



WAVE 2

National Income Dynamics
Study (NIDS) – Coronavirus
Rapid Mobile Survey (CRAM)

Determinants of Attrition in NIDS-CRAM Waves 1 & 2

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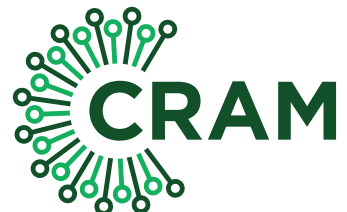
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NATIONAL INCOME DYNAMICS STUDY



CORONAVIRUS RAPID MOBILE SURVEY 2020

Determinants of Attrition in NIDS-CRAM Waves 1 & 2

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Abstract

This paper investigates the determinants of attrition between Waves 1 and 2 of the National Income Dynamics Study – Coronavirus Rapid Mobile Survey (NIDS-CRAM). The number of successfully interviewed respondents reduced from 7073 in Wave 1 to 5676 in Wave 2, which represents almost 20 percent of the sample. We fit probit regression models to predict the determinants of attrition and estimate marginal effects for four different specifications of the model. A useful finding is that attrition appears to be random across all four regression models based on the observed covariates, when measured by standard goodness of fit statistics. However, one of the most important findings is that respondents who underwent Covid-19 tests are 3 percent more likely to drop out of the survey. While this rate is low, it is a worrying trend that must be closely monitored in future Waves because it will negatively affect the efficacy of the survey to track Covid-19 testing behaviour. More generally, we find that attrition in NIDS-CRAM is not based on the same observable characteristics as its predecessor NIDS, which showed clear evidence that it was correlated with higher income households. Attrition is also not influenced by how often respondents previously participated in NIDS. It is affected by language of the interviewer, the sample batch the respondent was in during Wave 1, and contact effort by the survey organization. The most important factors influencing attrition are therefore related to survey operations rather than respondents. That said, researchers still need to conduct their own investigations about whether attrition on observable characteristics of respondents affect their estimation samples.

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Introduction

This paper conducts an analysis of attrition in the National Income Dynamics Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM) Wave 2. Attrition occurs when sample units drop out of longitudinal surveys (also called panel surveys). Attrition in panel surveys is important because it can negatively affect the representativeness of the survey sample compared to the population, reducing the validity of the survey over time. Furthermore, if variables that predict attrition are correlated with outcomes of interest in the survey, it can negatively affect the reliability of point estimates and inference about those estimates. The combination of these factors can lead to statistical bias in the data.

Cognisant of the importance of attrition and the biased inference it can cause, implementers of panel surveys have employed a variety of methods before and during fieldwork to reduce attrition, which broadly cover retention and tracking strategies (Ribisl et al., 1996). Methods of dealing with attrition ex-post have included weighting and refreshing the sample in future Waves of the survey, among others (Deng et al., 2013). However, the corrective power of all these procedures is limited, and these procedures should be informed by the correlates and drivers of attrition in order to be most effective.

In the NIDS-CRAM survey, one of the most important outcomes is related to data gathered about the behaviour of individuals and households with respect to Covid-19 testing. The year 2020 has been one of the most impactful on the human population due to lockdown restrictions that have been imposed in almost every country in the world, in an attempt to slow down the spread of the disease. However, it has become increasingly apparent that these lockdown restrictions have had negative effects on every economy that has implemented them. NIDS-CRAM is currently the only dataset in South Africa (SA) that allows researchers and policy makers to evaluate the effects of the lockdowns on key socio-economic and health outcomes. Anything that can be done to maximize data quality, which in this instance means minimizing attrition in future waves, should therefore be implemented expeditiously. The NIDS-CRAM sampling team have already developed panel weights to correct for the effect of attrition in Wave 2 (see Kerr, Ardington & Burger, 2020; and Ingle, Brophy and Daniels, 2020). The overall objective of this paper is to assess which further actions the survey organisation should take to minimize the probability of attriting in future Waves of the survey.

We investigate the determinants of attrition by fitting probit regression models and estimating the marginal effects of sets of explanatory variables on the outcome. We are interested not only in the magnitude, direction and statistical significance of the variables, but also in the overall model fit, measured by McFadden's pseudo R-squared – a statistic that is broadly analogous to the R-squared in linear probability models, but differs because it evaluates the log likelihoods in the model rather than the explained variance (for discussion see Louviere, Hensher and Swait, 2000). Consequently, one of the analytical objectives is to assess the goodness of fit of the predictive models because it would provide evidence suggesting that attrition is either systematically or not systematically related to the explanatory variables in the model (Outes-Leon and Dercon, 2008). We find that in all four specifications of our regression model, the pseudo R-squared is never greater than 8%, which is a good thing because it suggests that attrition is not systematically related to key outcomes of the survey. While this would suggest a random attrition process, the pseudo R-squared itself is not a sufficient statistic to prove this because there could be other, unobservable factors affecting attrition.

From a review of the literature, attrition is explained by at least the following sets of factors:

1. The mode of data collection, whether face-to-face, telephonic, or mixed-mode;
2. Observable characteristics of the respondent, including age, race, sex, income, education, employment status, etc;
3. Geographical location of the respondent and the likely mobility of the respondent in terms of their migration propensities;
4. Auxiliary data associated with the respondent's experience of the last available interview, as well as their attachment to the survey as measured by their previous successful interviews in earlier waves of the panel; and

5. Auxiliary data associated with the actions of the interviewing company and the performance of the interviewer.

We generate variables that capture all five sets of factors enumerated above. We then formulate key research questions to guide our discussion. While we cannot rigorously answer causal questions relating to the data, we can evaluate the magnitude, sign and statistical significance of the variables that help us understand the influence of these factors on the probability of attriting. The main research questions are:

- Is attrition in NIDS-CRAM based on the same observable characteristics of respondent as in NIDS?
- Is attrition associated with respondents who get tested, or who live in households where members get tested for Covid-19?
- Is attrition associated with respondents who are generally evasive, as measured by the proportion of their total responses to the survey that are either “Don’t Know” or “Refuse”, or if they have refused to participate in previous Waves of NIDS?
- Is attrition associated with respondents who have greater “attachment to the panel”, which is where the respondent that stays in the panel longer has a lower probability of attriting?
- Is attrition associated with variables that capture the interaction between the respondent and the interviewer in the survey company?
- Is attrition correlated with the batch in which the respondent was placed by the sampling team? This reflects the conjecture that the survey company itself may have gotten better at conducting the survey over time (a learning-by-doing effect), reducing the probability of attrition with later batches of the sample.
- Is attrition correlated with contact effort by the survey organization? The more contact attempts, the higher the likelihood of attrition.

The rest of the paper proceeds as follows: we firstly provide some background to the determinants of attrition by evaluating the literature in the field. Then we discuss the methodology employed before turning to the results. We conclude with an explanation of how our findings relate to the overall objective of this paper, which is to assess which further actions the survey organisation should take to minimize the probability of attriting in future Waves of the survey.

Background & Literature Review

This section conducts a review of available literature on attrition, while paying attention to context. South Africa is a developing country with a long history of migrating populations due to labour market opportunities. Hill (2004) reports that one of the most important predictors of attrition in panel surveys of individuals in developing countries is migration. This is in part attributed to high mobility as well as factors which increase the difficulties and costs of tracking migrants in developing countries (ibid, 2004). Some studies in developing countries have opted not to follow respondents if they move, but this raises concerns of attrition bias if movers are different to non-movers in unobservable ways. The drivers of migration and refusals intuitively differ and likely also differ across different development contexts (Lee, 2003). Although the correlates of attrition often overlap across developed and developing countries, the directionality of their effects sometimes differ.

