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Navigating Statistical Uncertainty: How Urban and Regional Planners Understand and Work With American Community Survey (ACS) Data for Guiding Policy

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Problem, research strategy, and findings: The American Community Survey (ACS) is a crucial source of sociodemographic data for planners. Since ACS data are estimates rather than actual counts, they contain a degree of statistical uncertainty—referred to as *margin of error* (MOE)—that planners must navigate when using these data. The statistical uncertainty is magnified when one is working with data for small areas or subgroups of the population or cross-tabulating demographic characteristics. We interviewed ($n = 7$) and surveyed ($n = 200$) planners and find that many do not understand the statistical uncertainty in ACS data, find it difficult to communicate statistical uncertainty to stakeholders, and avoid reporting MOEs altogether. These practices may conflict with planners' ethical obligations under the AICP Code of Ethics to disclose information in a clear and direct way.

Takeaway for practice: We argue that the planning academy should change its curriculum requirements and that the profession should improve professional development training to ensure planners understand data uncertainty and convey it to users. We suggest planners follow 5 guidelines when using ACS data: Report MOEs, indicate when they are not reporting MOEs, provide context for the level of statistical reliability, consider alternatives for reducing statistical uncertainty, and always conduct statistical tests when comparing ACS estimates.

Keywords: American Community Survey (ACS), demographic data, margin of error (MOE), statistical uncertainty

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Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/rjpa.

Census data have been an integral part of planning practice from the original 1909 Plan of Chicago (IL) to present-day planning efforts (Burnham & Bennett, 1993). Today, the U.S. Census Bureau's (USCB) American Community Survey (ACS) serves as a key data set in contemporary planning practice. ACS data, however, are estimates based on a sample rather than complete counts and are drawn from a smaller sample than the decennial long-form data. Therefore, ACS data possess a *greater* amount of statistical uncertainty or unreliability, referred to as *margin of error* (MOE). This statistical uncertainty is magnified for smaller geographies (e.g., census tracts) or subpopulations (e.g., poverty rate for children) and for cross-tabulations (e.g., race/ethnicity by income).

We know little about how planners understand and communicate the statistical uncertainty of ACS data, although we believe that doing so is part of a planner's ethical responsibility under the AICP Code of Ethics. We address this gap in the literature by interviewing seven planners in depth and surveying 200 planners to explore their familiarity with statistical uncertainty in ACS data, to understand how and to what extent they use ACS data in research and practice, and to identify their approaches for conveying statistical uncertainty to policymakers and the public. Our results suggest that some planners have a limited understanding of the nuances of statistical uncertainty. Many planners discount the importance of

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the MOE in using ACS data for policy-specific decision-making tasks and rarely, if ever, communicate statistical uncertainty to clients, policymakers, and the public. Just 27% of the planners we surveyed indicated they would warn the end user about unreliable ACS data.

There is an apparent disconnect between the ethical responsibilities set forth by the AICP Code of Ethics and actual on-the-ground practice. The planning academy, through Planning Accreditation Board curricular requirements, and the profession, through professional development training, should underscore the importance of understanding and conveying to users the MOE in ACS data. We also suggest the developers of popular web resources that use demographic data (e.g., Social Explorer, Policy Map, and Tableau) report the associated statistical uncertainty. We also recommend that planners follow five guidelines when using ACS data: Report the MOE of ACS estimates, indicate when they are not reporting the MOE, provide context for the (un)reliability of ACS data, consider alternatives for reducing statistical uncertainty, and conduct a test of statistical significance when comparing ACS estimates over time.

We provide here background on the USCB's transition to the ACS, summarize the literature on sampling error, illustrate the limitations of the ACS for planners with on-the-ground examples, and draw from survey and interview findings to describe actual practice. We then identify opportunities for future research to better understand how planners use ACS data in day-to-day planning practice, better understand the ways in which educators and the profession can respond responsibly to the problems we identify, and suggest guidelines for planners working with ACS data.

Navigating Statistical Uncertainty in the ACS

Today's data-driven policy landscape requires accessible and reliable sociodemographic data. Historically planners turned to the decennial U.S. Census, specifically the long form, which through Census 2000 sampled roughly 1 in 6 households. Long-form data were used widely in planning practice because they captured detailed social, economic, and housing characteristics, aiding in the design, implementation, and assessment of comprehensive plans. These data allowed planners to better understand the community they served and to implement social justice and equity initiatives. A major limitation was that census data were often obsolete by the time they were used, especially for rapidly changing communities (Citro & Kalton, 2007). This forced many communities to compute their own estimates, purchase data from data vendors, or make policy decisions with outdated decennial long-form estimate data (MacDonald, 2006).

The mid- to late 1990s exposed the rising cost of administering the decennial census even as data users demanded timelier small-area data. The 1970 decennial census, for example, cost on average $76 to enumerate a housing unit; this cost remained relatively constant through Census 2000 (the cost actually declined to $71 per household in constant 2010 dollars). By Census 2010 the cost per housing unit escalated to roughly $97 (Government Accountability Office, 2012; MacDonald, 2006). Increasing costs undoubtedly helped fuel congressional opposition to fully funding the decennial long form, although some representatives also cited confidentiality concerns (Anderson & Fienberg, 1999; Rampell, 2012). These issues in the end, along with recommendations by the National Research Council and others (C. Alexander, 1993; Kish & Fellegi, 1981; Steffey & Bradburn, 1994), led the USCB in the late 1990s to test the ACS in four counties (e.g., Hough & Swanson, 2004; USCB, 2003). The USCB fully implemented the ACS in 2005, replacing the decennial long form (Torrieri, 2007).

ACS data, like decennial long-form data, are derived statistical estimates rather than actual counts, which means that they contain sampling error. The USCB expresses sampling error through an accompanying MOE, which represents a range of values expected to contain the true value of the quantity being estimated. A particularly salient difference between the two statistical samples is that the Census 2000 long form sampled roughly 1 in 6 households, whereas ACS annual estimates are derived from a sample of roughly 1 in 40.[1] USCB officials initially estimated that the ACS's smaller sample size would yield statistical uncertainty roughly 33% greater than that of the decennial long form. The statistical uncertainty of the ACS data actually ended up being closer to 75% higher (Navarro, 2012; Spielman, Folch, & Nagle, 2014).[2]

Figure 1 illustrates the crucial importance of understanding statistical uncertainty when reporting data. In Census Tract 5.02 in Brooklyn (NY), for example, combined 5-year (2011–2015) ACS data show that 7.3% of individuals live below the poverty line, with a MOE of ±4.6%. Correctly interpreting the accompanying MOE requires subtracting and adding the MOE from/to the ACS estimate, yielding an estimated poverty range of 2.7% (7.3% – 4.6%) to 11.9% (7.3% + 4.6%). This means that somewhere between 2.7% and 11.9% of individuals live below the poverty line. ACS data are reported at the 90% statistical confidence level, however, which means that

Subject	Census Tract 5.02, Kings County, New York					
	Total		Below poverty level		Percent below poverty level	
	Estimate	Margin of Error	Estimate	Margin of Error	Estimate	Margin of Error
Population for whom poverty status is determined	2,504	+/-288	184	+/-114	7.3%	+/-4.6
AGE						
Under 18 years	301	+/-91	28	+/-46	9.3%	+/-15.3
Under 5 years	147	+/-98	28	+/-46	19.0%	+/-27.6
5 to 17 years	154	+/-59	0	+/-11	0.0%	+/-17.6
Related children of householder under 18 years	301	+/-91	28	+/-46	9.3%	+/-15.3
18 to 64 years	1,762	+/-224	156	+/-79	8.9%	+/-4.6
18 to 34 years	656	+/-154	70	+/-56	10.7%	+/-7.7
35 to 64 years	1,106	+/-187	86	+/-66	7.8%	+/-6.0
60 years and over	563	+/-119	0	+/-11	0.0%	+/-5.2
65 years and over	441	+/-102	0	+/-11	0.0%	+/-6.6

Figure 1. U.S. Census Bureau, American FactFinder data table.
Source: U.S. Census Bureau, American FactFinder, American Community Survey (5-year estimates, 2011–2015, Table S1701).

there is a 10% chance that the actual poverty rate lies outside of this range. Data users desiring greater statistical confidence (e.g., 95%) will encounter even wider margins of error.

