observed background characteristics constant. This is an important result as it indicates that mode effects – i.e., mode-related answering behavior and sampling – are a key driver of response differences between onliners and offliners in the mixed-mode setting (i.e., when onliners are sampled in the web mode and offliners are sampled face-to-face, see section 3). In contrast to mode effects, inherent population differences in unobserved characteristics between onliners and offliners seem to be rather unimportant for their survey responses, because they are hard to reconcile with the insignificance of the differences between the two groups when using the same survey mode and conditioning on observed background characteristics.[15]

[14] One of the eight differences remains marginally significant at the 10 percent level.

[15] Appendix Table A1 reports additional results for the question on whether public spending for schools should increase. We ran an experiment on this survey item in which a randomly selected treatment group was informed about the actual level of public school spending before answering the same question as the uninformed control group

5. Re-weighting the Online Sample as a Pragmatic Solution

The results so far indicate that response differences between onliners and offliners in the mixed-mode setting mainly stem from mode effects rather than inherent unobserved population differences. Based on this insight, this section examines whether re-weighting our sample of onliners observed only in the online survey to match basic characteristics of the entire population can recover response patterns of the mixed-mode setting (which includes onliners and offliners). If successful, this approach poses a pragmatic, economic solution to deriving population-representative statements from online surveys. Note that this approach is effectively used by researchers who wish to draw representative conclusions from online surveys (e.g., Alesina et al., 2018; Haaland and Roth, 2018; Roth and Wolfahrt, 2018). To our knowledge, ours is the first paper that explicitly tests the validity of this approach.[16]

Table 4 summarizes background characteristics of the mixed-mode sample (column (1)) and the re-weighted online sample (column (3)).[17] The analysis uses two sets of weights: the first one aligns the combined mixed-mode sample of onliners surveyed in the web mode and offliners surveyed in the face-to-face mode to the entire population with respect to age, gender, parental status, school degree, federal state, and municipality size, the other one does the same for the sample of onliners surveyed in the web mode.[18] As columns (5) to (7) show, all differences in background characteristics between the two weighted samples are small and statistically insignificant. While this finding is not surprising for those background characteristics which directly entered the construction of the weights (age, gender, parental status, school degree,

(see West et al. (2016) for details). The coefficients on the information-treatment indicator show large, significant, and negative information effects on support for higher school spending among onliners interviewed in the web mode. The interactions between the treatment indicator and the subgroup indicators (*Offliner* and *Onliner face-to-face*) are insignificant, indicating that treatment effects do not differ significantly across the three groups. However, these tests are relatively low powered because all three groups were randomly divided into treatment and control groups, leaving us with relatively small numbers of observations per treatment-group cell. Therefore, we cannot fully exclude the possibility of economically relevant treatment effect heterogeneities due to inherent differences or mode effects.

[16] See Solon et al. (2015) for a general discussion on when and how to use survey weights.

[17] The list of background characteristics included in Table 4 is slightly longer than the one included in Table 2 as some of these items were not included in the shorter questionnaire of onliners in the face-to-face mode.

[18] While we also weight the mixed-mode sample to account for small differences with respect to sociodemographic characteristics between the actual German population and the mixed-mode survey respondents, these weights have only minor effects on response patterns in the mixed-mode sample. The average absolute deviation between unweighted and weighted responses in Table 5 for this sample is 1.1 percentage point, and it never exceeds 3.1 percentage points (not shown). This corroborates the high quality of our raw data.

federal state, and municipality size), it is reassuring that the weights also balance the other background characteristics.

Next, we investigate whether the re-weighting approach also harmonizes the response patterns in the mixed-mode sample and the online sample. Table 5 reports results for all 79 survey items. We find that the population mean estimated from the re-weighted responses of the online sample differ from the population mean estimated from the mixed-mode sample significantly (at the 5 percent level) in only two of the 79 survey items (2.5 percent). The two significant differences occur for the item of whether respondents give a good grade to the schools in Germany overall (estimated population means of 23.8 percent versus 21.0 percent) and for the item of whether they consider themselves as a winner of digitalization (54.3 percent versus 62.0 percent). For more than half of the items, the difference in the population means estimated by the two approaches is less than one percentage point, and it exceeds three percentage points in only four cases. Thus, for most of the binary-coded responses that reflect population shares holding the respective opinion, the difference in the estimated population mean between the two approaches is not only statistically, but also quantitatively unsubstantial.

Interestingly, we find the single largest and highly significant difference on a question that is directly related to the onliner status of respondents: whether they see themselves as winners or losers of digitalization. The share of respondents who see themselves as winners is substantially larger in the re-weighted online sample than in the mixed-mode sample (7.7 percentage points). While this indicates that re-weighting is less suitable for questions which directly relate to respondents' onliner status, it is notable that differences between the re-weighted online sample and the mixed-mode sample are very small and insignificant in most cases, including other questions on digitalization.

Overall, our results suggest that online surveys may be an inexpensive alternative to mixed-mode surveys, as they are able to produce results that represent responses of the entire population, including onliners as well as the offliners, reasonably well.

6. Conclusion

In this paper, we investigate whether online surveys can be representative for the entire population by comparing responses to a large-scale opinion survey between (1) onliners sampled in the web mode, (2) offliners sampled in the face-to-face mode, and (3) onliners sampled in the face-to-face mode. Our unique survey setup allows us to test whether differences in response patterns between onliners and offliners exist, whether they are robust to the inclusion of control variables, and to what extent they can be attributed to inherent population differences versus mode effects.

