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An Evaluation of Persons per Household (PPH) Estimates Generated by the American Community Survey: A Demographic Perspective

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Abstract The American Community Survey (ACS) is a U.S. Census Bureau product designed to provide accurate and timely demographic and economic indicators on an annual basis for both large and small geographic areas within the United States. Operational plans call for ACS to serve not only as a substitute for the decennial census long-form, but as a means of providing annual data at the national, state, county, and subcounty levels. In addition to being highly ambitious, this approach represents a major change in how data are collected and interpreted. Two of the major questions facing the ACS are its functionality and usability. This paper explores the latter of these two questions by examining "persons per household (PPH)," a variable of high interest to demographers and others preparing regular post-censal population estimates. The data used in this exploration are taken from 18 of the counties that formed the set of 1999 ACS test sites. The examination proceeds by first comparing 1-year ACS PPH estimates to Census 2010 PPH values along with extrapolated estimates generated using a geometric model based on PPH change between the 1990 and 2000 census counts. Both sets of estimates are then compared to annual 2001–2009 PPH interpolated estimates generated by a geometric model based on PPH from the 2000 census to the 2010 census. The ACS PPH estimates represent what could be called the "statistical perspective" because variations in the estimates of specific variables over time and space are viewed largely by statisticians with an eye toward sample error. The model-based PPH estimates represent a "demographic perspective" because PPH estimates are largely viewed by demographers as varying systematically and changing relatively slowly over time, an orientation stemming from theory and empirical evidence that PPH

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estimates respond to demographic and related determinants. The comparisons suggest that the ACS PPH estimates exhibit too much "noisy" variation for a given area over time to be usable by demographers and others preparing post-censal population estimates. These findings should be confirmed through further analysis and suggestions are provided for the directions this research could take. We conclude by noting that the statistical and demographic perspectives are not incompatible and that one of the aims of our paper is to encourage the U.S. Census Bureau to consider ways to improve the usability of the 1-year ACS PPH estimates.

Keywords Housing unit method · Population estimation · Sub-national

Introduction

The American Community Survey (ACS) is a U.S. Census Bureau product designed to provide accurate and timely demographic and economic indicators on an annual basis for both large and small geographic areas within the United States (Citro and Kalton 2007; U.S. Census Bureau 2004a, b). Operational plans call for ACS to serve not only as a substitute for the decennial census long-form, but as a means of providing annual data at the national, state, county, and subcounty levels (Cork et al. 2004; U.S. Census Bureau 2001a, b, 2003, 2004a, 2009a, b). In addition to being highly ambitious, this approach represents a major change in how data are collected and interpreted (Citro and Kalton 2007; Hough and Swanson 1998, 2006; Swanson 2010; U.S. Census Bureau 2009a).

Two of the major questions facing the ACS are its functionality and usability (Citro and Kalton 2007). This paper explores the latter of these two questions by examining "persons per household" (PPH), a variable of high interest to demographers and others preparing regular post-censal population estimates (Bryan 2004; Devine and Coleman 2003; Kimpel and Lowe 2007; Lowe et al. 1977; Roe et al. 1992; Smith 1986; Smith and Cody 1994; Smith and Lewis 1980; Smith and Mandell 1984; Smith et al. 2002; Swanson 2004; Swanson et al. 1983; Velkoff and Devine 2009).

The reason why PPH is a variable of high interest to analysts preparing post-censal population estimates is that it is a key component in the housing unit method (HUM), which for at least 30 years has been the most widely-used technique for producing sub-national population estimates in the United States (Byerly 1990; California Department of Finance 2010; Devine and Coleman. 2003; Hoque 2010; Kimpel and Lowe. 2007; Smith and Cody 2010, 2011; U.S. Census Bureau 1978; Velkoff 2007; Washington State Office of Financial Management 2000).

The ACS data used in this exploration are taken from 18 counties that were in the 1999 ACS test sites (See Table 1). These 18 counties represent the smallest pieces of geography for which ACS PPH data are available for the entire inter-censal period, 2000–2010. The examination proceeds in four phases. In the first phase, we examine the accuracy of PPH estimates extrapolated from a geometric model. Here, we construct models from 1980 and 1990 census data for each of the 39 counties of Washington state and then compare the 2000 PPH estimates extrapolated from these

Table 1 The 18 counties used in the analysis

Pima County, AZ	Madison County, MS
Jefferson County, AR	Douglas County, NE
San Francisco County, CA	Bronx County, NY
Tulare County, CA	Rockland County, NY
Broward County, FL	Franklin County, OH
Lake County, IL	Multnomah County, OR
Black Hawk County, IA	Schuylkill County, PA
Calvert County, MD	Sevier County, TN
Hampden County, MA	Yakima County, WA

county-specific models to the 2000 census PPH values. Second, we compare single-year (1-year) 2010 ACS PPH estimates for these 18 counties to the 2010 census PPH values. Third, we compare PPH estimates extrapolated from a geometric model based on PPH change from Census 1990 to Census 2000 to Census 2010 PPH values. In the fourth and final phase we compare the accuracy of the 1-year ACS PPH for 2001–2009 to PPH estimates extrapolated from the 1990–2000 based geometric model for the same years as well as PPH estimates interpolated from a 2000–2010 based geometric model.

The ACS PPH estimates represent what could be called the "statistical perspective" because variations in the estimates of specific variables over time and space are viewed by statisticians with an eye toward sample error (Citro and Kalton 2007; Fay 2005, 2007; Federal Register 2010; Kish 1998; Purcell and Kish 1979; Starsinic 2005; U.S. Census Bureau 2001a, b, 2003, 2004a, b, 2009a, b). Applied to an on-going survey such as the ACS, this implies that fluctuations over time are not necessarily viewed with alarm because they are due to statistical uncertainty.

The model-based PPH estimates represent a "demographic perspective" because PPH estimates are viewed by demographers as not likely to change abruptly over time. Instead, they are viewed as changing slowly over time, an orientation stemming from theory and empirical evidence that PPH estimates respond to a constellation of demographic and related determinants that taken as a whole changes slowly over time (Burch 1967, 1970; Burch et al. 1987; Coale 1965; De Vos and Palloni 1989; Goldsmith et al. 1982; Kimpel and Lowe 2007; Korbin 1976; Myers and Doyle 1990; Smith et al. 2002; Swanson 1982; Washington State Office of Financial Management 2000). As a consequence, even in the face of statistical uncertainty, demographers view abrupt changes in PPH over short periods of time as a problem. We return to this problem in the section "PPH and Demographic Theory."

Another difference between the statistical and demographic perspectives has to do with tradition and usage. In terms of summarizing a variable derived from sample data, the statistical perspective is oriented toward a range of values for an estimate (i.e., its upper and lower confidence bounds) based on sample error. That is, it is oriented toward "interval" estimates. The demographic perspective is oriented toward a single "value" for an estimate of a given variable in terms of summarization. That is, it is oriented toward "point" estimates. While the statistical perspective is technically correct in regard to the ACS, it can be problematic in terms of the demographic perspective in that PPH usability is linked to point estimates. In this regard, it is useful here to note that the ACS has been promoted by the Census Bureau as "…a nationwide survey designed to provide communities with *reliable* and timely demographic, social, economic, and housing data every year" (U.S. Census Bureau 2008, IV) while acknowledging that its estimates are subject to sample errors, which may be substantial at the substate level (see, e.g., Fay 2007; Reamer 2010a; Swanson 2010; Van Auken et al. 2006; Williams 2010).

In undertaking our assessment, we note that our examination of ACS PPH data is consistent with the Census Bureau's (2008, p. 25) guideline that: "…the ACS was designed to provide estimates of the characteristics of the population, not to provide counts of the population in different geographic areas or population subgroups." That is, PPH is a "characteristic," not a "count." In addition, we note that PPH has not been identified as one of the ACS variables that should not be compared either to census data or to itself over time, given that 1-year ACS estimates are not compared to multi-year ACS estimates (see, e.g., 'Guidance for Data Users,' http://www.census.gov/acs/www/guidance_for_data_users/handbooks/). We also note that unlike sub-county areas ACS variance levels for counties (e.g., census tracts and block groups), the ACS variance levels for counties have not been viewed as requiring special variance reduction measures by the Census Bureau (Fay 2005, 2007; Starsinic 2005). For example, as shown in Table 2, among the 18 counties we examine, the percent of *interviewed* housing units in the 2010 1-year sample is lowest in Sevier County, Tennessee (0.096%) and highest in Schuykill County, Pennsylvania (2.32%). Moreover, with 450 as the approximate "floor" for these samples and the fact that the official population estimates are used as "controls" at the county level (U.S. Census Bureau 2003; Fay 2005, 2007; Starsinic 2005), we believe that our examination of the ACS PPH estimates at the county level is consistent with the view of how the ACS should be used as promulgated by the U.S. Census Bureau U.S. Census Bureau (2008, IV). At the same time, we believe the demographic perspective presented in this paper is consistent with how population analysts interested in PPH estimates as input to the HUM will view and use ACS data.

In our assessment, we are only using the ACS 1-year estimates and excluding the 3-year and 5-year ACS estimates. A major reason is that only the 1-year PPH estimates are really useful to use with the HUM "as is," which will be made clear in the following section. The multi-year PPH estimates are not usable for the HUM because they are "temporally aggregated estimates" that are not usable "as is" for the HUM. Why the multi-year PPH estimates are not usable for the HUM is explained by the U.S. Census Bureau (2008, p. 9), which states that the multi-year estimates should not be referenced to any specific point in time as follows:

> …ACS estimates based on data collected from 2005–2007 should not be called "2006" or "2007" estimates. Nor should 2005–2009 period estimates be labeled "2007" estimates, even though that is the midpoint of the 5-year period. Multiyear estimates should be labeled to indicate clearly the full period of time (e.g., "The child poverty rate in 2005–2007 was X percent.")