Planners consult different sources of demographic data to develop comprehensive plans, address social justice issues, write grant applications, and complete other day-to-day tasks. The ACS, arguably *the* go-to source of demographic data for planners, holds this title largely because it is used to determine a large proportion of government program funding. In 2008, data from the ACS determined roughly 29% of government assistance program funding and more than 69% of all federal grant funding (Carpenter & Reamer, 2010). The ACS, despite its importance in contemporary planning practice, has received little attention in the planning literature (see MacDonald, 2006, for an exception).

AICP Code of Ethics

The AICP Code of Ethics clearly states that planners should not "deliberately or with reckless indifference fail to provide adequate, timely, clear and accurate information" (American Institute of Certified Planners, 2009) to clients, constituents, policymakers, or the general public. Yet Williamson (2008) notes that "report writers should, but probably will not, include a discussion of ACS data quality" (p. 5).[3] The existing literature does not empirically assess these observations, which highlight a potential disconnect between on-the-ground planning practice and the ethical responsibility of planners to report and convey all relevant data to affected persons and government officials.

Several factors make it difficult for planners to more closely engage with ACS data quality issues. One practical factor is the emergence of Social Explorer, PolicyMap, Tableau, and other online demographic data resources. These websites, which are user-friendly alternatives for accessing, downloading, and displaying demographic data with various visualization tools, are easy to navigate and are useful for carrying out data-intensive tasks. A key drawback, however, is that most of these sites do not report the accompanying MOE values with ACS estimates, which means that most planners using these sites are less likely to closely engage with ACS data quality issues, as Williamson suggested in 2008.

Three interrelated structural factors also likely contribute to this issue. First, some planners may not be familiar with data quality issues or may lack the statistical training required to interpret these issues. Edwards and Bates (2011) point out that most planning schools require that students enroll in a quantitative methods course, often focusing on inferential statistics; communicating results is a critical part of teaching these methods. This observation reflects the enduring debate about planning education and what planners need to know (E. R. Alexander, 2001; Dalton, 2007; Ozawa & Seltzer, 1999; Seltzer & Ozawa, 2002). It remains unclear the extent to which students are taught how to accurately interpret and communicate data and statistical uncertainty to policymakers and constituents using tables and charts as well as to navigate the unique challenges of conveying uncertainty in mapping (e.g., Aerts, Clarke, & Keuper, 2003; Leitner & Buttenfield, 2000; MacEachren, Brewer, & Pickle, 1998; MacEachren et al., 2012; Monmonier, 1996; Senaratne, Gerharz, Pebesma, & Schwering, 2012; Sun & Wong, 2010; Vullings, Blok, Wessels, & Bulens, 2013; Wong & Sun, 2013; Zhang, Blok, & Tang, 2008).

Second, there may be situations in which planners have been properly educated in statistics but have forgotten how to use them or have not kept abreast of applicable skills.

There is little, if any, empirical evidence on this topic, unfortunately. Third, many federal agencies (e.g., the U.S. Department of Agriculture's Supplemental Nutrition Assistance Program) do not consider MOE in eligibility guidelines (see Nesse & Rahe, 2015); moreover, bosses/clients may instruct planners *not* to report MOE (perhaps because of its complexity). These are examples of potential structural problems preventing planners from engaging closely with statistical uncertainty in ACS data. The limited empirical evidence in the current literature about the (absence of) MOE in funding decisions makes it difficult to gauge the relative importance of these factors. In July 2017 the Appropriations Committee in the U.S. House of Representatives underscored the importance of this issue, however, approving a legislative bill for a floor vote. This bill would require the U.S. Department of Housing and Urban Development to report areas in the United States where income data used to determine program eligibility have a MOE of 20% or higher (Caster, 2017).

Conveying Statistical Uncertainty: An On-the-Ground Example

Perhaps the most challenging aspect of ACS data is that the already high sampling error increases for smaller geographies (e.g., census tracts) and subpopulations (e.g., poverty rate for children) and for cross-tabulated data (e.g., race/ethnicity by income). Consider, for example, Figures 2 and 3, which reveal poverty rates for all individuals and children (under 18 years of age), respectively, in the city of Portland (OR) and the Portland Metropolitan Statistical Area (MSA) for 2007 to 2015 (1-year ACS estimates). Here error bars, illustrated with I-beams, convey MOE values and underscore three important points. First, data from geographic areas with smaller populations contain a greater degree of statistical uncertainty than data from areas with larger populations. Figure 2 shows that the poverty rate in the city of Portland (15.8%, ±1.2%, in 2015) contains greater statistical uncertainty than the comparable rate in the Portland MSA (12.2%, ±0.7%) because the city of Portland has a smaller population. Second, Figure 3 shows that the statistical uncertainty for both the city of Portland (16.6%, ±3.0%) and the Portland MSA (14.9%, ±1.5%) is considerably higher for children because children are a subpopulation. Third, although the *estimates* in Figure 3 appear to change quite a bit from year to year,[4] evaluating the estimates with the accompanying MOE values reveals that only the 2011 city of Portland estimate of child poverty is statistically different from the 2007 estimate, with 90% statistical confidence across the 8-year period (2010, 2011, 2012, 2013, and 2014 for the MSA).[5]

Assessing the reliability of ACS data, especially for small-area geographies (i.e., census tracts and block