Lee (2003) reviews research on attrition in panel surveys across developed and developing countries and summarizes that in developed countries, attrition tends to be highest among minority groups, younger people and those with lower income. In developing country contexts, however, attrition associated with migration has typically been linked to higher economic status and upward mobility. Economic and social shocks have been associated with higher attrition in both developing and developed countries. The life stage of the respondent is also important in both contexts, with youth having a higher prevalence of attrition. Attrition rates were also found to vary by a variety of socio-economic and demographic characteristics of respondents and the households that they live in, in both developed and developing countries.

Interviewer and interview characteristics have also been found to be predictors of attrition in future rounds of panel surveys. When examining whether the characteristics of the interviewer who conducted a respondent's survey in the Indonesia Family Life Survey in 1997 was predictive of re-interview in the next round of the survey in 2007 (controlling for respondent and fieldworker team fixed effects), Thomas et al. (2012) found that respondents interviewed by more experienced interviewers were more likely to be re-interviewed. Interviewers with higher pay in their previous job and those planning on returning to school, had a lower likelihood of their respondents participating in the following round. Furthermore, it was found that respondents who were rated by their enumerators as having a "good" accuracy of responses, were more likely to participate, as were respondents whose interviews took longer.

Zabel (1998) analysed attrition in two American panel surveys: the Panel Study of Income Dynamics (PSID) and the Survey of Income and Program Participation (SIPP). He found that interviewer and interview characteristics were important in predicting attrition in these surveys too. He also found a negative relationship between attrition and longer interview length, but explained that this was not driven by the interview length itself. Rather, it was a result of unobserved survey attachment of the respondents who had longer interview lengths. One type of survey attachment is when a respondent has participated in the longitudinal survey for a long period of time, having been successfully interviewed many times before. When testing an exogenous change in interview length in 1972, Zabel (1998) found that the reduction in interview length was associated with lower attrition.

Not only do the drivers of attrition appear to be slightly different in developed and developing country contexts, but they appear to be changing over time as well. Examining retention rates in eleven of the American National Election Studies between 1964 and 2004, Olson and Witt (2011) found that over the period, respondent retention relationships changed across age, gender, education and race groups.

Compared to face-to-face panel surveys, limited research has been undertaken to investigate how the correlates of attrition differ for other modes of interview; or indeed for phone surveys in particular. Using data from the Swiss Household Panel, a telephone survey, Lipps and Voorpostel (2020) investigated whether interviewer evaluations could predict participation in future waves. The researchers were particularly interested in investigating the predictive power of these measures in a phone survey, since relative to face-to-face surveys, this mode of interview limits the respondents' behavioural cues that interviewers could pick up on. When controlling for other predictors of survey participation, they found that interviewer evaluations were important predictors of attrition, in particular when assessing the respondent's reluctance to participate. Besides socio-demographic characteristics and the likelihood of the household moving, respondent's survey language competence, engagement, participation in the panel in the past, indicators of response quality of questions and social engagement of the respondent were also controlled for.

Attrition in South African longitudinal studies

The National Income Dynamics Study (NIDS), which was the sample frame for NIDS-CRAM, had a refreshment sample added in its fifth wave in 2017. This was as a result of attrition over the first four waves of NIDS. White and Indian respondents were significantly less likely to be re-interviewed between Waves 2-4 and attrition was highest amongst the highest income respondents across all race groups. As a result, the aim of the sample refresh was to interview more high-income respondents. Given the correlation of race and income in South Africa, this was anticipated to also result in more white and Indian respondents being interviewed (Branson, 2019).

While NIDS is the only panel study in South Africa which was designed to be nationally representative, South Africa has had several region and age-specific longitudinal studies and researchers have investigated the correlates of attrition in these studies.

For example, the 2000 and 2004 Khayelitsha Panel Study was a face-to-face study of respondents

in Khayelistsha which was not initially designed as a panel survey. Magruder and Natrass (2006) investigated which socio-economic characteristics were associated with attrition in this survey. Their analysis found that women, shack-dwellers and residents of smaller households were more likely to attrit. However, the impact of these characteristics on attrition was found to be limited.

The Cape Area Panel Study (CAPS) was a five-wave panel survey of young adults in the metropolitan Cape Town area between 2002 and 2009. CAPS did not attempt to re-interview respondents if they moved out of Cape Town, other than in Wave 4 when some respondents were tracked and interviewed in the Eastern Cape. The sample for Wave 5 only included those interviewed in at least the 2003 portion of Wave 2, Wave 3 or Wave 4. In 2010, CAPS conducted telephonic interviews and proxy telephonic interviews for respondents that they were unable to successfully interview in 2009. Interviews in CAPS were otherwise typically face-to-face interviews (Lam et al., 2012).

The CAPS overview documentation (ibid, 2012) includes an examination of the determinants of non-response across the first five waves of CAPS. Determinants included were years of age, gender, population group, school enrolment, employment status, quintiles of per capita income; missing income in Wave 1; place of birth; household composition and physical household characteristics. For Waves 2-5, non-response was higher among older youth, those not in school, born outside of Cape Town, from the richest per capita income quintile, with missing household income and white. Relative non-response rates switched between African and coloured respondents across the waves. For Waves 2-5, variables that represented family and household composition suggested that young adults with greater familial ties to their Wave 1 households were more likely to be re-interviewed. In Wave 5, non-response was also higher for coloured respondents and those from wealthier households. Living in a dwelling with a connection to an electricity supply was associated with an increased likelihood of re-interview between Waves 2-4.

For Wave 5, non-response was also investigated for the different modes of interview. Higher non-response to the face-to-face interview was observed among coloured and white respondents, those born outside of Cape Town and those from wealthier households. Higher non-response to face-to-face or telephonic interviews was also observed among coloured and white respondents and those born outside of Cape Town, but also those who lived in dwellings with a connection to electricity (ibid, 2012).

The KwaZulu–Natal Income Dynamics Study (KIDS) in 1998 was a follow up of African and Indian households in the Project for Statistics on Living Standards and Development (PSLSD) which was conducted in 1993 (and not designed as a panel survey). Maluccio (2004) considered whether community characteristics, mean household characteristics in the community, household characteristics and quality of interview variables in 1993, predicted attrition. He found that larger households were less likely to attrit. Further, the average completion rate of 1993 interview questions and whether there was a health clinic in the community, had negative relationships with attrition while the proportion of in-migrating households in the community in the past 5 years had a positive relationship; but these were only at 10% level of significance.

Birth to Twenty is a birth cohort study which began in 1990 in which potential sample members were restricted to children born within a specific time period and who resided at least 6 months after their birth within Johannesburg or Soweto. Norris et al. (2007) provide an overview of the characteristics of attriters over 16 years of the Birth to Twenty, compared to non-attriters. The analysis found some statistically significantly different characteristics of those who were lost to follow up in the first year of the study, compared to those lost to follow up at some stage over the 16 years. Those initially lost to follow up were associated with characteristics of the mother. The authors suggested that this collection of characteristics were consistent with rural woman going to the city to give birth and then returning to rural homelands.

