European Journal of Political Economy 78 (2023) 102382

Contents lists available at ScienceDirect

European Journal of Political Economy

journal homepage: www.elsevier.com/locate/ejpe

Can internet surveys represent the entire population? A practitioners' analysis[☆]

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ARTICLE INFO

JEL classification:
C83
D91
I20

Keywords:
Internet survey
Representativeness
Mode effects
Offliner
Public opinion

ABSTRACT

A general concern with the representativeness of internet 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 internet-survey mode, (2) offliners in face-to-face mode, and (3) internet users in face-to-face mode. We find marked response differences between onliners and offliners in different modes (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.

1. Introduction

Over the past years, internet surveys have become increasingly popular in economics (see, e.g., Haaland et al., 2022, for an extensive review of recent applications).[1] Internet 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, internet surveys have a major drawback concerning their external validity: While they cover individuals who use the internet

☆ We would also like to thank the editor and two anonymous referees for their constructive comments as well as Franziska Kugler for her help in preparing the survey. This work was supported by the Leibniz Competition (SAW-2014-ifo-2) and the German Science Foundation (SFB-TRR 190).

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[1] Major areas of application include many aspects of public economics and political economy (e.g., Kuziemko et al., 2015; Abraham et al., 2018; Alesina et al., 2018; Haaland and Roth, 2020; Aksoy et al., 2021; Roth et al., 2022; Barton and Pan, 2022), but also macroeconomics (e.g., Armantier et al., 2016), labor economics (e.g., Bursztyn et al., 2020; Settele 2022), and many other fields.

https://doi.org/10.1016/j.ejpoleco.2023.102382
Received 21 February 2022; Received in revised form 6 February 2023; Accepted 1 March 2023
Available online 4 March 2023

for participating in surveys – whom we refer to as "onliners" throughout the paper – they often 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 internet surveys can be representative for the entire population (e.g., Best et al., 2001; Berrens et al., 2003). 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, offliners still make 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 internet surveys to the offline population. A common method to address this bias are offline-population inclusion strategies such as providing offliners with internet equipment or mixed-mode surveys which complement internet-survey data for onliners with face-to-face or postal survey data for the offline population (e.g., van Soest and Kapteyn, 2011; Cornesse and Schaurer, 2021).

In this paper, we assess the extent to which the costly face-to-face complement of mixed-mode surveys is necessary to achieve representativeness with non-probabilistic internet surveys, addressing the practitioners' question of applied researchers faced with the choice between a pure internet survey and a mixed-mode survey. 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 interviewed in internet mode in an online access panel (N = 3699), (2) offliners interviewed in face-to-face mode in a probabilistic household survey (N = 382), and (3) internet users interviewed in face-to-face mode in the same probabilistic household survey (N = 622). The combination of groups (1) and (2) corresponds to a mixed-mode survey aimed at covering both onliners and offliners. For the purposes of this paper, we implemented the extension to group (3) which allows us to address several practical questions about results obtained from internet surveys.

In mixed-mode settings, any existing differences between onliners in group (1) and offliners in group (2) can either stem from (i) inherent population differences between the two groups or from (ii) mode effects that arise because onliners and offliners are sampled and surveyed in different modes. The first source is the potential reason that would necessitate the direct coverage of offliners, whereas the second source gives rise to the interpretability problems of mode-specific results inherent to any mixed-mode survey. Importantly, the internet users 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 internet users and offliners while holding sampling and survey mode constant. And comparing groups (1) and (3), we can shed light on potential mode effects, which in this paper we conceive broadly to encompass differences in answering behavior (in internet vs. face-to-face surveying), sampling (non-probabilistic vs. probabilistic), and reachability and participation (in online panels vs. home surveys). As it was not possible for us to interview offliners via an online-access panel, we cannot disentangle these different dimensions of the mode effect; instead, our analysis investigates the combined difference between commonly used internet surveys and traditional face-to-face surveys.[3] Note that because of these different types of mode differences, there is no "gold standard" that would describe the "true" values to which any population estimate could be compared. By necessity, applied research on the preferences, opinions, and beliefs of the population must depend on the voluntary participation of respondents in a given survey mode. Our goal here is more humble: We address the practitioner's question of whether a pure non-probabilistic internet survey can provide estimates similar to a mixed-mode setup with a probabilistic offline part – i.e., whether applied researchers can do without the expensive offline component of a mixed-mode survey.

