### **Employment Outcomes for Low-Income Families Receiving Child Care Subsidies in Illinois, Maryland, and Texas**

#### **Final Report**

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DISCLAIMER: The research in this report was conducted while the authors were Special Sworn Status researchers of the U.S. Census bureau at the Chicago Research Data Center. Research results and conclusions expressed are those of the authors and do not necessarily reflect the views of the Census Bureau. This report has been screened to insure that no confidential data are revealed.

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#### **ABSTRACT**

This research study analyzes child care subsidy (CCS) participation and employment outcomes among low-income families in Illinois, Maryland, and Texas. The study seeks to learn who among low-income eligible families participates in the child care subsidy program, and the effect of subsidy participation on employment and eligibility status.

This study was conducted by a unique collaboration of the U.S. Census Bureau and three University-based research centers using linked individual-level data from the American Community Survey/Supplemental Survey for 2001 (ACS/SS01) and state administrative data. Independent variable included characteristics of program participation, characteristics of the parents, characteristics of the family, and characteristics of the parent's jobs.

Results across all three states demonstrated that those who had received Temporary

Assistance to Needy Families (TANF) within 3 months of the ACS survey participated in the

CCS at higher rates than those who had not received TANF. Results also showed higher levels
of participation among younger parents (24 years of age or younger) than older parents (25 years
and older). CCS participation was higher among single parents with less than a high school
education than among those with at least a high school diploma and among those families who
reported having more than 3 children under age 13 in the home.

Parents residing in the major urban areas of Illinois, Maryland and Texas had lower rates of CCS participation than those in non-urban areas. Single parents who worked late hours had higher levels of CCS participation than those who worked early or standard hours in all three states.

For employment outcomes, CCS receipt was associated with longer employment spells only in Illinois, although the direction of the effect was similar in Maryland and Texas.

Additionally, low educational attainment was associated with employment outcomes in all three states. Respondents who had less than a high school education exhibited shorter employment spells and reduced odds of exceeding the income threshold for CCS eligibility. Having at least three children under age 13 was associated with reduced odds of exceeding the income threshold in Illinois and Maryland.

A key contribution of this report is a better understanding of the association of CCS program use with the duration of employment and eligibility spells. The authors hypothesized that CCS use would extend the length of employment spells for single parent heads of families and this hypothesis was confirmed in Illinois. The competing risk for eligible employed individuals was not, however, in the predicted direction. This analysis found that single parent heads of families who took up the child care subsidy were less likely to end eligibility by exceeding income thresholds compared with respondents who did not take up the subsidy.

#### **BACKGROUND AND SIGNIFICANCE**

Prior research on the role of the child care subsidy (CCS) in supporting family self-sufficiency has largely focused on current and former recipients of TANF rather than all low-income families (Schaefer et al., 2005; Schaefer et al., 2006). Through collaboration with the U.S. Census Bureau and by using household-level Census Bureau survey records, the current study has overcome past data restrictions that have impeded study of the entire low-income population of a state. We analyzed child care subsidy (CCS) participation and employment outcomes among a representative sample of all low-income families in 2001 in Illinois, Maryland, and Texas—not just those with a history of TANF receipt. This study analyzed participants' employment, TANF utilization, and their eligibility for the child care subsidy through 2003. This report describes who uses the child care subsidy; how employment outcomes

such as employment duration and exceeding the CCS income eligibility threshold differ between those who use the CCS and those who do not; and whether these employment outcomes differ for sub-groups of low-income families and by state.

This work is significant for several reasons. First, this study improves federal and state policymakers' and administrators' understanding of who uses the child care subsidy and how the subsidy aids different groups of low-income families in their quest for economic independence. The study population—representing nearly 1 million households in three states—is the largest of which we are aware that has analyzed the topic of child care subsidies. The fact that a small share of eligible families actually participate in the child care subsidy program makes it necessary to have a large sample of low-income, working families, which the 2001 ACS has. Our large sample size allows us to look at how outcomes differ by household structure, demographic and geographic characteristics, transportation to work characteristics, and TANF receipt. By following the trajectories of low-income working families and tracing the multiple and varied pathways to self-sufficiency, we insight into the dynamic interplay between child care subsidy eligibility, receipt, and employment.

The study also makes methodological contributions. The Census Bureau's data programs benefit from this study's prototyping of an eligibility microsimulation model for a specific federal poverty program (the Child Care and Development Fund, or CCDF, in this case) that can be tailored for other programs. Because federal poverty programs are dependent on surveys for program administration and program size estimates, the quality of the data collection is of great interest to the Census Bureau as well as to federal anti-poverty program administrators. The study uses the U.S. Census Bureau's American Community Survey/Supplementary Survey for 2001 (ACS/SS01), which does not provide significant detail on program utilization, but does

have a large sample size, thus affording an opportunity to improve eligibility modeling.

Although the Survey of Income Program Participation (SIPP) is the Census Bureau's official survey for measuring program eligibility and participation, it is not representative at the state or local level—at which the CCDF operates.

To conduct this study, a unique collaboration was formed among the U.S. Census Bureau, Chapin Hall Center for Children at the University of Chicago, the National Center for Children in Poverty at Columbia University, the Jacob France Institute at the University of Baltimore, and the Ray Marshall Center at the University of Texas at Austin. The Census Bureau provided access to individual-level Supplemental Survey data (American Community Survey) and matched these data with individual-level administrative data from CCS, Unemployment Insurance (UI) wage records, and TANF programs in each of the three states to create the Social Services Administrative File (SSAF). Detailed income data as well as an expanded range of socioeconomic and demographic variables in the census data allowed us to estimate the CCS income eligibility of all families and provided us with an enhanced set of explanatory factors for our models. Matched CCS data enabled us to examine subsidy participation among all eligible populations. Matched UI wage reporting data and TANF data through 2003 enabled us to examine how participation is related to a range of employment outcomes. UI wage records were used to track income to determine continued CCS eligibility as well as employment outcomes. The SSAF provides us with a rich dataset, and this project and report only addresses a small set of questions that could be addressed with these data.

#### LITERATURE REVIEW

The high cost of child care is a deterrent to many low-income, working families attempting to enter and remain in the workforce. In response, federal and state governments have invested considerable resources in providing child care subsidies to reduce barriers to employment for low-income workers with children. The use of these subsidies among eligible families, however, remains low, and we are only beginning to learn about employment outcomes associated with subsidy receipt. Recent research, including a study funded by the Child Care Bureau and conducted by some of the principal investigators in this study, has demonstrated a strong, positive relationship between subsidy utilization and employment duration among current and former TANF recipients (Lee et al., 2004; Schexnayder et al., 2002). These results provide critical evidence that the CCS system plays an important role in supporting the self-sufficiency of families. However, much remains to be learned. How, for example, does subsidy use differ, and does use affect the employment outcomes among other low-income families who may or may not have history of TANF use (i.e., the working poor)? Answers to these questions can better guide policymakers in targeting, planning and projecting need within the child care subsidy program, and in understanding who benefits most from the program.

#### **Child Care Subsidy Participation Rates**

The statistics reported in this report have been developed with data sources not previously used to estimate the percent of eligible children or families who are participating in the CCDF subsidy program.

Estimating child care participation rates is fraught with many challenges. There are many different ways to approach this depending on the choice of state or national eligibility

requirements, how one calculates the denominator given this choice, the data used, unit of analysis (child, family, household), and the time periods of interest.

Our strategy involves estimating the eligibility of families in the American Community Survey using multiple statistical models and determining whether they participated from state administrative data. We compare our statistics to data combined from two sources at HHS. The first is eligibility determined by Office of the Assistant Secretary for Planning and Evaluation (ASPE) using Current Population Survey data (HHS, 2008). The second is CCDF subsidy numbers supplied by ACF. Both data sources are for points in time in 2001.

The results of both our direct calculations in this project and calculations using available data are displayed in Table 1. The percent of families participating in the CCDF program using the two different methods are surprisingly similar in each of the three states. In Illinois, the percent using either method is essentially the same, while in Texas and Maryland, there are 1-2 percentage point differences. It may be the case that these numbers are so close simply by coincidence—that the errors in all of the numbers "cancel" each other out on both the high and low ends. It would be difficult to determine this for certain without dissecting the numbers from the HHS sources and comparing the methods used to arrive at each of the numbers. This activity is beyond the scope of this project, but it is clear that the statistics in this report are reasonable.

The seemingly low participation rate in the child care subsidy program, both by families using cash assistance and other low-income families, has been a concern to policymakers for some time. However, the most recent statistics show improvement with approximately 29 percent of eligible families participating in the child care subsidy program. It is also the case that parents have many options, including Head Start and State Pre-K programs, and often prefer to use informal care that may or may not be subsidized.

Several studies have explored rates of participation, using either national survey data or small-sample state data based largely on information collected at a given point in time. In a review of TANF studies in 17 states, Schumacher and Greenberg (1999) found that, at most of the study sites, fewer than 30 percent of those who left TANF used child care subsidies.

Research completed by three of the organizations involved in the current research used population-level, longitudinal, linked administrative data to examine the factors related to participation patterns over time among *current* and *former* TANF recipients in Illinois, Maryland, and Massachusetts. Strikingly, subsidy use did not exceed 35 percent of the eligible population in any of the three states. Participation rates in Maryland were notably lower (24%) than in the other two states (34%) (Lee et al., 2004). In Texas, between 17 and 24 precent of employed TANF leavers used child care subsidies. Overall participation rates for all leavers were much lower (Schexnayder et al., 2002).

Looking at all low-income and moderate-income working families in the United States, a study by the Urban Institute found even lower participation rates. Using three years of Current Population survey (CPS) data, researchers found that only 15 percent were using the subsidy for which they were eligible (Administration for Children and Families, 1999). Additionally, Blau and Tekin (2007) used data from the 1999 National Survey of America's Families to learn that the child care subsidies were used by only 12 percent of single mothers. It should be noted that this study did not account for State income eligibility limits or individual State polices which is essential in determining the number of families eligible for the CCDF program, since it is a block grant and States set their own income guidelines. This method significantly overstates the actual

<sup>&</sup>lt;sup>1</sup> This study, conducted by the Urban Institute, used the institute's transfer income model methodology (TRIM3) (http://www.acf.dhhs.gov/programs/ccb/research/ccreport/ccreport.htm#3.

number of families who are eligible for a child care subsidy using the federal maximum of 85 percent, and subsequently understates the percentage of actually eligible families based on State policies enrolled or covered by the program.

Other studies describe the socioeconomic and demographic characteristics of families that do and do not use child care subsidies. In one of the first studies of its kind, Schumacher and Greenberg (1999) found, for example, that families in Washington State were less likely to use subsidies if they had more than one worker or adult in the family. Similarly, Burstein et al. (2002) found that two-parent families were less likely to use subsidies than single-parent families. Other authors found that families with young children (under age 7) were more likely to use subsidies than those with older children, a finding confirmed by the principal investigators in this study (Huston, Chang, & Gennetian, 2002; Lee et al., 2004; Meyers, Heintze, & Wolf, 1999). Pearlmutter et al. (1999), examining families with a child between the ages of 3 to 5 and left cash assistance in 1996, found that 82 percent of subsidy users were African American, and more than 90 percent of parents were between ages 18 and 34.

Race is a significant predictor of child care subsidy participation. Blau and Tekin (2007) and Burstein et al. (2002) found that African American mothers were more likely to apply for or receive subsidies than white mothers. Blau and Tekin also found that Hispanics were slightly less likely to receive subsidies than non-Hispanics. African Americans were significantly more likely to use the subsidy than their white or Hispanic counterparts. Hispanics in Illinois were also significantly less likely to participate in the subsidy program when eligible to do so compared with whites (Lee et al., 2004).

Finally, those in urban areas were less likely to use the child care subsidy when eligible, perhaps reflecting greater networks of alternative care in urban areas (Lee et al., 2004).

#### **Child Care Subsidy Use and Employment Outcomes**

Important research on the effects of child care subsidies on employment outcomes has begun to emerge in the last few years. In their study of the use of the child care subsidy by welfare leavers in Pennsylvania, Shlay, Weintraub, and Harmon (2007) found that subsidy use increased the likelihood of parental employment by 148 percent. Blau and Tekin (2007), using the 1999 National Survey of America's Families, demonstrated that receipt of the child care subsidy is associated with a 13-percentage-point increase in the likelihood of employment. Similarly, Tekin (2005) studied a representative sample of low-income mothers and found that receipt of the child care subsidy increased their probability of employment by 15 percent.

In addition to this evidence that the child care subsidy does increase the probability of employment for welfare leavers, there is also evidence that subsidies shorten the length of time it takes for low-income families to move from unemployment or marginal employment to substantial employment as defined by earnings. Using administrative data merged with unemployment insurance records in three states (Connecticut, Florida, and Minnesota), Ficano, Gennetian, and Morris (2006) found that participation in the child care subsidy is associated with a reduction in the time to substantial employment ranging from 11 percent to 34 percent.

Distinguishing low-income women by race, Kimmel (1995) finds that white women are more sensitive to increases in subsidies than are African American women. Finally, distinguishing low-income women by education level, Anderson and Levine (1999) find that reducing child care expenses resulted in the largest gains in employment for women with the least education, although their employment levels still remain well below those of women with more education.

Other studies have examined the role of subsidies on earnings. As reported by the Administration for Children and Families (1999), research in Florida among TANF recipients found that increased funding for child care subsidies increased both earnings and the likelihood of a mother's employment. Increasing per-child subsidy funding by \$145 increased earnings by 3.9 percent for those with few barriers to employment and by 7.2 percent for those current and former TANF recipients with moderate to severe barriers to employment. In Texas, families receiving subsidies earned \$260 more per quarter than eligible families without subsidies (Administration for Children and Families, 1999). Shlay, Weintraub, and Harmon (2007) also found higher earnings among subsidy users than non-users—an average of \$450 more per month.

A three-state study (Lee et al., 2004), using administrative data, examined the interaction of subsidies and work force participation as measured by job duration for both current and former TANF recipients. This study found that, in all three states, employment is longer for those who use the subsidy within two quarters of eligibility than among those who do not. Controlling for a host of variables that are known to be correlated with employment duration (e.g., marital status, age and number of children, TANF history), a significant relationship between using the subsidy and employment in all three states was found. Using the child care subsidy lowers the probability of ending employment by 43 percent in Illinois, by 31 percent in Maryland, and by 25 percent in Massachusetts.

#### **RESEARCH QUESTIONS**

This report focuses on questions that fall into two primary domains: (1) the patterns of participation in CCS among different sub-groups of low-income families; and (2) the relationship between child care subsidy use and employment outcomes among low-income families. Our first research question addresses the domain of participation.

## 1. What are the factors related to child care subsidy use among CCS-eligible, low-income families in 2001?

To answer this question, we identify the state-defined income-eligible population, using the state definition of eligibility in 2001 and determine which families use the subsidy in each state. We draw on bivariate and multivariate methods to measure the strength of associations between individual, family, and transportation to work-related variables and participation in the CCS. We examine these associations at the time of the ACS 2001 interview using logistic regression for all families and longitudinally for new participants in the CCS, using discrete time hazard models for families with a single parent family head.

Our second research question examines the relationship of CCS participation and employment outcomes.

