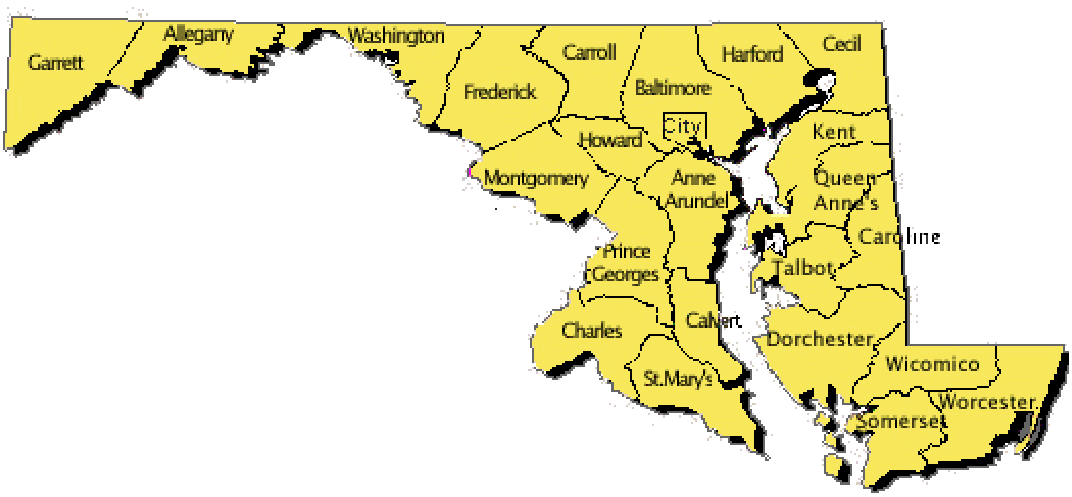
UNDERSTANDING TANF OUTCOMES IN CONTEXT: THE RELATIONSHPS AMONG FRONT-LINE ASSESSMENT, AGENCY CHARACTERISTICS, LOCAL ECONOMIC/DEMOGRAPHIC CHARACTERISTICS AND CUSTOMER AND JURISDICTIONAL LEVEL TANF OUTCOMES

FINAL PROJECT REPORT



Leanne W. Charlesworth, Ph.D.
Pamela Caudill Ovwigho, Ph.D.
Mary Morris Hyde, Ph.D.
Catherine E. Born, Ph.D.

School of Social Work
University of Maryland, Baltimore
525 West Redwood Street
Baltimore, MD 21201
410-706-5134

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TABLE OF CONTENTS

LIST OF TABLES & FIGURES

INTRODUCTION

This is the last in a series of reports describing the design, conduct and findings of a multi-year, multi-method Maryland study of welfare reform implementation and outcomes. Using traditional variable sets such as customer and caseload characteristics, the study documents customer- and county-level reform outcomes. The study also systematically examines how variations in front-line client assessment practice and other important **local** contextual factors such as characteristics of local welfare agencies and local jurisdictions influence those outcomes. The study was carried out by the School of Social Work, University of Maryland (SSW-UM) between October 1997 and March 2001 for the Maryland Department of Human Resources (DHR), pursuant to a grant awarded to DHR by the Administration on Children and Families, U.S. Department of Health and Human Services (ACF-HHS).[1]

The impetus for this study was passage of the landmark Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA, P.L. 104-196) which repealed the 65 year old Aid to Families with Dependent Children (AFDC) program and devolved an unprecedented amount of authority to individual states to design and operate AFDC s replacement, the Temporary Assistance for Needy Families (TANF) program. In Maryland, as in many other states, responsibility for deciding many of the details of welfare reform, including client assessment approaches, customer pathways, and modes of service delivery, was further devolved to the local level. An important consequence of these shifts in responsibility was to make obvious the long-standing reality that a state s overall success or failure in achieving

[1]Cooperative Agreement #90PE0020/02.

federally-mandated benchmarks (e.g., work participation), depends very heavily on decisions made, processes implemented and outcomes achieved on the front-line - that is, at the local level.

This recognition, Maryland s explicit choice of local flexibility as a dominant theme of its reformed welfare program, and the very real fiscal and other risks associated with the new state and local responsibilities made it clear that, there was need to ...not only gather data about intended policy parameters, but also to develop an understanding of what is really happening at the ground level (Welfare Indicators Board, 1996). For three years, through this project, we have worked diligently to develop this ground-level understanding of local welfare reform processes, perceptions, pathways and outcomes, believing that as a number of authors have suggested, the true nature of policies, once enacted, is best discovered through examination of front-line implementation (Hasenfeld, 1983, 1992; Lipsky, 1980). We have developed this understanding by gathering and analyzing survey, interview, observational and administrative data, descriptive findings about which have been presented in a series of prior project reports.

Today s final report takes us full circle. It brings all of our efforts and data together, presenting results of multi-variate analyses that were carried out in an attempt to answer the study s original important question: to what extent and in what ways do welfare reform outcomes differ based on such factors as variations in local agency variables (including assessment practices), local socioeconomic conditions and customer characteristics?

BACKGROUND

There were and still are myriad important questions to be asked and answered with regard to the operation, influences, outcomes and impacts of welfare reform. Research on some of these topics has already been considerable. Studies of so-called welfare leavers have been most common. By September 2001, 79 such studies had been completed or were underway (Research Forum on Children, Families and the New Federalism, 2001). Leavers studies have predominated, but research has also been undertaken on such subjects as diversion (Maloy, 1999), front-line management and practice (Nathan, 2000) and the child-only caseload (Lewin, 2000). Similarly, a body of research is accumulating which focuses on the broad topic of customer and caseload characteristics in the post-TANF era. Some studies compare pre- and post-TANF customer characteristics (Ovwigho, 2001; Zedlewski and Alderson, 2001), some profile new entrants (Charlesworth, Hyde, Ovwigho and Born, 2001) and still others focus on those who have not transitioned from welfare to work, the so-called welfare stayers (Welfare and Child Support Research and Training Group, 2001). Other areas of post-TANF research are not yet as well-developed, including such topics as recidivism, domestic violence, substance abuse, and the long-term effects of time limits and full family sanctioning.

Even in areas where much research is underway, with only a few notable exceptions (see, for example, Allen and Kirby, 2000; Born, Ovwigho and Cordero, 2000; Urban Institute, 1999), there appears to be little research emphasis to date on documenting or evaluating sub-state or local variations in welfare realities or outcomes. Likewise, there have been few published reports which attempt to ascertain how pre-existing local differences in socioeconomic and other population characteristics or variations in local welfare agency practice may influence welfare outcomes at the client, subdivision and, ultimately, state-level.

This omission may largely be a carryover from the pre-TANF era when welfare research studies most often looked at how customer characteristics or the nature of services influenced outcomes. Understandably, in the far less discretionary AFDC system, considerably less systematic attention was paid to considering how clients were assessed or directed to certain pathways and to the local context within which the customer and system interaction took place. Now that welfare is block-granted, however, local contextual factors, including the nature of up-front assessment processes, are important areas warranting programmatic and research attention. As aptly stated by Bloom and Butler (1995), t he fate of time-limited welfare will be determined in local welfare offices .

Stiffer work requirements, sanctioning policies and lifetime limits likewise heighten the importance of accurate client assessments. Assessment/allocation practices matter under TANF because greater flexibility brings greater responsibility and risk...if [state and local] policy-makers guess wrong, they could easily incur substantial costs (Corbett, 1997). The research challenge then is to examine if and how variations in assessment practices influence the outcomes achieved by clients and localities. The reality is that successful welfare agencies used to be those which eschewed highly personalized services for operations and procedures conducive to high volume productivity and consistency (Rosenthal, 1989); the new, post-TANF reality demands almost the opposite.

Indeed, there is virtually no aspect of public welfare practice that has been untouched or unchanged by the passage of PRWORA. The extensive multi-state, field network research done by Nathan and colleagues has amply documented the veritable sea change that the federal reform bill has had all across the nation. In a recent publication, Nathan (2000) notes:

In response to the act, new agency missions and arrangements were adopted.

> Delivery systems became more complex and diverse, and there was a redistribution of discretion, pushing downward to local offices, and ultimately to case managers. Local offices operating under new institutional arrangements, spurred by the federal block grant, came to have a wide range of tools and services available for assisting families and greater discretion in how to use them. A major consequence was the emergence of considerable diversity in local systems. (p. 150)

Our experiences in Maryland - as long-time state-level welfare researchers - and as participant-observers in the state s welfare reform decision-making processes - convinced us that welfare reform was, indeed, likely to play out differently across our small, but diverse state. Thus, we requested and received federal funding to carry out a study of Maryland s Temporary Assistance to Needy Families (TANF) program which would examine the relationships among local agency and jurisdictional variables and reform outcomes. In this multi-year study, we chose to address one of the less obvious, but in our view no less important questions: to what extent and how do **local** factors such as the characteristics of welfare agencies and the socioeconomic and population characteristics of individual state subdivisions affect welfare reform outcomes, especially in the areas of welfare program participation and employment?

Initial data collection activities focused on documenting assessment practices and key dimensions thereof, customer pathways (or flow), and staff perceptions of welfare reform, in local welfare offices across the state. Multiple methods of data collection were used. Field visits to 32 of 47 local welfare offices took place between March and September, 1998. All 22 offices in the state s smaller counties were visited, as were a sample of 10 offices in the state s largest jurisdictions (Baltimore City, Baltimore, Montgomery, and Prince George s counties). The visits resulted in 140 face-to-face interviews with: Assistant Directors ($\underline{n}$ = 24), District Managers ($\underline{n}$ = 13), supervisors ($\underline{n}$ = 32), and workers ($\underline{n}$ = 71). Data from observations of more than 65 worker-customer interactions and case record reviews supplemented the interview data.

A survey was mailed to all front-line staff involved with TANF customer assessment and/or case management to investigate perceptions of welfare reform and to collect more standardized data on customer pathway and assessment processes, worker/customer ratio, and worker demographics. A total of 426 completed surveys were returned.[2] Combined with the field visit data, this information yielded a rich understanding of perceptions of recent welfare reform efforts as well as the diversity of local offices approaches to welfare reform.

Some of the key findings from this phase of the study were consistent with our initial expectations. Others were not. All findings, however, lent support to our original hypothesis that research emphasizing local variations was worth undertaking. We learned first that many local welfare agencies had, indeed, altered TANF application processes as well as components of their subsequent customer pathway and, second, that beyond a few basic similarities (mandated by state policies), substantial structural and procedural differences existed at the local level.[3]

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[2] The overall response rate was 64% (n = 426 of 661), which is within the range generally considered acceptable by social scientists (Mangione, 1995, p. 60). Response rates for individual counties varied from 33.3% (Prince George s County) to 100% (Carroll, Cecil, Frederick, Garrett, Queen Anne s and Talbot Counties), with two-thirds of all jurisdictions having response rates greater than 70%. The overall response rate raises concerns about how respondents may differ from non-respondents. Unfortunately, the only information we have to compare are jurisdiction and district office within jurisdiction. Correlational analyses reveal a significant negative relationship between survey response rate and percent of the caseload who have already received cash assistance for more than 60 months ($r = -.52$, $p < .01$). Although Maryland s second largest jurisdiction (Prince George s County) had the lowest response rate and contains the district office with the lowest response rate (14.3%), the relationship between jurisdiction size and response rate was not significant. It should also be noted that subsequent to survey mailing, several offices called to report staff (n = 26) unable to participate due to resignation or other reasons. In addition, several workers called to express concerns about the sensitive nature of survey questions and respondents true anonymity.

[3] Local jurisdictions also vary on many other dimensions. Thus, while not discussed in this particular report, we also developed, maintained and updated a database containing a wide array of jurisdictional, agency, demographic and economic variables thought potentially relevant to our planned multi-variate analyses of individual and jurisdictional outcomes.

With regard to customer assessment, three basic approaches were in use during our site visits: a true team process (n=3 departments); a one-on-one approach (n= 9 departments); and, in 12 departments, a variation of the one-on-one approach where each customer met with two different workers (one focused on eligibility, the other employment-oriented). Virtually all managerial/supervisory staff described assessment as an ongoing process which played a major role in service delivery within their offices, but was in need of some improvement. Interviewed line staff were more specific, indicating that assessment enabled them to determine customer needs and barriers (n = 58); to get to know the customer better (n = 30); to determine eligibility (n = 23); to provide the customer with information (n = 13); to determine the appropriate customer pathway (n = 10); to help the customer determine her own goals (n = 10); to divert the customer from applying for TCA (n = 7); and to support the customer (n = 5). When asked the same question, managerial/supervisory respondents generally mentioned the same issues but added that assessment should also allow the worker to offer the customer support services.

Variations were also noted with regard to customer pathway(s) following assessment. In 12 of 24 departments, all work-mandatory customers followed a common pathway; multiple pathways existed for these clients in the other 12 jurisdictions. In addition, vendor provision of welfare-to-work services was common, reported in their agency by nine of 10 survey respondents (90.2%, n = 368); in general, the number of vendors was seen as about right (56.9%, n = 169).[4]

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[4]Baltimore City was unique in that front-line workers in this jurisdiction mentioned the need to meet monthly vendor quotas (for customer referrals). The City was unique also in appearing to make much heavier use of vendors than other subdivisions. The pressures to meet quotas reported by Baltimore City workers may have resulted from unintended overcapicity of vendor slots caused by underestimates of the percentage of cases with barriers to participation.

Perceptions of welfare reform were generally positive. However, line staff, while commenting favorably on being able to approach their work with customers in a new way and be more flexible, also described challenges. Chief among these were many rapid policy changes, increased paperwork, and the expectation that all prior eligibility-oriented responsibilities would continue to be fulfilled, along with new time-consuming tasks such as work activity monitoring.

Subsequent analyses of the survey and interview data revealed that caseload size (average monthly paid cases, 1998) was a consistent, significant predictor of worker perceptions and practices. In general, the larger the caseload, the less positive were staff perceptions of reform and the lower reported worker morale and job satisfaction.

In sum, results from our front-line data-gathering activities and analyses indicated that local departments had taken advantage of the new flexibility and, as a result, offices varied widely in their practices and approaches to customers. The process of system reform appeared to be well underway in most places and a work focus had been integrated into the welfare service delivery system. At the same time, the front-line data also revealed that staff were feeling some degree of pressure from the new, rapid changes. The data also suggested that managerial/ supervisory staff perhaps viewed welfare reform more positively or optimistically than line staff.

The most consistent finding from interviews, observations and survey responses was that jurisdiction size (as determined by size of the cash assistance caseload), was associated with a variety of practices and perceptions in local offices. In particular, metropolitan jurisdictions appeared to consistently differ from others on important dimensions. For example, they were most likely to use a standard assessment procedure and their front-line staff reported less positive perceptions of reform. In general, the data suggested that front-line staff in the very largest jurisdictions may have been slower to experience and/or perceive the positive aspects of welfare reform and less likely to believe that the new approach would be a lasting one. These results are generally consistent with those from other studies which have shown that, during the first three years of welfare reform in Maryland, cash assistance caseloads declined more slowly in the largest jurisdictions (Born, Caudill, Cordero, and Kunz, 2000; Born, Caudill, Spera, and Cordero, 1999; Welfare and Child Support Research and Training Group, 1998). However, these correlational analyses do not allow us to determine the causes of the relationship, if worker attitudes are slowing caseload decline, if slower caseload decline negatively influences worker attitudes, or if a third, unmeasured variable is driving the relationship.

Having confirmed that, indeed, local variation in assessment practices was characteristic of TANF-inspired reform in the state s local subdivisions, the next major research task was to identify an appropriate sample of TANF families whose outcomes under welfare reform could be tracked and data about whom would be central to the multi-variate analyses. Ultimately, the study sample consisted of the universe of 13,093 cases experiencing a TANF certification (resulting in benefit eligibility) in Maryland between January 1 and June 30 1998.

