EVALUATING THE HOUSING UNIT METHOD:
A CASE STUDY OF 1990 POPULATION ESTIMATES IN FLORIDA*

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ABSTRACT

The housing unit (HU) method is the most commonly used approach to making small-area population estimates in the United States. This study evaluates the accuracy and bias of HU population estimates produced for counties and subcounty areas in Florida for April 1, 1990. The major findings are that population size has a negative effect on estimation errors (disregarding sign) but no effect on bias; growth rates have a U-shaped effect on estimation errors (disregarding sign) and a negative effect on bias; electricity customer data provide more accurate household estimates than do building permit data; errors in household estimates contribute more to population estimation error than do errors in estimates of average household size or group quarters population; and the application of professional judgment improves the accuracy of purely mechanical techniques. We believe the HU method offers a number of advantages over other population estimation methods and provides planners and demographers with a powerful tool for small-area analysis.

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Introduction

Postcensal population estimates for states and local areas are used for a wide variety of purposes in the United States. They form the basis for the distribution of billions of dollars of federal, state, and local government funds. They determine boundaries and representation for city councils, county commissions, school boards, and other political entities. They are used for planning when and where to build new schools, roads, hospitals, banks, electric power plants, and shopping centers. They provide an important tool for marketing a wide variety of goods and services, and even determine the salaries of some public officials. Clearly, there is a profound need for accurate and timely postcensal population estimates.

Several different methods can be used to make population estimates (see Murdock and Ellis 1991; National Research Council 1980; and Rives, Serow, Lee, and Goldsmith 1989). At the substate level, the HU method is by far the most commonly used (U.S. Bureau of the Census 1983, 1990). This method is widely accepted because it can use a variety of data sources and estimation techniques, can be applied virtually everywhere, and can produce reasonably accurate estimates. Given its widespread use and the importance of population estimates for many types of planning and budgeting, it is essential to evaluate the performance of the HU method from time to time.

This article provides such a critical evaluation. It focuses on April 1, 1990 population estimates for counties and subcounty areas in Florida.[1] It evaluates estimation errors by size of place and rate of growth, by component (i.e. households, persons per household, and group quarters population), and by technique. It calculates the contribution of each component to overall estimation error, considers the role of judgment in producing population estimates, and compares the performance of 1990 estimates with that of 1980 estimates. It confirms some results that have been found before and reports others that are new. Although this study focuses on Florida, it provides insights into the HU method that will be useful in a much broader context.

Many planners have used the HU method to produce small-area population estimates; others have used similar concepts, data sources, and techniques for analyses of fiscal impacts (e.g., Burchell and Listokin 1978), residential mobility (e.g., Varady 1984), age structure (e.g., Myers and Doyle 1990), household size (e.g., Gober 1990), and housing demand (e.g., Myers 1987).

Planners have thus been intimately involved in developing the HU method and extending its application into new areas. We believe the present study will help both planners and demographers make more effective use of this increasingly important tool for small area analysis.

Demographers typically distinguish between population estimates and population projections (or forecasts). Estimates refer to the present or some time in the past, whereas projections refer to the future. In terms of methodology, the primary difference between estimates and projections is that estimates can be based on symptomatic data corresponding to the date of the estimate, whereas projections cannot be based on such data; rather, projections must be based on the extrapolation of past trends or assumptions about future demographic change. In this article we focus solely on population estimates.

Brief Description of Methodology[2]

The foundation of the HU method is the fact that almost everyone lives in some type of housing structure, whether a traditional single family unit, an apartment, a mobile home, a college dormitory, or the state penitentiary. The population of any geographic area can therefore be calculated as the number of occupied housing units (households) times the average number of persons per household (PPH), plus the number of persons living in group quarters facilities (e.g., college dormitories, prisons, military barracks) or without traditional housing (e.g., the homeless):

$$P_t = (H_t \ \square \ PPH_t) + GQ_t \qquad\qquad (1)$$

where P_t = total population at time t, H_t = occupied housing units at time t,

PPH_t = average number of persons per household at time t, and GQ_t = group quarters population at time t (including the homeless population).

This is an identity, not an estimate. If these three components were known exactly, the total population would also be known. The problem, of course, is that these components are almost never known exactly. They must rather be estimated from various data sources, using one or more of several possible techniques. In this section we provide a brief description of the data and techniques used to estimate these three components for counties and subcounty areas in Florida. More detailed descriptions of the HU method can be found in Smith and Lewis (1980), Rives and Serow (1984), and Smith (1986).

Households. A number of different types of data can be used to estimate households, such as building permits, certificates of occupancy, electricity customers, telephone customers, property tax records, and aerial photographs. The most commonly used types of data are building permits and electricity customers (U.S. Bureau of the Census 1983), since they are widely available and correlate closely with population change. These are the data sources we use in Florida.

The housing inventory for a city or county can be estimated by adding building permits issued since the most recent census (net of demolitions) to the units counted in that census. Building permit data are available from the U.S. Department of Commerce, which collects them directly from cities and counties throughout the United States.[3] The time lag between issuance of permit and completion of unit is assumed to be three months for single family units and ten months for multifamily units; these assumptions are based on surveys of developers in Florida. For mobile home units, there is no time lag. Although building permit data are not available everywhere, it has been estimated that approximately 90 percent of new housing units in the United States are built in areas requiring building permits (Siskind 1980). In Florida, building permit data are available in 82 percent of the subcounty areas for which we produce population estimates; these areas contain 90 percent of the state's population.