Because HUM estimates are done annually, the preceding directive from the Census Bureau renders the multi-year data unusable in the absence of

Table 2 Population, housing and ACS sample size information for the 18 counties

ACS test site (county & state)	Census population		Percent change in population	Census housing units		Percent change in housing units	*N* of housing units interviewed in 1-year ACS	Ratio of interviewed housing units to census housing units
	2000	2010	2000–2010	2000	2010	2000–2010	2010	2010
Pima, AZ	843,746	980,263	16.18	366,737	440,909	20.22	5,388	0.0122
Jefferson, AR	84,278	77,435	−8.12	34,350	33,006	−3.91	450	0.0136
San Francisco, CA	776,733	805,235	3.67	346,527	376,942	8.78	4,393	0.0117
Tulare, CA	368,021	442,179	20.15	119,639	141,696	18.44	2,136	0.0151
Broward, FL	1,623,018	1,748,066	7.70	741,043	810,388	9.36	8,726	0.0108
Lake, IL	644,356	703,462	9.17	225,919	260,310	15.22	3,853	0.0148
Black Hawk, IA	128,012	131,090	2.40	51,759	55,887	7.98	916	0.0164
Calvert, MD	74,563	88,737	19.01	27,576	33,780	22.50	440	0.0130
Hampden, MA	456,228	463,490	1.59	185,876	192,175	3.39	2,605	0.0136
Madison, MS	74,674	95,203	27.49	28,781	38,558	33.97	494	0.0128
Douglas, NE	463,585	517,110	11.55	192,672	219,580	13.97	3,261	0.0149
Bronx, NY	1,332,650	1,385,106	3.94	490,659	511,896	4.33	5,753	0.0112
Rockland, NY	286,753	311,687	8.70	94,973	104,057	9.56	1,465	0.0141
Franklin, OH	1,068,978	1,163,414	8.83	471,016	527,186	11.93	6,878	0.0130
Multnomah, OR	660,486	735,334	11.33	288,561	324,832	12.57	4,443	0.0137
Schuylkill, PA	150,336	148,289	−1.36	67,806	69,323	2.24	1,608	0.0232
Sevier, TN	71,170	89,889	26.30	37,252	55,918	50.11	537	0.0096
Yakima, WA	222,581	243,231	9.28	79,174	85,474	7.96	1,039	0.0122

modifications—a topic we discuss in the final section. In addition to the Census Bureau's description of is temporally aggregated ACS estimates, we note that several authors have found that temporally aggregated data are subject to bias and "hidden heterogeneity" (Bass and Leone 1983; Blundell and Stoker 2005; Rossana and Seater 1995). We also find that interval PPH estimates for a given year (i.e., estimates defined by lower and upper bounds of a confidence interval) are not useable "as is" with the HUM for reasons similar to those describing why the multi-year PPH estimates are not useable. Thus, we: (1) focus on the "point" PPH estimates provided by the 1-year ACS rather than "interval" PPH estimates for a given year; and (2) use the 1-year ACS PPH estimates as if they were "point-in-time" estimates that can be used "as-is" with the HUM, at least in principle.

Having stated these reservations, we recognize that the multi-year ACS surveys represent the only viable source of data for sub-county PPH estimates and that, as such, they will have to be examined. However, this examination is beyond the scope of this paper, as are detailed discussions of how the multi-year PPH estimates might be used to make adjustments to 1-year ACS PPH estimates.

Finally, it is important to note that the ACS data are subject to population and housing unit "controls" that are developed under the auspices of the Census Bureau's annual population estimates program (PEP) (U.S. Census Bureau 2003, 2009a). These controls extend directly to the county level and indirectly to sub-county levels in that subcounty estimates must be consistent with the county estimates. As such, the "controlled" ACS PPH estimates we examine here are not simply subject to sample, coverage, non-response, and measurement errors but also to potential biases that are related to the controls (Breidt 2006).

The Housing Unit Method

As noted earlier, a major reason why PPH is a variable of high interest to demographers and others preparing post-censal population estimates is that it is a key component in a widely-used method of population estimation known as the HUM. For at least 30 years, the HUM formula has been the method most widely used to develop sub-national population estimates (Byerly 1990; California Department of Finance 2010; Devine and Coleman 2003; Hoque 2010; Kimpel and Lowe 2007; Smith and Cody 2010, 2011; U.S. Census Bureau 1978; Velkoff 2007; Washington State Office of Financial Management 2000) The HUM formula used to generate the population of an area at a given point in time is:

$$\mathrm{P} = \mathrm{GQ} + (\mathrm{PPH})(\mathrm{H})(\mathrm{OR})$$

where P is the total population; GQ is the population in groups quarters; PPH the persons per household; H the total number of housing units; and OR is the occupancy rate. Note that (H)(OR) is the total number of households and that PPH is the ratio of persons living in households to the number of occupied housing units (i.e., the number of households).

The HUM is based on the assumption that virtually everyone lives in some type of housing structure (Devine and Coleman 2003; Smith and Cody 2011). A major reason why the HUM is the most commonly used method for making sub-national population estimates in the United States and has been for at least 30 years is it works well. That is, it provides reasonably accurate annual post-censal (and inter-censal) estimates (Devine and Coleman 2003; Hoque 2010; Smith 1986; Smith and Cody 2011; Velkoff and Devine 2009). Another reason is that current (or near current) counts for two of its elements are generally available for the year in which a given set of estimates is needed: (1) the number of households; and (2) the group quarters population (Devine and Coleman 2003; Kimpel and Lowe 2007; Smith et al. 2002; Swanson et al. 1983). With these two elements in hand, PPH is the only remaining element needed to implement the HUM—hence the interest in the 1-year ACS.

An important criterion in the development and evaluation of population estimates (and projections) is accuracy (National Research Council 1980; Smith et al. 2001; Swanson 1980, 1981; Swanson et al. 2000). However, it is not just for reasons of professional pride that accuracy is important; the estimates are used to distribute resources, and in many of these distributions each person estimated generates thousands of dollars over the course of a decade (Murray 1992; U.S. GAO 2006; Walashek and Swanson 2006). As an example, the "official" estimates produced by the U.S. Census Bureau are used to allocate billions of dollars annually (Wetrogan 2005).[1] This means that estimates are routinely scrutinized and even challenged (U.S. Census Bureau, no date 1). This drive toward accuracy affects all elements of the HUM, including PPH. Making PPH even more an object of attention is the fact that relatively small changes in it can generate relatively large changes in the estimates produced by the HUM. For example, an area with 100,000 households will have a household population estimate of 260,000 with a PPH of 2.6; with a PPH of 2.5, it becomes 10,000 people fewer. With thousands of dollars riding on each estimated person, it should not come as a surprise that PPH is typically the element of the HUM that is most often in dispute (Swanson et al. 1983).

In addition to the fact that relatively small changes in PPH can trigger relatively large changes in HUM-based population estimates, there are three more reasons why a PPH estimate is usually the HUM element in dispute. The first, alluded to earlier, is that the Group Quarters population can generally be estimated to the satisfaction of all parties because most of this population resides in large complexes that have been identified and are monitored annually (Devine and Coleman 2003; Kimpel and Lowe 2007; Smith et al. 2002; Swanson et al. 1983). The second is that housing unit data are typically benchmarked to the last census and updates are provided by the local governmental entities for which the estimates are produced by the U.S. Census Bureau or a State Demographic Center (Devine and Coleman 2003; Kimpel and Lowe 2007; Smith et al. 2002; Swanson et al. 1983). The third reason is that turning housing unit counts into households is done via occupancy rates. Like the housing unit counts, occupancy rates are usually informed by the last census result and, if needed, they updated either by external data such as the U.S. Postal

[1] The population data available from the ACS are not the "official" estimates of the U.S. Census Bureau. However, along with the official estimates, the ACS data are being used to drive a portion of the geographic allocation of billions of federal funds (Blumerman and Vidal 2009; Reamer 2010b; Wetrogan 2005).

Service (Lowe 1988; Lowe and Mohrman 2003; Lowe et al. 2003) or surveys, which are often done by the local governmental entities themselves (Swanson et al. 1983). In contrast to the Group Quarters, Housing Unit, and Occupancy Rate elements of the HUM, the PPH element is typically not as well grounded in current data.

Typically, current annual PPH estimates are obtained by using a model based on PPH values from the two most recent censuses to extrapolate the most recent PPH census value into the post-censal period (Bryan 2004; Smith et al. 2004; Swanson et al. 1983). While, as previously implied, the model-based method has generally been found to work well, demographers producing annual HUM estimates are always interested in data that could prove useful. This is particularly the case as the post-censal estimate date becomes more removed from the last census. That is, there is much more uncertainty about the accuracy of a HUM-based estimate for a given area in a year ending in nine than there is for a year ending in one. For all of these reasons, the availability of annual PPH estimates from the ACS has piqued interest as an input source for the HUM.

Thus, with the expansion of the ACS to its full design in 2005 (Griffin and Waite 2006) and a decade of 1-year data available, it is not surprising that among the large number of demographers using the HUM to generate post-censal population estimates, more than a few are interested in seeing if the ACS can provide more accurate annual PPH estimates than the model based extrapolations. Consequently, this paper largely represents an attempt to answer this question, which as just pointed out, is an important one in terms of the resources allocated using HUM generated estimates.

PPH and Demographic Theory

Before moving on, it is important to note that the PPH estimates generated by geometric trend extrapolation are used not only because they generally are the only way that PPH values can be obtained, but as alluded to earlier, the HUM has generally been found sufficiently accurate to warrant its wide use for the more than 30 years it has been the most widely used method to generate sub-national population estimates (Byerly 1990; California Department of Finance 2010; Devine and Coleman. 2003; Hoque 2010; Kimpel and Lowe. 2007; Smith and Cody 2010, 2011; U.S. Census Bureau 1978; Velkoff 2007; Washington State Office of Financial Management 2000). In addition, the model-based PPH estimates represent the type of temporal change demographers (and the stakeholders involved with HUM estimates) expect to see in PPH estimates over time (Akkerman 1980; Bongaarts 1983; Burch 1967, 1970; Burch et al. 1987; Coale 1965; De Vos and Palloni 1989; Goldsmith et al. 1982; Kimpel and Lowe 2007; Korbin 1976; Myers and Doyle 1990; Smith et al. 2002; Swanson 1982; Swanson and Lowe 1980). This expectation is due to the factors that determine PPH.

De Vos and Palloni (1989) developed a conceptual framework of the demographic theory that underlies household composition, which we have reproduced as Fig. 1. This framework reveals the factors that determine PPH.

