Determinants of participation in a longitudinal survey during the COVID-19 pandemic: The case of a low-infection country

ANU Centre for Social Research and Methods

Professor Nicholas Biddle and Kate Sollis

ANU Centre for Social Research and Methods

Australian National University

June 2021

Acknowledgements

The authors would like to thank a number of people who were involved in the development of the ANUpoll questionnaires, including Diane Herz, Dr Benjamin Phillips, Dr Paul Myers, Matilda Page, Diana Nguyen, Anna Lethborg and Charles Dove from the Social Research Centre, and Professor Ian McAllister from the ANU. Financial support for the ANU COVID-19 Impact Monitoring Survey Program has been provided by the Australian Institute of Health and Welfare.

Abstract

In this paper, we utilise a longitudinal sample with responses from prior to the COVID-19 pandemic to measure the factors associated with participation in longitudinal surveys during the COVID-19 period. The benefit of this sample for the analysis is that factors collected in pre-COVID waves can be used to measure survey participation. This is in comparison to cross-sectional or longitudinal surveys that only commenced once the pandemic had commenced. We find a number of demographic groups that are identified as being more likely to not respond to COVID-19 surveys, despite having completed pre-COVID surveys, as well as a number of other economic and personality factors. Reassuringly though, there were many more factors that did not have an association. The study also highlights that two simple questions (with a low time cost) on subjective survey experience early in the pandemic were highly useful for predicting future survey participation. These findings can help to support survey practitioners and data collection companies to develop more robust sampling strategies during the COVID-19 period.

1 Introduction

Maintaining low levels of attrition within longitudinal surveys is vital in ensuring that surveys are representative of the population. If individuals with certain characteristics are less likely to respond to a particular wave of a survey or to attrite from a longitudinal survey, the representativeness of that survey can be jeopardised (e.g. Behr, Bellgardt, & Rendtel, 2005; Lillard & Panis, 1998). Thus, it is important to gain a clear understanding of the characteristics of individuals who are more or less likely to respond to a survey.

The COVID-19 pandemic has resulted in substantial changes to people's lives, which may have had an impact on whether they continue participating in longitudinal surveys. Importantly, this impact may have increased the chances of participation for some, but decreased it for others. On the one hand, COVID-19 and the associated social and economic shocks may have added a burden to people's lives, making it harder for them to participate. On the other hand though, the lockdown period may have led to more time available for individuals to participate and a desire for any form of social interaction that is on offer.

Previous research has found varying levels of participation based on survey topic, with individuals more likely to participate in studies that they have a keen interest in (Zillmann, Schmitz, Skopek, & Hans-Peter, 2014). Some people may have found surveys on COVID-19 engaging, others may have found them uninteresting. Therefore, it is important to understand how the COVID-19 pandemic may have altered the attributes of non-responders at the population level, given that this has likely changed compared to the pre-pandemic period.

There is a substantial literature related to the determinants of participation in longitudinal surveys that predates the COVID-19 period. These studies broadly examine sociodemographic characteristics, personality, and survey experience correlates of survey participation. The most well-researched area is that of sociodemographic characteristics. Unsurprisingly, given the different time availability, interest, and trust in data/research amongst different population groups, some are less likely to respond to longitudinal surveys. While the direction of the associations tend to vary, studies have found differences in propensity to respond to longitudinal surveys by:

- sex (Cheng, Zamarro, & Orriens, 2018; Satherley et al., 2015),
- age (Chin, Couper, & Beckett, 2020; Daniels, Ingle, & Brophy, 2020; Lugtig, 2014; Watson & Wooden, 2009),
- marital status (Cheng et al., 2018; Chin et al., 2020; Fitzgerald, Gottschalk, & Moffitt, 1998; Watson & Wooden, 2009),
- birthplace (Cheng et al., 2018; Rothbaum & Bee, 2020; Watson & Wooden, 2009),
- level of education, with those having lower education being more likely to be non-responders (Barber, Kusunoki, Gatny, & Schulz, 2016; Chin et al., 2020; Lugtig, 2014; Rothbaum & Bee, 2020; Watson & Wooden, 2009),
- minority group, with those part of a minority group being more likely to be non-responders (Barber et al., 2016; Cheng et al., 2018; Rothbaum & Bee, 2020; Satherley et al., 2015), and
- income and employment (Cheng et al., 2018; Chin et al., 2020; Daniels et al., 2020; Fitzgerald et al., 1998; Rothbaum & Bee, 2020; Watson & Wooden, 2009).

Numerous studies have also examined the impact of personality traits on likelihood of responding to surveys. Personality traits have found to be associated with a number of life outcomes (e.g. Bruck & Allen, 2003; Judge, Higgins, Thoresen, & Barrick, 1999; Komarraju, Karau, Schmeck, & Avdic, 2011; Leutner, Ahmetoglu, Akhtar, & Chamorro-Premuzic, 2014), suggesting that personality may also have an impact on survey participation. The majority of these studies examining survey participation and personality have used the Big Five personality traits, developed and validated by McCrae and Costa (1987). Overall, conscientiousness, agreeableness, openness to experience and extraversion have been found to be associated with propensity to respond to a longitudinal survey, although the direction of the association varies between studies (Brüggen & Dholakia, 2010; Cheng et al., 2018; Lugtig, 2014; Marcus & Schuetz, 2005; Nestler, Thielsch, Vasilev, & Back, 2015).

