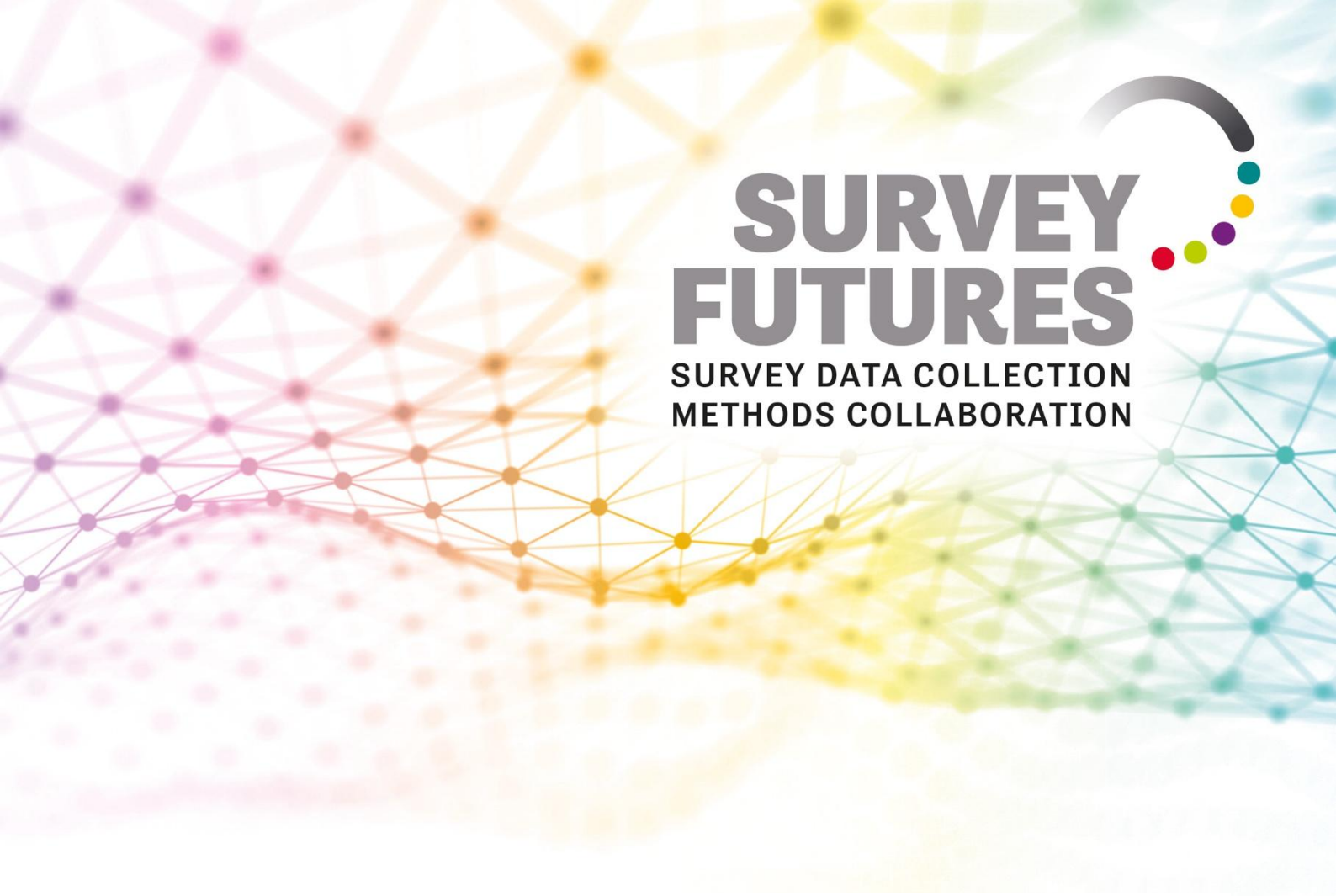

Survey Practice Guide 9: Using integrated non-survey data to plan, monitor and intervene in survey data collection

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Survey Futures is an Economic and Social Research Council (ESRC)-funded initiative (grant ES/X014150/1) aimed at bringing about a step change in survey research to ensure that high-quality social survey research can continue in the UK. The initiative brings together social survey researchers, methodologists, commissioners and other stakeholders from across academia, government, private and not-for-profit sectors. Activities include an extensive programme of research, a training and capacity-building (TCB) stream, and dissemination and promotion of good practice. The research programme aims to assess the quality implications of the most important design choices relevant to future UK surveys, with a focus on inclusivity and representativeness, while the TCB stream aims to provide understanding of capacity and skills needs in the survey sector (both interviewers and research professionals), to identify promising ways to improve both, and to take steps towards making those improvements. Survey Futures is directed by Professor Peter Lynn, University of Essex, and is a collaboration of twelve organisations, benefitting from additional support from the Office for National Statistics and the ESRC National Centre for Research Methods. Further information can be found at www.surveyfutures.net.

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Executive Summary

- This guide outlines the framework of Adaptive Survey Designs (ASD). ASD involves treating sample units differently based on their characteristics. In so doing, ASD maximises the quality of survey data within a budget constraint by ensuring a more representative sample compared to the target population.
- Using integrated non-survey data to inform an ASD broadens the range of options available and makes it more likely that the objectives of ASD will be achieved. This guide sets out how such data can fruitfully be used.
- The guide explains technical terms associated with ASD -e.g. stratification, targeting. It also explains the importance of costs and measures of data quality in implementing ASD.
- There is a wide variety of data that can be integrated into ASD from numerous different sources, including geo-spatial, administrative and commercial data.
- In ASD, non-survey data can be used to inform the processes of targeting, intervention and optimisation.
- The type, timing and quantity of an intervention all play an important role in its success. The efficiency with which the intervention is applied depends on the optimisation approach.
- There are four options for optimisation – Trial and Error, Stopping Rules, Propensity-based prioritisation and Mathematical optimisation. Most ASDs in the UK have been limited to a trial-and-error approach due to a lack of methodological expertise and a sparsity of granular data.
- To improve the standard of ASDs in the UK, Survey Commissioners should investigate possibilities of using administrative records to supplement information available on sample frames. Survey Commissioners could also look to organise training for Survey Agencies.
- Improved knowledge regarding when it is best to apply an ASD to a survey and when it is not would provide important guidance for Survey Agencies.
- Survey Agencies can also play a role in improving ASDs in the UK. They should engage more with expert survey methodologists in their data collection protocols to guide their implementation of ASDs. Furthermore, a formalised process for evaluating, analysing and considering the non-survey data available for a project is needed.
- Finally, Survey Agencies should be more transparent with the results of ASDs to build an evidence base for their use in different contexts.

1. Targeting and intervention in the context of survey design

The notable decline in survey response rates, particularly among some groups, and the corresponding increased cost of data collection, have prompted agencies to explore alternative data-collection designs. In this context, one of the main methodologies being explored is the use of adaptive survey designs (ASD) (Lynn, 2017; Schouten et al., 2017). These are survey designs that use auxiliary data to inform targeted interventions during data collection, to maximise data quality while observing the survey manager's budgetary constraints. This contrasts with standardised designs which have dominated until now, where targeting of subgroups does not take place. The fundamental aim of an ASD is to achieve the best possible data for any given cost, thereby alleviating the problems of reduced response rates while accounting for the rise in survey costs.

One of the main challenges in implementing ASDs is having information at the outset to decide how different parts of the sample should be approached during fieldwork. This usually requires linking survey data with alternative (non-survey) data sources, such as paradata (data arising from the survey process), administrative data, or geographic data. Often, this requires considerable knowledge of the most effective approach, and can be a technical exercise, requiring input from statisticians or experienced survey managers. This document provides a guide to the use of linked non-survey data for implementing ASDs.

The overall aim of this guide can be broken down into three parts. First, the guide is designed to provide the reader with a basic understanding of ASD. In the first section, we detail the terminology used in ASDs and explain its importance to the ASD framework. The second aim of this guide is to provide a list of linkable data sources and their utility for targeting in survey data collection. Section two addresses the UK data landscape by discussing the different types of non-survey data currently available to researchers, along with their advantages and disadvantages. Third, it will provide recommendations on best practices for implementing ASDs using linked data. Sections three and four lay out the theoretical underpinnings and practical recommendations for implementing ASDs. Finally, multiple case studies are discussed to illustrate the implementation of different targeting and intervention approaches across different contexts.

1.1. Overview of targeting

The purpose, motivation and types of ASDs

Survey managers use the ASD framework to monitor and intervene in data collection based on information already available about sampled units before or during data collection. This information is referred to as **auxiliary data.** An ASD is defined as tailoring the survey design to different groups in the sample depending on their characteristics (Wagner, 2008). This contrasts with the standardised survey design that uses a common methodology for the entire sample. Although standardised survey designs are traditionally more common, recent challenges due to falling response rates

and rising survey costs have made ASDs more attractive. The precipitous decline in response is not in itself a reason to diverge from a standardised approach, because response rates are not necessarily the cause of non-response bias (Groves and Peytcheva, 2008). However, the fall in participation has not been uniform across all sections of society, being highest among certain subgroups, notably young people, people from minority ethnic backgrounds, and those from more socio-economically disadvantaged backgrounds (Groves and Couper, 1998; Groves and Peytcheva, 2008). The issue of low participation has also coincided with an increase in the costs associated with surveys and a general decrease in budgets afforded to survey agencies (Groves, 2005).

In response, survey methodologists have explored more cost-efficient survey designs that minimise budgetary pressures (Tourangeau et al., 2017). To do so, a sample can be divided into subgroups based on their characteristics. ASDs allow data collection to be tailored to each subgroup based on their characteristics. Thus, ASDs facilitate interventions to improve response rates from under-represented subgroups, to achieve a more balanced sample on a set of auxiliary variables (Brick and Tourangeau, 2017). The benefit of this approach is that resources are allocated efficiently, implying that the design is intended to maximise data quality within the survey's budgetary and design constraints.

Chun et al. (2018) outline four fundamental pillars which inform the development of an ASD. The first of these is the presence of auxiliary information. This can come from different sources such as a sampling frame, paradata and other linkable external data. In this guide, we will focus mainly on situations where the auxiliary data comes from linked data. The second pillar is the intervention, which is implemented to increase participation for targeted groups. The third is a Quality and Cost Analysis that considers the value of treating particular subgroups. Finally, an optimisation strategy that provides the survey manager with a basis for understanding the optimal level of intervention associated with the ASD. Each of these will be addressed throughout this guide. It is essential to bear these pillars in mind when considering the specific types of ASD and the different approaches to ASD within broader research.