Our analysis proceeds in three steps. In the first step, we compare groups (1) and (2) to test whether offliners provide different answers 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 internet survey and offliners interviewed face-to-face. 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 internet users and offliners or due to differences in the internet vs. face-to-face survey mode. To do so, we draw on group (3), i.e., internet users surveyed in the face-to-face mode, who were asked a subset of eight survey items that we had selected based on prior evidence of relatively large onliner-offliner differences.[4] When comparing the responses of internet users 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.[5] 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 mode effects.

A comparison of onliners interviewed in the internet mode and internet users 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

[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 3 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.

[3] Interviewing offliners in the online mode (e.g., by providing them with internet access) and comparing response patterns to the other groups is an interesting extension for future research.

[4] 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 3).

[5] One of the eight differences remains marginally significant at the 10 percent level, which may well be due to chance.

whether conditioning on respondents' characteristics or not. Interestingly, these differences all occur for survey items on relatively sensitive topics, namely policies related to refugees and how respondents grade schools.[6] Arguably, such survey items are particularly susceptible to interviewer-demand or social-desirability effects, which are more likely to occur in the presence of an interviewer in the face-to-face mode than in the anonymous internet mode.

Furthermore, we provide evidence of heterogeneous sample selection across survey modes. Comparing background characteristics of onliners surveyed on the internet vs. internet users in the 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. That is, at least part of the response differences between internet and face-to-face surveying stems from the fact that the different sampling and surveying modes reach different subpopulations even within the group of internet users. Together, our findings suggest that mode effects – i.e., mode-related differences in answering behavior, sampling, and participation – are an important factor that drives onliner-offliner response differences in our mixed-mode setting. In contrast, inherent differences between the answers of onliners and offliners stemming from unobserved characteristics seem to be rather unimportant in our setting.

The third step of our analysis investigates the extent to which an approach that re-weights the responses of the internet survey can recover response patterns of the entire population (onliners *and* offliners) as observed in the mixed-mode setup. This analysis builds on the result that response differences are driven by differences in sampling and participation rather than inherent population differences between onliners and offliners. Such differences between samples are commonly corrected using probability weights. We compare internet-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 city 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 internet survey differs significantly (at the 5 percent level) from the estimated population mean of the mixed-mode survey. Not only are differences in estimated population means statistically insignificant, but they are also small in magnitude: For more than half of the survey items, the difference 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 non-probabilistic internet surveys can produce response patterns that are mostly indistinguishable, statistically and quantitatively, from those of mixed-mode surveys. Interestingly, the single largest difference of 7.7 percentage points between the two approaches is observed for the item 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' internet user status. But overall, our results suggest that re-weighting onliners can be a pragmatic, economical solution for applied researchers in many contexts to depict preferences, opinions, or beliefs of the entire (online and offline) population.

The remainder of the paper proceeds as follows. Section 2 briefly describes our contribution to the literature. Section 3 introduces our data source, the ifo Education Survey 2017. Section 4 presents differences between onliners and offliners in the mixed-mode setting. Section 5 introduces our conceptual framework to differentiate between inherent population differences and mode effects and presents our main results. Section 6 shows that re-weighting online samples can be a pragmatic alternative to mixed-mode surveys. Section 7 concludes.

2. Related literature

The main goal of our analysis is to address the practitioners' question whether internet surveys require an offliner complement to warrant representativeness of the entire population. As such, the paper particularly speaks to the growing literature in economics that employs internet surveys to study preferences, opinions, and beliefs (e.g., Kuziemko et al., 2015; Armantier et al., 2016; Alesina et al., 2018; de Quidt et al., 2018; Haaland and Roth, 2020; Almås et al., 2020; Aksoy et al., 2021; Roth et al., 2022; Settele 2022). 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). In this context, one fundamental question is to what extent low-cost non--probabilistic internet surveys are representative for the entire population, including those individuals without access to the internet. 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. While we cannot do justice to the entire survey literature in the brief discussion here, the literature on representativeness of internet surveys has a strong focus on aspects of non-probability sampling as another potential source of non-representativeness (e.g., Malhotra and Krosnick, 2007; Chang and Krosnick, 2009; Yeager et al., 2011; see Blom et al., 2017, for a recent German contribution). Our paper contributes to this lively debate only indirectly by investigating the extent to which complementing a non-probability online sample with a probabilistic offline sample helps to

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

overcome potential non-coverage bias of internet surveys, an issue of particular relevance in applied research.[7] On a practical level, our finding on re-weighting onliners as a pragmatic solution for applied researchers is partly in line with the findings by Malhotra and Krosnick (2007) on election data.