Combining building permit data with housing data from the decennial census provides an estimate of the current housing stock. The next step in the process 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 or surveys are rarely conducted. A common procedure is simply to use the occupancy rates from the most recent census (U.S. Bureau of the Census 1983). This is the procedure we follow in Florida.

The product of the housing stock and the occupancy rate (preferably performed separately for each type of housing unit) gives an estimate of the number of households. There are several problems with this estimate. Time lags between issuance of permit and completion of unit may 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 non-existent or of poor quality. Certificate-of-occupancy data can eliminate problems of

estimating time lags and completion rates, but not problems of estimating current occupancy rates, demolitions, or conversions from one use to another.

Our second source of data avoids some of those problems. Active residential electricity customer data are available for all cities and counties in Florida and are often of better quality than building permit data. More important, households can be estimated <u>directly</u> from electricity customer data, avoiding the intermediate steps of estimating time lags, completion rates, demolitions, conversions, and occupancy rates. A number of studies have concluded that household estimates based on electricity customer data are generally more accurate than those based on building permit data (e.g., Starsinic and Zitter 1968; Smith and Lewis 1980, 1983; Rives and Serow 1984). We collect electricity customer data from 54 electric power companies in Florida; the five largest companies serve 81 percent of the state's population.

There are several ways to estimate the number of households from active residential electricity customer data. One uses the net change in customers as a measure of the net change in households (Starsinic and Zitter 1968). However, a number of factors may prevent a perfect one-to-one relationship between permanent households and residential electricity customers: housing units occupied by seasonal and other non-permanent residents; master meters serving more than one household; separate meters for pumps, barns, and other non-housing uses; geographic boundaries for utility companies that do not correspond exactly to those used by the Census Bureau; and the bookkeeping practices of individual utility companies. These differences can be accounted for by forming a ratio of the number of households counted in the most recent census to the number of customers reported for the same date, and applying this ratio to the current number of customers. This approach has been found to produce more accurate household estimates than the first approach does (Smith and Lewis 1980, 1983). The ratio approach is the one we follow in Florida.[4]

Our final estimates of households are not based on the same data sources and techniques for all places, however. Rather, we use our professional judgment to decide which sources and techniques are likely to be most reliable for each individual place. In a majority of places we use only electricity customer data, but we occasionally adjust the household/customer ratio to account for evidence of changes in seasonal populations (e.g., shifts in the composition of the housing stock; seasonal fluctuations in the number of active residential electricity customers). When

electricity customer data are of dubious quality and building permit data appear to be good, we use only building permit data. When the data sources differ substantially and it is not clear which is better, we average the two. Our choices of data and techniques are determined primarily by the consistency of the data series over time, the presence (or absence) of gaps in the data series, and the availability of additional evidence about data quality or demographic trends. We believe the application of professional judgment provides better household estimates than does the mechanical application of the same data and techniques for all places. The next section offers some evidence supporting this belief.

Persons per household. The second component of the HU method is the average number of persons per household (PPH). Although trends nationally and in Florida have been toward steadily smaller PPH, trends for local areas vary considerably from one place to another. Between 1980 and 1990, PPH declined in all but two of Florida's 67 counties, with declines ranging from 0.9 percent to 11.4 percent. Values of PPH for Florida counties in 1990 ranged from 2.18 to 3.00. Variation in PPH levels and changes over time are even greater for cities than for counties.

To estimate PPH for cities and counties, we developed a formula that combines the local PPH calculated 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 (single family, multifamily, mobile home) since the most recent census. We base local changes in PPH on national changes, but adjust them up or down depending on whether the initial PPH was higher or lower locally than nationally; on the average, declines are greater when initial levels are higher.[5] We further adjust the estimates to account for changes in the local mix of housing units and the PPH for each type of unit calculated in the most recent census. (Multifamily units typically have lower PPH than do single family units do).[6] This formula is described more fully in Smith and Lewis (1980). Again, we make some adjustments to the formula's estimates according to our professional judgment about factors affecting PPH (e.g., increases in the Hispanic population, which has a relatively large PPH). PPH could also be estimated by extrapolating past trends or holding values constant at levels found in the most recent census (e.g., Starsinic and Zitter 1968). The formula described above, however, has been found to produce more accurate estimates of PPH than either of these alternatives (e.g., Smith and Lewis 1980, 1983). We test several alternative estimation techniques for PPH in the next section.

Group quarters population. Population in households is estimated by multiplying the number of households times the PPH. Population in households accounted for 97.3 percent of total population in the United States in 1990 (97.6 percent in Florida). To obtain an estimate of total population, persons living in group quarters or without traditional housing must also be estimated. We do this in three steps. The first is to collect group quarters data from prisons, colleges, military bases, and long-term health care facilities, for the same date as in the most recent census. The second step is to subtract these numbers from the total non-household population counted in that census, and then to form a ratio of the residual to population in households; we call this ratio the GQ multiplier. In the third step, the current group quarters population is estimated by applying the GQ multiplier to the current estimate of the household population, and adding a direct count of the current number of persons residing in prisons, college dormitories, military barracks, and long-term health care facilities.[7]

Evaluating Accuracy and Bias

The obvious question to ask of any estimation methodology is "How accurate are the estimates?" We provide an answer to this question by comparing April 1, 1990 population estimates with April 1, 1990 census counts for counties and subcounty areas in Florida. This comparison doesn't provide a perfect measure of accuracy and bias, because census counts themselves are subject to error. Differences between estimates and census counts may therefore reflect errors in the decennial census as well as errors in the estimates. The decennial census is believed to be quite accurate for most places, however, and provides a widely used standard for evaluating population estimates. We refer to differences between estimates and census counts as estimation errors, but the reader is cautioned that they may have been caused by enumeration error as well as by estimation error.