One type of ASD is the Targeted Survey Design (Lynn, 2017). This uses a static planning stage in which the sample is divided into groups of interest before any survey data are collected. The survey data are then collected using a targeting and treatment approach devised in the planning stage. Groves and Heeringa (2006) outline a more dynamic version of ASD, called Responsive Survey Design (RSD). RSD refers to survey designs which are “organised about design phases” of the data collection (Groves and Heeringa, 2006, p. 440). RSD allows survey agencies to include data already collected in prior phases, as well as auxiliary data, to adapt data collection protocols as fieldwork progresses. For example, if the data from the first phase of collection indicate that older individuals are less likely to respond, the researchers may switch the survey mode or provide additional follow-up reminders to older respondents. Examples of this approach include mixed-mode surveys such as the Dutch Health Survey or the Dutch Labour Force Survey, where data from the web phase are used to inform resource allocation in the in-person follow-up phase (Van Berkel, 2022; Van Berkel et al., 2020).

In the UK, both Responsive and Targeted Survey Designs have been implemented by multiple survey agencies. Longitudinal surveys, which have prior survey data available on non-response and sample characteristics, provide a useful illustration for implementing an ASD. For example, both the Millennium Cohort Study and Understanding Society have used ASDs to target individuals with lower response propensity in the past (Ipsos MORI, 2017).

Cross-sectional surveys do not benefit from prior waves of data and are more reliant on linked non-survey data to implement ASD. Given the use of the Postcode Address File (PAF) for sampling, linked data is often based on sampled units' residential location in the UK. In repeated cross-sectional surveys, there may be data on characteristics that predict non-response; however, it is important to consider changes in sample composition and response propensities between survey iterations. In a one-off cross-sectional survey, the factors that influence non-response cannot draw on previous data but may be able to draw on data from other surveys to estimate response propensities. The majority of ASDs implemented in the UK fall into the cross-sectional category, including the British Election Study (Fieldhouse et al., 2025), the Generations and Gender Survey (Howe et al., 2023), the Community Life Survey (Verian, 2025a) and the HMRC participation survey (HMRC, 2025) among others (Sladka and Lynn, 2025).

1.2. Basic definitions for understanding ASDs

In recent years, a considerable literature has developed related to ASDs and their implementation (Tourangeau et al., 2017). However, this literature has led to a proliferation of jargon and complexity in discussions of targeting and ASDs. This can often be a stumbling block for survey agencies seeking to implement an ASD. This section will introduce some of the key terminology used in this literature.

1.2.1. Subgroups, survey strata and stratification in ASDs

Targeting, in this guide, refers to identifying groups for which a survey manager decides to alter the survey approach. The creation of subgroups that can be targeted depends on the variables available for all the sampled cases. The subgroups into which the cases are allocated are called **strata** (Schouten et al., 2017). The division of the sample into these subgroups is called **stratification**. Stratification can be built when the auxiliary variables are based on categorical variables. The goal of ASDs is to identify strata based on their characteristics and alleviate problems arising from differential non-response rates between these strata in the sample. Further details on the nuances of stratification and the different approaches available are provided in section 2.1.

Subgroups that are less likely to respond are usually targeted in an ASD with an added intervention to encourage participation. This approach is exemplified in the UK by Howe et al. (2023), who describe an ASD implemented in the Generations and Gender Survey. The analysis of non-response in previous surveys showed that those residing in more deprived areas were less likely to participate. In this case, those who resided in the most deprived decile represented one stratum. This stratum was then offered an increased incentive of £20 compared to those outside of this stratum who were offered £15.

Another example of implementing ASD comes from the use of participation patterns in a panel study like the Millennium Cohort Study. In this case, those considered to have a higher propensity for non-response were allocated to the highest-priority fieldwork, implying they would receive an earlier visit from an interviewer and more visits than those in lower-priority groups (Ipsos MORI, 2017). Strata may be classified based on more than a single variable (e.g. older people in more deprived areas). For example, during the same Millennium Cohort Study fieldwork, interviewers were partially allocated based on the ethnicity of sample members, so that Asian families were more likely to receive a female interviewer.

1.2.2. Tailoring, Intervention, Dosage and Sequencing

Having decided to target a specific subgroup, the survey manager then treats that subgroup differently from the rest of the sample. **The intervention** refers to a specific data-collection strategy used by the survey agency to elicit responses from a particular group. Any aspect of the data collection process that treats one stratum differently from another to improve data outcomes can be considered an intervention. This is also sometimes referred to as **a treatment**.

Sometimes, survey agencies may be implementing treatments implicitly, without specifically aiming to use an ASD. For example, rolling out fieldwork sooner in an area with lower response rates could be considered an intervention (Ipsos MORI, 2017). Alternatively, treatments can be extensive, with significant changes to the survey design, such as changing the survey mode to maximise response rates across different sections of the sample, as in the Dutch Labour Force Survey or the Dutch Health Survey (Van Berkel, 2022; Van Berkel et al., 2020). In these surveys, face-to-face interviewers were allocated to strata with a lower likelihood of response, while a web survey was used for others. Ultimately, the most appropriate treatment depends on the strata involved, the survey design, and the preferences and budget of the survey agencies.

Examples of types of treatment include, but are not limited to:

- Different incentives
- Tailoring invitation letters
- Extra follow-up reminder letters
- Availability of different language questionnaires
- Different modes of contact or interview
- A shorter questionnaire for some sub-groups
- Using more productive interviewers for some sub-groups
- Different interviewer incentives.

Lynn (2017a) explains that an intervention can be categorised based on three factors. First, there is the agent of change, the respondent or the interviewer. Second, there is the mechanism by which the intervention operates to increase the likelihood of response, e.g. increased motivation of the respondent, reduced burden on the respondent. Finally, the outcome it seeks to alter is the likelihood of locating the

individual, the likelihood of making contact, or the probability of responding given that contact has been made.

Sladka and Lynn (2025) review several types of intervention that have been implemented and provide details on the efficacy of different interventions in addressing non-response. Their findings as well as the theoretical basis for different interventions are discussed in section 3.2. Furthermore, building on the work of Sladka and Lynn, (2025), a table containing examples of ASDs carried out in the UK for which there is documentation is provided in the appendix.

Interventions can also vary quantitatively. This is referred to in the literature as the '**dosage' of the intervention** (Schouten et al., 2017). For example, a survey manager may decide to provide more follow-up letters, or incentives of a different value, to a particular stratum. An example of such a strategy is provided by the Real Time Assessment of Community Transmission study collected during the Covid-19 pandemic, where 13-17 year olds and 33-42 year olds received a £10 incentive, 18-32 year olds received a £20 incentive, and those aged over 43 received no incentive at all (Atchison et al., 2025).

Finally, if a survey manager decides to implement interventions, the question of timing also arises. This is referred to as **the sequencing of the intervention**. This requires careful consideration, as the timing of an intervention can impact its effectiveness. Examples of sequenced interventions include the Community Life Survey, the DCMS Survey, and the HMRC Customer Survey (HMRC, 2025; Verian, 2025a, 2025b). In all of these, follow-up reminders were sent to sample units to stimulate responses from specific strata, and they all targeted households predicted to have residents aged 65 or older. However, the surveys used different strategies for timing the additional follow up reminder. Further detail on how and why the sequence of an intervention has important implications for ASD will be provided in section 3.2.

1.2.3. Costs, Data Quality and Optimisation

Costs are at the heart of the ASD framework. In any survey design, survey managers face a trade-off between cost and quality. As costs of survey implementation have increased (Groves, 2011), the budgetary pressure on survey designers has become more intense, with the risk of decreased data quality. ASDs provide an approach to efficiently allocate resources available, thus maximising data quality given budget constraints. However, it is essential to consider how costs are factored into the ASD framework.

Costs can be broken down into fixed and variable costs. Fixed costs are independent of the sample size (e.g. costs of writing a questionnaire), whereas variable costs are a function of the targeted sample size. Schouten et al. (2017) explains that ASDs affect both fixed and variable costs. They can often lead to increased fixed costs, whereas the optimisation inherent to an ASD is centred around the minimisation of variable costs.

Both fixed and variable costs must be considered alongside the survey agency's desire to maximise data quality. Fixed costs arise primarily at the planning stage. Designing and implementing an ASD can increase these costs because it adds complexity and requires additional staff time and expertise. As such, the cost of planning depends on the type and mix of interventions chosen. The greater the number and variety of interventions, the greater the fixed cost in developing and managing the ASD.

Variable costs, by contrast, arise during implementation. Most interventions require some expense of resources, whether that be the direct cost of higher-value incentives, the staff time required to provide more complex interviewer instructions, or the cost of follow-up procedures. These can amount to considerable financial and time resources, placing pressure on the budget despite the overall goal of an ASD being to ensure that costs are efficiently allocated in support of data quality.

By making careful assumptions regarding how fixed costs and variable costs accumulate within an ASD, survey agencies and researchers have developed complex models of costs with the view to the efficient allocation to different methods in an ASD (Calinescu et al., 2012). In more advanced ASD frameworks, this can lead to a mathematical optimisation approach, laid out in section 3.3, and exemplified by Case Studies 1 and 2. However, regardless of the application of an ASD, all ASDs are conceptually governed by the survey agent's desire to improve the quality of the survey for a given budget.

Having addressed the cost aspects in ASD, we will now turn to the benefits. To understand these, it is necessary to consider the issue they are designed to remedy in most circumstances, namely, reducing non-response bias by improving the balance of the sample on a set of auxiliary variables. A fuller guide on non-response has been published previously (O'Toole et al., 2026). This guide describes in detail how nonresponse can lead to a host of problems with survey findings. Importantly, non-response does not necessarily lead to bias in survey estimates. As Schouten et al. (2012) explain, it is the differential response rates between subgroups within the sample that may lead to bias in these estimates. ASDs present a potential remedy to this problem, not by raising response rates but by increasing the representativeness of the sample relative to the population of interest. Note that survey weights following data collection aim to correct for the differential response rates between subgroups. By tackling this balance at the source of data collection, we can reduce the variability of final survey weights and improve the efficiency of the estimates.

ASDs are not a remedy for falling response rates. Though ASD can raise response rates for certain groups, ASD may also lead to lower response rates in certain circumstances. However, by maximising the representativeness of the sample, ASDs can mitigate the impact of falling response rates that are different across sub-groups (Tourangeau et al., 2017). Therefore, indicators which address representativeness and data quality are needed to calibrate the aims and judge the success of the ASD.