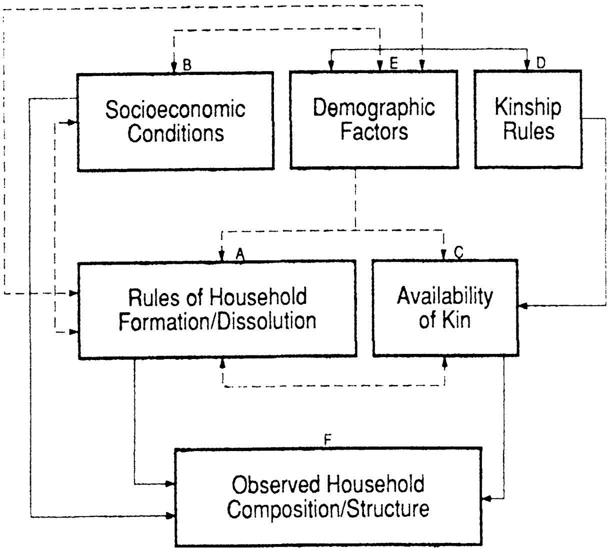

Fig. 1 Schematic overview of the demographic theory underlying household composition

The conceptual framework shows that household composition and structure (F) is determined directly by three factors: (1) the rules of household formation and dissolution (A); (2) Socio-economic Conditions (B); and (3) the availability of kin (C). Demographic factors (E) operate indirectly on household composition and size via a unidirectional effect on the availability of kin (C) and three interactive effects: (1) via socio-economic conditions (B); via the rules of household formation and dissolution (A); and kinship rules (D), which in turn affects observed household composition and structure via a unidirectional effect on the availability of kin (C) and an interactive effect via the rules of household formation and dissolution (A). While specifications may vary, Fig. 1 provides the conceptual framework that underlies the demographic perspective on PPH.

Of particular interest in Fig. 1 is the set of rules of household formation and dissolution, which refer to culturally determined preferences or social norms that regulate the co-residence, entrance into and exit out of households by household members, and the potential fission and fusion of entire households (De Vos and Palloni 1989, p. 177). These preferences and norms include (1) marriage (or cohabitation), divorce, and remarriage; (2) leaving home; (3) entering a primary household; (4) adoption; and (5) entrances and exits of individuals who are not related to the household head. Rules governing marriage (or cohabitation), separation, divorce, and remarriage are fundamental for the constitution of conjugal couples and in determining the timing of changes within the nuclear family while the rules for leaving home, entering a primary household, adoption, and governing the entrances and exits of individuals not related to the household head affect the contraction and expansion of households (De Vos and Palloni 1989, p. 177).

Clearly, the conceptual framework provided in Fig. 1 as well as specifications and variations of it are not consistent with PPH estimates that "jump around" from year to year, whether actually observed or in principle. Rather, the conceptual framework suggests that PPH experiences gradual changes observed over time, a process that is largely due to the complex interactions that cultural, social, demographic, economic, and technological factors have with one another (Glick et al. 1997; Moore 1963; Ogburn 1922). This suggests that while "inflection points" clearly exist for PPH, they are not likely to manifest themselves as going up 1 year, down the next, and then back up again (Korbin 1976; Myers and Doyle 1990; Washington State Office of Financial Management 2000).

Data and Methods

Table 2 provides background information on population, housing and ACS sample size (the number of housing units in which interviews were conducted). Population counts from the 2000 and 2010 censuses are provided for each of the 18 counties in the analysis, along with the percent change in population between 2000 and 2010. Similarly, housing counts from the 2000 and 2010 census are provided along with the percent change. Of the 18 counties, only two lost population,

To get an idea of the ACS sample size, Table 2 provides the number of housing units for which interviews were conducted in regard to the 2010 1-year ACS, along with The ratios of these numbers to the 2010 counts of housing units. As can be seen in Table 2, these ratios are consistently around 1.00%.

The U.S. Census Bureau established the operational structure for the ACS in 1994 when it put in place the "Continuous Measurement Office," which implemented the first operational test of the ACS in four test sites in 1995 (Griffin and Waite 2006). These test sites were subsequently expanded, and by 1999, operational tests took place in 36 counties spread across 26 states (Griffin and Waite 2006). Three-year ACS averages centered on 2000 were set up for these counties to support comparisons with Census 2000. Relevant among the many findings of these tests was that the arithmetic mean (2.63) of the PPH estimates found in the ACS for these 36 counties was the same as that found in Census 2000 and that there were no statistically significant differences for PPH (U.S. Census Bureau 2004b, p. 17). It was also noted that this result was not unexpected because the total household population and the total number of housing units found in Census 2000 are used as control variables in ACS weighting (U.S. Census Bureau 2004b, p. 17).

As mentioned earlier, the analytical method for generating the model-based PPH estimates is one commonly used by applied demographers for this purpose, namely, the geometric rate of change (Lowe et al. 1977; Smith et al. 2001, 2002; Swanson et al. 1983). In this approach, the rate of change is benchmarked to two most recent successive census counts and then applied to the PPH value found in the most recent census count, which is then extrapolated beyond the most recent census by applying the rate of change to it.

The process takes place in two steps. The first is the calculation of the ratio of change in PPH:

$$r = (\mathrm{PPH_l}/\mathrm{PPH_b})^{(1/y)}$$

where r is the ratio of change; PPH the persons per household; l the launch year (most recent census); b the base year (census preceding launch year; and y is the number of years between l and b (10 years).

The second step is applying the ratio of change to the launch year to find PPH estimates:

$$\mathrm{PPH_t} = (\mathrm{PPH_l})\left[(1 + r)^{(y)}\right]$$

where r is the ratio of change (from step 1); PPH the persons per household; t the target year; l the launch year (most recent census); and y is the number of years between t and l.

The preceding process is used with 1990 and 2000 census PPH estimates to generate 2010 PPH estimates for each of the 18 ACS test counties to compare with the 2010 census PPH values. It is important to again note that although simple, this method has a history of producing good PPH estimates as discussed earlier, In addition, as noted by Smith et al. (2001), there is nothing inherently wrong with a simple method that performs well.

In addition to the annual PPH estimates extrapolated for 2001–2010 from the 1990–2000 based geometric model, we also have generated annual PPH estimates for 2001–2009 that are interpolated from a 2000–2010 based geometric model. These interpolated PPH estimates are viewed as a benchmark against which to compare the 1-year ACS PPH estimates and the PPH estimates extrapolated from the 1990–2000 based geometric model.

Results

Before looking at the 1-year ACS results, we begin the first phase of our research, by examining the accuracy of county level PPH estimates generated by the geometric trend extrapolation method. We do not discuss their consistency with demographic theory because we already know that they are consistent. Table 3 shows the result of a test using the 39 counties in the state of Washington.

In this test, Census 1980 and 1990 PPH estimates are used as input to the geometric model. The annual ratios of change from 1990 to 2000 from each county's model are then applied to the 1990 census PPH and extrapolated to generate PPH estimates for 2000. These estimated PPH estimates are then compared to Census 2000 PPH estimates. To set the stage for this comparison, we first identify the level of accuracy that can be expected from a set of population estimates. We base these expectations on evaluations of 1980 and 1990 estimates of all counties and states conducted by the Census Bureau (Davis 1994; Long 1993); evaluations of 2,000 estimates for all counties, states, census tracts, and block groups conducted by a private data vendor (Hodges et al. 2002) and on accuracy criteria provided by the Committee on National Statistics (1980, pp. 10–12) that ideally should be met by postcensal estimates: (1) low average error; (2) low average relative error

Table 3 Accuracy test of the geometric method of estimating PPH estimates for counties: Washington State (2000)

	Washington State PPH values by county, 1980, 1990, and 2000							
	1980	1990	2000	1980–1990	Estimated 2000			
	PPH	PPH	PPH	Geometric rate of change	PPH	Absolute error	Percent error	MAPE (%)
State	2.6086	2.5348	2.5349	−0.0029	2.4631	−0.0718	−2.83	2.83
Adams	2.9113	2.9405	3.0949	0.0010	2.9700	−0.1249	−4.03	4.03
Asotin	2.5662	2.4727	2.4162	−0.0037	2.3826	−0.0336	−1.39	1.39
Benton	2.7971	2.6516	2.6795	−0.0053	2.5137	−0.1658	– 6.19	6.19
Chelan	2.4827	2.4863	2.6192	0.0001	2.4899	−0.1293	−4.93	4.93
Clallam	2.5374	2.4007	2.3066	−0.0055	2.2714	−0.0353	−1.53	1.53
Clark	2.7625	2.6625	2.6900	−0.0037	2.5661	−0.1239	−4.61	4.61
Columbia	2.5254	2.4368	2.3628	−0.0036	2.3513	−0.0115	−0.49	0.49
Cowlitz	2.6619	2.5588	2.5531	−0.0039	2.4597	−0.0934	−3.66	3.66
Douglas	2.7591	2.6769	2.7554	−0.0030	2.5971	−0.1583	−5.74	5.74
Ferry	2.8567	2.6978	2.4938	−0.0057	2.5477	0.0539	2.16	2.16
Franklin	2.8817	3.034	3.2637	0.0052	3.1943	−0.0693	−2.12	2.12
Garfield	2.5955	2.3948	2.3911	−0.0080	2.2096	−0.1815	−7.59	7.59
Grant	2.7986	2.7407	2.9204	−0.0021	2.6840	−0.2364	−8.09	8.09
Grays Harbor	2.5966	2.4813	2.4826	−0.0045	2.3711	−0.1115	−4.49	4.49
Island	2.6706	2.6149	2.5223	−0.0021	2.5604	0.0381	1.51	1.51
Jefferson	2.4537	2.3089	2.2122	−0.0061	2.1726	−0.0395	−1.79	1.79
King	2.4868	2.3982	2.3905	−0.0036	2.3128	−0.0777	−3.25	3.25
Kitsap	2.682	2.6469	2.6007	−0.0013	2.6123	0.0115	0.44	0.44
Kittitas	2.3976	2.3251	2.3314	−0.0031	2.2548	−0.0766	−3.29	3.29
Klickitat	2.7211	2.6409	2.5361	−0.0030	2.5631	0.0270	1.06	1.06
Lewis	2.6732	2.5997	2.5690	−0.0028	2.5282	−0.0408	−1.59	1.59
Lincoln	2.5726	2.4308	2.4233	−0.0057	2.2968	−0.1265	−5.22	5.22
Mason	2.5458	2.5162	2.4891	−0.0012	2.4869	−0.0022	−0.09	0.09
Okanogan	2.6674	2.5877	2.5762	−0.0030	2.5104	−0.0658	−2.56	2.56
Pacific	2.4465	2.3499	2.2711	−0.0040	2.2571	−0.0140	−0.62	0.62
Pend Oreille	2.8088	2.6029	2.5074	−0.0076	2.4121	−0.0953	−3.80	3.80
Pierce	2.6586	2.6231	2.6047	−0.0013	2.5881	−0.0166	−0.64	0.64
San Juan	2.2946	2.2489	2.1587	−0.0020	2.2041	0.0454	2.10	2.10
Skagit	2.5656	2.5495	2.6032	−0.0006	2.5335	−0.0697	−2.68	2.68
Skamania	2.7896	2.6921	2.6120	−0.0036	2.5980	−0.0140	−0.54	0.54
Snohomish	2.7606	2.67935	2.6547	−0.0030	2.6005	−0.0542	−2.04	2.04
Spokane	2.5789	2.4747	2.4646	−0.0041	2.3747	−0.0899	−3.65	3.65
Stevens	2.907	2.7318	2.6439	−0.0062	2.5672	−0.0768	−2.90	2.90
Thurston	2.6441	2.553	2.4987	−0.0035	2.4650	−0.0337	−1.35	1.35
Wahkiakum	2.7724	2.4762	2.4243	−0.0112	2.2116	−0.2127	−8.77	8.77