Five measures of accuracy and bias are used. Mean absolute percent error (MAPE) is the average error when the direction of error is ignored. The proportion of errors less than 5 percent and greater than 10 percent indicates the frequency of relatively small and of large errors, respectively. These are measures of accuracy, or how close estimates were to census counts, regardless of whether the estimates 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, a negative error indicates a tendency to underestimate. Since a few extreme errors in one direction can change the sign of MALPE, the proportion of estimates that were above the census count (%POS) is used as another measure of bias.

Errors by Population Size and Growth Rate. Table 1 shows the results for Florida's 67 counties. The average error (regardless of sign) was 5.4 percent. Weighted by population size, the average error was only 3.0 percent, reflecting an inverse relationship between size of place and size of error. The MAPE for counties with fewer than 50,000 population was almost three times larger than the MAPE for counties with more than 250,000 population. The proportion of small errors generally increased with population size, and the proportion of large errors generally declined. A negative relationship between estimation errors and population size is a common empirical finding (e.g., Kitigawa and Spencer 1981; Smith 1986; U.S. Bureau of the Census 1985).

[Table 1 about here]

The estimates had an upward bias. Almost three-quarters of the county estimates were higher than the census counts, and the MALPE was 3.3 percent. The MALPE weighted by population size was 1.6 percent, the same as the error for the state as a whole. There was no apparent relationship between bias and size of place, however; the tendency to overestimate was about the same for large and for small counties. An explanation for the overall upward bias in the 1990 estimates will be given later in this article.

Differences in county growth rates had a major impact on both accuracy and bias. There was a U-shaped relationship between MAPEs and the growth rate: errors declined with increases in growth rates through the first five categories, but increased for the last category. Differences were not large after the first two categories, perhaps because of small sample sizes. There was also a strong relationship between growth rates and the direction of errors: both the MALPE and %POS declined steadily as the growth rate increased. Every county that lost population or grew by less than 15 percent was overestimated, whereas every county that grew by more than 100 percent was underestimated.

Table 2 shows the results for subcounty areas, which include 386 incorporated cities and the unincorporated balances of 66 counties. (One county in Florida has no unincorporated area.)[8] The average error (regardless of sign) was 11.9 percent; weighted by population size, the average error was 4.5 percent. There was again a strong negative relationship between accuracy and population

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size; the MAPE for places with fewer than 250 residents was 10 times larger than the MAPE for places with more than 100,000 residents. The proportion of small errors increased steadily with population size, and the proportion of large errors declined.

[Table 2 about here]

Errors for subcounty areas were considerably larger than errors for counties, primarily because of differences in population size. Only eight counties had fewer than 10,000 residents in 1980, and none had fewer than 5,000, whereas 304 subcounty areas had fewer than 10,000 residents and 101 had fewer than 1,000. For size categories greater than 10,000, errors for subcounty areas were very similar to errors for counties.

As for counties, estimates for subcounty areas had a substantial upward bias. The MALPE was 6.0 percent, and more than two-thirds of the estimates were higher than the census counts. Again, there was no distinct relationship between bias and size of place; rather, the proportion of positive errors fluctuated inconsistently with population size. Although the MALPE became smaller as population size increased, this was due to smaller absolute percent errors, not to a declining tendency to overestimate.

Errors were strongly affected by differences in growth rates. The MAPE had a clear U-shaped relationship with the growth rate: errors were large for places with negative growth rates, became smaller as growth rates increased to 25-50 percent, and became larger as growth rates increased further. Similar results were found for the proportion of errors less than 5 percent and greater than 10 percent. Estimates were thus most accurate for places with positive, moderate growth rates and became less accurate as growth rates deviated in either direction from these moderate levels.

This U-shaped relationship between errors and growth rates has been reported before, both for population estimates (U.S. Bureau of the Census 1985) and projections (Smith 1987). There are several possible explanations for this finding: 1) Places losing population or growing very rapidly are undergoing large compositional changes that are not picked up in the data; 2) There is greater opportunity for estimates to deviate from the actual population in places with very high (or negative) growth rates; and 3) Errors in census coverage may be greatest for places showing very high or negative growth rates. If so, the large errors observed for those places would be due in part to larger-than-average enumeration errors.

Bias was also strongly related to the growth rate: MALPE and %POS each declined steadily as the growth rate increased. This reflects a strong tendency to overestimate declining or slowly growing places and to underestimate very rapidly growing places. It appears that the HU method has difficulty picking up both the full extent of population decline for places losing population and the full extent of population growth for places growing very rapidly. Research on other methods is needed to determine whether this is a general characteristic of population estimates; we suspect that it is.

To account for possible interactions between population size and growth rates, we divided subcounty areas into nine groups based on three size categories and three growth rate categories. The results are shown in Table 3. We again found accuracy to increase with population size: within all three growth categories, MAPEs and the proportion of large errors declined steadily as population size increased, while the proportion of small errors increased. Differences in growth rates affected accuracy primarily for smaller places: for each of the two smallest size categories, both the MAPE and the proportion of large errors had a strong U-shaped relationship with growth rates. For places with more than 10,000 population, however, there was only a weak relationship between growth rates and accuracy.