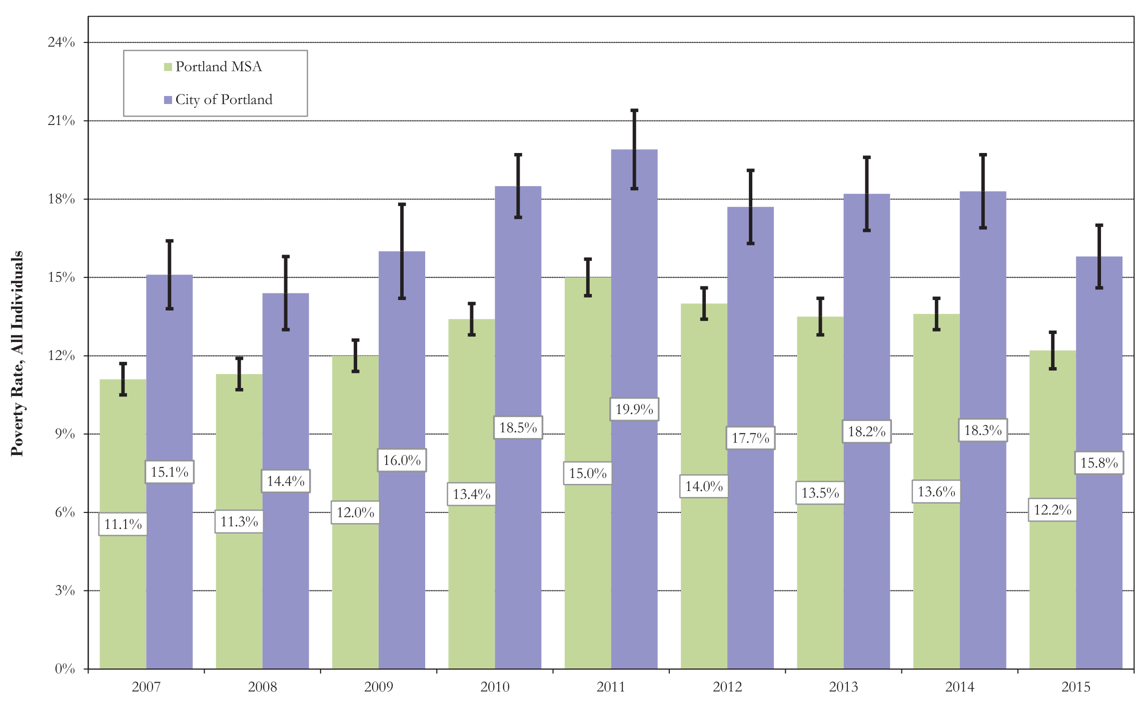

Figure 2. Percentage below poverty threshold, all individuals.
Source: Data from Charles Rynerson, Portland State University Population Research Center, American Community Survey (1-year estimates, 2007–2015, Table S1701).

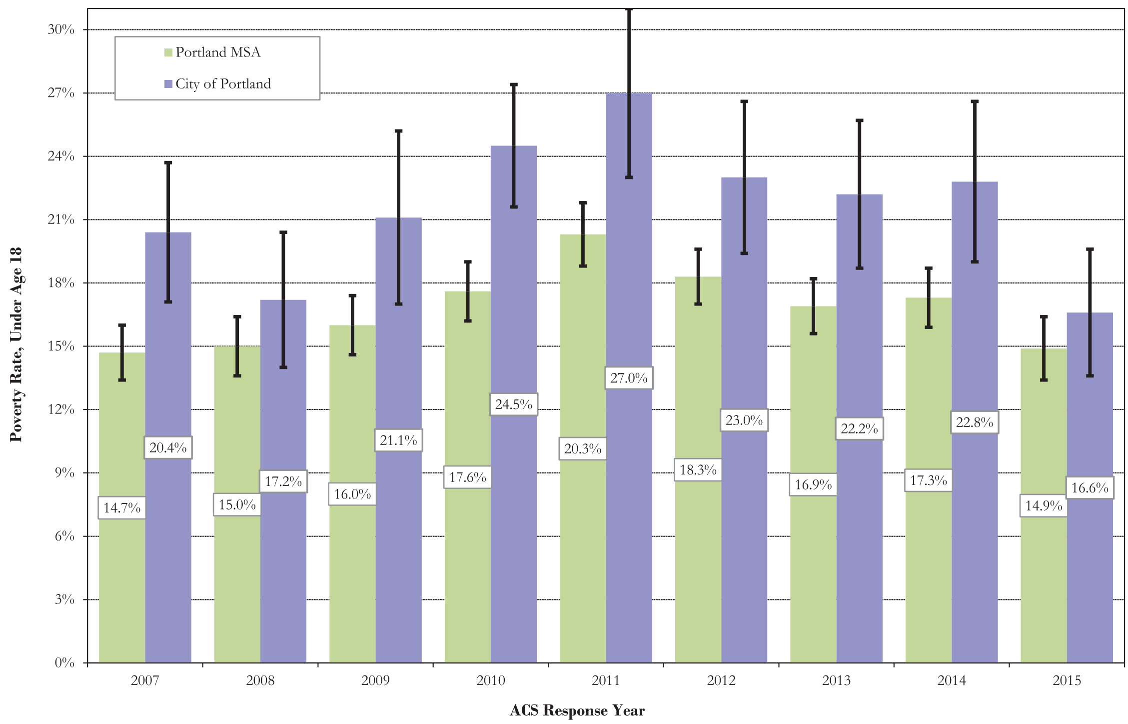

Figure 3. Percentage below poverty threshold, under age 18.
Source: Data from Charles Rynerson, Portland State University Population Research Center, American Community Survey (1-year estimates, 2007–2015, Table S1701).

groups), is important given that these data contain a substantial amount of statistical uncertainty (National Academy of Sciences, 2015; USCB, 2009). We provide an example to more clearly underscore the materially negative consequences for public policy development of failing to consider or communicate uncertainty in ACS data to clients, policymakers, and constituents. A planner using the 2010–2014 5-year ACS file would find that tract-level estimates of child poverty in Portland contain high levels of sampling error: 72% of tracts have unreliable poverty estimates, 28% of tracts are moderately reliable, and *none* of the tracts yields reliable estimates for child poverty.[6] This shows that planners must always examine the MOE of census estimates before drawing conclusions and, whenever possible, consider alternative approaches for reducing statistical uncertainty, including collapsing data detail or aggregating census geographies (Citro & Kalton, 2007; Heuvelink & Burrough, 2002; National Academy of Sciences, 2015; Spielman & Folch, 2015; Spielman et al., 2014; USCB, 2009).

MOE values and their corresponding confidence intervals are complex and often poorly understood by many data users, which makes it difficult to determine whether a statistic is reliable. The USCB recommends using the coefficient of variation (CV)[7] to assess fitness for use (USCB, 2009). The CV is a relative measure of uncertainty and expresses uncertainty as a percentage of the census estimate. Larger CV values indicate lower reliability. Environmental Systems Research Institute (2014) proposes that CV values smaller than 12% indicate a high degree of reliability, although there are no official thresholds for data quality. The same report suggests that values between 12% and 40% are somewhat reliable and that CVs greater than 40% indicate little, if any, reliability. The National Research Council (Citro & Kalton, 2007) argues that the threshold for an acceptable CV should be approximately 10% to 12%. The 2015 values in Figure 3, for example, for both the city of Portland (16.6%, ±3.0% = CV of 11%) and the Portland MSA (14.9%, ±1.5% = CV of 6%) estimates are reliable according to these rules of thumb.

Understanding Planners' Experience With Addressing Statistical Uncertainty

We wanted to evaluate whether and how planners addressed statistical uncertainty issues when using census and ACS data for planning and policy purposes. We took two approaches. We first evaluated the extent to which the APA offered professional development courses on using and evaluating census data. We then interviewed and surveyed planners from a variety of agencies across the United States to evaluate how they used ACS data in research and practice, their familiarity with statistical uncertainty in ACS data, and their approaches for conveying statistical uncertainty to colleagues and constituents.

APA Professional Development Courses and Statistical Uncertainty

We investigated the extent to which professional planners were offered or used professional development courses that addressed issues of statistical unreliability in census/ACS data. We surveyed Professional Development Officers from the 47 APA chapters to identify the number of certificate/professional development courses they had organized in the past 5 years (2012–2016) covering census/ACS data and/or MOE. A total of 67% of the chapters, or 28 Professional Development Officer chapter contacts, responded. Nine (32% of those who responded) identified no sessions addressing ACS and MOE issues. More than one-third (36% of respondents) referred us to the Certification Maintenance database on the APA website, where our searches for "ACS" and "margin of error" revealed four to five sessions in a 5-year period covering ACS-related topics in planning research and practice.[8]

The Experiences of Practicing Planners With Statistical Uncertainty

To explore how, and to what extent, planners engage with statistical uncertainty, especially in the context of real-world tasks situated in work environments, we collected data from urban and regional planners working in proifessional practice. We used a multimethod approach. First, we interviewed seven planners from a variety of planning agencies across the United States to inform the development of a survey questionnaire that could reach a larger sample of planners. Second, we conducted an online survey that recruited participants through whom we hoped to corroborate the limited interview findings.