Our results indicate that onliners and offliners indeed exhibit substantial differences in responses in a mixed-mode setting of groups (1) and (2) and that conditioning on respondents' observed background characteristics can account for some, but not all of these differences. Comparative analysis with group (3) suggests that these differences are mostly due to survey mode effects, whereas inherent population differences are rather unimportant: When both groups are surveyed in the face-to-face mode, onliners and offliners exhibit identical response patterns after conditioning on respondents' background characteristics. By contrast, onliners surveyed face-to-face differ in their responses markedly from onliners surveyed in the web mode.

Based on these results, we suggest re-weighting the online sample to resemble the characteristics of the entire population. This approach might be a pragmatic and inexpensive solution for survey researchers to derive conclusions that are representative for the entire population, including onliners as well as offliners. This re-weighting approach produces response patterns that generally cannot be distinguished, statistically or quantitatively, from the patterns produced using a mixed-mode method that combines data from web-surveyed onliners and face-to-face-surveyed offliners.

At the same time, our findings caution that the results of any survey should always be interpreted within the given survey mode, reflected both in potentially mode-specific populations participating in the survey and in their mode-specific answering behavior. For example, face-to-face surveys where interviewers are present may produce more socially desirable response patterns compared to anonymously answered online surveys. Furthermore, the re-weighting approach may have limits for questionnaire items that relate directly to respondents' status of being onliners or offliners. In our setting, this limitation appears to apply for the question of whether respondents consider themselves personally as winners of digitalization, although not for many other questionnaire items related to opinions about the digitalization of the education system and the effects of digitalization in society more generally.

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Table A1: Heterogeneous treatment effects by onliner-offliner status and survey mode in the school-spending experiment

	(1) Without controls	(2) With controls
Offliner	-0.019	-0.017
	(0.034)	*(0.040)*
Onliner face-to-face	0.041	0.019
	(0.027)	*(0.029)*
Information treatment	-0.180***	-0.174***
	(0.014)	*(0.014)*
Information treatment x Offliner	-0.062	-0.060
	(0.048)	*(0.053)*
Information treatment x Onliner face-to-face	0.024	0.039
	(0.038)	*(0.040)*
Difference Offliner vs. Onliner face-to-face		
Main effect	-0.061	-0.036
	(0.041)	*(0.047)*
Treatment effect	-0.087	-0.099
	(0.058)	*(0.063)*
Observations	4,667	4,513

Notes: Ordinary least squares (OLS) estimations. Offliner: respondents who do not use the internet, interviewed face-to-face. Onliner face-to-face: respondents who use the internet, interviewed face-to-face. Omitted category: respondents who use the internet, interviewed in the web mode. Dependent variable: dummy variable indicating support for increased public spending for schools. Controls: age, gender, living in West Germany, parental education, educational degree, income, living with partner in household, employment status, city size, and parental status. Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. Data source: ifo Education Survey 2017.

Table 1: Response differences between onliners and offliners in the mixed-mode survey

	(1) No controls		(2) Basic controls		(3) Full controls	
Education Spending						
Pro free preschool	-0.042	*(0.027)*	-0.014	*(0.032)*	0.009	*(0.034)*
Increase education expenditure	-0.030	*(0.036)*	-0.074*	*(0.039)*	-0.028	*(0.041)*
Increase education expenditure, info treatment	-0.085*	*(0.044)*	-0.082	*(0.050)*	-0.050	*(0.054)*
Increase education spending for preschools	0.125**	*(0.062)*	0.067	*(0.073)*	0.052	*(0.079)*
Increase education spending for elementary school	0.026	*(0.061)*	-0.017	*(0.069)*	-0.001	*(0.073)*
Increase education spending for secondary schools	-0.140**	*(0.057)*	-0.072	*(0.065)*	-0.042	*(0.067)*
Increase education spending for vocational education	-0.014	*(0.034)*	0.014	*(0.039)*	0.013	*(0.042)*
Increase education spending for universities	0.004	*(0.035)*	0.009	*(0.035)*	-0.022	*(0.025)*
Increase national security spending	0.103***	*(0.027)*	-0.020	*(0.032)*	0.000	*(0.034)*
Increase social security spending	0.090***	*(0.030)*	0.043	*(0.036)*	0.018	*(0.038)*
Increase culture spending	0.086***	*(0.027)*	0.089***	*(0.031)*	0.107***	*(0.033)*
Increase education spending	-0.009	*(0.028)*	-0.026	*(0.034)*	0.030	*(0.036)*
Increase defense spending	0.033	*(0.026)*	0.040	*(0.027)*	0.027	*(0.029)*
Pro increased spending on class size	-0.013	*(0.035)*	-0.029	*(0.041)*	-0.022	*(0.044)*
Pro increased spending on teaching material	0.020	*(0.035)*	0.021	*(0.041)*	0.022	*(0.044)*
General Education Policies						
Pro inclusion of disabled children in normal schools	-0.018	*(0.066)*	-0.044	*(0.076)*	-0.015	*(0.079)*
Pro abolishment of school grades	-0.085**	*(0.033)*	0.011	*(0.043)*	0.009	*(0.048)*
Pro grade repetition	-0.035	*(0.050)*	-0.052	*(0.057)*	-0.026	*(0.056)*
Pro full-time school	-0.028	*(0.064)*	-0.136*	*(0.071)*	-0.140*	*(0.076)*
Pro tenure for teachers	-0.016	*(0.060)*	0.085	*(0.071)*	0.122	*(0.074)*
Pro central exit exams in low-track high schools	0.047	*(0.034)*	-0.030	*(0.038)*	-0.018	*(0.042)*
Pro central exit exams in medium-track high schools	0.039	*(0.028)*	-0.013	*(0.029)*	0.022	*(0.028)*
Pro central exit exams in high-track high schools	0.031	*(0.029)*	-0.037	*(0.033)*	0.008	*(0.031)*
Pro grades binding for secondary school choice	0.104*	*(0.056)*	0.100	*(0.067)*	0.108	*(0.075)*
Pro eight-year *Gymnasium*	0.020	*(0.052)*	-0.023	*(0.057)*	-0.058	*(0.060)*
Increase teacher salary	-0.039	*(0.030)*	-0.091**	*(0.036)*	-0.069*	*(0.039)*
Good grade to schools in Germany	0.216***	*(0.031)*	0.200***	*(0.035)*	0.123***	*(0.037)*
Good grade to schools in own state	0.146***	*(0.032)*	0.110***	*(0.037)*	0.059	*(0.039)*
Good grade to local schools	0.199***	*(0.032)*	0.168***	*(0.037)*	0.117***	*(0.040)*
Pro experiments to test public policies	0.053	*(0.049)*	0.073	*(0.059)*	0.095	*(0.066)*
Pro small-scale studies to test public policies	0.091**	*(0.043)*	0.055	*(0.058)*	0.068	*(0.061)*