Differences in population size had little effect on bias, but differences in growth rates had a substantial effect: within all three size categories, MALPE and %POS each declined steadily as the growth rate increased. The results found when population size and growth rates were considered separately (Table 2) are thus confirmed when the two are considered jointly.

<div align="center">[Table 3 about here]</div>

Errors by Component. Which component of the HU method can be estimated most accurately? Table 4 shows that persons per household (PPH) had the smallest errors, group quarters population (GQ) the largest. For counties, MAPEs were 2.3 percent for PPH, 5.1 percent for households and 32.5 percent for GQ; for subcounty areas, MAPES were 5.0 percent for PPH, 11.2 percent for households and 67.2 percent for GQ. Small errors were common for PPH and large errors were common for GQ. Percentage errors for GQ were so large because they were often based on very small numbers of people. As shown in the bottom panel of Table 4, differences in population size affected estimation accuracy for all three components, but the effect was considerably greater for households than for PPH. **[Table 4 about here]**

Several studies have found errors for households to be greater than errors for PPH (e.g., Smith and Lewis 1983; Starsinic and Zitter 1968). This probably reflects the much more rapid rate of growth for households than for PPH: the number of households grew by more than 50 percent between 1980 and 1990 for many places in Florida, whereas PPH usually changed by less than 10 percent. There was simply more potential for error in estimates of households than in estimates of PPH.

The household estimates were also the major cause of the upward bias in the population estimates. For counties, MALPEs were 2.7 percent for households and 1.1 percent for PPH. Seventy-two percent of the household estimates were above the census counts for counties, compared to 66 percent for estimates of PPH. For subcounty areas, MALPEs were 6.6 percent for households and only 0.5 percent for PPH. Seventy-two percent of the household estimates were above the census counts for subcounty areas, compared to only 59 percent of the estimates of PPH. The weighted MALPE was actually negative for PPH, reflecting a small downward bias in the PPH estimate for the state as a whole.

In both counties and subcounty areas, errors for GQ were much larger than errors for households and PPH. Does this mean that GQ errors contributed the most to overall estimation error? One way to answer this question is to construct synthetic population estimates using a combination of estimated values and census enumeration values. We made synthetic population estimates for counties and subcounty areas under three scenarios. The first combined our estimates of households with 1990 census counts for PPH and GQ; the second combined our estimates of PPH with 1990 census counts for households and GQ; and the third combined our estimates of GQ with 1990 census counts for households and PPH. For each scenario, then, errors in the resulting population estimates were due solely to errors in the single estimated component. The results are shown in Table 5.

[Table 5 about here]

It is clear that errors in household estimates contributed the most to overall estimation error, and that errors in GQ estimates contributed the least. For both counties and subcounty areas, Scenario 1 had a MAPE more than twice as large as the MAPE under Scenario 2 and about five times larger than the MAPE under Scenario 3. It also had the greatest degree of bias, the most large errors, and the fewest small errors. Even with perfect estimates of PPH and GQ, errors in

household estimates would have created population estimation errors averaging 4.8 percent for counties and 10.8 percent for subcounty areas. Although errors were much larger for GQ than for households and PPH, those errors contributed relatively little to overall estimation error because in most places the group quarters population accounts for a very small proportion of total population.

Since the household estimates were based on symptomatic data (electricity customers, building permits), why were their errors so large? Part of the problem is data quality: data may be incomplete, erroneous, or contain errors in geographic allocation. We believe a more important source of error, however, is the changing relationship between symptomatic data and households. Changes in completion rates, time lags, and occupancy rates may affect the accuracy of household estimates from building permit data; changes in nonpermanent residents may affect the accuracy of household estimates from electricity customer data. The latter is particularly a problem in Florida, where a substantial proportion of the housing stock is occupied by nonpermanent residents (e.g., tourists, winter residents). New techniques for monitoring these changes over time could lead to better household estimates.

Errors by Technique: Households. A number of different data sources and techniques can be used to estimate each component of the HU method. Which are more accurate? For households we tested the following estimates:

1) **FINAL** - estimate actually used for counties and subcounty areas in Florida. This estimate was based on electricity customer and/or building permit data, but included our judgment regarding which data sources, techniques, and assumptions should be used in each specific place.

2) **EC** - estimate based solely on electricity customer data, using the ratio of households to active residential electricity customers, calculated at the time of the most recent census.

3) **BP** - estimate based solely on building permit data by type of unit, using the techniques described in the previous section.

4) **CONSTANT** - estimate that assumes that the number of households has not changed since the previous census (1980).

5) **TREND** - estimate that assumes that the linear change in the number of households between 1980 and 1990 was identical to the change between 1970 and 1980.

The results for households are summarized in Table 6.[9] Estimates based solely on electricity customers were clearly more accurate than those based solely on building permits. For both

counties and subcounty areas, the **EC** estimates had smaller MAPEs, more small errors, and fewer large errors than the **BP** estimates. The same result was found in a test of 1980 estimates in Florida (Smith and Lewis, 1983).

Both **EC** and **BP** estimates performed much better than **CONSTANT** and **TREND** estimates in subcounty areas: **CONSTANT** had very large errors and a strong downward bias, whereas **TREND** had large errors and a strong upward bias. **CONSTANT** also performed poorly at the county level, but **TREND** performed almost as well as **BP** in terms of accuracy and displayed very little bias, indicating that algebraic errors at the subcounty level tended to offset each other when aggregated. These results show that symptomatic data generally provided much more accurate household estimates than simply extrapolating past trends or assuming that no change has occurred.