A general finding from the survey 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, 2016). For Germany, Bosnjak et al. (2013) and Blom et al. (2017) find the offline population 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, patterns with which our findings in section 5.2 are largely consistent. A common approach to circumvent potential coverage bias due to such differences are mixed-mode surveys. Consequently, several studies within the methodological literature discuss the comparability of data collected by different modes in mixed-mode settings, because each mode may produce different response patterns or sampling effects (e.g., Jäckle et al., 2010; van Soest and Kapteyn, 2011; Ye et al., 2011; Bosnjak, 2017).[8]

Our specific setting which interviews internet users both via an internet survey and a face-to-face survey allows us to add to this mode-effects literature in several ways. First, we provide new survey evidence on systematic response differences between onliners interviewed in the internet mode and offliners interviewed in the face-to-face mode, which contributes to the literature on mixed-mode surveys. Second, we explicitly test whether internet users and offliners inherently differ in their response patterns when sampled and interviewed in the same face-to-face survey, thereby adding to the literature on coverage bias. Third, we add to the literature on mode comparability by investigating how onliners interviewed in the internet mode differ in their responses from internet users interviewed in the face-to-face mode. Finally, we compare response patterns between onliners in an internet survey, re-weighted to represent the entire population, and the weighted mixed-mode sample, thereby adding to the literature on the representativeness of internet surveys. This last comparison offers guidance for a cost-effective mode choice for applied researchers who aim to derive representative conclusions for the entire population.

3. Data source: the ifo education survey 2017

Our analysis is based on data from the 2017 wave of the ifo Education Survey, an annual repeated cross-section opinion survey on education policy that we have been conducting in Germany since 2014.[9] While the survey is focused on education topics and uses data from only one country, several indications speak for the applicability of our results to other contexts. First, the survey does include a limited set of non-education topics such as public spending on defense and social security. Second, parallel surveys in other countries (Switzerland and the United States) yield similar results (Cattaneo et al., 2020). Third, sample characteristics of the ifo Education Survey are virtually identical to the German population census (Lergetporer et al., 2016). Fourth, response patterns to questions repeated in different survey waves are generally stable across waves (e.g., Woessmann et al., 2017). Fifth, Lergetporer and Woessmann (2022) show in a survey experiment that the fact that survey responses are "cheap talk" (i.e., they have no direct political or monetary consequences) is unlikely to bias response behavior.[10]

The 2017 survey was carried out between April and July 2017 by Kantar Public (formerly TNS Infratest), a renowned German polling firm. Kantar Public administered sampling and interviewing of participants aged 18 years and older in three steps.

First, Kantar Public recruited 3699 respondents who are internet users via a non-probabilistic online access panel and interviewed them in internet mode (group (1): onliners surveyed in internet mode). Kantar Public is able to draw on more than 53,000 active German panelists and selected survey respondents using quota sampling based on the national marginal distributions of gender, age, and region.

Second, Kantar Public 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 surveyed in face-to-face mode). The sampling method for the face-to-face interviews was probability-based random sampling aimed at representativeness of the German population. Groups (1) and (2) 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): internet users surveyed in face-to-face mode). This third group was sampled and interviewed within the same household survey as the second group.[11] The third group allows us to investigate the reasons behind onliner-offliner response differences between groups (1) and (2) (see our conceptual framework in section 5.1 for greater detail).

[7] Note that non-probabilistic online access panels correspond to the sampling method of choice in many recent applications in economics (e.g., Alesina et al., 2018; de Quidt et al., 2018; Haaland and Roth, 2020; Almås et al., 2020; Roth et al., 2022). A more recent development is to use probability samples for online surveys, combined with specific tools to also include offliners, as is done, for instance, in the German Internet Panel (e.g., Dolls and Wehrhöfer, 2021). While such surveys have clear advantages over non-probabilistic online access panels in terms of representativeness, their higher costs and required data collection efforts limit access for applied researchers.

[8] A related literature compares economic experiments conducted online vs. 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).