Table 3 continued

	Washington State PPH values by county, 1980, 1990, and 2000							
	1980	1990	2000	1980–1990	Estimated 2000			
	PPH	PPH	PPH	Geometric rate of change	PPH	Absolute error	Percent error	MAPE (%)
Walla Walla	2.5411	2.4955	2.5388	−0.0018	2.4507	−0.0880	−3.47	3.47
Whatcom	2.5902	2.5324	2.5113	−0.0023	2.4759	−0.0354	−1.41	1.41
Whitman	2.4668	2.3868	2.3115	−0.0033	2.3094	−0.0021	−0.09	0.09
Yakima	2.7711	2.8039	2.9576	0.0012	2.8371	−0.1205	−4.08	4.08
County level summary statistics								
Mean error							−0.0680	
MAPE							2.97%	
MALPE							−2.60%	
N ABS %								
Error >10							0	

(disregarding direction of the error; (3) few extreme relative errors; and (4) absence of bias for subgroups. As acknowledge by the Committee, it is generally not possible to produce a set of estimates that will minimize the four criteria simultaneously. Given this, the Committee chose to focus on low average relative error and few extreme relative errors, with some attention to low average error or bias. Following these guidelines, we find that population estimates are considered to be accurate if a MAPE of 5.00% or less is achieved and if fewer than 3% of the absolute percent errors exceed 10%. Applying these standards to the 2,000 PPH estimates generated by the geometric method, we find that it is capable of providing estimates sufficiently accurate for use: (1) The mean error is 0.068; (2) the mean absolute percent error (MAPE) is 2.97; (3) the mean algebraic percent error is −2.60; and (4) the number of absolute percent errors that are 10.0 or greater is zero. In regard to the latter, the largest absolute percent error is 8.77% (Wahkiakum County, which has a small population. Here the estimated 2000 PPH is 2.21 and the 2000 census PPH is 2.42).

These results show that the geometric method does not provide perfect estimates, but at these error levels, they are sufficient for use, as is demonstrated by their ubiquity (Byerly 1990; Devine and Coleman 2003; Smith and Cody 1994; Smith et al. 2002; Velkoff and Devine. 2009; Washington State Office of Financial Management 2010; Wetrogan 2007). The results also provide a benchmark accuracy level for the 1-year ACS PPH estimates in that we would like to see that they provide at least this level of accuracy, if not higher.

Table 4 shows the results of the second phase of our examination, which is a comparison of the ACS 1-year 2010 PPH estimates to the 2010 census PPH values. The MAPE for the 18 counties is 3.51%. Moreover, we find that the census PPH

Table 4 Comparison of ACS single year 2010 PPH estimates to 2010 census PPH values

Area	Estimate	Margin of error	Census	Percent difference
Pima, AZ	2.71	0.03	2.46[a]	10.16
Jefferson, AR	2.48	0.1	2.49	−0.40
San Francisco, CA	2.46	0.03	2.26[a]	8.85
Tulare, CA	3.37	0.05	3.36	0.30
Broward, FL	2.67	0.03	2.52[a]	5.95
Lake, IL	2.99	0.04	2.82[a]	6.03
Black Hawk, IA	2.36	0.07	2.38	−0.84
Calvert, MD	2.94	0.11	2.85	3.16
Hampden, MA	2.56	0.03	2.49[a]	2.81
Madison, MS	2.64	0.05	2.61	1.15
Douglas, NE	2.53	0.03	2.49[a]	1.61
Bronx, NY	2.82	0.02	2.77[a]	1.81
Rockland, NY	3.02	0.05	3.07	−1.63
Franklin, OH	2.47	0.03	2.38[a]	3.78
Multnomah, OR	2.38	0.03	2.35	1.28
Schuylkill, PA	2.27	0.06	2.35[a]	−3.40
Sevier, TN	2.74	0.15	2.52[a]	8.73
Yakima, WA	2.93	0.06	2.97	−1.35
			MAPE	3.51

[a] Census PPH value is outside of the 90% margin of error of the ACS PPH Estimate

values are within the 90% margin of Error in only 44% (8) of the 18 counties, as can be seen in Table 4.

Table 5 provides the results of the third phase of our work, which is a comparison between the 2010 PPH estimates that are extrapolated from the 1990–2000 based geometric model (county specific) and the Census 2010 PPH values. The MAPE for the 18 counties is 2.25%.

As can be seen in comparing the summary results in Table 5 with those in Table 4, the 2010 PPH estimates extrapolated from the 1990–2000 based geometric model are closer on average to the 2010 census PPH values than are the 1-year 2010 ACS PPH estimates. It is worthwhile to note that this finding holds not only for 18 test counties, but for all of the 807 counties for which 2010 1-year ACS data are available.[2]

[2] This is a finding of no small interest if in fact the 2010 ACS PPH estimates are informed in some manner by the 2010 Census. We point out that the documentation of the PEP preliminary estimates for 2010 suggest that these estimates are not informed by 2010 Census results (U.S. Census Bureau, no date 2) and the documentation for the ACS suggests only that the 2010 ACS data would be informed by 2000 Census data and subsequent PEP estimates and not at this point in time, by 2010 Census data (U.S. Census Bureau 2009a). Thus, it appears that the 2010 1-year ACS estimates are not informed by the 2010 Census results. However, we note that in 10 of the 18 counties there are pronounced reversals in the direction of change observed between 2009 and 2010 compared to the period 2008–2009 trend for the 1 year-ACS PPH estimates and that these pronounced reversals bring the 2010 ACS PPH estimates much closer to the 2010 census PPH values than the 2008–2009 trends and 2009 PPH estimates suggest they would have been. These pronounced reversals are seen for the following 10 counties: Pima County, AZ

Turning to the fourth and final phase of our examination, we are primarily interested in the temporal stability of the 1-year ACS PPH estimates. Here, we do not want to see PPH estimates that "jump around" from year to year for the reasons already discussed. On the one hand, it has to do with the theory underlying PPH changes and, on the other, the resource allocations made using HUM-generated estimates. In regard to the latter, if a PPH estimate goes up and down from 1 year to the next in a manner not consistent with historical trends, the local government entity is likely to challenge the estimate when the PPH estimates goes down. Moreover, dramatic annual fluctuations in population estimates are likely to damage the credibility of the entity producing them. This could lead to a positive feedback cycle of the kind described by Walashek and Swanson (2006) that could prove damaging to all parties.

Exhibits 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, and 18 provide a graphic picture of the temporal stability of the 1-year ACS PPH estimates annually from 2000 to 2010 alongside the 2001–2010 PPH estimates extrapolated from the 1990–2000 based geometric model and the 2001–2009 PPH estimates interpolated from the 2000–2010 geometric model. As stated earlier, we view the interpolated PPH estimates as a benchmark against which both the 1-year ACS and extrapolated PPH estimates are compared.

Footnote 2 continued
(Exhibit 1), San Francisco County, CA (Exhibit 3), Broward County, FL (Exhibit 5), Lake County, IL (Exhibit 6), Hampden County, MA (Exhibit 9), Douglas County, NE (Exhibit 11), Rockland County, NY (Exhibit 13), Multnomah County, OR (Exhibit 15), Schuylkill County, PA (Exhibit 16), and Sevier County, TN (Exhibit 17). These pronounced changes suggest some sort of "external" influence on the ACS data and while we can only speculate, given the information we have seen on the development of the 2010 ACS data, the 2010 census seems to be a logical suspect.

Continuing to the remaining eight counties, there would appear to be little if any reason, however, to suspect an external influence. We find that in two cases, the reversals are pronounced, but they serve to "over-correct" in that the 2010 PPH estimates are farther away from the corresponding 2010 census PPH values than were the 2009 PPH estimates. These are Black Hawk County, IA (Exhibit 7) and Yakima County, WA (Exhibit 18). In one case, Jefferson County, AR (Exhibit 2), there is a reversal but it is not pronounced, while in two others, Calvert County, MD (Exhibit 8) and Madison County, MS (Exhibit 10), 2010 ACS PPH estimates are closer to the census 2010 PPH values than the 2009 ACS PPH estimates but the moves do not involve a reversal of direction from the trend observed between 2008 and 2009. In Franklin County, OH (Exhibit 14), there is basically no change from the 2009 ACS PPH estimate to the 2010 ACS PPH estimate while in two counties, Tulare, CA (Exhibit 4) and Bronx, NY (Exhibit 12), the changes observed between 2009 and 2010 move their 2009 PPH estimates away from the corresponding 2010 census PPH values.

As noted in the text, we also used the census 2010 PPH values as a basis for comparing the accuracy of the 1-year 2010 ACS PPH estimates to the accuracy of PPH estimates generated by the geometric method for all of the 807 counties for which ACS data are available. The latter were developed in the same manner as the estimates discussed in Table 3: the 1990–2000 trends in PPH values were extrapolated to 2010 using the geometric model. At 6.85%, the MAPE of the ACS PPH estimates is higher than the MAPE for the geometric model, 5.83%, indicating that the ACS is less accurate than the geometric model not only for the 18 test counties, but for all counties. We also found that the 90% margins of error provided by the Census Bureau for the 2010 1-year ACS PPH estimates contained the 2010 census PPH values in only 64% (515) of the 807 counties. This is a better showing than the 39% observed for the 18 test counties, but one would intuitively expect it to be higher than 64% for the entire universe of ACS counties in that 90% margins of error are used. These data and results are in an excel file that is available from the authors.