(continued on next page)

Table 1 (continued)

	(1) No controls		(2) Basic controls		(3) Full controls	
Pro compulsory preschool	0.056**	*(0.026)*	0.012	*(0.031)*	0.043	*(0.034)*
Increase education spending for refugees	0.008	*(0.024)*	0.041	*(0.062)*	0.070**	*(0.068)*
Pro public payment for refugee training costs	0.152***	*(0.032)*	0.124***	*(0.040)*	0.203***	*(0.042)*
Tertiary and Vocational Education Policies						
Pro tuition fees	0.110**	*(0.043)*	0.067	*(0.052)*	0.054	*(0.056)*
Pro tuition fees with info graduate salary	0.064	*(0.043)*	-0.005	*(0.050)*	-0.033	*(0.052)*
Pro deferred income-contingent tuition fees	0.028	*(0.058)*	-0.098	*(0.068)*	-0.063	*(0.074)*
Too many university students	-0.015	*(0.058)*	-0.008	*(0.070)*	-0.031	*(0.076)*
Pro shortening vocational education	-0.006	*(0.064)*	0.070	*(0.074)*	0.087	*(0.080)*
Increase further training cost by individual	0.084	*(0.054)*	0.105	*(0.064)*	0.091	*(0.065)*
Increase further training cost by employer	-0.056	*(0.063)*	-0.042	*(0.074)*	-0.009	*(0.079)*
Increase further training cost by state	-0.101	*(0.062)*	-0.111	*(0.072)*	-0.115	*(0.076)*
Political Voting Behavior						
Pisa important in voting decision	0.151***	*(0.037)*	0.066	*(0.044)*	0.052	*(0.049)*
Education important in voting decision	-0.054*	*(0.028)*	0.000	*(0.034)*	0.050	*(0.036)*
Friends important in forming opinion	0.059	*(0.057)*	0.031	*(0.066)*	0.010	*(0.074)*
Own school days important in forming opinion	-0.207***	*(0.060)*	-0.121*	*(0.067)*	-0.124*	*(0.071)*
Own children important in forming opinion	0.128**	*(0.050)*	0.033	*(0.060)*	0.095	*(0.060)*
Experts important in forming opinion	0.132**	*(0.060)*	0.066	*(0.068)*	0.062	*(0.075)*
Political parties important in forming opinion	0.052	*(0.057)*	-0.006	*(0.066)*	-0.025	*(0.072)*
News important in forming opinion	0.088	*(0.060)*	0.042	*(0.068)*	0.006	*(0.074)*
Instinct important in forming opinion	-0.030	*(0.061)*	0.021	*(0.069)*	0.006	*(0.074)*
Educational Aspiration						
University aspiration children	-0.102*	*(0.056)*	-0.054	*(0.069)*	0.041	*(0.073)*
University aspiration children, info treatment tuition fees	-0.077	*(0.061)*	-0.082	*(0.074)*	-0.018	*(0.072)*
University aspiration children, info treatment financial aid	-0.147**	*(0.060)*	-0.103	*(0.066)*	-0.012	*(0.070)*
University aspiration children, both info treatments	-0.114*	*(0.065)*	-0.051	*(0.077)*	-0.001	*(0.082)*
Educational Inequality						
Inequality a serious problem (early)	0.025	*(0.030)*	-0.018	*(0.035)*	-0.013	*(0.038)*
Inequality a serious problem (late)	0.106**	*(0.043)*	0.078	*(0.050)*	0.117**	*(0.052)*
Inequality a serious problem, with info treatment	0.020	*(0.039)*	0.033	*(0.049)*	0.044	*(0.053)*

(continued on next page)

Table 1 (continued)

