Using an online sample
to learn about an offline population

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Abstract

Online data sources offer tremendous promise to demography and other social sciences, but researchers worry that the group of people who are represented in online datasets can be different from the general population. We show that by sampling and anonymously interviewing people who are online, researchers can learn about both people who are online and people who are offline. Our approach is based on the insight that people everywhere are connected through in-person social networks, such as kin, friendship, and contact networks. We illustrate how this insight can be used to derive an estimator for tracking the digital divide in access to the internet, an increasingly important dimension of population inequality in the modern world. We conducted a large-scale empirical test of our approach, using an online sample to estimate internet adoption in five countries ($n \approx 15,000$). Our test embedded a randomized experiment whose results can help design future studies. Our approach could be adapted to many other settings, offering one way to overcome some of the major challenges facing demographers in the information age.

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1 Introduction

Online data sources offer tremendous promise to demography and other social sciences (Cesare et al. 2018; Lazer et al. 2009; Zagheni and Weber 2012), but researchers often worry that the group of people who are represented in online datasets can be different from the general population. In this study, we develop a strategy for addressing this challenge: we show that by sampling and anonymously interviewing people who are online, researchers can learn about both people who are online and people who are offline.

We illustrate our approach by developing a new way to study the digital divide in access to the internet around the world. The internet has the potential to improve economic and social wellbeing through a wide range of different mechanisms, but access to the internet is highly unequal: billions of people around the world have never been online (Hjort and Poulsen 2017; World Bank 2016); people in poor countries use the internet much less than people in wealthy countries (World Bank 2016); and even within countries that enjoy high levels of internet adoption, research suggests that access to the internet can differ considerably by age, gender, income, and race (Friemel 2016; Haight et al. 2014; Van Deursen and Van Dijk 2014; Vigdor et al. 2014). Thus, the digital divide is emerging as an important dimension of population inequality in the modern world.

Reliable estimates of internet adoption are typically based on methodologically rigorous household surveys or censuses (e.g., ICF 2004; Cohen and Adams 2011). However, this rigor comes at a price: these surveys can be very costly and typically take months to design and implement (e.g., Parsons et al. 2014; Greenwell and Salentine 2018; ICF 2018; Rojas 2015). These limitations are especially problematic because internet adoption appears to be changing on a much faster time-scale than many conventional indicators of social and economic wellbeing (Perrin and Duggan 2015; World Bank 2016).

The difficulty of obtaining up-to-date estimates of internet adoption is unfortunate because researchers need to be able to measure the digital divide in order to understand its implications for inequality and opportunity; and policymakers who want to implement and evaluate strategies for making internet access more widely available rely on being able to measure the level and rate of change in the number of people who have access to the internet; for example, the proportion of people using the internet in each country is one of the key indicators for the United Nations Sustainable Development Goals.

To help address this challenge, we develop an alternative approach to estimating internet adoption that is dramatically faster and cheaper than conventional surveys: we interviewed a sample of

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1See SDG indicator 17.8.1.
Facebook users and asked them whether or not members of their offline personal networks use the internet. Our approach is based on the insight that internet users are connected to many other people through in-person social networks such as kin, friendship, and contact networks. By interviewing a sample of Facebook users and anonymously asking about the members of these offline social networks, we can learn about both people who are online and people who are not online.

Asking survey respondents to report about others is an idea that has independently arisen in many different substantive areas (see, for example, Sirken 1970; Bernard et al. 1991; Hill and Trussell 1977; Marsden 2005). In demography, the approach can be traced back to Brass and colleagues’ innovative development of census and survey questions that ask respondents about their parents, spouses, or siblings (Brass 1975). Our approach can be seen as an extension of this previous work to the situation where the goal is to learn about everyone in a population, but respondents are only sampled and interviewed online. Thus, our study is an illustration of one way to overcome many of the challenges that face the sampling and survey research community in the information age.

2 Methods

People everywhere are connected to one another through kinship, friendship, professional activities and interpersonal interactions. Our strategy for obtaining fast and inexpensive estimates of internet adoption is based on asking people sampled online to report about internet adoption among other people they are connected to in these everyday, offline personal networks. The challenge is to determine how to turn people’s anonymous reports about their personal network members into estimates of internet adoption. We now explain how we used a formal framework called network reporting to understand which quantities we need to estimate in order to accomplish our goal (Feehan 2015; Feehan and Salganik 2016a). (A detailed derivation can be found in Appendix A.)

Fig. 1 illustrates the general setup with an example. Fig. 1a shows six people who are connected together in a social network. The network relation is symmetric, meaning that whenever person A is connected to person B, then B is also connected to A. We make a distinction between nodes that can potentially be sampled and interviewed—the frame population—and other nodes. For example, a frame population might be cell phone users; the users of a specific app such as Facebook; or people who live at addresses that can be reached by postal mail. In Fig. 1 nodes 2 and 3 are in the frame population.

Fig. 1b shows the reporting network that is generated when both nodes 2 and 3 are interviewed
about the people they are connected to in the social network. The reporting network is different from the social network: the social network has an undirected edge $A - B$ when $A$ and $B$ are socially connected; the reporting network, on the other hand, has a directed edge $A \rightarrow B$ whenever $A$ reports about $B$. When reporting is accurate, there will be structural similarities between the social network and the reporting network, but this need not be true in general. The reporting network is a useful formalism that can help researchers develop estimators, understand possible sources of reporting errors, and derive self-consistency checks.

Fig. 1c shows a rearrangement of Fig. 1b that is helpful for deriving estimators from a reporting network. On the left-hand side of Fig. 1c is the set of nodes that makes reports (the frame population), and on the right hand side is the set of nodes that can be reported about (the universe\(^2\)). Drawn this way, every report must connect a node on the left-hand side to a node on the right-hand side. Thus, the total number of reports that leaves the left-hand side must equal the total number of reports that arrives at the right-hand side. Mathematically, this means that when everyone in the frame population is interviewed, we have the following identity:

$$\text{# internet users} = N_H = \left\lceil \frac{y_{F,H}}{\bar{u}_{H,F}} \right\rceil$$

The denominator of Eq. 1 is a quantity called the visibility of internet users. The visibility is the number of times the average internet user would get reported in a census of the frame population.

\(^2\)Note that a particular node can appear in both sides if it is in the frame population and in the universe.
Table 1: The two different networks survey respondents were asked about.

| Meal network                                                                 | Conversational contact network                                      |
|------------------------------------------------------------------------------|---------------------------------------------------------------------|
| How many people did you share food or drink with yesterday? These people could be family workers, neighbors, or other people. Please include all food or drink taken at any location, including at home, at work, at a cafe, or in a restaurant. | How many people did you have conversational contact with yesterday? By conversational contact, we mean anyone you spoke with face to face for at least three words. |

Intuitively, Eq. 1 divides by the visibility to adjust for the fact that the average internet user would be reported multiple times in a census of the frame population.