Finally, there has been limited research on the relationship between survey experience and survey participation, with Roßmann and Gummer (2015) finding that a participant's response history is a significant predictor of panel attrition (indicating that survey satisfaction, measured through participation in previous surveys, is associated with a higher propensity to respond). Furthermore, Frankel and Hillygus (2013) have found that a negative survey experience is highly predictive of panel attrition.

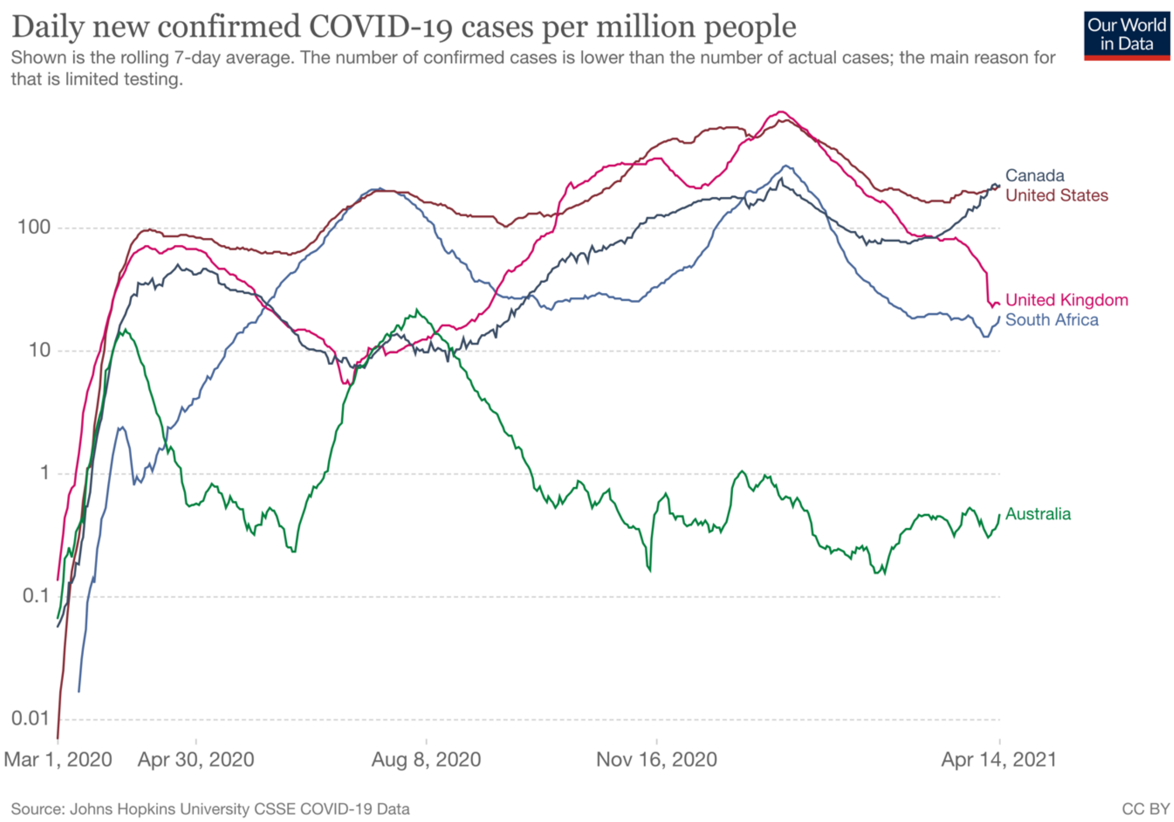
While a large body of research examining the predictors and correlates of longitudinal survey participation exists, there have been only limited studies conducted within the COVID-19 context. Research findings from the United States, the United Kingdom and Canada has indicated that the COVID-19 pandemic has influenced participation in surveys.

For example, the U.S. Census Bureau have found that levels of non-response are higher during the pandemic and have a stronger association with income compared to previous years. Furthermore, there was a change in response patterns by age, sex, employment status, education, Hispanic origin and citizenship and nativity (Berchick, Mykyta, & Stern, 2020; Rothbaum & Bee, 2020). Analysis by Ward and Edwards (2020) of labour force data in the US have shown that post-pandemic respondents are on average more than a year older, more likely to be Black or Hispanic, more likely to be married, and more likely to have higher levels of education. A number of studies have highlighted that this change in the demographic composition of responders has led to potential bias in official statistics (e.g. Heffetz & Reeves 2020; Ward & Edwards 2020)

The ONS (2020) in the UK have also found a reduction in response rates to their Labour Force Survey during the pandemic, with a different distribution in responders compared to previous years. Finally, Daniels et al. (2020) through analysis of the National Income Dynamics Study in South Africa show that attrition during the pandemic is associated with different observable characteristics compared to pre-pandemic, with attrition being higher for young people, those living in urban areas, and those with higher income and who are employed. Interestingly, they note that individuals who underwent COVID-19 tests are 3% more likely to drop out of the survey, highlighting the difficulties in capturing representative information on those who are more likely to have been affected by the virus.