[9] For substantive research papers using data from the ifo Education Survey, see, for instance, Lergetporer et al. (2018, 2020, 2021) and Lergetporer and Woessmann (2022).

[10] The research data from the ifo Education Survey 2014–2021 are available free of charge for scientific use (see Freundl et al., 2022, for details on methodology, content, and data access).

[11] 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.

Onliners sampled in the internet 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 internet users and offliners: While 79 percent of the offliners in group (2) requested assistance, the share is only 36 percent among the internet users in group (3).[12]

The ifo Education Survey 2017 comprised 79 substantive questions on education policy covering different areas such as preferences for education spending, general education policies, 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.[13] 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.[14]

Median completion time was 17 min for onliners surveyed in the internet mode, 20 min for offliners surveyed face-to-face, and 3 min for internet users surveyed with the shortened questionnaire 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.[15]

For the analysis in section 6, we employ probability weights to account for observable differences between groups. 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 city size. Weights were calculated using iterative proportional fitting (Deming and Stephan, 1940; Cochran, 1968). In this paper, we use two different sets of weights: The first set is calculated using the mixed-mode sample (i.e., onliners surveyed in the internet mode and offliners surveyed face-to-face) and the second set is calculated using only the onliners surveyed in the internet 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 6).

4. 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 surveyed in the internet mode and offliners surveyed in the face-to-face mode.

Table 1 shows results from regressions of binary responses to each of the different survey items 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, which include age, gender, being born in Germany, living in West Germany, and parental education. Column (3) includes our full set of controls, which additionally includes educational degree, income, living with partner in household, employment status, city size, and parental status.

We find that responses to 22 of the 79 survey items (28 percent) differ significantly (at the 5 percent level) between onliners and

[12] By providing respondents in the face-to-face mode with tablet computers, we intended to make the internet 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. Data recorded by the interviewers show that for respondents who received help in filling out the survey, in 97 percent of cases this was due to problems arising from the fact that respondents did not have experience with computers. 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 internet mode, even if they were provided with the necessary devices. In addition, some respondents received help due to medical issues precluding participation, in particular vision impairments, or a lack of motivation. These latter categories suggest that for a minority of offline respondents, accessibility of the survey and survey length might play a role in facilitating participation (details available upon request).

[13] For efficiency reasons, several questions were only posed to randomly selected subgroups of onliners sampled in the internet 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 internet users 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.

[14] 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 internet mode (group (1)) and offliners surveyed face-to-face (group (2)). Results from previous survey waves are available upon request.

[15] 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." Qualitative results are very similar when using outcomes on five-point scales instead of the dichotomized responses (results available upon request).

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

	(1)		(2)		(3)	
	No controls		Basic controls		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)*
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	*(0.029)*	0.070**	*(0.031)*
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)*
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%	−0.035	*(0.065)*	−0.058	*(0.071)*	−0.079	*(0.078)*

(*continued on next page*)

Table 1 (*continued*)

	(1)		(2)		(3)	
	No controls		Basic controls		Full controls	
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***	*(0.063)*	−0.393***	*(0.067)*
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.

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. 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 surveyed in the internet mode and offliners surveyed 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 sampled 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, sampling, or participation. In what follows, we analyze the additional sample of internet users surveyed in the face-to-face mode to investigate the empirical relevance of these alternative explanations.

5. Distinguishing population differences from mode effects

We present our analysis of inherent population differences vs. mode effects based on the additional sample of internet users observed in the face-to-face mode in three steps. We start with a conceptual framework for the empirical analysis. Then, we provide analyses of differences in background characteristics and survey responses, respectively, across onliner-offliner status and survey modes.

5.1. Conceptual and empirical framework

The analysis so far reveals significant response differences between onliners interviewed in the internet 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 samples 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 internet surveys and would make it impossible to draw conclusions from internet surveys that are valid for the entire population (comprising onliners and offliners).