Indicators of data quality can broadly be divided into two sets. Overall indicators describe the representativeness of the sample as a whole, providing a metric of the

representativeness of the responding sample, while partial indicators describe the representativeness of a particular variable or category within a variable and can be used to form the strata. Moreover, indicators can be broken down into two types. The first, covariate-based indicators, are reliant solely on auxiliary data. Overall indicators that fall within this type include the R-indicator, the Coefficient of Variation, and other related indicators (Särndal and Lundquist, 2014). R-indicators are statistics that describe the representativeness of the sample with respect to the population with respect to the auxiliary data, based on the standard deviation of the response propensities. Coefficients of Variation are another indicator of representativeness, which refer to the ratio of the standard deviation of the response propensities to the mean propensity (Schouten et al., 2009). These are discussed in further detail in a previous Practitioner Guide (O'Toole et al., 2026).

The second type refers to item-based indicators that rely on survey target variables to explicitly define the covariance between certain survey variables and non-response. However, without data on non-respondents, it is impossible to know the true covariance between the survey variable and non-response. As a result, survey variables can be imputed or taken from proxy data (e.g. past census data) and are based on assumptions regarding the consistency of the covariance between the collected sample and the uncollected sample. Overall indicators that fall into this type include the Fraction of Missing Information (FMI) and the covariance between survey variables and response propensities (Wagner, 2010).

In all cases, auxiliary data form the basis for these types of indicators. The modelling or imputation of non-response rests primarily on the auxiliary data on which they are carried out. Each of these types of indicators has been used as a benchmark statistic against which the efficacy of an ASD is calibrated (Ashenfelter, 2010; Jessop et al., 2019; Schouten and Shlomo, 2017).

However, ASDs provide a framework to address other issues affecting data quality. Calinescu et al. (2012) describes an approach to ASDs that have been used in the Netherlands to address the issue of measurement error. Moreover, they also point out that ASDs could be applied to coverage error. In the UK and, for the most part, internationally, ASDs have been focused on addressing the consequences of non-response (Tourangeau et al., 2017).

The trade-off between costs and data quality is the crux of ASD. Ultimately, the goal of an ASD is to maximise data quality subject to the budgetary constraint. This process of implementing the most efficient design to improve data quality is the optimisation at the heart of the ASD framework. In this context, it is now necessary to understand how auxiliary data contributes to the viability of an ASD.

2. Non-survey data availability and its role in ASD

Non-survey data is becoming a factor of increasing importance in ASDs. In section 2.1. we will explain what auxiliary data can be used to guide ASDs with various examples to explain how valuable they can be. We will then provide details on how this data is applied to ASD through the process of stratification, at the heart of the ASD framework.

2.1. The types of linked data and their applicability to ASD

Linked non-survey data are becoming increasingly important for measuring the representativeness of survey samples, stratifying sample frames, and developing targeting methods. As surveys move online (Dillman, 2017) due to the cost of implementing face-to-face or telephone interviews, less survey-associated paradata is available. As such, survey managers need to look for alternative data sources.

Linked data comes in a range of forms, from granular data on the past behaviour of potential respondents to administrative or geospatial data that characterise the area in which the sample unit resides. A previous practitioner guide has dealt with the range of options open to survey managers who are seeking to integrate survey and non-survey data sources (O'Toole et al., 2025). However, it only briefly touched on the applicability of these types of linked data to inform ASDs in surveys. This section will discuss each type of linked data in turn and explain its applicability to ASDs, based on their availability, linkage level and usefulness for stratification. In turn, the theoretical basis for using each of these types of data is explained based on the concept of tailored survey designs (Dillman, 2011).

2.1.1. Sampling frame data

Often, data present in the sample frame can serve as a source of auxiliary information. Although this is not common in the UK, some sampling frames are informative. An example is the Growing Up in the 2020s survey, which uses the National Pupil Database as its sample frame (Anna Freud, 2026). This data was then used to target sample members, most notably, based on access to Free School Meals. In this case, higher incentives were allocated to students eligible for Free School Meals to encourage participation. Thus, sample frames themselves can often provide sufficient auxiliary information to inform a targeting and intervention strategy.

In the Netherlands and Scandinavia, the availability of administrative sampling frames has resulted in the use of sample frame data to inform sample stratification. However, in the UK, many general population surveys are carried out using the Postcode Address File (PAF), a list of all the addresses in the UK. This results in limited data for stratification, because it is not possible to link the sample frame to individual-level characteristics or aggregated geo-spatial data at the LSOA level (Keyes and Smith, 2026). Sample frames in many European countries are based on population registers. Population registers contain granular administrative data (i.e. education level, gender, ethnicity, etc.) that can provide valuable insight into non-response, resulting in more effective stratification. There are some notable surveys in the UK which use more informative sample frames, including those that contain valuable administrative data

like the GP Patient Survey, the England Annual Drivers Survey or the Hospital Utilisation Survey. These could conceivably provide opportunities for ASD implementation. However, many general population surveys of the UK continue to rely on the PAF. This implies that many surveys are limited to the use of aggregated geo-spatial data without the benefit of registers. In the next section, we will discuss the opportunities available with the significant availability of aggregated geo-spatial data in the UK. However, it is important to highlight that they represent fewer opportunities than detailed, granular, and robust register data.

2.1.2. Geospatial data

General targeting of nationality, regionality or ethnicity

The UK presents an interesting case where it is split into different nations. As a result, survey agencies typically tend to address each nation differently. Scotland, Wales, and Northern Ireland, because of their devolved governments, often present different policy contexts for health, education, and even taxation. As such, survey managers can choose to emphasise different aspects of their survey in their invitations to participate and indeed in their questionnaires. For example, invitation letters in the Labour Force Survey are adapted to the region in which people reside (ONS, 2026), to reflect the importance of participation within that region. Similar actions are taken to emphasise inclusion in different regions and localities, especially in sample boost surveys and in surveys of particular countries in the UK (Welsh Government, 2025).

However, this is not limited to invitation letters. There are explicit differences in the questionnaires associated with each country. The question of National Identity is posed differently across the Nations of the UK. Indeed, the Ethnicity harmonised standard sets out specifications for how to ask about ethnicity differently across the constituent nations of the United Kingdom (Government Statistical Service, 2011). This implies that questions regarding identity and ethnicity may need to be changed or altered in different countries, regions or areas, where the nuances regarding ethnicity and national identity have different connotations.

Aggregated census data and targeting based on addresses

In the UK, adaptive survey designs often rely on aggregated census and other area-level data rather than individual-level data. This is because most survey sample frames contain only addresses. By linking each sampled address to the characteristics of its surrounding area, survey agencies can use area-level information to help target fieldwork. In England, the smallest geography for which much of these data are available is the Lower Layer Super Output Area (LSOA). Each LSOA contains between 400 and 1,200 households, which in turn are comprised of between 1,000 and 3,000 people (Lloyd, 2016). Similar LSOA units are used in Wales for aggregated small area data. In Scotland and Northern Ireland, these data are available for each data zone (equivalent of LSOA for Scotland) (Flowerdew et al., 2007) and super data zone, equivalent of LSOA for Northern Ireland. Moreover, LSOAs are constructed so that there is little heterogeneity within LSOAs, which increases the operational capacity to use them to characterise sample units. Although this is less informative than individual-level data, it does offer an option for the stratification of the sample.

Numerous variables are aggregated at the LSOA level in England. Most notably, it is possible to characterise the composition of an LSOA by sex, age and ranking in the Index of Multiple Deprivation (IMD). However, the ONS provides data on numerous other variables at the LSOA level via the ONS NOMIS database (Department of Work and Pensions, 2014). Considering characteristics specifically relevant to ASDs, information on household sizes, family types, and urban/rural classification is especially valuable.

The Nomis database contains a significant amount of data about a relatively small area where an individual resides. LSOAs are also designed with the goal of social homogeneity, minimising the information lost by aggregation (ONS, 2024). As such, it can be leveraged to develop relatively complex models to identify LSOAs in which non-response is more likely. These data are limited in that they can only provide (at best) an indicative estimate of the overall characteristics of the neighbourhood. As such, while recognising the significant opportunity the availability of such data at the LSOA level represents, it is also important to understand its limitations when developing an ASD in the UK.

2.1.3. Administrative data

Another informative source of data that could be linked to sample frames is administrative data. These are data that generally take the form of registers based on individuals' interactions with government organisations (e.g., the NHS). In some European countries like the Netherlands, Finland or Sweden, it is possible to access data through comprehensively linked registers which include data on Labour market activity, housing, as well as live events like the birth, marriage and death of the sample unit (Laugesen et al., 2021; Prins, 2017). These administrative records are often used as sample frames for surveys in these countries, providing comprehensive individual-level information. This further facilitates the creation of detailed models that can estimate the probability that an individual will respond to a survey.

In the UK, administrative data can be made available to researchers but is highly restricted. Often, administrative datasets are not available for use as sample frames, which limits their utility. As a result, most forms of administrative data have limited applicability for targeting survey respondents in the UK. However, in some cases, particularly in health surveys, researchers have leveraged National Health Service (NHS) data to implement ASDs (Elliott et al., 2023; NHS, 2025). This contains data on any patient engagement with the NHS, based on hospital and GP data. The mixed-mode GP Patients Survey is an example of a study using such data. Whereas all sample members aged 70 or older received a paper questionnaire, only half of those under 70 received one, and the remainder completed the survey online.

Notably, in those countries with population registers, where register-style data have been used to support ASD, they have been useful in characterising different strata within the sample. A demonstration of the efficacy of administrative records in calibrating an ASD can be drawn from the Netherlands. The Dutch Health Survey (Case Study 1) used register data on the age, income level, and ethnicity of potential respondents to cluster the sample into strata (Van Berkel et al., 2020). A similar process

was carried out in the Dutch Labour Force Survey (Van Berkel, 2022). These approaches have been shown to considerably reduce the survey's coefficient of variation of the response propensity.

2.1.4. Digital trace data and modern forms of data

With the advent of social media and the move of many activities online, there may come the opportunity to use new forms of data, also called Digital Trace Data (Stier et al., 2020) to generate targeted strata. As this is an emerging area, it has not been applied at a large scale to ASDs. This data, if linked to a sample frame, could provide useful information on the best method for targeting cases. For example, an individual with multiple social media accounts may be more likely to complete a web survey than one who does not engage with social media at all. Digital trace data, such as GPS and web browsing behaviour, could also be used to send location-based survey invitations via geofencing or to schedule them based on app and browsing behaviour. More research is needed to explore the use of this data in the context of ASDs.

2.1.5. Commercial data

In addition to publicly available data, commercial data is available for use through a license, usually including information on the behaviour and purchasing history of potential respondents. Examples of this data include the Acorn, Paycheck, and Streetvalue datasets from CACI, or Mosaic from Experian. These are examples of commercial geographic datasets that can be linked to the addresses of potential respondents and are specifically designed for effective segmentation of the UK population. This commercial data may include characteristics related to factors like health, household income, or house prices in a particular area. For example, commercial data often contains information on the commercial behaviour of sample units or the general commercial behaviour in a specific area.