This study will contribute to the existing literature base in a number of ways. Firstly, the studies published in the COVID-19 context have tended to utilise only official statistics for analysis, which generally result in higher response rates compared to other types of surveys. Thus, we may find differing conclusions for a web-based survey run by a research institute. Secondly, no study has previously looked at the impact of personality on non-response in the COVID-19 context. Finally, no study has previously examined how the COVID-19 pandemic may have affected response patterns within a country that has been relatively less affected by the virus (in the case of this paper, Australia). This may result in differing conclusions, in contrast to the US, UK and South Africa, where the number of cases and deaths have been substantially higher. As shown in Figure 1, after reaching a similar peak during the first wave of infections and then again during the second wave of infections in Australia (at least compared to the UK and South Africa at the time), Australia has had substantially lower rates of COVID-19 infection for most of 2020 and particularly in 2021.

Figure 1 COVID-19 infection per million people from March 2020 to April 2021 – Australia, Canada, South Africa, UK, and US (log scale)



Source: ourworldindata.org

With that background in mind, the remainder of the paper is structured as follows. In the next section of the paper, we describe the data used in the paper. This is followed (in Section 3) by a descriptive analysis of survey participation over the January 2020 to January 2021 periods, with Section 4 providing more detailed econometric modelling. Section 5 provides some concluding comments.

2 Introducing the data

Between the 18th of January and the 1st of February 2021, the Social Research Centre on behalf of the ANU Centre for Social Research and Methods undertook an ANUpoll as part of the sixth wave of the ANU's COVID-19 Impact Monitoring Survey Program. Previous waves of data collection as part of the COVID-19 program occurred in April, May, August, October, and November 2020, with a non-COVID related ANUpoll occurring in January 2020.

Data was collected from members of the Life in Australia™ panel. Recruitment to the panel has occurred over a number of stages, with the most significant refresh of the sample occurring in late 2019, just prior to our

The ANUpoll data collection does not capture all the survey waves that were completed by participants between January 2020 and January 2021, as the Life in Australia™ panel participants are also invited to participate in other surveys not commissioned by the ANU. These waves are excluded from our analysis as we do not have access to the questionnaires or unit record data. While the February 2020 survey was conducted by the ANU, it has also been excluded from this analysis as there were no COVID-related questions on this survey, infection had not yet spread to Australia, and there were very few COVID-related policy interventions in Australia when most people had undertaken the survey. It was also a much longer survey than January 2020, due to the inclusion of a number of modules from the European Social Survey.

In each wave of data collection, the Social Research Centre collected data online and through Computer Assisted Telephone Interviewing (CATI) in order to ensure representation from the offline Australian population. Around 4.9 per cent of interviews in January 2021 were collected via CATI. The contact methodology adopted for the online Life in Australia™ members is an initial survey invitation via email and SMS (where available), followed by multiple email reminders and a reminder SMS. Telephone reminders of panel members who had not yet completed the survey commenced in the second week of fieldwork and consisted of reminder calls encouraging completion of the online survey. The contact methodology for offline Life in Australia™ members was an initial SMS (where available), followed by an extended call-cycle over a two-week period. A reminder SMS was also sent in the second week of fieldwork.

Much of the analysis presented in this paper is based on unweighted data. However, where applicable, data in the paper is weighted to population benchmarks using January 2020 weights. For Life in Australia™, the approach for deriving weights generally consists of the following steps:

1. Compute a base weight for each respondent as the product of two weights:
   a. Their enrolment weight, accounting for the initial chances of selection and subsequent post-stratification to key demographic benchmarks
   b. Their response propensity weight, estimated from enrolment information available for both respondents and non-respondents to the present wave.
2. Adjust the base weights so that they satisfy the latest population benchmarks for several demographic characteristics.

The ethical aspects of the ANUpoll data collection have been approved by the ANU Human Research Ethics Committee (2014/241).

3 Describing survey participation during the COVID-19 period

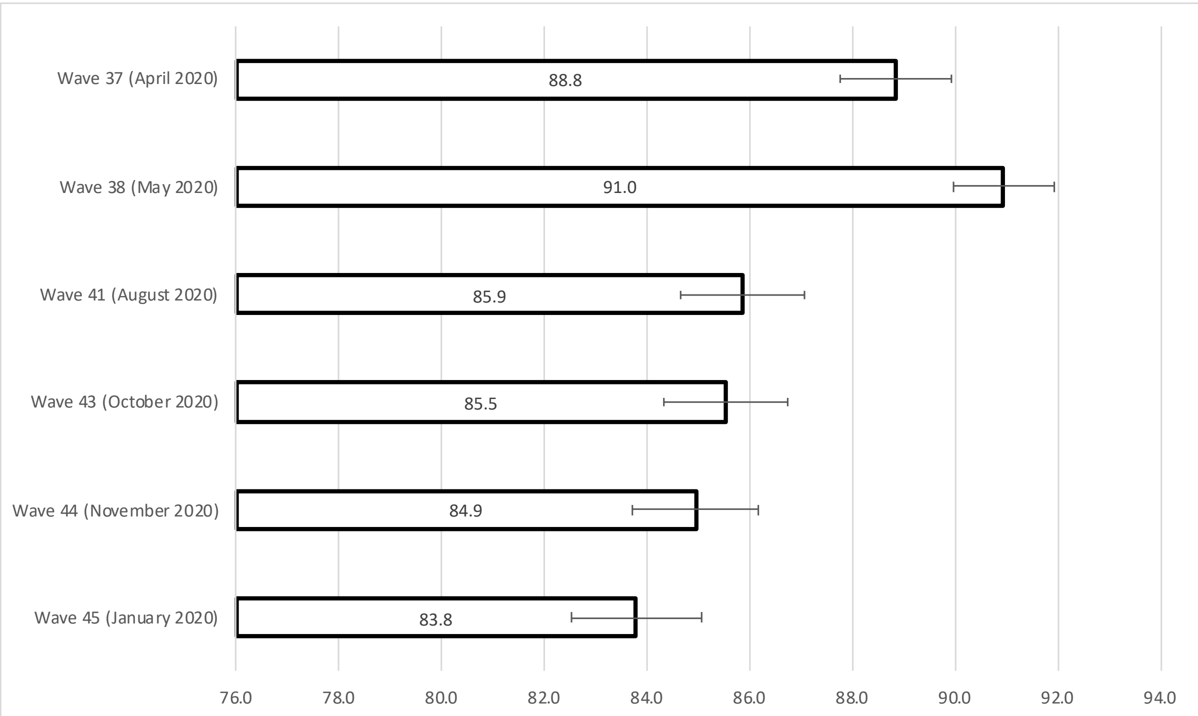
There were 3,249 respondents who participated in the January 2020 ANUpoll. Taking this as our baseline, 70.0 per cent of these respondents completed all six of the COVID-19 surveys that took place between April 2020 and January 2021. That is, if we were to construct a balanced panel across the period then, conditional on being in the January 2020 survey and therefore having pre-COVID-19 data, we would have a total sample of 2,273 respondents.