In summary then, we can summarise the main factors that affect attrition as follows:

1. The mode of data collection, whether face-to-face, telephonic, or mixed-mode;
2. Observable characteristics of the respondent, including age, race, sex, income, education, employment status, etc;

3. Geographical location of the respondent and the likely mobility of the respondent in terms of their migration propensities;
4. Auxiliary data associated with the respondent's experience of the last available interview, as well as their attachment to the survey as measured by their previous successful interviews in earlier waves of the panel; and
5. Auxiliary data associated with the actions of the interviewing company and the performance of the interviewer.

Descriptive Overview of Attrition in NIDS-CRAM Wave 2

Attrition in Wave 2 can be summarized as follows:

Table 1: Wave 2 interview outcomes

Wave 2 NIDS-CRAM outcome	Frequency	Percent	Cumulative Percent
Successfully Interviewed	5,676	80.25	80.25
Refused/ Not Available	127	1.80	82.04
Not Contacted in Wave 2	1,212	17.14	99.18
Not Tracked in Wave 2	29	0.41	99.59
Moved outside of SA	7	0.10	99.69
Deceased this wave	22	0.31	100.00
Total	7,073	100.00	

The overall level of attrition between Waves 1 and 2 is about 20%. This was an interesting finding because on a-priori grounds it was uncertain whether attrition would be lower or higher – lower because the time-frame between Waves is much shorter than in NIDS for example (which was every two years); higher because it was a telephonic survey where respondents could easily hang up the phone. What is also important to note is that unlike in NIDS where “Refusals” were the dominant group of attriters, in NIDS-CRAM it is “Uncontactables” who are the largest group. This is unsurprising because in a telephonic survey respondents can easily screen calls, becoming “uncontactable”.

The subsample of attriters is further refined to exclude “Not tracked in Wave 6”⁶, “Moved outside of SA”, and “Deceased this wave”. This results in the following distribution of attriters:

Table 2: Attrition in Wave 2

	Frequency	Percent	Cumulative Percent
Successfully interviewed in in Waves 1 & 2	5,676	80.91	80.91
Attriter in Wave 2	1,339	19.09	100.00
Total	7,015	100.00	

For the rest of this paper, all analysis of attrition will be based on a binary variable equal to one if the respondent has attrited (1,339 observations), and zero if they did not (5,676 observations).

⁶ Note that “not tracked in Wave 6” means that the wrong person was interviewed. This was identified only after fieldwork was completed and therefore dropped from the sample.

Explanatory Variables Relevant to Understanding Attrition

In an initial analysis of the determinants of attrition for the purpose of creating weights, the NIDS-CRAM sampling team⁷ found that attrition on observable characteristics of respondents was statistically significantly higher among people with the following characteristics:

- Under 50 years of age.
- Urban dwellers⁸.
- Employed.
- Had missing (answered “Refused” or “Don’t know”) household income.
- Lived in households that in NIDS Wave 5 were in the top per capita income quintile.
- Were either Coloured or Indian.

We differ in our approach compared to the sampling team because we expand on the specification of the determinants of attrition to include not only observable characteristics of the respondent, but also auxiliary data reflecting aspects of the interview process, the respondent’s attachment to the survey, and how rigorously the survey company attempted to contact the respondent in terms of the text messages sent and the number of call attempts⁹. These auxiliary variables added to the regression models include:

- Sample source
 - Whether the respondent was from a household with members from the original NIDS sample or was added through the NIDS Wave 5 top-up sample.
 - NIDS-CRAM batch the respondent was in as part of sampling in Wave 1.
- Panel attachment
 - Proportion of times that the respondent was personally (not via proxy) successfully interviewed as an adult (15+ years)¹⁰ in NIDS Waves 1-5, of the times they were a resident adult in a successfully interviewed household;
 - Times the respondent was resident in successfully interviewed household in NIDS Waves 1-5¹¹, regardless of their age at the time (dummies for 1,2,3,4 and 5);
 - Times the respondent previously refused or was unable to participate in NIDS Waves 1-5 as an adult (aged 15+), or were interviewed as a proxy respondent¹² (dummies for 1,2,3 and 4).
- Interviewer-interviewee experience
 - The Wave 1 interviewer’s level of education (dummies for less than matric, matric and post-matric);
 - Wave 1 interviewer experience (in years);
 - Wave 1 interview duration (in minutes);
 - Matched Wave 1 interviewer-interviewee gender (binary yes-no);
 - Matched Wave 1 interviewer-interviewee race (binary yes-no);
 - Matched Wave 1 interviewer first language and language of Wave 1 interview¹³ (binary yes-no);

⁷ Rulof Burger, Andrew Kerr and Cally Ardington.

⁸ Due to concerns with the “urban” variable in NIDS-CRAM, we use an indicator for metropolitan district council instead.

⁹ Tabulations of indicators of the respondent’s attachment to the survey, and how rigorously the survey company attempted to contact the respondent in terms of the text messages sent and the number of call attempts, against Wave 2 contact status are contained in the appendix.

¹⁰ Child interviews were not included as the child questionnaire is asked of the caregiver or guardian of the child, so the child is not interviewed directly themselves. However, they are measured if they agree and are available. In future research, some child interviews may be relevant to incorporate as an indicator of NIDS attachment. Those where a child anthropometric measurement was taken would be relevant to incorporate here.

¹¹ Even if a respondent was not personally interviewed, if they were in a household that was successfully interviewed by NIDS, they would likely have been reminded about NIDS either by the interviewer trying to interview them, a co-resident mentioning that they were interviewed by NIDS, or by seeing a NIDS incentive from that wave.

¹² In NIDS, proxy questionnaires are answered on behalf of adults (aged 15+) who are not available. One of the reasons a proxy questionnaire would be used is when an adult refused to participate and someone was interviewed about them on their behalf. There are however other reasons for a proxy interview, such as the sample member having moved to an out of scope destination, such as prison. A future refinement to this analysis would be to only include those for whom a proxy was done because they refused.

¹³ In some of the interviews multiple languages were used; for these the dominant language of interview was used. For the 59 interviews which had 2 languages tied as the dominant language, this language match variable was set to “yes” if the interviewer’s first language matched either of the 2 tied dominant languages from the interview. The language of interview was missing for 13 respondents.

- Wave 1 interviewer evaluation of how the respondent acted towards them during the interview (dummies for friendly, neither hostile nor friendly and hostile).
- Contact effort and contacts supplied
 - Wave 1 call attempts (summed across all numbers supplied and collected for the respondent);
 - Wave 1 call attempts squared (to test whether there is a quadratic relationship to the outcome);
 - Number of phone numbers provided to the field company for the respondent for Wave 2 (for operational reasons, these were limited to a maximum of 4 per respondent);
 - Respondent did not receive an initial SMS¹⁴ prior to being called, either due to delivery failure or not having a valid cell phone number to send an SMS to (binary yes-no);
 - Respondent sent reminder SMS after some call attempts were made because they were found at that stage to be difficult to get a hold of (binary yes-no);

A descriptive summary table of all the variables and their ranges, means and observation sizes, differentiated by whether they have attrited or not, is provided in Table 3.

¹⁴ More information on the SMSs is contained in the appendix.