## 2. What is the relationship between subsidy use and employment outcomes for single parent family heads?

We address this question using longitudinal data on CCS eligibility. Again, discrete time hazard models are used to describe the association between CCS participation and either ending an employment spell or exceeding the income threshold for family size. Ending employment is measured by the lack of an unemployment insurance (UI) wage report with positive earnings for

a particular head of household. Exceeding the income threshold is similarly identified with a UI wage report.

We also attempted to examine the relationship between subsidy use and welfare outcomes. However, the number of eligible respondents in the ACS 2001 who eventually participated in TANF was too small to conduct these analyses.

#### **DATA SOURCES**

The primary dataset used for analysis was the *Social Services Analysis File (SSAF)*, an output of an internal Census Bureau project, PRED-607 TANF/Child Care Subsidy Research. This file consists of individual-level data from the U.S. Census Bureau's American Community Surveys (ACS)/Supplemental Survey data (SS01) blended with individual-level state administrative data from the child care subsidy, Unemployment Insurance (UI) wage report data, and TANF programs from each of the three states, in addition to records from the U.S. Census Bureau's LEHD (Longitudinal Employer-Household Dynamics) Program, and other federally held administrative data for each of the three states. CCS, UI wage, and TANF data from October 1998 through December 2003 were included in the file. Detailed income data in the ACS/SS01, along with a compilation of all the program eligibility rules across the states, enabled us to estimate CCS income eligibility for all families.

American Community Survey/2001 Supplementary Survey (ACS/SS01). Through the use of individual-level Census data, we were able to expand upon and improve prior analyses that only made use of UI wage report data. We used the U.S. Census Bureau's American Community Survey (ACS)/2001 Supplementary Survey (SS01). The U.S. Census Bureau conducted three Supplementary Surveys in 2000, 2001 and 2002. These surveys used the methods developed for

the American Community Survey and were part of the ACS research and demonstration program. The surveys were conducted yearly, were national in scope and included about 800,000 households each year; hence these surveys provide representative data at the state level and for some sub-state geographic areas. The content is comparable to the decennial Census "long form," which gathers detailed social, economic and housing data about every member of a household from an overall sample of about 1 in 6 households.

UI wage records provide information only on gross income from employment and do not cover all jobs. The individual-level Census data on income from all sources enabled us to attain a more accurate approximation of eligibility for the CCS by providing measures such as income from employment as well as other earnings (e.g., Social Security benefits and pensions). The unemployment insurance wage reports only provide information on quarterly earnings from employment. Access to individual-level data from the Census long form also enabled us to expand our set of explanatory variables. In the current study, we focused on the following socioeconomic and demographic measures available in the ACS/SS01: marital status, citizenship, educational attainment, disability, household composition, labor force participation, work status and income, and sources and amount of income.

Child Care Subsidy Data. The source data in each state came from a database constructed of existing administrative data on child care subsidy receipt. Each state's system records monthly subsidy information as well as subsidized families' basic characteristics and child care arrangements. Each state's database contains longitudinal information on child care subsidy receipt on a monthly basis at the individual, child and family level.

Chapin Hall receives monthly extracts of the Illinois Department of Human Services

Child Care Tracking System (CCTS). Illinois makes child care subsidy payments through two

methods: vouchers and contracts. Vouchers are issued to eligible families to purchase care from providers that accept state payments, while the contracts are negotiated with providers to serve blocks of eligible children. Chapin Hall has created a longitudinal database tracking information such as month of subsidized child care use and demographic information about the family, using the monthly extracts of CCTS for families using both vouchers and contracts. The database contains subsidy information from January 1996 to the present.

The National Center for Children in Poverty (NCCP) receives monthly subsidy data from the Maryland Department of Human Resources as four text files: a child file, a family file, a voucher file, and a provider file. Maryland makes all of its child care subsidy payments through vouchers. The NCCP has developed processes for converting these four files into SPSS-readable files and "cleaning" them using syntax files. For this study, the Jacob France Center implemented the data processing steps developed by NCCP. Files are archived by service month.

The Ray Marshall Center (RMC) in Texas currently receives monthly subsidy data files via an interagency agreement with the Texas Workforce Commission (TWC), which administers the subsidy program and maintains its own data archive. Texas, like Maryland, makes all child care subsidy payments through vouchers. The data consist of client, family, and payment files, with the payment files containing child, provider, and payment detailed data. The Center's subsidized child care archive spans subsidy receipt from late 1993 to the present.

Unemployment Insurance Wage Report Data. Unemployment Insurance (UI) wage records consist of total quarterly earnings reported by employers to state UI agencies for each covered employee. The database contains information on quarterly earnings. Any employer paying \$1,500 in wages during a calendar quarter to one or more employees is subject to a state

UI tax and must report the quarterly amount paid to each employee. Coverage of UI employment differs very little among the states; typically, more than 90 percent of each state's employed population is covered. Types of employees that are not covered include federal government civilian and military employees, U.S. Postal Service employees, railroad employees, employees of some philanthropic and religious organizations, independent contractors, and out-of-state employees. A potential limitation of the data is that the coverage extends only to a state's borders, so Maryland residents who work in Virginia or in Washington, D.C., for example, do not appear in the Maryland wage data.

TANF Data. The source data in each state were TANF receipt career histories for all families that received TANF since 1998 (Maryland since 1999). Data were drawn directly from the administrative data systems operated by each state's TANF agency. The unique properties of this information are that it is comprehensive and longitudinal at the individual level.

Socioeconomic and demographic information, including educational level, work experience, and marital status, are available on all those who receive cash grants.

Chapin Hall receives monthly extracts of the Illinois Department of Human Services (DHS) client database, a subsystem of the Client Information System. Each extract contains cross-sectional data with some limited historical information. From these extracts, Chapin Hall has created the Illinois Longitudinal Public Assistance Research Database (ILPARD), a longitudinal database of public assistance cases (including AFDC/TANF receipt) containing data from February 1989 to the present.

The Jacob France Institute has created a longitudinal database of welfare recipients in Maryland, extending from July 1989 forward. The Maryland TANF data for this study were transferred directly from DHR to Census per an amendment to the data sharing agreement

between the Family Investment Administration at the Maryland DHR and the U.S. Census Bureau.

The Ray Marshall Center researchers currently receive Texas TANF records under its interagency agreement with TWC. The RMC AFDC/TANF archive dates from 1993.

#### Variables

#### **Dependent Variables**

We examine four dependent variables: CCS participation at a point in time, CCS participation over time, employment termination, and exceeding the CCS income eligibility threshold. The dependent variable included in the logistic regression models predicting CCS participation was an indicator of participation in the CCS within 3 months of the ACS 2001/SS01 interview date. The dependent variable included in the discrete time hazard models predicting CCS participation was a time-varying indicator of participation in the CCS during a particular quarter during or after the ACS 2001 interview. Both of these measures were created from a combination of the ACS 2001 interview date and the CCS project data. The dependent variable included in the employment termination discrete time hazard models is the first exit from employment after the ACS 2001 interview. The dependent variable in the discrete time hazard models of families exceeding the CCS income eligibility threshold is an indicator of the first quarter during which the working parent's income exceeded the eligibility threshold for their particular family size. We created these last two variables from the ACS 2001 interview date and the quarterly wage report project data.

#### **Independent Variables**

We examine four categories of independent variables: characteristics of program participation, individual characteristics of the parent, characteristics of the parent's family, and characteristics of the parent's transportation to work.

Family program participation. We included a point-in-time indicator in the logistic regression models predicting CCS participation based on the date of the ACS interview and TANF project data, indicating whether the parent received TANF anytime during the 3 months before or after the ACS 2001 interview. The longitudinal models predicting employment termination and exceeding the CCS income eligibility threshold included several time-varying measures. The first, which was only included in the longitudinal model examining the employment outcome, is an indicator created from the ACS 2001 interview date and TANF program data comparing parents who received TANF during a particular quarter at the time of or after the ACS 2001 interview with those who were not receiving TANF. The second time-varying measure, created from the ACS 2001 interview date and the CCS receipt data, was an indicator of CCS receipt during the quarter of parental employment prior to the ACS 2001 interview. The third varied depending on the outcome. For each longitudinal model, a count of the number of quarters at risk for first CCS participation, first termination of employment, or first instance of exceeding the CCS income eligibility threshold was calculated.

Individual characteristics. We conducted all descriptive, bivariate, and point-in-time analyses for subgroups based on marital status examining two-parent and single-parent headed families. The longitudinal analyses were conducted only for single parent families. We also included the following measures of parent's characteristics in all models: urban residence, age, gender, race, ethnicity, disability, citizenship, and education. Urban residence was measured

differently in each of the three states. In Illinois, we compared parents living in Cook County with parents living in the rest of the ACS-sampled areas of the state. In Maryland, we compared parents living in Baltimore City with parents living in the rest of the ACS-sampled areas of the state. Last, in Texas, we compared parents living in the six largest metropolitan areas with parents living in the rest of the ACS-sampled areas of the state.<sup>2</sup>

We constructed a three-category variable for parental age, comparing those age 24 and under with those ages 25 to 34 and with those age 35 and older. The ACS captures race and Hispanic ethnicity in separate variables and allows for a respondent to identify with multiple races. Because of small numbers of certain race or ethnicities, we included parental race in the models in one of two ways. In some cases, we compared black parents and "other" race parents with white parents. In other cases, we compared non-white parents, who were all parents who did not indicate white race, with white parents. Whenever possible, we compared parents of Hispanic ethnicity with non-Hispanics. Our measure of disability was dichotomous comparing parents with a disability to those with no disability. The ACS data classified someone as having a disability if they report one of the following six conditions: sensory limitations; physical limitations; mental limitations; self-care limitations; going-outside-home limitations; or employment limitations. Citizenship was a dichotomous measure that compared parents who were not citizens of the United States with parents who were citizens (including those born in the United States; those born in Puerto Rico, Guam, the U.S. Virgin Islands, or the Northern Marianas; those born abroad of American parents; and those who are U.S. citizens by naturalization). The parental education variable had a three-level categorization, comparing

<sup>&</sup>lt;sup>2</sup> We define a household as "urban" if it resided in one of the 36 counties which comprise the MSAs of the six largest cities in Texas (Houston, San Antonio, Dallas, Austin, Ft Worth, El Paso).

parents with less than a high school education (up to and including grade 12 with no diploma), or more than a high school education (including some college but no degree, vocational/technical/business school degree, associate's degree, bachelor's degree, master's degree, professional school degree, and doctoral degree) with those with only a high school diploma or GED.

Family demographic characteristics. We included three binary variables of family characteristics—whether the parent had a child under age 2, whether the parent had a child in preschool, and whether the parent had three or more children under the age of 13. The measure of having a child under age 2 was based on the child's date of birth and included children ages 0 and 1. The measure of having a child in preschool was created from a variable that collected information on the grade level the child was attending at the time of the interview. We coded responses of "nursery school/preschool" as having a child in preschool. All other responses (not attending school, kindergarten, grades 1-12, college, and graduate or professional school) were included in the comparison category. We counted the number of children under age 13, and we positively coded the parent on the family size indicator if she or he had at least three children under 13. All other parents were included in the comparison category.

Transportation to work characteristics. We included three characteristics of parent's transportation to work: length of commute, taking public transportation to work, and time of departure for work. Respondents reported their travel time to work in minutes. From this we created a three-level measure comparing parents with a short commute (1 to 9 minutes) or long commute (25 minutes or longer) to parents with an average commute (between 10 and 25 minutes). Parents also reported the means of transportation they used to get to work. Public transportation included of bus or trolley bus, streetcar or trolley car, subway or elevated, railroad,

ferryboat, and taxicab. Other responses (including car, truck or van; motorcycle; bicycle; walked; worked at home; other method; and not a worker) were included in the comparison category. The survey collected exact time of departure for work for parents. From this variable, we created a three-level measure comparing parents who had an early departure (leaving before 6 a.m.) or late departure (leaving for work at 2 p.m. or later) to parents with an average departure time (leaving between 6 a.m. and 2 p.m.).

#### **METHODS**

#### **Creating the Matched Database**

The first step in creating a matched database was to have state agencies establish the necessary confidentiality agreements to allow state teams to share individual-level administrative records with the U.S. Census Bureau. The Census Bureau had the task of matching the databases at the individual level. The matched and de-identified database was then shared with project analysts at the Census Bureau's Research Data Center (RDC) in Chicago. All analysis of the data for this project took place at the RDC after project staff completed the necessary steps to have Special Sworn Status (SSS). With SSS, project staff were subject to the same training and background investigation as permanent Census Bureau employees. All research output removed from the RDC and contained in this report was reviewed extensively by the Disclosure Review Board of the Census Bureau.

#### **Determining Eligibility**

#### **CCS Eligibility Rules**

In each state, the eligibility rules have three key components: family size determination, income determination, and eligible child determination. In all of the states during the study period, children under age 13 were eligible for child care services. In addition, children under age 19 with a documented disability or under court supervision were eligible. However, we did not include this population in our analysis. We also did not explicitly include the population that is categorically eligible in all three states. This group includes heads of household in families receiving TANF who were participating in certain approved activities (i.e., job search, job training). If these categorically eligible families were income-eligible, they were included.

With respect to eligible household members, the states were fairly similar in terms of who was counted. The only difference appears between Maryland and the other two states. Maryland had no provision to count children away at school and dependent on the family for support or other adults who may have been partially dependent on the family (see Table 2).

Income determination is governed by more complicated rules. Still, the states were similar in terms of the types of income that were counted toward income used to determine eligibility. The biggest difference was the treatment of TANF and SSI payments in Maryland. Maryland did not count these payments in the family's total income, but Illinois and Texas did include them. Maryland is also the most generous with respect to the lump sum deductions for children against the family's overall income. In Illinois, only child support paid out is specified as a deduction against the family's income. In Texas, there were no specific income deductions (see Table 3). Other differences across states are listed in Table 3.

Although there were some differences in the sources of family income that were used to determine eligibility, it is important to note that the income thresholds against which the family's income was measured varied across states. In fact, in Texas, the income thresholds varied by geographic location across the state (see Table 4). Texas used 28 Local Workforce Boards (LWBs) to set income thresholds during the time of the study. LWBs also determine the length of time between recertifications and whether the maximum income thresholds at recertification are the same as the initial maximum income thresholds.

An important issue in interpreting the results is whether or not there was any form of service rationing during the study period. The states differed in their ability to provide service to all eligible individuals. In Illinois, there appeared to be no service rationing.<sup>3</sup> The state was committed to serving all income- and activity-eligible applicants. To our knowledge, Illinois did not have a waiting list to receive the CCS at any time during the study period. In Maryland, the commitment to serve all income- and activity-eligible applicants ended in January 2003. From that time through the end of the study, Maryland committed to serve families leaving TANF for work, receiving SSI, and militarily deployed families. We are unaware of a waiting list for services among any eligible families in Maryland during the study period. Texas did ration services during the entire study period. Participants of the TANF Choices program were given priority over other eligible applicants. Unlike the other states, Texas had waiting lists for subsidy benefits for income-eligible applicants in some parts of the state throughout most of the study period. This suggests that Texas participants may be unlike participants in the other states because of the priority given to TANF Choices participants.