Consistent with the profile of the national TANF caseload at this time (Committee on Ways and Means, U.S. House of Representatives, 2000), the typical customer in our sample was a never-married, African-American woman who gave birth to her first child at a fairly early age. The typical payee had some history of attachment to the labor force, having worked at some point in the past in a Maryland job covered by the Unemployment Insurance program (83.6%). However, she had been out of the labor force more than in it. Moreover, earnings from past jobs were generally low, perhaps reflecting the fact that the most common industries in which payees recently worked tend to have been service sector jobs.

About two-thirds of payees had been on cash assistance in Maryland, as an adult, prior to the certification that brought them into this study. However, roughly one in three were embarking on their first (adult) episode of cash assistance in Maryland. At the time of certification, about 44% of clients (n=5,768/13,093) qualified for exemption from work requirements.

During the one year follow-up period, 55% of customers (n=7,201/13,093) exited cash assistance at least once, while 45% (n=5,892) did not.[5] About three-fifths (n=8,122/13,093) of customers worked in a Maryland job covered by the Unemployment Insurance program during the follow-up period, but 38% (n=4,971/13,093) had no such employment during that one year period.[6] Readers familiar with the emerging body of post-TANF research studies will recognize that this brief sketch of our samples demographics and their short-term welfare participation and employment outcomes is similar to what has been reported in most studies (Acs and Loprest, 2001; Ver Ploeg, 2001).

While these descriptive data are informative, the ultimate goal of our project was to tease out and attempt to understand how reform outcomes are influenced by several constellations of factors, ranging from the oft-studied caseload and client characteristics to the much less often examined local economic conditions. A prerequisite to this type of multi-variate analysis, however, is careful specification of the models, based on theory, univariate and bivariate analyses. The next chapter discusses these and other methodological issues. The chapter

[5]For purposes of this analysis, an exit is operationally defined as no receipt of cash assistance for at least 60 consecutive days.

[6]Among those who qualified for a work exemption, 43.9% (2,531/5,768) had no Maryland UI-covered employment in the follow-up period.

summarizes certain key methodological information which has been presented in more thorough form in prior reports and provides detailed discussion of methodological issues germane to the main topic of today s report, our multi-variate analyses of welfare reform outcomes.

METHODS

The purpose of our multi-variate analyses was to examine the extent to which client demographic variables, agency variables and jurisdictional variables were able to predict a number of customer-level outcomes in the areas of cash assistance program participation and employment. This chapter presents the methods we used and begins by discussing the outcomes of interest (i.e., the dependent variables) and the predictor (i.e., independent) variables used in the analyses. Data sources and our specific analytic approaches and models are also presented.

Dependent Variables[7]

Three dependent or outcome variables describing customers participation in cash assistance during the 12 months immediately following their 1998 TANF certification were used in the multi-variate analyses. These are:

Total Months of Receipt

This variable ranges from zero (no TANF receipt during the 12 month follow-up period) to 12 (continuous TANF receipt). As noted in an earlier report, sample members, on average, received aid for close to eight months (M=7.9). Not quite two of five clients (37.4%) received assistance for six months or less, while about one in four (25.7%) received assistance for all 12 months.

[7]Unless otherwise indicated, all dependent variables are based on data retrieved by the authors from two statewide administrative data systems. Welfare participation data were extracted from CARES (Client Automated Resources and Eligibility System); employment and earnings data come from MABS (Maryland Automated Benefits System). Both data systems have been described in more detail in earlier project reports.

Exiting

This trichotomous variable indicates whether or not, during the 12 month follow-up period, the customer exited TCA for employment for at least 60 consecutive days, exited for at least 60 days but not for employment, or did not experience a break in cash assistance receipt of at least 60 consecutive days. Using this definition, 28% of cases (n = 3,724) exited for employment, 27% of cases (n=3,477) without employment, and 45% (n=5,892) did not exit at all.

Recidivism

Among those who did experience an exit during the follow-up period (n=7,201), this variable describes whether, also during the follow-up period, a return to cash assistance was observed. As previously reported, the vast majority of exiters did not return before the end of the follow up period (82.3%, n=5,930/7,201)

Two dependent variables describing customers employment in a Maryland job covered by the Unemployment Insurance program were examined using multi-variate techniques.[8] These variables are: total quarters employed and total earnings.

Total Quarters Employed

This variable ranges from zero (no record of any UI-covered employment/wages in Maryland during the one year or four quarter follow-up period) to four (a record of some UI-covered employment/wages in each of the four follow-up quarters). As described in prior reports, nearly one in five clients (18.9%, n=2,469) worked in all four quarters in the follow-up

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[8]Approximately 93% of all Maryland jobs are covered. Unfortunately, we have no access to employment data for the District of Columbia or the four states which border Maryland. This is a significant problem because, in some Maryland counties, one-third or more of employed residents are known to work outside the state.

year. However, twice as many customers, about two-fifths of the sample (38.0%, n=4,971) had no record of employment during that same period of time.

Total Earnings

Among customers with some record of UI-covered employment in Maryland during the 12 month follow-up period, we also examined total earnings for the year. Of the 8,122 sample members with some employment during this time frame, total earnings averaged $6,003, with a median of $3,779 and a standard deviation of $7,062.

Independent Variables[9]

Three sets of independent or predictor variables were used: variables describing client characteristics; variables describing local welfare agencies; and variables describing local subdivisions or jurisdictions. Each set of predictors and the individual variables included in each set are described below.

Client Demographics

The relationship between customer characteristics and patterns of welfare use, post-exit employment and recidivism is a well-studied area, as has been discussed in previous project reports. Based on the extensive body of published research in this area, 11 demographic variables were included in our multi-variate models. These 11 variables are listed and described in Table 1 on the next page.

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[9]Unless otherwise indicated, all predictor variables are based on data retrieved by the authors from two statewide administrative data systems. Welfare participation data were extracted from CARES (Client Automated Resources and Eligibility System); employment and earnings data come from MABS (Maryland Automated Benefits System). Both data systems have been described in more detail in earlier project reports.

Table 1: Client Demographics

Variable Name	Description	Variable Type	Summary Statistics
Casehead age	Age at 1998 TCA certification	Continuous, ranging from 18 to 83	M=31.8, S.D.= 10.8
Casehead marital status	Marital status: spring 1998 certification.	Dichotomous, where 1=never married	68.0% never-married
Casehead race	Race: 1998 certification	Dichotomous, where 1=African American	74.2% African American
Number of children	# on TCA grant, 1998 certification	Continuous, ranging from 0 to 9	M=2.6, S.D. = 1.2
Child under five	Presence of child <5 on TCA grant, Spring 1998 certification.	Dichotomous, where 1=child <5 on grant	54.2% of cases, child <5
Child under one[10]	Presence of child <1 on TCA grant, Spring 1998 certification.	Dichotomous, where 1=child <1 on grant	13.8% of cases, child <1
Pregnancy status	Pregnancy status as of Spring 1998 certification	Dichotomous, where 1=casehead with worker verified/coded pregnancy	15.8% pregnant
Disability status	Disability status as of Spring 1998 certification	Dichotomous, where 1 =caseheads with worker verified/ coded disability	7.8% disabled caseheads
Child-only case	Child-only case status as of Spring 1998 certification	Dichotomous, where 1 =caseheads not on TCA grant	13.0% child-only cases
Cash assistance participation history	# out of 60 months before Spring 1998 certification in which casehead got TCA	Continuous, ranging from 0 to 60	M = 21.2 months, S.D. = 21.3
Employment history	# of quarters of the 8 before Spring 1998 certification, in which client was employed	Continuous, ranging from 0 to 8	M = 3.1 quarters, S.D. = 2.9

Agency Characteristics

[10]Although there are two variables related to age of children in the assistance unit, they actually represent different theoretical concepts. Child under five is used as a proxy for the payee s need for child care for a preschool-age child. Child under one indicates the payee was likely eligible for an exemption from TANF work requirements based on her child s age.

In the post-AFDC world of welfare, the field network research done by Nathan and colleagues (2000) has done much to expand implementation research methods pioneered by Derthick (1972) and Pressman and Wildavsky (1973). This research has documented that the big story of what is going on in the country to implement welfare reforms is local. (Working Seminar, 1998, pg 2). Our own field work, done as part of the present project, confirmed this statement and documented that, indeed, local welfare agencies in Maryland varied considerably on many dimensions related to process, culture and caseload. For purposes of the multi-variate analyses, seven agency process variables, two agency culture variables and two caseload variables were used as independent or predictor variables. More specific information about each of these independent variables appears below.

Agency Process Variables

Assessment approach. Based on field visits, this variable initially characterized each jurisdiction s assessment approach as: one on one (eligibility worker responsible for all aspects of assessment, n=12); two workers (eligibility worker and employment worker share responsibility for assessment though meet separately with clients, n=9); or team (eligibility, child support and services workers met jointly with clients, n=3). Subsequently, the two workers and team categories were collapsed into one (n = 12), which was coded as 1" for analysis.

Standardized testing. This dichotomous variable indicates, based on field visit data, whether local agencies regularly used standardized testing as part of their assessment process; the 10 which did so were coded 1" for analysis purposes.[11]

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[11]The testing could be conducted in-house or by a vendor but, if the latter, there had to be substantial evidence that results were regularly shared with TCA staff.

Orientation. This dichotomous variable indicates (based on field visit data), whether agencies held an orientation during the (TCA) application period that was mandatory for virtually all TCA applicants (n = 7 which were coded 1" for analysis purposes).

In-House job readiness. Based on field visit data, this dichotomous variable indicates whether an in-house job readiness class was offered on a regular basis to virtually all TCA customers. In two of the 10 agencies offering such classes (coded 1"), the class was led by a vendor at the local department. In Baltimore City, some offices held these classes while others did not. Thus, this jurisdiction was excluded from all analyses utilizing this variable. In the remaining jurisdictions, a job readiness class was either not offered at all or was provided off-site by a vendor and available to only some customers.

Multiple pathways. This dichotomous variable, based on site visit data, denotes whether multiple trajectories, or pathways, were available to TCA clients. In 13 jurisdictions, most clients followed the same general pathway through the agency; in the other 11 multiple pathways jurisdictions, more than one pathway was consistently available. In other words, customers might be referred to many different vendors or more than one type of service was typically offered to some, but not other customers at the same point (in time) in their pathway, dependent upon customers characteristics or assessed needs.

Heavy reliance on vendors. Again based upon field visit data, local departments were coded regarding their use of vendors. Fifteen jurisdictions used vendors as an integral part of their customer service strategy, though the number of vendors varied widely, from one to more than 12. The remaining nine jurisdictions (coded 0") did not rely on vendors at all for direct-service provision, or used them only occasionally (on an as-needed basis).

Generalist versus specialist workers. Based on field visit data, 16 local agencies were categorized as having cash assistance-only staff members (specialists). In seven jurisdictions (coded 0"), staff members balanced a diverse (generalist) caseload, of which TCA clients were just one group. In the one remaining jurisdiction (Baltimore City), district offices varied in terms of whether staff assigned to TCA cases carried generalist or specialist caseloads. Thus, Baltimore City was excluded from analyses utilizing this variable.

Agency Culture Variables

Index of FIP Perceptions. This index consists of four, Likert-type items from the front-line staff mail survey. Response choices ranged from one (completely untrue) to four (completely true), so index scores range from four to 16. Using this scale, participants were asked to respond to the following four statements: (1) Since my agency began implementing FIP, there have been real changes in how we deal with customers;[12] (2) Since my agency began implementing FIP, I ve had more flexibility in how I carry out my job; (3) FIP is more likely to succeed in helping poor families become independent than previous welfare reform efforts; and (4) Like other welfare reform efforts, FIP will not be around long.

Index of Job Satisfaction. This index also consists of four items from the staff survey, each of which used a Likert-scale response format, ranging from one (very low) to five (very high), resulting in index scores from four to 20. These items asked respondents to rate: (a) worker morale within their agency; (b) personal job satisfaction; (c) change in personal job satisfaction since FIP implementation; and (d) importance of one s job to achieving welfare reform goals in Maryland.

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[12]Family Independence Program, the name of Maryland s overall approach to welfare reform (as opposed to TCA or Temporary Cash Assistance, the successor to AFDC in Maryland).

Agency Caseload Variables

Temporary Cash Assistance (TCA) caseload size. This variable indicates each jurisdiction s (monthly) average number of paid TCA cases during calendar year 1998. The range was from 54 (Kent) to 25,035 (Baltimore City).

Proportion of long term TCA recipients. This variable indicates the proportion of each jurisdiction s (1998 monthly) average number of paid cases that had received TCA for 60 months or more. Ranging from 13.5% to 48.3%, the monthly average proportion of long-term recipients for the state as a whole was 37.2%.

Jurisdictional Characteristics[13]

As has been discussed in detail in previous project reports, even within a small state like Maryland, local subdivisions vary widely on myriad dimensions ranging from unemployment and poverty rates to the proportions of adult citizens with at least a high school education. It is also becoming clear that welfare reform is not unfolding uniformly across all types of locales. Allen and Kirby (2000), to illustrate, have shown that caseloads in America s largest cities, including Baltimore, have declined more slowly than national caseloads and that urban areas shares of families on welfare have grown. Other of our own Maryland research studies have documented higher rates of returns to welfare among Baltimore City TANF leavers (Born, Ovwigho, Leavitt and Cordero, 2001). A number of jurisdictional variables were utilized as

[13]Data used to profile jurisdictions on a broad array of socioeconomic characteristics were obtained from various sources including the state Departments of Health and Mental Hygiene, Labor, Licensing and Regulation, the Maryland Office of Planning and the U.S. Bureau of the Census.

predictors in the multi-variate analyses. These are listed and described in Table 2, on the next page.[14]

[14]For more detail regarding our jurisdictional variables, please see Hyde, Charlesworth, & Born, 1998.

Table 2: Jurisdictional Characteristics

Variable Name	Variable Description	Variable Type	Summary Statistics
Population density	1998 population density	Continuous: 45 to 8,070 (persons/sq.m.)	M= 4,591 ; S.D. = 3,579
Total population	1998 total population	Continuous: 18,925 to 840,879	M = 566,482; S.D. = 234,394
Population change	% change in total population 1990-98	Continuous: -12.3% to 39.9%	M= -1.6%; S.D.= 12.0%
% Caucasian	1997 % of total population Caucasian	Continuous: 33.0% to 99.3%	M = 51.4% ; S.D. = 23.4%
% African American	1997 % of total population African American	Continuous: 0.3% to 65.4%	M = 46.1%; S.D. = 23.8%
Crime rate	1998 rate/100,000 (violent & theft-related crimes)	Continuous: 2,020 to 11,116	M = 8,066.1; S.D. = 3,307.5
Property crime rate	1996 rate/100,000 individuals	Continuous, ranging from 1,828 to 6,628	M = 4,728.9; S.D. = 1,513.0
Drug arrest rate	1998 rate/100,000 persons	Continuous, ranging from 259 to 2,726	M = 1,676.0; S.D. = 1,092.2
Owner-occupied housing units	1990 % total occupied housing units owner-occupied	Continuous, ranging from 48.6% to 85.0%	M = 57.7%; S.D. = 10.2%
Substandard housing units	1990 % sub-standard housing units	Continuous, ranging from 1.3% to 6.4%	M = 4.1%; S.D. = 1.4%
TCA recipient population	1998 average monthly % of total population receiving TCA	Continuous, ranging from 0.3% to 10.5%	M = 6.0%; S.D. = 4.5%
Female-headed households with child under 5	1990 % female-headed households with a child <5	Continuous, ranging from 1.1% to 7.7%	M = 5.2%; S.D. =2.6%
Non-marital births	1997 % non-marital (annual) births	Continuous, ranging from 13.7% to 69.6%	M = 51.2%; S.D. = 19.9%

Table 2: Jurisdictional Characteristics (continued)

Variable Name	Variable Description	Variable Type	Summary Statistics
Prenatal care	1997 % live births to mothers receiving late/ no prenatal care	Continuous, ranging from 0.5% to 5.5%	M = 4.0% ; S.D. = 1.7%
Child maltreatment investigation rate	1998 child abuse & neglect investigation rate/1,000 children	Continuous, ranging from 2.1 to 15.5	M = 10.9 ; S.D. = 4.9
Poverty rate	1993 poverty rate per 100 individuals	Continuous, ranging from 3.8 to 25.7	M = 17.4 ; S.D. = 8.8
Per capita income	1997 per capita income	Continuous, ranging from $15,241 to $41,539	M = $25,654; S.D. = $3,935
Household income	1998 median household income	Continuous, ranging from $28,400 to $69,200	M = $42,471; S.D. = 10,064
Unemployment rate	1998 annual average civilian unemployment rate	Continuous, ranging from 2.3 to 10.9	M = 7.0; S.D. = 2.6
Male unemployment rate	1997 annual average male civilian unemployment rate	Continuous, ranging from 2.5 to 15.4	M = 7.7; S.D. = 2.8
Education	1990 % population 25 $\geq$ with Bachelor s degree	Continuous, ranging from 9.5% to 49.9%	M = 19.7% ; S.D. = 7.9%

Data Analysis

Our previous reports on this project have presented detailed discussion of a large number and variety of descriptive findings arising from our work on this multi-method, multi-year project. In contrast to those earlier reports, the purpose of all analyses carried out during this final phase of the study was to examine relationships among customer, agency and jurisdictional characteristics and welfare reform outcomes. A particular focus was to identify statistically significant predictors of reform outcomes when the relationships among three types of variables are considered. Work on this complex task began with bivariate analyses, primarily correlation analysis, to investigate relationships among our predictor variables and between our predictor variables and the outcome variables.