Looking now at those who did not complete all the surveys, 12.0 per cent of the January 2020 sample completed five out of the six COVID-19 surveys, 5.3 per cent completed four of the six surveys, 3.3 per cent completed three out of six, 3.5 per cent completed two out of six, and 2.3 per cent completed only one out of the six COVID-19 surveys. This leaves 3.8 per cent of the January 2020 survey who did not complete any subsequent surveys.

There was some variation in the per cent of the January 2020 sample who completed each of the subsequent waves (Figure 2). Of those who completed the January 2020 survey, 88.8 per cent completed the April 2020 survey. It should be remembered that this was the peak of the first wave of COVID-19 infections in Australia, with significant uncertainty as to what the trajectory of the virus and associated social and economic shocks in Australia would be. It was also the first survey on issues related to COVID-19 that the panel had been asked to complete.

There was a significantly higher per cent of the January 2020 sample who completed the May 2020 survey (91.0 per cent), with participation rates then declining such that by January 2021, the percentage of the January 2020 sample completing the survey decreased to 83.8%.

Figure 2 Per cent of January 2020 sample who completed subsequent waves of data collection



4 Explaining survey participation

Using the Total Survey Error (TSE) framework (Groves and Lyberg 2020), sample attrition can have two major impacts on errors in a survey statistic. First, because sample sizes are reduced, sampling error can increase. That is, the precision of estimates decline. Secondly, and perhaps more problematically, non-response error can increase. This is because the characteristics of those who do not complete a particular wave of data collection may be different from the characteristics of those who do. Sampling error can be reduced by drawing a larger additional sample from the sample frame. However, this will have far less of an impact on coverage error, apart from the greater ease of doing post-survey adjustments on a larger sample. To reduce coverage error, we need to understand the characteristics of those who attrite, relative to those who do not.

In the first sub-section below, we analyse the demographic, socioeconomic, and geographic factors associated with ongoing participation in our longitudinal sample (conditional on being in the January 2020 survey). In the two sub-sections that follow, we extend the analysis to include social attitude and personality measures, as well as subjective measures collected at the end of our first COVID-19 survey.

4.1 Demographic, socioeconomic, and geographic measures of survey participation during the COVID-19 period

In order to understand the characteristics of those who participated in the COVID-19 surveys, we estimate three separate econometric models, each with a different dependent variable but the same set of independent variables. All our models are based on the sample of those who completed the January 2020 ANUpoll, with the dependent variable for the first estimation being a binary variable for whether or not the person completed all six of the COVID-19 waves (estimated using the probit model). The dependent variable for the second model is the number of waves the respondent completed, with values ranging from zero to six and estimated using negative binomial regression. The final model also uses a binary dependent variable and is estimated using the probit model, but is constructed as to whether or not the person completed the January 2021 survey, the last survey in our current panel.

There are three main characteristics that are associated with participation in our COVID-19 surveys, conditional on completing the survey prior to the spread of COVID-19 in Australia. These are sex, age, and post-school qualifications. Specifically, females have a lower probability of participating in the COVID-19 surveys; survey participation is lower for those aged 18 to 34 years but higher for those aged 55-64 years (cf. those aged 35 to 44 years); and those with a post-school qualification are more likely to participate, particularly those with a postgraduate degree.

Equally important are those characteristics that did not have an association with participation in the COVID-19 surveys. There were no differences for Indigenous Australians, those born overseas, those who spoke a language other than English at home, those who had not completed Year 12, those who lived in advantaged or disadvantaged areas, and those who lived outside of Australia's State/Territory capital cities (keeping in mind that Australia's capital cities are generally the more urban parts of the country).