[Table 6 about here]

The **FINAL** household estimates performed better than all the others, with the smallest MAPEs, the most small errors, and the fewest large errors, for both counties and subcounty areas. They had an upward bias, but in most instances the degree of bias was less than for the other estimates. Differences in errors were not always large, but they consistently favored the **FINAL** estimates. In these estimates, then, incorporating professional judgment led to better household estimates than did the mechanical application of any single technique.

Errors by Technique: PPH. For estimates of PPH we tested the following techniques:

1) **FINAL** - estimate actually used for counties and subcounty areas in Florida. This estimate was based primarily on the mathematical formula described in the previous section, but was occasionally adjusted to account for other factors expected to affect local PPH.

2) **FORMULA** - estimate based solely on the mathematical formula described in the previous section (see Smith and Lewis, 1980, for a more detailed description).

3) **CONSTANT** - estimate which assumes that PPH has not changed since the most recent census (1980).

4) **TREND** - estimate which assumes that the linear change in PPH between 1980 and 1990 was identical to the change between 1970 and 1980.

The results for PPH are summarized in Table 7. **FINAL** and **FORMULA** produced much better estimates than either **CONSTANT** or **TREND**. They had lower MAPEs, more small errors,

and fewer large errors for both counties and subcounty areas. They also exhibited relatively little bias, whereas **CONSTANT** had a strong upward bias and **TREND** had a strong downward bias. Similar results were found in a test of 1980 estimates in Florida (Smith and Lewis 1983). Results for **FINAL** were only slightly better than those for **FORMULA**; on the average, the application of professional judgment had very little effect on the accuracy and bias of PPH estimates.

[Table 7 about here]

A number of other techniques could be used for estimating PPH. Special censuses have been widely used by the State of Washington (Lowe et al. 1977). Sample surveys have been used in a few places, but to provide accurate estimates the samples must be carefully drawn and quite large. Roe, Carlson, and Swanson (1992) have developed an approach based on sampling and interviews with local experts. Several researchers have used regression analysis to relate changes in PPH to changes in variables such as births, school enrollment, exemptions per income tax return, and shifts in the composition of the housing stock (e.g., Voss and Krebs, 1979). Advances in housing demography could also lead to new techniques for estimating PPH by focusing research on the demographic characteristics of occupants of various types of housing (e.g., Myers and Doyle 1990). There are numerous opportunities for improving the accuracy of PPH estimates.

Discussion

Role of Judgment. Estimates of households which incorporated professional judgment performed considerably better than estimates based on the mechanical application of mathematical techniques (Table 6). What about estimates of total population? For counties, MAPEs were 5.4 percent for population estimates incorporating judgment and 6.5 percent for estimates derived from our most accurate mathematical formula; for subcounty areas, MAPEs were 11.9 and 13.3 percent, respectively. Population estimates incorporating judgment also had less bias, more small errors, and fewer large errors than estimates based solely on formulas. As professional demographers, we find this result to be quite gratifying. Accurate data and sound methodologies are essential for producing accurate population estimates, of course, but informed judgment regarding demographic trends, changing local conditions, and data idiosyncracies can improve the quality of population estimates as well.[10]

It is difficult to draw general conclusions regarding the application of professional judgment. Whose judgment should be heeded and whose ignored? Will professional judgment always improve estimates, or only under certain conditions? Will the application of professional judgment improve accuracy for other population estimation methods? Can the factors that affect professional judgment themselves be quantified and incorporated into the formal estimation model? Very few studies have empirically investigated the effects of judgment on the accuracy of population estimates; we believe this is a research area deserving further attention. (See Isserman 1984, for a discussion of the application of judgment in the production of population projections and forecasts).

Comparison with 1980 Results. How do the results for 1990 compare with those found in 1980? Table 8 summarizes the results for both years. In terms of accuracy, 1990 errors were generally smaller than 1980 errors, especially for subcounty areas. At the county level MAPEs were 5.4 percent in both years; weighted by population size, MAPEs were 3.0 percent in 1990 and 3.9 percent in 1980. Surprisingly, for counties there were more errors less than 5 percent and more errors greater than 10 percent in 1990 than 1980. At the subcounty level, MAPEs were 11.9 percent in 1990 and 14.4 percent in 1980; weighted by population size they were 4.5 and 5.6 percent, respectively. The 1990 subcounty estimates had slightly more small errors and fewer large errors than the 1980 estimates. For the state as a whole, the absolute error was 1.6 percent in 1990 compared to 2.7 percent in 1980.

[Table 8 about here]

In terms of bias, the results for 1990 were completely different from those for 1980: the 1990 estimates had a strong upward bias whereas the 1980 estimates had a strong downward bias. A majority of counties and subcounty areas had positive errors in 1990, whereas a majority had negative errors in 1980. The state estimate was 1.6 percent above the census count in 1990, 2.7 percent below the census count in 1980.

How can these differences in bias be explained? One possible explanation is that the HU method is inherently unbiased and that these differences simply reflect random fluctuations: errors tend to be predominantly high one year and predominantly low another, balancing out over time. We believe this is part of the explanation, but that another factor also played a role; namely, changes in census undercount. Nationally, net census undercount was estimated from demographic

analysis as 2.7 percent in 1970, 1.2 percent in 1980 and 1.8 percent in 1990 (U.S. Bureau of the Census, 1991). Since the population estimates were based on data from the previous census, an improvement in census coverage between 1970 and 1980 led to census counts that were generally above the 1980 estimates. Conversely, a decline in coverage between 1980 and 1990 led to census counts that were generally below the 1990 estimates. We believe that changes in the coverage of the 1970, 1980, and 1990 censuses affected the bias found in the 1980 and 1990 estimates.