The second potential source of onliner-offliner response differences are mode effects, broadly conceived to encompass effects attributable to differences in how onliners and offliners are sampled and interviewed. These effects can come in different forms, such as mode-related answering behavior (i.e., internet vs. face-to-face), specific sampling methods (i.e., non-probabilistic vs. probabilistic), and mode-specific reachability and participation. The first form means that different modes can 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 second form can arise because onliners and offliners are often recruited in different ways. For instance, our respondents surveyed in the internet mode are recruited via an online access panel, which is the mode of choice in many recent applications in economics. Respondents interviewed face-to-face, on the other hand, are drawn using probability-based random sampling. The third form refers to differences in the specific persons reached by different modes, e.g., in terms of who enrolls voluntarily in online access panels, who is at home when interviewers visit households, and who opens the door and chooses to participate in a home survey. The different sampling and recruitment frameworks 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 internet users interviewed in the face-to-face mode. This sample, which was specifically drawn for this analysis, allows us to hold the mode between internet users 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 internet-user status constant and comparing internet users interviewed in the internet mode vs. 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 compare the three groups of respondents: (1) onliners interviewed in the

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

	(1)	(2)	(3)	(4)	(5)	(6)			
	Onliners	Offliners	Internet users	Difference (2)–(1)		Difference (2)–(3)		Difference (3)–(1)	
	internet	face-to-face	face-to-face	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)*	−0.110	*(0.000)*
Between 45 and 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)*	0.533	*(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)*	−0.110	*(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	−0.121	*(0.000)*	−0.082	*(0.000)*	−0.039	*(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	−0.083	*(0.000)*	−0.083	*(0.000)*	0.000	*(0.995)*
Self-employed	0.042	0.005	0.063	−0.037	*(0.001)*	−0.057	*(0.000)*	0.020	*(0.026)*
Unemployed	0.047	0.053	0.039	0.006	*(0.625)*	0.014	*(0.303)*	−0.008	*(0.365)*
House wife/husband	0.059	0.042	0.064	−0.017	*(0.182)*	−0.022	*(0.146)*	0.005	*(0.630)*
Retired or ill	0.192	0.685	0.288	0.493	*(0.000)*	0.398	*(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)*	−0.133	*(0.000)*	0.060	*(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	−0.186	*(0.000)*	−0.225	*(0.000)*	0.039	*(0.055)*
City size>=100,000	0.373	0.230	0.334	−0.143	*(0.000)*	−0.104	*(0.000)*	−0.038	*(0.065)*
Parent	0.509	0.833	0.685	0.324	*(0.000)*	0.149	*(0.000)*	0.176	*(0.000)*
Grandparent	0.188	0.658	0.299	0.471	*(0.000)*	0.360	*(0.000)*	0.111	*(0.000)*
Education professional	0.094	0.045	0.107	−0.049	*(0.002)*	−0.062	*(0.001)*	0.013	*(0.327)*
Observations	3699	382	622						

Notes: Columns (1)–(3) show means of onliners interviewed in the internet mode, offliners interviewed face-to-face, and internet users 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.

internet mode, (2) offliners interviewed in the face-to-face mode, and (3) internet users interviewed in the face-to-face mode. In particular, we estimate the following type of regressions:

$$y_i = \alpha_0 + \alpha_1 Offliner_i + \alpha_2 Internet\ user_i^{face-to-face} + \gamma' X_i + \varepsilon_i \quad (1)$$

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 $Internet\ user_i^{face-to-face}$ is a dummy variable equal to 1 if the respondent belongs to the internet-user population and is interviewed in the face-to face mode. X_i is a vector of control variables.

In this specification, α_1 provides an estimate of the response difference between offliners interviewed in the face-to-face mode and onliners interviewed in the internet mode. The second coefficient of interest, α_2, captures the difference between internet users interviewed in the face-to-face mode and onliners interviewed in the internet 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 internet users 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.

5.2. Differences in background characteristics across internet-user 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 internet users in almost all dimensions, independent of whether they are compared to those sampled in the internet mode (column (4)) or to those sampled in the face-to-face mode (column (5)).[16]

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 internet mode also differs significantly from the sample of internet users interviewed face-to-face in a number of background characteristics (column (6)). Among others, the internet users 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 internet mode. These differences are not surprising and plausibly reflect sampling differences: Participants in the face-to-face interviews are sampled using probability-based random sampling, whereas onliners sampled in the internet mode are recruited using an online access panel. Furthermore, the former need to be encountered at home by the interviewers in order to be sampled, which is not the case for the latter. The existence of sampling differences underscores the importance of controlling for background characteristics in the regression analysis.

5.3. Differences in survey responses: inherent population differences vs. mode effects

Next, we turn to the question of whether the systematic differences in response behavior between onliners interviewed in the internet 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 4). Without control variables, six of the eight opinion survey items indicate a significant difference between onliners interviewed in the internet 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.[17]

Intriguingly, the coefficients on the *Internet user face-to-face* dummy also show significant differences between onliners interviewed in the internet mode and internet users 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 internet 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 internet mode (see Roberts, 2007, for discussion).