Table 5 Comparison of extrapolated geometric model-based 2010 PPH estimates to 2010 census PPH estimates

Area	Estimate	Census	Percent difference
Pima, AZ	2.45	2.46	−0.40
Jefferson, AR	2.48	2.49	−0.22
San Francisco, CA	2.31	2.26	−2.21
Tulare, CA	3.45	3.36	2.63
Broward, FL	2.55	2.52	1.36
Lake, IL	2.91	2.82	3.20
Black Hawk, IA	2.39	2.38	0.48
Calvert, MD	2.81	2.85	−1.29
Hampden, MA	2.44	2.49	−1.91
Madison, MS	2.60	2.61	−0.31
Douglas, NE	2.43	2.49	−2.37
Bronx, NY	2.82	2.77	1.83
Rockland, NY	2.99	3.07	−2.60
Franklin, OH	2.31	2.38	−2.83
Multnomah, OR	2.38	2.35	1.28
Schuylkill, PA	2.25	2.35	−4.05
Sevier, TN	2.38	2.52	−5.40
Yakima, WA	3.13	2.97	5.36
		MAPE	2.25

Models are county specific and based on 1990–2000 trends in PPH values

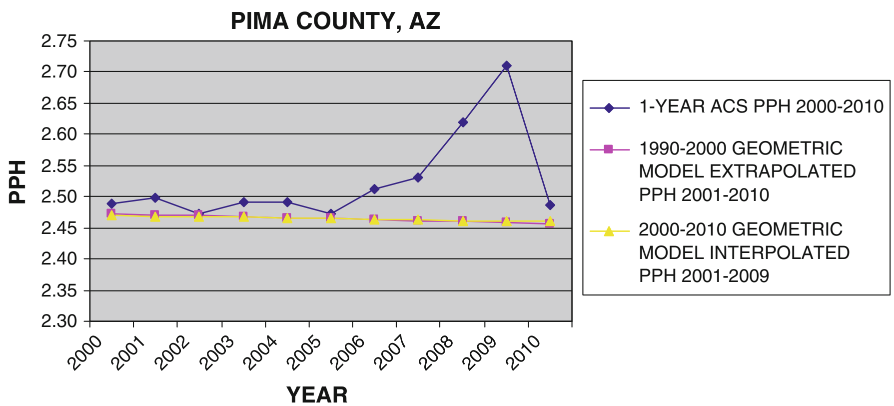

Exhibit 1 Pima County, AZ: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

Discussion

In beginning this discussion, keep in mind that for the inter-censal years, 2001–2009, the documentation for the ACS (U.S. Census Bureau 2009a) states that the ACS estimates are controlled to population and related estimates at the

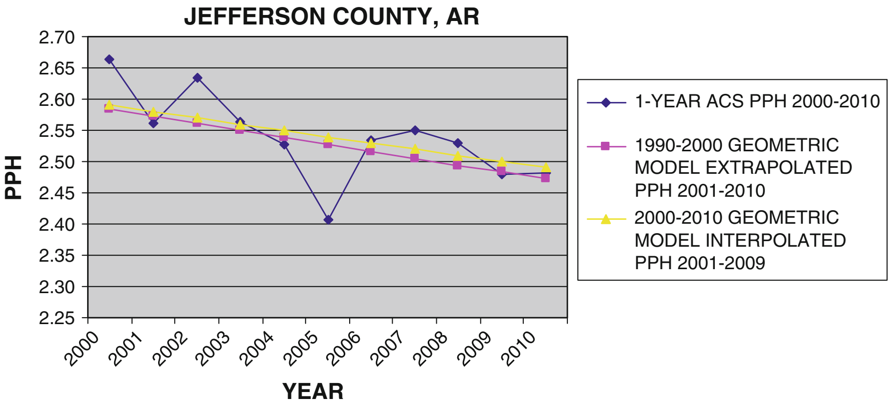

Exhibit 2 Jefferson County, AR: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

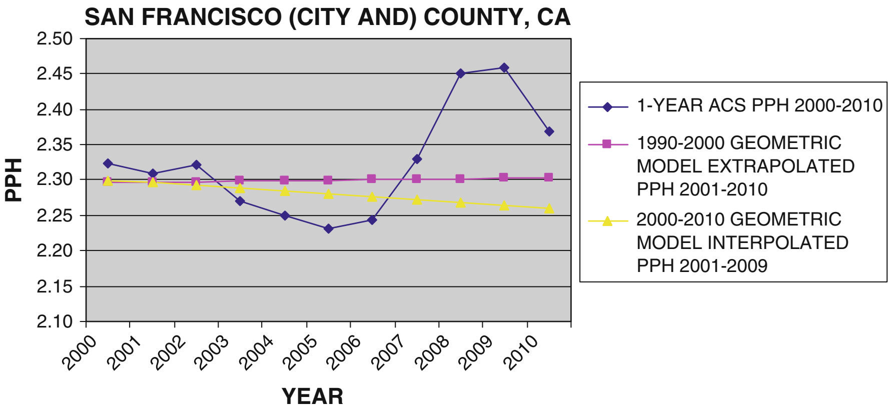

Exhibit 3 San Francisco County, CA: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

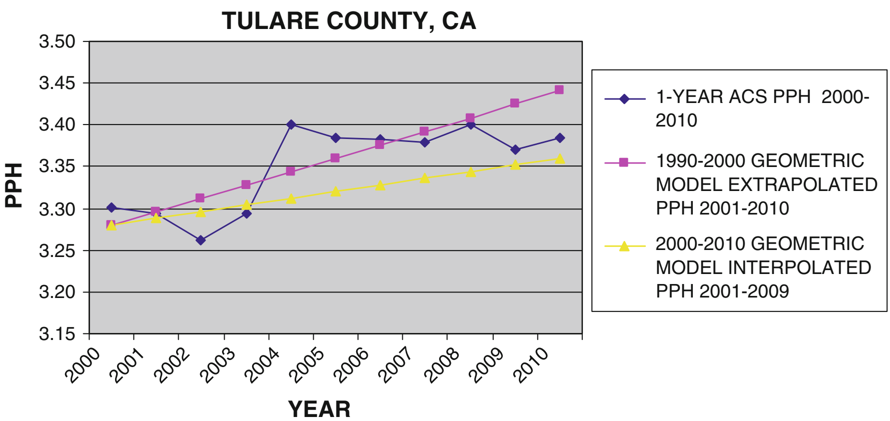

Exhibit 4 Tulare County, CA: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

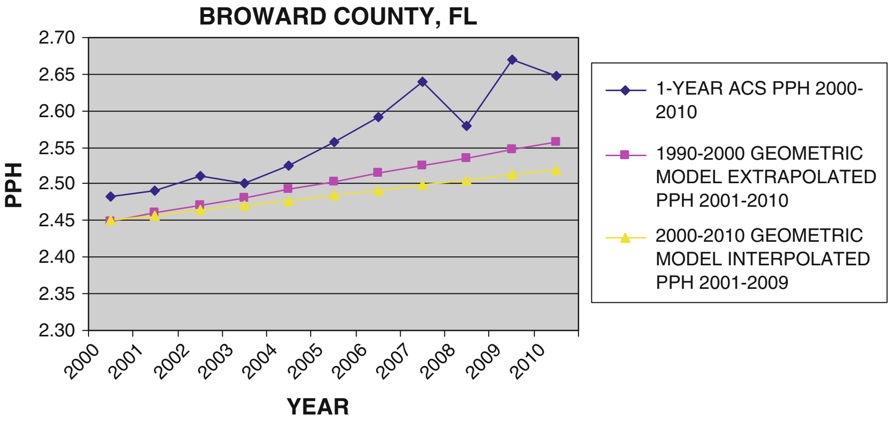

Exhibit 5 Broward County, FL: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

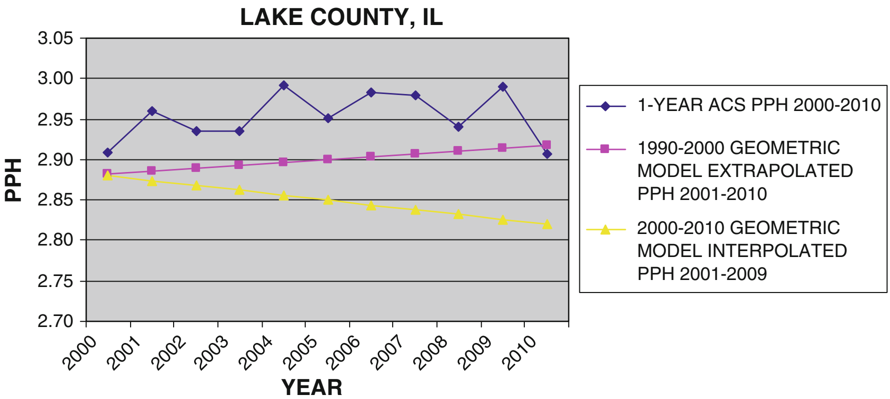

Exhibit 6 Lake County, IL: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

county level that are done annually by the Census Bureau's PEP. Some of the temporal instability and other issues are likely to be the result of these procedures (Breidt 2006). Another source of temporal instability related to these controls is also likely to be coming from the "challenges" that local governments can make to the Bureau's population estimates. These challenges can result in dramatic adjustments. An example of the effect of a challenge can be seen in Exhibit 1 for Pima County, Arizona, which successfully challenged its 2007 PEP estimate that changed the population from 967,089 to 996,593. As a result of this substantial adjustment (29,504 people, a 3.1% increase), the ACS PPH estimate increases dramatically between 2007 and 2008 and again from 2008 to 2009. Although not as dramatic as Pima County, three other counties were directly affected by successful challenges: (1) Bronx County, New York (2005, 2006, and 2007); Rockland County, New York (2005, 2006, 2007, and 2008); and San Francisco County, California (2007).