<sup>&</sup>lt;sup>3</sup> The lower income eligibility thresholds in IL, MD, and some TX LWB areas is one form of service rationing. By lowering the income eligibility threshold below the maximum authorized by federal regulation, these jurisdictions disallow services to an entire class of potential applicants—those with incomes above the state set limit who would be eligible for CCS in states that do not restrict eligibility in that way.

#### **Modeling Parental Status**

A key part of defining the eligible population is to identify parents of dependent children under the age of 13. When children under 13 years old live alone with their biological or adoptive parents, the identification is straightforward. In the case of blended families, families with adult children, or nonparent caregivers, the eligibility rules and thus the identification of the families are more difficult. The strategy used in this study was to identify adult-child pairs deterministically and then probabilistically weight potential caregivers based on characteristics of the father. For example, adults included any individual in the household over the age of 13, and children potentially eligible for the subsidy were age 12 or younger. Based on parameters estimated for families in the ACS/SS 2001 who were also receiving the CCS, the probability that an adult was the parent or guardian of the child in each adult-child pair was based on their age difference, the relationship codes reported in the ACS, and the adult's gender. This probability was summed across children for each adult and used to compute another predicted probability that the adult was a parent of at least one child under the age of 13. This probability was scaled to sum to 1 across all potential adult caregivers within a household.<sup>4</sup>

#### **Modeling Income Eligibility**

In addition to parental status, families must not exceed the state-specific income thresholds to be eligible for the CCS. Again, data from families who were participating in the CCS and found in the ACS/SS 2001 were used to develop income models. Separate models were estimated according to marital status and the availability of UI wage data at the time of the interview in making the prediction. Total income from the ACS was reported in several

<sup>&</sup>lt;sup>4</sup> In households with multiple adults, this method identified more than two potential parents. Relationship codes in the ACS related each individual in the household to a reference person.

categories. In this analysis, the sum of income from wages, self-employment, public assistance, Supplemental Security Income, Social Security, retirement benefits, and investment income was used to compute the individual's total income for the year. Using estimated model parameters, a predicted family income was determined. The model-based predicted family income was compared with the actual income threshold for a given family size. A hypothesis test was performed by subtracting the predicted family income from the actual income threshold and dividing by the root mean squared error. The probability that the predicted family income falls below the actual income threshold is used as the probability of eligibility for this analysis.

#### **Modeling Work Qualification**

The final piece of the eligibility determination involves the identification of work qualification. In general, parents and caregivers must be working to be eligible for the CCS. For all three states, a respondent was considered to be working if: 1) the employment status variable (ESR) from the ACS indicated employment; 2) there were positive self-employment earnings reported in the ACS; or 3) there were positive earnings in the UI data during the quarter of the ACS inteview. If any of these variables showed current work, the individual was considered to meet the work qualification. In addition, if the respondent is part of a married couple, then the respondent's spouse must also meet the work qualification criteria for the family to be eligible. In Illinois and Maryland, there are exceptions to this rule in the case of married couples in which one spouse is disabled or in the military. Under these circumstances, both spouses do not need to meet the work requirement in order to be considered eligible for the subsidy.<sup>5</sup>

<sup>&</sup>lt;sup>5</sup> Although Texas did not have an exception for couples with disabilities or involved in military service, there is a restriction involving a minimum number of work hours. We examined the number of hours worked as reported in the ACS but found there were very few cases to exclude. As a result, we did not exclude any cases.

#### **Statistical Methods**

To study the effects of individual, family, program, and work characteristics on the probability of taking up subsidies at the time of the ACS interview, we use the logistic regression method. The dependent binary variable is the receipt or non-receipt of a child care subsidy within three months of the ACS interview for those households determined to be eligible. The distribution of the dependent variable can be described by probabilities  $P(Y=1)=\pi$  if the family participates in the CCS and  $P(Y=0)=1-\pi$  if the family does not participate. One way to model the relationship between the expected value of the binary participation variable as a function of individual, family, program, and community characteristics is to use the logistic regression function, namely:

$$\log \left(\frac{\pi(x)}{1-\pi(x)}\right) = \alpha + \beta(x),$$

where X is a vector of individual, family, program, and community variables. This model allows us to estimate the effect of a one-unit change in X on the log-odds of participation in the CCS. By using the exponential function, we can transform coefficients to interpret the effect of a one-unit change in X on the odds of participation in the CCS, namely:

$$\left(\frac{\pi(x)}{1-\pi(x)}\right) = \exp(-\alpha + \beta x) = e^{\alpha}(e^{\beta})^{x}$$

This exponential relationship provides a useful interpretation for  $\beta$ . Specifically, the odds of CCS participation will increase multiplicatively by  $e^{\beta}$  for each one-unit increase in X. If  $\beta$  has no effect on the odds of CCS participation, then  $\beta$ =0 and  $e^{\beta}$  will equal 1.

<sup>&</sup>lt;sup>6</sup> All analyses were weighted with weights adjusted to our sample sizes such that the mean of the weights is 1 and the sum of weights equals the number of cases in sample.

In addition to examining the relationship between CCS participation and individual, family, program, and transportation to work characteristics at the time of the ACS interview, we are able to expand our analysis to examine these variables over time in relationship to CCS program participation and employment outcomes. The longitudinal employment history contained in the UI wage report data calls for event history analysis. Specifically we model the relationship between individual, family, program, and transportation to work characteristics as a latent variable that controls the occurrence of the event and the time to the event. This latent variable is called the *hazard rate* (Allison, 1982; Tuma, Hannan, and Groeneveld, 1979; Kalbfleisch and Prentice, 1980). In this application, time is measured in discrete quarterly units. The hazard rate is the conditional probability that the event occurs at time **t** for individual **i**, given that the individual has not yet experienced the event and has covariate values **X** that may or may not vary over time, namely:

$$P_{it} = \Pr[T_i = t \mid T_i \ge t, x_{it}]$$

There are several ways to describe how the hazard rate depends on time and explanatory variables. A widely used model is the proportional hazards model. When **t** is a discrete random variable McCullagh (1980) shows that the proportional hazards model becomes,

$$-\log(1-P_{it}) = \exp(\alpha_t - \beta x_{it})$$

where  $\alpha_t$  is a set of constants. In its linear form, this model is identical to the form of a generalized linear model with a complementary log-log link function, namely:

$$\log[-\log(1-P_{it})] = \alpha_t + \beta x_{it}.$$

This form is useful for discrete time event history data because the coefficient vector  $\beta$  is identically equal to  $\beta$  in the continuous time proportional hazards model (Prentice and Gloeckler, 1978). Practically, this allows one to estimate the  $\beta$  coefficients in discrete time hazard models

using ordinary methods for fitting generalized linear models and still have relative risk interpretations as in continuous time models. We analyze three events using this method: new participation in the CCS, exiting employment, and exceeding the CCS income threshold.

#### STUDY POPULATION

#### **Point-in-Time Study Population**

The study population for this analysis includes all families eligible for the CCS in the three states according to the state employment and income related eligibility rule. As explained above, this population is identified by selecting all families with children under 13 and weighting respondents by the following:

- 1. The probability that respondents are parents to a child under 13
- 2. The probability that respondents are eligible for the subsidy based on income
- 3. The population weight provided in the ACS

In addition, the population is limited to those individuals who meet the work qualification. As seen in Table 4, the number of eligible households ranges from 162,000 in Maryland, to 265,000 in Illinois, to 656,000 in Texas. A rough comparison with households with children under 18 reveals that eligible households represent between 13 and 18 percent of total households with children in the three states. Because the majority of eligible families in each state were single-parent families and the original program design was intended to serve women who are single heads of families, we limit some of our analysis below to the single-parent study population. In each state, at least one-fifth of single parent families appeared to be eligible for the CCS (see Table 5). Significantly fewer two-parent families were eligible (8-13%).

#### **Longitudinal Study Populations**

In addition to the point-in-time study population described above, we exploited the longitudinal nature of our UI data to explore longitudinal participation and longitudinal questions of employment outcomes for single parent families. In each of the longitudinal analyses, the point-in-time study population was limited to those families who are eligible by virtue of their UI wage report during the quarter of the ACS interview. For example, when analyzing longitudinal participation in the CCS, we deterministically identified families who had UI wage reports indicating wages below the income thresholds. ACS income values and the probability of eligibility were not used to identify this study group. In addition, we excluded families who were receiving the CCS in the quarter prior to the ACS interview. In this way, we created discrete period-quarter records that can follow eligible families for up to 12 quarters to identify new CCS participation. Similarly, our longitudinal analysis of employment outcomes restricted the point-in-time study population to families eligible according to their UI wage reports. Parents are followed for up to 12 quarters to identify the end of an employment spell or an increase in UI earnings above the CCS income eligibility threshold. Table 5 shows that these two-parent study populations are considerably smaller than the point-in-time single parent study population.

#### **RESULTS**

#### **Demographic Characteristics of the Study Population**

Table 7 summarizes demographic characteristics of the study populations in Illinois, Maryland, and Texas. More than one-half of the study population in each state was single parents. Illinois had the greatest proportion of single parent families (64%), followed by Maryland (61%) and Texas (58%). Parents in Maryland had the lowest levels of recent welfare participation. Five percent of the population of single parent families in Maryland received TANF in the 3 months before or the 3 months following the 2001 ACS interview. Eight percent of single parent families in Texas and 10 percent of single parent families in Illinois had received TANF within 3 months of the ACS interview. TANF receipt among two-parent families was only measurable in Texas, where less than 1 percent of the two-parent family population received TANF benefits.

A greater proportion of both the two-parent and single-parent families in Texas (53% two-parent, 62% single-parent) lived in a large urban area than in Illinois (37% two-parent and 46% two-parent) or Maryland (28% two-parent, 38% single-parent). Between 20 and 25 percent of single parents were ages 24 or younger at the time of the ACS interview, and more than one-half of the two-parent population was age 35 or older. Over 80 percent of respondents in the study population were females.

In Texas, the majority of the single parent population was white (59%), but only one-third of the single parent population in Maryland was white (33%). The two-parent population in all three states was predominantly white (Illinois, 74%; Maryland, 66%; Texas, 71%). Parental educational attainment varied across states and by marital status within states. Parents in

Maryland were more likely than parents in Illinois or Texas to have completed at least some education after receiving a high school degree, and in all three states two-parent families were more likely than single parent families to have some post-high school education.

Parents in Maryland were less likely than parents in Illinois or Texas to have three or more children under age 13. Approximately 20 percent of parents in all three states had a child under the age of 2, and between 11 percent and 16 percent of parents had a child in preschool.

Commuting times are dependent on the availability of public transportation as well as many other factors. Interpretation of these results may be problematic because of inadequate contextual information about local transportation infrastructure. That being said, across the board, single parents had longer commutes than married parents. Single parents in Maryland had the longest commutes, with 44 percent of single parents commuting 25 minutes or more. Single parents in Texas had the shortest commutes, with 26 percent traveling 10 minutes or less to get to work. Use of public transportation could only be measured for single parents, and we found that those in Illinois and Maryland were more likely than those in Texas to use public transportation (15% and 19% versus 4%). Time of departure for work did not vary much by marital status or across states: in all three states, between 76 percent and 84 percent of parents worked standard hours.

#### **Rates of Child Care Subsidy Participation**

Table 8 shows the proportion of the study populations in all three states that took up the child care subsidy within 3 months of the ACS interview. In Illinois, the 22 percent rate of CCS participation was approximately three times the rate of CCS participation in either Maryland (8%) or Texas (7%). In Illinois, 31 percent of single parents participated in the CCS, compared with only 5 percent of two-parents. Although smaller proportions of parents overall participated

in the CCS in Maryland and Texas than in Illinois, we observed a similar difference between the participation patterns of two-parent and single parents. Eleven percent of single parents in Maryland and Texas participated in the CCS, compared with 2 percent and 1 percent of two-parents, respectively.

Table 9 shows the relationship between CCS participation and other characteristics of the individual respondents, their families, and their work. In all three states, those who had received TANF within 3 months of the ACS survey<sup>7</sup> participated in the CCS at higher rates than those who had not received TANF around the time of the survey. Patterns of CCS participation in major metropolitan areas varied across states. In Illinois, single parents living in Cook County were more likely than parents living outside Cook County to participate in the CCS (38% versus 26%). Conversely, parents living in Baltimore, Maryland, and those living in the major urban areas of Texas participated in the CCS at lower rates than parents living outside those areas (10% versus 13% in both states).

Across states and marital statuses, we found higher levels of CCS participation among younger parents and among non-whites. Patterns of CCS participation that emerged for single parents include higher levels of participation among females than among males, and among parents with less than a high school education than among parents with at least a high school diploma. We could only examine the relationship between citizenship and CCS participation in Illinois and Texas, and we found higher levels of participation among citizens than among non-citizens.<sup>8</sup>

<sup>&</sup>lt;sup>7</sup> Results for TANF receipt were disclosed only for the single-parent samples in IL and MD.

<sup>8</sup> CCDF policy requires States to verify that the child receiving CCDF-subsidized services is a U.S. Citizen or qualified alien. Therefore, differences in participation rates among these two groups could be impacted by the extent to which non-citizen parent's are more likely to have children who are also not citizens or qualified aliens, and therefore not eligible to receive services through the program.

Single parents with a child age 0 or 1 exhibited lower levels of CCS participation than their counterparts whose youngest child was age 2 or older. For both two-parent and single parents in all three states, we found higher levels of CCS participation among parents with a child in preschool than among parents without a child in preschool, and among parents with three or more children under age 13 than among parents with fewer than three children under 13, except for two-parent families in Texas.<sup>9</sup>

Lastly, the relationship between length of commute and CCS participation was different in each state included in our analyses. In Illinois, parents with the longest commutes exhibited the highest levels of participation, while participation was greatest among parents with average length commutes in Maryland, and married parents with the shortest commutes and single parents with average length commutes in Texas. Single parents who worked late hours had higher levels of CCS participation than those who worked early or standard hours in all three states.

## **Multivariate Analysis**

# Point-in-Time Child Care Subsidy Participation

TANF receipt was associated with higher levels of CCS participation at a point in time. In Table 10, we present results of logistic regression analyses predicting the likelihood of participating in the CCS within 3 months of the ACS interview. In Illinois and Texas, TANF receipt in the 3 months before or after the interview was associated with increased CCS participation for unmarried parents. The odds of participation in the CCS were 50 percent greater in Illinois and nearly five times greater in Texas for parents who were receiving TANF

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<sup>&</sup>lt;sup>9</sup> This finding raises the question of the difference between child care and preschool. It may be the case that some families use the terms interchangeably.

within 3 months of the interview than for parents who were not receiving TANF. While not statistically significant, similar patterns were also observed in Maryland.

Most likely, this reflects a combination of preferences for TANF recipients and the rules and dynamics of the TANF program itself. For example, the fact that Illinois has a high income-disregard for TANF means many CCS recipients are still going to be eligible for TANF. There were significant differences in the characteristics of TANF populations in the three states. Only 6 percent of TANF recipients in Maryland were employed in 2001, while 22 percent in Texas and 41 percent in Illinois were employed (Administration for Children and Families, 2002).

Living in an urban area was related to reduced point-in-time CCS participation. Married parents residing in urban areas in Illinois, Maryland, and Texas had lower odds of CCS participation than their counterparts living in the other ACS-sampled areas of the states.