Bivariate Analysis

Correlation analysis was used to examine bivariate relationships among the predictor variables and between the predictor and dependent variables. Some degree of relationship was expected because many of our predictor variables are conceptually related. Since multi-variate analysis is of maximum utility when multicolliearity is minimized, it was important to empirically determine the degree of inter-correlation among predictors beforehand[15].

Multivariate Analysis

Several types of multi-variate statistical techniques were employed in the last phase of the study: factor analysis; multiple linear regression; and discrete-time event history analysis. Each of these techniques and its application in our project is described below.

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[15]When two or more independent or predictor variables are highly correlated in a multi-variate analysis it is extremely difficult to determine each variable s independent effect on the dependent, or criterion, variable.

Factor Analysis

Factor analysis is a technique that can be used to reduce a large number of variables to a smaller number of variables, or factors, and to eliminate problems of multicollinearity, by finding patterns among the variations in the values of several variables. A factor then is a set of variables or a cluster of highly inter-correlated variables, such as items on a questionnaire, that can be conceptually and statistically related or grouped together and are thought to measure the same underlying concept(s). Having identified factors, it is then possible to create factor, or index, scores to express the relationship between two or more variables or two or more measures of the same variable (Vogt, 1999). In the present study, factor analysis, specifically the technique of principal components analysis, was used as a data reduction technique for both jurisdictional and agency-level predictor variables. Through use of this technique, our 21 independent jurisdictional variables were reduced to three factors, while our seven agency variables were reduced to two factors. The index (or factor) scores for the five resulting factors were used in our subsequent multi-variate analyses of client outcomes[16].

Multiple Linear Regression

Multiple linear regression is a method that uses more than one independent, or predictor, variable to predict a single dependent, or criterion, variable. The coefficient for any particular predictor variable is an estimate of the effect of that variable on the dependent variable while holding constant the effects of the other predictors in the model. Multiple linear regression was used in this study to determine predictors of the two customer employment outcomes (number of quarters employed in post-certification year and total earnings during the post-certification year)

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[16]For both the jurisdictional and agency analyses, some variables loaded on more than one component. The highest loading was used to determine final indices.

and total months of TCA receipt during the post-certification year. For each dependent variable, four models were tested: (1) client demographic variables alone; (2) client and agency variables together; (3) client and jurisdictional variables together; and (4) client, agency and jurisdictional variables together.

Discrete-Time Event History Analysis

Discrete-time event history analysis is the most appropriate statistical method for analyzing data concerning the timing and correlates of the occurrence of an event (Allison, 1984; Yamaguchi, 1991). The technique was used in this study to analyze the relationship between client, agency and jurisdictional predictors and two study outcomes: (1) the probability of exiting cash assistance during the one year post-certification period; and (2) the probability of returning to cash assistance after an exit. This method was chosen because it allows the use of data which are right-censored (i.e., cases where no exit occurs during the follow-up period) and the incorporation of time-varying predictors (e.g., length of time since exit).

In the present study, the events of interest (probability of exiting during the follow-up period and probability of returning after an exit) are modeled using the logistic regression technique for discrete-time data developed by Allison (1984). Discrete-time is appropriate because although our data contain a precise case closing date, exactitude of these date data is questionable because, typically, cases are closed automatically at the beginning or end of the month. Thus, the day recorded has little relationship to the timing of the event that actually led to the case closure.

To conduct the discrete-time analysis, we first created person-period records for each participant (Allison, 1984; Yamaguchi, 1991). The first outcome variable, probability of an exit, has three levels: (1) did not exit (or right-censored), 45.0%, n=5,892/13,093); (2) exited but not for employment, 26.6%, n=3,477/13,093); and (3) exited for employment, 28.4%, n=3,724/13,093). For our analysis of exiting, each customer contributes as many records as she has months of welfare receipt from her certification date to her exit or the end of the follow-up period, whichever comes first.

For the analysis of recidivism, each customer who experienced an exit (55.0%, n = 7,201/13,093) contributes as many records as she has months of non-receipt between her exit date and the date she returned to TCA or the end of the study follow-up period, whichever comes first. Each record contains all of the values for the predictors and a dichotomous dependent variable coded as zero if the customer was still off TCA in that month or one if the customer returned to TCA in that month.

Using logistic regression, the relationships among the individual, agency and jurisdictional predictors and the described outcomes are modeled. There are 119,692 person-month records in the exiting analysis and 52,083 in the recidivism analysis. As in our multiple regression analysis, for each dependent variable, four models were tested (see p. 25). In addition to the mentioned predictors, the variable time until exit entered the equation for exiting and all recidivism models include the variables exit for employment and time since exit.

FINDINGS: RELATIONSHIPS AMONG PREDICTOR VARIABLES

Because many of our predictor variables are conceptually related, six bivariate correlation analyses were run to investigate relationships among them.[17] Following presentation of these results, we briefly discuss the factor analyses drawn upon to create factor scores for conceptually related and inter-correlated predictor variables.

Correlation Analyses

Client Demographic Variables

The magnitude of the correlations among individual client characteristics are generally small (see Table 3), but due to our large sample size, most associations are statistically significant. Observed relationships are logical. For example, it is not surprising that older customers are more likely to have a child-only exemption ($\underline{r} = .48$, $\underline{p} < .01$), given that grandparents or other relatives often head child-only cases. Other examples include the finding that older customers are less likely to have children under five in the assistance unit ($\underline{r} = -.43$, $\underline{p} < .01$) and that longer welfare histories are associated with more children in the assistance unit ($\underline{r} = .29$, $\underline{p} < .01$).

[17] Readers interested in the bivariate correlations between the predictor variables and the outcome variables may refer to Appendix A.

Table 3: Correlations among Client Demographic Variables

	1	2	3	4	5	6	7	8	9	10	11
Client Demographic Variables											
1. Age	1.00	-.02*	-.33**	.04**	-.09**	.13**	-.30**	-.19**	.48**	-.43**	.09**
2. Race	-.02*	1.00	.29**	.16**	.01	-.08**	-.09**	-.05**	.03**	-.01	.03**
3. Marital Status		.29**	1.00	-.11**	.02	-.07**	.07**	.06**	-.16**	.16**	-.07**
4. Welfare History	.04**	.16**	-.11**	1.00	-.12**	.02**	-.24**	-.14**	-.16**	-.11**	.29**
5. Work History	-.09**	.01	.02	-.12**	1.00	-.07**	.11**	-.04**	-.04**	-.04**	-.08**
6. Disability Exemption	.13**	-.08**	-.07**	.02**	-.07**	1.00	-.04**	-.04**	.02*	-.08**	-.02
7. Pregnancy Exemption	-.30**	-.09**	.07**	-.24**	.11**	-.04**	1.00	.02	-.15**	.15**	-.24**
8. Under One Exemption	-.19**	-.05**	.06**	-.14**	-.04**	-.04**	.02	1.00	-.05**	.39**	.05**
9. Child Only Exemption	.48**	.03**	-.16**	-.16**	-.04**	.02*	-.15**	-.05**	1.00	-.13**	-.05**
10. Child Under Five in AU	-.43**	-.01	.16**	-.11**	-.04**	-.08**	.15**	.39**	-.13**	1.00	.11**
11. Number of Children in AU	.09**	.03**	-.07**	.29**	-.08**	-.02	-.24**	.05**	-.05**	.11**	1.00

* p < .05 ** p < .01

Agency Predictor Variables

The correlations among agency predictor variables are fairly large, reflecting the inter-connected nature of many agency characteristics and processes (See Table 4). Several variables exhibited correlations greater than .50. The FIP Perceptions and Job Satisfaction indices[18] are positively related ($r = .76$, $p <.01$), indicating that more positive views of FIP are associated with higher job satisfaction. The FIP perceptions index and TCA caseload size were negatively related ($r = -.56$, $p < .01$), indicating that workers with more positive perceptions of FIP are more likely to be located in agencies with smaller TCA caseloads.[19]

Agency TCA caseload size is also highly related to a number of other variables, including the proportion of the caseload considered long-term ($r = .94$, $p < .01$), assessment approach ($r = -.79$, $p < .01$), multiple pathways ($r = .56$, $p < .01$), presence of an orientation ($r = -.59$, $p < .01$), and the inclusion of standardized testing in the assessment process ($r = -.58$, $p < .01$). These correlations suggest that agencies with larger overall TCA caseloads are more likely to have a higher proportion of long-term recipients, a one-on-one approach to TCA customer assessment and multiple pathways available to TCA customers, but are less likely to include standardized testing in the assessment process or mandate an orientation for TCA customers than agencies with smaller overall TCA caseloads.

Assessment approach is highly related to the inclusion of standardized testing in the assessment process ($r = .74$, $p < .01$) and the presence of a mandatory orientation ($r = .58$, $p <$

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[18]Readers are reminded that these indices are sum scores based upon worker responses to items within the survey of front-line staff (n = 426) conducted during the first year of the study.

[19]This variable refers to the agency s overall TCA caseload size, <u>not</u> an individual worker s caseload size.

.01), indicating that agencies with a team or two worker assessment approach were more likely to include standardized testing and mandate an orientation for TCA customers than agencies with a one on one approach to assessment. Multiple pathways is highly related to standardized testing ($r = .71$, $p < .01$) and reliance on vendors ($r = .59$, $p < .01$), indicating that agencies with multiple customer pathways are more likely to include standardized testing in the assessment process and rely heavily on vendors for service delivery.

Finally, the proportion of the TCA caseload considered long-term is highly negatively related to assessment approach ($r = -.76$, $p < .01$), the presence of a mandatory orientation ($r = -.55$, $p < .01$) and the inclusion of standardized testing in the assessment process ($r = -.60$, $p < .01$), indicating that agencies with a high proportion of long-term cash assistance customers are more likely to use a one-on-one assessment approach and less likely to mandate an orientation or include standardized testing in the assessment process than agencies with a low proportion of long-term customers within their TCA caseload.

Table 4: Correlations among Agency Characteristics[20]

	1	2	3	4	5	6	7	8	9
Agency Characteristics									
1. Index of FIP Perceptions	1.00	.76**	-.56**	-.49**	.31**	-.47**	.25**	-.19**	.13**
2. Index of Job Satisfaction	.76**	1.00	-.35**	-.37**	-.03**	-.40**	-.03**	-.13**	-.08**
3. TCA Caseload (1998)	-.56**	-.35**	1.00	.94**	-.79**	.56**	-.59**	.37**	-.58**
4. % of Caseload > 60 months receipt (1998)	-.49**	-.37**	.94**	1.00	-.76**	.47**	-.55**	.31**	-.60**
5. Assessment Approach	.31**	-.03**	-.79**	-.76**	1.00	-.29**	.58**	-.28**	.74**
6. Multiple Pathways	-.47**	-.40**	.56**	.47**	-.29**	1.00	-.06**	.59**	.04**
7. Orientation	.25**	-.03**	-.59**	-.55**	.58**	-.06**	1.00	.16**	.71**
8. Reliance on Vendors	-.19**	-.13**	.37**	.31**	-.28**	.59**	.16**	1.00	.06**
9. Standardized Testing	.13**	-.08**	-.58**	-.60**	.74**	.04**	.71**	.06**	1.00

* p < .05, ** p < .01

[20] Two agency process variables, In-House Job Readiness and Generalist versus Specialist Workers, were excluded from the analysis because of missing data in a large jurisdiction.

Jurisdictional Predictor Variables

The magnitude of correlations among jurisdictional characteristics, or variables, is extremely large (see Table 5). In fact, the vast majority of variables are correlated at the r = .90 level or above. Only four variables stand out as only moderately (below r = .50) related to the other examined jurisdictional variables. These four variables are the total population, per capita income, property crime rate, and the percentage of the population (age 25 or over) with a Bachelor s degree.

Table 5: Correlations among Jurisdictional Characteristics and Customer Outcomes

	1	2	3	4	5	6	7	8	9	10	11
Jurisdictional Characteristics											
1.Population Density	1.00	.96**	-.94**	.68**	.99**	.98**	.93**	.45**	-.91**	.97**	-.84**
2. Crime Rate	.96**	1.00	-.97**	.98**	.97**	.98**	.92**	.54**	-.91**	.93**	-.92**
3. Owner-Occupied Units	-.94**	-.97**	1.00	-.80**	-.94**	-.96**	-.92**	-.57**	.92**	-.89**	.92**
4. Property Crime Rate[21]	.68**	.98**	-.80**	1.00	.78**	.75**	.23**	.68**	-.38**	.11**	-.80**
5. % of Population on TCA	.99**	.97**	-.94**	.78**	1.00	.99**	.96**	.37**	-.92**	.98**	-.85**
6. % Female-Headed Household with Children Under 5	.98**	.98**	-.96**	.75**	.99**	1.00	.95**	.40**	-.92**	.96**	-.91**
7. Child Abuse/Neglect Investigation Rate	.93**	.92**	-.92**	.23**	.96**	.95**	1.00	.29**	-.94**	.94**	-.77**
8. Total Population	.45**	.54**	-.57**	.68**	.37**	.40**	.29**	1.00	-.45**	.27**	-.58**
9. Total Population % Change	-.91**	-.91**	.92**	-.38**	-.92**	-.92**	-.94**	-.45**	1.00	-.88**	.78**
10. Drug Arrest Rate	.97**	.93**	-.89**	.11**	.98**	.96**	.94**	.27**	-.88**	1.00	-.79**
11. % White	-.84**	-.92**	.92**	-.80**	-.85**	-.91**	-.77**	-.58**	.78**	-.79**	1.00
12. % Black	.86**	.93**	-.93**	.79**	.88**	.93**	.80**	.53**	-.80**	.82**	-.997**
13. % of Non-Marital Births	.94**	.96**	-.95**	.60**	.97**	.99**	.96**	.34**	-.93**	.95**	-.89**
14. Poverty Rate	.95**	.92**	-.90**	.04**	.98**	.97**	.97**	.24**	-.93**	.97**	-.79**

[21] Readers may note that the correlations between property crime rate and the other jurisdictional variables are markedly lower than the correlations for crime rate, despite the high correlation between property crime rate and crime rate. The definition of crime rate includes both property crime and crimes against persons. The lower correlations between property crime and the other variables may indicate that property crimes are not as strongly related to other jurisdictional characteristics as crime against people.