	(1) No controls		(2) Basic controls		(3) Full controls	
Digitalization						
Pro digital equipment in schools	-0.133**	*(0.058)*	-0.175***	*(0.062)*	-0.104	*(0.065)*
Computer time in classroom at least 30%	0.018	*(0.016)*	-0.005	*(0.019)*	-0.006	*(0.020)*
Pro computer for each student	-0.020	*(0.056)*	-0.037	*(0.067)*	-0.020	*(0.072)*
Pro smartphones in class	0.060	*(0.060)*	0.028	*(0.071)*	-0.027	*(0.074)*
Pro wireless internet in class	-0.178***	*(0.065)*	-0.178**	*(0.072)*	-0.134*	*(0.080)*
Pro digital use in class in elementary school	-0.002	*(0.058)*	-0.174**	*(0.069)*	-0.142*	*(0.073)*
Pro digital use in class in secondary school	-0.008	*(0.038)*	-0.078*	*(0.041)*	-0.043	*(0.044)*
Pro teacher digital competencies	-0.024	*(0.051)*	-0.065	*(0.051)*	0.015	*(0.055)*
Pro digital communication with students and parents	-0.076	*(0.061)*	-0.073	*(0.075)*	-0.066	*(0.077)*
Pro teaching digital competencies in preschool	-0.042	*(0.047)*	-0.057	*(0.057)*	-0.081	*(0.061)*
Pro teaching digital competencies in elementary school	0.024	*(0.060)*	-0.118*	*(0.072)*	-0.045	*(0.078)*
Pro teaching digital competencies in secondary school	0.028	*(0.034)*	-0.007	*(0.033)*	0.032	*(0.028)*
Pro teaching digital competencies in vocational education	0.022	*(0.034)*	-0.022	*(0.031)*	0.016	*(0.026)*
Pro teaching digital competencies in university	0.042	*(0.034)*	-0.022	*(0.031)*	0.007	*(0.026)*
Pro teaching digital equipment in vocational education	-0.028	*(0.047)*	-0.024	*(0.053)*	0.002	*(0.058)*
Pro diploma online studies	-0.108*	*(0.065)*	-0.134*	*(0.072)*	-0.070	*(0.077)*
Pro public funds for digital equipment at firms	-0.067	*(0.059)*	-0.116*	*(0.070)*	-0.145**	*(0.073)*
More winners with digitalization	-0.097	*(0.062)*	-0.108	*(0.075)*	-0.159**	*(0.079)*
Personally a winner of digitalization	-0.444***	*(0.048)*	-0.407***	*(0.072)*	-0.393***	*(0.079)*
Agree digitalization will increase inequality in education	0.027	*(0.064)*	0.078	*(0.075)*	0.076	*(0.076)*
Agree digitalization will increase inequality in Germany	0.095	*(0.062)*	0.151**	*(0.070)*	0.123*	*(0.074)*
Number (share) of coefficients significant at the 10% level	28 (0.35)		18 (0.23)		15 (0.19)	
Number (share) of coefficients significant at the 5% level	22 (0.28)		11 (0.14)		9 (0.11)	
Number (share) of coefficients significant at the 1% level	11 (0.14)		7 (0.09)		5 (0.06)	

Notes: Ordinary least squares (OLS) estimations. Each cell stems from a separate regression of the binary response to the question indicated in the first column on an "Offliner" dummy (coded 1 if a respondent is an offliner sampled in the face-to-face mode and 0 otherwise). Column (1) does not include any controls. Column (2) conditions on basic controls for age, gender, born in Germany, living in West Germany, and parental education. Column (3) conditions on the full set of controls, which additionally includes educational degree, income, living with partner in household, employment status, city size, and parental status. Regressions weighted by survey weights. Robust standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Data source: ifo Education Survey 2017.

Table 2: Differences in background characteristics by onliner-offliner status and survey mode

	(1)	(2)	(3)	(4)		(5)		(6)	
	Onliners web	Offliners face-to-face	Onliners face-to-face	Difference (2)-(1)		Difference (2)-(3)		Difference (3)-(1)	
				Mean	*p* value	Mean	*p* value	Mean	*p* value
Younger than 45	0.492	0.036	0.383	-0.456	*(0.000)*	-0.347	*(0.000)*	-0.109	*(0.000)*
Between 45 to 64	0.374	0.181	0.367	-0.193	*(0.000)*	-0.186	*(0.000)*	-0.007	*(0.739)*
65 or older	0.134	0.783	0.251	0.649	*(0.000)*	0.532	*(0.000)*	0.117	*(0.000)*
No degree/*Hauptschule*	0.212	0.650	0.234	0.438	*(0.000)*	0.416	*(0.000)*	0.022	*(0.221)*
Realschule	0.380	0.268	0.379	-0.112	*(0.000)*	-0.111	*(0.000)*	-0.001	*(0.948)*
University entrance degree	0.408	0.082	0.387	-0.326	*(0.000)*	-0.305	*(0.000)*	-0.021	*(0.338)*
Student or apprentice	0.128	0.008	0.090	-0.120	*(0.000)*	-0.082	*(0.000)*	-0.038	*(0.008)*
Full-time employed	0.401	0.159	0.327	-0.242	*(0.000)*	-0.168	*(0.000)*	-0.074	*(0.001)*
Part-time employed	0.130	0.048	0.130	-0.082	*(0.000)*	-0.082	*(0.000)*	0.000	*(0.995)*
Self-employed	0.042	0.005	0.063	-0.037	*(0.000)*	-0.058	*(0.000)*	0.021	*(0.026)*
Unemployed	0.047	0.053	0.039	0.006	*(0.629)*	0.014	*(0.303)*	-0.008	*(0.365)*
House wife/husband	0.059	0.042	0.064	-0.017	*(0.179)*	-0.022	*(0.146)*	0.005	*(0.630)*
Retired or ill	0.192	0.685	0.288	0.493	*(0.000)*	0.397	*(0.000)*	0.096	*(0.000)*
Income	2.374	1.715	2.835	-0.659	*(0.000)*	-1.120	*(0.000)*	0.461	*(0.000)*
Female	0.533	0.602	0.500	0.069	*(0.010)*	0.102	*(0.002)*	-0.033	*(0.129)*
West Germany	0.767	0.694	0.826	-0.073	*(0.001)*	-0.132	*(0.000)*	0.059	*(0.001)*
Partner in household	0.584	0.390	0.585	-0.194	*(0.000)*	-0.195	*(0.000)*	0.001	*(0.963)*
Parental education	0.317	0.130	0.356	-0.187	*(0.000)*	-0.226	*(0.000)*	0.039	*(0.055)*
City size >= 100,000	0.373	0.230	0.334	-0.143	*(0.000)*	-0.104	*(0.000)*	-0.039	*(0.065)*
Parent	0.509	0.833	0.685	0.324	*(0.000)*	0.148	*(0.000)*	0.176	*(0.000)*
Grandparent	0.188	0.678	0.328	0.490	*(0.000)*	0.350	*(0.000)*	0.140	*(0.000)*
Voter	0.806	0.830	0.000	0.024	*(0.268)*	0.830	*(0.000)*	-0.806	*(0.000)*
CDU voter	0.229	0.298	0.000	0.069	*(0.002)*	0.298	*(0.000)*	-0.229	*(0.000)*
SPD voter	0.197	0.165	0.000	-0.032	*(0.130)*	0.165	*(0.000)*	-0.197	*(0.000)*
Education professional	0.094	0.045	0.106	-0.049	*(0.001)*	-0.061	*(0.001)*	0.012	*(0.346)*
Observations	3699	382	622						