Four characteristics of individual respondents were associated with CCS participation for single parents. We found that young parents (24 years or younger versus 35 years or older) had increased odds of CCS participation among single parents at a point in time in all three states. African American single parents in Illinois and Texas had higher odds of CCS participation at a point in time that white single parents, as did Hispanic single parents in Texas. Also, in Illinois and Texas, citizen single parents participated more than non-citizen single parents. In Illinois and Maryland, single parents with low educational attainment had increased odds of CCS participation at a point in time (Table 10). Married parents exhibited similar patterns of association at a point in time as their single counterparts, with a few exceptions. <sup>10</sup>

<sup>&</sup>lt;sup>10</sup> Among two-parent households in Texas, we found reduced odds of CCS participation among those who were Hispanic (versus non-Hispanic) and who were disabled, and increased odds of take-up among those age 35 or older at the time of the interview. In Illinois, we found that two-parent households who were disabled and who had less than a high school education (versus a high school education) were less likely to participate in the CCS. two-parent households in Maryland who had not finished high school had lower levels of CCS participation than their counterparts who had completed high school.

Few family or work characteristics of the respondent were associated with point-in-time CCS participation across states. Having a large number of young children and working non-standard hours are related to increased need of these families for child care. We found increased odds of CCS participation at a point in time in Illinois and Texas for single-parent respondents who had three or more children under age 13 and those who had a child in preschool and for single parents in Illinois who worked late hours (see Table 10).

## Participation in the Child Care Subsidy Over Time

Older age of parents was related to reduced CCS participation over time. As with the point-in-time findings, the results of discrete time hazard models predicting CCS participation over time among single parents, presented in Table 11, indicate a reduced likelihood of CCS participation among parents who were age 35 or older (vs. less than age 24) at the time of the interview.

White race (vs. non-white race) was associated with a reduced likelihood of CCS participation over time in Texas. Educational attainment and parental disability status were associated with longitudinal CCS participation only in Illinois. Parents in Illinois who had a disability and those with more than a high school education were more likely to participate in the subsidy than their counterparts who did not have a disability or who only had finished high school (see Table 11).

Over time, CCS receipt was higher among parents in Texas who had a child between the ages of 0 and 1 and those with a child in preschool were more likely to participate in the CCS than parents whose oldest child was at least 2 years old or those without a child in preschool (see Table 11). It may be that preschool was equated with child care by some respondents.

# **Employment Outcomes: Employment Termination**

CCS receipt was associated with longer employment spells. Table 12 presents results from discrete time hazard models predicting employment termination after the ACS interview. We ran two sets of models examining employment termination: Model 1 includes characteristics of transportation to work and Model 2 does not. We found that CCS receipt had a significant influence on length of employment spell in Illinois. Parents who were receiving the subsidy in the previous quarter had longer employment spells than parents who were not receiving the subsidy. In Illinois, the hazard that a parent would end employment was 28 percent lower for those who received the CCS in the previous quarter compared with those who did not receive the subsidy in the previous quarter. While findings did not reach statistical significance in Texas and Maryland, we observed similar patterns in these two states. In Texas and Maryland, parents who received the CCS in the previous quarter had a 14 percent and 5 percent lower hazard (in Model 1 only), respectively, of ending their current employment spell. The significant, positive interaction between prior quarter CCS receipt and the number of quarters at risk for employment termination observed in Illinois and Texas indicates that the strength of the association between prior CCS receipt and length of employment spell weakens over time (see Appendix, Table 1).

TANF receipt was associated with shorter employment spells. Compared with parents who were not receiving TANF, TANF receivers were more likely to terminate an employment spell (see Table 12). In Texas and Illinois, the hazard of ending an employment spell was 44 percent and 56 percent greater, respectively, for parents who were receiving TANF than it was for parents who were not. This difference was even more pronounced in Maryland, where TANF receipt increased the hazard of ending an employment spell more than two-and-half fold (relative risk ratio, 2.59).

Low educational attainment was associated with shorter employment spells in all three states. Respondents in Illinois and Texas who had less than a high school education exhibited shorter employment spells (see Table 12). Two other characteristics of the individual respondent were consistently related to employment termination across the states: urban residence and younger age (24 or younger) were associated with an increased likelihood of terminating an employment spell (see Table 12).

In models predicting employment termination, we found similarities between Illinois and Maryland, where parents with three or more children under 13 had longer employment spells than their counterparts with fewer than three children under 13 (see Table 12).

## **Employment Outcomes: Exceeding the Income Threshold**

CCS recipients were less likely to lose CCS eligibility by exceeding the income threshold. Table 13 presents findings for analyses of the risk that parents lose CCS eligibility by exceeding the income threshold. In all three states, parents who had participated in the CCS in the previous quarter were less likely than parents who were not participating in the CCS to become ineligible for the CCS because their income exceeded the threshold. This relationship was strongest in Maryland, where prior quarter CCS participation was associated with a 61 percent reduction in the odds that the parent would exceed the income threshold. We also tested the interaction between prior quarter CCS participation and the number of quarters at risk for exceeding the income threshold and found that the association between prior quarter CCS participation and exceeding the income threshold diminished over time in Maryland and Texas (see Appendix, Table 2). Therefore, if a family is not participating in the subsidy program, they are both more likely to terminate employment and to become ineligible due to higher income sooner than those who are participating. This suggests that employed parents might have a prior sense of how long

they might be employed or how long they might require child care. and, therefore, not apply when they are eligible.

Low educational attainment was associated with reduced odds of exceeding the income threshold for CCS eligibility in all three states. In models predicting loss of CCS eligibility by exceeding the income threshold, respondents with less than a high school education exhibited reduced odds of exceeding the income threshold for CCS eligibility. Gender was the only other characteristic of the individual respondent with a consistent association in all three states: females were less likely than males to exceed the income threshold (see Table 13).

The relationships between individual respondent characteristics and the odds of exceeding the income threshold were different in Illinois and Texas than they were in Maryland. Our analyses revealed a number of characteristics of the individual respondents that were associated with a greater likelihood of exceeding the income threshold among parents in Illinois and Texas but were not significantly associated with the likelihood of exceeding the threshold among parents in Maryland. In Illinois and Texas, parents who lived in an urban area were more likely to surpass the income threshold than their counterparts. Similarly, parents who were at least age 35 at the time of the interview and those who were disabled were less likely to exceed the income threshold in Illinois and Texas (see Table 13).

Number of children was associated with the odds of exceeding the income threshold. Having at least three children under age 13 was associated with reduced odds of exceeding the income threshold in all three states (see Table 13).

In models predicting the loss of CCS eligibility by exceeding the income threshold, we found differences between Maryland and Texas. Parents in Texas who had a child in preschool were more likely to surpass the income threshold than their counterparts. In Maryland, by

contrast, parents with a child in preschool were less likely to surpass the income threshold than those without a child in preschool (see Table 13).

## SIGNIFICANCE OF THE STUDY AND POLICY IMPLICATIONS

## Participation in the Subsidy Program

In Illinois and Texas, child care subsidy participation rates are much lower among non-U.S. citizens than among U.S. citizens. This indicates that noncitizen parents are not taking up benefits for which their children may be eligible. Due to the structure of the survey and the imprecise nature of the measure, we could not distinguish between documented and undocumented noncitizens, nor did the survey provide information on the citizenship of the parent's children. Therefore, we do not know if noncitizens are not collecting the subsidy because of a lack of knowledge about the program or fear of the government or because their children are not eligible. This finding is consistent with other research that shows that immigrants are not coming to the United States and exhausting social benefits designed for citizens (Douglas-Hall & Koball, 2004).

Another significant finding that bears discussion is the issue of preschool and its relationship to our findings regarding participation in the child care subsidy program. Our study demonstrated a strong positive effect on child care subsidy participation among families in Illinois and Texas who responded to the ACS question, "Is your youngest child in preschool?" by answering "Yes." Indeed, families with preschool-age children could be using it as a form of child care, particularly Head Start and/or state-funded pre-K programs.

Unfortunately, there is no consensus on what constitutes preschool, and respondents could answer this question based on a wide variety of experiences. Clearly, full-day Head Start

programs, for example, could serve as child care for a working parent, while other intermittent arrangements would not suffice (e.g., Mother's Day Out programs, a preschool program run two mornings a week). Better measurement on early childhood education and care would help to flush out these differences in non-parental care arrangements for 2- to 4-year-olds and provide a better indicator of how preschool both enhances and inhibits the ability of low-income parents to gain employment when leaving welfare.

The issue of standard versus nonstandard hours in employment also merits discussion. Previous research (Jefferys & Davis, 2004; Okuyama & Weber, 2001; Schaefer, Kreader, & Collins, 2006) has shown that parents receiving child care subsidies are most likely to be employed in the retail and service industries, both of which may operate outside of the traditional standard employment hours, generally considered Monday through Friday from 8 a.m. to 6 p.m. Finding child care outside of these traditional work hours can be quite challenging and therefore may impact the likelihood of subsidy participation. Shlay, Weintraub, and Harmon (2007) looked at the differences between subsidy-eligible users and nonusers and found that subsidy users were more likely than nonusers to work the same work days and times each week, and that eligible nonusers were more likely to work irregular hours. Similarly, Tekin (2007) found that subsidy recipients were more likely to work standard hours compared with nonrecipients. In his examination of what he called the "standard work decision" of single mothers, Tekin found that receiving the child care subsidy was associated with a 7-percentage-point increase in the probability of working a job during standard hours.

On the other hand, our research has shown that for the single-parent population in Illinois, those respondents who were "working early" (leaving home to go to work before 6 a.m.) or "working late" (leaving home to go to work after 2 p.m.) were actually more likely to take up

the child care subsidy than those who did not work early or late. Texas results were split, with those who work early less likely to take up, and those who work late more likely.

Clearly, there is a relationship between the subsidy participation decision of low-income workers and the time child care is needed. This suggests that working irregular days and/or hours may be an impediment to subsidy participation if policies largely limit participation to families using formal arrangements.

## **Employment Outcomes**

The CCS program effects in both models must be interpreted cautiously owing to potentially informative selection bias. For example, it may be that individuals who were more motivated to participate in the CCS were also more motivated and equipped to maintain continuous employment. In this case, the lower risk of ending employment that we find with participation in the CCS is simply a reflection of unmeasured characteristics of the individual rather than an effect of program participation. Similarly, but in a slightly different direction, it may be that individuals who participate in the CCS are less likely to exceed income thresholds because only individuals with weak earnings trajectories choose to participate or (as suggested earlier) individuals forgo raises in order to retain eligibility. For example, those eligible individuals who are likely to have future incomes above the thresholds may decide not to participate in the CCS in the short term. In this situation, it is the unmeasured characteristics affecting the decision to participate rather than program participation itself that leads to the effect. Future research should employ experimental or quasi-experimental techniques to better understand the strength of the participation effect and the characteristics of program participation that are most related to positive employment outcomes.

A key contribution of this report is a better understanding of the association of CCS program use with the duration of employment and eligibility spells. The direction of some of the program effects coincided with our hypotheses. We predicted that CCS use would extend the length of employment spells for single heads of families. This result was consistent in all three states, with Illinois having the strongest effect and Maryland having the weakest. The competing risk for eligible employed individuals was not in the predicted direction. We found that single heads of household who took up the child care subsidy were less likely to end eligibility by exceeding income thresholds compared with respondents who did not take up the subsidy.

Table 1. Comparison of CCDF Participation Rates With Published Data

	Illinois	Maryland	Texas
Calculated in this study	29.2%	10.4%	10.7%
Calculated from available data	29.3%	11.9%	8.3%

Table 2. Household members included in eligible family unit

Household Member	Illinois	Maryland	Texas
Mother	Yes	Yes	Yes
Father	Yes	Yes	Yes
Step-Father	Yes	Yes	Yes
Step-Mother	Yes	Yes	Yes
Legal Guardian or Caretaker Relative	Yes	Yes	Yes
Biological or Adoptive Children of applicant or spouse (under age 21)	Yes	Yes	Yes
Step Children (under age 21) of applicant or spouse	Yes	Yes	Yes
Child(ren) in care of Legal Guardian or Caretaker Relative	Yes	Yes	Yes
Biological, Adoptive or Step Children of applicant or spouse living outside the household	Yes <sup>a</sup>	No	Yes
Other persons related by blood or law to the applicant or spouse, living in the same household.	Yes <sup>b</sup>	No	Yes <sup>c</sup>

<sup>&</sup>lt;sup>a</sup>Only children under 21 who are dependent upon the family for more than 50% of his/her support and who is a full-time student away at school, provided he/she has not established legal residence outside the household are included.

included.

<sup>&</sup>lt;sup>b</sup>Only other persons who are dependent upon the family for more than 50% of his/her are included. <sup>c</sup>Only adults who are considered dependents for tax purposes are

Table 3. Sources of family income counted for eligibility

Source	Illinois	Maryland	Texas
Adult Family Members' Pre-Tax Earnings from Employment—gross wages and salary	Yes <sup>a</sup>	Yes	Yes
Child Family Members' Monthly Pre-Tax Earnings from employment	Yes <sup>b</sup>	Yes <sup>c</sup>	Yes
Net income from farm and non-farm self-employment	Yes	Yes	Yes
Social Security, including Disability, Survivors and, Railroad Retirement benefits	Yes	Yes	Yes
Supplemental Security Income (SSI)	Yes	No	Yes
Net Rental Income	Yes	$Yes^d$	Yes
Dividends, Royalties & Interest Income	Yes	Yes	Yes
Public Assistance (TANF) payments	Yes	No	Yes
Pensions, annuities, trust fund payments	Yes	Yes	Yes
Educational loans and grants	No	No	Yes
Unemployment Compensation	Yes	Yes	Yes
Workers' Compensation & permanent Disability payments	Yes	Yes	Yes
Spousal Maintenance or Alimony	Yes	Yes	Yes
Child Support Received	Yes	Yes	Yes
Estate Income	Not mentioned	Yes	Not mentioned
Lump sum Inheritances or insurance payments	No	No	Yes
Foster care payments	No	No	Yes
Adoption assistance payments	Yes	No	Yes
Sale of Property (such as stocks, bonds, a house, or a car)	No	No	Yes
Tax refunds or any Earned Income Tax Credits	No	No	Not mentioned
Gifts and Money Borrowed	No	No	Not mentioned
Capital Gains	No	Not mentioned	Yes
Value of Food Stamps and School Lunches	No	No	Not mentioned
Home produce for household consumption	No	No	Not mentioned
Deductions	Yes (child support paid)	Yes (child support paid and \$2200 per child)	Not mentioned

<sup>&</sup>lt;sup>a</sup>Ten percent of this amount was subtracted from the family's total income

until 8/2003.

bIncome for children under age 19 is not counted unless the child is the applicant.

<sup>&</sup>lt;sup>c</sup>Income for children under age 18 is not counted as long as the child is in public school. Income is counted for children ages 15-17 if they are not in school. In addition, all income is counted for children over age 18 who reside in the household.

<sup>&</sup>lt;sup>d</sup>Gross income is counted if only a room is rented. If the rental income is from an apartment building then the net income is counted.