There are several advantages to these types of data. First, they are flexible, as they can be used to supplement LSOA data based on respondents' addresses. Equally, there is a wide variety of variables describing numerous different characteristics that feed into this process. It is also notable that these data have been designed by companies like Experian and CACI with the specific goal of segmenting the population.

However, there are several disadvantages associated with these types of data. This includes the fact that they are costly to acquire. Any cost allocated to data acquisition is a financial resource that cannot be allocated to other aspects of the survey.

Finally, the quality of such data might vary. There is little rigorous publicly available research which can guide survey managers in evaluating the quality of these data. Although it is difficult to assess the quality of commercial data, it has been used in several surveys in the UK (DESNZ, 2025; HMRC, 2025). This suggests that these data have proved useful in identifying non-response as a supplement to publicly available data.

2.2. How non-survey data can inform stratification

Ultimately, the primary purpose of the data listed in section 2.1 in the context of ASD is to stratify the sample efficiently. The process of stratification depends significantly on the data available, its applicability to stratification, and the preferences of the survey manager. The use of non-survey data has become more relevant in circumstances where other sources of data are dwindling due to evolving trends within the survey industry (e.g. shifts to online data collection). For example, there is a reduction in available survey paradata, such as observational or contextual data, which would previously have been collected in face-to-face interviewing but is impossible to collect in surveys that have moved online.

However, the process of stratification also depends on the type of ASD being carried out and the type of survey. Targeted Survey Designs that utilise a static approach to targeting and are decided in a preliminary planning stage, have to rely on non-survey data to guide whom an intervention will target and why. In this planning stage, predicted response propensities must be generated based on observed relationships from a similar survey or previous versions of the survey. On the other hand, in Responsive Survey Designs that rely on an intervention following initial phases of data collection, survey managers can use data on response propensities from prior phases to guide interventions in later phases.

In all cases, non-survey data as discussed in the previous section is becoming increasingly relevant for both Targeted and Responsive Survey Designs. In the next section, we will elaborate on this point and explain how auxiliary data serves as the basis for stratification.

2.2.1. Data as the key to stratification

The identification of strata in the sample depends on the auxiliary data available. The most readily available examples of ASD auxiliary data have tended to come from data, which is generated by the practitioner, either from previous waves or from data generated from the process of doing the survey. To illustrate the importance of these data to the ASD framework, we will consider these examples and then explain how non-survey data can provide similar support for stratification.

An example where such data is readily available is the use of data from respondents in previous waves of panel studies (Lynn, 2017). After the initial wave is complete, the target sample consists of individuals who have previously been surveyed. Therefore, survey data on the respondents from this previous wave are available and can be used for stratification and targeting. An example of previous survey data being used for an ASD comes from the NatCen Online Panel, which recruited members from participants from the British Social Attitudes Survey. Based on data on their prior participation in the British Social Attitudes Survey, sample units were differentially targeted to achieve an improved R-indicator (Jessop et al., 2019). Using prior information, individuals in under-represented groups who were moderately likely to respond were placed in a higher-priority strata.

Another option is the use of survey paradata to implement ASD. Paradata refers to secondary information created as part of data collection, such as contact history, web survey behaviour or interviewer observations. Wagner et al. (2012) demonstrated their use in the US 2006-2010 Survey of Family Growth. Paradata was used to evaluate interviewers' responsiveness to case prioritisation, to classify sample units by their likelihood of eligibility for the survey, and to adjust for non-response bias using a statistic similar to an R-indicator. In all three cases, they showed that a responsive approach based on paradata succeeded.

Traditionally, targeting within surveys has relied on paradata based on data collected from the interviewer or prior survey data (Tourangeau et al., 2017). Although these approaches are not within the purview of this guide, they provide important examples of how data can be leveraged effectively to create strata based on the principles laid out in (Schouten et al., 2017). However, most surveys do not have prior survey data on which to draw information, and more surveys are moving online (Dillman, 2017), leading to less available paradata. This, combined with the significant reductions in response rates discussed in section 1, has led to an increased focus on non-survey data.

2.2.2. Stratifying a sample based on linked non-survey data

The question then remains: what is the best approach to stratifying a sample based on the available non-survey data? To gauge how best to stratify, Schouten et al. (2017) suggest that three key goals should inform the creation of strata. First, the strata should have a meaningful impact on estimates of key survey outcomes; the key outcome should be significantly different between strata. Second, the strata should be responsive to different recruitment strategies. Third, the cost associated with the strategies for some strata should be lower.

There are two primary ways to stratify a sample. The first method is an informal approach to stratification using prior experience of non-response within similar surveys to stratify the sample, most typically a subgroup based on one variable. Alternatively, and more pertinent in the context of this guide, they can use a formal modelling approach to identify the strata most likely to exhibit non-response. This decision has important implications for ASD because it determines the scope for optimisation, and therefore the possible efficiencies that the ASD can create.

Informal approaches to stratification

Informal approaches are often used in Targeted Survey Designs where there is no data from previous waves to calculate response propensities. However, though no formal modelling takes place, it can still rely on non-survey data to determine subgroup stratification. Examples of this approach that use non-survey data include the English Housing Survey, where different leaflets were provided to sample units depending on their housing tenure or the Childcare and Early Years Survey of Parents, where those in the most deprived quintile were allocated an increased incentive.

Response propensities and formal approaches to stratification

The data-based approach to ASD can be useful in multi-phase surveys like the Dutch Health Survey (Van Berkel, 2022), a multi-wave survey like the Millennium Cohort Study (Ipsos MORI, 2017) or a survey where there may be data from previous iterations of the survey, like the HMRC Customer Service Survey (HMRC, 2025). As a result, these approaches tend to predominate in Responsive Survey Designs, but they can also be applied in Targeted Survey Designs like the Generations and Gender Survey. The requirement is the availability of auxiliary data (such as non-survey data) that are associated with non-response and are available for all sample members. Variables drawn from the auxiliary data can then be used to model non-response, and strata can be created based on these models. Response propensities can then be used to develop targeted interventions in the survey. This approach also enables stratification based on multiple variables rather than targeting a single subgroup based on a single identifying characteristic.

There are numerous ways to stratify the sample based on prior data. The simplest method to stratify a sample with a formal propensity model is to use a regression-based approach. Rather than targeting a single subgroup characteristic, regression allows targeting multiple characteristics. This process involves taking the auxiliary linked-data variables and regressing them on an individual's response. The dependent variable in the regression model is a binary variable indicating whether an individual responded. Typically, the process for predicting non-response uses logistic regression, but other methods such as probit, log-log, or linear probability models can also be applied. The Transformed Labour Force Survey (TLFS) in the UK is a useful example of this approach (Fraser, 2024). Initially, the entire sample was sent a web survey. Logistic regression was used to model the association between area-level characteristics (age and deprivation level) and non-response at the area level. This facilitated the creation of estimates of the effects of age and deprivation on non-response, which could be used to develop area-level response propensities. Areas defined as less likely to respond based on their age profile and deprivation level were allocated to the treatment group and received a Knock-to-Nudge design (see section 3.2). Similar approaches were used to target follow up reminders in the HMRC customer survey and the DCMS participation survey.

Another modelling strategy is to use machine learning to predict which individuals are unlikely to respond based on their characteristics. Popular methods include classification trees, random forests, or neural networks (Küfner et al., 2022). However, it is notable that in most cases, these methods fall short of the accuracy of logistic regression (Kolenikov and Buskirk, 2015). However, the simple method for creating defined strata based on the data provided by classification trees has led some ASDs to use this approach. Most notable of these is described in section 5.1 of this guide, the Dutch Health Survey, where classification trees were used to sort individuals by their likelihood to respond to surveys based on past survey response data and auxiliary register data (Van Berkel et al., 2020). More advanced approaches, which postulate the use of more complex forms of classification mechanisms, have been theorised but have not been utilised in practice yet (Collins, 2025).

3. The process of informing, intervening and optimising an ASD

The likely improvement in data quality relative to the cost involved should ideally inform the decision to adopt an ASD. Typically, the focus is not on increasing participation but on improving representativeness. Given the emphasis on representativeness, ASDs are not simply an additional complexity to be added to a design (Groves and Heeringa, 2006; Schouten et al., 2017; Tourangeau et al., 2017) However, rather a framework for allocating resources to maximise the survey's representativeness within fixed cost constraints. In any ASD, the guiding principle remains to improve the quality of the data collected at the same cost as a standardised design. If the design fails on this point, it represents an ineffective intervention and requires modification, alteration or removal.

3.1. Informing an ASD: Experimentation, simulation and the evidence base

To date, few examples of large surveys that implemented an ASD have been published as case-study reports or peer-reviewed papers, especially in the UK. Unfortunately, the ASDs that have been implemented in the UK have offered sparse detail on the process, the process of stratification, and the results of the ASD. As a result, survey methodologists and survey managers have relied on simulation or experimentation to provide evidence for the efficacy of an ASD.

In several cases, researchers have used simulation or experiments to illustrate the possible benefits of an ASD with respect to a particular survey (Tourangeau et al., 2017). Internally, survey agencies and researchers tend to implement extensive experimentation in either cross-sectional or panel surveys. There are numerous examples of instances where experiments have highlighted the possible benefits of ASDs and led to the introduction of ASDs. These include the Childcare and Early Years Survey of Parents in the UK (Huskinson et al., 2024), the Next Steps Survey (Ipsos MORI, 2024), and the REACT study (see case study 3).

Simulations have provided an evidence base on the impact of implementing an ASD on survey performance. Several simulations have highlighted how ASD can mitigate the impact of budgetary constraints. Indeed, one of the Case Studies in this guide illustrates how cost savings can be achieved in the Italian Population Census by targeting face-to-face follow-ups (De Vitiis et al., 2024). Similarly, Watson and Cernat (2023) used a simulation on data from Household, Income and Labour Dynamics in Australia and Understanding Society in the UK to demonstrate the efficacy of an ASD to improve the balance of the sample (based on the R-indicator) while modelling the cost of survey implementation. They showed that making fieldwork decisions at the household level rather than the individual level maximised efficiency in reducing costs while maintaining the R-indicator. However, simulations have also illustrated the possible benefits for data quality. Einarsson et al. (2024) illustrated that ASDs could be applied to address the difficulties associated with cross-national surveys wherein there are differential response rates between countries. The study simulated an ASD in six

countries to minimise the Coefficient of Variation among survey respondents. They showed that an ASD can reduce non-response bias but that its effect depends on the covariates available in the auxiliary data.