Table 3: Descriptive statistics of relevant variables to investigate attrition in NIDS-CRAM

Variable	Total sample				Non-attriters				Attriters			
	min	max	mean	non-missing	min	max	mean	non-missing	min	max	mean	non-missing
Male	0	1	0.39	7073	0	1	0.388	5676	0	1	0.401	1339
African/Black	0	1	0.855	7073	0	1	0.861	5676	0	1	0.83	1339
Coloured	0	1	0.088	7073	0	1	0.085	5676	0	1	0.103	1339
Asian/Indian	0	1	0.011	7073	0	1	0.009	5676	0	1	0.019	1339
White	0	1	0.046	7073	0	1	0.046	5676	0	1	0.049	1339
Age <=29	0	1	0.254	7073	0	1	0.254	5676	0	1	0.258	1339
Age 30-39	0	1	0.295	7073	0	1	0.289	5676	0	1	0.324	1339
Age 40-49	0	1	0.208	7073	0	1	0.208	5676	0	1	0.212	1339
Age >=50	0	1	0.242	7073	0	1	0.249	5676	0	1	0.205	1339
Education: less than matric	0	1	0.316	7050	0	1	0.322	5654	0	1	0.294	1338
Education: matric	0	1	0.228	7050	0	1	0.226	5654	0	1	0.241	1338
Education: tertiary / vocational / NTC	0	1	0.216	7050	0	1	0.211	5654	0	1	0.237	1338
Education: missing	0	1	0.24	7050	0	1	0.241	5654	0	1	0.229	1338
Missing Household Income	0	1	0.377	7072	0	1	0.364	5675	0	1	0.428	1339
Wave 5 household per capita income quintile 1	0	1	0.2	7051	0	1	0.204	5676	0	1	0.182	1339
Wave 5 household per capita income quintile 2	0	1	0.2	7051	0	1	0.204	5676	0	1	0.185	1339
Wave 5 household per capita income quintile 3	0	1	0.2	7051	0	1	0.197	5676	0	1	0.211	1339
Wave 5 household per capita income quintile 4	0	1	0.2	7051	0	1	0.2	5676	0	1	0.199	1339
Wave 5 household per capita income quintile 5	0	1	0.2	7051	0	1	0.195	5676	0	1	0.223	1339
Change in employment participation: remains not employed	0	1	0.52	7073	0	1	0.53	5676	0	1	0.469	1339
Change in employment participation: employed in Feb & April	0	1	0.285	7073	0	1	0.275	5676	0	1	0.331	1339
Change in employment participation: not employ Feb, employed Apr	0	1	0.104	7073	0	1	0.104	5676	0	1	0.108	1339
Change in employment participation: employ Feb, not employed Apr	0	1	0.091	7073	0	1	0.091	5676	0	1	0.092	1339

Table 3 (continued): Descriptive statistics of relevant variables to investigate attrition in NIDS-CRAM

Variable	Total sample				Non-attriters				Attriters			
	min	max	mean	non-missing	min	max	mean	non-missing	min	max	mean	non-missing
Self-assessed health status: Excellent, very good, good	0	1	0.704	7026	0	1	0.7	5641	0	1	0.727	1328
Self-assessed health status: Fair	0	1	0.216	7026	0	1	0.222	5641	0	1	0.19	1328
Self-assessed health status: Poor	0	1	0.08	7026	0	1	0.078	5641	0	1	0.083	1328
Anyone in household have Covid-19 test/screening	0	1	0.37	7073	0	1	0.363	5676	0	1	0.4	1339
Respondent had Covid-19 test	0	1	0.217	7073	0	1	0.21	5676	0	1	0.247	1339
Western Cape	0	1	0.076	7065	0	1	0.077	5670	0	1	0.073	1337
Eastern Cape	0	1	0.099	7065	0	1	0.1	5670	0	1	0.096	1337
Northern Cape	0	1	0.06	7065	0	1	0.059	5670	0	1	0.064	1337
Free State	0	1	0.064	7065	0	1	0.063	5670	0	1	0.067	1337
KwaZulu-Natal	0	1	0.294	7065	0	1	0.29	5670	0	1	0.315	1337
North West	0	1	0.064	7065	0	1	0.062	5670	0	1	0.07	1337
Gauteng	0	1	0.152	7065	0	1	0.151	5670	0	1	0.157	1337
Mpumalanga	0	1	0.091	7065	0	1	0.09	5670	0	1	0.093	1337
Limpopo	0	1	0.1	7065	0	1	0.107	5670	0	1	0.065	1337
Metro District Council	0	1	0.244	7051	0	1	0.237	5676	0	1	0.274	1339
Within/across province migrant for April lockdown	0	1	0.101	7066	0	1	0.101	5672	0	1	0.1	1336
Original NIDS sample	0	1	0.951	7073	0	1	0.953	5676	0	1	0.94	1339
Proportion respondent successfully interviewed as adult in NIDS	0	1	0.927	7073	0	1	0.931	5676	0	1	0.909	1339
Times respondent previously resident in successfully interviewed, hh: 1	0	1	0.155	7073	0	1	0.151	5676	0	1	0.171	1339
Times respondent previously resident in successfully interviewed, hh: 2	0	1	0.102	7073	0	1	0.102	5676	0	1	0.102	1339
Times respondent previously resident in successfully interviewed, hh: 3	0	1	0.064	7073	0	1	0.061	5676	0	1	0.075	1339
Times respondent previously resident in successfully interviewed, hh: 4	0	1	0.12	7073	0	1	0.121	5676	0	1	0.115	1339
Times respondent previously resident in successfully interviewed, hh: 5	0	1	0.559	7073	0	1	0.565	5676	0	1	0.536	1339

Table 3 (continued): Descriptive statistics of relevant variables to investigate attrition in NIDS-CRAM

Variable	Total sample				Non-attriters				Attriters			
	min	max	mean	non-missing	min	max	mean	non-missing	min	max	mean	non-missing
Times respondent previously refused / unavailable / interviewed by proxy: 0	0	1	0.794	7073	0	1	0.802	5676	0	1	0.758	1339
Times respondent previously refused / unavailable / interviewed by proxy: 1	0	1	0.163	7073	0	1	0.159	5676	0	1	0.183	1339
Times respondent previously refused / unavailable / interviewed by proxy: 2	0	1	0.034	7073	0	1	0.031	5676	0	1	0.047	1339
Times respondent previously refused / unavailable / interviewed by proxy: 3	0	1	0.007	7073	0	1	0.007	5676	0	1	0.009	1339
Times respondent previously refused / unavailable / interviewed by proxy: 4	0	1	0.001	7073	0	1	0.001	5676	0	1	0.003	1339
Evasive respondent: proportion don't knows and refusals to total	1	5	2.86	7073	1	5	2.826	5676	1	5	2.988	1339
Respondent sample batch	1	7	3.812	7073	1	7	3.831	5676	1	7	3.744	1339
Respondent sample batch squared	1	49	18.558	7073	1	49	18.686	5676	1	49	18.158	1339
Interviewer's evaluation of Respondent: friendly	0	1	0.866	7072	0	1	0.864	5675	0	1	0.872	1339
Interviewer's evaluation of Respondent: neither hostile or friendly	0	1	0.049	7072	0	1	0.047	5675	0	1	0.058	1339
Interviewer's evaluation of Respondent: hostile	0	1	0.085	7072	0	1	0.089	5675	0	1	0.07	1339
Interviewer's education: some secondary education	0	1	0.058	6992	0	1	0.058	5611	0	1	0.056	1323
Interviewer's education: matric education	0	1	0.594	6992	0	1	0.59	5611	0	1	0.613	1323
Interviewer's education: post-matric education	0	1	0.348	6992	0	1	0.352	5611	0	1	0.331	1323
Interviewer years of experience (excl. NIDS-CRAM)	0	14	2.366	6993	0	14	2.351	5612	0	14	2.459	1323

Table 3 (continued): Descriptive statistics of relevant variables to investigate attrition in NIDS-CRAM