Table 4. Example of income thresholds per family size

Family Size	Monthly Threshold in Dollars as of 1/2000							
	Illinois <sup>a</sup>	Maryland <sup>b</sup>	Texas					
2	1,472	1,157	\$1406 - \$2464					
3	1,818	1,514	\$1769 - \$3043					
4	2,165	1,872	\$2131 - \$3623					
5	2,511	2,226	\$2494 - \$4203					
6	2,857	2,582	\$2856 - \$4782					
7	2,922	2,938	\$3164 - \$4891					
8	2,987	3,005	\$3235 - \$5000					
9	c	3,072	\$3305 - \$5108					
10	c	3,138	\$3375 - \$5217					
11	c	3,205	\$3446 - \$5326					

<sup>&</sup>lt;sup>a</sup>The monthly thresholds increased for all family sizes in 9/2003.

Table 5. Characteristics of the study population in 2001: Illinois, Maryland, and Texas

		Illinois			Maryland			Texas	
	Weighted Number of	Number of		Weighted	Number of		Weighted	Number of Eligible	
	Households with	Eligible Households	Percent of Households	Number of Households	Eligible Households	Percent of Households	Number of Households	Households (children	Percent of Households
	Children	(children	Eligible for	with Children	(children	Eligible for	with Children	under age	Eligible for
	under 18 <sup>a</sup>	under age 13) <sup>b</sup>	the CCS	under 18	under age 13)	the CCS	under 18	13)	the CCS
Two-prarent	1,116,171	94,134	8%	484,972	63,429	13%	2,066,295	277,810	13%
Single parent	853,185	170,983	20%	409,335	98,577	24%	1,808,673	378,408	21%
Total Households	1,969,356	265,117	13%	894,307	162,006	18%	3,874,968	656,218	17%

 $<sup>{}^{\</sup>rm a}$ This number is based on the ACS 2001 public use household file.

<sup>&</sup>lt;sup>b</sup>The monthly thresholds increased for all family sizes in 5/2000 and again in 1/2002.

<sup>&</sup>lt;sup>c</sup>Monthly thresholds for family sizes over eight are not specified.

<sup>&</sup>lt;sup>b</sup>This number is based on the project data created at the RDC and based on the probability of parent status, probability of eligibility, work qualification, and ACS sample weight.

Table 6. Study populations for longitudinal analysis in 2001: Illinois, Maryland, and  ${\bf Texas}^{\rm a}$ 

Weighted Number of Single Parent

		Families	
	Illinois	Maryland	Texas
Longitudinal CCS Participation Employment Spell Termination	73,940 112,584	53,961 60,387	240,994 263,049
Exceeding Income Threshold	112,584	60,387	263,049

<sup>&</sup>lt;sup>a</sup> Study populations are based on the project data created at the RDC and based on the probability of parent status, UI income eligibility, UI work qualification, and ACS sample weight.

Table 7. Characteristics of the study population in 2001 by marital status: Illinois, Maryland, and Texas (column

Single   Two-parent   parent   paren	Table 7. Characteristics of the study p	Illinois			yland	Texas		
Total weighted N         265,117         162,006         656,218           Weighted N         170,983         94,134         98,577         63,429         378,408         277,810           Weighted %         64.49%         35.51%         60.85%         39,15%         57.66%         42.34%           Program participation           Received TANF in 3 months before or after interview         46.04%         37.25%         38.12%         27.94%         61.77%         52.67%           Individual respondent characteristics         Urban residence         46.04%         37.25%         38.12%         27.94%         61.77%         52.67%           Age         424         40.12%         7.00%         20.09%         6.36%         21.49%            <34          4.2.4         40.12%         7.00%         20.09%         6.36%         21.49%            <34                         47.67%         35.1%         52.33%         58.9 <t< th=""><th></th><th>Single</th><th>Two-</th><th></th><th></th><th></th><th></th></t<>		Single	Two-					
Weighted N Weighted N Weighted %         170,983 by 4,134 by 6,439 by 35.51% by 60.85% by 39.15% by 57.66% by 23.43%         277,810 by 23.43% by 57.66% by 27.810		parent	parent	parent	parent	parent	parent	
Weighted %         64.49%         35.51%         60.85%         39.15%         57.66%         42.34%           Program participation           Received TANF in 3 months before or after interview         10.05%         -*         4.81%         -*         8.30%         0.51%           Individual respondent characteristics           Urban residence         46.04%         37.25%         38.12%         27.94%         61.77%         52.67%           Age        24         40.12%         7.00%         20.09%         6.36%         21.49%            25-34         35.09%         35.47%         46.75%         35.11%         40.67%            8-male         84.99%         n/a         87.92%         n/a         84.98%         n/a           Race         Nomwhite         49.34%         25.99%         66.59%         33.95%             White         50.66%         74.01%         33.41%         66.05%         59.17%         70.63%           Black             17.64%         54.99%           Hispanic ethnicity         16.53%         21.37%           12.53%	Total weighted N	265	,117	162	,006	656	,218	
Weighted %         64.49%         35.51%         60.85%         39.15%         57.66%         42.34%           Program participation           Received TANF in 3 months before or after interview         10.05%         -*         4.81%         -*         8.30%         0.51%           Individual respondent characteristics           Urban residence         46.04%         37.25%         38.12%         27.94%         61.77%         52.67%           Age        24         40.12%         7.00%         20.09%         6.36%         21.49%            25-34         35.09%         35.47%         46.75%         35.11%         40.67%            8-male         84.99%         n/a         87.92%         n/a         84.98%         n/a           Race         Nomwhite         49.34%         25.99%         66.59%         33.95%             White         50.66%         74.01%         33.41%         66.05%         59.17%         70.63%           Black             17.64%         54.99%           Hispanic ethnicity         16.53%         21.37%           12.53%	-	170,983	94,134	98,577	63,429	378,408	277,810	
Received TANF in 3 months before or after interview         10.05%         -*         4.81%         -*         8.30%         0.51%           Individual respondent characteristics         Urban residence         46.04%         37.25%         38.12%         27.94%         61.77%         52.67%           Age         -24         40.12%         7.00%         20.09%         6.36%         21.49%            <=34         -         -         -         -         -         -         47.67%           35-99         24.79%         57.53%         33.16%         58.53%         37.84%         52.33%           Female         84.99%         n/a         87.92%         n/a         84.98%         n/a           Race         Nonwhite         49.34%         25.99%         66.59%         33.95%             White         50.66%         74.01%         33.41%         66.05%         59.17%         70.63%           Black         -         -         -         -         -         23.73%         5.30%           Other         -         -         -         -         -         -         43.60%         59.99%           Hispanic ethnicity		64.49%		60.85%	39.15%	57.66%	42.34%	
Individual respondent characteristics         Individual respondent characteristics           Urban residence         46.04%         37.25%         38.12%         27.94%         61.77%         52.67%           Age          22-34         40.12%         7.00%         20.09%         6.36%         21.49%            ≤3-34         35.09%         35.47%         46.75%         35.11%         40.67%            ≤34              47.67%           35-99         24.79%         57.53%         33.16%         58.53%         37.84%         52.33%           Female         84.99%         n/a         87.92%         n/a         84.98%         n/a           Race         Nonwhite         49.34%         25.99%         66.59%         33.95%             White         50.66%         74.01%         33.41%         66.05%         59.17%         70.63%           Black             23.73%         5.30%           Other             43.60%         59.17%         70.63%           Hispanic ethnici	Program participation							
Individual respondent characteristics Urban residence  Age  <=24  40.12% 7.00% 20.09% 6.36% 21.49% 25.34 35.09% 35.47% 46.75% 35.11% 40.67% 25.34 35.99% 35.47% 46.75% 35.11% 40.67% 35.99 24.79% 57.53% 33.16% 58.53% 37.84% 52.33% Female  84.99% n/a 87.92% n/a 84.98% n/a  Race  Nonwhite  49.34% 25.99% 66.59% 33.95% White  50.66% 74.01% 33.41% 66.05% 59.17% 70.63% Black White  50.66% 74.01% 33.41% 66.05% 59.17% 70.63% Black Urban	Received TANF in 3 months before or	10.05%	*	A Q10%	*	8 30%	0.51%	
Urban residence A6.04% 37.25% 38.12% 27.94% 61.77% 52.67% Age	after interview	10.03%	'	4.0170		6.30%	0.5170	
Age           2-24         40.12%         7.00%         20.09%         6.36%         21.49%            25-34         35.09%         35.47%         46.75%         35.11%         40.67%            35-99         24.79%         57.53%         33.16%         58.53%         37.84%         52.33%           Female         84.99%         n/a         87.92%         n/a         84.98%         n/a           Race         Nonwhite         49.34%         25.99%         66.59%         33.95%             White         50.66%         74.01%         33.41%         66.05%         59.17%         70.63%           Black             23.73%         5.30%         51.7%         70.63%           Black              17.64%         24.09%           Other             17.64%         24.09%           Hispanic ethnicity         16.53%         21.37%           17.64%         24.09%           Has a disability         9.39%         15.06%         6.	Individual respondent characteristics							
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Urban residence	46.04%	37.25%	38.12%	27.94%	61.77%	52.67%	
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Age							
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	<=24	40.12%	7.00%	20.09%	6.36%	21.49%		
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	25-34	35.09%	35.47%	46.75%	35.11%	40.67%		
Female Race         84.99%         n/a         87.92%         n/a         84.98%         n/a           Race         Nonwhite         49.34%         25.99%         66.59%         33.95%             White         50.66%         74.01%         33.41%         66.05%         59.17%         70.63%           Black             23.73%         5.30%           Other             17.64%         24.09%           Hispanic ethnicity         16.53%         21.37%           43.60%         51.99%           Has a disability         9.39%         15.06%         6.57%         12.53%         9.55%         9.25%           Non-US citizen         8.69%         17.37%           12.78%          *           Keilducation         21.17%         21.55%         16.41%         14.50%         30.54%         28.09%           High school         39.43%         31.19%         41.67%         32.61%         31.69%         29.78%           > High school         39.40%         47.26%         42.19%         52.89%         37.78%	<=34						47.67%	
Race       Nonwhite       49.34%       25.99%       66.59%       33.95%           White       50.66%       74.01%       33.41%       66.05%       59.17%       70.63%         Black            23.73%       5.30%         Other           17.64%       24.09%         Hispanic ethnicity       16.53%       21.37%         43.60%       51.99%         Has a disability       9.39%       15.06%       6.57%       12.53%       9.55%       9.25%         Non-US citizen       8.69%       17.37%      *      *       12.78%      *         Education       21.17%       21.55%       16.41%       14.50%       30.54%       28.09%         High school       39.43%       31.19%       41.67%       32.61%       31.69%       29.78%         > High school       39.40%       47.26%       42.19%       52.89%       37.78%       42.13%         Family characteristics         Has a child cage 2       21.93%       21.16%       19.30%       19.85%       21.69%       23.15%         Has a chil	35-99	24.79%	57.53%	33.16%	58.53%	37.84%	52.33%	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Female	84.99%	n/a	87.92%	n/a	84.98%	n/a	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Race							
Black Other              1.7           17.64%         24.09%           Hispanic ethnicity         16.53%         21.37%           43.60%         51.99%           Has a disability         9.39%         15.06%         6.57%         12.53%         9.55%         9.25%           Non-US citizen         8.69%         17.37%        *        *         12.78%        *           Education         *        *        *         12.78%        *           Education          21.17%         21.55%         16.41%         14.50%         30.54%         28.09%           High school         39.43%         31.19%         41.67%         32.61%         31.69%         29.78%           > High school         39.40%         47.26%         42.19%         52.89%         37.78%         42.13%           Family characteristics           Has a child cage 2         21.93%         21.16%         19.30%         19.85%         21.69%         23.15%           Has a child in preschool         16.14%         16.41%         10.53%        *         15.92%	Nonwhite	49.34%	25.99%	66.59%	33.95%			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	White	50.66%	74.01%	33.41%	66.05%	59.17%	70.63%	
Hispanic ethnicity       16.53%       21.37%         43.60%       51.99%         Has a disability       9.39%       15.06%       6.57%       12.53%       9.55%       9.25%         Non-US citizen       8.69%       17.37%      *      *       12.78%      *         Education       21.17%       21.55%       16.41%       14.50%       30.54%       28.09%         High school       39.43%       31.19%       41.67%       32.61%       31.69%       29.78%         > High school       39.40%       47.26%       42.19%       52.89%       37.78%       42.13%         Family characteristics       14.30%       47.26%       42.19%       52.89%       37.78%       42.13%         Has a child < age 2	Black					23.73%	5.30%	
Has a disability       9.39%       15.06%       6.57%       12.53%       9.55%       9.25%         Non-US citizen       8.69%       17.37%      *      *       12.78%      *         Education      *      *       12.78%      *         4 High school       21.17%       21.55%       16.41%       14.50%       30.54%       28.09%         High school       39.43%       31.19%       41.67%       32.61%       31.69%       29.78%         > High school       39.40%       47.26%       42.19%       52.89%       37.78%       42.13%         Family characteristics         Has a child < age 2	Other					17.64%	24.09%	
Has a disability       9.39%       15.06%       6.57%       12.53%       9.55%       9.25%         Non-US citizen       8.69%       17.37%      *      *       12.78%      *         Education      *      *       12.78%      *         4 High school       21.17%       21.55%       16.41%       14.50%       30.54%       28.09%         High school       39.43%       31.19%       41.67%       32.61%       31.69%       29.78%         > High school       39.40%       47.26%       42.19%       52.89%       37.78%       42.13%         Family characteristics         Has a child < age 2	Hispanic ethnicity	16.53%	21.37%			43.60%	51.99%	
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	· •	9.39%	15.06%	6.57%	12.53%	9.55%	9.25%	
		8.69%	17.37%	*	*	12.78%		
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$								
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	< High school	21.17%	21.55%	16.41%	14.50%	30.54%	28.09%	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	•							
Has a child < age 2	-							
Has a child < age 2	Family characteristics							
Has a child in preschool $16.14\%$ $16.41\%$ $10.53\%$ $*$ $15.92\%$ $12.45\%$ Has ≥ 3 children < age 13		21.93%	21.16%	19.30%	19.85%	21.69%	23.15%	
Has ≥ 3 children < age 13       19.00%       20.35%       10.68%       13.69%       16.89%       19.50%         Transportation to work characteristics         Length of commute         ≤10 minutes       22.15%       23.01%       13.13%       21.13%       25.93%       27.64%         Average (>10 and <25 minutes)								
	=				13.69%			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Transportation to work characteristics							
Average (>10 and <25 minutes)	Length of commute							
≥25 minutes 35.92% 28.48% 43.81% 27.77% 26.89% 23.47% Takes public transportation to work 15.21%* 18.88%* 4.17%* Time of departure for work Leaves home before 6am 6.87% 9.04% 12.69%* 8.28% 8.14%	≤10 minutes	22.15%	23.01%	13.13%	21.13%	25.93%	27.64%	
≥25 minutes 35.92% 28.48% 43.81% 27.77% 26.89% 23.47% Takes public transportation to work 15.21%* 18.88%* 4.17%* Time of departure for work Leaves home before 6am 6.87% 9.04% 12.69%* 8.28% 8.14%	Average (>10 and <25 minutes)	41.92%	48.51%	43.05%	51.10%	47.18%	48.89%	
Time of departure for work  Leaves home before 6am  6.87%  9.04%  12.69% *  8.28%  8.14%		35.92%	28.48%	43.81%	27.77%	26.89%	23.47%	
Time of departure for work  Leaves home before 6am  6.87%  9.04%  12.69% *  8.28%  8.14%							*	
Leaves home before 6am 6.87% 9.04% 12.69%* 8.28% 8.14%								
		6.87%	9.04%	12.69%	*	8.28%	8.14%	
11.01.00 00.10/0 00.01/0 00.00/0 00.01/0	Average	80.45%	82.22%	76.27%	*	83.50%	83.54%	
Leaves home after 2pm 12.67% 8.74% 11.03% 9.47% 8.22% 8.32%	_				9.47%			