3.2. Interventions and the role of data in their implementation

Once the sampled units have been stratified, the next step is to develop an intervention that will elicit a greater response among the strata of interest. There is a depth of methodological theory concerning why individuals respond to surveys, and based on this, the reasoning behind the use of different types of interventions to stimulate response (Gideon, 2012). With respect to ASD, the most salient theoretical approach is Leverage Salience theory, posited by Groves and Couper (1998), and extended to tailored or targeted designs by Groves et al. (2000).

In the context of ASD, the most appropriate intervention depends on which requires the greatest leverage for the least cost. Naturally, this depends on the strata of interest, which in turn depends on the auxiliary data used for stratification. The most suitable intervention is the one that raises response amongst the strata of interest for the least cost.

The basic foundation of the theory is that leverage is the centrality of a survey characteristic to a respondent. Salience refers to the extent to which this aspect is advanced. In this context, the leverage of different survey topics, different aspects of the design and other factors may differ across sample units. In this context, it is logical to treat cases differently depending on the leverage they assign to particular aspects of the survey design. There are many ways that interventions that increase the leverage or salience of a particular survey can be tailored to a stratum.

To illustrate the options available to a survey manager regarding the best intervention, this section will describe the most prolific examples of interventions and explain when they are most useful. For further detail on this, Sladka and Lynn (2025) lay out the efficacy for the different procedures for targeting groups. However, it is noteworthy that survey managers do not typically comment on the effectiveness of different interventions or, indeed, why they may have implemented a specific intervention. Therefore, it is striking that there is a need for greater evidence to inform when particular interventions are appropriate and why.

Types of intervention

Differential fieldwork rollout

One relatively straightforward intervention involves varying the timing of the survey's fieldwork rollout for certain strata. In the Millennium Cohort Study, participants predicted to have a low propensity to respond were assigned to the earliest fieldwork stage. The aim was to increase the response rate amongst those from deprived areas and areas with greater Asian populations by maximising time in the field for these cases. Assignments which had a high proportion of respondents from the Asian

community were also more likely to be assigned a female interviewer, as it was judged that these populations might be more amenable to responding to a female interviewer.

In this case, prior wave data was used in conjunction with aggregated geo-spatial data to prioritise cases within fieldwork. Similarly, the example illustrates that the characteristics can provide important insight into the efficacy of an intervention. Asian households may have demonstrated higher response rates to female interviewers in previous waves. This shows how data can be leveraged to illustrate not only whom to target, but how to tailor the intervention to maximise response.

Invitation Letters

Targeted invitation letters can also be used to increase response rates. Dillman (2011) lays out that survey tailoring can either increase response rates, lower response costs, or increase trust. Invitation letters fall into the category of interventions that increase trust (Manzo and Burke, 2012). They often bear the seal of a government organisation, which increases the survey's legitimacy and may therefore be useful in attracting responses from particular sample units. As previously discussed in section 2.2.2, there is also scope to tailor this credential to different nations, regions or localities, as occurs with the Labour Force Survey in the UK and the English Housing Survey. In the latter case, invitation letters were targeted toward sample units based on the housing tenure, where private renters, owner-occupiers and social renters were sent pictures and informative details which were considered “particularly relevant to each group” (Ministry of Housing Communities and Local Government, 2024).

Invitation Letters can therefore be used where the survey manager observes an opportunity to illustrate the benefits to a particular community of participating in a survey. Geo-spatial data can describe the parts of the country which are most reliant on government spending as a subsidy for those communities. This can inform the type of language used in these invitation letters. Equally, where there is a significant difference in identity between nations or between regions, the lan

Follow-up reminders

Another popular method, used in multiple UK surveys, is to provide certain strata with more follow-up reminders. The theoretical basis of a follow up reminder can be considered similar to that of an invitation letter. Sending different groups an additional follow-up reminder for the survey, or a different type of follow-up reminder, has been shown to elicit improved response rates on several occasions. This has been used by the Attitudes to Mental Illness Survey 2023 and the HMRC Customer Survey of individuals (HMRC, 2025; Mind, 2023). Both surveys sent a further reminder to individuals with a lower response propensity.

There is significant experimental evidence that they serve as effective interventions to increase response rates in the US as well as in Europe (Manzo and Burke, 2012; Smith et al., 2019; Svensson et al., 2012). However, while there is significant detail on the use of follow-up reminders in ASDs carried out in the UK, there is little evidence base

concerning their effectiveness under different circumstances. However, they have continued to be used in several surveys, suggesting they have some effect.
It is plausible that paper follow-up reminders may increase response rates when targeting individuals from older or more deprived communities who are less able to access the internet. This is particularly the case where paper follow-up reminders are sent for web-based surveys.

Differential incentives

A common type of intervention is to tailor the incentive to an individual's characteristic. There is extensive research on the theoretical and empirical foundations for using incentives to improve response (Gideon, 2012). In contexts where those in certain strata are less likely to participate, enhancing the leverage of this group may lead to a greater response, thereby equalising response rates across strata. An example of this approach is the Generations and Gender Survey, in which the survey design targeted those in the most deprived areas with a £15 incentive, compared to a £10 incentive for the survey (Howe et al., 2023).

There is extensive experimental evidence for the effectiveness of incentives as an intervention which can increase response rates. However, the effect of incentives depends not only on the size (dosage) of the incentive but also on its sequencing (see the next section for details). Moreover, as shown in Case Study 3 detailed in section 5.3, there is scope to offer and vary incentives so that some receive a large incentive, others a smaller one, and others receive no incentive at all. The flexibility and its record of increasing response rates are clear advantages of this approach. The disadvantage is that incentives can be significantly more costly to administer to a target population than an additional follow-up reminder. For this reason, they are used sparingly.

Gaia et al. (forthcoming) have examined the role of incentives in the UK context. They describe the multitude of possibilities available to survey agents when considering incentives within their survey designs. As discussed in section 2.1, they indicate that one impediment to effective targeting of differential incentives is the lack of individual-level administrative data to inform sample frames. Despite this limitation, they point out that differential incentives have gained ground in the UK in recent years. However, they indicate that the timing of incentives is crucial to determining their effectiveness, as will be discussed in further detail in the section on sequencing.

Differential modes

One of the methods proven most effective at eliciting a stronger response is using differential modes based on the respondent's characteristics. There is a wealth of literature on the use of multi-mode surveys and their impact on response rates (Dillman, 2017; Lynn, 2020). This intervention aims to ease the respondent's burden and increase their trust by providing them with the mode they prefer.

To date, in the UK, sequential mixed-mode designs in ASDs have been used to garner increased response from those in older age cohorts by providing them with paper questionnaires as opposed to a web-based one (NHS, 2025; Verian, 2025a).

Useful examples of this method include the Attitudes to Mental Illness Survey, the Community Life Survey, and the DCMS Participation Survey. These surveys provided paper questionnaires to addresses which were predicted based on their modelling to have residents aged 65 or over, based on the LSOA of the respondent (Mind, 2023; Verian, 2025b, 2024). For an example that uses more complex register data, we can turn to the Dutch health survey, where they use linked register data to classify individuals who have a lower propensity into a face-to-face group and those of a higher propensity into a web group (Van Berkel et al., 2020). In all cases, the mode was altered to improve response rates amongst groups considered less likely to respond.

Differential modes have been used extensively in multiple contexts to tackle differential response. Often, they are used to target low propensity respondents with a mode linked to higher response rates. This is the case with the Dutch Health Survey and the Dutch Labour Force Survey, where in-person interviewers are sent to low propensity respondents to increase response rates from particular groups. However, it can also be used to tackle specific issues with response amongst particular groups. For example, older people or those from more deprived areas may be more likely to respond to a paper survey compared to a web-based survey.

Knock-to-Nudge

A method similar to a change in mode is the knock-to-nudge approach. With the increased push toward web surveys during and after the COVID-19 pandemic, there has been a need to reach individuals and gather responses through human interaction, without necessarily using a face-to-face design. One compromise is to use a knock-to-nudge approach, whereby some individuals, depending on their characteristics, receive different types of follow-up reminders; for example, some sample units receive a letter reminder while others receive an in-person follow-up. The theoretical justification for this approach is similar to that described for differential-mode design.

There is evidence of knock-to-nudge having a significant improvement in response rates and in sample representativeness in the UK and overseas, when it has been implemented (Domarchi et al., 2025). For the most part, this has been used to stimulate response from all sampled addresses or from all non-respondents. However, (Domarchi et al. (2025) mentions some cases where it has been implemented on a differential basis. There is evidence that differential use of knock-to-nudge leads to a lower Coefficient of Variation and increases the R-indicator of the survey when used in the TLFS in the UK (Fraser, 2024). These effects are not exclusive to designs which have moved online. For example, the Welsh National Survey uses a telephone mode but also provides a knock-to-nudge for addresses where there is no phone number, and has shown a significant increase in response rates among that group (Welsh Government, 2025).

In this case, the type of intervention used is designed to be effective in accessing hard-to-reach groups. Groups such as older people, who may be less likely to respond to online surveys, can be targeted through this mechanism. Groups and individuals that

are less likely to respond to web-based surveys, either due to lack of access to the internet or due to lack of IT skills.

Optimisation of interviewer allocation

When an ASD is conducted in face-to-face surveys, there may be scope to improve response rates in certain areas by instructing interviewers to prioritise some households. Wagner et al. (2012) has demonstrated that using interviewer instructions to prioritise sample units is an effective strategy. They showed that interviewers were responsive to case prioritisation and that this can reduce non-response bias. A more extensive intervention would be to provide different interviewers for households with certain characteristics. Where some interviewers are found to be more effective at eliciting response from sample units, it may be possible to allocate them to sample units which had previously been unresponsive. In the Chicago Mind and Body Study, in the third phase of their data collection, in addition to an increased incentive, they allocated only the most productive interviewers to remaining cases and waived the restrictions for gathering responses from proxy informants (Tourangeau et al., 2017). A less intensive approach is supplied by the Millennium Cohort Study, where an effort was made to allocate female interviewers to households thought to have Asian heritage.

Considering the dosage of an intervention

When implementing any of the interventions described above, it is incumbent on the survey agency to assess the extent to which the intervention will be applied within the target stratum. The higher the dosage, the greater the cost associated with the intervention. Therefore, in some cases, as in Case Study 3, the greatest incentive may be allocated to the group with the lowest response rate (Atchison et al., 2025). However, sometimes interventions can be smaller for certain groups, such as those under 18, who tend to be more responsive to incentives than their adult counterparts (Wong, 2020)

In principle, allocating resources to an intervention for individuals with certain characteristics implies allocating resources away from the rest of the sample. Therefore, the cost of the intervention is mirrored in the cost of data gathered from a standardised group. Furthermore, a larger intervention may be more likely to introduce bias in the data. Ultimately, the optimal dosage depends on the magnitude of the differential response, the effectiveness of the intervention, and its cost.