Table 5: Correlations among Jurisdictional Characteristics and Customer Outcomes (continued)

	1	2	3	4	5	6	7	8	9	10	11
Jurisdictional Characteristics											
15. Late or No Prenatal Care	.92**	.95**	-.92**	.61**	.95**	.97**	.89**	.38**	-.87**	.92**	-.92**
16. Per Capita Income	-.25**	-.30**	.29**	.06**	-.36**	-.40**	-.45**	.41**	.33**	-.36**	.31**
17. % with Bachelors Degree	-.47**	-.48**	.43**	.20**	-.56**	-.57**	-.64**	.30**	.54**	-.60**	.35**
18. Male Unemployment Rate	.88**	.86**	-.83**	.001	.91**	.90**	.94**	.21**	-.90**	.91**	-.71**
19. Unemployment Rate	.85**	.83**	-.79**	.005	.89**	.88**	.92**	.12**	-.87**	.91**	-.69**
20. Median Household Income	-.69**	-.71**	.71**	-.03**	-.77**	-.77**	-.88**	.03**	.81**	-.78**	.57**
21. % of Substandard Housing	.62**	.69**	-.72**	.47**	.65**	.73**	.54**	.37**	-.56**	.60**	-.89**
22. Infant Mortality Rate	.86**	.90**	-.86	.57**	.84**	.87**	.76**	.56**	-.74**	.82**	-.86**

Client and Agency Predictor Variables[22]

The magnitude of the correlations among client and agency variables are generally small (see Table 6), but again due to our large sample size, most associations are statistically significant. Only two variables race and welfare history exhibit correlations with other variables that approach a moderate size. Client race is moderately related to the Index of FIP perceptions ($r = -.30$, $p < .01$), the Index of Job Satisfaction ($r = -.30$, $p < .01$), TCA caseload size ($r = .36$, $p < .01$), the proportion of the caseload considered long term ($r = .38$, $p < .01$), and multiple pathways ($r = .24$, $p < .01$). These coefficients indicate that agencies with higher proportions of African-American customers tend to be those with a large overall TCA caseload, a high proportion of long term TCA customers, in which multiple customer pathways are present and in which workers report less positive perceptions of FIP and lower job satisfaction.

Welfare history (among sample members) is moderately related to TCA caseload size ($r = .27$, $p < .01$), the proportion of the caseload considered long term ($r = .24$, $p < .01$), and approach to assessment ($r = -.20$, $p < .01$). These coefficients indicate that customers with a longer history of welfare receipt are more likely to be served by agencies with a large overall TCA caseload size, a high proportion of the long-term recipients, and a one-on-one assessment approach.

[22]For these analyses, client variables are aggregated to the jurisdictional level.

Table 6: Correlations among Client and Agency Predictors

	Index of FIP Perceptions	Index of Job Satisfaction	TCA Caseload (1998)	% of Caseload > 60 months of receipt (1998)	Assessment Approach	Multiple Pathways	Orientation	Reliance on Vendors	Standardized Testing
Age	-.01	-.01	.03**	.03**	-.03**	.01	.00	.01	-.01
Race	-.30**	-.30**	.36**	.38**	-.17**	.24**	-.11**	.19**	-.07**
Marital Status	-.13**	-.11**	.17**	.17**	-.09**	.12**	-.08**	.08**	-.07**
Welfare History	-.14**	-.07**	.27**	.24**	-.20**	.15**	-.17**	.08**	-.16**
Work History	.06**	.08**	-.05**	-.07**	.02*	-.07**	-.04**	-.06**	-.01
Disability Exemption	.06**	.08**	-.01	-.01	-.03**	-.04**	-.02*	-.03**	-.04**
Pregnancy Exemption	.09**	.05**	-.14**	-.13**	.12**	-.08**	.06**	-.07**	.07**
Under One Exemption	.05**	.03**	-.07**	-.05**	.05**	-.03**	.03**	-.02	.02**
Child Only Exemption	-.02	-.02**	.00	.00	.02	.00	.01	.00	.02
Child Under Five in AU	.03**	.01	-.04**	-.03**	.03**	-.02	.02	.00	.02
Number of Children in AU	.00	.00	-.01	.00	.00	.00	.01	.01	.00

* p < .05 ** p < .01

Client and Jurisdictional Predictor Variables

The magnitude of the correlations among client characteristics and jurisdictional characteristics are generally small to moderate (see Table 7), but again due to our large sample size, most associations are statistically significant. Two client variables consistently exhibit correlation coefficients of a moderate ($r = .25$ or larger) magnitude: race and welfare history. Indeed, the only jurisdictional characteristics that these two variables are not moderately related to are per capita and median income and percentage of the population (over age 25) with a Bachelor s degree. In general, coefficients indicate that African American clients and clients with a longer history of welfare receipt are more likely to reside in at-risk jurisdictions.

Table 7: Correlations among Client and Jurisdictional Predictors

	Age	Race	Marital Status	Welfare History	Work History	Disability Exemption	Pregnancy Exemption	Child < 1 Exemption	Child Only Exemption	Child < 5 in AU	# of children
Population Density	.03**	.35**	.17**	.27**	-.04**	-.01	-.14**	-.07**	.00	-.04**	-.01
Crime Rate	.03**	.40**	.19**	.26**	-.06**	-.02**	-.14**	-.07**	.01	-.04**	-.01
Owner-Occupied Units	-.03**	-.41**	-.18**	-.24**	.07**	.04**	.14**	.06**	-.01	.04**	.00
Property Crime Rate	.03**	.43**	.19**	.25**	-.06**	-.04**	-.14**	-.07**	.01	-.04**	-.01
% of Population on TCA	.03**	.35**	.17**	.27**	-.04**	-.01	-.14**	-.07**	-.01	-.04**	-.01
% Female-Headed Household with Children < 5	.03**	.38**	.18**	.26**	-.05**	-.02	-.14**	-.06**	.00	-.04**	.00
Child Abuse/Neglect Investigation Rate	.02	.29**	.15**	.25**	-.03**	.00	-.13**	-.06**	.00	-.04**	-.01
Total Population	.04**	.34**	.13**	.12**	-.08**	-.06**	-.09**	-.05**	.03**	-.03**	.00
Total Population % Change	-.02**	-.31**	-.16**	-.25**	.04**	.01	.13**	.07**	.01	.05**	.01
Drug Arrest Rate	.02**	.31**	.16**	.26**	-.03**	.01	-.13**	-.06**	-.01	-.04**	-.01
% White	-.03**	-.47**	-.18**	-.20**	.10**	.05**	.13**	.05**	-.01	.03**	.00
% Black	.03**	.46**	.18**	.21**	-.09**	-.04**	.13**	-.06**	.01	-.03**	.00
% of Non-Marital Births	.02	.37**	.17**	.25**	-.05**	-.02	-.13**	-.06**	.00	-.04**	-.01
Poverty Rate	.02*	.30**	.15**	.26**	-.03**	.00	-.13**	-.06**	-.01	-.04**	-.01
Late or No Prenatal Care	.02*	.40**	.18**	-.24**	.07**	-.02	-.13**	-.06**	.00	.04**	.00
Per Capita Income	.02**	-.03**	-.03**	-.06**	.03**	.00	.02	.01	.02*	.00	.01
% with Bachelors Degree	.02*	-.03**	-.06**	-.14**	.00	-.02*	.04**	.02**	.02**	.01	.02

Table 7: Correlations among Client and Jurisdictional Predictors (continued)

	Age	Race	Marital Status	Welfare History	Work History	Disability Exemption	Pregnancy Exemption	Child < 1 Exemption	Child Only Exemption	Child < 5 in AU	# of children
Male Unemployment Rate	.02	.23**	.13**	.24**	-.04**	.02*	-.12**	-.06**	-.01	-.04**	-.01
Unemployment Rate	.01	.23**	.13**	.22**	-.02*	.02*	-.11**	-.06**	-.02*	-.04**	-.01
Median Household Income	.00	-.18**	-.11**	-.19**	.01	-.01	.09**	.04**	.02*	.03**	.02*
Substandard Housing	.02*	.41**	.14**	.12**	-.11**	-.04**	-.10**	-.03**	.01	-.02**	.01*
Infant Mortality Rate	.04**	.38**	.17**	.22**	-.07**	-.03**	-.13**	-.07**	.01	-.04**	.00

* p < .05 ** p < .01

Agency and Jurisdictional Predictor Variables

The magnitude of correlations between jurisdictional variables and agency variables is extremely large (see Table 8); most variables are correlated at the r = .50 level or above. Three agency variables are correlated with jurisdictional variables at the r = .75 level or above: TCA caseload size; proportion of the caseload considered long term; and assessment approach. The direction of the relationships indicates that agencies located in at-risk jurisdictions are more likely to have large overall TCA caseloads, a large proportion of long term recipients, and a one-on-one customer assessment approach.

For the other agency variables examined, moderate relationships are present. In general, it appears that agencies in at-risk jurisdictions are less likely to have positive (worker) perceptions of FIP and job satisfaction. These agencies are also likely to have multiple customer pathways and vendors available. They are generally less likely to mandate a TCA customer orientation and to include standardized testing in their assessment process.

Table 8: Correlations among Agency and Jurisdictional Variables

	Index of FIP Perceptions	Index of Job Satisfaction	TCA Caseload (1998)	% of Caseload > 60 months of receipt (1998)	Assessment Approach	Multiple Pathways	Orientation	Reliance on Vendors	Standardized Testing
Population Density	-.54**	-.31**	.99**	.94**	-.82**	.51**	-.62**	.35**	-.63**
Crime Rate	-.63**	-.45**	.98**	.92**	-.69**	.60**	-.53**	.39**	-.44**
Owner-Occupied Units	.68**	.51**	-.96**	-.92**	.69**	-.64**	.48**	-.49**	.43**
Property Crime Rate	-.67**	-.50**	.95**	.90**	-.63**	.59**	-.48**	.41**	-.38**
% of Population on TCA	-.52**	-.30**	.99**	.94**	-.80**	.52**	-.66**	.33**	-.61**
% Female-Headed Household with Children < 5	-.57**	-.37**	.99**	.95**	-.76**	.54**	-.63**	.34**	-.56**
Child Abuse/Neglect Investigation Rate	-.51**	-.23**	.94**	.86**	-.77**	.57**	-.63**	.42**	-.51**
Total Population	-.61**	-.64**	.47**	.45**	-.21**	.50**	.27**	.43**	.06**
Total Population % Change	.57**	.37**	-.92**	-.86**	.71**	-.53**	.53**	-.34**	.50**
Drug Arrest Rate	-.49**	-.22**	.96**	.90**	-.80**	.47**	-.72**	.27**	-.66**
% White	.66**	.57**	-.87**	-.90**	.56**	-.56**	.39**	-.36**	.33**
% Black	-.65**	-.55**	.89**	.91**	-.57**	.57**	-.44**	.35**	-.35**
% of Non-Marital Births	-.56**	-.35**	.96**	.93**	-.73**	.55**	-.63**	.32**	-.52**
Poverty Rate	-.46**	-.20**	.95**	.91**	-.79**	.48**	-.71**	.29**	-.62**
Late or No Prenatal Care	-.51**	-.35**	.94**	.95**	-.70**	.52**	-.58**	.32**	-.52**
Per Capita Income	.13**	.11**	-.29**	-.26**	.14**	-.30**	.44**	.02**	.15**
% with Bachelors Degree	.19**	.06**	-.49**	-.41**	.37**	-.40**	.58**	.03**	.37**
Male Unemployment Rate	-.40**	-.16**	.89**	.81**	-.72**	.53**	-.59**	.29**	-.49**

Table 8: Correlations among Agency and Jurisdictional Variables (continued)

	Index of FIP Perceptions	Index of Job Satisfaction	TCA Caseload (1998)	% of Caseload > 60 months of receipt (1998)	Assessment Approach	Multiple Pathways	Orientation	Reliance on Vendors	Standardized Testing
Unemployment Rate	-.36**	-.08**	.82**	.75**	-.66**	.45**	-.63**	.24**	-.49**
Median Household Income	.33**	.10**	-.71**	-.63**	.56**	-.49**	.59**	-.26**	.34**
Substandard Housing	-.50**	-.46**	.65**	.76**	-.46**	.40**	-.31**	.19**	-.31**
Infant Mortality Rate	-.61**	-.42**	.88**	.79**	-.64**	.59**	-.40**	.38**	-.40**

To address the high correlations that exist among the agency variables and jurisdictional variables, principal components analysis was utilized. The process and outcomes of these analyses are presented next.

Principal Components Analyses

Principal components analysis[23] (PCA) was used to address multicollinearity within the agency and jurisdictional variables. Four components were extracted after analysis of the nine agency process variables;[24] analysis of the 22 jurisdictional (demographic and economic) variables also resulted in extraction of four components. In both analyses some variables loaded on more than one component; the highest loading was used to determine final components.

Agency Components

The first component extracted reflects two indices: an index of job satisfaction and an index of front-line staffs perceptions of FIP (see Table 9). A factor score was created from this component and named **Perceived Culture**. The Perceived Culture score was then used as a predictor variable in the multi-variate analyses. Higher scores on this factor indicate more positive perceptions of agency climate.

Orientation, multiple pathways, and reliance on vendors comprise the second component extracted. A factor score was created from this component and is hereafter referred to as

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[23]Principal components analysis is an empirical approach that yields results similar to those obtained through factor analysis (Vogt, 1999). Both approaches enable researchers to reduce a large number of variables to a smaller number of variables, or factors. Specifically, principal components analysis was used to transform our large set of correlated variables into a smaller group of uncorrelated variables. This makes analysis easier by grouping data into more manageable units and eliminating problems of multicollinearity.

[24] Generalist versus specialist and in-house job readiness were dropped from all analyses due to missing data. The reader is referred to our explanation in the methods chapter regarding Baltimore City s district offices.

Customer Pathways. The Customer Pathways score was then used as a predictor variable in the multivariate analyses. Higher scores on this component represent agencies with multiple customer pathways, a mandatory orientation, and heavy reliance on vendors.

Assessment approach primarily defines the third component and standardized testing alone defines the fourth component. With the goal of reducing the number of predictors used in the multivariate models in mind, we decided to drop standardized testing from further analyses for several reasons. First, standardized testing and assessment approach are highly correlated (r = .74). Second, our confidence in the assessment approach measure as an indicator of actual agency assessment processes is greater than our confidence in the testing measure. Thus, assessment approach was kept as a separate predictor and standardized testing was excluded.

Percentage of the caseload with more than 60 months of receipt does not load strongly on any component. It is also highly correlated (r = .94) with TCA caseload size. Given its lack of a clear loading and its strong association with caseload size, the variable was dropped from further analyses. Because TCA caseload size loads on components one and two and our findings from our previous reports suggest that it underlies many of the patterns and relationships under investigation in this study, we decided to retain this variable as a separate predictor in the multivariate analyses.