Notes: Columns (1)-(3) show means of onliners interviewed in the web mode, onliners interviewed face-to-face, and offliners interviewed face-to-face, respectively. Columns (4)-(6) display the respective differences between columns (2) and (1), (3) and (1), and (3) and (2) together with their respective *p* values. Data source: ifo Education Survey 2017.

Table 3: Differences in survey responses by onliner-offliner status and survey mode

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Free preschool	School spending increase	Teacher salary increase	Education important for vote	Refugee training subsidies	Good grade for schools		
						in Germany	in state	in local area
Without controls								
Offliner	-0.026	-0.019	-0.058**	-0.076***	0.117***	0.209***	0.149***	0.188***
	(0.021)	*(0.030)*	*(0.027)*	*(0.024)*	*(0.029)*	*(0.024)*	*(0.027)*	*(0.028)*
Onliner face-to-face	0.027	0.041*	-0.009	0.020	0.148***	0.077***	0.057***	0.089***
	(0.017)	*(0.024)*	*(0.022)*	*(0.019)*	*(0.023)*	*(0.019)*	*(0.021)*	*(0.022)*
Difference Offliner vs. Onliner face-to-face	0.053**	0.061*	0.049	0.095***	0.032	-0.131***	-0.092***	-0.099***
	(0.024)	*(0.036)*	*(0.033)*	*(0.029)*	*(0.033)*	*(0.029)*	*(0.033)*	*(0.034)*
Observations	2,821	2,288	4,663	4,681	2,863	4,585	4,591	4,573
With controls								
Offliner	0.028	-0.037	-0.051	0.028	0.164***	0.125***	0.078**	0.119***
	(0.027)	*(0.038)*	*(0.034)*	*(0.029)*	*(0.037)*	*(0.030)*	*(0.033)*	*(0.035)*
Onliner face-to-face	0.030*	0.016	-0.033	0.000	0.131***	0.068***	0.046**	0.063***
	(0.018)	*(0.026)*	*(0.023)*	*(0.020)*	*(0.024)*	*(0.020)*	*(0.022)*	*(0.023)*
Difference Offliner vs. Onliner face-to-face	0.002	0.053	0.017	-0.028	-0.033	-0.057*	-0.032	-0.056
	(0.029)	*(0.043)*	*(0.039)*	*(0.033)*	*(0.040)*	*(0.034)*	*(0.038)*	*(0.040)*
Observations	2,670	2,203	4,507	4,515	2,723	4,445	4,451	4,435

Notes: Ordinary least squares (OLS) estimations. Offliner: respondents who do not use the internet, interviewed face-to-face. Onliner face-to-face: respondents who use the internet, interviewed face-to-face. Omitted category: respondents who use the internet, interviewed in the web mode. Dependent variable in columns (1)-(3) and (5): dummy variable indicating support for policy indicated in the table header; column (4): dummy variable indicating assertion that education is important for respondent's voting decision; columns (6)-(8): dummy variable indicating good grades ("A" or "B") for schools at different regional levels. Controls: age, gender, living in West Germany, parental education, educational degree, income, living with partner in household, employment status, city size, and parental status. Robust standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Data source: ifo Education Survey 2017.