Variable	Total sample				Non-attriters				Attriters			
	min	max	mean	non-missing	min	max	mean	non-missing	min	max	mean	non-missing
Wave 1 interview duration	5.42	94.5	19.594	7072	5.42	91.17	19.548	5676	5.8	94.5	19.713	1338
Matched interviewer-interviewee gender	0	1	0.162	7073	0	1	0.156	5676	0	1	0.184	1339
Matched interviewer-interviewee race	0	1	0.892	7073	0	1	0.896	5676	0	1	0.875	1339
Matched interviewer-interview first language	0	1	0.675	7073	0	1	0.684	5676	0	1	0.634	1339
Wave 1 call attempts	1	118	10.931	7051	1	118	10.449	5676	1	77	12.907	1339
Wave 1 call attempts squared	1	13924	215.155	7051	1	13924	200.065	5676	1	5929	277.761	1339
Number of phone numbers provided for Wave 2: 1	0	1	0.124	7073	0	1	0.112	5676	0	1	0.179	1339
Number of phone numbers provided for Wave 2: 2	0	1	0.251	7073	0	1	0.242	5676	0	1	0.291	1339
Number of phone numbers provided for Wave 2: 3	0	1	0.235	7073	0	1	0.235	5676	0	1	0.23	1339
Number of phone numbers provided for Wave 2: 4	0	1	0.39	7073	0	1	0.41	5676	0	1	0.299	1339
Respondent did not receive initial SMS	0	1	0.083	7073	0	1	0.073	5676	0	1	0.124	1339
Respondent sent reminder SMS	0	1	0.032	7073	0	1	0.013	5676	0	1	0.114	1339

We combine these variables into four sets to investigate the determinants of attrition as follows:

- Specification 1: Observable characteristics of the respondent, including whether they moved for the April lockdown¹⁵, geographical location, whether their answer to household income was missing, their self-reported health status and whether the respondent or anyone in the household had been tested for Covid-19;
- Specification 2: The above variables plus attachment to the panel variables;
- Specification 3: The above variables plus the sampling batch the respondent was in, and variables reflecting characteristics of the interview, including observable characteristics of the interviewer and the interviewer-interviewee experience;
- Specification 4: The above variables plus variables capturing contact effort of the survey organisation, both with respect to pre-contact and reminder SMSs sent and call attempts;

The results of the regression models are displayed in Table 4.

¹⁵ This is created from the combination of the answers to “Did you move to a different province when the lockdown was announced?” and “Did you move to another house or dwelling within the same province to spend the April lockdown?” If they answered yes to either, it equals 1 “Yes”. Of the rest: if they said no to both, then it equals “No”; if -8 “Refused” or -9 “Don’t know” to either, then it is missing.

Table 4: Determinants of Attrition: Probit model, marginal effects (standard errors in parentheses)

Explanatory Variables	Spec. 1	Spec. 2	Spec. 3	Spec. 4
Male	-0.004 (0.010)	-0.010 (0.010)	-0.023 (0.013)	-0.020 (0.012)
Coloured	0.053* (0.021)	0.049* (0.021)	0.058* (0.025)	0.036 (0.024)
Asian/Indian	0.103** (0.034)	0.099** (0.035)	0.085* (0.043)	0.072 (0.041)
White	0.023 (0.027)	0.013 (0.032)	0.025 (0.041)	0.031 (0.041)
Age 30-39	0.011 (0.014)	0.007 (0.014)	0.006 (0.014)	0.015 (0.013)
Age 40-49	-0.008 (0.015)	-0.012 (0.015)	-0.015 (0.015)	-0.000 (0.015)
Age >=50	-0.041** (0.016)	-0.043** (0.016)	-0.043** (0.016)	-0.017 (0.015)
Education = matric	0.015 (0.012)	0.016 (0.012)	0.017 (0.012)	0.024* (0.012)
Education = tertiary / vocational / NTC	0.015 (0.013)	0.013 (0.013)	0.011 (0.013)	0.017 (0.013)
Education = missing	0.033* (0.014)	0.031* (0.014)	0.033* (0.014)	0.020 (0.014)
Missing Household Income	0.048*** (0.010)	0.044*** (0.011)	0.044*** (0.011)	0.040*** (0.011)
Wave 5 household per capita income quintile 2	-0.002 (0.017)	-0.002 (0.017)	-0.002 (0.016)	-0.004 (0.016)
Wave 5 household per capita income quintile 3	0.028 (0.016)	0.027 (0.016)	0.028 (0.016)	0.023 (0.015)
Wave 5 household per capita income quintile 4	0.010 (0.016)	0.009 (0.016)	0.008 (0.016)	0.005 (0.016)
Wave 5 household per capita income quintile 5	0.023 (0.018)	0.021 (0.018)	0.023 (0.018)	0.020 (0.017)
Change in EPR: employed in Feb & April	0.039*** (0.012)	0.039*** (0.012)	0.038** (0.012)	0.035** (0.012)
Change in EPR: not employ Feb, employed Apr	0.021 (0.017)	0.018 (0.017)	0.016 (0.017)	0.013 (0.016)
Change in EPR: employ Feb, not employed Apr	0.017 (0.016)	0.016 (0.017)	0.018 (0.017)	0.015 (0.015)
Health = fair	-0.026* (0.012)	-0.025* (0.012)	-0.023 (0.012)	-0.024 (0.012)
Health = poor	0.010 (0.017)	0.010 (0.017)	0.008 (0.017)	0.014 (0.017)
Anyone in household have Covid-19 test/screening	0.007 (0.014)	0.006 (0.014)	0.005 (0.014)	0.004 (0.014)
Respondent had Covid-19 test	0.028 (0.016)	0.029 (0.016)	0.029 (0.016)	0.033* (0.016)
Eastern Cape	0.049 (0.027)	0.049 (0.026)	0.047 (0.027)	0.049 (0.027)

Northern Cape	0.038 (0.031)	0.041 (0.031)	0.046 (0.030)	0.051 (0.029)
Free State	0.056 (0.029)	0.059* (0.029)	0.060* (0.029)	0.071* (0.030)
KwaZulu-Natal	0.061* (0.025)	0.059* (0.024)	0.047 (0.025)	0.064* (0.025)
North West	0.074* (0.029)	0.074** (0.028)	0.073* (0.029)	0.090** (0.029)
Gauteng	0.028 (0.027)	0.030 (0.026)	0.030 (0.027)	0.047 (0.027)
Mpumalanga	0.046 (0.030)	0.046 (0.030)	0.039 (0.030)	0.057 (0.030)
Limpopo	-0.021 (0.030)	-0.021 (0.030)	-0.022 (0.030)	-0.003 (0.031)
Metro District Council	0.026 (0.014)	0.025 (0.014)	0.023 (0.014)	0.011 (0.013)
Within/across province migrant for April lockdown	-0.005 (0.015)	-0.006 (0.015)	-0.007 (0.015)	-0.004 (0.015)
From original NIDS sample		-0.002 (0.032)	0.009 (0.033)	0.006 (0.033)
Proportion R successfully interviewed as adult in NIDS		-0.038 (0.046)	-0.046 (0.047)	-0.026 (0.045)
Times R previously resident in succ. int. hh: 2		-0.010 (0.021)	-0.010 (0.021)	-0.008 (0.020)
Times R previously resident in succ. int. hh: 3		0.028 (0.023)	0.025 (0.022)	0.018 (0.022)
Times R previously resident in succ. int. hh: 4		-0.022 (0.021)	-0.020 (0.021)	-0.020 (0.020)
Times R previously resident in succ. int. hh: 5		-0.020 (0.016)	-0.020 (0.016)	-0.023 (0.016)
Times R previously refused / unavail / proxy: 1		0.011 (0.020)	0.009 (0.020)	0.016 (0.019)
Times R previously refused / unavail / proxy: 2		0.058 (0.034)	0.052 (0.035)	0.058 (0.033)
Times R previously refused / unavail / proxy: 3		-0.008 (0.064)	-0.032 (0.065)	-0.024 (0.064)
Times R previously refused / unavail / proxy: 4		0.165 (0.112)	0.161 (0.110)	0.161 (0.102)
Evasive R: proportion DK & Refusals to total		0.002 (0.001)	0.001 (0.001)	0.001 (0.001)
Respondent sample batch			-0.018 (0.011)	-0.025* (0.011)
Respondent sample batch squared			0.002 (0.001)	0.003* (0.001)
Interviewer's evaluation of R: neither hostile or friendly			0.028 (0.025)	0.019 (0.024)
Interviewer's evaluation of R: hostile			-0.027 (0.018)	-0.021 (0.018)
Interviewer with matric education			-0.011 (0.021)	0.004 (0.021)