We made cold calls to identify planners who were willing to be interviewed ($n = 7$), ensuring that the interviewees were purposively selected to represent planners from a range of types of agencies and professional practice. The seven interviewees worked in a range of locations, including a mid-size city ($n = 2$), a suburb of a major metropolitan area ($n = 1$), the central city of a major metropolitan area ($n = 3$), and a regional planning authority ($n = 1$). The interviewees worked in a variety of positions: as urban planners ($n = 2$), a dedicated GIS analyst within a planning department, a principal planner with responsibility for infrastructure, a long-range planner, a transportation planner, and a travel demand modeler. The planners working in agencies with larger jurisdictional focus had more specialized job duties.

Two authors conducted the interviews in person; each lasted between 30 and 60 min. We did not pretest the interview questions; instead, we conducted semistructured interviews following a predetermined set of questions, which allowed us to ask follow-up questions to explore specific statements or ideas in more detail. We asked planners about a) training and work experience, b) specific projects involving ACS data and decision making, c) experience with and use of statistics and maps, d) familiarity with statistical uncertainty in ACS data, and e) documents produced for conveying information to colleagues and constituents. One author transcribed, coded, and analyzed the interview questions using iterative coding, which allowed us to identify and extract common themes to inform the development of the survey questions (Srivastava & Hopwood, 2009). The same author also conducted an analysis of any written products that some participants were willing to share (e.g., reports, presentations, fact sheets, and other publications) to evaluate how these documents used the data and the approaches they used to convey statistical uncertainty. Our interviews with planners reveal a gap in knowledge about the ACS that impedes the ability of some planners to effectively use ACS data; we also find that planners had difficulty communicating statistical uncertainty to affected individuals, communities, and policymakers.

We then conducted an online survey to corroborate these limited findings, recruiting participants from three electronic listservs whose members include a large number of planners. The three groups were 1) the USCB's State Data Center network, 2) the Urban Institute, and 3) the Census Transportation Planning Products Program network. We recruited respondents ($n = 200$) by sending a letter of introduction and the link to the survey. We were unable to calculate a response rate because some listserv participants forwarded the survey link to colleagues who were not members of the listserv.

The survey took respondents roughly 20 min to complete. We used multiple-choice and some open-ended questions to ask respondents about their job in the planning organization they worked for, their educational background and completed coursework in statistics and mapping, what kind of demographic data sources they used and how often they used data for completing planning-related tasks, and approaches for communicating data to clients and constituents. We also asked a set of questions to gauge their knowledge of statistical uncertainty (the instrument appears in the Technical Appendix).

We pilot-tested the survey questionnaire with other planning academics, planning graduate students, and custodians of some of the listservs we relied on in order to test both the logical order and clarity of questions. We reordered some questions and clarified the wording of others in response to this pilot testing. One author coded the responses to the open-ended survey questions using iterative coding to ensure intercoder reliability.

In all, 60% of survey respondents held a master's degree as their most advanced degree;[9] 36% of respondents had worked in planning 15 years or longer.[10] More than half of the survey respondents identified regional-scale planning as the focus of their work: 19% at the county scale and 37% at the regional/metropolitan scale.[11]

Our sample potentially *overrepresents* statistical competence and understanding within the planning community because of the specialized knowledge some of our respondents had. Our sample may simultaneously *underrepresent* statistical competence because those working in regional planning organizations might be less familiar with the challenges of ACS data, which are more serious in smaller geographic areas. We assessed how representative our responses were because specialized knowledge, including familiarity with statistics and mapping, varies considerably across planning fields and by organizational focus. Figure 4 shows that the top three specializations of survey respondents were long-range, transportation, and economic development planning; these are specializations that, on the balance, require strong quantitative competency and technical analytical methods (compared with a specialization such as historic preservation, for example).[12] Planners working for regional planning organizations, for example, might be less likely to consult census data at geographies with the greatest statistical uncertainty (e.g., the census block group or tract level).

How Planners Navigate the Statistical Uncertainty of ACS Data in Professional Practice

Our interviews, analyses of written documents, and survey results provide empirical evidence on four specific topics: 1) how often planners use demographic data and the source(s) of those demographic data; 2) planners' ideas about statistical uncertainty and knowledge of approaches for working with uncertainty in the ACS; 3) how planners communicate uncertainty, if at all, to policymakers and constituents; and 4) the primary tasks planners accomplish using demographic data. We report, where appropriate,

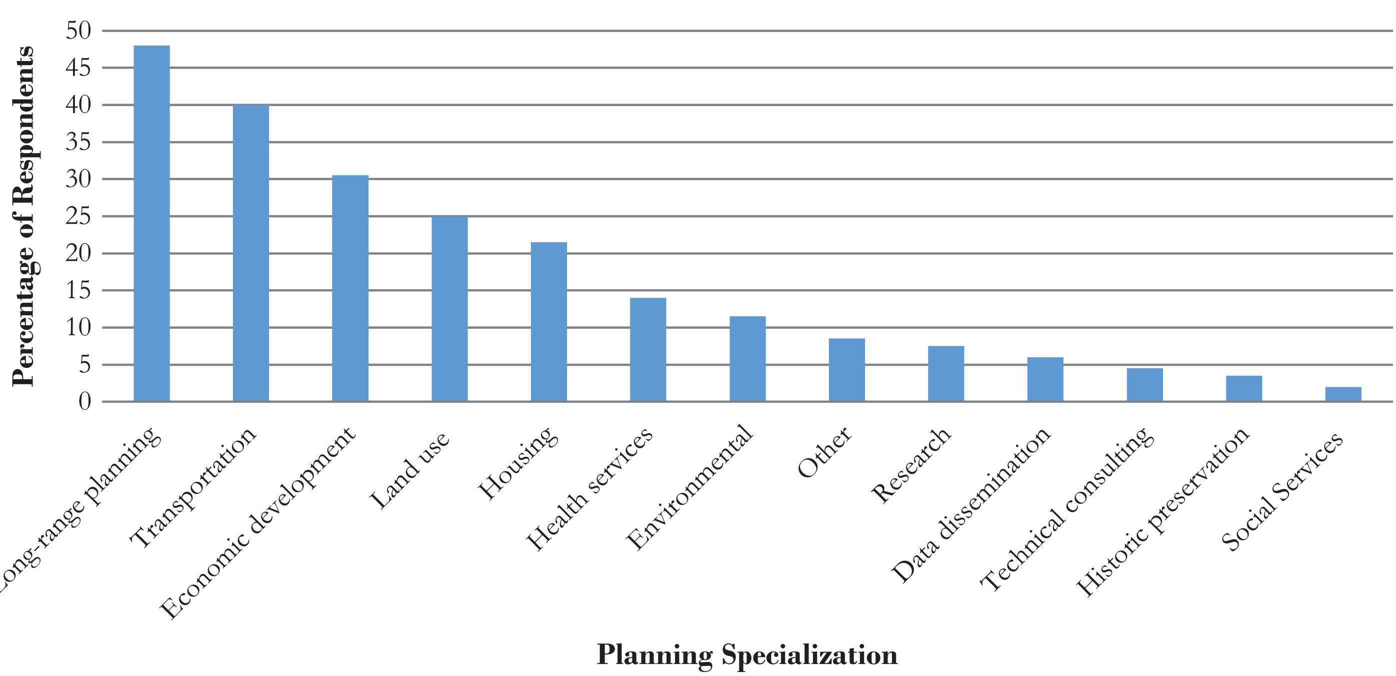

Figure 4. Survey respondent planning specializations.
Notes: Survey respondents (n = 200) indicated the specialization areas most germane to their current position. Nineteen respondents provided no answer. Source: Calculated by the authors.