**Instrument design**

In principle, people can be asked to report about any type of personal network relationship that is symmetric. Thus, the specific type of personal network that respondents are asked to report about—the tie definition—is a study design parameter that researchers are free to vary (Feehan et al. 2016). To explore the impact of this study design parameter, we randomized survey respondents to report about one of two different tie definitions: the meal tie definition and the conversational contact tie definition (Tbl. 1). We chose these two tie definitions because (1) previous research led us to believe that respondents can plausibly report the number of people that they interacted with in the previous day, avoiding the need to indirectly estimate personal network sizes; (2) researchers have had success using versions of these tie definitions in previous studies (Feehan et al. 2016; Mossong et al. 2008).

Each survey interview took place in two phases: in the first phase, survey respondents were asked to report the size of their personal networks (e.g., “How many people did you share food or drink with yesterday?”; Tbl. 1). In the second phase, the goal was to obtain information about internet use among the members of each respondent’s personal network. Ideally, the respondent would provide information about every single person in her network one by one. However, this approach seemed likely to produce unacceptable levels of respondent fatigue (Eckman et al. 2014; Tourangeau et al. 2015). Therefore, in the second phase of the interview respondents were asked for information about the three members of their personal networks who ‘came to mind’ first (Fig. S1). We call these people that we obtain additional information about *detailed alters*.\(^3\)

\(^3\)We did not ask for any sensitive or personally identifying information about these three detailed alters.
Estimators

The identity in Eq. 1 would hold if we obtained a census of monthly active Facebook users. In practice, we have a sample and not a census; therefore, we construct an estimator for the number of internet users by developing sample-based estimators for the numerator and the denominator of Eq. 1. We now describe these two components in more detail.

Given information about respondents’ network sizes and the detailed alters’ internet use, the numerator of \( y_{F,H} \) can be estimated from our sample with:

\[
\hat{y}_{F,H} = \sum_{i \in s} w_i \frac{d_i}{r_i} o_i, \tag{2}
\]

where \( s \) is the sample of Facebook users; \( w_i \) is the expansion weight for \( i \in s \); \( d_i \) is the network size (degree) of \( i \in s \); \( r_i \) is the number of detailed alters from \( i \in s \) \( (r_i \in \{1, 2, 3\}) \); and \( o_i \) is the number of detailed alters reported to be online.

We calculate \( w_i \) by approximating our design as a as a simple random sample, post-stratified by age and gender. In order to use information about the \( r_i \) detailed alters to make inferences about the \( d_i \) people in the respondent’s network, the estimator in Eq. 2 makes the additional assumption that the detailed alters are a simple random sample of respondents’ personal networks. Thus, \( \frac{d_i}{r_i} \) can be seen as a weight that accounts for sampling \( r_i \) out of the \( d_i \) personal network members. Previous work on egocentric survey research suggests that, instead of being a simple random sample, network members who come to mind first may be more likely to come from the same social context, and may be more likely to be strongly connected to the respondent (Marsden 2005). Therefore, we develop two different ways to assess this assumption: first, we introduce internal consistency checks that can detect systematic biases that would emerge if detailed alters are very different from other personal network members (sec. 3.1); and, second, we introduce a sensitivity framework which enables us to formally assess the impact that different magnitudes of selection bias among the detailed alters would have on our estimates (Appendix C).

The denominator of Eq. 1 \( \bar{v}_{H,F} \) is a quantity called the visibility of internet users, which is defined as the number of times that the average internet user would be reported in a census of active Facebook users. Many different strategies could be used to estimate or approximate the visibility of internet users; here, we adopt a simple approach: we use the average number of times that a Facebook user shares a meal with another Facebook user to approximate the visibility of internet users. Mathematically, this assumption can be written
Figure 2: Estimated degree distributions for the conversational contact network (left) and the meal network (right). The vertical line on each panel shows the average. Average personal network size is smaller for the meal network than for the contact network; further, the contact network shows greater evidence of heaping on multiples of 5 and 10 than the meal network. These findings are consistent with a hypothesized tradeoff between the quality and the quantity of information reported in personal networks. Responses higher than 30 are coded as 30 in these plots.
The condition in Eq. 3 requires that two quantities be equal: (1) the rate at which someone who is on the internet shares a meal with someone who is on Facebook ($\bar{d}_{H,F}$); and, (2) the rate at which someone who is on Facebook shares a meal with someone who is also on Facebook ($\bar{d}_{F,F}$). This assumption would hold if, for example, people who are on the internet do not pay attention to whether or not another internet user is on Facebook when deciding to share a meal together. This assumption could be violated if, for example, people frequently organize sharing a meal together using Facebook without inviting other people. We explore how violating this condition affects estimates as part of a sensitivity analysis in Appendix C and, in Sec. 4, we discuss how additional data collection could remove the need for this condition altogether.

Given the condition in Eq. 3, we can estimate $\bar{v}_{H,F}$ with an estimator for $\bar{d}_{F,F}$, the average number of meals that someone on Facebook reports sharing with someone else on Facebook. In order to estimate $\bar{d}_{F,F}$, we use

$$\hat{d}_{F,F} = \frac{\sum_{i \in s} w_i d_{i,F}}{\sum_{i \in s} w_i},$$

where the new quantity, $f_i$, is the number of Facebook users that respondent $i$ reports among her detailed alters.

Putting Eq. 2 and Eq. 4 together, we have

$$\hat{N}_H = \frac{\hat{y}_{F,H}}{\hat{d}_{F,F}} = \frac{\sum_{i \in s} w_i d_{i,F}}{\sum_{i \in s} w_i} \times \sum_{i \in s} w_i.$$

Appendix A has a detailed derivation of the estimator and a precise description of all of the conditions it relies upon, and Appendix C has a framework for sensitivity analysis which can be used to understand how estimates are affected by violations of these conditions.

### 3 Results

We used Facebook’s survey infrastructure to obtain a simple random sample of people who actively use Facebook in five countries around the world: Brazil ($n=3,761$), Colombia ($n=4,157$),
Great Britain (n=781), Indonesia (n=2,794), and the United States (n=4,288)\(^4\). We chose these countries because they span a breadth of expected levels of internet adoption and economic development. Respondents were slightly more female than male in all countries except for Indonesia, and age distributions are typical of monthly active Facebook users in these countries. Figure 3 shows the age and gender distribution of survey respondents for each tie definition\(^5\). All estimates below are weighted to account for the sample design and to be representative of the universe of monthly active Facebook users in each country. Estimates of sampling uncertainty are based on the rescaled bootstrap method (Feehan and Salganik 2016b; Rao and Wu 1988; Rao et al. 1992).

Fig. 2 shows the distribution of personal network sizes reported by respondents from each country, and for each tie definition. The average size of meal networks was smaller than conversational contact networks in all countries (Table S2): the average reported size of the meal network varied from about 4 (Great Britain) to about 8 (Indonesia), while the average reported size of the conversational contact network varied from about 11 (Colombia and Indonesia) to about 13 (Brazil, Great Britain, and the United States). For both networks, Fig. 2 suggests that there may be heaping in reported network sizes that are multiples of five and ten; this heaping is more evident in the reported number of conversational contacts than for meals, suggesting that reports about the meal network may more accurate than reports about the conversational contact network.