Table 9: Factor Analysis of Agency Variables

	Rotated Component			
Variable	**1**	**2**	**3**	**4**
Index of Job Satisfaction	.87	-.03	.13	.02
Index of FIP Perceptions	.79	-.15	.03	-.004
TCA Caseload	-.59	.29	.58	-.25
% of Caseload > 60 months receipt	-.33	.45	.41	-.33
Orientation	.20	.56	.19	.39
Assessment Approach	-.12	.04	-.83	-.08
Multiple Pathways	-.12	.75	.07	.01
Standardized Testing	-.10	.05	-.03	.90
Reliance on Vendors	-.07	.84	-.12	-.06
Eigenvalues	2.82	1.77	1.30	1.18
% of Total Variance Explained	28.19	17.71	13.03	11.82

Note: Varimax rotation

Jurisdictional Components

In the factor analysis of jurisdictional predictors, ten variables loaded on the first component: 1) population density; 2) crime rate; 3) percentage of total owner-occupied units; 4) property crime rate; 5) percentage of total population receiving cash assistance; 6) percentage of female-headed households with children under 5; 7) child abuse/neglect investigation rate; 8) total population; 9) total population percent change; and 10) drug arrest rate (see Table 10). This component was converted to a factor score and used as a predictor, hereinafter referred to as **Social Instability**. Higher scores reflect jurisdictions characterized by high population density, high crime rates (violent crime and theft), high property crime rates, high percentages of the total population receiving cash assistance, high percentages of female-headed households with children under five, high rates of child abuse and neglect investigations, larger total populations, high drug arrest rates, low percentages of owner-occupied housing units, and low percentages of population change.

The second component extracted consists of six variables: poverty rate; per capita income; percentage of individuals age 25 and over with a Bachelors Degree; male unemployment rate; unemployment rate; and median household income (see Table 10). This component was also transformed into a factor score and used as a predictor, **Economic Risk**, in the multivariate analyses. Higher scores reflect jurisdictions characterized by high poverty rates, low per capita income, low percentages of individuals age 25 and over with a Bachelors degree, high male unemployment rates, high unemployment rates, and low median household incomes.

The third component extracted consists of five variables: percent Caucasian; percent African-American; percentage of non-marital births; percent of live births to mothers receiving late or no prenatal care; and percent of substandard housing units (see Table 10). A factor score referred to as **Sociodemographic Risk** was created. Higher scores reflect jurisdictions with low Caucasian and high African-American populations and high percentages of non-marital births, births to mothers receiving late or no prenatal care, and substandard housing units.

Finally, the fourth component consists primarily of the infant mortality rate (although drug arrest rate loads on this component as well). Again consistent with the goal of creating parsimonious multivariate models, we decided to exclude this variable from further analyses. This decision was based on the fact that it comprised its own component (doing nothing to create further synthesis of predictor variables) and because it is highly correlated (r is .60 or higher) with a majority of the other jurisdictional variables.

Table 10: Factor Analysis of Jurisdictional Employment and Demographic Variables

	Rotated Component			
Variable	**1**	**2**	**3**	**4**
Population Density	.88	-.05	.15	.20
Crime Rate	.87	.05	.29	.31
Owner-Occupied Units	-.87	-.06	-.26	.13
Property Crime Rate	.85	-.04	.30	.23
% of Population on TCA	.81	.28	.30	.20
% of Female-Headed Household with Children Under 5	.75	.28	.49	.21
Child Abuse/Neglect Investigation Rate	.69	.62	.004	-.08
Total Population	.68	-.54	.05	-.11
Total Population % Change	-.59	-.52	-.16	.39
Drug Arrest Rate	.56	.32	.20	.54
% Caucasian	-.56	.06	-.79	-.12
% African-American	.53	.05	.80	.16
% of Non-Marital Births	.52	.55	.61	.03
Poverty Rate	.44	.77	.38	-.05
Late or No Prenatal Care	.36	.29	.78	-.03
Per Capita Income	.25	-.84	-.21	-.10
Infant Mortality Rate	.23	-.03	.15	.80
% With Bachelors Degree	.21	-.86	-.15	-.17
Male Unemployment Rate	.20	.84	-.04	-.09
Unemployment Rate	.17	.85	.16	.06
Median Household Income	-.12	-.93	-.16	.06
% of Substandard Housing Units	-.003	.30	.86	.16
Eigenvalue	10.86	4.82	1.78	1.20
% of Total Variance Explained	49.36	21.93	8.10	5.47

Note: Varimax rotation

The ultimate purpose of PCA is to enhance conceptual and statistical parsimony by reducing the number of variables considered as predictors in a multivariate analysis. However, as the preceding discussion illustrates, factor analysis does not always yield perfect results. For example, it could be argued that the variables used to created the Social Instability score and the Sociodemographic Risk score represent one underlying construct rather than two. Certainly all of these variables describe a jurisdiction s social and demographic dimensions and therefore could be treated as one index. Mathematically, however, these data load onto distinct factors and thus are considered measures of two different constructs.

Despite the imperfections of PCA, it is commonly used to integrate both conceptual and mathematical approaches to data reduction. In the present analyses, our goal in employing factor analysis was to reduce multicollinearity among our predictor variables and ensure a conceptually parsimonious approach to our multivariate analyses. It is to these analyses that we now turn.

FINDINGS: MULTIVARIATE ANALYSES OF CLIENT OUTCOMES

Several multivariate models were constructed to examine the influence of individual, agency, and jurisdictional characteristics on customer outcomes. All models consist of the same predictor variables[25] (hereafter referred to as predictors). Individual customer characteristics (age[26], race, marital status, welfare history, work history, number of children in the assistance unit, verified work exemption[27], and presence of a child under age five in the assistance unit) comprise one set of predictors. The agency characteristics of caseload size, process and practices (assessment approach and customer pathways[28]), and perceived culture[29] are another set of predictors. Social instability, economic risk status, and sociodemographic risk status, as defined in the preceding chapter, are the predictors used to represent jurisdictional characteristics.

An overview of the multivariate models is provided first, followed by a brief discussion of the specific statistical methods used and presentation of findings. Where appropriate, findings

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[25] The term predictor variable is often used when discussing non-experimental research designs like this study and is another name for independent variable . In the context of correlational studies (and regression analyses) prediction refers to using data to predict outcomes that have already occurred rather than the more common meaning of using data to make a statement about the future as is done in forecasting. (Vogt, 1999)

[26] Because customer age is confounded with at least two of the individual predictors, work history and welfare history, and because we are more interested in their predictive power rather than that of age, we forced age into the equation first for all regression models.

[27] The disabled, pregnant women, individuals with a child under the age of one, and child only cases in which the payee is not a member of the benefit-receiving TCA case are groups eligible for work exemptions.

[28] The reader will recall that customer pathways was transformed into a factor analysis score using the orientation, multiple pathways, and reliance on vendors variables (factors).

[29] The reader will recall that perceived culture was transformed into a factor analysis score using an index of workers job satisfaction and an index of workers perceptions of FIP.

are compared to descriptive jurisdictional findings reported in our Year Three Project Report (Charlesworth, et al., 2001).[30] For each criterion variable[31] (hereafter referred to as customer outcome) four models were built: Model 1 includes just the individual customer predictors; Model 2 includes individual and agency predictors; Model 3 includes individual and jurisdictional predictors; and Model 4 (hereafter referred to as the full model) includes all sets of predictors - individual, agency, and jurisdictional.[32]

Discrete-time event history analysis and regression analyses were the statistical methods used to assess the characteristics that predict customer outcomes. Discrete-time event history analysis is appropriate when examining the timing and correlates of categorical outcome variables such as an exit versus no exit or a return to cash assistance versus no return. Regression analysis is appropriate for continuous outcome variables such as months of cash assistance receipt, quarters employed, and earnings. Stepwise regression[33] is used in the exploratory phase of research for purposes of pure prediction, not theory testing, and was therefore the method of choice for this study. Ideally, model/variable selection is based on theory and not on a computer

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[30] This report reviewed the demographic and economic profile of each of Maryland s 24 jurisdictions and summarized customer TANF outcomes aggregated by jurisdiction.

[31] The term criterion variable is also often used when discussing non-experimental research designs and is used as another name for dependent variable (Vogt, 1999).

[32] All analyses were also run (using all four models) excluding Baltimore City. The coefficients, model significance, and outcome variance explained by the predictors altered very little.

[33] Stepwise regression is a technique for calculating a regression equation that finds the best equation by entering independent variables (predictors) in various combinations and orders. Methods of back elimination and forward selection are combined, so that variables are selected and eliminated until there are none left that meet the criteria for inclusion or removal. (Vogt, 1999)

algorithm. Our models were based on theory to the extent possible, but should be viewed primarily as exploratory. In discrete-time event history analysis all predictors enter the model simultaneously and are also ideally selected based on theory.

The exploratory nature of these analyses does not negate the legitimacy of the findings. To the contrary, we think the information presented in this report will prove meaningful and useful to policy makers and program administrators. Our point is simply that the findings should not be considered definitive without replication. Results from each analysis are presented next.

Predicting Exits from Cash Assistance

The likelihood of a customer exiting from her TCA spell in the 12 months following certification was the first client outcome modeled. Three levels of this outcome variable were examined (employment exit vs. no exit; other exit vs. no exit; and employment exit vs. other exit). Examination of the significant predictors reveals that different factors are involved depending on which levels of the outcome variable are being compared. Tables 11 and 12 display the results for this event history analysis.[34]

Employment Exit vs. No Exit

In Model 1, six individual variables are significantly related to exiting for employment versus not exiting. Older payees, those with a child under 1, those with a disability, and child only cases are less likely to exit for employment, compared to not exiting. Odds of exiting for

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[34] In Table 11, the coefficients and standard errors are displayed. For ease of interpretation, odds ratios are presented in Table 12. Coefficients represent the change in the log-odds of exiting from the TCA spell for each unit change in the predictor. In addition, for each the Model ^{2} statistic, which compares the hypothesized model to chance. Although not a test of model fit per se, a pseudo R^2 value is included for each model that indicates an estimate of the amount of variance in the criterion variable accounted for by the predictors in the model. The pseudo R^2 value is calculated by the formula: 1 - exp[-L/n] where L is twice the positive difference between the log-likelihoods of the full model and a null model.

employment decrease over time during the follow-up period. Those with a longer work history have higher odds of exiting for employment versus not exiting.

In Model 2, eight individual and two agency predictors differentiate between those who exit for employment and those who do not exit at all in the year following certification. Younger payees, African-American payees, those with a longer work history, and those with a child under 5 are more likely to exit for employment. Those with a child under 1, those with a disability, and those who are pregnant are less likely to exit for employment. Odds of exiting for employment decrease over time during the follow-up period. At the agency level, more positive perceptions of FIP and smaller caseloads are associated with greater odds of exiting for employment.

In Model 3, eight individual level and one jurisdictional level predictors are statistically significant in predicting employment exits versus not exiting. Higher odds of exiting for employment are associated with younger age, African-American racial origin, and longer work histories. For all work-exemption categories (child under one, disability, pregnancy, and child only case), those with a reason for exemption are less likely to exit for employment than to not exit at all. Again, the odds of exiting for employment decrease the longer the customer is receiving assistance. Contrary to expectations, those living in jurisdictions with high Social Instability scores are more likely to exit for employment.

In the full model, eight individual level predictors differentiate between those who exit for employment and those who do not exit at all in the year following certification. None of the agency and jurisdictional predictors are statistically significant and the model accounts for only 2 to 28% of the variance in the outcome. Younger payees, African-American payees, and those with a longer work history are more likely to exit for employment. Those with a child under 1, those with a disability, those who are pregnant and payees of child only cases are less likely to exit for employment. Odds of exiting for employment decrease over time since certification.

Other Exit vs. No Exit

The predictors for a non-work exit vs no exit are slightly different from those which predict a work exit vs no exit. In Model 1, seven individual level variables are statistically significant: age; work history; child under 5; child under 1; disability, pregnancy and time. Higher odds of experiencing a non-work exit, compared to not exiting, are associated with older age, shorter work history, not having a child under 5, having a child under 1, having a disability, being pregnant, and child only case status.

In Model 2, seven (of 11) individual and two (of 4) agency predictors are statistically significant. African-American payees, those with a longer work history, and those with a child under 5 have lower odds of experiencing a non-work exit. Odds of a non-work exit are higher for those with a child under 1, disability or who are pregnant. Longer time since certification is associated with lower odds of exiting for a reason other than employment. At the agency level, less positive perceptions of FIP and higher customer pathway scores are associated with higher odds of experiencing a non-work exit.

In Model 3, seven (of 11) individual and all three jurisdictional level predictors are statistically significant. Again, African American heritage, work history, having a child under 5 and time since certification have a negative relationship with exiting for a reason other than employment. Having a child under 1, disabilities, and pregnancies are associated with higher odds of experiencing a non-work exit. Customers in jurisdictions with high Social Instability, high Socio-Demographic Risk, and low Economic Risk scores are less likely to have a non-work exit.

In the full model, seven individual level predictors are statistically significant. African-American heritage, work history, having a child under five and time since certification have a negative relationship with existing for a reason other than employment. Having a child under one, disability, and pregnancies are associated with higher odds of a non-work exit. In addition, one agency level and one jurisdictional predictor are associated with the outcome. Higher Customer Pathways Score and lower Economic Risk Scores lower the odds of experiencing a non-work exit.

Employment Exit vs. Other Exit

The final comparisons displayed in Tables 11 and 12 are between the two types of exits. In Model 1, higher odds of experiencing a non-work exit, compared to a work exit, are associated with being older, having a shorter work history, not having a child under 5, having a child under 1, having a disability and being pregnant.

In Model 2, eight individual level and two agency level predictors distinguish between the two exit types. In addition to the individual level predictors significant in Model 1, the second model shows that African American heritage and more months of receipt since the certification date are associated with lower odds of a non-work exit versus a work exit. At the agency level, lower Customer Pathways scores and larger caseloads are associated with lower odds of experiencing a non-work exit.

In the model with individual and jurisdictional level predictors (Model 3), the same individual predictors are statistically significant. In addition, Model 3 reveals that the odds of experiencing a non-work exit are higher among newly certified customers who live in jurisdictions with high Social Instability Scores, high Socio-Demographic Risk Scores, and low Economic Risk Scores.

In the full model, comparing the odds of exiting for employment versus experiencing a non-work exit reveals a slightly different set of statistically significant predictors. Older payees and those with a work exemption because of pregnancy, disability or having a child under one are more likely to experience a non-work exit than a work exit. Lower odds of experiencing a non-work exit are associated with African-American heritage, longer work histories, having a child under five, and length of time since certification. In addition, two agency level predictors and one jurisdiction level predictor are statistically significant. Customers served by agencies with higher Customer Pathways scores have higher odds of a non-work exit. Higher Perceived Culture Index and Economic Risk scores are associated with lower odds of customers experiencing non-work exits.

