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An evaluation of population estimates in Florida: April 1, 2000

STANLEY K. SMITH & SCOTT CODY
University of Florida

Abstract. The housing unit (HU) method is the most commonly used method for making small-area population estimates in the United States. These estimates are used for a wide variety of budgeting, planning, and analytical purposes. Given their importance, periodic evaluations of their accuracy are essential. In this article, we evaluate the accuracy of a set of HU population estimates for counties and subcounty areas in Florida, as of April 1, 2000. We investigate the influence of differences in population size and growth rate on estimation errors; compare the accuracy of several alternative techniques for estimating each of the major components of the HU method; compare the accuracy of 2000 estimates with that of estimates produced in 1980 and 1990; compare the accuracy of HU population estimates with that of estimates derived from other estimation methods; consider the role of professional judgment and the use of averaging in the construction of population estimates; and explore the impact of controlling one set of estimates to another. Our results confirm a number of findings that have been reported before and provide empirical evidence on several issues that have received little attention in the literature. We conclude with several observations regarding future directions in population estimation research.

Keywords: Accuracy, Census data, Demographic estimates, Estimation error, Housing unit method

Introduction

The Bureau of Economic and Business Research (BEBR) at the University of Florida has made population estimates for all cities and counties in Florida each year since 1972. These estimates are used for monitoring growth trends, choosing site locations, determining eligibility for government programs, tracking emerging markets, and studying urban sprawl. They form the basis for distributing more than $1.5 billion each year to local governments through the state's revenue-sharing program. They even affect the salaries of some public officials. It is not surprising that these estimates are of so much interest to so many people.

BEBR uses the housing unit (HU) method to construct population estimates. This is by far the most commonly used method for making small-area population estimates in the United States. A 1990 survey of state and local agencies preparing population estimates found that 89% used the HU method, either alone or in combination with other methods (U.S. Census Bureau 1990). This method is widely used because it can be applied at virtually any level of geography, can accommodate a variety of data sources and application techniques, and can produce accurate estimates (Lowe et al. 1984; Smith 1986; Smith & Cody 1994; State of New Jersey 1984). The U.S. Census Bureau has relied exclusively on the HU method for producing subcounty population estimates since 1996 (U.S. Census Bureau 1998).

Previous BEBR estimates were evaluated following both the 1980 and 1990 censuses (Smith 1986; Smith & Cody 1994; Smith & Lewis 1983; Smith & Mandell 1984). This article presents a similar evaluation using estimates and census counts for 2000. We begin with a description of the estimation methodology used by BEBR; discuss the accuracy of the 2000 estimates and the influence of differences in population size and growth rate; discuss the accuracy of several techniques for estimating the two major components of the HU method; compare the accuracy of the 2000 estimates with that of previous BEBR estimates and the 2000 estimates produced by the U.S. Census Bureau; evaluate two different approaches to making estimates consistent across several levels of geography; and investigate the role of judgment and the benefits of averaging. This article provides additional evidence regarding the accuracy of the HU method and addresses several issues that have received little attention in the literature.

Methodology

The HU method is based on the assumption that almost everyone lives in some type of housing structure. In this method, population can be estimated as

$$P_t = (HH_t \times PPH_t) + GQ_t,$$

where P is population, HH is households, PPH is the average number of persons per household, GQ is the group quarters population, and t refers to a specific date. Estimates of the group quarters population typically include persons without permanent living quarters (e.g., the homeless). Although the HU method can be used for estimates of seasonal residents and for projections of future population, in this study it is used solely for estimates of the current number of permanent residents (i.e., as of April 1, 2000).

Each of the components of the HU method can be estimated using a variety of data sources and estimation techniques. In this section we describe the data and techniques used by BEBR for population estimates in Florida. Other descriptions of the HU method can be found in Rives and Serow (1984), Smith (1986), and Siegel (2002).

Households

Households can be estimated using data sources such as building permits, certificates of occupancy, electric customers, telephone customers, property tax records, and aerial photographs. Because they are widely available and correlate closely with population change, building permits and electric customers are the most frequently used (U.S. Census Bureau 1983). These are the data sources we use in Florida.

The current housing inventory for a city or county can be estimated by adding the number of building permits issued since the most recent census (net of demolitions) to the units counted in that census. The time lag between the issuance of a permit and the completion of a unit is assumed to be three months for single family units and nine months for multifamily units; these assumptions were based on surveys of developers in Florida. Building permit (BP) data are available from the U.S. Department of Commerce, which collects them directly from cities and counties throughout the United States.

Building permits are no longer issued for mobile homes. Consequently, mobile home data must be collected from sources such as tax appraiser files, industry records, and vehicle registration data. In general, mobile home data are not as reliable as building permit data. For simplicity of exposition, we include mobile homes with the single family and multifamily units covered by the BP data.

Once an estimate of the current housing stock has been developed, the next step is to estimate the proportion of housing units occupied by permanent residents. The most effective way to determine current occupancy rates is to conduct a special census or sample survey. Given their high costs, however, such censuses and surveys are rarely conducted. A common procedure is simply to use the occupancy rates from the most recent decennial census (U.S. Census Bureau 1983). This is the procedure we follow in Florida.