### 3.1 Internal consistency checks

In order to more formally assess the accuracy of reports about each network, we develop internal consistency checks (Bernard et al. 2010; Feehan et al. 2016). These internal consistency checks use the information about the age group and gender of each detailed alter that respondents reported about. The idea is to find reported quantities that can be estimated from the data in two different ways. To the extent that these independent estimates of the same quantity agree, the reported network connections are internally consistent. For example, using survey responses from only men, we can estimate the number of connections between men and women; similarly, using survey responses from only women, we can estimate the number of connections between women and men. By definition, these two quantities are equal; thus, under perfect conditions where our survey does not suffer from any reporting errors or selection biases, we would expect these two independent estimates to agree (up to sampling noise).
We devised internal consistency checks based on reported connections to and from each of twelve different age-sex groups, by country and by tie definition. For each age-sex group $\alpha$, we estimate the average number of connections from Facebook users in age-sex group $\alpha$ to Facebook users not in $\alpha$ ($d_{F,\alpha,F,-\alpha}$). We also estimate the average number of connections from Facebook users not in age-sex group $\alpha$ to Facebook users who are in age-sex group $\alpha$ ($d_{F,-\alpha,F,\alpha}$). We then define the average normalized difference $\Delta_\alpha$ to be

$$\Delta_\alpha = K (\hat{d}_{F,-\alpha,F,\alpha} - \hat{d}_{F,\alpha,F,-\alpha}),$$

where $K$ is a scaling factor that is intended to make it easier to compare different countries and age-sex groups (Appendix B). In the absence of any reporting error, selection biases, or sampling variation, we would expect $\Delta_\alpha = 0$. On the other hand, if there is homophilic selection bias in the respondents’ choice of detailed alters or if members of group $\alpha$ are especially conspicuous then we expect $\Delta_\alpha > 0$; similarly, if there is heterophilic selection bias in respondents’ choice of detailed alters or if members of group $\alpha$ are especially inconspicuous, then we expect $\Delta_\alpha < 0$.

Fig. 4 shows the average normalized difference ($\Delta_\alpha$) for internal consistency checks based on reported connections to and from each of twelve different age-sex groups, by country and by tie definition. Several notable features emerge from Fig. 4. First, for many of the internal consistency checks, the averaged normalized differences are close to zero, or have confidence intervals that contain zero. Second, Fig. 4 suggests that reports based on the meal network are, on average, more internally consistent than reports based on conversational contact (confirmed in Appendix D). Third, there appears to be no universal pattern that describes deviations in internal consistency checks that are not close to zero. Taking the example of Indonesia, the average normalized differences for younger age groups suggest that young women may be relatively conspicuous or that young women are relatively homophilous. On the other hand, young men are relatively inconspicuous or relatively heterophilous. In Brazil and Colombia, similar patterns appear for the conversational contact network. In Great Britain and the United States, however, most of the IC checks suggest that reports are internally consistent.

### 3.2 Comparing tie definition accuracy

Fig. 5 directly compares the difference in internal consistency results for the conversational contact and meal networks. The figure shows the estimated sampling distribution of TAE, the

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6Conspicuousness and homophilic reporting are not distinguishable from the data. In this discussion, we focus on conspicuousness; however, instead of Indonesian women being inconspicuous, it could also be the case that Indonesian women have homophilic selection biases in choosing their detailed alters (i.e., they tend to report other women at a higher rate than would be expected from simple random sampling of their network members).
total absolute difference between the internal consistancy checks for the conversational contact network and the internal consistency checks for the meal network:

$$TAE = \sum_\alpha \left( |\Delta_{\alpha,cc}| - |\Delta_{\alpha,meal}| \right), \quad (7)$$

where $|\Delta_{\alpha,cc}|$ and $|\Delta_{\alpha,meal}|$ are the absolute internal consistency check statistics based on group $\alpha$ for the conversational contact and meal networks (i.e., the square of Eq. 6). Thus, TAE is a summary of how well the internal consistency checks perform across all age-sex groups for the conversational contact network minus the meal network. Since values of $|\Delta_\alpha|$ close to 0 indicate more internally consistent reports, when TAE is positive, that suggests that the meal network is more internally consistent; conversely, when TAE is negative, that suggests that the conversational contact network is more internally consistent. For all countries except for Indonesia, the majority of the mass of the estimated distribution is greater than 0, suggesting that the meal network reports are more internally consistent than conversational contact network reports (Tbl. S3).

**Estimates of internet adoption**

Fig. 6 shows estimated internet adoption for each country in our sample, using each tie definition. Two findings emerge from Fig. 6. First, estimated internet adoption rates are very similar for the conversational contact and for the meal networks; in all countries, the confidence intervals for estimates from the two tie definitions overlap. Second, the countries can be divided into three groups according to estimated adoption rates: the United States and Great Britain have the highest rates of internet adoption (above 75%); Brazil and Colombia have estimated internet adoption rates between 50% and 75%; and Indonesia has estimated adoption rates below 50%. This ordering is consistent with what would be predicted if economic factors such as GDP per capita were the main driver of internet adoption.

Ideally, we would evaluate our estimator by comparing it to gold standard measurements of internet adoption in each of the five countries. Unfortunately, no such gold standard currently exists. Therefore, in order to further assess the plausibility of the estimates presented in Fig. 6, we compared our results to existing internet adoption estimates for Great Britain and for the United States, two countries where high-quality alternative estimates were available. The

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7 For the purposes of this study, we say that a person has adopted the internet if she has used the internet on a computer or a phone in the last 30 days.

8 Our comparisons come from the Pew Research Center (Pew Research Center 2018), which is based on a national phone survey in the US; from an Ofcom Survey in the UK (Ofcom 2016), and from estimates produced by the International Telecommunications Union (ITU 2018). Note that the ITU estimate for the US has all people
results show that the fast and inexpensive network reporting estimates are within the range of other estimates (in the United States) and similar to or slightly lower than other estimates (in Great Britain).

**Summary and discussion**

We found that estimates of internet adoption from the two different networks were very similar (Fig. 6). We could not validate our estimates by comparing them to gold-standard measurements of internet adoption rates because such a gold standard was not available. However, a comparison to high-quality alternative estimates in the United States and Great Britain showed that the network reporting estimates are consistent with other sources of estimates in the United States and consistent or slightly lower than other estimates from Great Britain (Fig. 6). Thus, we conclude that our fast and inexpensive strategy for obtaining approximate estimates of internet adoption is very promising.

We also found that (1) in all five countries, reports from the stronger network tie, meals, produced information about fewer people than the weaker network tie, conversational contact; but, (2) reports from the stronger network tie produced, on average, more accurate information than reports from the weaker tie in all countries except for Indonesia (Fig. 5). This finding is consistent with a hypothesized trade-off between the quantity and quality of information produced by network reports (Feehan et al. 2016); previous work found support for this theory in network reports about interactions in the 12 months before the interview. We find that this tie strength trade-off may operate even when reports are about interactions that took place the day before the interview. Future research could compare different time-windows to see if the hypothesized tradeoff between the quantity and quality of information operates across time within a fixed type of network tie. Over time, we hope that a deeper understanding of the relationship between reporting accuracy and the different dimensions of network tie definitions will accumulate, leading to useful guidance about how to design studies like ours.