Table 11: Survival Analysis Predicting Odds of Exiting - Coefficients and Standard Errors

Predictors	Model 1: Individual			Model 2: Individual & Agency		
	No Exit vs Employment Exit	No Exit vs Other Exit	Employment Exit vs Other Exit	No Exit vs Employment Exit	No Exit vs Other Exit	Employment Exit vs Other Exit
Payee Age	-.012 (.003)***	.007 (.003)*	.019 (.004)***	-.011 (.003)***	.006 (.003)	.018 (.005)***
Payee Race	.035 (.050)	-.071 (.053)	-.107 (.068)	.089 (.053)**	-.164 (.057)**	-.253 (.073)**
Payee Marital Status	.017 (.052)	-.013 (.055)	-.030 (.072)	.029 (.053)	-.024 (.056)	-.053 (.072)
Work History	.102 (.008)***	-.128 (.009)***	-.230 (.011)***	.101 (.008)***	-.123 (.009)***	-.225 (.011)***
Welfare History	.001 (.001)	-.001 (.001)	-.002 (.002)	.002 (.001)	-.001 (.001)	-.003 (.002)
Number of children	-.006 (.021)	-.019 (.023)	-.013 (.029)	-.012 (.021)	-.015 (.023)	-.004 (.029)
Child under 5	.092 (.052)	-.130 (.058)*	-.221 (.073)**	.096 (.052)**	-.133 (.058)*	-.229 (.074)**
Child under 1	-.133 (.062)*	.159 (.067)*	.293 (.087)**	-.136 (.062)**	.164 (.067)*	.300 (.087)**
Disability	-.356 (.096)***	.285 (.077)***	.641 (.117)***	-.361 (.096)***	.319 (.078)***	.679 (.117)***
Pregnancy	-.107 (.071)	.198 (.078)*	.305 (.100)**	-.144 (.072)***	.225 (.079)**	.370 (.101)***
Child only	-.548 (.266)*	.019 (.181)	.567 (.313)	-.533 (.266)	.016 (.181)	.549 (.313)
Time	-.401 (.007)***	-.414 (.007)***	-.012 (.010)	-.397 (.007)*	-.420 (.007)***	-.023 (.010)*
Assessment Approach				.080 (.071)	-.061 (.078)	-.141 (.098)
Perceived Culture Index				.031 (.019)***	-.076 (.021)***	-.107 (.026)***
Customer Pathways Score				-.021 (.031)**	.122 (.036)**	.143 (.045)**
Caseload Size				<-.001 (<.001)	<-.001 (<.001)	<-.001 (<.001)
Social Instability Score						
Economic Risk Score						
Socio-Demographic Risk Score						
Model ^{2} Pseudo R^2	9684.916*** .122			9739.935*** .123		

* p < .05 ** p < .01 *** p < .001

Table 11: Survival Analysis Predicting Odds of Exiting (continued) - Coefficients and Standard Errors

Predictors	Model 3: Individual & Jurisdiction			Model 4: Individual, Agency & Jurisdiction		
	No Exit vs Employment Exit	No Exit vs Other Exit	Employment Exit vs Other Exit	No Exit vs Employment Exit	No Exit vs Other Exit	Employment Exit vs Other Exit
Payee Age	-.011 (.003)**	.005 (.003)	.017 (.005)***	-.011 (.003)**	.006 (.003)	.017 (.005)***
Payee Race	.116 (.056)*	-.208 (.59)***	-.325 (.076)***	.111 (.056)*	-.204 (.059)**	-.315 (.077)***
Payee Marital Status	.033 (.052)	-.029 (.056)	-.062 (.072)	.029 (.053)	-.026 (.056)	-.055 (.072)
Work History	.101 (.008)***	-.123 (.009)***	-.224 (.011)***	.101 (.008)***	-.121 (.009)***	-.222 (.011)***
Welfare History	.002 (.001)	-.001 (.001)	-.002 (.002)	.002 (.0101)	<.001 (.001)	-.002 (.002)
Number of children	-.012 (.021)	-.018 (.23)	-.006 (.029)	-.011 (.021)	-.018 (.023)	-.006 (.029)
Child under 5	.096 (.052)	-.132 (.058)*	-.228 (.074)**	.094 (.052)	-.133 (.058)*	-.227 (.074)**
Child under 1	-.134 (.062)*	.162 (.067)*	.295 (.087)**	-.135 (.062)*	.164 (.067)*	.299 (.087)**
Disability	-.362 (.096)***	.319 (.078)***	.681 (.117)***	-.366 (.096)***	.328 (.078)***	.693 (.118)***
Pregnancy	-.143 (.072)*	.218 (.79)**	.361 (.101)***	-.145 (.072)*	.221 (.079)**	.365 (.101)***
Child only	-.529 (.266)*	.013 (.181)	.542 (.313)	-.527 (.266)*	.019 (.181)	.546 (.313)
Time	-.397 (.007)***	-.419 (.007)***	-.022 (.010)*	-.397 (.007)***	-.421 (.008)***	-.024 (.010)*
Assessment Approach				.090 (.073)	-.055 (.080)	-.144 (.101)
Perceived Culture Index				.018 (.022)	-.057 (.024)(	-.075 (.030)*
Customer Pathways Score				-.008 (.034)	.099 (.040)*	.106 (.049)*
Caseload Size				<.001 (.000)	<.001 (.000)	<.001 (.000)
Social Instability Score	-.053 (.017)**	.067 (.020)**	.120 (.025)***	-.069 (.087)	-.062 (.103)	.007 (.126)
Economic Risk Score	.030 (.028)	-.123 (031)***	-.153 (.039)***	.019 (.032)	-.084 (.037)*	-.104 (.046)*
Socio-Demographic Risk Score	-.032 (.026)	.082 (.028)**	.113 (.036)**	-.039 (.036)	.024 (.043)	.063 (.052)
Model ^{2} Pseudo R^2	9737.047*** .123			9750.410*** .123		

* $p < .05$ ** $p < .01$ *** $p < .001$

Table 12: Survival Analysis Predicting Odds of Exiting - Odds Ratios

Predictors	Model 1: Individual			Model 2: Individual & Agency		
	No Exit vs Employment Exit	No Exit vs Other Exit	Employment Exit vs Other Exit	No Exit vs Employment Exit	No Exit vs Other Exit	Employment Exit vs Other Exit
Payee Age	0.988	1.007	1.019	0.989	1.006	1.018
Payee Race	1.036	0.931	0.899	1.093	0.849	0.776
Payee Marital Status	1.017	0.987	0.970	1.029	0.976	0.948
Work History	1.107	0.880	0.795	1.106	0.884	0.799
Welfare History	1.001	0.999	0.998	1.002	0.999	0.997
Number of children	0.994	0.981	0.987	0.988	0.985	0.996
Child under 5	1.096	0.878	0.802	1.101	0.875	0.795
Child under 1	0.875	1.172	1.340	0.873	1.178	1.350
Disability	0.700	1.330	1.898	0.697	1.376	1.972
Pregnancy	0.899	1.219	1.357	0.866	1.252	1.448
Child only	0.578	1.019	1.763	0.587	1.016	1.732
Time	0.670	0.661	0.988	0.672	0.657	0.977
Assessment Approach				1.083	0.941	0.868
Perceived Culture Index				1.031	0.927	0.899
Customer Pathways Score				0.979	1.130	1.154
Caseload Size				0.999	0.999	0.999
Social Instability Score						
Economic Risk Score						
Socio-Demographic Risk Score						

Predictors	Model 3: Individual & Jurisdiction			Model 4: Individual, Agency & Jurisdiction		
	No Exit vs Employment Exit	No Exit vs Other Exit	Employment Exit vs Other Exit	No Exit vs Employment Exit	No Exit vs Other Exit	Employment Exit vs Other Exit
Payee Age	0.989	1.005	1.017	0.989	1.006	1.017
Payee Race	1.123	0.812	0.723	1.117	0.815	0.730
Payee Marital Status	1.034	0.971	0.940	1.029	0.974	0.946
Work History	1.106	0.884	0.799	1.106	0.886	0.801
Welfare History	1.002	0.999	0.998	1.002	1.001	0.998
Number of children	0.988	0.982	0.994	0.989	0.982	0.994
Child under 5	1.101	0.876	0.796	1.099	1.142	0.797
Child under 1	0.875	1.176	1.343	0.874	1.178	1.349
Disability	0.696	1.376	1.976	0.694	1.388	2.000
Pregnancy	0.867	1.244	1.435	0.865	1.247	1.441
Child only	0.589	1.013	1.719	0.590	1.019	1.726
Time	0.672	0.658	0.978	0.672	0.656	0.976
Assessment Approach				1.094	0.946	0.866
Perceived Culture Index				1.018	0.945	1.078
Customer Pathways Score				0.992	1.104	1.112
Caseload Size				1.001	1.001	1.001
Social Instability Score	0.948	1.069	1.127	0.933	1.064	1.007
Economic Risk Score	1.030	0.884	0.858	1.019	0.919	0.901
Socio-Demographic Risk Score	0.969	1.085	1.120	1.040	1.024	1.065

Predicting Number of Quarters Employed

Table 13, following, presents the results for the multiple regression analyses of our second client outcome, number of quarters employed in a Maryland UI-covered job during the 12 months after TCA certification. In each column, the coefficient[35], standard error[36], and significance level[37] for each predictor are displayed as well as each model s R Square (R^2)[38]. The control variable, age, was entered first in all models. It was a significant predictor in all models such that older payees worked fewer quarters than younger payees. In the first model which examines the relationship among individual predictors and the number of quarters employed post-certification, six customer characteristics are significant.

Employment during the one year follow-up period is greater for African American customers, clients who are currently or previously married and those with recent work histories. Work-

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[35] coefficients are the unstandardized, or raw, regression coefficients. They define the prediction equation, i.e., NUMBER OF QUARTERS EMPLOYED = -.019AGE + .212WORK HISTORY + .103RACE....etc. The coefficient of -.019 for AGE means that for every unit change on AGE there is a decrease of .019 units on NUMBER OF QUARTERS EMPLOYED. The coefficient of .212 for WORK HISTORY means that for every unit change in WORK HISTORY there is a change of .212 units on NUMBER OF QUARTERS EMPLOYED, etc.

[36] Standard error is short for standard error of estimate. The smaller the standard error, the better the sample statistic is as an estimate of the population parameter - at least under most conditions. The standard error is a measure of sampling error; it refers to error in estimates resulting from random fluctuations in samples. The standard error goes down as the sample size (N) goes up. (Vogt, 1999).

[37] P-values govern whether a predictor will enter the equation or be deleted. A predictor must be significant at the .05 level to enter, or must not be significant at the .10 level to be deleted.

[38] R^2 indicates the amount of variance in the outcome variable explained by the model/predictors. In other words, we want to know how powerful an explanation (or prediction) our regression model provides and this statistic shows how well any model predicts the outcome of interest. (Lewis-Beck, 1980).

exempt customers (disability, pregnancy, or heading a child only case) worked fewer quarters in the follow-up period. This model explains 18 percent of the outcome variance.

The addition of agency predictors to the individual variables (the 2nd model), does not change the nature of relationships among the individual customer predictors and this outcome variable. Their relative importance in predicting the number of quarters employed during the follow-up period does change, however, with the addition of the caseload, process, and culture predictors. In addition, two predictors enter the model (having a child under the age of one and under the age of five) and marital status is dropped. Customers with a child under one in their assistance unit experienced fewer quarters of employment. The presence of older children (but still under five years) in the assistance unit is associated with more quarters of employment. Customers served by agencies with smaller caseloads experienced more quarters of post-certification employment as did those certified for assistance by front-line staff with positive perceptions of the FIP. Furthermore, customers served by agencies with more diverse customer pathways (a higher orientation, multiple pathways, and multiple vendors index score) had fewer quarters of post-certification employment. This model explains 19 percent of the variance in the outcome.

When jurisdictional predictors are added to the individual model, the nature of the relationships among the individual customer predictors and the number of quarters employed during the follow-up period remain the same as in those obtained in Model 2. Their relative importance in predicting the customer outcome does alter, however, under Model 3 which adds the jurisdictional predictors (social instability score; economic risk score; sociodemographic risk score). Customers residing in socially at-risk jurisdictions experienced fewer quarters of employment post-certification. However, customers living in economically at-risk jurisdictions were employed for more quarters post-certification. Furthermore, customers residing in sociodemographically at-risk jurisdictions were employed for fewer quarters. This model explains 19 percent of the variance in the outcome.

The final column in Table 13 presents the results of the full model including individual, agency, and jurisdictional predictors. Seven of the eleven individual predictors are significantly correlated with number of quarters employed post-certification. The four work exemption predictors are negatively correlated with this outcome variable which, according to our model, means that an individual with a work exemption worked fewer quarters than an individual without a work exemption. More specifically, with the other variables held constant, an individual with a disability worked .61 fewer quarters than someone without a disability. Customers who were pregnant when they began receiving TCA worked .47 fewer quarters than those who were not pregnant. Individuals exempt from employment requirements because they headed a child-only case worked .40 fewer quarters than individuals without a child-only exemption. Furthermore, individuals with a child under one exemption worked .12 fewer quarters than someone without this exemption.

The remaining three individual level predictors are significantly and positively correlated with quarters employed post-certification. Recent work history, African American heritage, and the presence of a child under five in the assistance unit predict more quarters of employment. For each additional quarter in an individual s work history[39], the person worked .21 more quarters in the year following certification. African American individuals worked .25 quarters more than

[39] Values for the recent work history variable range from zero quarters to eight quarters.

individuals of other ethnic backgrounds. Those with a child under five in the assistance unit worked .08 quarters more than individuals without pre-school aged children.

Three of the four agency predictors are significantly correlated with number of quarters employed. Customer pathways and caseload size are negatively related. Perceived culture is positively related. According to our model, with other variables held constant, an individual served by an agency characterized by a positive perceived culture worked .06 quarters more than someone served by an agency with a less positive perceived culture. Individuals served by agencies with fewer customer pathways worked .10 quarters more than those served by agencies with more customer pathways. In addition, an individual served by an agency with a smaller TCA caseload worked .01 quarters more than someone served by an agency with a larger caseload.

One of the three jurisdictional variables is significantly and positively correlated with post-certification employment. With other variables held constant, an individual residing in an economically at-risk jurisdiction worked .06 more quarters than someone residing in a less economically at-risk jurisdiction. Though counterintuitive, our review of descriptive findings across the 24 jurisdictions indicates that some classified as economically at-risk did have relatively high levels of employment.[40]

The full model explains 19 percent of the variance in the outcome. It should be noted that the full model explains only one additional percentage point of the outcome variance than the first model (individual predictors only). In other words, the individual predictors explain much

[40] Relatively large percentages of TCA customers residing in Caroline and Dorchester counties, for example, were employed post-certification and these two counties are also among the top third jurisdictions with respect to economic risk indicators. The economies of these two counties are also heavily affected by seasonal employment.

more variance in this outcome than either the agency or jurisdictional predictors. Furthermore, the full model explains no more variance in post-certification employment than Models 2 (individual and agency predictors) and 3 (individual and jurisdictional predictors). This suggests that agency and jurisdictional variables have the same predictive ability for this employment outcome. Individual predictors, therefore, emerged as the most influential factors affecting this customer outcome. Knowing an individual s race, work history, and work exempt status is particularly useful for predicting her (or his) post-certification employment - at least for this sample.

Table 13: Regression Analysis Predicting Quarters Employed

Predictors	Model 1: Individual	Model 2: Individual & Agency	Model 3: Individual & Jurisdiction	Model 4: Individual, Agency, & Jurisdiction
	Coefficient / Standard Error	**Coefficient/ Standard Error**	**Coefficient/ Standard Error**	**Coefficients/ Standard Error**
Payee Age	-.019 (.002)***	-.017 (.002)***	-.017 (.002)***	-.172 (.002)***
Payee Race	.103 (.037)**	.240 (.038)***	.259 (.040)***	.253 (.039)***
Payee Marital Status	-.078 (.038)*	ns	ns	ns
Work History	.212 (.006)***	.207 (.006) ***	.208 (.006)***	.206 (.006)***
Welfare History	ns	ns	ns	ns
Number of children	ns	ns	ns	ns
Child under 5	ns	.077 (.037)*	.076 (.037)*	.078 (.037)*
Child under 1	ns	-.121 (.044)**	-.117 (.044)**	-.119 (.044)**
Disability	-.564 (.059)***	-.604 (.059)***	-.595 (.059)***	-.606 (.059)***
Pregnancy	-.408 (.051)***	-.468 (.051)***	-.467 (.051)***	-.468 (.051)***
Child only	-.417 (.107)***	-.045 (.106)***	-.392 (.106)***	-.401 (.106)***
Assessment Approach		ns		ns
Perceived Culture Index		.069 (.014)***		.058 (.015)***
Customer Pathways Score		-.115 (.025)***		-.096 (.026)***
Caseload Size		-.066 (.000)***		-.011 (.000)***
Social Instability Score			-.113 (.014)***	ns
Economic Risk Score			.110 (.023)***	.061 (.027)*
Socio-Demographic Risk Score			-.062 (.019)***	ns
R^2	.182	.194	.192	.194

Note: For ease of interpretation, the caseload size variable was transformed so that the coefficient represents unit change in the dependent variable for each 100 additional individuals in the TCA caseload.
* p < .05 ** p < .01 *** p < .001

Predicting Earnings

Total quarterly earnings is the second employment-related client outcome we examined. Table 14 displays the results of these multiple regression analyses. The control variable, age, was entered first in all models and was significantly positively related to earnings. Examination of the relationships among individual-level predictors and customers follow-up earnings (Model 1) indicates that four customer characteristics are associated with this outcome. Earnings are higher among customers with recent work histories and lower among customers with longer welfare histories and work exemptions (disability and pregnancy). This model explains 10 percent of the outcome variance. There is no change when agency predictors are added (Model 2); in other words, there are no statistically significant relationships among the agency variables(caseload, process, and perceived culture predictors) and follow-up earnings.