Table 1 Demographic, socioeconomic, and geographic factors associated with longitudinal survey participation, January 2020 to January 2021

Explanatory variables	Wave 45 (Probit)		Number of waves (Neg. Binomial)		All waves (Probit)	
	Coeff.	Signif.	Coeff.	Signif.	Coeff.	Signif.
Female	-0.108	*	-0.028	*	-0.176	***
Aged 18 to 24 years	-0.584	***	-0.169	***	-0.398	***
Aged 25 to 34 years	-0.258	***	-0.050	*	-0.304	***
Aged 45 to 54 years	-0.025		0.001		-0.061	
Aged 55 to 64 years	0.273	***	0.066	**	0.316	***
Aged 65 to 74 years	0.367	***	0.078	***	0.406	***
Aged 75 years plus	-0.021		0.026		0.115	
Indigenous	0.008		-0.004		0.027	
Born overseas in a main English-speaking country	0.018		-0.010		-0.007	
Born overseas in a non-English speaking country	-0.105		-0.009		0.051	
Speaks a language other than English at home	0.003		-0.009		-0.099	
Has not completed Year 12 or post-school qualification	-0.041		-0.026		-0.095	
Has a post graduate degree	0.194	*	0.033		0.196	**
Has an undergraduate degree	0.165	*	0.026		0.110	
Has a Certificate III/IV, Diploma or Associate Degree	0.076		0.011		0.071	
Lives in the most disadvantaged areas (1st quintile)	0.037		-0.009		-0.003	
Lives in next most disadvantaged areas (2nd quintile)	0.024		0.001		-0.021	
Lives in next most advantaged areas (4th quintile)	0.132		0.020		-0.011	
Lives in the most advantaged areas (5th quintile)	0.039		0.005		-0.025	
Lives in a non-capital city	-0.052		0.000		0.051	
Constant	0.935	***	1.639	***	0.517	***
Sample size			3,094			

Source: ANUpoll, January and April 2021

Notes: Probit or Negative Binomial Regression Model. The base case individual is female; aged 35 to 44 years; non-Indigenous; born in Australia; does not speak a language other than English at home; has completed Year 12 but does not have a post-graduate degree; lives in neither an advantaged or disadvantaged suburb (third quintile); and lives in a capital city. Coefficients that are statistically significant at the 1 per cent level of significance are labelled ***; those significant at the 5 per cent level of significance are labelled **, and those significant at the 10 per cent level of significance are labelled *.

4.2 The role of personality and survey history in survey participation

The previous sub-section has shown that there are some demographic, socioeconomic, and geographic factors that are associated with participation in our COVID-19 surveys. Importantly though, there are many more that aren't. Because there are known benchmarks for these variables, it is a little more straightforward to adjust for these correlates of participation in post-survey adjustment (i.e. weighting). A more challenging set of correlations from an analyst's perspective is those that are more subjective, less likely to be captured in benchmarks, or more time varying. They are more difficult to adjust for.

In Table 2, we extend the analysis from the previous section by controlling for an additional set of variables, collected prior to COVID-19. One of these questions (volunteering in the previous 12 months) was collected as part of the panel recruitment process. Another set of variables gives an indication of which wave of recruitment the participant was collected in (the earlier the recruitment the greater number of surveys they had done by January 2020). The final set of explanatory variables are from the February 2020 wave of data collection, which involved an application of a subset of European Social Survey questions to the Australian population. While this does mean that there are a range of explanatory variables available for analysis, it does come with the cost of having to condition our sample on having completed the January and February 2020 waves of data collection.

The first variable that is statistically significant is our measure of self-reported altruism, or the extent to which the respondent thinks they 'help the people around them' and 'wants to care for their well-being.' Perhaps surprisingly, this is negatively correlated with survey participation. The second variable that is statistically significant is an index of social cohesion, or the extent to which the respondent thinks that people are fair, can be trusted, and won't take advantage of others. This was positively associated with participation. The third variable that was significant related to respondent's main economic activity, with those who are retired far more likely to have participated than those who were employed. Finally, those who were recruited in the most recent panel recruitment prior to the January 2020 survey (October 2019 to December 2019) were less likely to participate than those who were recruited during the original panel recruitment period (October to December 2016).

Once again, it is important to point out those variables that were not statistically significant. Having been a volunteer prior to January 2020 was not significantly associated with participation. Neither was time spent engaging with the news, whether or not the respondent was a parent, their self reported religiosity, and the extent to which they met socially with friends and family in February 2020.

Table 2 Personality and economic factors associated with longitudinal survey participation, January 2020 to January 2021