The internal consistency checks suggest that people’s reports about their network members can suffer from reporting errors, and that these reporting errors vary by who is being reported about (Fig. 4). One possible mechanism for this result would be differential salience of interactions; another possible mechanism could be homophilic selection of the detailed alters. This phenomenon is important to understand for measurement, and scientifically interesting in its own right; future research could explore different study designs to try and distinguish between the salience of different demographic groups on the one hand and selection bias among the detailed alters on the other. More generally, the internal consistency checks provide a way to evaluate the quality of

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over aged 3 in the denominator while all other estimates are for adults.
reporting from different survey designs, enabling researchers to experiment with new designs each time data are collected. Over time, this process may help discover tie definitions that minimize reporting error.

4 Conclusion

We showed that a sample of people who are online can be used to estimate characteristics of a population that is not entirely online. Our approach is based on the idea that people who are sampled online can be asked to anonymously report things about other people to whom they are connected through different kinds of personal networks. We illustrated our approach by estimating internet adoption in five different countries around the world. Our study included a survey experiment that can help inform future efforts to use online samples to estimate population characteristics.

Our results suggest several possible avenues for future work. In this study, we focused on simple, design-based estimators. A natural next step would be to start to build more complex models using these data. These models could exploit the relationships that are embedded in the internal consistency checks as a kind of constraint, estimating adjustments to ensure that reports are internally consistent. Such a model could potentially improve the accuracy of the resulting estimates. A second next step would be to use our approach to produce estimates of internet adoption by age and gender. Finally, future work could explore the possibility of an even simpler estimator based on asking each respondent about aggregate connections to people who use the internet (e.g. “How many of your network members use the internet?”; Bernard et al. (2010)). This approach would forgo the ability to conduct internal consistency checks and to produce estimates by age and gender, but it would be even simpler and shorter than the approach we used here.

We view our method as a complement to other promising approaches to producing population-level estimates using online samples. For example, one stream of research focuses on using changes over time among members of the online sample to estimate population changes; this approach can be useful for studying topics like migration (e.g., Zagheni and Weber 2012). A second stream of research uses models that relate people in the online sample to the general population using covariate information observed in both sources (e.g., Goel et al. 2015; Fatehkia et al. 2018). We expect sampling and interviewing people about members of their offline networks will be especially promising in situations where few or no people in the group being studied can be expected to be in the online sample; but we also expect that there will be situations where these alternatives are more appropriate than network reporting. As the field of digital
demography emerges, it will be important deepen our understanding of the trade-offs between these approaches, and to continue to develop new methods for producing population estimates from an online sample.

We also see our approach as a complement, rather than a replacement for conventional surveys. The ideal situation would combine frequent, inexpensive estimates, such as the ones described here, with less frequent conventional surveys. For example, a conventional probability sample of the general population in a country could be used to empirically estimate the average number of meals shared between an internet user and a Facebook user; with direct estimates of that quantity, the need for a key assumption in our estimator could be completely removed. More generally, a conventional probability sample survey can both be used to assess the accuracy of the fast and cheap estimates, and they can also be used to try to measure and relax some of the assumptions required by the faster, cheaper strategy.
Figure 3: Age and gender of survey respondents in each country. Estimates throughout this article use sampling weights to account for sample design and nonresponse.
Figure 4: Internal consistency checks. By estimating the same quantity using independent parts of our sample, we can assess the internal consistency of respondents’ network reports. Estimated difference between two independent estimates of the same quantity and 95% confidence intervals are shown for each age-gender group and each type of network; an estimate of 0 means that the two independent estimates are exactly the same. Across most age-sex groups, results are internally consistent with one another, within sampling error; however, some groups show evidence of reporting errors (e.g. young people in Indonesia). Results also suggest that reports about the meal definition are more internally consistent, even though meal networks are smaller than conversational contact networks.
Figure 5: Estimated sampling distribution of the difference between the normalized square error for internal consistency checks from the conversational contact network and from the meal network. For all countries except for Indonesia, the meal network was more internally consistent than the conversational contact network (Table S3).
Figure 6: Estimated percentage of 2015 adult population that uses the internet, by country and for each of the two networks. 95% confidence intervals are based on the estimated sampling distribution from the rescaled bootstrap. For comparison, estimates from alternate sources are shown where available. In Great Britain, comparison estimates are available from the ITU and from an Ofcom survey; in the United States, comparison estimates are available from a Pew survey.
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Supporting Information

A Derivation of the estimators

Sampling setup

We assume a conventional probability sampling setup, following the theory of design-based sampling; see Sarndal et al. (2003) for an overview. When we refer to an estimator as ‘consistent’, we mean design-consistent (also called Fisher consistent; Sarndal et al. (2003)). Similarly, ‘unbiased’ means design-unbiased.

Our frame population $F$ – the set of people who could potentially be sampled – is monthly active Facebook users in a given country. The population whose size we are trying to estimate is $H$, the number of internet users in the country. The goal is to use information about people on Facebook’s reported offline personal network connections in order to estimate the size of $H$.

We assume that we obtain a probability sample $s$ from the frame population, where we use the same definition of a probability sample as Sarndal et al. (2003). To briefly review, we assume that the sample $s$ is chosen from among the members of the frame population $F$ using a known random sampling method. The probability that $i \in F$ is included in the sample $s$, called $i$’s inclusion probability, is written $\pi_i$. We require that $\pi_i > 0$ for all $i \in F$. We call the $w_i = \frac{1}{\pi_i}$ the expansion weight for unit $i \in F$.

Several of the estimators we study are ratio or compound ratio estimators. The literature on design-based sampling has established that if each component estimator is consistent and unbiased, then compound ratio estimators are design-consistent but, strictly speaking, compound ratio estimators are not unbiased. Fortunately, a large literature has studied this problem and such estimators are typically found to be very nearly unbiased, both in theory and in practice. Thus, we refer to these compound ratio estimators as essentially unbiased. The following result formally establishes these important properties of compound ratio estimators; which we will use these properties below.

Result A.1. Suppose that $\hat{y}_1, \ldots, \hat{y}_n$ are estimators that are consistent and unbiased for $Y_1, \ldots, Y_n$ respectively. Then the compound ratio estimator

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9 Throughout this paper, we use the term Facebook users to refer to monthly-active Facebook users.
10 We do not expect the situations in which compound ratio estimators would be biased to be relevant to our study; the biggest concern is typically when the denominator of $R$ is very small, which is not likely in our applications.
\[ \hat{R} = \frac{\hat{y}_1 \cdots \hat{y}_k}{\hat{y}_{k+1} \cdots \hat{y}_n}. \]  

is consistent and essentially unbiased for \( R = (Y_1 \ldots Y_k)/(Y_{k+1} \ldots Y_n) \).