Why were the 1990 estimates somewhat more accurate than the 1980 estimates? This may have been due to more reliable base data in 1980 than 1970; a larger change in net undercount from 1970 to 1980 than from 1980 to 1990; higher growth rates in Florida during the 1970s than during the 1980s; or to improved judgment due to additional years of experience in producing population estimates. Perhaps it was simply the result of randomness. Whatever the cause of these improvements, they were relatively small, and there is a striking similarity between 1990 and 1980 results with respect to accuracy characteristics by population size, growth rate, component, and technique. We believe these similarities strengthen the generalizability of the results presented in this paper.

Comparison to Other Methods. How do HU population estimation errors compare with those produced by other methods? We don't yet have results for other methods in 1990, but in 1980 the HU estimates for counties in Florida were found to be more accurate and less biased than estimates produced by the Administrative Records, Component II, and Ratio Correlation methods (Smith and Mandell 1984). For subcounty areas, HU estimates were found to be more accurate and less biased than Administrative Records estimates in Florida, California, Washington, and New Jersey (Smith 1986).[11] To our knowledge, no study has found HU population estimates to be less accurate than estimates produced by other methods. We believe the evidence clearly shows that HU population estimates perform at least as well as those produced by other methods, when proper data and techniques are applied.

Generalizability of Results. We cannot say, of course, that all HU population estimates will have errors similar to those reported here for Florida. Errors are affected by the specific data and techniques used in applying the HU method; by differences in growth rates and population size; and by changes in seasonal population, racial/ethnic make-up, age distribution, and socioeconomic characteristics. Errors will vary from one set of estimates to another.

From this and other studies, however, we believe we can draw the following conclusions about the HU method: 1) Population size has a strong negative effect on average estimation errors (disregarding sign), but no effect on bias; 2) Growth rates have a U-shaped effect on average estimation errors (disregarding sign) and a strong negative effect on bias; 3) Symptomatic data generally provide more accurate and less biased estimates of households and PPH than do historical values or the extrapolation of historical trends; 4) Electricity customer data generally provide more accurate household estimates than do building permit data; 5) Errors in household estimates generally contribute more to population estimation error than do errors in estimates of PPH and GQ; 6) The application of professional judgment can improve the performance of purely mechanical estimation techniques; and 7) The accuracy of population estimates from the HU method is similar to (or greater than) the accuracy of estimates from other methods, if proper data and techniques are applied. Future research may eventually cause us to change some of these conclusions, but we believe they accurately reflect the current state of the art.

"Generalizability" refers not only to the universality of error characteristics, but also to whether the method can be applied in all states and for different levels of geography (e.g., counties, cities, census tracts). In the latter sense, the HU method is extremely generalizable. It is currently used by public and private agencies in many states, for estimates from the state level down to small subcounty areas (U.S. Bureau of the Census, 1990). We believe the HU method is an ideal candidate for population estimates in many different settings.

Further Research. "Housing demography" refers to the union of population and housing analysis (Myers 1990). In recent years housing analysts have become increasingly aware of the importance of demographic characteristics in determining housing dynamics, and demographers have become increasingly aware of the impact of housing on the distribution and characteristics of local populations. These population-housing connections can be approached from either direction, focusing on the housing characteristics of different subgroups of the population or on the demographic characteristics of occupants of different types of housing. Both approaches lead to many interesting and useful types of research.

Research on the HU method falls squarely within this emerging field. Housing demography provides a theoretical foundation for the HU method and promises to enhance its usefulness in several ways. For example, Sweet (1990) studied family life cycle events (e.g., marriage, divorce,

childbearing) and how those events affect the demand for various types of housing. Sweet and Bumpass (1987) studied the relationship between stages in the family life cycle and average household size; they also looked at differences in the household characteristics of various social and ethnic groups. Myers and Doyle (1990) focused on relationships among type of housing unit, age of unit, number of bedrooms, turnover, and the age composition of households. Gober (1990) studied relationships between residential location and household composition, including the effects of distance from city center on average household size. Morrow-Jones (1989) studied the relationship between changes in owner-renter status and the age, sex, race, marital status, income, and size characteristics of households. Burchell and Listokin (1978) used the HU method to project age groups and the demographic impact of new development. All these studies suggest ways to improve the accuracy of the HU method or to extend its application into new areas.

We believe the development of Geographic Information Systems (GIS) will also enhance the usefulness of the HU method. These systems have become increasingly important in the planning profession in recent years (e.g., Levin and Landis 1990). Vast computerized databases containing information on building permits, electricity customers, property tax records, income tax returns, vehicle registrations, address lists, and other types of data can be used in conjunction with the HU method to produce housing and population estimates.   There is a tremendous demand for such estimates from state and local governments, planning agencies, and private businesses, especially for estimates of very small areas (e.g., zip codes, census tracts). A few analysts are already working on the integration of demographic and GIS techniques to produce small-area estimates (e.g., Batutis and Prevost 1991; Tayman 1991); we believe the HU method will play a central role in this continuing development.