Explanatory variables	Wave 45 (Probit)		Number of waves (Neg. Binomial)		All waves (Probit)	
	Coeff.	Signif.	Coeff.	Signif.	Coeff.	Signif.
Volunteered in 12 months prior to late 2019	0.083		0.007		0.067	
Self-reported altruism index – Feb20	-0.061	*	-0.003		-0.067	**
Time spent on news – Feb20	0.001		0.000		0.000	
Social cohesion index – Feb20	0.025		0.004		0.028	*
Main activity in Feb20 - In education	-0.015		-0.037		-0.073	
Main activity in Feb20 - Unemployed and actively looking for a job	-0.010		-0.022		-0.168	
Main activity in Feb20 - Unemployed, not actively looking for a job	0.118		-0.003		0.033	
Main activity in Feb20 - Permanently sick or disabled	0.135		0.013		-0.020	
Main activity in Feb20 - Retired	0.241	*	0.018		0.280	**
Main activity in Feb20 – Housework or caring	0.076		-0.005		-0.008	
Main activity in Feb20 - Other	0.048		-0.002		0.001	
Parent of a child in the household	-0.037		-0.008		-0.100	
Self-reported religiosity – Feb20	0.012		0.001		0.004	
Frequency of social interaction – Feb20	-0.029		-0.004		-0.033	
Recruited to panel in first wave of recruitment	-0.043		0.006		-0.029	
Recruited to panel in late 2019	-0.339	***	-0.026		-0.151	**
Female	0.012		-0.001		-0.089	
Aged 18 to 24 years	-0.495	***	-0.061		-0.278	*
Aged 25 to 34 years	-0.299	**	-0.035		-0.301	***
Aged 45 to 54 years	-0.139		-0.012		-0.094	
Aged 55 to 64 years	0.138		0.021		0.259	**
Aged 65 to 74 years	0.032		0.013		0.149	
Aged 75 years plus	-0.361	*	-0.011		-0.205	
Indigenous	-0.042		0.002		0.116	
Born overseas in a main English-speaking country	0.142		0.004		-0.017	
Born overseas in a non-English speaking country	-0.015		0.004		0.111	
Speaks a language other than English at home	-0.026		0.001		-0.093	
Has not completed Year 12 or post-school qualification	0.108		0.009		0.159	
Has a post graduate degree	0.197		0.016		0.234	**
Has an undergraduate degree	0.210	*	0.018		0.177	*
Has a Certificate III/IV, Diploma or Associate Degree	0.127		0.009		0.192	*
Lives in the most disadvantaged areas (1st quintile)	0.192		0.006		-0.002	
Lives in next most disadvantaged areas (2nd quintile)	0.159		0.006		0.008	
Lives in next most advantaged areas (4th quintile)	0.163		0.005		-0.045	
Lives in the most advantaged areas (5th quintile)	0.014		-0.003		-0.018	
Lives in a non-capital city	-0.037		0.001		0.019	
Constant	1.464	***	1.734	***	1.147	***
Sample size			2,574			

Source: ANUpoll, January and April 2021

Notes: Probit or Negative Binomial Regression Model. The base case individual is female; aged 35 to 44 years; non-Indigenous; born in Australia; does not speak a language other than English at home; has completed Year 12 but does not have a post-graduate degree; lives in neither an advantaged or disadvantaged suburb (third quintile); and lives in a capital city. Coefficients that are statistically significant at the 1 per cent level of significance are labelled ***; those significant at the 5 per cent level of significance are labelled **, and those significant at the 10 per cent level of significance are labelled *.

4.3 The role of early-COVID experience in survey participation

In this final set of analysis, we include variables from the first wave of our COVID-19 survey (April 2020) to explain participation in subsequent surveys. The dependent variable for Model 2 is therefore measured over the five additional surveys, with Model 3 estimating the factors associated with having participated in all five of the remaining COVID-19 surveys (May, August, October, and November 2020, as well as January 2021).

The first two variables in Table 3 relate to two questions we asked at the end of the first of our COVID-19 surveys – on a scale of 0-10 the extent to which the survey was distressing, and on a scale of 0 to 10 the extent to which respondents were glad they participated in the survey. These variables have been analysed in Sollis et al. (2020).

We find that those who were more distressed were less likely to have participated in subsequent waves, whereas those who were more glad to have participated were more likely to have participated in subsequent waves. While the direction of these associations are perhaps not surprising, it is important to note that subjective experiences of survey participation are significantly associated with subsequent participation.

Controlling for these measures (as well as the demographic, socioeconomic, and geographic measures), there was no significant association between anxiety and worry due to COVID-19, the expected likelihood of being infected, and whether or not the person felt their income was able to meet their expenditure. It is important to be clear with this set of analysis compared to that presented earlier is that the analysis is conditional on having participated in the April 2020 survey and that those who had a negative experience with COVID-19 in the early months of the pandemic may not have participated in any of the COVID-19 surveys (and therefore would not be in the sample for the estimations in Table 3).

Table 3 COVID-19 factors associated with longitudinal survey participation, January 2020 to January 2021

Explanatory variables	Wave 45 (Probit)		Number of waves (Neg. Binomial)		All waves (Probit)	
	Coeff.	Signif.	Coeff.	Signif.	Coeff.	Signif.
Level of distress from completing Apr20 survey	-0.057	***	-0.007	*	-0.051	***
Gladness in completing Apr20 survey	0.080	***	0.012	***	0.081	***
Anxious and worried due to COVID-10 in Apr20	0.006		0.003		0.094	
Thinks it likely to be infected by COVID-19 in six months after Apr20	0.064		0.004		-0.001	
Financial stress in Apr20	0.105		0.002		-0.009	
Female	-0.068		-0.009		-0.127	**
Aged 18 to 24 years	-0.552	***	-0.069		-0.267	*
Aged 25 to 34 years	-0.306	***	-0.038		-0.301	***
Aged 45 to 54 years	-0.119		-0.009		-0.101	
Aged 55 to 64 years	0.244	*	0.034		0.330	***
Aged 65 to 74 years	0.267	**	0.034		0.378	***
Aged 75 years plus	-0.059		0.017		0.117	
Indigenous	0.078		-0.003		0.012	
Born overseas in a main English-speaking country	0.257	**	0.012		0.063	
Born overseas in a non-English speaking country	0.000		0.011		0.167	
Speaks a language other than English at home	0.013		-0.005		-0.120	
Has not completed Year 12 or post-school qualification	-0.055		-0.007		-0.012	
Has a post graduate degree	0.178		0.020		0.252	**
Has an undergraduate degree	0.172		0.021		0.184	**
Has a Certificate III/IV, Diploma or Associate Degree	0.025		0.003		0.120	
Lives in the most disadvantaged areas (1st quintile)	0.119		0.010		0.029	
Lives in next most disadvantaged areas (2nd quintile)	0.086		0.006		-0.010	
Lives in next most advantaged areas (4th quintile)	0.150		0.014		-0.012	
Lives in the most advantaged areas (5th quintile)	-0.020		-0.005		-0.063	
Lives in a non-capital city	-0.032		0.005		0.046	
Constant	0.550	***	1.605	***	0.044	
Sample size			2,574			