Sequence of intervention within the context of linked data

A further important consideration is the sequence of the intervention within the ASD. Schouten et al. (2017) argues that the timing of an intervention can matter just as much as the intervention itself. There is considerable theoretical discussion about why this is important to a sample unit's decision to respond to a survey. The sequencing of the intervention depends on the type of ASD being administered, the groups being targeted and the desired effect of the intervention.

Early intervention is often useful in a Targeted Survey Design with a static planning phase, where researchers seek to boost responses among predetermined groups. As such, this approach may be appealing when targeting strata characterised by geographic factors like national identity or local authority. By appealing to specific national or local policy concerns in key areas, it may be possible to enhance leverage over the sample unit, thus increasing their likelihood of response.

An intervention administered later can be useful in responsive designs where data from previous phases can be used to inform stratification. For example, carrying out a knock-to-nudge within a push to web design can be useful where the survey agencies seek to improve response amongst groups that have not responded in previous waves of data collection. Sequencing also plays an important role in ensuring that an intervention does not result in a loss of data quality, thereby avoiding effects on key outcomes due to temporal differences between those who receive a treatment and those who do not. In the same example, the knock-to-nudge runs the risk of introducing bias, as it can increase response rates depending not only on where or to whom it is delivered but also on when. This can be important when key indicators vary over time. Thus, careful consideration is needed regarding the sequencing and the method of targeting selected from the options laid out in section 3.2.

The work on incentives clearly illustrates sequencing and its importance to the efficacy of the intervention. For example, Singer and Ye (2013) have shown that prepaid incentives can be better at eliciting response compared to post-participation incentives. Targeting prepaid incentives towards a particular group may allow for reduced cost compared to an incentive for the sample while minimising the non-response associated with that group. However, Gaia et al. (forthcoming) shows that the timing of incentives can play a key role in their effect. 'Early Bird' incentives allow for improvement in early response but also may provide for improvement in overall response and provide valuable data for further interventions at later waves, though they can be costly and much of their effect is to bring forward responses from those who would respond anyway. Meanwhile, refusal-conversion incentives, after initial phases of data collection, are a more direct approach to improving response that allows for improved targeting of only those who have not responded in previous phases. However, these have often proved less effective and can run into similar issues of data quality discussed in relation to knock to nudge.

As such, the sequencing of interventions is key to their effectiveness. It depends heavily on the type of strata being targeted, the data available and the desired effect of the intervention. This can have significant implications for both the cost of the survey and therefore requires careful consideration before implementation.

3.3. Optimisation of ASDs based on non-survey linked data

The fundamental goal of an ASD is to achieve an optimised outcome, whereby the quality of the data obtained is maximised with respect to the cost incurred. The process of optimisation relies on the components previously introduced (i.e. planning, auxiliary data, stratification and intervention) combined into a single framework. Numerous

methods for optimising an ASD have been advanced in recent years. These vary in their level of complexity, the likelihood of their efficacy, their synergy with different strategies for data collection, and their dependence on accurate response propensity estimates (Schouten and Shlomo, 2017). However, they are consistent in their reliance on auxiliary variables to guide survey optimisation. As such, the processes described for optimising an ASD will be considered in the context of auxiliary data. However, it is important to note that optimisation as a process combines the processes of planning, stratification and intervention; thus, the choices regarding the auxiliary data, method of stratification and the intervention used will all inform the optimisation for a particular ASD.

Trial-and-error

The first optimisation approach is simple subgroup distinctions to guide stratification. Typically, this method is used in conjunction with univariate blanket targeting based on the informal stratification method described in section 2.2.2. Indeed, survey managers who use informal stratification to guide their ASD are restricted to using a Trial-and-Error approach. Different strata are allocated different interventions, which are effective based on prior survey research or the surveyor's experience. Costs in this scenario are kept within budget through ad hoc budgetary decisions by the survey manager.

The improvement in response resulting from a trial-and-error process is unknown and may, in fact, be negative until the fieldwork results are analysed. This method does not have a set process; therefore, other survey managers may struggle to reproduce it in different circumstances. This approach leaves scope for survey agencies to apply their own knowledge and experience to survey data, but it leaves no room for some of the complex models described in section 2.2.2. Therefore, this approach relies least on auxiliary linked data to build models of non-response propensity within the sample.

However, it is notable that, as Schouten and Shlomo (2017) explain, partial R-indicators based on auxiliary data can be used to implement structured trial-and-error approaches for stratification and optimisation of the ASD. They articulate that the efficacy of the design depends on the "auxiliary variables from frame data, administrative data or paradata that are relevant to the key survey variables" (Schouten and Shlomo, 2017, p. 81). The trial-and-error approach is the most commonly used by survey managers in the UK at the time of writing. An example of its implementation can be shown in Case Study 3.

Stopping rules

The second optimisation approach used in ASDs is the Stopping Rule. This approach involves efforts to raise response rates within a certain stratum until a minimum target is reached. The level of intervention, therefore, depends on the target. This target depends on a function of some measure of survey quality (e.g., R-indicator, Coefficient of Variation, or response rate). Rao et al. (2008) proposed the concept of stopping rules within targeted designs as a methodology by which these responsive survey designs, as well as static ASDs, could be optimised.

A simple approach is shown by Lundquist and Särndal (2013), in their use of an ASD in the Swedish Living Conditions Survey. They set a target response rate of 60%, at which they will stop collecting data from each stratum in the sample. However, more complex applications of stopping rules have also been considered. For example, Wagner et al. (2023) describe the implementation of a stopping rule that targets hard-to-reach groups while accounting for the added cost to reduce error in the estimates. The study showed a significant decrease in error from estimates derived from the survey. However, to our knowledge, stopping rules have not been implemented in UK surveys to date, despite their proven efficacy.

Propensity-based prioritisation

The third approach is to use modelling to allocate case priority based on the likelihood of survey participation. Survey respondents who are deemed less likely to respond will receive less effort or a lower dosage than those considered more likely to respond. The goal in this case is to equalise response propensities across strata within the sample. However, it is unlikely this goal will be fully achieved. Rather, the aim is to significantly increase response rates among certain strata of the sample to develop a more representative sample. Peytchev et al. (2022) provides a useful illustration of this approach, in which they develop a model that prioritises reducing bias rather than simply reducing response rates. Data from the High School Longitudinal Study of 2009 showed a strong ability to reduce bias with this type of approach.

An example of this approach in the UK is the TLFS. The survey used logistic regression to estimate the probability that an individual responds to the TLFS, depending on their LSOA of residence. The average age and deprivation decile of the LSOA are used as predictors, which facilitated the classification of respondents into strata. Individuals in particular strata are considered more likely not to respond and are allocated to the treatment group. Those individuals are then assigned an intervention if they fail to respond after the second contact is made with them (Fraser, 2024). Similar approaches have been carried out in several cross-sectional surveys in the UK (Verian, 2024).

This method ensures that, to some extent, the quality of the data collected will be improved, as it will be more representative than a standardised design. However, it is sensitive to the accuracy of the non-response model. This implies that the availability of linked data is crucial to this approach.

Mathematical optimisation

The final and most methodologically complex method of optimisation is a mathematical optimisation of the ASD. In this case, the allocation of strata to the intervention, the role of quality statistics, and the cost are all addressed within the same decision problem. These are then optimised through mathematical derivation. The parameters are fed into a computer programme (e.g., the Alabama package in R) that optimises the survey design according to the parameters set by the survey agency. This case is likely to yield the greatest improvement in the ASD's efficiency. However, this approach is most heavily dependent on the accuracy of the non-response models and the assumptions made by the survey manager.

An example is shown in the Italian Population Census (case study 2), which combines case prioritisation with mathematical optimisation. Following the initial web phase of the simulation, face-to-face is allocated with greater probability to the higher non-response strata through mathematical optimisation. This includes consideration of a minimum response sample size and a maximum possible face-to-face allocation. The study illustrates that significant cost savings can be generated. Indeed, mathematical optimisation is guaranteed to improve data quality by design, but its disadvantage is that it is inflexible and sensitive to parameters, making it impractical in certain circumstances (Van Berkel et al., 2020). Moreover, this approach requires considerable technical skills, which illustrates the benefit of working with statisticians and survey methodologists to implement these forms of complex designs.

However, it is important to note that other methodologies can be implemented within the framework of an ASD. For example, Ma et al. (2025), using the Dutch Health Survey, shows that a Bayesian framework can reduce the coefficient of variation for estimates from the survey.

4. Recommendations

Having outlined the theoretical context for implementing an ASD in the UK, it is appropriate to provide recommendations for survey agencies and survey commissioners. These recommendations can be grouped into two categories. First, for survey commissioners to facilitate improved implementation of ASDs; second, for survey managers to improve the implementation of ASDs.

4.1. Recommendations for survey commissioners

One of the major obstacles to implementing ASDs in the UK is the limited availability of linked data, particularly detailed household and individual-level administrative data. Where survey agencies are working on behalf of a survey commissioner who has access to such data (e.g., NHS, Department for Education, HMRC), more effort should be made to facilitate access to it for sampling and ASD purposes.

Beyond this, survey commissioners and data administrators should explore ways to improve the current UK data landscape. One key challenge to tackle should be easing access to administrative data and expanding the possibilities for data linkage. Reducing the hurdles to accessing administrative data, as well as enabling faster access, could significantly increase the use of available data. Additionally, exploring the use of administrative data as a sampling frame could enable more efficient ASD designs. As the government relies on many of the surveys discussed in this guide to inform policy, improving data accessibility should be given greater priority.

In tandem with this approach, further training and opportunities for sharing experience should be provided. ASDs can be complex and rely heavily on alternative data sources. Better knowledge of possible ASDs, as well as available data, would allow for more efficient data collection designs. This could also be achieved through training covering

these topics, as well as workshops where researchers can share experiences of what works.

Finally, guidance on whether an ASD is viable or cost-effective would be helpful for survey commissioners. Survey agencies may advertise ASD as an innovative way to improve data quality or save costs, but it can be hard to evaluate. Publishing results from previous studies as well as evaluations of different ASD strategies would help guide the decision-making process. Moreover, they should be carried out only when the appropriate auxiliary data is available to survey agencies to improve survey data quality within a given budget constraint.

4.2. Recommendations for Survey Agencies

Although this section describes specific recommendations for survey managers within agencies, the most important and overarching recommendation of this guide is that survey managers should involve statisticians and methodologists within the agency to work in collaboration with the data collection team to design and implement an ASD. Most surveys to date that have used an ASD have employed the trial-and-error approach described in section 3.4. However, as the challenges to participation and costs increase, it will be necessary to consider more systematic strategies for ASD. Considerable theoretical research is being conducted on the use of various optimisation methods (Ma et al., 2025; Van Berkel, 2022). As discussed in section 3.3, more advanced approaches to the optimisation of ASDs exist and often lead to better outcomes. Unlike informal trial-and-error approaches, these approaches provide a prospect for a guaranteed increase in the representativeness of the data collected.