Table 4: Estimates of population means of background characteristics: Mixed-mode method vs. re-weighted online sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mixed-mode sample		Re-weighted online sample		Difference (1)-(3)		
	Mean	Std. err.	Mean	Std. err.	Mean	Std. err.	*t* statistic
Younger than 45	0.401	*(0.008)*	0.390	*(0.010)*	0.011	*(0.013)*	0.841
Between 45 to 64	0.367	*(0.008)*	0.359	*(0.010)*	0.009	*(0.013)*	0.659
65 or older	0.232	*(0.007)*	0.252	*(0.012)*	-0.020	*(0.014)*	-1.426
No degree/*Hauptschule*	0.367	*(0.009)*	0.383	*(0.011)*	-0.016	*(0.015)*	-1.104
Realschule	0.308	*(0.008)*	0.301	*(0.009)*	0.007	*(0.012)*	0.566
University entrance degree	0.325	*(0.008)*	0.316	*(0.009)*	0.009	*(0.012)*	0.752
Student or apprentice	0.095	*(0.005)*	0.091	*(0.005)*	0.004	*(0.008)*	0.540
Full-time employed	0.361	*(0.009)*	0.339	*(0.009)*	0.022	*(0.013)*	1.714
Part-time employed	0.122	*(0.006)*	0.124	*(0.007)*	-0.002	*(0.009)*	-0.220
Self-employed	0.039	*(0.003)*	0.041	*(0.004)*	-0.002	*(0.005)*	-0.330
Unemployed	0.049	*(0.004)*	0.043	*(0.004)*	0.006	*(0.005)*	1.188
House wife/husband	0.061	*(0.004)*	0.063	*(0.005)*	-0.002	*(0.007)*	-0.295
Retired or ill	0.273	*(0.008)*	0.300	*(0.011)*	-0.027	*(0.014)*	-1.918
Income	2.274	*(0.025)*	2.301	*(0.030)*	-0.026	*(0.039)*	-0.684
Female	0.504	*(0.009)*	0.511	*(0.011)*	-0.007	*(0.014)*	-0.477
West Germany	0.796	*(0.007)*	0.801	*(0.009)*	-0.005	*(0.011)*	-0.415
Partner in household	0.553	*(0.009)*	0.577	*(0.011)*	-0.024	*(0.014)*	-1.704
Parental education	0.273	*(0.008)*	0.271	*(0.009)*	0.002	*(0.012)*	0.165
City size >= 100,000	0.320	*(0.008)*	0.318	*(0.010)*	0.002	*(0.013)*	0.170
Parent	0.573	*(0.009)*	0.578	*(0.010)*	-0.005	*(0.014)*	-0.381
Grandparent	0.264	*(0.008)*	0.269	*(0.011)*	-0.005	*(0.013)*	-0.389
Voter	0.807	*(0.007)*	0.815	*(0.008)*	-0.008	*(0.011)*	-0.729
CDU voter	0.245	*(0.008)*	0.242	*(0.009)*	0.003	*(0.012)*	0.206
SPD voter	0.198	*(0.008)*	0.214	*(0.010)*	-0.016	*(0.012)*	-1.332
Education professional	0.084	*(0.005)*	0.083	*(0.006)*	0.001	*(0.008)*	0.127
No vocational degree, not in training	0.094	*(0.006)*	0.075	*(0.006)*	0.019	*(0.008)*	2.295
Vocational degree	0.563	*(0.009)*	0.579	*(0.011)*	-0.016	*(0.014)*	-1.152
Higher vocational degree	0.138	*(0.006)*	0.141	*(0.007)*	-0.003	*(0.009)*	-0.291
University of applied sciences degree	0.066	*(0.004)*	0.062	*(0.004)*	0.004	*(0.006)*	0.593
University degree	0.085	*(0.005)*	0.083	*(0.005)*	0.002	*(0.007)*	0.314
Other professional degree	0.049	*(0.004)*	*0.057*	*(0.005)*	*-0.008*	*(0.006)*	*-1.272*

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Table 4 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mixed-mode sample		Re-weighted online sample		Difference (1)-(3)		
	Mean	Std. err.	Mean	Std. err.	Mean	Std. err.	*t* statistic
Currently in vocational training	0.028	*(0.003)*	0.028	*(0.003)*	0.000	*(0.005)*	0.060
Currently student	0.062	*(0.004)*	0.060	*(0.004)*	0.002	*(0.006)*	0.400
Born in Germany	0.948	*(0.004)*	0.958	*(0.004)*	-0.010	*(0.006)*	-1.693
Risk preference	4.254	*(0.045)*	4.328	*(0.055)*	-0.074	*(0.071)*	-1.042
Discount rate	6.043	*(0.045)*	6.165	*(0.053)*	-0.122	*(0.070)*	-1.754

Notes: Columns (1) and (2) show means and standard errors of the mixed-mode sample (including onliners and offliners), using survey weights. Columns (3) and (4) show means and standard errors of the online sample, using weights to represent the entire population. Column (5) displays the differences in means between columns (1) and (3), and columns (6) and (7) display the standard errors and *t* statistics of the differences, respectively. Data source: ifo Education Survey 2017.