Conclusion

The HU method is an accurate, comprehensive, and extremely flexible form of population estimation. It has a number of characteristics that make it very useful for producing population estimates. First, it is conceptually clear and can be explained to and understood by people with little or no background in planning or demography; this is an important characteristic when population estimates must be described and defended in public forums. Second, it is not confined to a single technique or source of data; rather, it can incorporate a number of different techniques

and unique data sources available only in a small number of places. Third, it can be applied virtually everywhere and at any level of geography, from states down to counties, cities, census tracts, zip code areas, and even individual blocks. (This is a striking advantage over most population estimation methods, for which data are often not available for small areas.) Fourth, it can be customized to produce estimates for unique geographic entities such as school districts, voting districts, traffic analysis zones, and customer service areas. Finally, it can produce estimates of population change that are at least as accurate as those produced by any other method. We believe the HU method is an extremely powerful tool for planners and demographers engaged in small-area analysis.

NOTES

1.   The population estimates evaluated in this study were the official estimates used for revenue-sharing, budgeting, and planning by the State of Florida. They were produced by the Bureau of Economic and Business Research at the University of Florida under the terms of a contract with The Florida Legislature. The estimates refer solely to permanent residents of Florida, thereby excluding tourists, snowbirds, and other seasonal or part-time residents.

2.   This section is based on Smith 1986. Readers already familiar with the HU method and its application in Florida may want to skip to the next section.

3.   The reports issued by the U.S. Department of Commerce provide data on both single family and multifamily units. Prior to 1987, they also provided data on mobile homes. Since 1987, however, mobile home data have not been included in these reports. Mobile home data can be collected directly from city and county building departments, vehicle registration systems, and surveys of mobile home parks. These are the sources we use in Florida. Data for mobile homes are often less reliable than data for single family and multifamily units.

4.   For the state of Florida as a whole, the ratio of permanent households to active residential electricity customers was .873 in 1990, down from .919 in 1980. Thirteen counties had ratios between 0.9 and 1.0 in 1990; 31, between 0.8 and 0.9; 19, between 0.7 and 0.8; and four, between 0.6 and 0.7. These ratios are probably lower in Florida than in most states because of the large number of seasonal housing units found in many Florida counties.

5.   In Florida, PPH declined by 8.1 percent between 1980 and 1990 for places with 1980 PPH values greater than 3.0; by 5.4 percent for places with 1980 PPH values between 2.5 and 3.0; and by 0.9 percent for places with 1980 PPH values less than 2.5.

6.   1990 PPH values for the state of Florida were 2.72 for single family units and 1.99 for multifamily units.

7.   The homeless population is included in the estimate of total population only to the extent that it was included in the most recent census. Given the very small number of homeless persons counted in the 1990 census, it is unlikely that changes in the homeless population will have much effect on total population estimates for most places. For a few places, however, the numerical

impact of the homeless population may be substantial. This creates an estimation problem not only for the HU method, but for other methods as well.

8.   Estimates were made directly for the unincorporated balance of each county, using the same techniques used for cities; in other words, unincorporated areas were <u>not</u> calculated simply as residuals when city estimates were subtracted from county estimates.

9.   For estimates of subcounty areas, we analyzed only the 370 places that had complete building permit data for the entire decade. The other 82 places (mostly small towns) either did not issue building permits or were missing substantial amounts of data.

10.   Every estimation and projection methodology requires the application of judgment in choosing models, techniques, variables, and data sources. What we refer to as "judgment" in this article goes beyond these decisions to cover adjustments made to estimates for specific places <u>after</u> the basic methodology has been chosen.

11.   The Component II and Ratio Correlation methods were not used for subcounty estimates in these states.

TABLE 1. Population estimation errors by population size and growth rate: Counties, 1990

Size - 1980	N ≤10%	MAPE	MALPE	%POS	Percent of Absolute Errors <5%	
<10,000	8	5.3	0.3	62.5	62.5	12.5
10,000 - 24,999	19	7.8	6.7	84.2	36.8	26.3
25,000 - 49,999	7	7.6	5.4	71.4	28.6	42.9
50,000 - 99,999	12	3.8	0.5	66.7	75.0	8.3
100,000 - 249,999	11	4.3	2.4	63.6	63.6	9.1
250,000+	10	2.5	2.2	90.0	90.0	0.0
Total	67	5.4	3.3	74.6	58.2	16.4
Wtd. Total*	-	3.0	1.6	--	--	--
1980 - 1990 Growth Rate						
<0%	2	16.0	16.0	100.0	0.0	100.0
0 - 15%	6	11.9	11.9	100.0	16.7	83.3
15 - 25%	16	4.5	3.5	75.0	56.3	0.0
25 - 50%	28	4.7	2.7	75.0	64.3	10.7
50 - 99%	12	3.4	-0.1	75.0	83.3	8.3
100%+	3	5.1	-5.1	0.0	33.3	0.0
TOTAL	67	5.4	3.3	74.6	58.2	16.4

*Weighted by population size in 1990

TABLE 2. Population estimation errors by population size and growth rate: subcounty areas, 1990

					Percent of Absolute Errors	
Size - 1980	N □10%	MAPE	MALPE	%POS	<5%	≥10%
<250	25	36.6	6.2	52.0	8.0	84.0
250 - 499	27	22.6	14.5	74.1	11.1	77.8
500 - 999	49	16.6	9.7	71.4	16.3	65.3
1,000 - 2,499	73	14.2	8.9	74.0	27.4	57.5
2,500 - 9,999	130	9.1	4.6	66.2	42.3	34.6
10,000 - 24,999	64	6.6	4.2	78.1	40.6	18.8
25,000 - 49,999	43	5.7	1.5	60.5	53.5	16.3
50,000 - 99,999	21	5.0	2.7	57.1	57.1	14.3
100,000+	20	3.4	1.4	65.0	80.0	0.0
Total	452	11.9	6.0	68.4	36.5	40.5
Weighted Total*	-	4.5	1.6	--	--	--
1980 - 1990 Growth Rate						
<-10%	53	32.0	28.5	96.2	1.9	90.6
-10 - 0%	58	11.6	11.3	96.6	29.3	55.2
0 - 10%	89	8.8	5.3	74.2	36.0	34.8
10 - 25%	78	7.3	2.9	67.9	44.9	25.6
25 - 50%	83	6.8	1.7	54.2	45.8	20.5
50 - 100%	55	9.1	1.9	54.5	50.9	30.9
100%+	36	17.1	-11.4	22.2	38.9	50.0
TOTAL	452	11.9	6.0	68.4	36.5	40.5