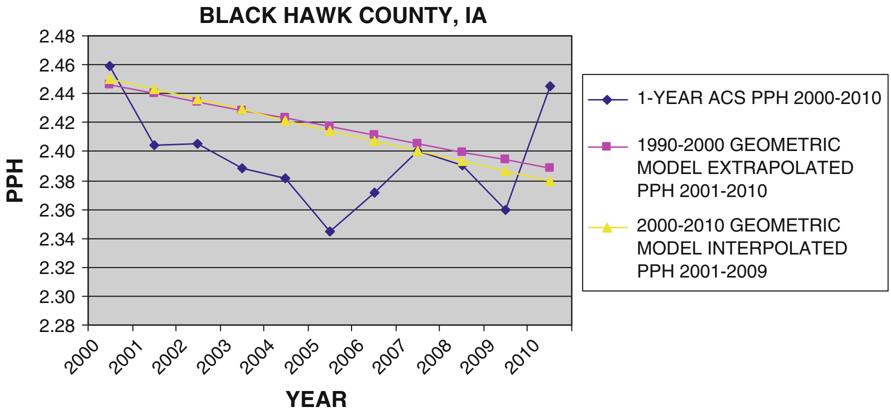

Exhibit 7 Black Hawk County, IA: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

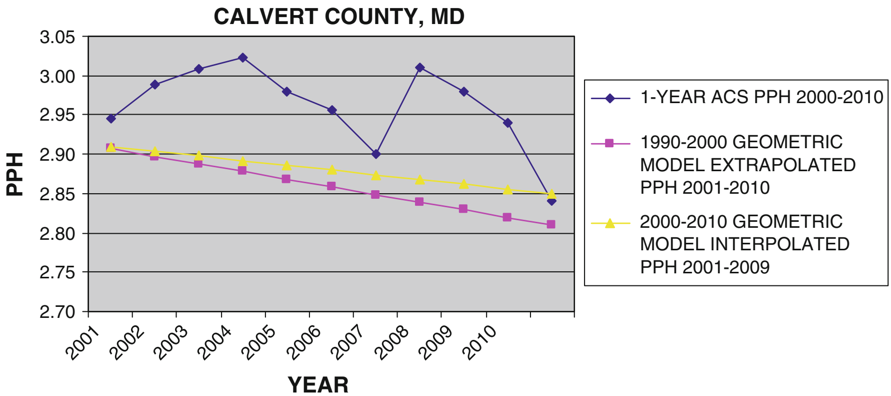

Exhibit 8 Calvert County, MD: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

Although much less dramatic changes occurred, two other counties were affected by challenges made by cities within them: (1) Broward County, Florida (Coconut Creek in 2005 and Lauderdale Lakes in 2008); and (2) Hampden County, Massachusetts (Ludlow 2007; Springfield 2007, 2008; Westfield 2008).

The interpolated PPH estimates for 2001–2009 (based on the 2000 and 2010 census PPH values) are viewed as the benchmark estimates during the decade for the reasons discussed earlier in regard to the demographic theory underlying changes in PPH. Using this benchmark, we find that the ACS PPH estimates remain above the interpolated PPH estimates for the entire period, 2001–2009 in seven counties for the entire period, that they are never below the interpolated estimates for the entire period and cross-over the interpolated estimates in 11 counties over the period 2001–2009. In terms of directional changes, the single-year ACS PPH estimates change direction two or more times in all 18 counties.

The 1-year ACS PPH estimates are not encouraging in terms of usability with the HUM. Over the period 2001–2009, the extrapolated PPH estimates perform better in

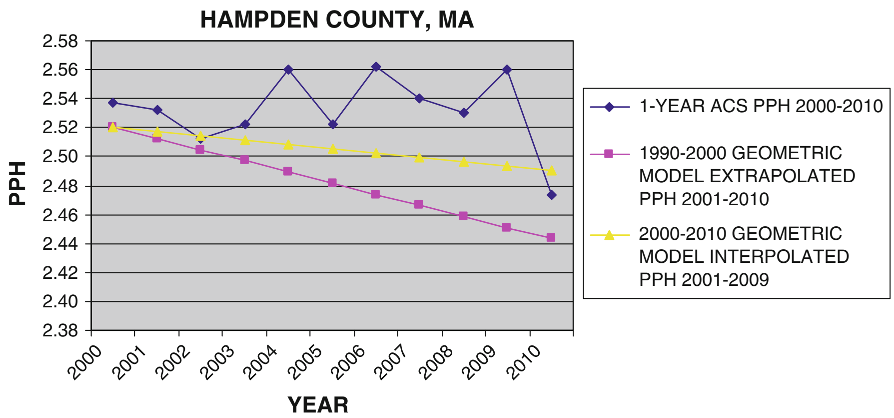

Exhibit 9 Hampden County, MA: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

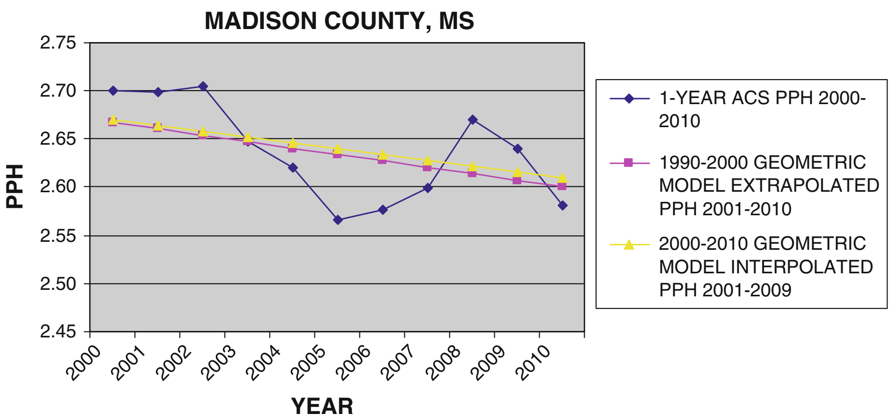

Exhibit 10 Madison County, MS: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

comparison with the interpolated PPH estimates than do the annual ACS PPH estimates. Moreover the extrapolated PPH estimates for 2010 perform better in comparison with the census PPH values than do the 2010 ACS PPH estimates. Moreover, as expected, the extrapolated PPH estimates generate annual changes that are far more consistent with both theory and use than do the ACS estimates in that the latter "jump around" too much.

For reasons already discussed, annual "jumping around" is an undesirable PPH characteristic for both demographers who employ the HUM and the stakeholders for whom HUM estimates are done.[3] Here, we also observe that if one followed the

[3] This is because there is an expectation on the part of both these demographers and the stakeholders that PPH estimates should exhibit systematic changes unless there is compelling substantive evidence (e.g., the PPH estimates jumped because of a surge of in-migrants with high fertility and large family sizes) to the contrary. If such PPH estimates are used in the absence of compelling substantive evidence justifying

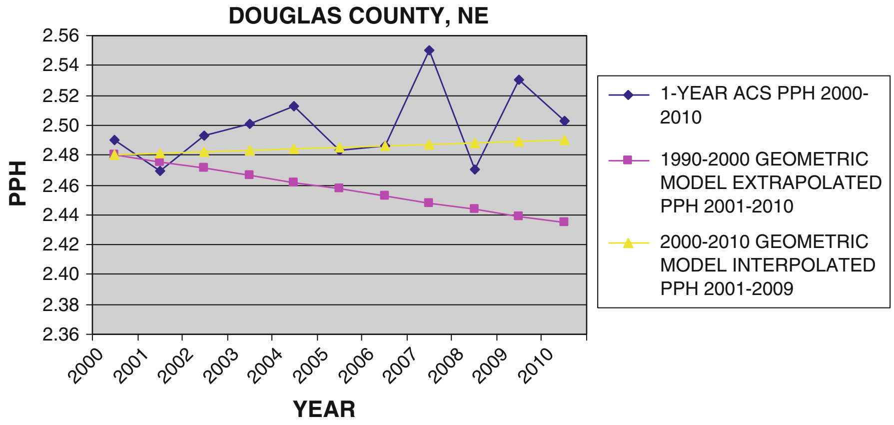

Exhibit 11 Douglas County, NE: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

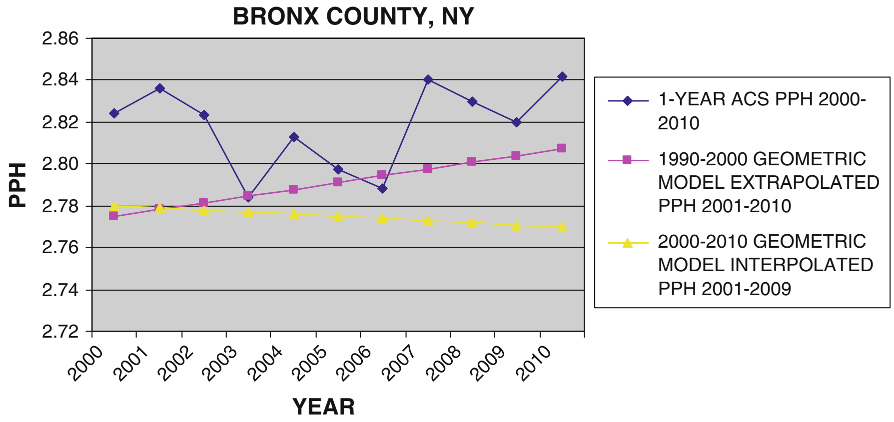

Exhibit 12 Bronx County, NY: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

Census Bureau's advice about using statistical procedures to determine if ACS estimates change over time for a given county (see, e.g., U.S. Census Bureau 2009b, p. 6), one could end up looking at its annual PPH estimates for the county in question as not changing over time because of small PPH differences (e.g., a PPH estimate of 2.503 in 2001 may not be statistically different from one of 2.509 in 2002 and even one of 2.717 in 2006). This is problematic because it would be inconsistent with the theoretical and empirical determinants of PPH change. That is, if theory and empirical evidence suggest that PPH values are decreasing in Jefferson

Footnote 3 continued
their temporal instability then it appears that the risk of challenges and related administrative and legal actions increases (see, e.g., Walashek and Swanson 2006), especially when these estimates are used to allocate resources, which is often the case (National Research Council 1980, 2003; Scire 2007).