The product of the housing stock and the occupancy rate gives an estimate of the number of households. (This calculation can be performed separately for single family, multifamily, and mobile home units, but such a distinction is not essential.) There are several problems with this estimate. Time lags between issuance of a permit and completion of a unit vary from place to place and from year to year. The proportion of permits resulting in completed units is generally unknown. Occupancy rates may be going up or down. Data for mobile homes may be incomplete or inaccurate. In addition, some places do not issue building permits or have gaps in their data series. In Florida, for example, building permit data for the 1990s were missing for at least one year in 172 of the state's 455 subcounty areas.

The second source of data avoids several of these problems. Active residential electric customer (EC) data are available for all cities and counties in Florida and are often of better quality than BP data. Perhaps more important, households can be estimated directly from EC data, eliminating the intermediate steps of estimating time lags, completion rates, demolitions, conversions, and occupancy rates. We collect these data as of April 1 of each year from the 53 electric utility companies in Florida; the five largest companies serve about 80% of the state's population.

There are several ways to estimate the number of households from EC data. One uses the net change in customers since the previous census as a measure of the net change in households since that census (Starsinic & Zitter 1968). The major problem with this approach is that there is rarely a perfect one-to-one relationship between households and electric customers. For example, housing units may be occupied by seasonal residents; master meters may serve more than one household; and separate meters may be installed for pumps, barns, and other non-housing uses.

To deal with this problem, we form a ratio of the number of households counted in the most recent census to the number of customers on census day, and apply this ratio to the current number of customers. In some instances, we adjust the ratio up or down according to our judgment regarding local trends in the household/customer ratio (e.g., increases over time in the number of seasonal housing units).

Our household estimates are based on EC and BP data, but we use our professional judgment to decide which data sources and techniques are likely to be most reliable for each individual place. We rely most heavily on EC data, but sometimes use BP data or take an average of EC and BP estimates. Our choices are determined by the quality of each data series (e.g., missing data, unusual year-to-year fluctuations), their consistency with each other, and their accuracy in previous estimates. We hypothesize that applying professional judgment will lead to better estimates than can be obtained using the same data and techniques everywhere. We test this hypothesis later in the article.

Persons per household

The second component of the HU method is the average number of persons per household (PPH). Although PPH remained relatively stable at the national level between 1990 and 2000, PPH values and trends vary considerably from one place to another. In Florida, for example, county PPH values ranged from 2.13 to 3.09 in 2000, and 1990–2000 PPH changes ranged from −9.2% to 4.5%. Variations in PPH levels and changes over time were even greater for cities than for counties.

We construct estimates of PPH using a formula combining the local PPH in the most recent census, the national change in PPH since that census (as measured by the Current Population Survey), and the local change in the mix of housing units since that census. We base local PPH changes on national changes, but adjust them upward or downward depending on whether the initial PPH was higher or lower locally than nationally; on average, declines are greater when initial levels are higher. Since PPH tends to vary by housing type, we further adjust the estimates to account for changes in the local mix of housing units (single family, multifamily, mobile home). This formula is described more fully in Smith and Lewis (1980). Again, we sometimes make adjustments based on our professional judgment regarding local PPH trends; for example, we may raise our estimate of PPH for a place with a rapidly increasing Hispanic population because, on average, Hispanic households tend to be larger than non-Hispanic households.

Group quarters population

Population in households is estimated by multiplying the number of households by the PPH; this population accounted for 97.6% of Florida's population in 2000, the same proportion as in 1990. The remaining population is persons living in group quarters facilities (e.g., prisons, nursing homes, college dormitories) or without traditional housing (e.g., the homeless). We refer to this remainder as the *group quarters* (GQ) population.

We estimate the GQ population using a three-step procedure. First, we collect data on the number of persons living in large group quarters facilities on the same date as the most recent census. Second, we subtract the number of residents in these facilities from the total non-household population counted in that census and form a ratio of the residual to population in households; we call this ratio the *GQ multiplier*. Finally, we apply this multiplier to the current estimate of the household population and add direct counts of persons currently living in large group quarters facilities.

Evaluating precision and bias

We constructed estimates for April 1, 2000, for each county, incorporated city, and unincorporated balance of county in Florida; all estimates were produced in July 2000, well before census results became available. We evaluated the estimates by comparing them with census counts for the same date. We refer to the differences as estimation errors, although they may have been caused partly by enumeration errors as well.

Nationally, net census undercount has declined slowly but steadily since 1950, except for a small increase between 1980 and 1990. In 2000, both demographic analysis and post-enumeration surveys showed a slight net *overcount* at the national level (Robinson et al. 2002; U.S. Census Bureau 2003).

For cities and counties, however, no direct estimates of census coverage are available; rather, undercounts or overcounts must be estimated indirectly from survey data for larger places. Furthermore, coverage estimates for the individual components of the HU method are not available. For these reasons, we did not attempt to adjust the results for changes in census coverage over time. Although such changes undoubtedly affected the estimation errors calculated for some individual places, we believe their net effect was small when aggregated over a large number of places and had little impact on the results shown here.