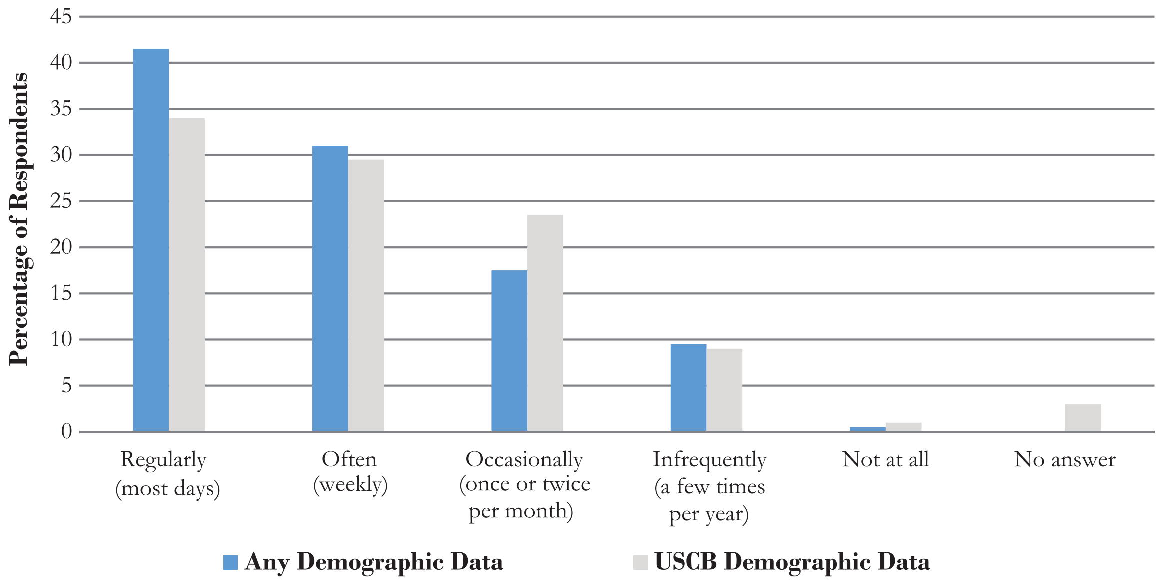

Figure 5. Frequency of use of demographic data.
Notes: n = 200. Six respondents provided no answer to the U.S. Census Bureau demographic data question. Source: Calculated by the authors.

results from our analysis of the interview transcripts and our review of the planning reports that some respondents provided to add richness to the description of patterns identified in the survey of 200 planners.

Use of Demographic Data

We already know that planners working in long-range, transportation, economic development, and other quantitatively oriented planning specializations rely heavily on demographic data. How frequently planners consult these data, what sources of data are most important, and how planners use the data are less well known. Figure 5 shows that 7 of 10 respondents indicated that they use demographic data (from all sources) at least once a week; most of all respondents (6 of 10) rely on data from the USCB. We asked survey respondents why they use non-USCB sources of demographic data;[13] 44% said they do so to evaluate the reliability of ACS data. We questioned what the planner would do in a scenario when the MOE is greater than the estimate: "Find other data sources and review their estimates: Compare and contrast and decide how reliable the ACS data are, then decide what sources to use and cite" (metropolitan regional planning consultant survey respondent). Another respondent said the following:

> You know...if...I see some of these larger margins of error where the margin of error is bigger than the number, I guess our interaction is probably very basic..."Wow, [the MOE is] big, maybe I shouldn't use it," and then figure something else out.... (Long-range planner and GIS specialist, medium-size city, interviewee)

We asked survey respondents their primary reasons for pursuing non-USCB data sources; Table 1 shows that the major reasons are to address geographic scale and data availability (50%), determine whether they can trust census statistics (44%), obtain more timely data (40%), and acquire more reliable data (18%). It appears that many planners are cognizant of the embedded statistical uncertainty in ACS data and pursue alternative data sources to evaluate and potentially bypass what they believe to be unreliable data. They also pursue alternative sources of data that are more timely, available, and better suited to the geographic scale of analysis.

We also asked survey respondents about their familiarity, experience, and level of formal training with statistics/quantitative analysis as well as how often they use GIS (because demographic data are often analyzed using GIS).

Table 1. Reasons for using data from other demographic data sources.

Reason	% of respondents
Geographic scale fits my needs better	50
As corroboration for census statistics	44
Data frequency is better	40
Data reliability is better	18
Census data do not provide needed variables	14
State requires their use	9
Grants program mandates their use	4
Need population projections	2

Source: Calculated by the authors.

In all, 44% of planners indicated that they have no formal training in GIS; however, 55% have taken two or fewer formal courses in statistics. Moreover, 56% of respondents said that they use GIS at least weekly, and 74% indicated that they use GIS at least on a monthly basis.

These results confirm the importance of quantitative analysis and demographic data, including census data, in contemporary planning practice. Our survey data also underscore another particularly noteworthy point: Respondents reported pursuing alternative non-USCB data sources when necessary to avoid working with and reporting uncertain USCB data for day-to-day tasks. This suggests that many planners possess some important quantitative reasoning skills. We infer that many practicing planners gain a high degree of on-the-job quantitative and statistical learning because they are able to recognize USCB data deficiencies despite having limited formal training in statistics.

Knowledge of Statistical Uncertainty

Users must first become familiar with the nuances of statistical uncertainty to carefully engage with ACS data. The quality of ACS data varies from place to place because of variations in sample size, composition of the community, and response rate. We asked survey respondents whether they understood this elementary principle by questioning the extent to which respondents agreed with the following two statements using a 5-point Likert scale (1 = *strongly agree* and 5 = *strongly disagree*): "The reliability of the data from the ACS (5-year estimates) is the same for all places" and "I should be more careful when using ACS data for small geographies (census tracts) than for large geographies (counties)."

Roughly 6 of 10 planners (63%) responded correctly to both questions; that is, they disagreed with the first statement and agreed with the second statement. We then asked participants whether they agreed with the statement "Demographic and economic estimates from the ACS are only suitable for making comparisons between places if margins of error are considered."

A smaller percentage (53%) responded correctly to this statement. Almost 1 in 4 respondents (23%) admitted to not paying much attention to MOE values when using ACS data. Together, these survey responses underscore an important point: About one-third of planners are not knowledgeable about statistical uncertainty in ACS data (i.e., were unable to answer all three questions correctly), and some admit to not paying much attention to MOE values when using ACS data (almost 1 in 4 respondents; 23%).