Interviewer with post-matric	-0.006 (0.021)	0.013 (0.022)		
Interviewer years of experience (excluding NIDS-CRAM)	0.001 (0.002)	0.003 (0.002)		
Interview duration	0.000 (0.001)	0.001 (0.001)		
Matched interviewer-interviewee gender	0.030 (0.017)	0.022 (0.016)		
Matched interviewer-interviewee race	0.013 (0.027)	0.013 (0.027)		
Matched interviewer-interview first language	-0.025* (0.012)	-0.020 (0.011)		
Wave 1 call attempts		0.003** (0.001)		
Wave 1 call attempts squared		-0.000 (0.000)		
Number of phone numbers=2		0.052** (0.018)		
Number of phone numbers=3		0.033 (0.018)		
Number of phone numbers=4		0.004 (0.019)		
Respondent did not receive initial SMS		0.084*** (0.015)		
Respondent sent reminder SMS		0.352*** (0.027)		
Estimation sample size	6933	6933	6850	6850
Pseudo R-squared	0.018	0.022	0.024	0.072

Notes: Significance denoted * p<0.05, ** p<0.01, *** p<0.001. Reference categories: African / Black population group, age-group 18-29, Western Cape, poorest Wave 5 household per capita income quintile, change in employment to population ratio (EPR): unemployed in Feb and April, self-reported health=excellent/very good/good, times respondent previously resident in a successfully interviewed NIDS household=1, times respondent previously refused / was unavailable / was interviewed with proxy questionnaire in NIDS, interviewer evaluation of respondent in Wave 1=friendly, interviewer with less than matric education, number of phone numbers of respondent=1.

We discuss the findings of Table 4 in terms of the overall model significance and degree to which it explains the variation in attrition, before turning to specific research questions about attrition.

Overall model fit and explained variation

For each of the fitted probit models, the Wald Chi-Square statistics for overall model significance indicated that all four specifications of the model were highly significant (note that to check this finding against an alternative estimator, linear probability models (LPM) were also fitted. Here it was again found that the F-Statistics in the LPMs were significant at p<0.001). However, in regression models of the determinants of attrition, the amount of variance explained by the model is a useful diagnostic of whether that attrition is well explained by the model or not (Outes-Leon and Dercon, 2008). McFadden's pseudo R-squared statistic is the closest approximation to that for a probit model. Here we find that for each of the regression models estimated, the pseudo R-squared was never over 8 percent. It should be noted that the pseudo R-squared has a lower range for interpreting good model fit compared to an LPM, where values between 0.2-0.4 represent good model fit (as quoted in Louviere, Hensher and Swait, 2000). But despite this lower range for interpreting good model fit, the values in each of the four regression models is still low with a range of 0.018-0.072.

In the case of all four models estimated, we observe the greatest increase in the pseudo R-squared between models 3 and 4, where it increases by nearly 300%. However, the estimate is still only 7.2 percent in Specification 4. This suggests that attrition is random across all four models. Although the pseudo R-squared itself is not a sufficient statistic to identify random attrition, the low value of it implies that – on the observed covariates at least – attrition is not systematically related to them. Given that we have exhausted the list of possible explanatory variables from all public-use data and auxiliary data sources, this is a very important finding and should be assessed after each new wave of NIDS-CRAM.

Results in terms of the primary research questions

In Table 4, the coefficients are interpreted as the marginal effects of each explanatory variable on the outcome attrition, which can be interpreted as the change in the probability for a small change in each independent continuous variable, and the discrete change in the probability for dummy variables. Therefore, the first significant coefficient in Specification 1 of the regression model is that Coloured people have a 5 percent greater probability of attriting than Black South Africans (the reference category for the variable population group).

We now turn to answering our main research questions.

Is attrition in NIDS-CRAM based on the same observable characteristics of respondent as in NIDS? Branson (2019) found that in the National Income Dynamics Study (NIDS), the people most likely to attrit out of the sample were high income individuals, particularly those from White or Indian/Asian population groups. Consequently, when NIDS refreshed the sample in Wave 5 (2017), a disproportionate sample of respondents was drawn to top up these group numbers. In NIDS-CRAM, however, while attrition is negatively correlated with the Indian population for the first three specifications, it is not in the fourth specification. Furthermore, Coloured people have a higher probability of dropout compared to Black South Africans, while for White people the coefficients are always insignificant. The fact that Wave 5 household per capita income quintiles are always insignificant (relative to the poorest income quintile), also indicates that the previous NIDS finding of attrition being correlated with income is not present in NIDS-CRAM.

That said, attrition is always higher for the employed and for those who refuse to answer the household income question (this is separate from Wave 5 household income included as quintiles in the model). But it is not correlated with higher levels of educational attainment, though it is with missing on education for the first three model specifications. This suggests that people who refuse to respond to questions for any reason – whether they feel the question is socially sensitive for example – are more likely to attrit out of the survey (we investigate this tendency further in Specifications 2-4 of the model).

Consequently, the answer to this research question is that attrition in NIDS-CRAM is not similar to attrition in NIDS. This is likely due to the change in survey mode from face-to-face to telephonic, though this is not a suggestion of a causal effect. Rather, it may simply be that a phone call is easier to prematurely terminate than having someone in your home to interview you, and this tendency is not always correlated with higher income groups.

Is attrition associated with respondents who get tested, or who live in households where members get tested or screened for Covid-19? A very important finding in Specification 4 of the model is that attrition is 3 percent more likely if respondents get tested or screened for Covid-19. However, this result is not consistent across all specifications of the model. Only when contact effort by the survey organization is included as a set of explanatory variables does the result manifest. Statistically, this can be caused by omitted variable bias in Specifications 1-3. This does not render the simpler model specifications mis-specified though; rather, the findings of the simpler specifications are pertinent to researchers who will only be interested in whether attrition is correlated with their variables of interest, which are unlikely to include variables associated with the performance or effort of the survey company.

For the purposes of the survey planning team though, this result is meaningful because although it is a small effect size of only 3 percent, it is a crucial outcome variable for the NIDS-CRAM survey and its efficacy with respect to understanding Covid-19 test behavior. Because data on Covid-19 test results are shared nationally in South Africa via hospital records that are regularly updated by the Department of Health, and because test results are also communicated to people via Covid-19 cell phone apps – which can now tell you whether you are in close proximity to someone who has tested positive, if they are using the app too and share their status – there is likely to be considerable trepidation of respondents in disclosing their testing behavior. Therefore, all efforts should be directed to minimizing attrition on this variable by the survey planning team in future Waves of NIDS-CRAM.