We used five measures of accuracy. Mean absolute percent error (MAPE) is the average error when the direction of error is ignored. The proportions of errors less than 5% and greater than 10% indicate the frequency of relatively small and large errors, respectively. These are measures of precision, or how close the estimates were to census counts, regardless of whether they were high or low. Mean algebraic percent error (MALPE) is the average error when the direction of error is included. This is a measure of bias: A positive error indicates a tendency to overestimate and a negative error indicates a tendency to underestimate. Since a few extreme errors in one direction can change the sign of the MALPE, the proportion of estimates above the census count (%POS) was used as another measure of bias. These measures have often been used to evaluate the precision and bias of population estimates (Davis 2001; Harper et al. 2001; Siegel 2002; Smith & Cody 1994).

Errors by size and growth rate

Table 1 summarizes the errors for the 2000 county estimates in Florida. The MAPE for all counties was 4.2%. Almost three-quarters of the errors were less than 5% and only one in ten was greater than 10%. The estimates displayed very little bias, as the MALPE was only 0.8% and errors were about evenly split between those that were too high and those that were too low.

There was a strong positive relationship between precision and population size. MAPEs were largest for small counties and declined as population size increased. The MAPE for the smallest size category was almost three times larger than the MAPE for the largest category. The proportion of small errors rose with population size and the proportion of large errors declined. There was a slight tendency to overestimate small counties and underestimate large counties, but this relationship was fairly weak.

There was a weak U-shaped relationship between MAPEs and population growth rates. MAPEs were largest in the lowest growth-rate category, smallest in the second-lowest category, and slightly larger in each of the following two categories. Similar patterns can be seen for the proportions of small and large errors. Bias, however, was strongly related to growth rates:

Table 1. Population estimation errors by population size and growth rate: Counties in Florida, 2000

					Percent of absolute errors	
Size-1990	N	MAPE	MALPE	%POS	<5%	>10%
<25,000	20	6.5	2.5	65.0	50.0	20.0
25,000–99,999	18	4.4	1.3	61.6	77.8	16.7
100,000–249,999	14	2.7	0.1	42.9	85.7	0.0
250,000+	15	2.3	−1.3	26.7	86.7	0.0
Total	67	4.2	0.8	50.7	73.1	10.4
Growth rate 1990–2000						
<20.0%	22	4.7	4.0	72.7	68.2	13.6
20.0–29.9%	20	3.4	1.1	50.0	75.0	5.0
30.0–39.9%	15	4.1	−1.3	40.0	80.0	13.3
40.0%+	10	4.2	−3.6	20.0	70.0	10.0
Total	67	4.2	0.8	50.7	73.1	10.4

There was a clear tendency to overestimate the most slowly growing counties and underestimate the most rapidly growing counties.

Table 2 shows population estimation errors for subcounty areas (i.e., incorporated cities and unincorporated balances of counties). The MAPE for all subcounty areas was 10.4%, more than twice as large as the MAPE for counties. Almost half of the errors were less than 5%, but about one-third were greater than 10%. It is clearly more difficult to develop precise estimates for subcounty areas than for counties. There was a slight upward bias in the subcounty estimates, as indicated by a MALPE of 2.3% and 51.2% positive errors.

Differences in population size and growth rate had the same impact on errors for subcounty areas as for counties, but the patterns were more clearly visible for subcounty areas because the number of observations was larger and variability in size and growth-rate characteristics was greater. MAPEs declined from 48.3% for places with fewer than 250 residents to 3.0% for places with 100,000 residents or more. The proportion of small errors rose with population size and the proportion of large errors fell. Again, there was

Table 2. Population estimation errors by population size and growth rate: Subcounty areas in Florida, 2000

					Percent of absolute errors	
Size – 1990	N	MAPE	MALPE	%POS	<5%	>10%
<250	22	48.3	33.8	63.6	4.5	77.3
250–499	27	15.0	4.6	55.6	25.9	59.3
500–999	48	12.4	6.3	54.2	41.7	43.8
1,000–2,499	70	14.3	−0.2	48.6	32.9	55.7
2,500–9,999	117	7.5	0.4	57.3	43.6	27.4
10,000–24,999	73	4.8	0.4	58.9	63.0	17.8
25,000–49,999	34	5.3	−3.8	29.4	55.9	14.7
50,000–99,999	37	4.8	0.6	43.2	64.9	8.1
100,000+	27	3.0	−2.0	29.6	77.8	3.7
Total	455	10.4	2.3	51.2	46.6	32.3
Growth rate 1990–2000						
<−10%	32	42.0	42.0	100.0	6.2	90.6
−10–0%	44	12.6	12.6	95.5	15.9	59.1
0–10%	112	5.2	2.5	54.5	67.9	13.4
10–25%	116	5.3	−1.9	44.8	56.0	17.2
25–50%	98	7.4	−4.1	35.7	46.9	31.6
50–100%	40	12.4	−11.8	20.0	37.5	45.0
100%+	13	31.4	−1.1	23.1	7.7	61.5
Total	455	10.4	2.3	51.2	46.6	32.3

a slight tendency for estimates to be too high for small places and too low for large places.