Source: ANUpoll, January and April 2021

Notes: Probit or Negative Binomial Regression Model. The base case individual is female; aged 35 to 44 years; non-Indigenous; born in Australia; does not speak a language other than English at home; has completed Year 12 but does not have a post-graduate degree; lives in neither an advantaged or disadvantaged suburb (third quintile); and lives in a capital city. Coefficients that are statistically significant at the 1 per cent level of significance are labelled ***; those significant at the 5 per cent level of significance are labelled **, and those significant at the 10 per cent level of significance are labelled *.

5 Concluding comments

One of the features of the COVID-19 pandemic has been the extensive use of epidemiological data in media reporting and government announcements. Supplementing this use of infection, mortality, and more recently vaccination data has been a range of surveys on attitudes, experiences, outcomes, and behaviours. Many of these surveys are based on opt-in (non-probability based) panels or use other recruitment methods that are known to create significant biases in prevalence estimates. Where this is not disclosed or made obvious in reporting, there is potential for misleading results to lead to poor decision making.

A small proportion of the surveys during COVID-19 have been based on longitudinal samples where the same individuals are tracked through time. These surveys have many benefits, including the ability to accurately measure the factors associated with changes in outcomes, the ability to control for unobserved time invariant characteristics, and the availability of historical information without recourse to recall. This comes at a cost though, with nonrandom attrition from the sample potentially biasing cross-sectional estimates. This can be overcome to some extent through the use of longitudinal survey weights, which have been developed for analysis of this longitudinal data source.

Measuring the factors associated with participation in such samples is therefore important for understanding biases in estimations that are derived from them. In this paper, we utilise a longitudinal sample with responses from prior to the COVID-19 pandemic. The benefit of this sample for the analysis is that factors that are only observable from survey data can be used to measure survey participation, and that pre-COVID factors can be analysed. This is in comparison to cross-sectional or longitudinal surveys that only commenced once the pandemic had commenced.

It is hoped that this paper provides insights, but also assurances, for analysts of longitudinal surveys and those that rely on the data and insights generated from them. It is also hoped though that this data can be used to support survey practitioners and data collection companies. There are demographic groups that are identified as being more likely to not respond to COVID-19 surveys, despite having completed pre-COVID surveys. Females have a lower probability of participating in the COVID-19 surveys; survey participation is lower for those aged 18 to 34 years but higher for those aged 55-64 years (cf. those aged 35 to 44 years); and those with a post-school qualification are more likely to participate, particularly those with a postgraduate degree.

Self-reported altruism is negatively correlated with survey participation, whereas social cohesion had a positive association. Those who are retired are far more likely to have participated than those who were employed. Finally, those who were recruited in the most recent panel recruitment prior to the January 2020 survey (October 2019 to December 2019) were less likely to participate than those who were recruited during the original panel recruitment period (October to December 2016).

Equally important are those characteristics that did not have an association with participation in the COVID-19 surveys. There were no differences for Indigenous Australians, those born overseas, those who spoke a language other than English at home, those who had not completed Year 12, those who lived in advantaged or disadvantaged areas, and those who lived outside of Australia's State/Territory capital cities. Having been a volunteer prior to January 2020 was not significantly associated with participation. Neither was time spent engaging with the news, whether or not the respondent was a parent, their self-reported religiosity, and the extent to which they met socially with friends and family in February 2020.

A final key insight is that two simple questions (with a low time cost) on subjective survey experience early in the pandemic were highly useful for predicting future participation. This style of question should be considered in similar circumstances that arise in the future, and used by survey companies to target (perhaps with specific incentives or correspondence) those who are at elevated risk of dropping out.

References

Barber, J., Kusunoki, Y., Gatny, H., & Schulz, P. (2016). Participation in an Intensive Longitudinal Study with Weekly Web Surveys Over 2.5 Years. Journal of Medical Internet Research, 18, e105. doi:10.2196/jmir.5422

Behr, A., Bellgardt, E., & Rendtel, U. (2005). Extent and Determinants of Panel Attrition in the European Community Household Panel. European Sociological Review, 21(5), 489-512. doi:10.1093/esr/jci037

Berchick, E. R., Mykyta, L., & Stern, S. M. (2020). The influence of COVID-19-related data collection changes on measuring health insurance coverage in the 2020 CPS ASEC. Retrieved from https://www.census.gov/content/dam/Census/library/working-papers/2020/demo/sehsd-wp2020-13.pdf

Bruck, C. S., & Allen, T. D. (2003). The relationship between big five personality traits, negative affectivity, type A behavior, and work–family conflict. Journal of vocational behavior, 63(3), 457-472.