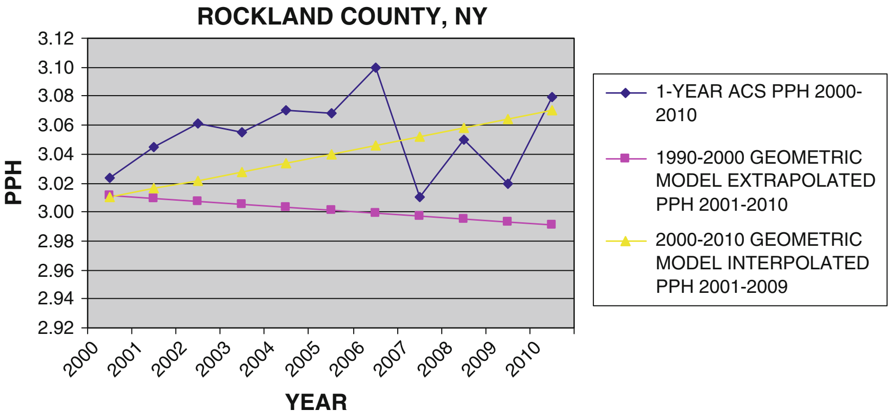

Exhibit 13 Rockland County, NY: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

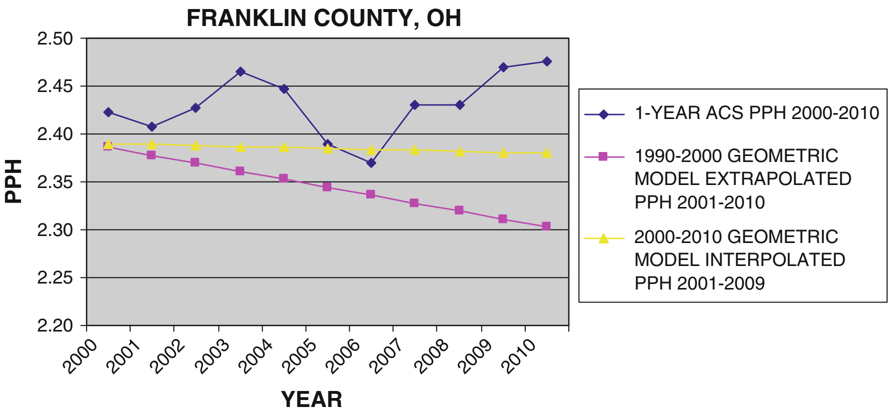

Exhibit 14 Franklin County, OH: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

County, Arkansas over the period 2001–2009 (see Exhibit 2 and Appendix Table 6) while little if any statistical difference is found for its ACS PPH estimates over the same period, then the usability of the PPH estimates generated by the ACS come into question for use with annual population estimation employing the HUM. Specifically, the 90% margins of error provided by the U.S. Census Bureau for Jefferson County's 1-year ACS PPH estimates are 0.05, 0.08, 0.09, 0.09, 0.07, 0.10, 0.10, 0.11 and 0.10 for each year from 2001 to 2009, respectively. Given the 2000 census PPH of 2.56 and the "interval" PPH estimates stemming from the 90% MOEs annually from 2001 to 2009, the annual PPH estimates from 2001 to 2009 for Jefferson County would be, respectively: 2.56, 2.63, 2.63, 2.53, 2.41, 2.53, 2.53, 2.53, and 2.53 (see Appendix Table 6). Thus, we have no change from 2000 to 2001, a dramatic change from 2001 to 2002 (from 2.56 to 2.63) and then no change (2.63) until 2004, when PPH declines (to 2.53), followed by another decrease in 2005 (to 2.41), then an increase in 2006 (back to 2.53), followed by no change

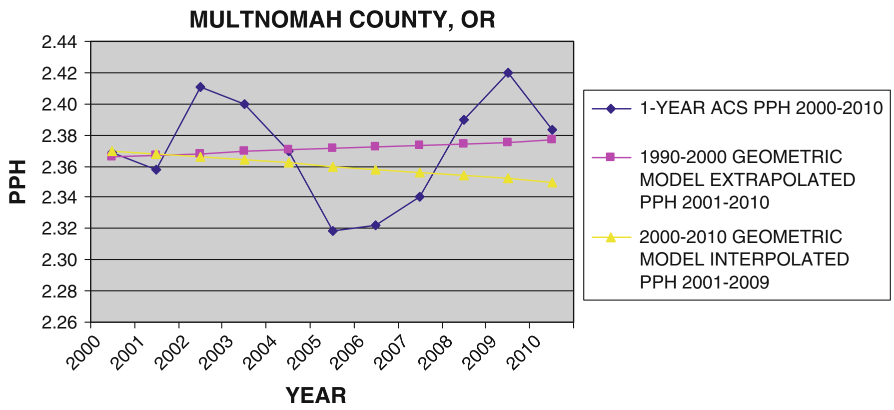

Exhibit 15 Multnomah County, OR: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

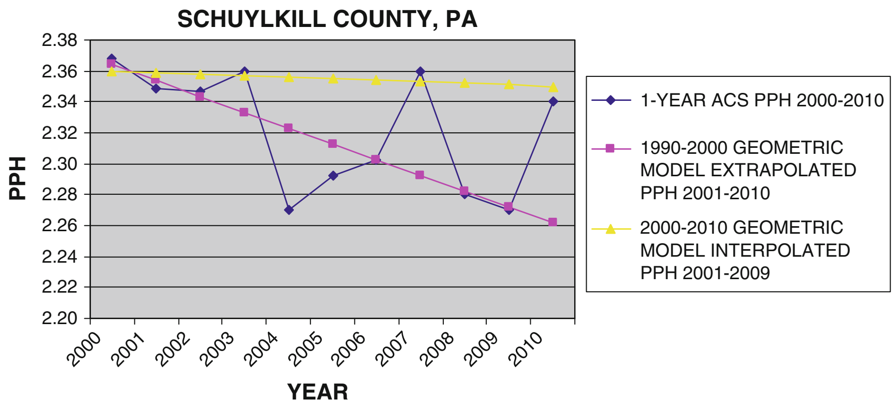

Exhibit 16 Schuylkill County, PA: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

(2.53) in PPH from 2006 to 2009. This pattern of annual change in PPH is neither consistent with demographic theory nor useful to an analyst seeking PPH estimates to use in the HUM for purposes of making annual population estimates.[4] As you can

[4] We need to make two points here. First, we selected Jefferson County as an example simply because it illustrates that using inferential statistics to identify change in the ACS PPH neither yields trends that are consistent with demographic theory nor annual PPH estimates that would be useful as input into the HUM for purposes of making annual population estimates. In point of fact, for all of the 18 counties statistical inference yields annual changes in the ACS PPH estimates that neither conform to demographic theory nor provide annual PPH estimates that would be useful as input into the HUM, as can be seen in Appendix Table 6.

The second point is that some may argue that in using statistical inference to identify PPH changes, we are actually making "multiple comparisons," which require adjustments. In response, we argue that most multiple comparison adjustments (e.g., analysis of variance) are not appropriate because these adjustments are generally designed to be used when three or more *simultaneous* comparisons are being made (Iversen and Norpoth 1973; Toothaker 1993), which is not the case for an analyst attempting to use the ACS PPH estimates over the course of a decade. Instead, such an analyst would be only going out surmise from the discussion of the theory underlying the demographic perspective on PPH, this sequence of change makes no sense to a demographer.[5] The sequences of change for virtually all of the other 17 counties pose similar problems from the demographic perspective.

Footnote 4 continued
1 year at a time and making a comparison of the most current ACS PPH estimate against the ACS PPH estimate in use, which through the decade would yield a *series of pair-wise* comparisons rather than three or more simultaneous comparisons. Of course, the one in use might be from 2 years ago if the previous two comparisons indicated "no change," but the point holds: it is a series of pair-wise comparisons that would be made, not three or more comparisons simultaneously.

In making a series of pair-wise comparisons, one adjustment that could be made is the Bonferroni correction (Hough and Swanson 2006; Kirk 1968; Perenger 1998), which is designed to reduce the probability of making a Type I error. An analyst seeking to use the ACS PPH estimates over the course of a decade can quickly estimate the probability of making a Type I error. Since the Census Bureau is using a 90% confidence interval, the corresponding alpha level in a series of pair-wise T-tests would be .10 ($\alpha = .10$). Given this, the probability of making at least one Type I error in making nine pair-wise comparisons (2001 compared to 2000, 2002 compared to 2001,…, 2008–2007, and 2009–2008) over the course of a decade is $1 - (.9)^9 \approx .67$. That, is we have a 67% chance of stating that a change in PPH has occurred when in fact it is not, if all nine pair-wise comparisons are made. Assuming in advance that nine comparisons would be made, the analyst could employ the Bonferroni correction, which is $\acute{\alpha} = \alpha/n$, where $\alpha =$ the alpha level (.10), $n =$ the number of pair-wise comparisons to be made (for which we can use nine, which is the maximum), and $\acute{\alpha} =$ the corrected alpha level (Hough and Swanson 2006). In this situation with $\alpha = .10$ and $n = 9$, the analyst would find $\acute{\alpha} \approx 0.01 \approx .10/9$. This would correspond to adjusting the margins of error from 90 to 99%. This can be done as follows: $\text{MOE}' = 2.576/1.645*\text{MOE}$ (U.S. Census Bureau 2009b, A12). Appendix Table 7 shows the results of using the Bonferroni correction to make this adjustment in the MOEs for all of the 18 counties over the period from 2001 to 2009.

As can be seen in Appendix Tables 6 and 7, whether or not an attempt is made to correct for multiple comparisons, the results in either case generally do not make demographic sense for any of the 18 counties. That is, the annual "change" in the ACS PPH estimates is either abrupt and discontinuous or non-existent. In either case, the change is neither consistent with the demographic theory underlying PPH change over time nor the needs of an analyst in terms of PPH estimates being used as input to the HUM for purposes of making annual population estimates. Continuing with our example of Jefferson County, if we use the Bonferroni correction to adjust the 90% margins of error provided by the U.S. Census Bureau for 1-year ACS PPH estimates, from 2001 to 2009 (with the adjusted 2001 MOE being compared to the 2000 census PPH of 2.66), we get, respectively: 2.66, 2.66, 2.66, 2.53, 2.53, 2.53, 2.53, 2.53, and 2.53. Thus, we would have no change in the 2000 census PPH of 2.66 from 2001 to 2003, then an abrupt decrease to 2.53 in 2004, followed by a constant PPH of 2.53 through 2009.

As a final note, we have looked into procedures designed to deal with detecting temporal change from other perspectives, including change-point analysis (Bai 1997; Bai and Perron 2003) and interrupted time series (Lewis-Beck 1986). These techniques appear to be ill-suited for use here since the 1-year ACS PPH estimates do not appear to be able to provide the requisite quality for an historical time series that could be used as a basis for developing models.

[5] By a "substantive difference" we mean an "important difference." This is not the same as "statistical significance." The developer of the T-test, W.S. Gossett (aka "Student"), was acutely aware of the difference between statistical significance and an important difference since he was trying to brew high quality beer for the Guinness Brewery at reasonable prices (Ziliak and McCloskey 2008). However, this important distinction was late to come both to R.A. Fisher, and to J. Neyman and E. Pearson, whose ideas became widespread and literally "ritualized" into the practice of statistical testing without conveying the idea of taking into account whether or not there was an "important difference" (Hubbard and Bayarri 2003; Ziliak and McCloskey 2008); unfortunately, the ritualized nature of statistical testing exacerbated this by placing "statistical significance" as the only result worth reporting in scientific research (Ziliak and McCloskey 2008).