Proof. See Rao and Pereira (1968), Wolter (2007) (pg. 233), and Feehan and Salganik (2016a) for more details.

We adhere to the notation used in previous papers about network scale-up and network reporting (Feehan 2015; Feehan and Salganik 2016a;Feehan et al. 2016):

- \( y_{i,B} \) is the number of reported connections from person \( i \) to members of group \( B \)
- \( y_{A,B} = \sum_{i \in A} y_{i,B} \) is the number of reported connections from members of group \( A \) to group \( B \)
- \( d_{i,B} \) is the number of undirected connections in the social network between \( i \) and members of group \( B \)
- \( d_{A,B} = \sum_{i \in A} d_{i,B} \) is the total number of undirected connections in the social network between members of group \( A \) and members of group \( B \)
- \( v_{i,A} \) is the visibility of \( i \) to group \( A \) – i.e., the number of times that \( i \) would be reported if everyone in \( A \) was interviewed
- \( v_{B,A} = \sum_{i \in B} v_{i,A} \) is the total visibility of members of group \( B \) to group \( A \)
- \( \hat{y} \rightarrow Y \) is shorthand for \( \hat{y} \) is a consistent and unbiased estimator for \( Y \)
- \( \hat{y} \rightsquigarrow Y \) is shorthand for \( \hat{y} \) is a consistent and essentially unbiased estimator for \( Y \)
- \( y_{F,H}^+ \) is the number of reported connections from \( F \) to \( H \) that actually lead to \( H \). If \( y_{F,H}^+ = y_{F,H} \) then we say that there are no false positive reports
- \( N_A \) is the size of set \( A \) (i.e., the number of people in \( A \))

Aggregate reporting framework

We develop an estimator using the network reporting framework, an approach that builds upon insights from several different streams of previous research on sampling (Bernard et al. 1991; Feehan 2015; Feehan and Salganik 2016a; Lavallee 2007; Sirken 1970). Feehan (2015) shows that researchers can develop estimators based on network reports using either an individual or an aggregate multiplicity approach. Since we do not collect information at the level of detail required by individual multiplicity estimation, we adopt an aggregate multiplicity approach in this study. This aggregate multiplicity approach is similar to the network scale-up method (Bernard et al. 2010, 1991; Feehan and Salganik 2016a; Maltiel et al. 2015).
**Result A.2.** Suppose that a census of the frame population $F$ is interviewed and asked to report about their connections to a group $Z$. Call the total number of reported connections $y_{F,Z}$ and suppose $y_{F,Z} > 0$. Further, suppose that there are no false positive reports, so that $y_{F,Z} = y_{F,Z}^+$. Finally, suppose that $\bar{v}_{Z,F}$ is the average visibility of members of $Z$; that is, $\bar{v}_{Z,F}$ is the average number of times that a member of $Z$ is reported by someone in $F$. Then

$$N_H = \frac{y_{F,H}}{\bar{v}_{H,F}}.$$  

(9)

*Proof.* See Feehan (2015) and Feehan and Salganik (2016a). □

To see the intuition behind the aggregate multiplicity approach from Result A.2, suppose we conducted a census of the frame population, asking every frame population member to tell us how many members of her personal network were online. Simply adding up the number of reported connections to internet users would produce a number that is larger than the number of internet users because each internet user can be reported more than once. Thus, in order to adjust for this over-counting, aggregate multiplicity estimators divide an estimate for the total number of reports by an estimate of hidden population members’ visibility. The visibility is the number of times an average member of the hidden population would be reported if everyone on the frame population responded to the survey. In this study, the visibility is the number of times that the average internet user in a given country would be reported as an internet user, if everyone on Facebook in the country responded to the survey. Dividing the estimated total number of reported connections to people on the internet by the estimated visibility adjusts for the over-counting that would occur if the reports were used to directly estimate the number of internet users.

Given the aggregate multiplicity identity, our basic approach is to develop data collection strategies and statistical estimators that enable us to estimate the numerator and denominator of the identity in Eq. 9. In the remainder of this Appendix, we develop necessary technical results to use the identity in Eq. 9 to estimate the number of internet users in a given country.

**Estimates about detailed alters**

Result A.3 formalizes a situation where respondents are sampled and then asked about a sample of their network members. Result A.3 is stated in terms of an arbitrary dichotomous trait $z$ that respondents report about their personal network members; for example, $z$ could be Facebook usage, internet usage, gender, or membership in an age group.
**Result A.3.** Suppose we have a sample $s$ taken from the frame population using a probability sampling design. Call the expansion weights given by the sampling design $w_i$ for each $i \in s$. Further, suppose that for each $i \in s$, we obtain information from a simple random subsample $s_i$ of size $r_i$ from the $d_i$ people in i’s personal network. Let $z_{ij}$ be an indicator variable for whether or not $i$ reports that $j$ has trait $Z$, and let $z_i = \sum_{j \in s_i} z_{ij}$ be the total number of detailed alters respondent $i$ reports having trait $Z$. Then the estimator

$$\hat{y}_{F,Z} = \sum_{i \in s} w_i \frac{d_i}{r_i} z_i$$

(10)

is consistent and unbiased for $y_{F,Z}$, the total number of reported connections to people with trait $Z$ in a census of the frame population in which respondents report about everyone in their networks.

**Proof.** First, we note that we can consider this to be a multi-stage sample, where the first stage(s) lead to selection of the respondent and the final stage is the subsampling of detailed alters within each respondent’s network. Since the final stage is a simple random sample of $r_i$ out of $d_i$ network members, the design weight for the final stage is $\frac{d_i}{r_i}$ for each detailed alter. In order to show that the estimator is unbiased, we take expectations with respect to the multi-stage sampling design:

$$E[\hat{y}_{F,Z}] = E_{s}\left[\sum_{i \in s} w_i E_{s_i}\left[\frac{d_i}{r_i} z_i|s\right]\right]$$

$$= \sum_{i \in F} \pi_i w_i E_{s_i}\left[\frac{d_i}{r_i} z_i|s\right]$$

$$= \sum_{i \in F} \pi_i w_i \left(\sum_{j \sim i} \pi_j \frac{d_i}{r_i} z_{ij}\right),$$

(11)

where the outer expectation $E[\cdot]$ is taken with respect to the sampling of respondents and the inner expectation $E_{s_i}[\cdot|s]$ is taken with respect to the sampling of detailed alters within each sampled respondent; $j \sim i$ indexes over all of the network members $j$ that $i$ could potentially report about; and we have written $\pi_i$ for the inclusion probability of respondent $i$ under the sampling design, and $\pi_j^i$ for the inclusion probability of respondent $i$’s $j$th network member under the subsampling design.