When jurisdictional predictors are added to the individual predictors (Model 3), the nature and relative importance of the relationships among the individual customer predictors and follow-up earnings are the same as observed in Models 1 and 2. All three jurisdictional level predictors are statistically significant. Customers residing in economically at-risk jurisdictions earned less. Economic and Socio-demographic Risks are negatively correlated with total earnings. With other variables held constant, according to our model, an individual residing in an economically low-risk jurisdiction earned $457 more during the follow-up period than someone residing in an economically at-risk jurisdiction. Similarly, an individual residing in a socio-demographically at-risk jurisdiction earned $202 less than a peer residing in a socio-demographically low-risk jurisdiction. Finally, Social Instability is positively correlated with earnings during the follow-up period. According to our model, a customer living in a socially unstable jurisdiction earned $233 more than a customer living in a socially stable jurisdiction.

While somewhat illogical, this finding must be interpreted in the study context (that is, Maryland and its unique 24 jurisdictions). The model containing individual and jurisdictional predictors explains 10 percent of the variance in the outcome.

The final column in Table 14, following, present the results of the full model including individual, agency, and jurisdictional predictors. Age (the control variable), four individual predictors and all three jurisdictional predictors are statistically significant. Because none of the agency predictors are significantly correlated with earnings, Model 2 (individual and agency predictors) is identical to Model 1 (individual predictors) and Model 3 (individual and jurisdictional predictors) is identical to Model 4 (all predictors, or the full model). Given that agency processes and practices may be more likely to directly impact employment rather than earnings, their lack of predictive power for this customer outcome is not entirely surprising.

The full model explains 10 percent of the variance in this outcome, while Model 1 explains 9.6 percent of the variance. As with employment, the individual predictors account for the majority of the variance in this earnings outcome. For this sample, to predict customer earnings it is most useful to know an individual s work and welfare history as well as her (or his) work exempt status.

Table 14: Regression Analysis Predicting Earnings

Predictors	Model 1: Individual	Model 2: Individual & Agency	Model 3: Individual & Jurisdiction	Model 4: Individual, Agency, & Jurisdiction
	Coefficient / Standard Error	Coefficient/ Standard Error	Coefficient/ Standard Error	Coefficients/ Standard Error
Payee Age	87.159 (9.347)***	87.159 (9.347)***	86.380 (9.365)***	86.380 (9.365)***
Payee Race	ns	ns	ns	ns
Payee Marital Status	ns	ns	ns	ns
Work History	450.165 (25.594)***	450.165 (25.594)***	449.277 (25.768)***	449.277 (25.768)***
Welfare History	-36.425 (3.402)***	-36.425 (3.402)***	-37.431 (3.537)***	-37.431 (3.537)***
Number of children	ns	ns	ns	ns
Child under 5	ns	ns	ns	ns
Child under 1	ns	ns	ns	ns
Disability	-1811.715 (321.663)***	-1811.715 (321.663)***	-1760.919 (322.122)***	-1760.919 (322.122)***
Pregnancy	-703.431 (231.157)**	-703.431 (231.157)**	-676.433 (234.090)***	-676.433 (234.090)***
Child only	ns	ns	ns	ns
Assessment Approach		ns		ns
Perceived Culture Index		ns		ns
Customer Pathways Score		ns		ns
Caseload Size		ns		ns
Social Instability Score			232.650 (58.889)***	232.650 (58.889)***
Economic Risk Score			-456.618 (100.376)***	-456.618 (100.376)***
Socio-Demographic Risk Score			-201.569 (85.272)*	-201.569 (85.272)*
R^2	.096	.096	.100	.100

* p < .05 ** p < .01 *** p < .001

Predicting Receipt of Cash Assistance

Table 15 displays the multiple regression analysis results for our fourth customer outcome, number of months of cash assistance receipt during the follow-up period. Under Model 1, several customer characteristics are associated with this outcome. The duration of cash assistance receipt in the follow-up period is greater for customers who never married, African American customers, and customers with a work exemption (disability, pregnancy, a child under one, or heading a child only case). Longer welfare histories and shorter work histories predict more months of cash assistance receipt post-certification. Finally, the duration of cash assistance receipt post-certification increases as the number of children in an assistance unit increases. This model explains close to nine percent of the variance in the outcome.

When agency predictors are added to the individual model, the nature of the relationships among the individual customer predictors and the duration of cash assistance receipt during the follow-up period remains the same. However, their relative importance is altered with the addition of caseload, process, and culture predictors. In addition, having a child under the age of one drops from the model.

Customers certified for cash assistance by front-line staff with negative perceptions of FIP and those assessed by more than one worker or a team experienced longer durations of cash assistance receipt post-certification. Furthermore, customers certified for cash assistance in agencies that provided diverse customer pathways (an orientation, multiple pathways, and multiple vendors) also received cash assistance for more months, as did those certified in jurisdictions with larger TCA caseloads. This model explains 13 percent of the variance in the outcome.

When jurisdictional predictors are added to the individual model, the nature of the relationships among the individual customer predictors and the duration of cash assistance is unchanged. However, their relative importance is altered with the addition of social instability, economic risk, and sociodemographic risk. In addition, having a child under the age of one drops from the model. Customers residing in socially unstable jurisdictions experienced longer durations of cash assistance receipt post-certification, as did those residing in socio-demographically at-risk jurisdictions. Surprisingly, customers residing in economically at-risk jurisdictions experienced shorter durations of cash assistance receipt post-certification. This model explains 12 percent of the variance in the outcome.

The fourth column of Table 15 presents results of the full model, including individual, agency and jurisdictional predictors. Eight of the eleven individual predictors are significantly correlated with months of cash assistance receipt post-certification, including three work exemptions. More specifically, with the other variables held constant, an individual pregnant at the time of certification received cash assistance 1.5 months more than someone without a pregnancy exemption. An individual exempt from employment because she heads a child-only case received cash assistance 2.3 months more than an individual without a child-only exemption. In addition, someone with a disability received cash assistance .51 months more than an individual without a disability.

The four other individual predictors are positively correlated with months of cash assistance receipt. Longer welfare histories, a never-married marital status, more children in the assistance unit, and African American heritage predict more months of cash assistance receipt post-certification. According to our model, an individual with a longer welfare history received assistance .01 months more than an individual with a shorter history. Never married individuals received cash assistance .54 months more than individuals currently or previously married. Those with more children in their assistance unit received cash assistance .14 months more than those with fewer children. African American individuals received assistance .21 months more than non-African American individuals. Finally, work history is negatively correlated with months of post-certification TCA receipt. Younger individuals received cash assistance .01 months more than older individuals. Individuals without a recent work history received assistance .15 months more than persons with a recent work history.

Three of the four agency predictors are significantly and positively correlated with the cash assistance outcome variable. Holding the other variables constant, an individual served by an agency characterized by a negative perceived culture received TCA .18 months more than someone served by an agency with a more positive culture. In addition, an individual served by an agency with a higher TCA caseload received assistance for more months than someone served by an agency with a smaller caseload. Furthermore, an individual assessed by either a team or more than one worker received cash assistance .64 months more than someone assessed by one worker.

Two of three jurisdictional variables are significantly and negatively correlated with this customer outcome variable. According to our model, with other variables held constant, an individual residing in an economically viable jurisdiction received cash assistance .32 months longer than an individual residing in a more at-risk jurisdiction. Similarly, someone residing in a sociodemographically stable jurisdiction received assistance .14 months more than someone residing in a more at-risk jurisdiction. Both findings are counterintuitive but descriptive jurisdictional findings offer some support for both.[41]

This model explains 13 percent of the variance in this outcome. Similar to the employment model, the full model explains no more variance in post-certification cash assistance receipt than Models 2 (individual and agency predictors) and 3 (individual and jurisdictional predictors). Relative to Model 1 (individual predictors only), the full model does explain four additional percentage points of the outcome variance. This suggests that knowledge about agency or jurisdictional characteristics somewhat increases our ability to predict the number of months customers will receive cash assistance. Again, knowing a customer s work exempt status and her work history will help predict how long she receives cash assistance. In addition, agency culture and caseload size appear to influence assistance receipt as do a jurisdiction s economic and demographic characteristics.

[41] With the exception of Baltimore City and Wicomico County, jurisdictions with the largest percentages of customers receiving cash assistance cumulatively post-certification are NOT among the most at-risk economically and sociodemographically.

Table 15: Regression Analysis Predicting Receipt of Cash Assistance

Predictors	Model 1: Individual	Model 2: Individual & Agency	Model 3: Individual & Jurisdiction	Model 4: Individual, Agency, & Jurisdiction
	Coefficient / Standard Error	Coefficient/ Standard Error	Coefficient/ Standard Error	Coefficients/ Standard Error
Payee Age	.001 (.005)	-.007 (.005)	-.009 (.005)	-.008 (.005)
Payee Race	1.037 (.097)***	.209 (.093)*	.221 (.097)*	.207 (.097)*
Payee Marital Status	.677 (.099)***	.557 (.092)***	.568 (.092)***	.543 (.092)***
Work History	-.161 (.014)***	-.143 (.013)***	-.147 (.013)***	-.146 (.013)***
Welfare History	.026 (.002)***	.013 (.002)***	.013 (.002)***	.013 (.002)***
Number of children	.098 (.037)**	.136 (.034)***	.136 (.034)**	.138 (.034)***
Child under 5	ns	ns	ns	ns
Child under 1	.229 (.113)*	ns	ns	ns
Disability	.452 (.152)**	.508 (.139)***	.474 (.139)***	.513 (.139)***
Pregnancy	.947 (.132)***	1.470 (.101)***	1.480 (.102)***	1.463 (.101)***
Child only	2.558 (.276)***	2.342 (.267)***	2.311 (.268)***	2.325 (.267)***
Assessment Approach		.482 (.139)***		.635 (.137)***
Perceived Culture Index		-.207 (.036)		-.175 (.039)***
Customer Pathways Score		.172 (.059)**		ns
Caseload Size		.008 (.005)***		.011 (.001)***
Social Instability Score			.610 (.003)***	ns
Economic Risk Score			-.344 (.054)***	-.319 (.060)***
Socio-Demographic Risk Score			.136 (.046)**	-.139 (.051)**
R^2	.085	.126	.122	.128

Note: For ease of interpretation, the caseload size variable was transformed so that the coefficient represents unit change in the dependent variable for each 100 additional individuals in the TCA caseload.
* p < .05 ** p < .01 *** p < .001

Predicting Returns to the TCA Program

Table 16 displays the results of the event history analysis predicting returns to TCA among customers who experienced at least one 60-day exit in the follow-up period. In Model 1, four individual level predictors are statistically significant: welfare history; pregnancy; type of exit; and number of months since exit. Higher odds of returning to TCA are associated with having a longer welfare history, not being pregnant at the time the TCA case was certified, having exited for a reason other than employment, and less time since the exit occurred.

In Model 2, only one individual level predictor is significant, as is one agency level variable. Higher odds of returning to TCA are associated with having exited for a reason other than employment and residing in a jurisdiction with fewer customer pathways.

Four individual level and two jurisdictional level predictors are significant in Model 3. Those who are of African American heritage, were not pregnant at the time of certification, exited for a reason other than work, and had only been off cash assistance a short time are at higher risk of returning to TCA. Residents of jurisdictions with high Economic Risk Scores and with low Socio-Demographic Risk Scores also have higher odds of returning to TCA.

In terms of predicting this outcome, none of the models fit the data well, as indicated by the log-likelihood and chi square statistics. Adding the agency variables or the jurisdictional variables does not significantly increase the percent of variance in the outcome accounted for, as indicated by the pseudo R^2. Each model accounts for only 5% of the variance in returning to cash assistance during the follow-up year.

In the full model, four individual, two agency, and one jurisdictional predictors were significant. Higher odds of returning to TCA are associated with African-American racial background and shorter time since exit. Payees who were pregnant at the time of certification have lower odds of recidivism than their non-pregnant counterparts. Customers served by agencies with low Customer Pathways scores and smaller caseloads are more likely to return to cash assistance as are those living in socially unstable jurisdictions.

While somewhat counterintuitive, these findings are consistent with our jurisdictional-level descriptive findings. With the exception of Baltimore City, which has a high Social Instability score, recidivism rates are highest among small jurisdictions (e.g., Dorchester, 18.9%; Kent, 18.2%; and Caroline 16.7%).

The final model also accounts for 5% of the variance in the outcome. Although two agency and one jurisdictional predictor are significant in the final model, the overall R^2 suggests that adding these variables does not increase our ability to predict recidivism over the information provided by the individual level predictors.

Table 16: Survival Analysis Predicting Odds of Returning to TANF

Predictors	Model 1: Individual		Model 2: Individual & Agency		Model 3: Individual & Jurisdiction		Model 4: Individual, Agency, & Jurisdiction	
	Coefficient / S. E.	Odds Ratio	Coefficient / S. E.	Odds Ratio	Coefficient / S. E.	Odds Ratio	Coefficient / S. E.	Odds Ratio
Payee Age	-.001 (.006)	0.999	<-.001 (.006)	0.999	<.001 (.006)	1.001	<.001 (.006)	1.001
Payee Race	.150 (.093)	1.162	.179 (.099)	1.196	.249 (.104)*	1.283	.233 (.104)*	1.262
Payee Marital Status	.158 (.097)	1.171	.151 (.098)	1.163	.167 (.098)	1.182	.173 (.098)	1.189
Work History	.026 (.014)	1.026	.018 (.014)	1.018	.017 (.014)	1.017	.015 (.014)	1.015
Welfare History	.004 (.002)*	1.004	.003 (.002)	1.003	.002 (.002)	1.002	.002 (.002)	1.002
Number of children	.032 (.033)	1.033	.041 (.033)	1.042	.046 (.033)	1.047	.044 (.033)	1.045
Child under 5	.085 (.088)	1.088	.085 (.089)	1.089	.075 (.089)	1.078	.087 (.089)	1.091
Child under 1	-.141 (.110)	0.868	-.138 (.111)	0.871	-.127 (.111)	0.881	-.125 (.111)	0.882
Disability	-.106 (.140)	0.899	-.156 (.141)	0.856	-.193 (.142)	0.824	-.191 (.142)	0.826
Pregnancy	-.369 (.136)**	0.691	-.317 (.138)*	0.728	-.306 (.138)*	0.736	-.300 (.138)*	0.741
Child only	-.390 (.372)	0.677	-.411 (.373)	0.663	-.408 (.373)	0.665	-.423 (.374)	0.655
Exited for work	-.304 (.076)***	0.738	-.313 (.076)***	0.731	-.316 (.077)***	0.729	-.324(.077)***	0.723
Number of months since exit	-.627 (.018)***	0.534	-.627 (.019)	0.534	-.625 (.019)***	0.535	-.628 (.019)***	0.534
Assessment Approach			-.133 (.153)	0.875			-.221 (.155)	0.802
Perceived Culture Index			.088 (.040)	1.092			.072 (.045)	1.075
Customer Pathways Score			-.240 (.062)***	0.787			-.207 (.069)**	0.813
Caseload Size			<.001 (.000)	1.001			<-.001 (.000)**	<0.999
Social Instability Score					-.025 (.034)	0.975	.518 (.188)**	1.679
Economic Risk Score					.328 (.060)***	1.388	.255 (.067)	1.290
Socio-Demographic Risk Score					-.115 (.051)*	0.891	.044 (.075)	1.045
Model ^{2} Pseudo R^2	1923.511*** .052		1964.922*** .053		1974.132*** .053		1990.060*** .054	

* $p < .05$ ** $p < .01$ *** $p < .001$

DISCUSSION

The purpose of this chapter is to summarize the numerous and varied findings presented throughout the present report. We begin with a brief review of the most pertinent knowledge gained via the bivariate analyses. Next, we discuss the diverse findings produced through our multivariate analyses. Finally, we conclude with a summary of program and policy implications.