Is attrition associated with respondents who are generally evasive, as measured by the proportion of their total responses to the survey that are either “Don’t Know” or “Refuse”, or if they have refused to participate in previous Waves of NIDS? Given the finding that it is unlikely that attrition in NIDS-CRAM is similar to NIDS, but rather that it is correlated with respondents who refuse to answer questions like household income or educational attainment, the question does arise about whether it’s just evasive or belligerent respondents who have a higher probability of attriting. We evaluate this contention by evaluating the outcomes for (1) if a respondent reports “Don’t Know” or “Refuse” for a higher proportion of the questions they respond to, which we will call an evasive respondent; (2) whether the interviewer’s evaluation of the respondent’s behavior in Wave 1 was “hostile” compared to respondents who were “friendly”; or (3) whether the respondent refused to participate in any previous NIDS Wave.

We find that for evasive respondents and those who previously refused, were unavailable or interviewed by a proxy in NIDS, tested in Specifications 2-4, the results are of a small effect size (under 2.5 percent) and never statistically significant. For “hostile” respondents, tested in Specifications 3-4, the effect size is also small and insignificant, suggesting that these characteristics (perhaps surprisingly) do not influence attrition. This suggests that the survey company should keep on trying to interview hostile respondents in future Waves of the survey until such time as they give a hard refusal.

Is attrition associated with respondents who have greater “attachment to the panel”, which is where the respondent that stays in the panel longer has a lower probability of attriting? This research question is related to the fact that the response rates in Wave 1 of NIDS-CRAM were generally considered by the survey company to be higher than most other phone surveys in South Africa at approximately 40 percent. These were the 7,073 respondents that became continuing sample members of the survey and that will be interviewed in every Wave until such time as they give a hard refusal. Given that we had a higher than average survey participation rate, it seemed plausible that because NIDS-CRAM respondents had a history of participation in at least one Wave of NIDS, they may be less likely to attrit.

We evaluate this question in Specifications 2-4 in Table 4. Here we find that the coefficients for whether the respondent was in the original 2008 NIDS sample (or whether they were part of the refreshed NIDS sample in 2017), has both a small effect size (always less than 1 percent) and is always insignificant. When we evaluate the proportion of times the respondent was successfully interviewed as an adult in NIDS, again the results are always insignificant. Lastly, when we evaluate if the respondent was at least resident in a household that was successfully interviewed in NIDS, implying that they would have been aware of the survey taking place, we also never find statistically significant results, suggesting that there is no significant positive attachment effect in NIDS-CRAM.

Is attrition associated with variables that capture the interaction between the respondent and the interviewer in the survey company? We evaluated this in Specifications 3-4 of the model. Here we find that in terms of the characteristics of the interviewer themselves, their education, years of interviewing experience, gender and race don’t matter significantly for the probability of attriting, but their language does in Specification 3 of the model (though not in Spec. 4). This result makes sense in Spec. 3 because an interviewer’s voice is what matters on a phone call – their tone, their accent, etc. So while it is indeed an important finding in Spec. 3, the fact that it becomes insignificant in Spec. 4 when call attempts are included in the model is interesting because it

suggests that contact effort (measured by call attempts) is more important than language per-se. But once you get through to the respondent on the telephone, language does matter.

Is attrition correlated with the batch in which the respondent was placed by the sampling team? This reflects the conjecture that the survey company itself may have gotten better at conducting the survey over time (a learning-by-doing effect), reducing the probability of attrition with later batches of the sample. In NIDS-CRAM Wave 1, the sampling method was a responsive design that allowed the sampling team to optimize the representivity of the sample incrementally by supplying batches of the sample to the telephonic interview company that compensated for observable characteristics of survey non-participation in the previous batch, thereby optimizing on the cost and effort of the survey (See Kerr, Ardington and Burger, 2020). There were 7 batches in the sample. We know from this process that the interviewing company initially had some difficulty with their software, and so Batch 1 of the sample took considerably longer to close off compared to later batches. The learning-by-doing effect is tested by including the seven batches of the sample as a continuous variable, and then squaring it to investigate whether there was a quadratic relationship.

We find that there is evidence of a quadratic relationship between batches of the sample and attrition. This means it first reduces and then increases with later batches. The turning point is estimated at between the second and third batch. There is not much that can be done about this, but it is an interesting operational finding. It could have been due to the survey company rushing to finish off batches 3-7 of the sample towards the end of Wave 1 of the survey, though quite how this affects attrition in Wave 2 is difficult to interpret. We did find that if we changed the specification of the regression models to include dummy variables for batch and compared later batches to batch 1, then all later batches had a lower probability of attrition, though the results were not statistically significant except for batch 3 in Specification 4. The learning-by-doing effect is therefore inconclusive.

Is attrition correlated with contact effort by the survey organization? The more contact attempts, the higher the likelihood of attrition. Contact effort is evaluated by creating variables that capture different dimensions of it: (1) total call attempts made in Wave 1, and its square; (2) number of phone numbers supplied to the survey company for each respondent in Wave 2, (3) whether the respondent did not receive the initial SMS notifying them that they will be called by the survey company in Wave 2, and whether the respondent was sent a reminder SMS in Wave 2.

We find that the number of call attempts is significant, but with a small effect size of less than half a percent, while its square is not significant. The number of phone numbers does increase the probability of attrition, but only when two numbers are provided rather than three or four. If a respondent did not receive an initial SMS informing them that they would be contacted to participate in NIDS-CRAM, then it increases the probability of attrition by 8.4 percent, and if they had to be sent a reminder SMS, it increases the probability of attrition by 35 percent, by far the biggest effect size in the model. The key contact effort variables are thus related to providing the respondent with notification that they will be interviewed as part of NIDS-CRAM. If one does not have the correct telephone number for the respondent, and they do not receive the SMS, it clearly increases the probability of attrition by a significant magnitude.

Conclusion

This paper has conducted an analysis of attrition between NIDS-CRAM Waves 1 and 2, in which approximately 20 percent of the sample dropped out of the panel. The most important, yet unsurprising finding was that contact information and effort by the survey organization matters most for reducing the probability of attrition, rather than interviewer-interviewee interactions, the respondent's evasive or hostile behavior during the Wave 1 interview, or most observable characteristics of the respondent itself. In fact, when we accounted for variables that reflected contact effort, many of the observable characteristics of the respondent and interview process that were previously significant in simpler specifications of the model were no longer significant. Our approach to this was to point out that this did not render simpler model specifications as necessarily mis-specified due to omitted variable bias (on contact effort); rather, it was important to relate the findings of the simpler models to future risk mitigation strategies that the survey organisation could take to minimize attrition. In this respect, the simpler models still offer very valuable operational insights.

Foremost among these insights is the fact that NIDS-CRAM is a telephonic interview survey, which means that respondents can screen calls and quickly hang up the phone if they don't want to participate in the survey. This distinguishes it from its predecessor NIDS, which was a face-to-face household survey where, if the interviewer was invited inside the dwelling, all household members had a chance of being interviewed (even if only by proxy). Unsurprisingly then, variables that captured contact effort by the survey organization turned out to have the highest probabilities of predicting attrition. This suggests that the quality of information on respondents' telephone numbers, alternative contacts and whether their main phone numbers change between the Waves is important. Going forward in NIDS-CRAM, it will become increasingly relevant for the survey organisation to monitor the quality of contact information for respondents in order to minimize future attrition.