Differences in population growth rates also had a strong influence on errors. There was a clear U-shaped relationship between MAPEs and growth rates. MAPEs were smallest in places with small but positive growth rates and grew rapidly as growth rates deviated in either direction from those levels. MAPEs were just over 5% for places growing 0–25% during the decade, but were 42.0% for places losing more than 10% of their residents and 31.4% for places that more than doubled in size. The proportion of small errors fell

Table 3. Population estimation errors by size-growth category: Subcounty areas in Florida, 2000

						Percent of absolute errors	
Size-1990	Growth rate	N	MAPE	MALPE	%POS	<5%	>10%
<1,000	<0%	29	41.2	41.2	96.6	10.3	89.7
<1,000	0–50%	58	8.6	−0.8	41.4	41.4	34.5
<1,000	>50%	10	36.8	2.2	30.0	10.0	80.0
1,000–9,999	<0%	38	15.5	15.5	97.4	13.2	63.2
1,000–9,999	0–50%	130	6.9	−1.4	46.9	50.0	26.2
1,000–9,999	>50%	19	20.1	−19.3	15.8	21.1	68.4
>10,000	<0%	9	12.7	12.7	100.0	11.1	55.6
>10,000	0–50%	138	3.8	−0.8	45.7	71.0	8.7
>10,000	>50%	24	6.4	−5.8	20.8	45.8	20.8
Total		455	10.4	2.3	51.2	46.6	32.3

as growth rates deviated from low but positive levels and the proportion of large errors rose. Again, there was a strong tendency for estimates to be too high for places that were losing population and too low for places that were growing rapidly.

In order to account for potential interactions between population size and growth rate, we divided subcounty areas into nine groups based on three size categories and three growth-rate categories (Table 3). The same patterns observed in Tables 1 and 2 can be seen in Table 3. Within each size category, MAPEs had a U-shaped relationship with growth rates and %POS declined as growth rates increased. Within each growth-rate category, MAPEs declined as population size increased but %POS had no consistent relationship with differences in population size.

Based on these results and those reported in previous studies (Davis 2001; Harper et al. 2001; Smith 1986; Smith & Cody 1994; State of New Jersey 1984), we have drawn the following conclusions regarding population estimation errors.

1. Precision tends to increase as population size increases.
2. Precision tends to decline as growth rates deviate (in either direction) from low but positive levels.
3. Bias is largely unaffected by differences in population size.

Table 4. Population estimation errors by component: Counties and subcounty areas in Florida, 2000

	Component	MAPE	MALPE	%POS	Percent of absolute errors <5%	Percent of absolute errors >10%
Counties	Households	3.5	−1.4	26.9	70.1	3.0
	PPH	3.3	2.5	80.6	83.6	1.5
	GQ	19.1	3.3	49.3	20.9	58.2
Subcounty areas	Households	10.2	1.5	41.5	49.2	25.1
	PPH	5.1	0.7	66.2	64.0	9.9
	GQ	73.7	33.7	57.4	32.1	62.6

4. Bias is strongly affected by differences in population growth rates: Estimates tend to be too high for places that are losing population and too low for places that are growing rapidly.

Errors by component

Which component of the HU method can be estimated most accurately? Table 4 shows that errors were smallest for PPH and largest for the group quarters population (GQ). For counties, MAPEs were 3.3% for PPH, 3.5% for households, and 19.1% for GQ; for subcounty areas, they were 5.1%, 10.2%, and 73.7%, respectively. There was a slight tendency for PPH estimates to be too high and household estimates to be too low. The proportion of small errors was highest for PPH and lowest for GQ, and the proportion of large errors was lowest for PPH and highest for GQ. Errors for GQ were so large because they were often based on very small numbers of people.

Several studies have found errors for households to be greater than errors for PPH (Lowe et al. 1984; Smith & Cody 1994; Smith & Lewis 1983; Starsinic & Zitter 1968; State of New Jersey 1984). This most likely reflects the fact that growth rates are generally higher and more variable for households than for PPH. Whereas PPH changed by less than 5% between 1990 and 2000 for most places in Florida, households often changed by 10%, 20%, 30%, or more. There was simply more potential for error in estimates of households than in estimates of PPH.

Which component of the HU method contributes the most to overall estimation error? To answer this question, we made three sets of synthetic population estimates using combinations of estimated values and census

Table 5. Population estimation errors under alternate scenarios: Counties and subcounty areas in Florida, 2000

Errors	Scenario	MAPE	MALPE	%POS	Percent of absolute errors <5%	>10%
Counties	1	3.3	−1.4	25.4	73.1	3.0
	2	3.1	2.3	80.6	88.1	0.0
	3	0.8	−0.2	49.3	100.0	0.0
Subcounty areas	1	9.9	1.4	40.9	51.0	24.0
	2	5.0	0.7	66.4	66.2	9.2
	3	1.7	0.0	34.3	92.7	3.3

Scenario 1: Estimates for households, counts for PPH and GQ.
Scenario 2: Estimates for PPH, counts for households and GQ.
Scenario 3: Estimates for GQ, counts for households and PPH.

counts. The first used estimates of households and counts for PPH and GQ; the second used estimates of PPH and counts for households and GQ; and the third used estimates of GQ and counts for households and PPH. For each scenario, then, errors in the population estimates were due solely to errors in the single estimated component. The results are shown in Table 5.

For both counties and subcounty areas, Scenario 1 had the largest MAPE, the most large errors, and the fewest small errors. Even with perfect estimates of PPH and GQ, errors in household estimates would have created MAPEs of 3.3% for counties and 9.9% for subcounty areas. With perfect estimates of households and GQ, errors in PPH estimates would have created MAPEs of 3.1% for counties and 5.0% for subcounty areas (Scenario 2). Scenario 3 had the smallest MAPE, the most small errors, and the fewest large errors. Although GQ errors were much larger than household and PPH errors, they contributed relatively little to overall estimation error because the group quarters population accounts for a very small proportion of total population in most places.