There is a clear contrast between knowledge and willingness to address statistical uncertainty directly. We asked respondents what "uncertainty" meant to them; one of the seven interviewees, a long-range planner and GIS specialist in a medium-size city, commented, "I would define uncertainty as...in the most simple terms...a question mark. And when you're working with data, is it a big question or a little question mark?" Several other planners we interviewed commented that they simply do not engage with MOE values:

> As long as we're all using ACS data, it doesn't really matter because they all have the same margin of error, you know.... I also found when I started bringing it in this time around, I eliminated the MOE. I took it out. Because it's just all these extra columns that I don't need. (Demographics researcher in the planning department, central city major metropolitan area, interviewee)

> Any good statistics class, software, person who just does statistics will...include a margin of error.... However, we just don't use it. Nobody...unless you're a statistics type person presenting to statistics professors where you have to have your footnotes in there...for the actual real-world studies.... If you're comparing ACS to ACS, it really doesn't matter. They're going to have the same margin of error, more or less. (Principal planner, central city major metropolitan area, interviewee)

Both our survey and interview data indicate that planners do not always understand the nuances of statistical uncertainty in ACS data and suggest that some planners are unfamiliar with data quality issues and/or do not possess the technical skills to address (and potentially communicate) data reliability. In our survey we asked planners where they learned about ACS data to understand why they were unfamiliar with these issues. Our findings show that more than 2 of 3 (69%) respondents learned about the ACS using data in on-the-job tasks; only 15% said that they learned about the ACS in a university class.

Communicating Statistical Uncertainty

The AICP Code of Ethics requires planners to fully disclose information affecting individuals and communities in a clear and direct way; we believe this obligation includes reporting the accompanying MOE estimates in ACS data. We asked survey respondents, in an open-ended, scenario-based question, what they would do when the MOE was reported to be equal to the size of the ACS estimate (e.g., 10% poverty, ±10%). Just 27% of respondents indicated that they would warn the user about the reliability of the data; only

16% of respondents identified how they would communicate statistical reliability. Just 9% specifically mentioned that they would communicate the corresponding MOE.

Our results suggest that although some planners are familiar with and have substantive knowledge of statistical uncertainty, they rarely communicate that uncertainty. Our research also points to other factors that explain why some planners avoid engaging with and reporting statistical uncertainty if they do understand it. Engaging with MOE values is "cumbersome" for some respondents, which suggests that they appreciate their significance but consciously choose to not report the MOE because of time constraints and other limiting factors:

> I should not use the data or provide a range from 0–200, but often I don't have the time to look in detail at the MOEs for as many geographies and years of data that we have to provide data for. It gets overlooked much too often but it's hard to have a good solution when there isn't better data available. (Planner working at a regional planning agency, survey respondent)

Practitioners sometimes indicated that they understand statistical uncertainty but are not able to convince others of its significance, which is why they do not address or report MOE values. More than half of planners surveyed (51%) said that agencies evaluating grant applications do not require MOE data. Many planners also cited the difficulty of communicating statistical uncertainty to clients, decision makers, and the public; they noted that many of their clients do not have a substantive understanding of statistical uncertainty:

> It [uncertainty] gives us a lot.... It makes us much more nervous about sharing that information with the public. And exactly about how to frame it to the public, because the whole concept of uncertainty and confidence intervals is, you know, you start talking about that and people's eyes glaze over, and you've lost them. So how do you present the information in a way that's honest, in terms of conveying the level of certainty that is associated with it...? And sometimes it means we just choose not to.... Like we use that information for internal analysis to, you know, kind of help us understand the issues, but we're not comfortable with sharing it at the fine-grained level externally because it just implies a level of precision that's absolutely not there. (Transportation planner, regional planning organization, interviewee)

Tasks Involving Demographic Data

Figure 6 shows what respondents told us when we asked what tasks they use both ACS and non-ACS

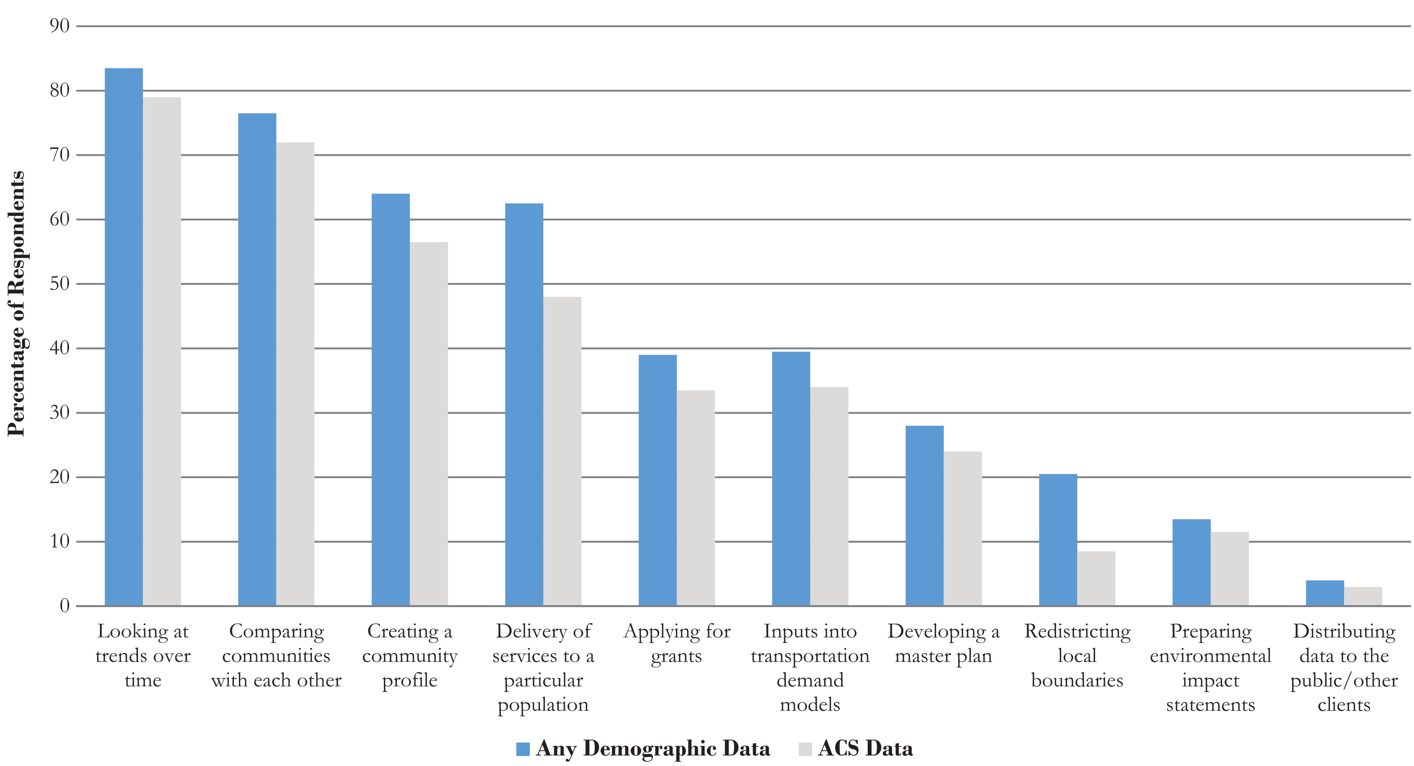

Figure 6. Tasks involving demographic data.
Source: Calculated by the authors.

Table 2. Approaches for communicating demographic data.