[16] When conducting multiple comparisons as in Table 2, one would expect that a certain proportion of the pairwise comparisons is statistically significant purely by chance. For instance, with 22 comparisons as in column 4 and a significance level of p = 0.05, the number of expected significant comparisons is 0.05 x 22 = 1.1, which is substantially lower than the actual number of significant differences (20).

[17] While the onliner-offliner difference in the 2017 survey wave remains economically and statistically significant for six out of eight questions, it turns insignificant for the questions on preferences for free preschool and increased school spending. Exploring the underlying reason for this instability of the onliner-offliner gap across survey years is beyond the scope of this paper. However, it may be that it is at least partly due to the fact that the offliner share in the population has decreased over the past years. This may have attenuated the onliner-offliner difference through changes in offliners' characteristics across years.

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)*
Internet users 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. Internet users 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	2821	2288	4663	4681	2863	4585	4591	4573
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)*
Internet users 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. Internet users 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	2670	2203	4507	4515	2723	4445	4451	4435

Notes: Ordinary least squares (OLS) estimations. Offliner: respondents who do not use the internet, interviewed face-to-face. Internet users face-to-face: respondents who use the internet, interviewed face-to-face. Omitted category: respondents who use the internet, interviewed in the internet 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.

Comparing responses between internet users 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).[18] 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 differences – are a key driver of response differences between onliners and offliners in the mixed-mode setting (i.e., when onliners are interviewed in the internet mode and offliners are interviewed face-to-face, see section 4). In contrast to mode effects, inherent population differences in unobserved characteristics between onliners and offliners seem to be rather unimportant for their survey responses in our setting, 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.[19]

6. 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 internet survey to match basic characteristics of the entire population can

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

[19] Appendix Table A1 reports additional results for the question of 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 (see Lergetporer et al., 2018, 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 internet mode. The interactions between the treatment indicator and the subgroup indicators (*Offliner* and *Internet users 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.

recover response patterns of the mixed-mode setting (which includes onliners and offliners). If successful, this approach poses a pragmatic, economical solution to deriving population-representative statements from internet surveys. Note that this approach is effectively used by researchers who wish to draw representative conclusions from internet surveys (e.g., Alesina et al., 2018; Haaland and Roth, 2020; Roth et al., 2022). We explicitly test the validity of this approach.[20]

Table 4 summarizes background characteristics of the mixed-mode sample (column (1)) and the re-weighted online sample (column (3)).[21] The analysis uses two sets of weights: the first one aligns the combined mixed-mode sample of onliners surveyed in the internet 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 city size; the other one does the same for the sample of onliners surveyed in the internet mode.[22] As columns (5) to (7) show, almost 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, federal state, and city size), it is reassuring that the weights also balance most 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 vs. 21.0 percent) and for the item of whether they consider themselves as a winner of digitalization (54.3 percent vs. 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. In addition, in virtually all cases the population means are estimated precisely enough in both approaches that quantitatively notable differences would be detected.

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 internet 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 offliners, reasonably well.

7. Conclusion

In this paper, we investigate whether non-probabilistic internet surveys can be representative for the entire population by comparing responses to a large-scale opinion survey between (1) onliners interviewed in the internet mode, (2) offliners interviewed in the face-to-face mode, and (3) internet users interviewed in the face-to-face mode. Our specific survey setup – which, for the purposes of this paper, adds the third group to the mixed-mode setup of the first two groups – 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 vs. 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, internet users and offliners exhibit identical response patterns after conditioning on respondents' background characteristics. By contrast, internet users surveyed face-to-face differ in their responses markedly from onliners surveyed in the internet mode.

Based on these results, we suggest re-weighting the online sample to resemble the characteristics of the entire population. This

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

[21] 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 internet users in the face-to-face mode.

[22] Note that we did not compute weights for the sample of internet users surveyed in the face-to-face mode (group (3)). 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.