*Weighted by population size in 1990

TABLE 3. Population estimation errors by size-growth category: subcounty areas, 1990

SIZE	GROWTH RATE	N	MAPE	MALPE	%POS	Percent of Absolute Errors	
						<5%	>10%
<1,000	<0%	47	28.7	24.4	93.6	6.4	83.0
<1,000	0-50%	38	12.6	2.9	50.0	23.7	52.6
<1,000	>50%	16	32.1	-14.6	31.3	6.3	93.7
1,000 - 9,999	<0%	48	19.0	18.9	97.9	12.5	77.1
1,000 - 9,999	0-50%	115	7.7	3.6	65.2	43.5	30.4
1,000 - 9,999	>50%	40	10.4	-1.9	45.0	47.5	37.5
▢10,000	<0%	16	6.9	6.9	100.0	56.3	25.0
▢10,000	0-50%	97	5.6	3.2	72.2	47.4	13.4
▢10,000	>50%	35	5.3	0.0	42.9	62.9	14.3
Total		452	11.9	6.0	68.4	36.5	40.5

TABLE 4. Estimation errors by component: counties and subcounty areas, 1990

	Component	MAPE	MALPE	%POS	<5%	Percent of Absolute Errors ▢10%
Counties	Households	5.1	2.7	71.6	65.7	14.9
	PPH	2.3	1.1	65.7	92.5	0.0
	GQ	32.5	-12.3	25.4	10.4	79.1
Subcounty Areas	Households	11.2	6.6	71.9	43.8	33.6
	PPH	5.0	0.5	58.8	65.7	10.2
	GQ	67.2	8.9	50.4	32.3	63.7

Errors weighted by population size in 1990:

	Component	MAPE	MALPE
Counties	Households	3.5	2.7
	PPH	2.2	-0.8
	GQ	27.2	-15.0
Subcounty Areas	Households	4.6	2.7
	PPH	2.9	-0.7
	GQ	35.5	-13.0

TABLE 5. Population estimation errors under alternate scenarios

	Scenario ≥10%	MAPE	MALPE	%POS	Percent of Absolute Errors <5%	
Counties	1	4.8	2.5	71.6	68.7	13.4
	2	2.2	1.0	64.2	92.5	0.0
	3	1.0	-0.4	25.4	100.0	0.0
Subcounty Areas	1	10.8	6.5	71.9	44.7	33.0
	2	5.0	0.5	58.8	66.8	10.0
	3	1.8	-0.3	50.2	93.4	3.1

Note: 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.

TABLE 6. Errors by technique for household estimates: counties and subcounty areas, 1990

	Technique ≥10%	MAPE	MALPE	%POS	Percent of Absolute Errors <5%	
Counties	FINAL	5.1	2.7	71.6	65.7	14.9
	EC	6.2	4.6	85.1	46.7	19.4
	BP	9.4	6.5	70.1	41.8	32.8
	CONSTANT	28.1	-28.1	0.0	1.5	91.0
	TREND	9.9	-0.4	47.8	26.9	37.3
Subcounty Areas	FINAL	10.3	6.5	72.7	45.1	30.8
	EC	11.9	8.0	77.3	41.9	33.8
	BP	15.2	9.8	69.5	33.2	41.9
	CONSTANT	27.0	-16.4	18.1	14.6	74.1

| TREND | 25.2 | 11.5 | 62.7 | 16.2 | 63.2 |

TABLE 7. Errors by technique for PPH estimates: counties and subcounty areas, 1990

	Technique ▢10%	MAPE	MALPE	%POS	Percent of Absolute Errors <5%	
Counties	FINAL	2.3	1.1	65.7	92.5	0.0
	FORMULA	2.4	0.8	65.7	92.5	0.0
	CONSTANT	6.3	6.1	98.5	37.3	6.0
	TREND	7.9	-7.7	3.0	20.9	22.4
Subcounty Areas	FINAL	5.0	0.5	58.8	65.7	10.2
	FORMULA	5.1	0.3	58.2	65.0	11.1
	CONSTANT	7.5	5.0	81.9	38.5	23.7
	TREND	11.9	-9.4	17.7	25.2	46.9

TABLE 8. Accuracy and bias of population estimates, 1980 and 1990: counties and subcounty areas

	YEAR ▢10%	MAPE	WTD MAPE*	MALPE	WTD MALPE*	PERCENT OF ERRORS POSITIVE	<5%	
Counties	1980	5.4	3.9	-2.9	-2.7	34.3	53.7	10.4
	1990	5.4	3.0	3.3	1.6	74.6	58.2	16.4
Subcounty Areas	1980	14.4	5.6	3.5	-2.7	46.7	33.6	42.4
	1990	11.9	4.5	6.0	1.6	68.4	36.5	40.5

*Weighted by population size in estimation year

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