Communication method	% of respondents
Table	84
Maps	83
Bar chart	74
Textual description	71
Line graph	70
Pie chart	61
Other statistical graph	36

Source: Calculated by the authors.

demographic data to accomplish. The top three responses were to examine trends over time, create community profiles, and pursue data-driven tasks. Each of the these tasks presents unique challenges for planners in terms of communicating statistical uncertainty to colleagues and constituents. Table 2 shows that the most common approaches to communicating demographic patterns and trends include tables (84%), maps (83%), bar charts (74%), textual descriptions (71%), and line graphs (70%). Only three survey respondents (2%), however, suggested that they would use a graphic or data visualization to communicate uncertainty:

> Depending on the use of the data—that is, if no capital or human life issues are involved—I might present the value as a range rather than just the number. Graphing can be helpful in this regard, as it allows the viewer to understand that the value is "somewhere" in the range but we can't be precise enough to name it. (Health services and economic development planner working at metropolitan and regional scales, survey respondent)

We also examined the reports and documents that the seven planners whom we first interviewed provided to further assess how planners communicated statistical uncertainty. Most did not report uncertainty information in those public documents; they rarely communicated embedded statistical uncertainty or described statistical tests for significance to end users.

Takeaways of Navigating the Statistical Uncertainty of ACS Data in Professional Planning Practice

Today, tackling complex urban and regional issues requires robust, customized cross-tabulations of ACS data and other types of specialized, data-driven analytics. The ACS has become a powerful resource in a planner's toolbox for empowering data-driven analysis because the ACS produces sociodemographic data for many different scales of analysis annually.

A key limitation, however, is that ACS data are drawn from a smaller sample size than the decennial long-form data, so ACS data possess a greater amount of statistical uncertainty that is magnified for small-area geographies, subpopulations, and cross-tabulated data. These challenges have real and potentially limiting effects for planning policy and governance. MacDonald (2006, p. 501) emphasizes the importance of this issue, noting that "we will be able to use the ACS effectively only if we have a clear grasp of its limitations and are able to communicate these clearly."

We interviewed seven planners and surveyed 200 to understand planners' familiarity with statistical uncertainty in ACS data, to what extent they use ACS data in research and practice, and their approaches for conveying statistical uncertainty to policymakers and the public. Our research shows that that some planners know little about the limitations of the ACS or how to address them; they tend not to report accompanying MOEs at all because they have difficulty communicating statistical uncertainty to affected individuals, communities, and policymakers. Some planners do seek additional data to evaluate the reliability of ACS data or to use as a second source. This shows that many have gained some measure of statistical sophistication on the job because most told us they had not been formally trained to use MOEs or report uncertainty to stakeholders.

The inability to effectively use ACS and other data has very salient implications for contemporary planning practice: There is an apparent disconnect between the ethical responsibilities set forth by the AICP Code of Ethics—that planners report and convey all relevant data to affected persons and government officials—and what planners actually do with ACS data and the calculations they make using those data. We argue that addressing this issue is crucial: Planners should know and understand how to meet their ethical obligation by reporting all information—including statistical uncertainty—in a clear and direct way that informs public policy.

What steps can planners take to meet their ethical obligations? First, there is a clear gap in knowledge that impedes the ability of some planners to effectively use ACS data and communicate statistical uncertainty to stakeholders.[14] We suggest that the planning academy, through the Association of Collegiate Schools of Planning and the Planning Accreditation Board, reevaluate its requirements

Population, Housing, Social and Economic Profile
Sherman County, Oregon

	2006-2010			2011-2015			Compare
	Estimate	CV *	MOE** (+/-)	Estimate	CV *	MOE** (+/-)	Statistically Different?
POPULATION							
Total population	1,819	🟢	144	1,795	🟢	128	
Percent under 18 years	*22.6%*	🟢	*2.7%*	*17.9%*	🟢	*3.0%*	***
Percent 65 years and over	*19.0%*	🟢	*2.8%*	*24.3%*	🟢	*2.2%*	***
Median age (years)	45.3	🟢	4.0	49.8	🟢	1.4	***
Percent white alone, non-Latino	*93.2%*	🟢	*3.3%*	*85.0%*	🟢	*3.0%*	***
HOUSING							
Total housing units	967	🟢	54	938	🟢	39	
Occupied housing units	813	🟢	63	804	🟢	56	
Owner occupied	545	🟢	50	495	🟢	49	
Percent owner-occupied	*67.0%*	🟢	*6.0%*	*61.6%*	🟢	*4.8%*	
Renter occupied	268	🟢	60	309	🟢	46	
Vacant housing units****	154	🟡	44	134	🟡	42	
Vacancy rate	*15.9%*	🟡	*4.5%*	*14.3%*	🟡	*4.5%*	
Average household size	2.24	🟢	0.14	2.22	🟢	0.14	
Renter households paying more than 30 percent of household income on rent plus utilities	*40.0%*	🟡	*15.3%*	*52.0%*	🟢	*11.7%*	
SOCIAL							
Age 25+ with a bachelor's degree or higher	*15.4%*	🟢	*3.0%*	*17.3%*	🟢	*3.3%*	
Foreign-born population	66	🔴	47	60	🔴	40	
Percent foreign-born	*3.6%*	🔴	*2.5%*	*3.3%*	🔴	*2.2%*	
Age 5+ language other than English at home	81	🔴	51	80	🟡	37	
Percent language other than English	*4.7%*	🔴	*2.9%*	*4.8%*	🟡	*2.1%*	
ECONOMIC							
Median household income (2015 dollars)	$44,956	🟢	$8,741	$38,362	🟢	$5,362	
Per capita income (2015 dollars)	$23,577	🟢	$1,968	$26,178	🟢	$2,810	
Percent of persons below poverty level	*20.0%*	🟡	*5.0%*	*21.6%*	🟢	*5.0%*	

** Green, yellow, and red icons indicate the reliabilty of each estimate using the coefficient of variation (CV). The lower the CV, the more reliable the data. High reliability (CV <15%) is shown in green, medium reliability (CV between 15-30% - be careful) is shown in orange, and low reliability (CV >30% - use with extreme caution) is shown in red. However, there are no absolute rules for acceptable thresholds of reliability. Users should consider the margin of error and the need for precision.*

*** Margin of error at the 90 percent confidence level.*

**** Indicates that the two estimates are statistically different based on results of z-test taking into account the difference between the two estimates as well as an approximation of the standard errors of both estimates.*

***** Vacant units include those for sale or rent, those sold or rented but not yet occupied, those held for seasonal, recreational, or occasional use, as well as other vacant such as homes under renovation, settlement of an estate, or foreclosures.*

****** Indicates that the estimate is controlled. A statistical test for sampling variability is not appropriate.*

Source: U.S. Census Bureau, American Community Survey 5 year estimates. Surveys are collected over a 60 month period. Estimates represent average characteristics over the entire period. Tabulated by Population Research Center, Portland State University, with additional calculations from source data as needed.

Figure 7. Example table illustrating best practices for reporting American Community Survey data.
Source: Charles Rynerson, Portland State University Population Research Center, American Community Survey (5-year estimates).

for quantitative curricula, ensuring that students are taught how to interpret and communicate data and statistical uncertainty in graduate planning programs. A significant number of APA members in 2014, however, did not have a planning degree (Lauria & Long, 2017), and our data show that most planners learn about ACS data through day-to-day tasks. It is crucial, therefore, for the planning profession to offer and actively promote quantitatively oriented courses in professional development training, making clear the link to the AICP Code of Ethics and the ethical standards required of practicing planners.[15] We encourage the AICP to treat reporting and communicating statistical uncertainty as an ethics topic as part of the 1.5 minimum certification maintenance credits.