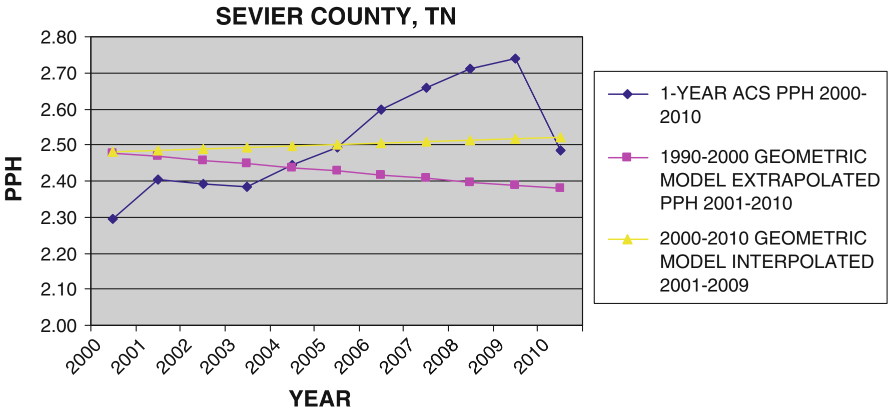

Exhibit 17 Sevier County, TN: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

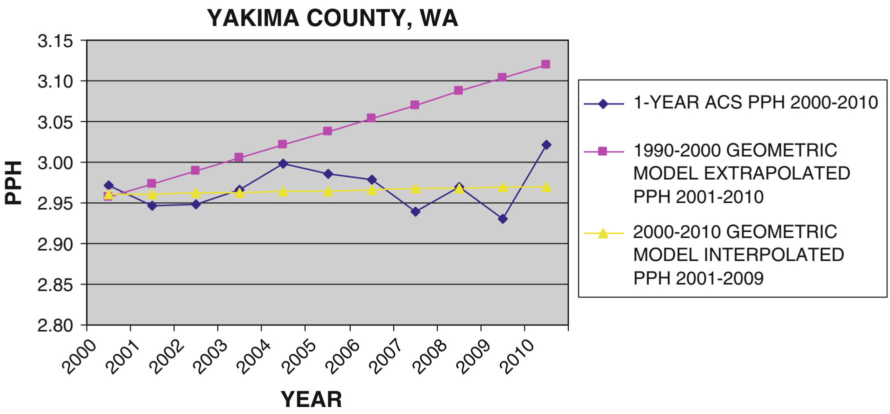

Exhibit 18 Yakima County, AR: 2000–2010 PPH estimates and census PPH values for 2000 and 2010

In addition to the temporal instability issue illustrated by the sequence of PPH change for Jefferson County, Arkansas, one must ask what causes some of the substantial differences observed elsewhere between the model-based PPH estimates and the 1-year ACS PPH estimates. As discussed earlier, by 2009, Pima County, Arizona (Exhibit 1) the 1 year ACS PPH estimates are not only substantially different from the 1990–2000 geometric model's extrapolated 2009 estimate, but clearly way off track to hit the 2010 census PPH value. As discussed, the PEP challenge clearly has an effect, but in addition, one could ask the question how much, if any, of the differences are due to the ACS residency rule? After all, the ACS residency rule is not the same as the Decennial Census residency rule, the one that is inherent in the model-based ACS PPH estimates (Cork and Voss 2006, pp. 53–570).

Conclusions and Suggestions for Future Research

As described at the start of this paper, the ACS provides annual PPH estimates that are subject to sample (and non-sample) error. This means that they can fluctuate from year to year in a given population, which reflects a “statistical perspective.” Demographers, however, view PPH as a population characteristic that has determinants. Such that PPH is viewed as changing systematically and slowly over time—the “Demographic Perspective.” The comparisons suggest that the ACS PPH estimates exhibit too little slow systematic change and too much “noisy” variation for a given area over time to be usable by demographers and others preparing annual post-censal population estimates with the HUM.

In regard to the importance of the PPH estimates changing in a systematic manner over time, our experience in producing and defending estimates makes us appreciate model-based PPH estimates because the changes are easily understood by stakeholders. This is an important point, whether defending projections or estimates (Smith et al. 2001, p. 296). Based on what we see in the temporal instability of ACS PPH values, we would have difficulty defending their use to stakeholders. This is especially the case when, as noted earlier is often the case, when these estimates are used to allocate resources.

Our finding that the 1-year ACS PPH estimates are not particularly usable for purposes of making HUM-based population estimates at the county level is preliminary in nature. More work not only needs to be done not only to confirm this finding, but also to examine ways the ACS PPH estimates might be modified so that they could become more useful. With this in mind, our suggestions for further analysis include: (1) conducting a broader scale comparison, taking into account the full range of counties; (2) examining 1-year ACS PPH estimates that are not controlled; and (3) making adjustments (e.g., smoothing a series and then extrapolating it) to 1-year ACS PPH estimates, perhaps in conjunction with the multi-year estimates, such that more systematic temporal change can be obtained. Once this was done, then, depending on the results, the assessment could proceed to other geographies, such as places, census tracts, and block groups. In addition, it may be worthwhile to look at the difference between the 2010 ACS and the 2010 census PPH numbers in terms of total error, which suggests that the differences could be decomposed into variance and bias as was attempted by Multry and Spencer (1993) in regard to estimating 1990 census error.

We note that the demographic perspective described in this paper is not incompatible with a statistical perspective. At one level, it can be viewed as a model-based approach, a perspective that is shared with statistics (Hill 1990; Jiang and Lahiri 2006). Further, as noted in many places throughout this paper, demographers view PPH as a variable that responds to demographic and related determinants. Thus, at another level, the demographic perspective we have described represents ‘causality.’ This also is a perspective that is shared with statistics (Cox and Wermuth 2006). Finally, at a third level, the demographic perspective is empirical, which also is a perspective that is shared with statistics—Stigler (1986: 1) observes, for example, that “…Modern statistics provides a quantitative technology for empirical science…” In short, we argue that the view that PPH is a variable that responds to demographic and related determinants is not only worthy of consideration, but one that is compatible with statistics. Toward this end, we have identified three shared commonalities that support this argument: (1) a model-based perspective; (2) a causal perspective; and (3) an empirical perspective.

In conclusion, we point out that this paper is intended to broaden this view among those who have developed and implemented the ACS and to trigger ideas that could yield higher levels of usability of the 1-year ACS PPH estimates. As such we hope that we are following in the footsteps of other demographers who were among the first (if not the first) to point out that ACS variance levels at the sub-county level were disturbingly high (Van Auken et al. 2006), which prompted work to mediate this problem on the part of those who have developed and implemented the ACS (Fay 2005, 2007; Starsinic 2005).

Appendix

See Tables 6 and 7.

Table 6 Annual PPH estimates using statistical inference (90% MOEs) to determine change

County	2001	2002	2003	2004	2005	2006	2007	2008	2009
Pima, AZ	2.49	2.47	2.47	2.47	2.47	2.51	2.51	2.62	2.71
Jefferson, AR	2.56	2.63	2.63	2.53	2.41	2.53	2.53	2.53	2.53
San Francisco, CA	2.32	2.32	2.27	2.27	2.23	2.23	2.33	2.45	2.45
Tulare, CA	3.30	3.26	3.29	3.40	3.40	3.40	3.40	3.40	3.40
Broward, FL	2.48	2.51	2.51	2.51	2.56	2.59	2.64	2.58	2.67
Lake, IL	2.96	2.96	2.96	2.99	2.95	2.98	2.98	2.94	2.99
Black Hawk, IA	2.40	2.40	2.40	2.40	2.35	2.35	2.40	2.40	2.40
Calvert, MD	2.94	2.94	3.02	3.02	3.02	2.90	3.01	3.01	3.01
Hampden, MA	2.54	2.51	2.51	2.56	2.52	2.56	2.56	2.53	2.53
Madison, MS	2.70	2.70	2.70	2.62	2.62	2.62	2.62	2.62	2.62
Douglas, NE	2.47	2.49	2.49	2.49	2.49	2.49	2.55	2.47	2.53
Bronx, NY	2.82	2.82	2.78	2.81	2.81	2.79	2.84	2.84	2.84
Rockland, NY	3.02	3.06	3.06	3.06	3.06	3.10	3.01	3.01	3.01
Franklin, OH	2.42	2.42	2.47	2.47	2.39	2.39	2.43	2.43	2.47
Multnomah, OR	2.37	2.41	2.41	2.37	2.32	2.32	2.34	2.39	2.39
Schuykill, PA	2.37	2.37	2.37	2.27	2.27	2.27	2.36	2.28	2.28
Sevier, TN	2.40	2.40	2.40	2.40	2.49	2.60	2.60	2.60	2.60
Yakima, WA	2.97	2.97	2.97	2.97	2.97	2.97	2.94	2.94	2.94

Table 7 Annual PPH estimates using statistical inference (99% MOEs) to determine change per the Bonferroni correction

County	2001	2002	2003	2004	2005	2006	2007	2008	2009
Pima, AZ	2.49	2.49	2.49	2.49	2.49	2.49	2.53	2.62	2.71
Jefferson, AR	2.66	2.66	2.66	2.53	2.53	2.53	2.53	2.53	2.53
San Francisco, CA	2.32	2.32	2.27	2.27	2.27	2.27	2.33	2.45	2.45
Tulare, CA	3.30	3.30	3.30	3.40	3.40	3.40	3.40	3.40	3.40
Broward, FL	2.48	2.48	2.48	2.52	2.56	2.59	2.64	2.58	2.67
Lake, IL	2.96	2.96	2.96	2.96	2.96	2.96	2.96	2.96	2.96
Black Hawk, IA	2.40	2.40	2.40	2.40	2.35	2.35	2.35	2.35	2.35
Calvert, MD	2.94	2.94	2.94	2.94	2.94	2.94	2.94	2.94	2.94
Hampden, MA	2.54	2.54	2.54	2.54	2.54	2.54	2.54	2.54	2.54
Madison, MS	2.70	2.70	2.70	2.70	2.57	2.57	2.57	2.57	2.57
Douglas, NE	2.49	2.49	2.49	2.49	2.49	2.49	2.55	2.47	2.53
Bronx, NY	2.82	2.82	2.78	2.78	2.78	2.78	2.84	2.84	2.84
Rockland, NY	3.02	3.02	3.02	3.02	3.02	3.10	3.01	3.01	3.01
Franklin, OH	2.42	2.42	2.47	2.47	2.39	2.39	2.43	2.43	2.47
Multnomah, OR	2.37	2.41	2.41	2.41	2.32	2.32	2.32	2.39	2.39
Schuykill, PA	2.37	2.37	2.37	2.27	2.27	2.27	2.36	2.36	2.36
Sevier, TN	2.40	2.40	2.40	2.40	2.40	2.60	2.60	2.60	2.60
Yakima, WA	2.97	2.97	2.97	2.97	2.97	2.97	2.97	2.97	2.97

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