\*Note: Results cannot be disclosed due to small cell size

Table 8. CCS participation within 3 months of ACS interview, by marital status

•	Illin	nois	Mary	yland	Te	xas
	Weighted N	Weighted row %	Weighted N	Weighted row %	Weighted N	Weighted row %
Total	58,494	22.06%	12,715	7.85%	47,372	7.22%
Marital status						
Two-parent	4,813	5.11%	1,445	2.28%	3,911	1.41%
Single parent	53,682	31.40%	11,269	11.43%	43,461	11.49%
Total weighted N	265	,117	162	,006	656	,218

Table 9. CCS participation within 3 months of ACS interview, by marital status and characteristics of respondent (row %)

	Illinois		Maryland		Texas	
•	Unmarried	Married	Unmarried	Married	Unmarried	Married
Total	31.40%	5.11%	11.43%	2.28%	11.49%	1.41%
Program participation						
TANF receipt						
Not within 3 months of survey	28.19%	*	10.93%	*	8.65%	1.29%
Within 3 months of survey	60.07%	*	21.46%	*	42.82%	25.09%
Individual respondent characteristics						
Residence						
Urban area	38.05%	5.84%	9.46%	1.26%	10.30%	0.67%
Rest of state	25.72%	4.68%	12.65%	2.67%	13.39%	2.23%
Age	40.0004	20.010	22 - 424	4.5000	10.000	
<=24	42.22%	20.01%	22.64%	17.99%	18.00%	
25-34	33.49%	6.84%	12.57%	2.17%	14.40%	1.000/
<=34 35-99	21 250/	2 220/	2.040/	0.640/	4.650/	1.00%
Gender	21.35%	2.23%	3.04%	0.64%	4.65%	1.78%
Male	10.68%	6.46%	6.72%	3.70%	0.77%	1.06%
Female	35.05%	4.82%	12.08%	2.19%	13.38%	1.49%
Race	33.0370	4.02/0	12.0070	2.17/0	13.36 /0	1.47/0
Nonwhite	44.39%	12.42%	12.97%	3.07%		
White	18.74%	2.55%	8.37%	1.87%	10.69%	1.56%
Black					16.61%	3.78%
Other					8.61%	0.45%
Hispanic ethnicity	20.34%	3.54%			10.63%	0.25%
Disability status						
No disability	31.17%	5.44%	11.48%	1.73%	11.40%	1.47%
Disability	33.57%	3.27%	10.74%	6.10%	12.30%	0.79%
U.S. Citizenship						
Citizen	34.18%	6.02%	*	*	12.91%	*
Non-citizen	2.12%	0.81%	*	*	1.74%	*
Parent education						
< High school	42.12%	0.75%	23.05%	1.29%	12.79%	3.25%
High school	27.43%	4.94%	10.32%	3.32%	8.63%	0.36%
> High school	29.60%	7.21%	8.05%	1.91%	12.82%	0.92%
Family characteristics						
Has a child < age of 2						
No	40.48%	4.36%	13.87%	4.65%	22.48%	1.00%
Yes	28.84%	5.31%	10.84%	1.69%	8.44%	1.53%
Age of children	45.560/	0.250/	20.550/	ata	22.200/	c 000/
Has a child in preschool	45.76%	8.27%	29.57%	*	23.39%	6.80%
Parent does not have child in preschool	28.63%	4.49%	9.30%	*	9.23%	0.64%
Number of children under age 13 Has < 3 children under 13	26.010/	1.460/	10.510/	0.760/	0.050/	1 (20/
Has $\leq$ 3 children under 13	26.91% 50.54%	4.46% 7.65%	10.51% 19.19%	0.76% 11.83%	8.85% 24.44%	1.63% 0.49%
Transportation to work characteristics						
Length of commute						
<10 minutes	22.72%	2.78%	10.24%	0.72%	10.15%	2.72%
Average (b/t 10 & 25 minutes)	29.59%	5.00%	15.98%	2.95%	13.15%	0.84%
>25 minutes	38.85%	7.20%	7.32%	2.23%	9.85%	1.05%
Means of transportation to work						
No public transportation	27.33%	*	13.30%	*	11.36%	*
Public transportation	54.07%	*	3.41%	*	14.47%	*
Time of departure for work						
Early (before 6am)	30.79%	4.12%	5.67%	*	5.00%	9.57%
Average (b/t 6am & 2pm)	30.15%	5.76%	11.02%	*	11.61%	0.75%
Late (2pm or later)	39.63%	0.06%	20.90%	5.47%	16.78%	0.07%

Late (2pm or later) 39.63% (
\*Note: Results cannot be disclosed due to small cell size

 $Table~10.~Odds~ratios~from~logistic~regression~models~of~CCS~participation~within~3~months~of~ACS~interview:~Illinois,\\ Maryland,~and~Texas$ 

iviary and Texas	Illinois		Marylan	d	Texas		
•	Single parent	Two-parent	Single parent	Two-parent	Single parent	Two-parent	
	Sample	Sample	Sample	Sample	Sample	Sample	
Program participation							
Received TANF in 3 months before or	1.57 +		1.13		5.06 ***		
after interview	1.5/ +		1.13		5.06		
Individual respondent characteristics							
Urban residence	0.83	0.59 **	0.69	0.43 +	0.74 +	0.27 ***	
Age	0.03	0.57	0.07	0.15	0.711	0.27	
(< 24)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
25-34	0.72	0.12 ***	0.48 *	0.01 ***	0.92	(1.00)	
35+	0.44 ***	0.02 ***	0.11 ***	0.00 ***	0.49 **	1.26	
Female	3.93 ***	0.57 **	1.37	0.70	14.88 ***	1.24	
Race	3.73	0.57	1.57	0.70	14.00	1.24	
Nonwhite	3.27 ***	19.93 ***	1.38	8.56 ***			
(White)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
Black	(1.00)	(1.00)	(1.00)	(1.00)	1.65 *	5.20 ***	
Other					1.00	1.97	
Hispanic ethnicity	0.97	0.29 ***			1.43 +	0.06 ***	
Has a disability	1.04	0.46 **	2.01	1.23	1.40	0.00	
Non-US citizen	0.06 ***	0.40	2.01	1.23	0.14 ***	0.90	
Education	0.00	0.10			0.14		
< High school	2.22 ***	0.07 ***	2.02 *	0.19 **	1.37	16.69 ***	
			(1.00)	(1.00)	(1.00)	(1.00)	
(High school)	(1.00)	(1.00)	0.89	1.92	1.99 ***	(1.00)	
> High school	1.28	2.01 ***	0.89	1.92	1.99	2.97	
Family characteristics							
Has a child < age 2	1.54 *	0.20 ***	0.81	0.23 **	2.71 ***	2.72 **	
Has a child in preschool	2.15 ***	0.67 *			2.78 ***	8.22 ***	
$\text{Has} \ge 3 \text{ children} < \text{age } 13$	2.02 ***	2.91 ***	1.66	29.56 ***	2.15 ***	0.20 ***	
Transportation to work characteristics							
Length of commute							
<10 minutes	0.68 +	0.86			1.01	1.00	
(Average-b/t 10 & 25 minutes)	(1.00)	(1.00)			(1.00)	(1.00)	
>25 minutes	1.13	2.38 ***			1.02	1.05	
Takes public transportation to work	1.00				1.05		
Time of departure for work							
Leaves home before 6am	0.95	0.42 **			0.35 **	5.45 ***	
(Average-b/t 6am & 2pm)	(1.00)	(1.00)			(1.00)	(1.00)	
Leaves home after 2pm	1.76 *	0.01 **			1.47	0.03 *	

\*\*\*p<.001, \*\*p<.01, \*p<.05

Table~11.~Relative~risk~ratios~from~discrete~time~hazard~model~of~CCS~participation~after~ACS~interview:~Illinois,~Maryland,~and~Texas

	II	linois	Mai	ryland	Texas		
		Model with no transportation to work		Model with no transportation to work		Model with no transportation to work	
	Full Model	characteristics	Full Model	characteristics	Full Model	characteristics	
Individual respondent characteristics							
Urban residence	0.65	1.02			0.82	0.74	
Age							
(< 24)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
25-34	0.46 +	0.52 +	0.63	0.69	1.16	1.09	
35+	0.12 ***	0.18 ***	0.23 +	0.24 +	0.40 *	0.40 *	
Female	0.95	1.14			8.79 *	9.10 *	
Race							
Nonwhite	1.69	1.74	1.87	1.44	1.69 *	1.67 *	
(White)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
Hispanic ethnicity	0.52	0.51			0.96	0.92	
Has a disability	3.43 **	3.36 **			0.78	0.77	
Education							
< High school	1.77	1.45	0.60	0.56	0.70	0.72	
(High school)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
> High school	2.69 *	2.75 *	1.43	1.55	0.72	0.71	
Family characteristics							
Has a child < age 2	0.92	1.17	1.75	1.94	4.40 ***	4.49 ***	
Has a child in preschool	1.24	1.33			3.25 ***	2.96 ***	
Has > 3 children < age 13	1.66	1.47			1.23	1.22	
Transportation to work characteristics							
Length of commute							
<10 minutes	0.68		1.71		0.99		
(Average-b/t 10 & 25 minutes)	(1.00)		(1.00)		(1.00)		
≥25 minutes	2.35 +		2.38		0.62		
Takes public transportation to work	1.95		0.47				
Time of departure for work							
Leaves home before 6am	1.21				0.56		
(Average-b/t 6am & 2pm)	(1.00)		(1.00)		(1.00)		
Leaves home after 2pm	2.52 *		` <del></del>		0.92		
Number of quarters eligible	0.86 +	0.82 *	0.78 *	0.76 *	0.73 ***	0.73 ***	

\*\*\*p<.001, \*\*p<.01, \*p<.05

Table~12.~Relative~risk~ratios~from~discrete~time~hazard~model~of~employment~termination~after~ACS~interview:~Illinois,~Maryland,~and~Texas

1 exas	П	linois	Ma	nryland	Texas		
		Model with no transportation to work		Model with no transportation to work		Model with no transportation to work	
	Full Model	characteristics	Full Model	characteristics	Full Model	characteristics	
Program participation							
Received TANF in current quarter	1.60 +	1.51 +	2.59 *	2.66 ***	1.41 +	1.46 *	
CCS participation in previous quarter	0.75	0.71 +	0.94	0.97	0.87	0.85	
Individual respondent characteristics							
Urban residence	1.65 **	1.54 *	1.88 *	1.88 *	1.20 +	1.21 +	
Age							
(< 24)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
25-34	0.78	0.74	0.57 *	0.54 *	0.54 ***	0.55 ***	
35+	0.56 **	0.53 **	0.78	0.75	0.53 ***	0.54 ***	
Female	0.62 *	0.55 **	1.48	1.99	0.80	0.79	
Race							
(White)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
Black	1.17	1.24	1.42	1.51 +	1.12	1.11	
Other	0.63	0.49 *	0.63	0.52	1.25	1.21	
Hispanic ethnicity	1.48	1.85 *	1.74	1.37	0.51 ***	0.53 ***	
Has a disability	1.81 *	1.93 **	0.73	0.83	1.18	1.08	
Non-US citizen	0.44 +	0.44 +	2.28	2.79	0.94	0.93	
Education							
< High school	1.37 +	1.39 +	1.35	1.24	1.36 *	1.33 *	
(High school)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
> High school	0.81	0.80	0.49 **	0.54 *	1.17	1.19	
Family characteristics							
Has a child < age 2	1.18	1.04	1.29	1.22	1.13	1.13	
Has a child in preschool	0.63 *	0.56 *	0.57	0.55	1.14	1.19	
Has > 3 children < age 13	0.77	0.66 +	0.37 *	0.40 *	1.12	1.11	
Transportation to work characteristics							
Length of commute							
≤10 minutes	0.57 **		0.63		0.74 *		
(Average-b/t 10 & 25 minutes)	(1.00)		(1.00)		(1.00)		
≥25 minutes	0.54 *		1.17		0.92		
Takes public transportation to work	0.83		1.90 *		0.57 +		
Time of departure for work							
Leaves home before 6am	0.60		0.40 *		1.19		
(Average-b/t 6am & 2pm)	(1.00)		(1.00)		(1.00)		
Leaves home after 2pm	0.60 +		1.51		0.55 **		
Number of quarters eligible	0.95 +	0.94 +	1.04	1.00	0.92 ***	0.92 ***	
*** 001 ** 05							

\*\*\*p<.001, \*\*p<.01, \*p<.05

Table 13. Relative risk ratios from discrete time hazard models of exceeding income ceiling for CCS eligibility after ACS interview: Illinois, Maryland, and Texas

	Illinois		Maryland		Texas	
		Model with no transportation to work		Model with no transportation to work		Model with no transportation to work
	Full Model	characteristics	Full Model	characteristics	Full Model	characteristics
Program participation CCS participation in previous quarter	0.62 +	0.65 +	0.35 *	0.39 *	0.65 +	0.72
Individual respondent characteristics						
Urban residence	1.28	1.76 *	0.76	0.93	1.60 **	1.60 **
Age						
( <u>&lt;</u> 24)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
25-34	0.83	1.00	2.00 *	2.43 *	0.99	1.01
35+	0.44 **	0.58 +	1.53	1.53	0.55 **	0.60 *
Female	0.48 *	0.51 *	0.44 *	0.39 **	0.56 **	0.57 **
Race						
Nonwhite			1.58	1.09		
(White)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Black	0.72	0.91			1.02	0.87
Other	0.59	0.44 +			0.90	0.94
Hispanic ethnicity	0.74	0.97		-	1.05	0.98
Has a disability	0.16 **	0.22 *	1.69	1.85	0.55 *	0.53 *
Non-US citizen	0.36	0.31 +		-	1.02	0.97
Education						
< High school	0.49 +	0.40 *	0.38 *	0.34 *	0.50 ***	0.49 ***
(High school)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
> High school	1.47	1.52 +	0.64 +	0.71	1.08	1.15
Family characteristics						
Has a child < age 2	0.98	0.97	0.87	0.96	1.17	1.22
Has a child in preschool	1.39	1.55 +	0.69	0.51 +	1.43 *	1.41 *
Has > 3 children < age 13	0.43 *	0.53 +	0.18 **	0.51 **	0.53 **	0.54 **
Transportation to work characteristics Length of commute						
<10 minutes	0.39 **		0.45 +		1.07	
(Average-b/t 10 & 25 minutes)	(1.00)		(1.00)		(1.00)	
>25 minutes	2.02 **		2.36 **		1.61 **	
Takes public transportation to work	0.87		0.43 *		0.22 **	
Time of departure for work						
Leaves home before 6am	0.65				0.52 *	
(Average-b/t 6am & 2pm)	(1.00)		(1.00)		(1.00)	
Leaves home after 2pm	1.81 *		1.33		0.77	
Number of quarters eligible	0.89 **	0.88 **	1.02	0.97	0.85 ***	0.85 ***