Second, to help planners and other data users successfully navigate statistical uncertainty in ACS data, we recommend that increasingly popular web resources for demographic data (e.g., Social Explorer, PolicyMap, and Tableau) report corresponding MOE or CV values. Planners should use American FactFinder or National Historical GIS to download and report ACS estimates and accompanying MOE values in the meantime. Third, we are encouraged that more simplified, practical, and user-friendly handbooks showcasing actual case studies with ACS data will replace the ACS compass handbooks (USCB, 2009). Fourth, we suggest that planners try to follow the five guidelines below, whenever possible, when using ACS and other survey data:

1. Report the corresponding MOEs of ACS estimates.
2. Include a footnote when not reporting the corresponding MOEs of ACS estimates.
3. Provide context for the level of (un)reliability in ACS estimates; do not be afraid to advise against using data that are clearly unreliable.
4. Reduce statistical uncertainty by collapsing data detail when possible, aggregating census geographies, and/or using multiyear ACS estimates.
5. *Always* conduct a test of statistical difference when comparing ACS estimates before calculating or reporting any apparent differences in the estimates.

Planners in our survey said that tables are their most common method for communicating demographic data. Figure 7 (as well as Figures 2 and 3) illustrates our recommended guidelines for presenting ACS data and the accompanying statistical uncertainty in a table. First, the table shows the corresponding MOE for each ACS estimate, as Guideline 1 suggests. Second, the table indicates the CV using a green–yellow–red light schematic indicating high, moderate, and low levels of reliability to convey the level of (un)reliability in the ACS estimates, as Guideline 2 suggests. Third, data for the foreign-born population in both ACS periods are unreliable and should not be used (Guideline 3). If a constituent requested more reliable data for the foreign-born population, a planner could potentially aggregate data in one county with those in a neighboring county as a way to reduce the MOE (Guideline 4). Fourth, the tables present the data so that constituents can compare estimates between two nonoverlapping ACS periods, 2006 to 2010 and 2011 to 2015. Thus, the "compare" column tells constituents whether the change in the estimates between the periods is statistically significant, as indicated by Guideline 5. We believe that these guidelines are effective bright-lines for communicating ACS data, and related statistical uncertainty, to affected individuals and communities in a clear and direct way.

Planners need future research to better understand how the profession teaches about and uses ACS and other relevant data that bear directly on public policy by specifically considering the geographic scale in which they work, their comfort with numbers, and how knowledge of place informs their assessment of data reliability. Planners who use ACS and other demographic data have an ethical obligation to explore how and to what extent these data can and should be used to decide which jurisdictions get a variety of grants, how to assess who needs which services, where to locate public facilities, and how to fairly develop and implement a range of public policies. Planners need to integrate statistical uncertainty into the everyday language of planning practice to meet their ethical obligations.

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Supplemental Material

Supplemental data for this article can be found on the publisher's website.

Notes

1. We provide sampling odds as a way to compare the sampling frame of the decennial long form alongside the ACS. However, to be clear, the ACS sampling frame is based on a fixed number of housing units, not a sampling rate. Furthermore, ACS estimates are pooled over multiple years to produce estimates. For more information, see USCB (2017).
2. The USCB increased the ACS sample size in 2011, and thus sampling error will be lower in post-2011 estimates. For more information on the effective sampling size of the ACS, see USCB (n.d.).
3. Addressing the importance of statistical uncertainty in ACS data, Williamson (2008, p. 46) notes, "ACS data users will have to review all their data and decide if some tabulations should be discarded because of high margin of error and/or imputation rate. Conversely, tabulations may also be strong and cited as more reliable compared to the others."
4. Testing for statistical significance in ACS data is fully explained in Appendix 4 of the USCB ACS compass handbook (USCB, 2008). In graphical representations of ACS data, it is often tempting to assume that two estimates are statistically different from each other if their confidence intervals do not overlap (or conversely *not significant* if the confidence intervals overlap). Using the test for statistical significance as outlined in the ACS compass handbook provides data users with a paired *t* test that recomputes the MOE to assess whether the difference *between the estimates* is statistically significant. Therefore, we caution users against drawing inferences from graphical illustrations without conducting their own statistical tests.
5. Comparing the city of Portland's child poverty rate in 2007 (20.4%, ±3.3%) with the 2011 rate (27%, ±4%) yields a statistically significant *t* of 2.0937. Comparing the 2007 rate for the Portland MSA (14.7%, ±1.3%) with those of 2010 (17.6%, ±1.4%), 2011 (20.3%, ±1.5%), 2012 (18.3%, ±1.3%), 2013 (16.9%, ±1.3%), and 2014 (17.3%, ±1.4%) yields statistically significant *t*s of 2.4970, 4.6409, 3.2211, 1.9685, and 2.2387, respectively.
6. These percentages are based on a total of 141 census tracts in Multnomah County (out of 171 total tracts in the county) that lie either wholly or partly inside the Portland city limits. Forty-one tracts (29%) have coefficient of variation (CV) values of 75% or higher, 61 tracts (43%) have CV values between 41% and 74%, and 39 (28%) have CV values between 12% and 40%.
7. The CV expresses the error relative to the estimate by dividing the standard error by the statistical estimate and multiplying the result by 100. Given the importance of statistical techniques in making policy decisions, the USCB publishes a series of ACS compass handbooks guiding data users on constructing confidence intervals and conducting tests of statistical significance. For more information, see http://www.census.gov/acs/www/guidance_for_data_users/handbooks/.
8. APA chapters sponsoring sessions focusing on ACS/MOE topics include Federal Highway Administration, Florida, National APA, Nebraska, Nevada, Pennsylvania, Planetizen, and the Southern California Association of Governments.
9. The highest level of education for survey respondents was a bachelor's degree (17%), a master's degree (60%), other professional degree (1%), or a doctorate (11%); some respondents did not answer (12%). Respondents who had completed a master's degree had attained one of the following types of degrees: MA, MSc, MURP, MPH, MEng, MBA, or an equivalent degree.
10. The total number of years (M = 14.5 years, SD = 9.7 years) survey respondents had been working in planning was less than 5 (16%), 5 to 9 (21%), 10 to 14 (16%), 15 to 19 (10%), 20 to 24 (8%), 25 to 29 (7%), and 30 or more (12%); some respondents did not answer (13%).
11. The primary scale/focus of survey respondents' planning organizations was neighborhood (5%), city (8%), county (19%), regional/metro area (37%), state (15%), nation (6%), global (2%); some respondents did not answer (10%).
12. The planning specialization(s) that respondents reported included long-range planning (48%), transportation planning (40%), health services planning (14%), historic preservation (4%), environmental or natural resource planning (12%), economic development (31%), land use planning (25%), housing planning (22%), and other (respondent specified; 34%); some respondents did not answer (10%).
13. Non-USCB sources of demographic data used by survey respondents included state governments (70%), other federal agencies (57%), municipal or regional governments (46%), school districts (38%), their own organization (41%), and county governments (34%).
14. We asked survey respondents the extent to which they agreed with the following statement: "I feel like the Census Bureau does an adequate job of explaining the ACS and margins of error." Eighteen percent (n = 37) of respondents agreed with the statement, whereas 9% disagreed (n = 18) and 7% (n = 13) were neutral. A total of 132 respondents did not answer this question.
15. Chi-square tests of cross-tabulated data, specifically years of planning experience compared with correct responses to ACS questions (e.g., "I should be more careful when using American Community Survey data for small geographies [census tracts] than for large geographies [counties]"), revealed no statistically significant relationship between ACS knowledge and planning experience (χ^2 = 2.92, p = .81). This suggests that formal planning education and professional continuing education should both serve as arenas for improving knowledge of ACS data.

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