Table 5: Estimates of population means of opinions: Mixed-mode method vs. re-weighted online sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mixed-mode sample		Re-weighted online sample		Difference (1)-(3)		
	Mean	Std. err.	Mean	Std. err.	Mean	Std. err.	*t* stat.
Education Spending							
Pro free preschool	0.814	*(0.010)*	0.827	*(0.012)*	-0.012	*(0.015)*	-0.802
Increase education expenditure	0.806	*(0.011)*	0.816	*(0.011)*	-0.009	*(0.016)*	-0.606
Increase education expenditure, info treatment	0.621	*(0.013)*	0.644	*(0.015)*	-0.023	*(0.019)*	-1.193
Increase education spending for preschools	0.259	*(0.016)*	0.264	*(0.020)*	-0.005	*(0.025)*	-0.209
Increase education spending for elementary school	0.296	*(0.017)*	0.305	*(0.020)*	-0.009	*(0.026)*	-0.350
Increase education spending for secondary schools	0.334	*(0.017)*	0.334	*(0.020)*	0.000	*(0.026)*	0.001
Increase education spending for vocational education	0.068	*(0.010)*	0.057	*(0.009)*	0.010	*(0.013)*	0.776
Increase education spending for universities	0.043	*(0.008)*	0.039	*(0.007)*	0.004	*(0.011)*	0.377
Increase national security spending	0.676	*(0.009)*	0.677	*(0.010)*	0.000	*(0.013)*	-0.021
Increase social security spending	0.529	*(0.009)*	0.535	*(0.011)*	-0.006	*(0.014)*	-0.433
Increase culture spending	0.210	*(0.007)*	0.192	*(0.008)*	0.018	*(0.011)*	1.679
Increase education spending	0.701	*(0.008)*	0.696	*(0.010)*	0.005	*(0.013)*	0.406
Increase defense spending	0.190	*(0.007)*	0.175	*(0.008)*	0.015	*(0.011)*	1.412
Pro increased spending on class size	0.501	*(0.011)*	0.504	*(0.012)*	-0.003	*(0.016)*	-0.176
Pro increased spending on teaching material	0.418	*(0.011)*	0.418	*(0.012)*	0.000	*(0.016)*	-0.022
General Education Policies							
Pro inclusion of disabled children in normal schools	0.558	*(0.019)*	0.579	*(0.021)*	-0.021	*(0.028)*	-0.753
Pro abolishment of school grades	0.152	*(0.013)*	0.160	*(0.015)*	-0.008	*(0.020)*	-0.399
Pro grade repetition	0.826	*(0.015)*	0.839	*(0.016)*	-0.013	*(0.021)*	-0.603
Pro full-time school	0.594	*(0.018)*	0.609	*(0.020)*	-0.015	*(0.027)*	-0.547
Pro tenure for teachers	0.304	*(0.017)*	0.283	*(0.018)*	0.021	*(0.025)*	0.864
Pro central exit exams in low-track high schools	0.867	*(0.013)*	0.873	*(0.013)*	-0.006	*(0.019)*	-0.335
Pro central exit exams in medium-track high schools	0.910	*(0.010)*	0.913	*(0.011)*	-0.002	*(0.015)*	-0.148
Pro central exit exams in high-track high schools	0.907	*(0.011)*	0.913	*(0.011)*	-0.006	*(0.016)*	-0.376
Pro grades binding for secondary school choice	0.638	*(0.017)*	0.613	*(0.021)*	0.025	*(0.027)*	0.941
Pro eight-year *Gymnasium*	0.259	*(0.016)*	0.264	*(0.020)*	-0.005	*(0.025)*	-0.210
Increase teacher salary	0.430	*(0.009)*	0.442	*(0.011)*	-0.012	*(0.014)*	-0.837
Good grade to schools in Germany	0.238	*(0.008)*	0.210	*(0.009)*	0.028	*(0.012)*	2.312
Good grade to schools in own state	0.343	*(0.009)*	0.337	*(0.010)*	0.006	*(0.014)*	0.474
Good grade to local schools	0.402	*(0.009)*	0.385	*(0.011)*	0.018	*(0.014)*	1.267
Pro experiments to test public policies	0.741	*(0.016)*	0.709	*(0.021)*	0.033	*(0.026)*	1.229