By definition, $w_i = \frac{1}{\pi_i}$ and $\pi_j^i = \frac{r_j}{d_i}$. Thus, continuing from above, we have
\[ E[\bar{y}_{F,Z}] = \sum_{i \in F} \pi_i w_i \left( \sum_{j \sim i} \pi_j^i d_i z_{ij} \right) = \sum_{i \in F} \left( \sum_{j \sim i} \pi_j^i d_i z_{ij} \right) = \sum_{i \in F} y_{i,Z} = y_{F,Z}. \] (12)

So we have shown that the estimator is unbiased for \( y_{F,Z} \).

Finally, in a census of the frame population where every respondent reports about all of her network members, \( s = F, \pi_i = 1, \pi_j^i = 1, z_i = y_{i,Z}, \) and \( r_i = d_i \) for all \( i \) and \( j \). Thus

\[ \hat{y}_{F,Z} = \sum_{i \in s} w_i d_i z_i = \sum_{i \in F} y_{i,Z} = y_{F,Z}. \] (13)

So the estimator is design-consistent.

**Corollary A.1.** Under the conditions of Result A.3, the estimator

\[ \hat{y}_{F,Z} = \frac{\sum_{i \in s} w_i d_i z_i}{\sum_{i \in s} w_i} \] (14)

is consistent and essentially unbiased for \( \bar{y}_{F,Z} \).

**Proof.** By Result A.3 the numerator is consistent and unbiased for \( y_{F,Z} \), and the denominator is a sample-based estimate for the size of the frame population, \( \hat{N}_F = \sum_{i \in s} w_i \). Thus, this is a Hajek-type estimator. See (Sarndal et al. 2003) for a proof that Hajek estimators are consistent and essentially unbiased.

Note that Result A.3 implies that Eq. 2 is consistent and unbiased for \( y_{F,H} \) and Corollary A.3 implies that Eq. 4 is consistent and unbiased for \( \bar{y}_{F,F} \).

**Assembling the estimator**

The next estimator, Result A.4, shows that if we can estimate the total reported connections from frame population members to internet users, and if we can estimate the average visibility of internet users to frame population members, then we can estimate the number of internet users.
Result A.4. Suppose that the $\hat{y}_{F,H}$ is a consistent and unbiased estimator for $y_{F,H}$ and that $\hat{y}_{F,F}$ is a consistent and essentially unbiased estimator for $\bar{y}_{F,F}$. Further, suppose that reports are accurate in aggregate, so that $y_{F,H} = d_{F,H}$ and $y_{F,F} = d_{F,F}$. Finally, suppose that $\bar{d}_{H,F} = \bar{d}_{F,F}$. Then the estimator

$$\tilde{N}_H = \frac{\hat{y}_{F,H}}{\bar{y}_{F,F}}$$

is consistent and essentially unbiased for $N_H$.

Proof. Since $\hat{y}_{F,H} \rightarrow y_{F,H}$ and $\hat{y}_{F,F} \sim \bar{y}_{F,F}$, Result A.1 shows that $\tilde{N}_H = \frac{\hat{y}_{F,H}}{\bar{y}_{F,F}} \sim \frac{y_{F,H}}{y_{F,F}}$. It remains to show that $\frac{y_{F,H}}{y_{F,F}}$ is equal to $N_H$. By the condition that reports are accurate in aggregate, $y_{F,H} = d_{F,H}$ and $y_{F,F} = d_{F,F}$. Thus,

$$\frac{y_{F,H}}{y_{F,F}} = \frac{d_{F,H}}{d_{F,F}}.$$  \hspace{1cm} (17)

Next, using the condition that $\bar{d}_{F,F} = \bar{d}_{H,F}$, we have

$$\frac{d_{F,H}}{d_{F,F}} = \frac{d_{F,H}}{d_{H,F}} = N_H \frac{d_{F,H}}{d_{H,F}} = N_H,$$  \hspace{1cm} (18)

where the last step follows from the fact that we are assuming a symmetric type of network tie, meaning that the number of connections from $F$ to $H$ must be equal to the number of connections from $H$ to $F$.

Result A.4 relies upon the condition that $\bar{d}_{H,F} = \bar{d}_{F,F}$ (Eq. 15), which requires that two quantities be equal: (1) the rate at which someone who is on the internet shares a meal with someone who is on Facebook ($\bar{d}_{H,F}$); and, (2) the rate at which someone who is on Facebook shares a meal with someone who is also on Facebook ($\bar{d}_{F,F}$). This assumption could be violated if, for example, people frequently organize sharing a meal together using Facebook (without inviting other people).
To further understand the condition in Eq. 15 note that since $F \subset H$ (i.e., everyone on Facebook is also on the Internet), it follows that

$$d_{H,F} = p_{F|H} \bar{d}_{F,F} + (1 - p_{F|H}) \bar{d}_{H-F,F}$$

(19)

where $p_{F|H} = \frac{N_F}{N_H}$ is the prevalence of $F$ among $H$, i.e., the fraction of people on the internet that is also on Facebook. Therefore, when the condition in Eq. 15 holds, then it is also the case that

$$\bar{d}_{F,F} = \bar{d}_{H-F,F}.$$ 

(20)

Appendix C introduces a sensitivity framework that researchers can use to assess how sensitive size estimates are to this condition.

### B Internal consistency checks

The internal consistency checks start from an identity that relates two quantities: (1) $d_{F-\alpha,F\alpha}$, the population-level number of connections from everyone who is in $F$ but not group $\alpha$ to everyone who is in $F$ and in group $\alpha$; and (2), $d_{F\alpha,F-\alpha}$ – the population-level number of connections from everyone who is in $F$ and group $\alpha$ to everyone who is in $F$ but not in group $\alpha$. Since the networks we ask respondents to report about are symmetric, these two quantities are identical; however, they can be estimated independently from the data we collected: the first quantity can be estimated only from respondents who are not in group $\alpha$, and the second quantity can be estimated only from respondents who are in group $\alpha$.

In order to assess how internally consistent reporting is, we can directly compute a survey-based estimates for the discrepancy

$$\Delta^0_\alpha = \bar{d}_{F-\alpha,F\alpha} - \bar{d}_{F\alpha,F-\alpha}.$$ 

(21)

The closer this quantity is to 0, the more internally consistent reports about group $\alpha$ are. However, $\Delta^0_\alpha$ is influenced by the size of the group $\alpha$, which makes it challenging to plot internal consistency checks for several different groups in the same place (e.g. Fig. 4). Thus, we propose rescaling the
IC checks for different groups to put them on a more similar scale. Specifically, we scale $\Delta^0_\alpha$ by a factor $K$ given by

$$K = \frac{N_F}{N_{F_{-\alpha}} N_{F_\alpha}},$$

(22)

where $N_{F_{-\alpha}}$ is the number of people in the frame population not in group $\alpha$ and $N_{F_\alpha}$ is the number of people in the frame population who are in group $\alpha$. The factor $K$ is motivated by starting from the identity $d_{F_{-\alpha},F_\alpha} = d_{F_\alpha,F_{-\alpha}}$, and multiplying both sides by $\frac{1}{N_{F_{-\alpha}} N_{F_\alpha}}$. The result is an expression that shows that $d_{F_{-\alpha},F_\alpha}/N_{F_\alpha} = d_{F_\alpha,F_{-\alpha}}/N_{F_{-\alpha}}$. In words, this new expression equates (1) the proportion of $F_\alpha$ that the average person in $F_{-\alpha}$ is connected to; and (2) the proportion of $F_{-\alpha}$ that the average person in $F_\alpha$ is connected to. Finally, we multiply the new identity by $N_F$ to help compare countries of different sizes.