Household errors by technique

Households are frequently estimated using symptomatic data series such as electric customers, building permits, certificates of occupancy, or property tax records. They can also be estimated by holding past values constant or by extrapolating historical trends. Which approach produces the most accurate estimates? We tested the following techniques:

Table 6. Errors by technique for household estimates: Counties and subcountry areas in Florida, 2000

	Technique	MAPE	MALPE	%POS	Percent of absolute errors <5%	Percent of absolute errors >10%
Counties	BEBR	3.5	−1.4	26.9	70.1	3.0
	EC	4.1	0.6	44.8	74.6	9.0
	BP	4.6	−2.3	31.3	64.2	14.9
	CONSTANT	21.7	−21.7	0.0	1.5	95.5
	TREND	7.1	−0.3	46.3	38.8	17.9
Subcounty areas	BEBR	10.2	1.5	41.5	49.2	25.1
	EC	9.8	1.4	43.7	49.2	24.6
	BP	13.0	2.5	44.6	43.1	32.7
	CONSTANT	29.6	−3.5	14.9	18.5	64.8
	TREND	37.1	18.4	50.3	25.5	52.7

1. BEBR – a judgmental estimate based on EC and/or BP data and our evaluation regarding which data sources, techniques, and assumptions to use for each place;
2. EC – an estimate based on EC data, using the ratio of households to active residential electric customers at the time of the 1990 census;
3. BP – an estimate based on BP data, using the techniques described previously;
4. CONSTANT – an estimate based on the assumption that the number of households has not changed since 1990;
5. TREND – an estimate based on the assumption that the numerical change in households between 1990 and 2000 will be the same as it was between 1980 and 1990.

The results are summarized in Table 6. Household estimates based on EC data were more precise than those based on BP data, particularly for subcounty areas. For both counties and subcounty areas, the EC estimates had smaller MAPEs, more small errors, and fewer large errors than the BP estimates. Similar results were found in tests of 1980 and 1990 estimates in Florida (Smith & Cody 1994; Smith & Lewis 1983) and in several other studies as well (Rives & Serow 1984; Starsinic & Zitter 1968).

EC and BP estimates both performed better than CONSTANT and TREND estimates. CONSTANT had large errors and a strong downward bias for counties and subcounty areas, whereas TREND had large errors (especially for subcounty areas) but displayed relatively little bias. Clearly, household estimates based on symptomatic data series were superior to estimates based solely on past values or historical trends.

BEBR estimates performed substantially better than BP, CONSTANT, and TREND estimates, but did not perform consistently better than EC estimates: BEBR estimates were slightly more precise than EC estimates for counties, but slightly less precise for subcounty areas. The results were so similar because BEBR estimates were often based primarily (or completely) on EC data. For households, then, the application of expert judgment did not lead to better estimates than could be achieved by applying the EC technique by itself.

PPH errors by technique

PPH is frequently estimated by extrapolating past trends or holding values constant at previous levels (Starsinic & Zitter 1968; U.S. Census Bureau 1998). In Florida, we estimate PPH using both expert judgment and the formula described above. Which approach produces the most accurate estimates? We tested the following techniques:

1. BEBR – a judgmental estimate based on the local PPH value observed in the 1990 census, the national change in PPH since that census, the local change in housing mix since that census, and our evaluation of other factors expected to influence PPH;
2. FORMULA – an estimate based on a mathematical formula combining the local PPH value observed in the 1990 census, the national change in PPH since that census, and the local change in housing mix since that census;
3. CONSTANT – an estimate based on the assumption that PPH has not changed since 1990;
4. TREND – an estimate based on the assumption that the numerical change in PPH between 1990 and 2000 will be the same as it was between 1980 and 1990.

The results are summarized in Table 7. BEBR produced better PPH estimates than any other technique, with the smallest MAPE and least bias for both counties and subcounty areas. In most instances, it also had higher proportions of small errors and lower proportions of large errors. The application of expert judgment, then, improved on the performance of the other techniques.

BEBR estimates were only slightly better than those derived from FORMULA and CONSTANT, however. Errors for BEBR and FORMULA were similar because – in most instances – BEBR estimates were based primarily on the formula, with little or no further adjustment. Both techniques pro-

Table 7. Errors by technique for PPH estimates: Counties and subcountry areas in Florida, 2000

	Technique	MAPE	MALPE	%POS	Percent of absolute errors <5%	>10%
Counties	BEBR	3.3	2.5	80.6	83.6	1.5
	FORMULA	3.6	2.9	83.6	83.6	3.0
	CONSTANT	3.4	2.6	82.1	83.6	1.5
	TREND	4.0	−3.7	9.0	67.2	0.0
Subcounty areas	BEBR	5.1	0.7	66.2	64.0	9.9
	FORMULA	5.3	1.6	68.6	61.5	11.4
	CONSTANT	5.8	1.9	68.1	62.0	10.8
	TREND	8.5	−3.0	23.5	49.2	19.3

duced errors similar to CONSTANT because there was relatively little change in PPH between 1990 and 2000 for many cities and counties in Florida. This stands in contrast to previous evaluations, in which the CONSTANT technique had relatively large errors (Smith & Lewis 1983; Smith & Cody 1994).