<sup>\*\*\*</sup>p<.001, \*\*p<.01, \*p<.05

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**APPENDIX 1: TABLES** 

Appendix Table 1. Relative risk ratios from discrete time hazard model of employment termination after ACS interview, Illinois, Maryland, and Texas

	Illinois	Maryland	Texas
Program participation			
Received TANF in current quarter	1.63 ***	2.69 ***	1.49 ***
CCS participation in previous quarter	0.44 ***	0.88 ***	0.64 ***
CCS participation in previous quarter	1.20 ***	1.03 ***	1.09 ***
X # quarters 'at risk'	1.20	1.05	1.09
Individual respondent characteristics			
Urban residence	1.46 ***	1.88 ***	1.21 ***
Age	1.10	1.00	1.21
(≤ 24)	(1.00)	(1.00)	(1.00)
25-34	0.70 ***	0.54 ***	0.55 ***
35+	0.51 ***	0.74 ***	0.54 ***
Female	0.68 ***	1.96 ***	0.78 ***
Race			
(White)	(1.00)	(1.00)	(1.00)
Black	1.22 ***	1.51 ***	1.12 ***
Hispanic/Other	1.14 ***	0.62 ***	
Hispanic			0.57 ***
Other			1.42 ***
Has a disability	1.69 ***	0.84 ***	1.08 ***
Non-US citizen	0.56 ***	3.09 ***	0.92 ***
Education			
< High school	1.45 ***	1.24 ***	1.34 ***
(High school)	(1.00)	(1.00)	(1.00)
> High school	0.83 ***	0.54 ***	1.19 ***
Family share staristics			
Family characteristics	1.03 *	1.22 ***	1.12 ***
Has a child < age 2			1.12 ***
Has a child in preschool	0.57 ***	0.55 ***	
Has > 3 children < age 13	0.64 ***	0.41 ***	1.14 ***
Number of quarters eligible	0.86 ***	0.99 *	0.19 ***

<sup>\*\*\*</sup>p<.001, \*\*p<.01, \*p<.05

Appendix Table 2. Relative risk ratios from discrete time hazard model of exceeding income ceiling for CCS eligibility after ACS interview, Illinois, Maryland, and Texas

	Illinois	Maryland	Texas
Program participation			
CCS participation in previous quarter	0.66 ***	0.18 ***	0.45 ***
CCS participation in previous quarter	0.99	1.27 ***	1.19
X # quarters 'at risk'	0.99	1.27	1.19
Individual respondent characteristics			
Urban residence	1.79 ***	0.84 ***	1.62 ***
Age			
( <u>&lt;</u> 24)	(1.00)	(1.00)	(1.00)
25-34	0.99	2.46 ***	1.01
35+	0.57 ***	1.46 ***	0.60 ***
Female	0.57 ***	0.34 ***	0.58 ***
Race			
(White)	(1.00)	(1.00)	(1.00)
Black	0.87 ***	1.13 ***	0.83 ***
Hispanic/Other	0.59 ***	1.49 ***	0.90 ***
Has a disability	0.21 ***	2.02 ***	0.53 ***
Non-US citizen	0.32 ***		1.01
Education			
< High school	0.41 ***	0.33 ***	0.48 ***
(High school)			
> High school	1.53 ***	0.66 ***	1.15 ***
_			
Family characteristics			
Has a child < age 2	1.03	0.90 ***	1.19 ***
Has a child in preschool	1.54 ***	0.46 ***	1.41 ***
Has > 3 children < age 13	0.52 ***	0.17 ***	0.55 ***
-			
Number of quarters eligible	0.88 ***	0.95 ***	0.83 ***

<sup>\*\*\*</sup>p<.001, \*\*p<.01, \*p<.05

## **APPENDIX 2: PROJECT DELAY SUMMARY**

When the opportunity arose to build on previous work by undertaking a research project using matched Census Bureau and state administrative data, we were excited at the possibility. Cautioned by colleagues in California who had attempted a similar application with the Research Data Center (RDC) at the University of California Los Angeles, we felt confident that we were well-positioned to apply. We had firm commitment from the U.S. Census Bureau, strong relationships with key personnel there committed to moving the project forward, deep organizational resources, and a timeline we thought generous enough to accommodate the tasks required to complete the project as scheduled. We were up front with our partners and colleagues regarding the reality of the challenges faced by previous research teams attempting this kind of work, and were assured that this work fell into a priority research area for the Census and that as such, it would receive the highest degree of oversight and attention.

Undertaking such a research collaboration using U.S. Census data matched to state administrative data, however, was a far more time-consuming and complicated process than we could have anticipated. In short, the research project documented here encountered significant delays such that the entire project was extended by more than a year. Sources of significant delay (and therefore expense) are threefold: the process required for researchers to obtain the necessary Special Sworn Status (SSS) designation, which permits them to access data at the RDC(s) for analysis; the complex process of negotiating and securing the necessary agreements to share data between states, sponsoring research centers and the U.S. Census Bureau; and the RDC proposal process that one must navigate to obtain access to matched data at the RDC. Each of these areas contributed to significant project delay, and will be discussed below in further detail.

The American Community Survey is conducted under the authority of Title 13, United States Code, Sections 141 and 193, which requires that all information about respondents must be kept strictly confidential. Only Census employees and individuals with Census Special Sworn Status can have access to the Title 13-protected data files. Thus, in order to gain access to U.S. Census Bureau data or have access to a Census Bureau site (e.g. RDC), individual researchers must navigate a complex and detailed process to obtain SSS as a temporary Census Bureau employee. This process includes an extensive background investigation, fingerprinting, and the submission of several federal forms including:

- SF-171, Application for Federal Employment;
- OFI-86C, Special Agreement Check;
- SF-85, Questionnaire for Non-Sensitive Positions; and
- BC 1759, the application for Special Sworn Status

Once these forms are completed and reviewed, the applicant researcher must successfully complete RDC orientation and take the oath of non-disclosure of the data. He or she is then issued a Census Bureau Contractor badge and may begin work at the RDC.

The proposed timeline for this project underestimated the time required for each of the research team members to obtain Census Bureau SSS. The team met together in Washington D.C. in February 2005 to work on the analysis plan and discuss other project details, at which time the process for beginning the SSS was outlined and materials available were provided. Each of the team members individually set out to complete forms, obtain finger prints, and gather other necessary documentation. By September 2005, all forms and other requirements had been completed by each research team member and submitted to the Census Bureau. Team members were successfully sworn in at a group meeting in November 2005 at the Census Bureau in Suitland, Maryland. However, in January 2006, in order to improve security, the Census

Bureau implemented a new and updated process for obtaining SSS. Any temporary status granted prior to this date was null and void. In addition, any Title 13 and Title 26 training the team had completed in fall 2005 was now also void, as trainings are valid only by federal fiscal year. Team members set about to complete and submit all new paperwork, along with the entire staff of the U.S. Department of Commerce and all others requiring SSS renewal under the more stringent procedures. New SSS was granted to team members 9 months later, in November 2006, one full year after the initial approval.

The Census Bureau has, since this initial experience, been successful in reducing the time between application and approval. A new team member who began the SSS application process for this project in September 2007 required only 8 weeks for approval. It was the poor timing of our initial application (coinciding with security changes) that lengthened this process for us.

Another significant source of delay was obtaining the necessary permission needed from each of the state agencies in Illinois, Maryland and Texas to share with the U.S. Census Bureau confidential state data from each state's administrative data systems. The process undertaken to obtain permission varied across the three states. In Illinois and Texas, Memorandums of Understanding ("MOUs") were needed between each of the research institutions conducting this work (the Chapin Hall Center for Children and the Ray Marshall Center) and the Census Bureau in which the parties agreed on appropriate practices for both the transfer of the data and maintaining the confidentiality of the data, as well as safeguards around data transfer and maintenance. In Maryland, a three-way MOU was negotiated between the state agency, the research institution (National Center for Children in Poverty) and the U.S. Census Bureau specifying the terms under which the child care data could be shared. An amendment to an existing MOU was negotiated between another state agency and the U.S. Census Bureau for the

sharing of TANF data. Approval also had to be obtained from yet another state agency for the use of unemployment insurance wage data from the Census Bureau's LEHD data system.

Our original proposal to the Census Bureau suggested that this "data sharing agreement" phase of the project would require approximately 6 weeks (projected to occur between October 11, 2004 and December 15, 2004). In fact, all agreements were not signed and in place until February 2006, a delay of well over one year. The sources of this delay were many. First of all, the sheer number of states (3) and state agencies involved (6+) resulted in an iterative and complex web of communication and review involving state policy and legal teams which lasted several months longer than anticipated. Negotiating agreements to share sensitive administrative data with the Census Bureau is by its very nature a slow process, involving multiple reviews, checkpoints, edits and signatures to ensure confidentiality and integrity in the process. In our case, this process was further complicated by changing personnel at the Census Bureau, where those with whom we had been working were reassigned or otherwise left the Bureau before the completion of the agreement at hand. This made communication more difficult and interrupted the process.

Furthermore, the division of the Census we were originally working with was reorganized mid-project (the Planning, Research, and Evaluation Division of the Census Bureau became the Data Integration Division) and those who had been partners in this work from the outset within PRED were shifted toward other Bureau assignments and roles at a time when our project required their continued attention and leadership. While, again, personnel shifts and department reorganizations occur in the government sector as well as the private, and perhaps played a smaller role in delay, they did contribute to our general feeling of instability with our

Census partners and served as more change in the middle of what was already a much-delayed project.

Finally, the process to develop and submit a research proposal to the RDC took longer than anticipated. Again, we significantly underestimated the task at hand. The original project timeline almost glosses over this element of the project, never itemizing an "RDC project proposal" process line item. It skips directly from SSS being granted to team members to proposing that "researchers from [Chapin Hall] and [the Jacob France Center] [will] work at the Census Bureau as temporary employees" from October 1, 2005 through October 31, 2005, a period of 31 days.

The reality was that our final set of RDC proposal documents (which included a formal proposal, a description of the Title 13 benefits the Census would gain from our research and an abstract) were uploaded to the Center for Economic Studies website in December 2005. Because our project was "breaking new ground" and the RDC had not processed a request such as ours before, and because CES had to secure additional necessary agreements with the Census Bureau's Data Integration Division, the review period ended up being longer than expected, requiring a total of 6 months of review and revision. Preliminary approval was granted in June 2006. To obtain final approval, further negotiation was required between the RDC administrator and the Census Bureau. The RDC proposal was formally approved in November 2006, more than one year after the date when we had originally proposed to submit our final report.

Another complicating factor regarding the RDC proposal process was the debate at its inception as to whether or not this research should be classified as an internal or an external project. Initially classified as external, it was proposed among Census team members that we could benefit (procedurally) from classification as an internal project. By classifying the project

as internal, they suggested that we would be able to move more quickly through the approval process. Given that we were so far behind already, this was an appealing proposition. What was not anticipated, however, was that ultimately an internal project designation would actually result in greater project delay. The Census Bureau would now be the official 'author' of the work, and as such, would need to approve all project output. This additional layer of review and approval added time to the project that would have been unnecessary as an external project.

In sum, there were project complexities at every level for this work that could not have been anticipated at the outset. We proposed a research study involving three different states, multiple datasets, complex research questions, and a resulting set of procedures that were not routine for the Census Bureau's Data Integration Division nor for its Center for Economic Studies. To accommodate the delay in our project timeline, we successfully submitted two separate No Cost Extensions, each one for a 6-month period, which extended the end date of the overall project to November 30, 2007. This delay resulted in significant cost being absorbed by the sponsoring research institutions.

Finally, our project proposal specified that because this research work might be of interest to other states, we would produce a Resource Guide at the conclusion of the project. This guide would provide "lessons learned" and guidance on how other states could replicate this work. We have decided that because of the issues and problems encountered over the course of this project, we cannot recommend this kind of project to other researchers. These projects are costly in time and resources, particularly for those researchers who are not located close to one of the Census Bureau's eight RDCs. Institutional expertise in large data matching is essential. Projects must be consistent with the Census Bureau goals and Census Bureau partners committed to project success. Researchers have to undergo the SSS process, which even when it flows

smoothly is burdensome with periodic training required and serious penalties for those who violate the provisions of Title 13 (a fine of up to \$250,000 or a prison sentence of up to 5 years, or both). The Census Bureau is subject to periodic institutional and procedural changes that can seriously affect the continuity of projects. As a result, we are recommending in our Resource Guide that states use publicly available Census data in conjunction with public and non-public use state administrative data. For a discussion on the use of public use Census data in this research context, see Appendix 4.

# APPENDIX 3: DEVELOPING THE CHAPIN HALL CHILD CARE SUBSIDY ELIGIBILITY MODEL

### **Abstract:**

Administrative records are readily usable for analyzing the characteristics of program participants. However, they are significantly less directly usable for determining who is eligible or qualified for a program. One possible approach for making this type of imputation is applying known eligibility rules to relevant household characteristic data. Such an approach implicitly assumes that the household characteristic data are reliable and that the relationship of household members to each other is known or unimportant. The model described in this paper does not accept these assumptions. Instead it models family relationships and qualifying income based on recorded values for these in program administrative record data.

#### **Introduction:**

The Child Care Subsidy program is a federal-level program that is tailored and administered separately by each state. The program is intended to assist low-income families in paying for childcare so to allow adult family members the ability to seek and retain gainful employment. To evaluate the utilization and the efficacy of the Child Care Subsidy (CCS) program it is useful to be able to distinguish those families that are eligible to participate in the program from those that are not. Being able to make this distinction allows the computation of take-up rates both in aggregate and according to various demographic factors and also allows the comparison of outcomes among eligible families between those participating in the program and those not participating in the program. The Chapin Hall Center for Children in conjunction with the U.S.

Bureau of The Census, University of Chicago, Columbia University National Center for Children in Poverty, University of Texas at Austin Ray Marshall Center for the Study of Human Resources, University of Baltimore Jacob France Institute sponsored a project to establish a database that allowed for the evaluation of the use and performance of the Child Care Subsidy program in several states: Maryland, Illinois, and Texas. Critical to evaluation was the determination of Child Care Subsidy Eligibility for families included in the study database. For didactic simplicity, this paper will focus on the establishment of an eligibility model for Texas residents. Modeling for Maryland and Illinois largely follow the methods developed originally for Texas. Also, the modeling effort describe herein focused on CCS *income* eligibility. Additional work beyond this discussion added qualification by work- or work training-status to the modeling regime.

To operationalize the analysis of the Child Care Subsidy program, it was decided that this analysis would be conducted on the data collected from the 2001 American Community Survey and Supplementary Survey. These surveys use identical data collection instruments and differ only in the sampling methods used to select participants. Joint weights have been established such that the ACS/SS01 response data can be used to produce estimates for the U.S. resident population. Note that ACS/SS 2001 is ideal for the purposes of analysis due to the extensiveness of data elements, the availability of the data for Census researchers, and the size of the sample. Persons captured by the 2001 ACS/SS 2001 form the universe for the application of this model, and population projections can be made from it by applying existing ACS/SS 2001 weights to the results of the model.