Note that this rescaling does not affect whether or not the confidence intervals for the IC checks includes 0; instead, it controls for the relative size of group $\alpha$. It makes internal consistency checks across different groups easier to compare with one another.

Using the example of the conversational contact reports, the final discrepancy measure is defined to be

$$\Delta^c_{\alpha} = K \left[ \frac{d_{F_{-\alpha},F_\alpha}}{N_{F_\alpha}} - \frac{d_{F_\alpha,F_{-\alpha}}}{N_{F_{-\alpha}}} \right].$$

(23)

Eq. 23 can be computed for each bootstrap resample; the distribution of $\Delta^c_{\alpha}$ across bootstrap resamples is then an estimate for the sampling distribution of the discrepancy measure.

### C Sensitivity framework

In this Appendix, we describe a framework that can be used to assess the sensitivity of the estimated number of people who use the internet to the various conditions that the results in Appendix A rely upon.

In order to develop the sensitivity framework, we adapt previous work on network scale-up and other network reporting methods (Feehan 2015; Feehan and Salganik 2016a). We start by introducing three quantities, called *adjustment factors*:

$$\eta_H = \frac{\text{avg # reported connections from } F \text{ to } H \text{ that actually lead to } H}{\text{avg # reported connections from } F \text{ to } H} = \frac{y^+_{F,H}}{y_{F,H}},$$

(24)
and

$$\eta_F = \frac{\text{avg # reported connections from } F \text{ to } F \text{ that actually lead to } F}{\text{avg # reported connections from } F \text{ to } F} = \frac{y_{F,F}}{y_{F,F}}, \quad (25)$$

and

$$\nu = \frac{\text{avg # in-reports to } H \text{ from } F}{\text{avg # in-reports to } F \text{ from } F} = \frac{\bar{v}_{H,F}}{\bar{v}_{F,F}}. \quad (26)$$

Each of these new parameters is equal to 1 under ideal conditions, when the requirements of the results in Appendix A are satisfied. In general, $\nu$ can take on any value from 0 to $\infty$, while $\eta_F$ and $\eta_H$ can take on any value from 0 to 1.

The first sensitivity result reveals how estimated numbers of internet users will be affected if one or more of the three adjustment factors is not equal to 1.

**Result C.1.** Suppose that the sampling conditions for Result A.3 hold, but that the reporting and network structure conditions do not. That is, suppose we have a sample $s$ taken from the frame population using a probability sampling design. Call the expansion weights given by the sampling design $w_i$ for each $i \in s$. Further, suppose that for each $i \in s$, we obtain information from a simple random subsample $s_i$ of $r_i$ out of the $d_i$ people in $i$’s personal network.

Now suppose that $\hat{y}_{F,H}$ is consistent and unbiased for $y_{F,H}$ and that $\hat{y}_{F,F}$ is consistent and unbiased for $y_{F,F}$, but that $\eta_{F,H} \neq 1$, $\eta_{F,F} \neq 1$, and $\nu \neq 1$; that is, assume that the remaining conditions in Result A.4 do not hold. Then the estimator

$$\hat{N}_H = \frac{\hat{y}_{F,H}}{\hat{y}_{F,F}} \quad (27)$$

is consistent and unbiased for $(\eta_{F,H} \eta_{F,F} \nu)N_H$.

**Proof.** The proof follows along the lines of Feehan and Salganik (2016a). Briefly,

$$\hat{N}_H = \frac{\hat{y}_{F,H}}{\hat{y}_{F,F}} \xrightarrow{\text{by the sampling conditions}} \frac{y_{F,H}}{y_{F,F}} \quad (28)$$

by the sampling conditions. Next, we wish to use the adjustment factors to relate the estimand to $\hat{N}_H$:
\[
\frac{\bar{y}_{F,H}}{\bar{y}_{F,F}} = \frac{\eta_F}{\eta_H} \frac{\bar{y}_{F,H}^+}{\bar{y}_{F,F}^+} = \frac{\eta_F}{\eta_H} \frac{\bar{\nu}_{H,F}}{\bar{\nu}_{F,F}} = \frac{\eta_F}{\eta_H} \frac{\bar{\nu}_{H,F}}{\bar{\nu}_{F,F}} N_H = \frac{\eta_F}{\eta_H} \nu N_H. \tag{29}
\]

Thus, we conclude that

\[
\tilde{N}_H \sim \frac{\eta_F}{\eta_H} \nu N_H. \tag{30}
\]

**Corollary C.1.** Under the conditions listed in Result C.1

\[
\text{Bias} [\tilde{N}_H] = \mathbb{E}[\tilde{N}_H] - N_H = N_H (\frac{\eta_F}{\eta_H} \nu - 1). \tag{31}
\]

Now we show how problems with the sampling weights can affect estimates; this will be helpful in understanding what impact non simple random subsampling of detailed alters would have.

First, we must define *imperfect sampling weights*. We follow Feehan and Salganik (2016a) and repeat the definition here for convenience:

**Imperfect sampling weights.** Suppose a researcher obtains a probability sample \(s\) from the frame population \(F\). Let \(I_i\) be the random variable that assumes the value 1 when unit \(i \in F\) is included in the sample \(s\), and 0 otherwise. Let \(\pi_i = \mathbb{E}[I_i]\) be the true probability of inclusion for unit \(i \in F\), and let \(w_i = \frac{1}{\pi_i}\) be the corresponding design weight for unit \(i\). We say that researchers have *imperfect sampling weights* when researchers use imperfect estimates of the inclusion probabilities \(\pi'_i\) and the corresponding design weights \(w'_i = \frac{1}{\pi'_i}\). Note that we assume that both the true and the imperfect weights satisfy \(\pi_i > 0\) and \(\pi'_i > 0\) for all \(i\).

**Result C.2.** Suppose researchers have obtained a probability sample \(s\), but that they have imperfect sampling weights. Call the imperfect sampling weights \(w'_i = \frac{1}{\pi'_i}\), call the true weights \(w_i = \frac{1}{\pi_i}\), and define \(\epsilon_i = \frac{w'_i}{w_i} = \frac{\pi_i}{\pi'_i}\). Then
$\text{Bias}[\hat{y}_{F,Z}'] = N_F [\bar{y}_{F,Z}(\bar{\epsilon} - 1) + \text{cov}_F(y_i, \epsilon_i)]$, \hspace{1cm} (32)

where $\bar{\epsilon} = \frac{1}{N_F}\sum_{i \in F}\epsilon_i$ and $\text{cov}_F(\cdot, \cdot)$ is the finite population unit covariance in the frame population $F$.