Brüggen, E., & Dholakia, U. M. (2010). Determinants of Participation and Response Effort in Web Panel Surveys. Journal of Interactive Marketing, 24(3), 239-250. doi:https://doi.org/10.1016/j.intmar.2010.04.004

Cheng, A., Zamarro, G., & Orriens, B. (2018). Personality as a Predictor of Unit Nonresponse in an Internet Panel. Sociological Methods & Research, 49(3), 672-698. doi:10.1177/0049124117747305

Chin, A., Couper, M. P., & Beckett, D. (2020). Attrition in a Longitudinal Online Randomized Controlled Trial with Prospective Homeowners. Field Methods. doi:10.1177/1525822X20948308

Daniels, R. C., Ingle, K., & Brophy, T. (2020). Determinants of attrition in NIDS-CRAM Waves 1 & 2. Retrieved from Cape Town: http://www.caps.uct.ac.za/handle/11090/994

Fitzgerald, J., Gottschalk, P., & Moffitt, R. (1998). An Analysis of Sample Attrition in Panel Data: The Michigan Panel Study of Income Dynamics. The Journal of Human Resources, 33(2), 251-299. doi:10.2307/146433

Frankel, L., & Hillygus, D. S. (2013). Looking beyond demographics: Panel attrition in the ANES and GSS. Political Analysis, 22, 336-353. doi:10.1093/pan/mpt020

Groves, R.M. and Lyberg, L., 2010. Total survey error: Past, present, and future. Public opinion quarterly, 74(5), pp.849-879.

Heffetz, O., & Reeves, D. (2021). *Measuring Unemployment in Crisis: Effects of COVID-19 on Potential Biases in the CPS*(No. w28310). National Bureau of Economic Research.

Judge, T. A., Higgins, C. A., Thoresen, C. J., & Barrick, M. R. (1999). The big five personality traits, general mental ability, and career success across the life span. Personnel psychology, 52(3), 621-652.

Komarraju, M., Karau, S. J., Schmeck, R. R., & Avdic, A. (2011). The Big Five personality traits, learning styles, and academic achievement. Personality and Individual Differences, 51(4), 472-477.

Leutner, F., Ahmetoglu, G., Akhtar, R., & Chamorro-Premuzic, T. (2014). The relationship between the entrepreneurial personality and the Big Five personality traits. Personality and Individual Differences, 63, 58-63.

Lillard, L., & Panis, C. (1998). Panel Attrition from the Panel Study of Income Dynamics: Household Income, Marital Status, and Mortality. Journal of Human Resources, 33(2), 437-457. Retrieved from https://EconPapers.repec.org/RePEc:uwp:jhriss:v:33:y:1998:i:2:p:437-457

Lugtig, P. (2014). Panel Attrition: Separating Stayers, Fast Attriters, Gradual Attriters, and Lurkers. Sociological Methods & Research, 43. doi:10.1177/0049124113520305

Marcus, B., & Schuetz, A. (2005). Who Are the People Reluctant to Participate in Research? Personality Correlates of Four Different Types of Nonresponse as Inferred from Self- and Observer Ratings. Journal of Personality, 73, 959-984. doi:10.1111/j.1467-6494.2005.00335.x

McCrae, R. R., & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers. Journal of Personality and Social Psychology, 52(1), 81.

Nestler, S., Thielsch, M., Vasilev, E., & Back, M. (2015). Will They Stay or Will They Go? Personality Predictors of Dropout in an Online Study. International Journal of Internet Science, 2015, 37-48.

ONS. (2020). Coronavirus and its impact on the Labour Force Survey. Retrieved from https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/coronavirusanditsimpactonthelabourforcesurvey/2020-10-13

Roßmann, J., & Gummer, T. (2015). Using Paradata to Predict and Correct for Panel Attrition. Social Science Computer Review, 34(3), 312-332. doi:10.1177/0894439315587258

Rothbaum, J., & Bee, A. (2020). Coronavirus infects surveys, too: Nonresponse bias during the pandemic in the CPS ASEC. Retrieved from https://www.census.gov/content/dam/Census/library/working-papers/2020/demo/sehsd-wp2020-10.pdf

Satherley, N., Milojev, P., Greaves, L. M., Huang, Y., Osborne, D., Bulbulia, J., & Sibley, C. G. (2015). Demographic and Psychological Predictors of Panel Attrition: Evidence from the New Zealand Attitudes and Values Study. PLoS ONE, 10(3). doi:10.1371/journal.pone.0121950

Sollis, K., Biddle, N., Edwards, B., & Herz, D. (2020). Improved wellbeing or distress? Measuring the impacts of participation in a COVID-19 survey on participant wellbeing.

Ward, J. M., & Edwards, K. A. Assessing the Link Between Survey Interview Technology and Survey Outcomes: Evidence from the CPS and the COVID-19 Pandemic.

Ward, J. M., & Edwards, K. A. (2020). Statistics in the Time of Coronavirus: COVID-19-related Nonresponse in the CPS Household Survey: RAND Corporation.

Watson, N., & Wooden, M. (2009). Identifying factors affecting longitudinal survey response. In R. M. Groves, G. Kalton, J. N. K. Rao, N. Schwarz, C. Skinner, & P. Lynn (Eds.).

Zillmann, D., Schmitz, A., Skopek, J., & Hans-Peter, B. (2014). Survey Topic and Unit Nonresponse: Evidence from an Online Survey on Mating. Quality & quantity, 48, 2069-2088. doi:10.1007/s11135-013-9880-y