This guide has demonstrated the importance of having non-survey data available when implementing an ASD. As such, survey agencies should seek to leverage the data at their disposal insofar as is possible in the context of ASDs. As can be seen in the appendix, many ASDs limit their stratification to deprivation based on the IMD, and there is scope for survey agencies to go further even within the context of current constraints in the UK context. Such an approach would lead to Survey Agencies increasing the use of the significant data available to them in the NOMIS database, as well as other possibilities that may be present when dealing with specific partners like the NHS. Our overview of ASDs also suggests that administrative data should be seen as complementing survey data, rather than replacing them. To maximise the potential for ASDs in the UK, a more formalised framework for Survey Agencies in their approach to gathering and using non-survey data would be advisable. A structured approach which allocates time within projects to analyse and understand which non-survey data sources can be linked to the sample frame, and what can feasibly be planned, would be advisable as a rudimentary process for guiding ASDs in the UK. A checklist design phase of the survey could provide useful background for survey managers considering the implementation of an ASD. A sample checklist is provided below.

- What problem is ASD intended to address?
- What auxiliary non-survey data can be linked to the sample frame?

- How resource-intensive is the process of linking the non-survey data and deploying the ASD?
- Are these data useful for stratification or choice of intervention?
- What interventions are feasible and effective in this case?
- How will strata and interventions be determined?
- How will dosage and sequencing be decided?
- Will the ASD be deployed as an experiment or observationally for specific (or all) subgroups?
- How will the effectiveness of the ASD be evaluated?
- How will the cost-quality trade-off be determined?
- How should the results be published transparently?
- Is an ASD worth the effort?

Furthermore, survey agencies should be more open regarding the efficacy of different interventions and approaches within ASDs. In many technical reports in the UK related to ASDs, there is no detail regarding the effectiveness of treatments. Publishing either the perceived or measured effect of an intervention would allow the development of an evidence base in the UK on the impact of different interventions. This will ultimately lead to better survey designs and outcomes for the entire sector. Overall, effective ASD requires not only access to linked data, but also methodological expertise, operational planning, and clear evaluation of whether the benefits outweigh the added complexity.

5. Case Studies

To provide additional context to the discussion and description of ASDs, we will now present three case studies of ASDs. Each highlights the importance of different factors within ASDs. As such, the case studies are somewhat different in their exemplification of ASD. However, in each case, the scenario illustrates how data quality was maximised based on the use of interventions to improve response amongst particular strata, thus improving the quality of the data.

5.1. Dutch Health Survey

This is a summary of the ASD design implemented in the Dutch Health Survey based on the work of Van Berkel et al. (2020).

Context

The Dutch Health Survey has been running since 1981. Up until 2016, the Dutch Health Survey was run as a standardised design which did not employ interventions to stimulate response rates amongst targeted strata. In 2016, amongst several policy reforms, Statistics Netherlands decided to consider ASDs as a standard design choice. Based on this approach, the Dutch Health Survey, along with other surveys in the Netherlands have shifted towards an ASD. The purpose of the Dutch Health Survey is to provide an overview of health, contacts with medical practitioners, lifestyle choices and preventative behaviour amongst the Dutch population. Statistics Netherlands used comprehensive Dutch register data to inform its targeting approach. The survey follows a 2-phase approach. An initial web interview was implemented, followed by a face-to-face phase. Prior to 2016, the face-to-face follow-up had been allocated randomly to non-respondents, but from then on, it was allocated in a targeted fashion. As a blanket incentive, all participants were entered into a raffle for iPads.

Sample frame and Sample

The sample frame for the survey is based on Dutch register data with comprehensive data on the age, income, gender and geographic residence of the individual. These were used to carry out the targeting. The gross sample size consisted of 15,000-20,000 people. In total, 9,500 respondents responded to the survey.

Stratification approach

Individuals were stratified using a classification tree model. The classification tree was developed based on variables that were shown to affect response rates (e.g. ethnicity, income, regional characteristics). The higher up the classification tree that the branching occurred, the greater the level of importance associated with the variable in question. The classification tree first branched by ethnicity, age, income and whether the individual resided in an urban or a rural location. Overall, the sample frame was divided into nine strata.

Intervention approach

The intervention in this case involved a differential mode depending on the characteristics of the individual being surveyed. Data for most individuals in the sample was collected using web surveys. Those allocated to the treatment strata who had not responded after two follow-ups would receive a visit from an in-person interviewer.

Optimisation

The survey aimed to minimise the Coefficient of Variation while remaining within the capacity to provide face-to-face interviewers. The survey tests two methods: the first is described as a case prioritisation approach and the second as a mathematical optimisation approach. Additionally, the case prioritisation approach is also compared to a standardised design. The practicality of the case prioritisation approach led to it being selected as the best method for the survey.

The case prioritisation approach uses the nine strata but adds the complicating factor that the Netherlands is divided into ten interviewer regions, each with 10 to 15 interviewers. The case prioritisation approach increases the number of face-to-face follow-ups in regions where a high number of sample units fall into the low response strata. Within each region, a priority is defined after the web phase of the survey. The target group with the lowest response rate receives the highest priority. A sample of the web non-respondents is then drawn, with the highest priority placed amongst the lowest propensity response groups. The most face-to-face capacity is then allocated to the regions with the highest proportion of low-response cases.

The mathematical optimisation approach allocated face-to-face interviews purely based on the response rate of the strata into which they were stratified, to minimise the Coefficient of Variation. The optimisation approach was calibrated against two constraints. The face-to-face follow-up was limited to a certain proportion of the sample, and a minimum response rate of 53.5% was set (to ensure the sample size of 9,500 was met). The optimisation problem, including all of these constraints, was then solved using the Alabama R package (Varadhan and Varadhan, 2015).

Result

The result showed that the case prioritisation strategy led to a significantly lower Coefficient of Variation compared to a standardised design. The case prioritisation approach was shown to lead to a higher Coefficient of Variation compared to mathematical optimisation, but the difference was minimal. The ease of implementation and its practicability in a regionally divided population also made it successful. Mathematical optimisation was found to be highly dependent on the parameters set, which could change over time. This would lead to difficulties in a long-running survey like this, where the cost of altering these parameters from year to year was non-trivial. Thus, in this case, the use of a case prioritisation approach was found to be the best implementation of ASD.

5.2. Italian Population Census (Experiment/Simulation) (De Vitis et al., 2024)

Context

The permanent population and housing census in Italy has been running since 2018 as part of a modernisation process within the Italian National Statistical Institute (Istat). This paper presents a simulation study that demonstrates the efficacy of an ASD in improving the Italian Population Census. The Italian Population Census was part of an effort to place statistical registers at the core of the data collection process for censuses. Although named a census, it has moved from a traditional census to a cumulative survey that covers the whole population over a multi-year cycle. The survey integrates data from education and employment-related datasets as well as municipal population registers to characterise sample units (Bernardini et al., 2024). A proposed ASD has been developed for this survey, which forms the basis of this case study (De Vitis et al., 2024). The design aimed to use adaptive sampling to reduce the cost burden, particularly in the context of the COVID pandemic, when different modes became more common. The survey follows a sequential mixed-mode design in which a face-to-face interview always follows up to an initial web mode if a sample unit does not respond. Based on data response propensities for web and face-to-face, this simulation presents the impact of a sequential mixed-mode ASD where certain strata are more likely to be allocated a follow-up.

Sample frame and Sample

The sample frame for the survey is the Italian statistical population register. This was derived from administrative registers collected at the municipality level, which had details on the social status, employment and education of participants. The sample consists of 950,000 households from 2,850 municipalities.

Targeting approach

Individuals were targeted based on their response propensity. Based on data from the web phase of the sample, a logistic regression was used to evaluate the propensity to respond amongst the sample. The regression incorporated data on the type (number and age of individuals) of the household, the highest education level in the household, the region and type of municipality. The dependent variable was whether the individual responded to the web phase of the survey. The model was shown to be relatively effective in classifying non-response with a concordance rate of 68.7% (based on a cutoff probability of 0.5). A classification tree was also used to divide the sample based on response propensity. The classification tree approach broadly aligned with the results of the logistic regression.

Based on the classification tree, five strata were described as follows.

- Households where the highest degree is a middle school diploma.
- Households where an individual is foreign-born with a higher than middle school diploma
- Autochthonous households in Southern Italy where the highest degree is a high school diploma.

- Autochthonous households in Southern Italy where the highest degree is higher than a high school diploma.
- Autochthonous households in Central/Northern Italy where the highest degree is higher than a middle school diploma.

These groups are then demarcated by geographic area, as not all of the subgroups exist in each region of Italy. This results in the selection of 12 strata in three different regions of Italy.

Intervention approach

The intervention was intended to reduce non-response bias within the context of the budget constraint by attempting to reduce the Coefficient of Variation associated with the survey. The intervention in this context was the use of a web survey for some respondents while using face-to-face only for those respondents who were less likely to respond online.

Optimisation category

The experiment used a mathematical optimisation approach which aimed to reduce the Coefficient of Variation subject to a budget constraint and a minimum number of respondents. The R package *Alabama* (Varadhan and Varadhan, 2015) was used to implement the optimisation. This full optimisation approach was benchmarked against fully web-based data collection and then evaluated against optimisation with geographic constraints as well.

Result

Experimentation and simulation were used to investigate whether this method would improve the survey design. The simulation showed that the Coefficient of Variation was effectively constrained by using an ASD compared to all-web data collection. There was also significantly less bias in statistics at the national and municipality level in results derived from the optimised model compared to one based on other methods. However, the availability of good auxiliary information to inform the model was considered to be crucial in devising the model.

5.3. Real-time Assessment of Community Transmission-1 (REACT-1) (Atchison et al., 2025)

Context

In the midst of the COVID-19 pandemic, data concerning the transmission of the Coronavirus was necessary for a variety of policy planners. This resulted in the creation of surveys to evaluate the level of transmission in the UK and provide early warning signs of any upturn in transmission over the course of the pandemic. The REACT-1 survey was just one example of this type of survey. It was funded by the Department of Health and was implemented by IPSOS in conjunction with other stakeholders. In this study, each individual selected as part of the sample was sent a brief questionnaire to complete online or by telephone. As part of this process, they registered with the survey. Everyone who registered with the study, which was not mandatory, received a swab and

was invited to test themselves for Covid-19. More detailed questionnaires were used for individuals who provided a swab. Data derived from this process were used to calculate the R-number related to Covid in the UK. The survey involved 19 rounds between March 2020 and March 2022. This provided ample scope for experimentation, and eventually the implementation of an ASD. The ASD experiment was carried out in round 15, and implementation for the whole sample was carried out in rounds 18 and 19.