**Proof.** See Result D.2 in Feehan and Salganik (2016a).

Result [C.2] will be useful to us because we can use it to understand situations where respondents’ reports about the detailed alters are different from simple random sampling. In order to isolate the impact of such a difference, we assume in Result [C.2] that the expansion weights for respondent inclusion are accurate.

We also state the following fact, which will be useful in the subsequent derivation.

**Fact C.1.**

\[ \sum_{i \in A} a_i b_i = N_A[\bar{a}\bar{b} + \text{cov}_A(a_i, b_i)] \] \hspace{1cm} (33)

**Result C.3.** Suppose that respondents do not report about the detailed alters by picking $r_i$ out of $d_i$ of them uniformly at random, so that the estimator for $\hat{y}_{F,Z}$ in Result [A.3] uses imperfect weights $l_i' = \frac{d_i}{r_i}$ for the final-stage subsampling of detailed alters, while the true weight for each of respondent $i$’s detailed alters $j$ is given by $l_{ij}$. Let $\epsilon_i = \epsilon_i' = \frac{l_i'}{l_i}$. Suppose also that the expansion weights $w_i$ for the inclusion of respondents in the sample are accurate. Then the bias of $\hat{y}_{F,Z}'$ is given by

\[ \text{Bias}[\hat{y}_{F,Z}'] = \sum_{i \in F} \sum_{j \sim i} z_{ij} (\epsilon_{ij} - 1). \] \hspace{1cm} (34)

**Proof.**

\[ \mathbb{E}[\hat{y}_{F,Z}'] = \mathbb{E} \left[ \sum_{i \in s} w_i \times \sum_{j \sim i} l_i' z_{ij} | s \right] \]

\[ = \sum_{i \in F} w_i \mathbb{E}[I_i] \times \sum_{j \sim i} \mathbb{E}[I_{ij} | s] l_i' z_{ij} \]

\[ = \sum_{i \in F} \sum_{j \sim i} l_i' z_{ij} \]

\[ = \sum_{i \in F} \sum_{j \sim i} \epsilon_{ij} z_{ij}, \] \hspace{1cm} (35)
where $j \sim i$ indexes the people $j$ that are reported in respondent $i$’s network. Thus, the bias is

\[
\text{Bias}(\hat{y}_{F,Z}') = \mathbb{E}[\hat{y}_{F,Z}'] - y_{F,Z} = \sum_{i \in F} \sum_{j \sim i} \epsilon_{ij} z_{ij} - \sum_{i \in F} \sum_{j \sim i} z_{ij} = \sum_{i \in F} \sum_{j \sim i} z_{ij}(\epsilon_{ij} - 1). \tag{36}
\]

To understand Result C.3 better, we manipulate the expression for $\text{Bias}(\hat{y}_{F,Z}')$ with the aim of producing a more interpretable expression:

\[
\text{Bias}(\hat{y}_{F,Z}') = \sum_{i \in F} \sum_{j \sim i} z_{ij}(\epsilon_{ij} - 1)
= \sum_{i \in F} y_i [\bar{z}_i(\bar{\epsilon}_i - 1) + \text{cov}_{j \sim i}(z_{ij}, \epsilon_{ij} - 1)]
= \sum_{i \in F} y_i \bar{z}_i \bar{\epsilon}_i - \sum_{i \in F} y_i \bar{z}_i + \sum_{i \in F} y_i \sigma_i
= \sum_{i \in F} z_i \bar{\epsilon}_i + \sum_{i \in F} y_i \sigma_i - \sum_{i \in F} z_i, \tag{37}
\]

where $j \sim i$ indexes the people $j$ that are reported in respondent $i$’s network; $y_i = y_{i,U} = \sum_{j \sim i} 1$ is the total number of people $i$ would report about if there was no subsampling; $z_i = \sum_{i \sim j} z_{ij}$ is the total number of people $i$ would report as members of $Z$ if there was no subsampling; $\bar{z}_i = y_i^{-1} \sum_{i \sim j} z_{ij}$ is the average $z_{ij}$ among respondent $i$’s reported network members; $\bar{z} = N_F^{-1} \sum_{i \in F} \bar{z}_i$ is the average $\bar{z}_i$ across people in the frame; $\bar{\epsilon}_i = y_i^{-1} \sum_{i \sim j} \epsilon_{ij}$ is the average $\epsilon_{ij}$ among respondent $i$’s reported network members; $\bar{\epsilon} = N_F^{-1} \sum_{i \in F} \bar{\epsilon}_i$ is the average $\bar{\epsilon}_i$ across people in the frame; and $\sigma_i = \text{cov}_{i \sim j}(z_{ij}, \epsilon_{ij})$ is the covariance between the $\epsilon_{ij}$ and $z_{ij}$ among respondent $i$’s reported network members.

Finally, we use Fact C.1 twice–once within respondent and once between respondents:
Thus, Eq. 38 shows that when respondents do not choose detailed alters uniformly at random, the resulting bias can be decomposed into three terms: one term related to aggregate errors in the weights; one term that captures the relationship between personal network size and weight errors; and one term that captures the relationship between weight errors and alters’ internet use.

### D Additional results

Table S2 reports estimated average network size (degree) for each tie definition.

| country         | Conversational contact | Meal |
|-----------------|------------------------|------|
| Brazil          | 13.1 (12.5, 13.6)      | 6.3 (5.9, 6.6) |
| Colombia        | 10.5 (10, 11.1)        | 7.2 (6.9, 7.6) |
| Great Britain   | 12.7 (11.6, 13.9)      | 4.4 (3.7, 5.3) |
| Indonesia       | 11 (10.4, 11.6)        | 7.5 (7, 8) |
| United State    | 12.1 (11.6, 12.5)      | 5 (4.6, 5.4) |

Table S2: Estimated average degree and 95% confidence interval, by type of personal network

Fig. S1 illustrates the detailed alters subsampled from each respondent’s personal network.

Table S3 provides a summary of the comparison of TAE between the two tie definitions within each country (the information that is visualized in Fig. 5).
Figure S1: (a) A survey respondent who is sampled online can be asked to report about members of one of her offline personal networks (e.g. her kin, friendship, or contact networks). Her responses contain information about both people who are online and people who are offline. (b) In order to reduce respondent burden, we asked for more detailed information about internet use, gender, and age for three detailed alters in each respondent’s personal network (solid lines).

| Country      | Median TAE | Mean TAE (95% CI) |
|--------------|------------|-------------------|
| Brazil       | 8.62       | 8.64 (2.16, 15.54) |
| Colombia     | 4.77       | 4.82 (-1.36, 11.14) |
| Great Britain| 5.43       | 5.67 (-2.58, 14.22) |
| Indonesia    | -6.71      | -6.85 (-24.13, 8.82) |
| United States| 1.39       | 1.4 (-3.28, 6.52) |

Table S3: Estimated mean and 95% CI for the TAE, the difference in total absolute error in internal consistency checks across all age groups for the conversational contact network minus the same quantity for the meal network. Positive values mean that the conversational contact network was less internally consistent than the meal network, as measured by absolute error.