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

	Mixed-mode sample		Re-weighted online sample		Difference (1)–(3)		
	Mean	Std. err.	Mean	Std. err.	Mean	Std. err.	t statistic
Younger than 45	0.390	0.008	0.390	0.010	0.000	0.013	0.011
Between 45 and 64	0.359	0.008	0.359	0.010	0.000	0.013	0.008
65 or older	0.251	0.007	0.252	0.012	−0.000	0.014	−0.018
No degree/Hauptschule	0.382	0.009	0.382	0.011	−0.000	0.014	−0.005
Realschule	0.302	0.008	0.302	0.009	0.000	0.012	0.009
University entrance degree	0.316	0.008	0.316	0.009	−0.000	0.012	−0.003
Student or apprentice	0.092	0.005	0.092	0.005	0.001	0.007	0.069
Full-time employed	0.352	0.008	0.338	0.009	0.015	0.013	1.154
Part-time employed	0.118	0.006	0.124	0.007	−0.006	0.009	−0.660
Self-employed	0.038	0.003	0.041	0.004	−0.003	0.005	−0.596
Unemployed	0.049	0.004	0.043	0.004	0.006	0.005	1.056
House wife/husband	0.061	0.004	0.063	0.005	−0.001	0.007	−0.209
Retired or ill	0.290	0.008	0.300	0.011	−0.011	0.014	−0.755
Income	2.267	0.025	2.302	0.030	−0.035	0.039	−0.915
Female	0.511	0.009	0.511	0.011	−0.000	0.014	−0.000
West Germany	0.801	0.007	0.801	0.008	−0.000	0.011	−0.001
Partner in household	0.541	0.009	0.578	0.011	−0.037	0.014	−2.616
Parental education	0.269	0.008	0.273	0.009	−0.004	0.012	−0.372
City size $\geq$ 100,000	0.318	0.008	0.317	0.010	0.001	0.013	0.064
Parent	0.580	0.009	0.577	0.010	0.003	0.014	0.185
Grandparent	0.276	0.008	0.269	0.011	0.007	0.013	0.550
Voter	0.809	0.007	0.815	0.008	−0.006	0.011	−0.568
CDU voter	0.252	0.008	0.242	0.009	0.010	0.012	0.812
SPD voter	0.198	0.007	0.214	0.009	−0.016	0.012	−1.284
Education professional	0.082	0.005	0.083	0.006	−0.001	0.007	−0.188
No vocational degree, not in training	0.101	0.006	0.075	0.006	0.026	0.009	3.038
Vocational degree	0.566	0.009	0.579	0.010	−0.012	0.014	−0.885
Higher vocational degree	0.134	0.006	0.141	0.007	−0.007	0.009	−0.756
University of applied sciences degree	0.063	0.004	0.062	0.004	0.002	0.006	0.253
University degree	0.083	0.005	0.083	0.005	0.001	0.007	0.100
Other professional degree	0.047	0.004	0.056	0.005	−0.010	0.006	−1.506
Currently in vocational training	0.027	0.003	0.028	0.003	−0.001	0.005	−0.155
Currently student	0.060	0.004	0.060	0.004	−0.000	0.006	−0.008
Born in Germany	0.947	0.004	0.958	0.004	−0.010	0.006	−1.727
Risk preference	4.189	0.045	4.322	0.055	−0.133	0.071	−1.874
Discount rate	5.999	0.046	6.155	0.053	−0.156	0.070	−2.227

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.

approach might be a pragmatic and inexpensive solution for applied researchers who use internet surveys 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 internet-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 internet surveys. Consistent with this hypothesis, we observe differences predominantly on more sensitive questions. 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

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)*	−0.602
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
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)*	−0.790
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
Digitalization							

(*continued on next page*)

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 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%	0.633	*(0.017)*	0.652	*(0.020)*	-0.020	*(0.026)*	−0.754
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.

digitalization of the education system and the effects of digitalization in society more generally. Finally, the survey used for our analysis is focused on opinions on topics of education policy. While it includes a few items on preferences for non-education public spending, future research should examine the extent to which the response patterns prevail for a broader array of topics not covered in the ifo Education Survey.

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

	(1)	(2)
	Without controls	With controls
Offliner	−0.019	−0.017
	(0.034)	*(0.040)*
Internet users 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 Internet users 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	4667	4513

Notes: Ordinary least squares (OLS) estimations. Offliner: respondents who do not use the internet, interviewed face-to-face. Internet users face-to-face: respondents who use the internet, interviewed face-to-face. Omitted category: respondents who use the internet, interviewed in the internet 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.

Data availability

Data will be made available on request.

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