Sample frame and Sample

The sample frame for the survey was all individuals over the age of 5 years who were on the NHS list of patients at the time of the particular round of the survey between May 2020 and May 2022. Over the course of the 19 rounds of the survey, 14,036,117 invitations were issued using a random selection procedure. In total, they received 2,512,797 responses, amounting to a response rate of 17.9%. After round 12, the sampling procedure was adjusted to sample people from each of the Lower Tier Local Authorities in England. Data collected on each individual included their name, sex, general practitioner code, address, phone number, e-mail address, date of birth, and NHS number.

Experiment

In round 15, a conditional incentive in the form of gift vouchers was rolled out for all participants apart from those between the ages of 5 and 12. Participants were randomly allocated to different groups (£10, £20, £30 and control). The £30 incentive was limited to those between 18 and 32 because of the high cost and low response propensity. Participants were classified by their age, sex and Index of Multiple Deprivation. Several other types of intervention were also trialled, including changes to invitation letters and the timing/number of follow-up reminders. The maximum increase in response from these other methods was 3.1%. The results of the experiment showed a significant increase in response based on conditional incentives, particularly in the target age groups.

Implementing the ASD for the full sample

Based on the analysis of previous waves of data, age, derived from the NHS register data, was deemed the most important factor by which response was stratified. Those aged between 18 and 33 had a response rate below 5%, while those between 13 and 17, and those between 33 and 42 had response rates below 10%. This contrasted with response rates of over 20% among those over 58. As a result, older individuals (43+) were found to be more likely to respond to the survey generally and were offered no incentive. Recipients between 13 and 18 or those between 33 and 42 received a £10 incentive, while those between 18 and 33 (the lowest response rate group) received £20. Response rates among those between 18 and 42 rose to almost 15%, while those between 13 and 17 rose approximately 20%. As a result, the implementation led to a more balanced sample by age with more even response rates across groups.

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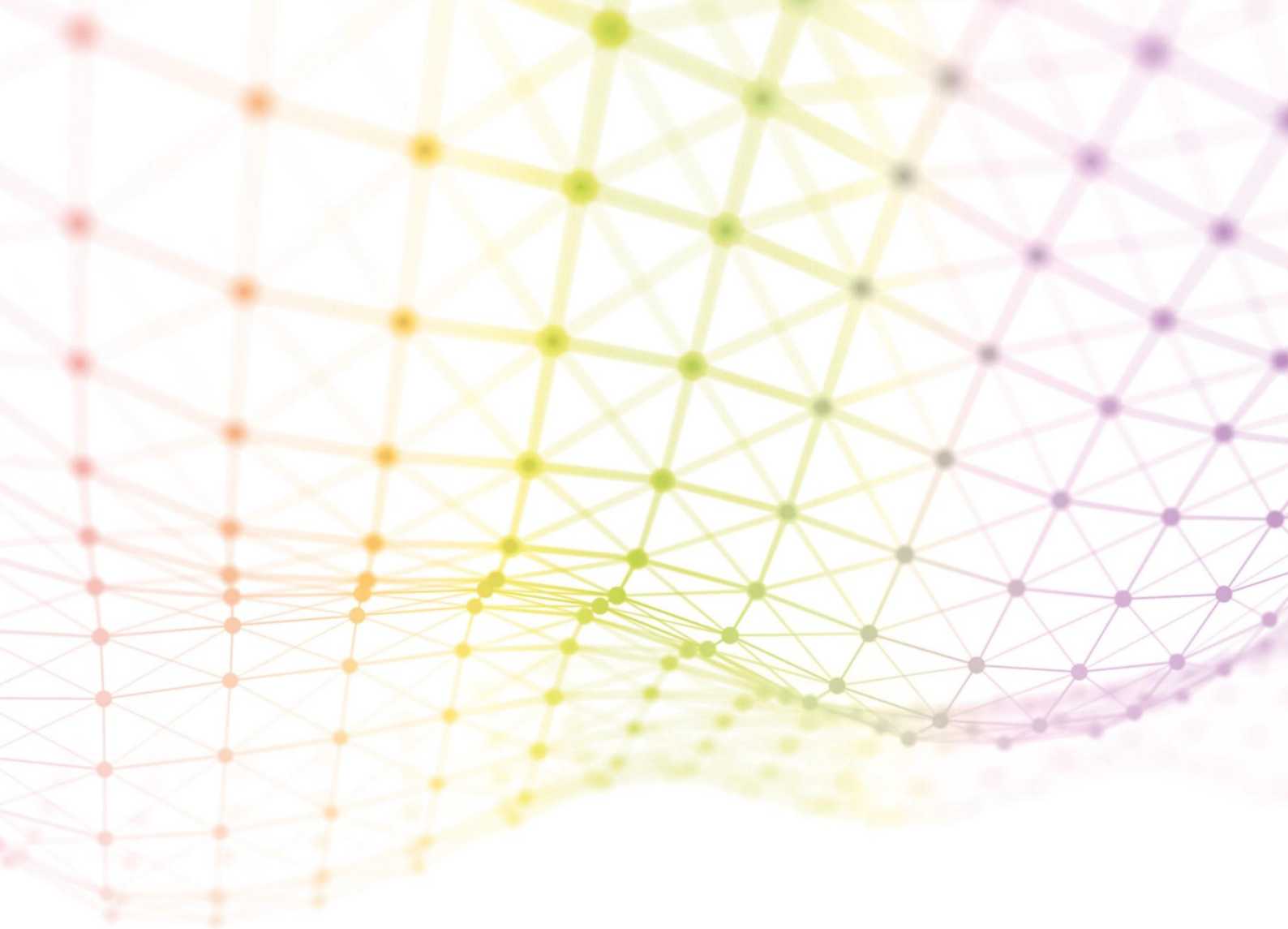
Appendix

Survey Name	Type of Survey	Sample frame	Linkage level	Mode of survey	Variables for stratification	Strata of interest	Treatment used
Millenium Cohort Study	Panel	Child benefit records	Individual	Mixed mode	Non-response from prior waves, ethnicity	Previous non-respondents, Asian community	Differential fieldwork rollout
Understanding Society	Panel	Postcode Address File	Individual	Mixed mode - CAWI +CAPI	Language, geographical location and participation history	Language, geographical location and participation history	Invitation letters targeted
English Housing Survey	Repeated cross-section	Postcode Address File	LSOA	CAPI	Housing tenure data	Different housing tenure	Information leaflets and invitation letters
Generations and Gender Survey	Repeated cross-section	Postcode Address File	LSOA	CAWI	IMD	Deprived areas	Higher value conditional incentives
Community Life Survey	Repeated cross-section	Postcode Address File	LSOA	CAWI	IMD, age demographics	Those predicted to only have residents 65+ and deprived areas	Paper questionnaire + Follow up reminders
DCMS Participation Survey	Repeated cross-section	Postcode Address File	LSOA	CAWI	IMD, age demographics, commercial data	Those predicted to only have residents 65+ and deprived areas	Paper Questionnaire + Follow-up reminder
HMRC Customer Relations Survey - Individuals	Repeated cross-section	Postcode Address File	LSOA	CAWI	Age + Commercial data	Those predicted to only have residents 65+	Paper Questionnaire and Follow-up reminder
Attitudes to Mental Illness Survey	Cross section	Postcode Address File	LSOA	CAWI	Age	Those predicted to only have residents 65+	Paper questionnaire

DESNZ Public Attitudes Tracker	Repeated cross-section	Postcode Address File	LSOA	CAWI	Age + Commercial data	Those predicted to be 65+	Paper questionnaire
Transformed Labour Force Survey	Core longitudinal and added cross-section	AddressBasePremum	LSOA	CAWI+ KtN	Age demographic + IMD data	Certain strata with more deprived areas and older demographic areas	Knock to nudge
British Election Survey (BES)	Repeated Cross-section	Postcode Address File	LSOA	CAPI+CAWI	IMD and Age	Deprived areas and age	Differential incentives
REACT study	Repeated Cross-section	NHS register data	Individual	Paper questionnaire	Age	Different age subgroups	Differential incentives (trialled others)
CEYSP	Repeated Cross-section	Child benefit data	Individual	F2F-CAWI	IMD	Deprived areas	Differential incentives
Next Steps, Sweep 9	Repeated Cross-section	School data	Individual	CAWI - Mixed-mode	Response history	Prior non-respondents	Differential incentives/ experiment on mixed mode
Children of the 2020s	Repeated Cross-section	Child Benefit records	Individual	CAPI+CAWI	Geographic region	Geographic region	Differential incentives
Growing up in the 2020s	Panel	National Pupil Database	Individual	CAPI+CAWI	Access to Free School Meals	Access to Free School Meals	Differential incentives
Early Life Cohort Feasibility Study (ELC-FS)	Repeated Cross-section	Live events data	Individual	CAPI + CAWI follow up	Region of UK/ Income level of family	Region of UK/ low socio-economic status families	Differential incentives
Omnibus survey of pupils and	Repeated Cross-section	National Pupil Database	Individual	CAWI+Paper	Free School meals	Access to Free School Meals	Differential incentives

their parents/carers							
NatCen panel	Panel	British Social Attitudes Survey	Individual	CAWI	Previous response, individual socio-economic status		Differential incentives
GP Patient Survey (GPPS)	Repeated Cross-section	GP data	Individual	CAWI+Paper/CATI	Age	Under 70 and over 60	Mode experiment
National Diabetes Experience Survey	Repeated Cross-section	National Diabetes Audit	Individual	CAWI+Paper	IMD, Ethnicity, Age	Young people, ethnic minorities and deprived areas	Paper Questionnaire vs Web questionnaire
Infant Feeding Survey	Repeated Cross-section	Live events-births	Individual	CATI+KtN	IMD	2 most deprived quintiles of LSOAa	Differential incentives
Inpatient Survey	Repeated Cross-section	NHS data	Individual	Mixed CAWI + paper questionnaire	Age	People over 80	Paper questionnaire
National Survey of Wales	Repeated Cross-section	Postcode Address File	LSOA	CAWI+KtN	Response in previous phase	People who didn't respond to CAWI	Knock to Nudge



University of Essex

University of Southampton

UKRI Economic and Social Research Council

NCRM National Centre for Research Methods

Office for National Statistics

UCL

Warwick The University of Warwick

Manchester 1824 The University of Manchester

City University of London Est 1894

National Centre for Social Research

LSE The London School of Economics and Political Science

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