One of the key decisions affecting the development of the eligibility modeling was to have certain of the determinations to be rendered probabilistically rather than deterministically. To clarify this point, consider that for a given family we could have made a yes or no determination regarding Child Care Subsidy eligibility. Rather than do this, the model establishes a probability of eligibility for each modeled family. Also, part of the modeling process consists of the identification of family relationships. This too is characterized probabilistically rather than deterministically. So in cases where more than one adult in a household may potentially be responsible for one or more of the children in a household, a probability characterizes the existence of such relationships. This probability replaces a definitive assignment of responsibility for each child to a particular adult household member.

The reason we chose to characterize eligibility and family relationships probabilistically rather that deterministically is our belief that these probabilistic characterization would provide more effective analysis given that

- They conform more to our state of knowledge that a deterministic characterization
- They allow the level of confidence of the determination to be accounted for in the generated analysis, presumably leading to more accurate results
- They do not result in determinations that later can be shown definitively to be untrue.

Our modeling procedure can be understood to comprise three tasks:

- Development of a family relationship model
- Development of an income eligibility model
- Application of models to database to establish eligibility likelihood.

# **Family Relationship Module:**

To understand the approach that we used, it is useful to review how Texas Department of Family and Protective Services consider families in establishing eligibility and enrollment under the Child Care Subsidy program. First, a childcare subsidy can only be provided to a family that needs this service for a child age twelve or under. Any family not having such a person will be considered not eligible for the subsidy. Based on our review of Texas child care subsidy data, we see that for each child enrolled in the subsidy program, there is a single adult who is recorded as being responsible for the child. Presumably this person is someone with legally established responsibility for the child. It is unclear who is selected as this person with primary responsibility in cases where there is more than one adult with legal responsibility for a child, such as a mother and father in a traditional family structure. Nevertheless, our modeling seeks to replicate the person indicated on administrative records as responsible.

The built model is a logistic regression estimating a probability that a household member is responsible for a specific 12-year-old or younger household member based on three main effects:

# Actual Responsible Adult Status (0 or 1)

## Modeled from

- Sex of Other Household Member
- Age Difference Between Other Household Member and Qualifying Child
- Joint Relationship to Reference Person

To estimate our model coefficients, we use data for enrolled CCS families who are also present in ACS/SS 2001. For each child enrolled in the Texas Child Care Subsidy program in calendar year 2001, we look to see if that same child was a reported on person to ACS/SS during one of the months in which he or she was enrolled. If so, then that child, and the other ACS/SS identified family members for that child form a unit of analysis in developing the family relationship model. For each such child, we look to see which other household members may

potentially be the person responsible for this child (we are looking to see if this household member could have been considered, potentially, to be the responsible person, in the absence of the knowledge of who actually is). We then characterize this household member's relationship to the child. The characterization is made by the age difference between the other member and the child, the sex of the other member, and the joint relationship to the household reference person. The age difference is categorized as follows:

- 17 Years Difference or Less
- 18 24 Years Difference
- 25 34 Years Difference
- 35 44 Years Difference
- 45 Years Difference or More

The household reference person is the person designated by the respondent as being the primary owner or renter of the household residence. The joint relationship is characterized by one of these categories:

Joint Relationship to Reference Person						
	Potentially Responsible Adult's Relationship to Reference Person	<u>Qualifying Child's</u> <u>Relationship to</u> <u>Reference Person</u>				
1.	Same or Spouse	$\leftarrow \rightarrow$	Child			
2.	Same	$\leftarrow \rightarrow$	Grandchild			
3.	Child	$\leftarrow \rightarrow$	Grandchild			
4.	All Other Joint Relationships					

The joint relationship to the household reference person is used rather than the direct relationship between the other member and the child because this direct relationship status is not collected in the ACS/SS survey interview; rather it must be inferred by the joint relationships to the reference person.

Next, for each household with an enrolled child, we use Texas Child Care Subsidy data to determine which household member was actually the responsible person for the enrolled child. If this person cannot be identified on the ACS/SS roster for this household, then this household is removed from the analysis set. Otherwise, we now can organize these data such that for each enrolled child, there are one or more records each for a potentially responsible adult, depending on the number of children 12 years old or younger in the household. On each of these records there is a Boolean variable indicating whether this adult is or is not the actually responsible person for the enrolled child as determined by reference to Texas CCS administrative records. With the data in this format, we are able to run a standard logistic regression. For this regression, we used no interaction terms.

The model just described can be considered the first stage sub-model of the family relationship model. The second stage seeks to summarize to a single value the potentially multiple probabilities for potentially responsible adults from the first stage sub-model: one for each child equal or under 12-years old. The summarized probability generated from the second stage model represents the probability that the person is the responsible party for *at least* one child in the household. The second-stage sub-model is built on the results (that is, the predicted probabilities of responsibility for each child) of the first-stage sub-model. For the second-stage model, the dependent variable is whether a household member is recorded as the responsible party for at least one child enrolled in the Texas Child Care Subsidy program. All of the independent variables are built on the complement,  $P'_{nr} = 1 - P_{nr}$ , of the calculated probability that a household member is not responsible for any child enrolled in the subsidy program, which is computed as  $P_{nr} = 1 - \prod_{i} (1 - p(r_i))$ ,

Where:

 $P_{nr}$  ~ Probability of not being responsible for any enrolled child in household  $p(r_i)$  ~ Calculated (from first-stage sub-model) probability of being responsible for the

i<sup>th</sup> enrolled child in the household.

This value,  $P'_{nr}$  and its square and cube comprise the independent variables for this logistic regression model, which includes no interaction terms:

$$P(\text{responsible for at least one child}) = 1/(1 + \exp(-\beta_0 - \beta_1 \cdot P'_{nr} - \beta_2 \cdot P'_{nr}) - \beta_3 \cdot P'_{nr})$$

Based on the first-stage and second-stage model, it is possible to assign a probability of being the responsible party for a child (twelve years-old or younger) should that family apply and be accepted for the subsidy. However, the results of this modeling, will, in general, not yield a total family probability of responsibility of 1, as is eminently desirable. To overcome this deficiency, we use a normalization procedure that forces the sum of potential responsible persons to equal 1, by dividing each calculated probability from the second-stage sub-model by the sum of these. Then, for developing imputations, we assume that only one person is responsible for all qualifying children in the family. While in some instances this assumption may not be correct, we think that due to the overall structure of the eligibility modeling this does not cause any significant biases in derived estimates of family eligibility.

## **Income Qualification Module:**

Income qualification forms the other probabilistic component of the eligibility model. This modeling compares modeled income to a deterministically referenced income-eligibility threshold. These thresholds conform to those actually applicable in the various workforce development districts in Texas in-place in 2001. Because we have an error model for modeled income, we are able to calculate a probability that income falls below the determined threshold.

To model income, we were able to use the administratively recorded income for enrolled families at the time of the survey. Based on our understanding of program administration, it seems that this recorded income will be most accurate near the time of original recordation. For this reason, when there is a series of recorded incomes for an enrolled family, we include this family in the model only if the first occurrence of any value of recorded income appeared in the month the same family was interviewed for ACS/SS 2001. To model this income, we made use of the ACS/SS reported categorical income: wage, self-employment, disability, etc. In addition to

these data elements, for many of the families used to build the model, we were able to locate the quarterly wage income as reported to the Texas unemployment insurance program, as is required for most employers. These quarterly wage values seemed likely to be in aggregate more accurate that self-reported wage income, a supposition that appeared to bear-out in the modeling process.

Note that our decision to use a model to infer income, and to model to subsidy-program-recorded income rather than make a one-to-one determination of this from ACS/SS and Unemployment Insurance reported values derives from our unwillingness *a-priori* to accept these reported values as unbiased and insubstantially inaccurate. Statistics provided later in this paper seem to confirm that this unwillingness is not unreasonable. Because of the sensitivity of income data and database elements holding these data as well as the complexity of the modeling, we will not present a fully detailed description of the structure of the income model and will instead adumbrate its most significant features.

First, the model was configured differently for married responsible family members that for those single-parent families. For this purpose, we determined marital status based on the recordation of this status for CCS. For two-parent persons, we included the income of the spouse, as best could be determined by us, as explanatory information in the model, yet included it distinctly from income of the primary. Also, the spouse was included in the count of household members. Otherwise only the responsible person and children of the responsible person, 22 year-old and under were counted as family members. The number of family members is relevant because it determines the applicable family income threshold. In fact we used a direct lookup to then existing income threshold tables, which depend wholly on family size for a given location of residence within Texas. Texas is unusual among states by having thresholds that vary by location of residence, all at a given moment.

Second, different models were used depending on the availability of UI quarterly wage data. So the model used depended on both marital status and UI wage income data availability. Where UI wage data was available, we used data from multiple periods, those nearest to the time of interview as this allowed us to model subsidy-program reported income better than using just a single value.

Third, all versions of the models used had a positive intercept and aggregate income coefficients (that is the sum of all the income coefficients in a given model) of less that one. We have not developed a theory of why this is so. Also, predicted income tends to be less than that computed additively from reported (on ACS/SS and UI) income. This may reflect applicants trying to game the system or may instead be an artifact of our modeling procedure. However, comparing the direct additive computation to appropriate threshold values for participants shows that a substantial number of these are enrolled even though that additive value exceeds the threshold. This provides some credence to our modeling strategy.

Fourth, income modeling did in no way depend on demographic factors other than family relationship status (marital partnership and responsibility for children) such as sex, race, and ethnicity. However, in evaluating model performance and generated take-up rates, we did take these factors into account.

Originally, we attempted to model the error of the income model as Normal with the variance estimated by the regression mean square error statistic. However, further analysis showed that in fact error was not normally distributed and instead had more spread than is found there. By performing an analysis that compared program-reported income to modeled income, we identified the best fitting distribution as a Student-T with six degrees of freedom and a standard deviation equal to the applicable regression root mean square error. Using the point estimate of program-reported income in conjunction with this error model allowed us to determine the probability that predicted income fell below the threshold.

# **Application of Model:**

To determine program eligibility, we used a two-stage process that was build correspondingly on the family relationship and income eligibility modeling. First, we selected all ACS/SS 2001 families that had at least one child 12-year-old or younger, and for these children, we used the family relationship model to assign probabilities for each potentially responsible other household member. Second for each potential household member, we computed a probability of income eligibility. For each household then, we computed the probability of being income eligible for CCS as  $P_{ie}^{TH} = \sum_{j} P_{R,j} \cdot P_{ie,j}$ ,

Where:

 $P_{i_e}^{TH}$  ~ Total household probability of being income eligible for CCS.

 $P_{R,i}$  ~ Probability of j<sup>th</sup> household member being responsible for children in household.

 $P_{ie,j}$  ~ Probability of j<sup>th</sup> household member (and their fellow program-application case members together) being income eligible for CCS.

Note, that there are requirements other than income-eligibility to qualify for CCS. Typically, these relate to the requirement for the responsible person (and their spouse, if married) to be either currently employed or in an approved job-training program. Also, these activities must occur at a certain minimum level specified by hours engaged per week. In addition, there are some families that are categorically eligible for CCS because they are enrolled in the Temporary Aid for Needy Families (TANF) program.

For this paper, we terminate our discussion of CCS eligibility modeling with income eligibility. However, the use of this model requires additional computation or modeling of other eligibility requirements, specifically work activity. Researchers using the modeling described in this paper have taken various approaches to modeling work-qualification (participation in approved work or work-training activities). Work qualification can be most readily ascertained by the existence of substantial UI wages for the quarter during which the ACS/SS interview took place. In addition, ACS/SS-reported employment status and hours-per-week at work may be used.

## **Results:**

We conclude this paper by presenting a computation of 2001 subsidy-eligible families and weighted counts of recipients. From this, putative take-up rates can be computed. For this purpose we considered only work-qualification, not training-based qualification, and excluded families categorically eligible due to TANF enrollment. For modeling purposes, we established work-qualification by the ACS/SS field ESR (Employment Status Recode) indicating anything but 'Unemployed' or 'Not in the Labor Force' for the responsible person and their spouse, if married.

# Estimates of the 2001 Mean Monthly Texas CCS Eligible Families

Hhlds. with Ratio of ACS Reported Income: Income Eligibility Threshold <= 1

Ranked into Quintiles By That Ratio

Weighted by ACS/SS 2001 Final Weight

Rank	Mean Ratio of Modeled Income to CCS Income Threshold	Mean Computed Probability of Income Eligibility	Mean Ratio of ACS/SS Reported Income to CCS Income Threshold	Households in Category Eligible Based on ACS/SS Reported Income	Income- Eligibility Model Derived Estimate of Eligible Households	Count of CCS Enrolled Households from Admin. Records
1	0.37	0.97	0.11	110,725	107,723	4,279
2	0.47	0.97	0.34	97,980	94,733	6,239
3	0.57	0.94	0.54	98,034	92,032	5,190
4	0.68	0.88	0.73	93,979	83,025	5,009
5	0.79	0.78	0.91	83,227	65,218	1,092
All	0.56	0.91	0.50	483,946	442,731	21,810

## **Estimates of the 2001 Mean Monthly Texas CCS Eligible Families**

Hhlds. with Ratio of ACS Reported Income: Income Eligibility Threshold > 1

Ranked into Quintiles By That Ratio

Rank	Mean Ratio of Modeled Income to CCS Income Threshold	Mean Computed Probability of Income Eligibility	Mean Ratio of ACS/SS Reported Income to CCS Income Threshold	Households in Category Eligible Based on ACS/SS Reported Income	Income- Eligibility Model Derived Estimate of Eligible Households	Count of CCS Enrolled Households from Admin. Records
1	0.93	0.60	1.24	0	130,224	4,116
2	1.18	0.28	1.75	0	53,775	852
3	1.49	0.10	2.40	0	18,375	78
4	1.91	0.05	3.33	0	7,545	142
5	3.40	0.04	7.35	0	5,937	0
All	1.64	0.25	2.87	0	215,856	5,189

One noteworthy element of these tables is that nearly one-fifth (comparing last-column "All" row values for the two tables) of eligible families have an ACS/SS calculated income greater than the identified threshold value. Derived take-up rates appear somewhat more uniform using the income-eligible model than the straight ACS/SS computation. Also, for households and families with low income, the probability of being income eligible is very high, near 1, as should be expected.

#### **Conclusion:**

The modeling approach taken here takes a hybrid approach of using statistical modeling and probabilistic characterization for some elements of eligibility, family relationship and income, but does not do so for others: age, sex, marital status, number of family members. Of these, we would expect all but marital status to be fairly well reported, and not likely to greatly bias estimates. For marital status, our survey-CCS administrative record matching shows significant levels of disagreement. Were we to attempt to improve this modeling effort, we would consider whether a marital status sub-model would be useful. For the elements that were probabilistically determined, we applied them to computing eligibility by multiplication, which assumes their independence. This does not seem unreasonable, because bias in family relationship determination can be supposed unrelated to bias in income determination. Nevertheless, if there is a covariance between these, they would act to bias our estimates.

While we believe our approach was reasonable given the nature of the data available to us, it is not especially easy to validate this belief based on available data. Tables such as those presented above give us some level of comfort with the results. Additional work is being done by project researchers to evidence the efficacy of our modeling approach. Of these, regressions relating take-up to various social and economic factors seem to produce reasonable associations. We welcome any suggestions that would further this validation or that would allow us to improve this modeling approach in additional iteration.