Comparison to other estimates

Previous BEBR estimates

BEBR's 2000 population estimate for the state of Florida was 15,693,075, about 1.8% below the census count of 15,982,378. Previous state estimates were 1.6% above the census count in 1990 and 2.7% below the census count in 1980. The change in errors from negative in 1980 to positive in 1990 and back to negative in 2000 was most likely caused – in part – by changes in census coverage. Nationally, census undercount declined between 1970 and 1980, rose between 1980 and 1990, and declined again between 1990 and 2000. Because each set of estimates is based on data from the previous census, errors in census counts are built into succeeding estimates. It is likely that the declines in undercount during the 1970s and 1990s contributed to state-level underestimates in 1980 and 2000, whereas the increase in undercount during the 1980s contributed to the overestimate in 1990.

Table 8. Errors of BEBR population estimates, 1980, 1990, and 2000: Counties and subcountry areas in Florida

	Technique	MAPE	MALPE	%POS	Percent of absolute errors <5%	Percent of absolute errors >10%
Counties	1980	5.4	−2.9	34.3	53.7	10.4
	1990	5.4	3.3	74.6	58.2	16.4
	2000	4.2	0.8	50.7	73.1	10.4
Subcounty areas	1980	14.4	3.5	46.7	33.6	42.4
	1990	11.9	6.0	68.4	36.5	40.5
	2000	10.4	2.3	51.2	46.6	32.3

Table 8 compares errors for 2000 with errors for 1980 and 1990 for counties and subcounty areas in Florida. According to every measure of precision and bias, the 2000 estimates performed better than estimates for previous years: MAPEs and the proportion of large errors were smaller, the proportion of small errors was larger, MALPEs were closer to zero, and the proportion of positive errors was closer to 50%. Whereas 1980 estimates tended to be too low and 1990 estimates tended to be too high, 2000 estimates displayed very little bias. Viewed as a whole, these results imply that the methodology employed by BEBR has no systematic bias toward either overestimation or underestimation.

Why were the 2000 estimates more accurate than previous estimates? There are several possible explanations. On average, population sizes were larger and population growth rates were lower in the 1990s than in previous decades; both of these factors tend to improve estimation accuracy. Data series may have become more reliable over time. The insights gained through additional years of studying estimation methods, sources of data, and the dynamics of Florida population growth may have improved the quality of judgmental adjustments. Blind luck may have played a role as well. Any (or all) of these factors may have contributed to the greater accuracy of the 2000 estimates.

Census Bureau estimates

How do BEBR estimates compare to those produced by other agencies? To our knowledge, the only other agency making independent population estimates for all cities and counties in Florida is the U.S. Census Bureau

Table 9. BEBR and the U.S. Census Bureau (USCB): Population estimation errors for counties and subcounty areas in Florida, 2000

					Percent of absolute errors	
		MAPE	MALPE	%POS	<5%	>10%
Counties	BEBR	4.2	0.8	50.7	73.1	10.4
	USCB	5.5	−5.1	11.9	62.7	14.9
Subcounty areas	BEBR	10.4	2.3	51.2	46.6	32.3
	USCB	16.1	4.2	38.7	35.8	39.1

(USCB). Although private data companies produce a variety of small-area population estimates, they typically control their estimates to the city and county estimates produced by the USCB or by state demographic agencies.

The USCB provides a good standard of comparison because it is the nation's premier demographic agency. It has been producing state and local population estimates for many years and has pioneered in the development of a number of methods and data sources. Currently, the USCB makes county estimates using the Tax Returns (TR) method. In this method, population estimates are based on births, deaths, Medicare enrollees, residents in group quarters facilities, foreign immigrants, and estimates of internal migration derived from the return addresses listed on federal income tax returns (U.S. Census Bureau 2001). County estimates are controlled to add to the USCB national population estimate and state estimates are calculated as the sum of the county estimates for each state. Subcounty estimates are developed using the HU method and are controlled to add to the USCB county estimates (U.S. Census Bureau 1998).

The USCB's population estimate for Florida on April 1, 2000, was 15,275,725, about 4.4% below the census count. This error was more than twice as large as the error for the BEBR estimate. A summary of BEBR and USCB errors for counties and subcounty areas in Florida is shown in Table 9. According to every measure, BEBR estimates were more precise and less biased than USCB estimates.

For counties, USCB estimates had a larger MAPE, a higher proportion of large errors, and a smaller proportion of small errors than BEBR estimates. Perhaps most notable, USCB estimates had a strong downward bias, as indicated by a MALPE of −5.1% and only 11.9% positive errors. BEBR estimates, on the other hand, had virtually no bias, with a MALPE of 0.8% and a distribution of 34 positive errors and 33 negative errors.

For subcounty areas, USCB estimates had a MAPE of 16.1%, compared to 10.4% for BEBR estimates. Again, USCB estimates had a higher proportion of large errors and a smaller proportion of small errors. USCB estimates showed mixed results regarding bias, with a MALPE of 4.2% but only 38.7% positive errors. This seemingly contradictory result occurred because, on average, places with overestimates had larger errors than places with underestimates. BEBR estimates for subcounty areas showed a slight upward bias, with a MALPE of 2.3% and 51.2% positive errors.