Another feature of a telephonic interview survey that poses a challenge to survey participation is respondents being generally averse to participating because of what may be perceived as too many "marketing surveys" from unsolicited companies. Interestingly though, the variable that captured whether the respondent was evasive / belligerent by answering "refuse" or "don't know" on a high proportion of total questions answered was never significant, suggesting that – to the extent that this variable accurately captures evasive behavior – it is not a significant predictor of dropout. Neither was respondents who had previously refused to participate in NIDS.

When we accounted for the interviewer-interviewee interaction using auxiliary data from the telephonic interview database, we found that matching first language of the interviewer and main language the interview was conducted in was significant and reduced the probability of attrition. But matching race and gender variables did not. This again speaks to the importance of the mode of data collection, where the interviewer's voice, tone and accent are more likely to influence participation in a telephonic survey, rather than their physical characteristics such as race and gender, which may matter more in face-to-face surveys. A key learning from this model is therefore that the survey company should try to match first language of the interviewer with the main language the previous interviews were conducted in with the respondent in order to minimize future attrition.

One of the most important findings coming out of this analysis has been that respondents who underwent Covid-19 tests were 3 percent more likely to drop out of the survey. While this rate is low, it is a worrying trend that must be closely monitored in future Waves because it will negatively affect the efficacy of the survey to track Covid-19 testing behaviour. Because the contact information of each positive Covid-19 case is stored and shared with central government authorities, the concern here is that respondents would deem such information to be too socially sensitive to disclose, increasing dropout. This set of predictors of attrition should be very carefully monitored in future Waves of NIDS-CRAM to ensure that it doesn't increase, lest the efficacy of the survey be compromised on this outcome.

As far as the observable characteristics of attriters was concerned, it was evident that it was positively associated with younger Coloured and Indian/Asian individuals who lived in metropolitan district councils, were employed and who refused to answer the household income question. For

future Waves of NIDS-CRAM, it will be important to disproportionately refresh the sample on these respondent domains to ensure that it maintains its representivity over time. For researchers who are the users of the survey data, this also means that they still need to conduct their own investigations about whether attrition on observable characteristics of respondents affect their estimation samples.

Finally, it should be reiterated that the overall goodness of fit of these models was relatively low when using McFadden's pseudo R-squared as a diagnostic statistic, suggesting that attrition appears to be random on the observed covariates. In this paper, we have mined the data to what the authors feel is a near maximum capability, drawing on (1) extant data in the public-use dataset; (2) auxiliary data from both the survey organisation and the data cleaning and quality control processes to understand the interview process and the survey company's performance; and (3) historical NIDS participation by the respondent. We therefore are of the view that it will not be possible to better explain attrition than what we have done in this paper. That said, it will still be useful to refresh the sample in future based on sub-populations with low sample sizes, to ensure that detailed analyses of the data are possible and have sufficient statistical power.

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Appendices

Appendix 1: SMSs sent in Wave 2

3 sets of SMSs were sent for Wave 2:

1. The first was before fieldwork began, for the first half of the sample.
2. The second was for the second half of the sample, before calls began for them.
3. The third was a reminder SMS which the service provider sent to people that they were battling to get a hold of (note: this was only sent to people who were already hard to get a hold of).

The number to send an SMS to was chosen by SALDRU. The number that SALDRU believed to be the most likely to result in successful interview, was selected. These were selected from the list of numbers that SALDRU provided the fieldwork company with for Wave 2 (which was limited to 4 per respondent).

5 respondents were not sent an SMS. This would have been where there was not a valid cell phone number to send an SMS to. This would have been in cases where the respondent only had landline phone numbers from Wave 1.

The service provider receives an SMS report which has 4 sub-sheets of interest:

- a) SMSs delivered
- b) – d) different types of non-delivery

However, for 14 people they had conflicting delivery statuses for the initial SMS– they appeared on both a) and either b), c) or d). For these, their delivery status was set to “Unclear delivery status of SMS” and they were set to “not delivered”.

Appendix 2: Analysis of uncontactable vs. contactable respondents and SMS and panel attachment variables

Table A1: Whether the respondent was sent an initial SMS and if it was delivered, by Wave 2 contact status

Did the person receive an initial SMS and was it delivered?	Uncontactable		
	No	Yes	Total
Delivered	5398 92.45%	1047 86.39%	6445 91.41%
Not delivered	428 7.33%	159 13.12%	587 8.33%
Not sent an SMS	2 0.03%	3 0.25%	5 0.07%
Unclear delivery status of SMS	11 0.19%	3 0.25%	14 0.20%
Total	5839 100.00	1212 100.00	7051 100.00

Contactable and uncontactable respondents were sent an initial SMSs at a very similar rate; 99.97% and 99.75% respectively. However uncontactable respondents were less likely to have their initial SMS delivered indicating the cell number might not be working or the phone not switched on frequently.

Table A2: Whether the respondent was sent a reminder SMS after some calls were attempted, by Wave 2 contact status

Respondent sent a reminder SMS?	Uncontactable		
	No	Yes	Total
No	5759 98.63%	1063 87.71%	6822 96.75%
Yes	80 1.37%	149 12.29%	229 3.25%
Total	5839 100.00	1212 100.00	7051 100.00

A higher proportion of eventual uncontactable respondents received a reminder SMS than those who were contactable by the end of the wave. This is expected, since respondents were only sent a reminder SMS if after some call attempts, they were already proving difficult to get a hold of.

Table A3: Times the respondent was previously resident in a successfully interviewed household (any age), by Wave 2 contact status

Uncontactable	mean	N	sd	min	max
No	3.844	5839	1.54	1	5
Yes	3.746	1212	1.578	1	5

Uncontactable and contactable respondents have been interviewed as adults a similar amount of times on average; 3.101 and 3.243 times respectively (not shown here). They also had similar measures of attachment to the NIDS panel. Given that they were previously resident in successfully interviewed households a similar amount of times on average, they would seem to be similarly likely to know about NIDS. However this does not mean they were interviewed themselves.

Table A4: Proportion of times interviewed personally when they were an adult resident in a successfully interviewed household, by Wave 2 contact status

Uncontactable	mean	N	sd	min	max
No	.931	5839	.169	0	1
Yes	.91	1212	.197	0	1

Of the times that they were resident in a successfully interviewed NIDS household and aged 15 years or older, uncontactable respondents were personally interviewed (successfully interviewed with an adult questionnaire) less often than contactable respondents.

Table A5: Proportion times refused/not available/interviewed via proxy when a resident adult in a successfully interviewed household, by Wave 2 contact status

Uncontactable	mean	N	sd	min	max
No	.069	5839	.169	0	1
Yes	.089	1212	.196	0	1

Wave 2 uncontactable respondents were 20 percentage points more likely than contactable respondents to have refused, been unavailable or interviewed via a proxy of the times that they were a resident adult in a successfully interviewed household in NIDS.

Table A6: Total number of call attempts to the respondent in Wave 1, by Wave 2 contact status

Uncontactable	mean	N	sd	min	max
No	10.493	5839	9.516	1	118
Yes	13.038	1212	10.73	1	77

Uncontactable respondents were more difficult to track in Wave 1 NIDS-CRAM, requiring more phone calls on average, than Wave 2 contactable respondents.

For further information please see cramsurvey.org and nids.uct.ac.za