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Table 5 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mixed-mode sample		Re-weighted online sample		Difference (1)-(3)		
	Mean	Std. err.	Mean	Std. err.	Mean	Std. err.	*t* stat.
Pro small-scale studies to test public policies	0.753	*(0.015)*	0.744	*(0.018)*	0.009	*(0.023)*	0.370
Pro compulsory preschool	0.728	*(0.008)*	0.720	*(0.010)*	0.008	*(0.013)*	0.622
Increase education spending for refugees	0.198	*(0.007)*	0.188	*(0.008)*	0.010	*(0.011)*	0.891
Pro public payment for refugee training costs	0.454	*(0.012)*	0.418	*(0.015)*	0.036	*(0.019)*	1.857
Tertiary and Vocational Education Policies							
Pro tuition fees	0.433	*(0.013)*	0.431	*(0.015)*	0.002	*(0.020)*	0.126
Pro tuition fees with info graduate salary	0.504	*(0.013)*	0.510	*(0.016)*	-0.006	*(0.020)*	-0.302
Pro deferred income-contingent tuition fees	0.654	*(0.018)*	0.656	*(0.020)*	-0.002	*(0.027)*	-0.080
Too many university students	0.603	*(0.018)*	0.604	*(0.022)*	0.000	*(0.028)*	-0.014
Pro shortening vocational education	0.439	*(0.018)*	0.428	*(0.021)*	0.011	*(0.028)*	0.400
Increase further training cost by individual	0.200	*(0.015)*	0.186	*(0.017)*	0.014	*(0.023)*	0.617
Increase further training cost by employer	0.503	*(0.019)*	0.526	*(0.022)*	-0.023	*(0.029)*	-0.789
Increase further training cost by state	0.534	*(0.019)*	0.555	*(0.022)*	-0.022	*(0.029)*	-0.758
Political Voting Behavior							
Pisa important in voting decision	0.758	*(0.016)*	0.755	*(0.018)*	0.003	*(0.024)*	0.128
Education important in voting decision	0.724	*(0.008)*	0.723	*(0.010)*	0.001	*(0.013)*	0.050
Friends important in forming opinion	0.596	*(0.018)*	0.591	*(0.021)*	0.005	*(0.028)*	0.172
Own school days important in forming opinion	0.669	*(0.018)*	0.694	*(0.020)*	-0.026	*(0.027)*	-0.969
Own children important in forming opinion	0.688	*(0.017)*	0.686	*(0.019)*	0.001	*(0.026)*	0.054
Experts important in forming opinion	0.517	*(0.018)*	0.511	*(0.021)*	0.006	*(0.028)*	0.208
Political parties important in forming opinion	0.318	*(0.017)*	0.330	*(0.021)*	-0.012	*(0.027)*	-0.435
News important in forming opinion	0.511	*(0.018)*	0.517	*(0.021)*	-0.005	*(0.028)*	-0.194
Instinct important in forming opinion	0.538	*(0.018)*	0.539	*(0.021)*	-0.001	*(0.028)*	-0.022
Educational Aspiration							
University aspiration children	0.492	*(0.018)*	0.487	*(0.021)*	0.005	*(0.028)*	0.190
University aspiration children, info treatment tuition fees	0.503	*(0.019)*	0.507	*(0.022)*	-0.004	*(0.029)*	-0.152
University aspiration children, info treatment financial aid	0.499	*(0.018)*	0.509	*(0.021)*	-0.010	*(0.028)*	-0.365
University aspiration children, both info treatments	0.476	*(0.019)*	0.481	*(0.021)*	-0.005	*(0.029)*	-0.172
Educational Inequality							
Inequality a serious problem (early)	0.615	*(0.009)*	0.610	*(0.011)*	0.006	*(0.014)*	0.405
Inequality a serious problem (late)	0.547	*(0.013)*	0.531	*(0.015)*	0.016	*(0.020)*	0.816
Inequality a serious problem, with info treatment	0.682	*(0.012)*	0.671	*(0.015)*	0.011	*(0.019)*	0.577

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Table 5 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mixed-mode sample		Re-weighted online sample		Difference (1)-(3)		
	Mean	Std. err.	Mean	Std. err.	Mean	Std. err.	*t* stat.
Digitalization							
Pro digital equipment in schools	0.801	*(0.015)*	0.823	*(0.016)*	-0.022	*(0.022)*	-0.989
Computer time use in classroom at least 30%	0.906	*(0.005)*	0.905	*(0.006)*	0.001	*(0.008)*	0.092
Pro computer for each student	0.672	*(0.017)*	0.684	*(0.020)*	-0.012	*(0.026)*	-0.446
Pro smartphones in class	0.415	*(0.019)*	0.417	*(0.022)*	-0.002	*(0.029)*	-0.052
Pro wireless internet in class	0.647	*(0.017)*	0.680	*(0.020)*	-0.033	*(0.026)*	-1.271
Pro digital use in class in elementary school	0.547	*(0.018)*	0.567	*(0.021)*	-0.021	*(0.028)*	-0.756
Pro digital use in class in secondary school	0.887	*(0.012)*	0.901	*(0.011)*	-0.014	*(0.016)*	-0.879
Pro digital communication with students and parents	0.653	*(0.018)*	0.660	*(0.021*	-0.007	*(0.028)*	-0.237
Pro teaching digital competencies in preschool	0.206	*(0.015)*	0.207	*(0.017))*	-0.001	*(0.023)*	-0.061
Pro teaching digital competencies in elementary school	0.550	*(0.018)*	0.570	*(0.021)*	-0.020	*(0.028)*	-0.733
Pro teaching digital competencies in secondary school	0.903	*(0.011)*	0.907	*(0.011)*	-0.004	*(0.015)*	-0.255
Pro teaching digital competencies in vocational education	0.908	*(0.010)*	0.910	*(0.011)*	-0.002	*(0.015)*	-0.117
Pro teaching digital competencies in university	0.892	*(0.011)*	0.896	*(0.011)*	-0.004	*(0.016)*	-0.233
Pro digital equipment in vocational education	0.846	*(0.014)*	0.848	*(0.016)*	-0.002	*(0.021)*	-0.112
Pro diploma online studies	0.614	*(0.018)*	0.625	*(0.021)*	-0.011	*(0.028)*	-0.399
Pro public funds for digital equipment at firms	0.672	*(0.018)*	0.696	*(0.020)*	-0.025	*(0.027)*	-0.920
Agree digitalization will increase inequality in education	0.442	*(0.019)*	0.426	*(0.022)*	0.016	*(0.029)*	0.559
Agree digitalization will increase inequality in Germany	0.495	*(0.019)*	0.475	*(0.022)*	0.020	*(0.029)*	0.682
More winners with digitalization	0.433	*(0.018)*	0.449	*(0.021)*	-0.016	*(0.027)*	-0.573
Personally a winner of digitalization	0.543	*(0.017)*	0.620	*(0.021)*	-0.077	*(0.027)*	-2.815

Notes: Columns (1) and (2) show means and standard errors of the mixed-mode sample (including onliners and offliners), using survey weights. Columns (3) and (4) show means and standard errors of the online sample, using weights to represent the entire population. Column (5) displays the differences in means between columns (1) and (3), and columns (6) and (7) display the standard errors and the *t* statistics of the differences, respectively. Data source: ifo Education Survey 2017.