Why were BEBR estimates more accurate than those produced by the USCB? Again, there are several possible explanations. First, the USCB national estimate for 2000 was substantially below the 2000 census count; since USCB subnational estimates are controlled to the national estimate, errors at the national level carry over to the state and local levels. Second, the TR method used by the USCB for county estimates may not be as accurate as the HU method; several studies have reported smaller errors for HU population estimates than TR population estimates (Smith 1986; Smith & Mandell 1984). Third, the USCB's application of the HU method relies solely on BP data, whereas BEBR's relies primarily on EC data. As mentioned previously, EC data generally provide more accurate estimates of households than do BP data. Finally, a greater familiarity with the details of Florida's population growth may have helped BEBR analysts uncover data errors and develop accurate assumptions more readily than USCB analysts.

Other issues

Top-down vs. bottom-up

Two approaches can be followed when making population estimates that are consistent across several levels of geography (e.g., subcounty, county, state). One is to adjust estimates for subareas so that they add exactly to an independent estimate of the larger area in which they are located. The other is to calculate the estimate for the larger area as the sum of the estimates of its constituent subareas. We refer to these as top-down and bottom-up approaches, respectively. Both lead to estimates for which the whole is equal to the sum of its parts.

Which approach is better? Some analysts have concluded that the first approach is preferable because large areas can generally be estimated more accurately than small areas (Shryock & Siegel 1973: 728). Others have questioned this conclusion, pointing out that this does not necessarily imply that

Table 10. Top-down vs. bottom-up: A comparison of EC population estimates

County estimates	County level	Sum of subcounty
MAPE	5.3	5.2
% < 5%	56.7	59.7
% > 10%	16.4	14.9
MALPE	2.9	2.9
% POS	64.2	65.7
Subcounty estimates	**Controlled**	**Uncontrolled**
MAPE	11.9	11.8
% < 5%	42.3	42.1
% > 10%	34.4	35.7
MALPE	3.2	3.3
% POS	54.0	54.0

the sum of the estimates for small areas is less accurate than an independent estimate of a larger area (Smith & Mandell 1984).

We can test these approaches using the EC population estimates discussed previously (similar tests using BP estimates cannot be conducted because complete BP data were not available for all subcounty areas in Florida). We address two separate questions: (1) Are county estimates based on county-level data and assumptions more accurate than county estimates based on the sum of subcounty estimates? (2) Are subcounty estimates more accurate when controlled to independent county estimates than when left uncontrolled?

The results of the analysis are shown in Table 10. The top panel shows errors for independent county estimates and county estimates based on the sum of subcounty estimates. The latter were slightly more precise, with a smaller MAPE, a larger proportion of small errors, and a smaller proportion of large errors. The MALPEs for the two estimates were identical, but the %POS was slightly larger for the county estimates based on the sum of the subcounty estimates. This evidence shows a slight advantage for the bottom-up approach, but the differences were very small.

The bottom panel shows errors for subcounty estimates. In the first set, the subcounty estimates were controlled to add to the independent county estimates; in the second, they were not controlled. Again, the differences between the two approaches were very small. The uncontrolled estimates had a slightly smaller MAPE and proportion of small errors, but the controlled estimates had a slightly smaller MALPE and proportion of large errors. The %POS was the same for both. In this sample, then, controlling to independent county estimates had virtually no impact on the accuracy of subcounty estimates.

Either approach can be used when making population estimates for two or more levels of geography. For example, the USCB controls subcounty estimates to independent county estimates (top-down) but calculates state estimates as the sum of each state's county estimates (bottom-up). In terms of accuracy, the evidence presented in Table 10 suggests that there may be very little difference between these two approaches. Similar conclusions have been drawn in several studies of population projections (Isserman 1977; Voss & Kale 1985).

Further research is needed before we can draw firm conclusions, but we believe that bottom-up estimates are likely to be as accurate as top-down estimates and that controlling smaller-area estimates to larger-area estimates is not likely to improve or reduce their accuracy. Decisions regarding which approach to use for any particular project must rest on considerations other than the expected accuracy of the estimates (e.g., data availability or legal mandates that require the use of a particular set of estimates).

Application of professional judgment

Population estimates using the HU method can be based on several different combinations of techniques and assumptions. Some are strictly mechanical, whereas others incorporate the application of professional judgment informed by knowledge of local population dynamics and data idiosyncrasies. Which approach provides the most accurate estimates?

We presented evidence regarding the impact of expert judgment on the accuracy of household and PPH estimates in Tables 6 and 7. We found that – compared to the best "mechanical" technique – applying expert judgment led to small improvements in the accuracy of PPH estimates, but had little impact on the accuracy of household estimates. We can provide further evidence on this question by comparing several alternative methods for estimating total population.

We evaluated six sets of population estimates for counties and subcounty areas in Florida. One (BEBR) was derived from the techniques and data sources described previously but included adjustments based on our judgment regarding the best practices and procedures to follow in estimating households, PPH, and the GQ population for each place. The other sets were based on the mechanical application of specific techniques. EC was based on EC household estimates and the formula for estimating PPH. BP was based on BP

Table 11. Population estimation errors by technique: Counties and subcounty areas in Florida, 2000

	Technique	MAPE	MALPE	%POS	Percent of absolute errors <5%	Percent of absolute errors >10%
Counties	BEBR	4.2	0.8	50.7	73.1	10.4
	EC	5.3	2.9	64.2	56.7	16.4
	BP	4.9	0.3	59.7	56.7	11.9
	AVE	4.8	1.6	61.2	59.7	13.4
	CONSTANT	21.0	−21.0	0.0	1.5	92.5
	TREND	8.0	−2.0	40.3	37.3	28.4
Subcounty areas	BEBR	10.4	2.3	51.2	46.6	32.3
	EC	11.8	3.3	54.0	42.1	35.7
	BP	13.5	3.6	53.1	40.3	38.5
	AVE	12.0	3.3	56.6	42.1	35.9
	CONSTANT	18.7	−12.9	16.5	19.8	64.3
	TREND	19.4	−2.6	44.5	27.3	52.6

household estimates and the PPH formula. Both of these estimates used the GQ estimation techniques described previously. AVE was an average of the EC and BP population estimates. CONSTANT was based on the assumption that the population in 2000 would be the same as in 1990, and TREND was based on the assumption that population change during the 1990s would be the same as during the 1980s. Errors for these techniques are summarized in Table 11.

The BEBR estimates outperformed the other techniques according to every measure of precision and bias. For both counties and subcounty areas, BEBR had the smallest MAPE, the highest proportion of small errors, the lowest proportion of large errors, and the least bias of all the techniques. Differences were not always large, but the application of professional judgment consistently improved the accuracy of the population estimates. An evaluation of 1990 estimates in Florida reported similar results (Smith & Cody 1994). We believe that – although reliable data series and sound estimation techniques are essential to the production of accurate population estimates – the application of sound professional judgment can play an important role as well.

It is difficult to draw general conclusions regarding the role of professional judgment, however. Whose judgment should be used? How should it be applied? Will it always lead to more accurate estimates? Can the role of judgment itself be formally incorporated into the estimation process (e.g., the Delphi technique)? Clearly, many questions remain to be answered. Although several studies have investigated the use of expert judgment in population forecasting (Lutz et al. 1999), few have considered its use in population estimation. Again, more research is needed before we can draw general conclusions.

Benefits of averaging

Of the mechanical techniques shown in Table 11, BP performed a bit better than EC for counties and EC performed a bit better than BP for subcounty areas. The average of estimates from these two techniques also performed well. For counties, AVE had a smaller MAPE than either EC or BP, the two techniques upon which the average was based. For subcounty areas, the MAPE for AVE was smaller than for BP but slightly larger than for EC.

Averages have been used in preparing economic and other forecasts for many years (Armstrong 2001), but have not been widely used for population estimates. When they have been used, however, they have generally performed well (Smith & Mandell 1984; Smith & Nogel 2003). We believe that averages will be useful for many purposes because they include more information than can be contained in a single estimate and they reduce the odds of making large errors. Further research is needed to determine the circumstances in which averaging will be most useful and what type of average will generally produce the best estimates (e.g., simple, weighted, trimmed).

Role of symptomatic indicators

CONSTANT performed very poorly in the tests reported in Table 11, with many large errors and a strong downward bias. TREND also performed poorly (especially for subcounty areas), but was not nearly as biased as CONSTANT. We believe that population estimates based on symptomatic indicators of population change (e.g., electric customers, building permits, property tax records) will generally be more precise and less biased than estimates based on the extrapolation of past trends or the assumption that no change has occurred. Similar results have been reported in several other studies (Davis 2001; Harper et al. 2001). Although estimates based on symptomatic indicators are not perfect, in most circumstances they will be better than the available alternatives.

Conclusions

Florida is a difficult state for which to make population estimates. Many places are very small; many are growing or declining rapidly; many have large numbers of temporary residents; and many are undergoing substantial changes in age, race, ethnicity, and other demographic characteristics. All these factors raise the degree of difficulty for making accurate estimates. Yet overall, the HU method produced relatively precise, unbiased estimates for most places in Florida.

This is not to say that further improvements cannot be made, of course. New data sources – or new uses of existing sources – might lead to better estimates of housing units. New techniques for monitoring changes in mobile homes might improve estimates based on BP data; such improvements would be particularly important in rural areas, where mobile homes often constitute a substantial proportion of the total housing stock. Advances in remote sensing and GIS technology might be used for housing estimates in areas lacking good data from other sources (Webster 1996). Developing indicators of changing occupancy rates and seasonal residency patterns might improve the accuracy of household estimates; data from the American Community Survey may prove to be particularly useful in this regard. The development of regression models incorporating symptomatic indicators of population change might lead to better PPH estimates (Smith et al. 2002).

The HU method provides an excellent tool for producing population estimates, both in Florida and elsewhere. It is flexible in terms of data sources and estimation techniques, can be applied at virtually any level of geography, and has a proven track record. Research on new techniques and data sources will undoubtedly lead to further improvements in the accuracy of its estimates. We believe the HU method will become ever more widely used for the production of state and local population estimates, not only in the United States but in other countries as well (Simpson et al. 1996).

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Address for correspondence: Stanley K. Smith, Bureau of Economic and Business Research, 221 Matherly Hall, University of Florida, Gainesville, FL 32611-7145, USA
Phone: 352-392-0171, Ext. 210; Fax: 352-392-4739; E-mail: sksmith@ufl.edu