Summary of Bivariate Analyses

Our bivariate analyses of the (individual, agency and jurisdictional) predictor variables revealed the complexity of the relationships among these variables. As discussed, the strong relationships present within and among our jurisdictional predictor variables and agency predictor variables indicated the need for principal components analysis. Such analysis proved to be a worthwhile data reduction tool and led to a more parsimonious set of jurisdictional and agency predictors used within our multivariate analyses.

However, the bivariate analyses also revealed moderate correlations between our individual and jurisdictional predictors and between our agency and jurisdictional predictors. Such multicollinearity among our predictor variables inevitably compromised the ability of our multivariate analyses to yield precise findings regarding the relative impact of each predictor variable on the outcomes examined. In addition, the bivariate analyses of relationships among our predictor and outcome variables revealed relatively small correlation coefficients. Weak to moderate correlation coefficients were observed between several individual, agency, and jurisdictional characteristics and customer outcomes. The magnitude of these coefficients suggested that while our multivariate analyses would be informative, the total amount of variance explained by our models might be relatively small. Multivariate analysis would be useful for its original purpose, however, of assessing the relative ability of these predictor variables to influence customer outcomes.

Summary of Multivariate Analyses

Findings produced via our multivariate analyses of relationships among individual, agency, and jurisdictional predictors and customer outcomes were consistent with the preliminary knowledge gained through bivariate examination of these relationships. The present discussion reflects our primary goal of assessing the relative importance of individual, agency, and jurisdictional variables in predicting our customer outcomes, and thus our full-model (all variables included in the model) findings are emphasized. With respect to the discrete-time event history analysis, we focus on comparing those who exited for employment and those who did not exit at all in the year following certification. This emphasis is based on the assumption that, in the work-oriented world of TANF, interest is greatest in attempting to understand which factors best predict exits for employment.

In general, multivariate findings confirm related research and our own expectations. However, some findings were surprising and should be carefully considered. Full model findings across the outcomes examined are illustrated in Table 17, which guides this discussion.

Exits from Cash Assistance and Employment

As described in the findings chapter, the individual customer characteristics of age, race, recent work history, and work exemption status were consistently the best relative predictors of exits for employment and total quarters worked during the one year follow-up period. Specifically, being young, of African American ethnicity, and possessing recent work history increased the likelihood of exiting for employment and being employed during more quarters through the follow-up period. Conversely, having a child under age 1, being pregnant, having a disability, and heading a child only case decreased the likelihood of exiting for employment and reduced total quarters of employment during the follow-up period. Notably, however, although payees of child only cases were less likely to exit for employment, they did not significantly differ in terms of number of quarters worked and prior descriptive analyses indicate employed child-only caseheads had relatively high earnings. For all sample members, the odds of exiting for employment decreased over time during the study follow up period.

Our finding that recent work history and work exemption status influence employment outcomes is consistent with previous research (see, for example, Ver Ploeg, 2001). However, it is surprising that payee marital status, welfare history, and number of children were not significantly related to employment outcomes. Moreover, our finding that younger, African American sample members were more likely to exit for employment, and be employed more quarters, is inconsistent with previous studies and may be influenced by data limitations or the specific study context (Maryland). That is, in Maryland, there is a higher proportion of African American residents and African American TCA recipients than the national average. Also, several border jurisdictions (where out-of-state employment is common) are also those with a high proportion of Caucasian residents.

Agency variables did not predict exits for employment but a positive perceived culture among front-line staff, fewer customer pathways, and smaller agency (TCA) caseload size predicted more total quarters worked during the study follow-up period. However, prior analyses indicate that these particular agency predictor variables themselves are inter-correlated, with agencies with smaller caseload sizes more likely to possess fewer customer pathways and staff with positive perceptions of agency culture. The relative importance of, and temporal relationships among, these agency characteristics is thus extremely difficult to assess.

Our jurisdictional variables also did not predict exits for employment but, surprisingly, residing in economically at-risk jurisdictions predicted more total quarters worked during the study follow-up period. Although this finding is counter-intuitive, a review of our descriptive findings indicates that in some relatively at-risk (economically speaking) jurisdictions, sample members did experience relatively positive employment outcomes. Thus this finding may be specific to our study context (the State of Maryland and its unique 24 jurisdictions) or may indicate that a strong economy may, at times, lead to surprising employment outcomes.

Earnings

Turning to examination of earnings during the study follow-up period, slightly different factors emerge as the best predictor variables. This is not surprising given that the characteristics predicting the ability to obtain a job certainly may differ from those that determine earnings levels among the employed. Older sample members with recent work histories and less welfare receipt history generally earned more during the study-follow up period than customers without this profile; this finding is also consistent with the literature. Employed customers eligible for a work exemption at the time of certification due to disability or pregnancy earned less during the follow-up period.[42] The nature of our quarterly employment data must be considered when interpreting this finding. That is, low earnings figures may reflect part-time employment rather than low hourly wages.

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[42]The reader is reminded that our exemption data simply indicate eligibility for a work exemption. Because our analysis of earnings was restricted to sample members employed at some point during the follow-up period, work-exempt sample members included in this analysis may have chosen not to utilize their work exemption or the exemption may have expired before the end of the follow-up period.

Perhaps not surprisingly, agency characteristics did not predict earnings levels among the employed. Jurisdictional characteristics, however, did. Specifically, all three jurisdictional factor scores (economic risk, social instability, and sociodemographic risk) predicted earnings. As one would expect, employed customers living in low (sociodemographic and economic) risk jurisdictions generally earned more. However, the social instability variable behaved in a somewhat surprising fashion, appearing to predict relatively higher earnings. However, this finding again must be interpreted within the study context (that is, Maryland and its unique 24 jurisdictions). For example, Baltimore City is a relatively unstable (according to our measures) jurisdiction, yet wage levels are relatively high in the City. And, as previously mentioned, employed sample members in the rural counties of Dorchester and Caroline had relatively high total earnings during the study follow-up period despite the fact that these counties are relatively socially unstable, according to the study definition.

In sum, individual characteristics were the strongest predictors, relative to the included agency and jurisdictional characteristics, of exiting for employment and earnings during the study follow-up period. The individual and jurisdictional variables that emerged as strong predictors of earnings are generally more consistent with logic and existing research than those which emerged as strong predictors of employment. This may be due to unique features of the current policy and economic context or to the possibility that restricting our analysis to (earnings among) those with UI-recorded employment within the State of Maryland eliminates our grossest employment data limitations, such as missing data for those employed out-of-State. Data limitations not withstanding, of interest is the fact that recent work history emerges as a strong, consistent predictor across the employment outcomes examined.

Cash Assistance Receipt

Turning to our analysis of total months of TCA receipt during the one year study follow-up period, a number of individual characteristics emerged as significant predictors. Consistent with the welfare research literature, African American ethnicity, never-married marital status, no or less recent work history, longer welfare receipt history, more children in the assistance unit, and eligibility for work exemptions (specifically, disability, pregnancy, and child under age 1) predicted more months of receipt in the year following certification.[43]

Three agency and two jurisdictional characteristics predicted total months of cash assistance receipt. The following agency characteristics predicted more months of receipt: a team or two-worker approach to assessment; negative perceived culture; and larger agency caseload size. Contrary to expectations, economic and socio-demographic risk predicted shorter durations of post-certification receipt. Again, descriptive findings previously reported indicate that in Maryland the jurisdictions with the largest percentages of customers receiving cash assistance cumulatively post-certification are NOT among the most at-risk economically and sociodemographically.

Returns to Cash Assistance

Our examination of the relative predictive ability of our various independent variables indicates that those who exited without employment were more likely to return to TCA and that the more months elapsed after the exit, the less likely a return to TCA became. In addition, two

[43] We speculate that the reason African American ethnicity predicts both increased employment and increased receipt of cash assistance may have to do with customers combining cash assistance and employment, a phenomenon which has become much more common under TANF (Committee on Ways and Means, 2000).

individual characteristics, two agency characteristics, and one jurisdictional characteristic predicted returns to TCA. That is, being Caucasian and being pregnant at the time of certification seem to lower the likelihood of returning to TCA among those who exited during the follow-up period. Controlling for other factors, customers served by agencies with more customer pathways and larger agency TCA caseload sizes were also less likely to return following an exit. Finally, customers residing in socially unstable jurisdictions were also less likely to return following an exit.

Table 17: Summary of Multivariate Findings

	Employment Outcomes				TCA Outcomes	
Predictors	**No Exit vs Employment**	**Employment vs Other Exit**	**Quarters Employed**	**Total Earnings**	**Months of TCA Receipt**	**Returning to TCA**
Payee Age						ns
Payee Race				ns		
Payee Marital Status	ns	ns	ns	ns		ns
Work History						ns
Welfare History	ns	ns	ns			ns
Number of children	ns	ns	ns	ns		ns
Child under 5	ns			ns	ns	ns
Child under 1				ns	ns	ns
Disability						ns
Pregnancy						
Child only		ns	ns	ns		ns
Exit for work						
Time						
Assessment Approach	ns	ns	ns	ns		ns
Perceived Culture Index	ns			ns		ns
Customer Pathways Score	ns			ns	ns	
Caseload Size	ns	ns	ns	ns	0	
Social Instability Score	ns	ns	ns		ns	
Economic Risk Score	ns					ns
Socio-Demographic Risk Score	ns	ns	ns			ns

Implications

These findings together suggest that no single variable consistently predicts each of the outcomes examined. However, individual characteristics as a group consistently emerges as the variable set best able to predict the outcomes examined. In particular, recent work history clearly increased the likelihood of exiting TCA and obtaining employment during the study follow-up period among our sample members. Perhaps validating one essential premise of welfare reform, our study findings suggest that facilitating stable employment among customers may, indeed, be among the best preventive interventions in terms of reducing welfare dependency. Study findings also lend support to the need for provisions to exempt portions of states TANF caseloads from time limits, as well as other program requirements. We found, to illustrate, that sample members with a disability or who were pregnant when they began receiving TCA were less likely to exit welfare or to become employed during the follow-up period.

One limitation of our analysis is that our final models accounted for little of the variance in customer outcomes. Additional variance may have been explained had we included individual-level variables that measure education level and the availability of resources such as child care and transportation in the models.

Agency predictors contributed less to our understanding of TANF outcomes than the individual predictors. However, positive staff perceptions do appear to be important for facilitating employment transitions and encouraging customers to use cash assistance for fewer months. The agency process dimensions included in the analyses are therefore salient, but it is likely that other equally important process dimensions were excluded. For example, other research suggests that a strong employment message and emphasis on up-front job search may lead to better short-term employment outcomes; unfortunately, we did not include variables which could be said to measure these dimensions. In addition, another potentially important dimension we did not include is a staff emphasis on personal customer attention and needs.[44]

With respect to jurisdictional or county-level predictors, we included those that have been included in similar studies, but the work done at this level of analysis is largely in the exploratory phase. For example, one area with known limitations concerns accurate indicators of the local economy. In a strong national economy, state and local level business cycle indicators may more strongly predict employment outcomes. Furthermore, the demographic and economic dimensions of a jurisdiction may be less relevant to customers outcomes than the same dimensions of their more immediate communities (such as their neighborhoods). Unfortunately, our results do not add much in the way of clarification.

We suspect that the inconsistent predictive power of agency and jurisdictional characteristics may be due to measurement error and data limitations, multicollinearity, and unaccounted for shared error among these variables rather than the lack of a relationship among these factors and the welfare outcomes examined. For example, we suspect that agency caseload size is related to a number of agency and jurisdictional variables, as well as our outcomes, in a complex fashion not yet understood and not clearly discernable from our findings.

Indeed an examination of agency and jurisdictional predictors and aggregated customer outcomes at the jurisdictional level indicates that a) the relationship between caseload size and customer outcomes is curvilinear and b) the multiple levels of analysis associated with our predictors weaken the ability of our multivariate models to predict customer outcomes. To

[44] See, for example, Freedman, Friedlander, Hamilton, Rock, Mitchell, Nudelman, Schweder, & Storto, 2000 and Michalopoulos, Schwartz, & Adams-Ciardullo, 2000 for research suggesting the importance of these dimensions.

illustrate the first point, Figure 1, following, shows the relationship between TCA caseload size and percent of customers who left TCA during the follow-up period. The relationship is clearly curvilinear with very small jurisdictions having the highest percentage of customers exiting TCA. When the caseload reaches approximately 1,000 cases, there is a bend in the curve and the line becomes much flatter. That is, it appears that once caseloads reach a certain point, increases in caseload size produce little change in the aggregate customer outcome of percentage of customers exiting TCA.[45]

An additional issue in our multivariate analyses is that our predictors represent at least two levels of analysis: individual and agency/jurisdiction. Because of the mainly methodological problems associated with ignoring levels of analysis, techniques such as hierarchical linear modeling (HLM) have been developed. However, it was not possible to use HLM in the present study because there are too few units at the highest level (i.e. jurisdiction, n = 24).

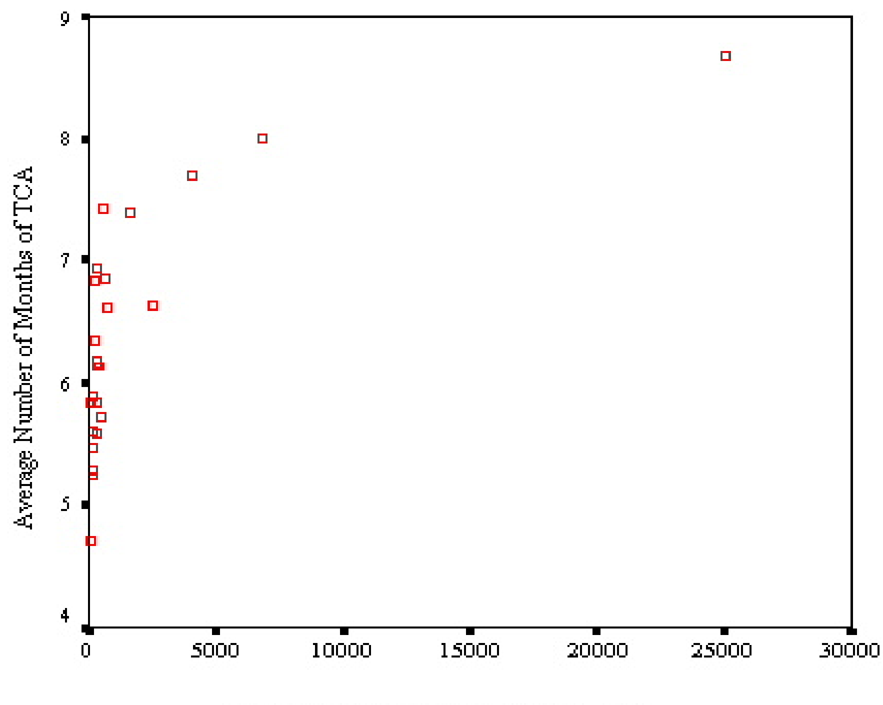
The multivariate analysis findings contained some surprises among many of our agency and jurisdictional predictors and customer outcomes. To explore if these findings were partly a result of the levels of analysis issue, we conducted a series of multiple regression analyses at the jurisdictional level. The same agency and jurisdictional level predictors used in the multivariate analyses reported in the previous chapter were used to predict the same customer outcomes, aggregated to the jurisdictional level: percent of customers exiting; average number of quarters employed; median customer earnings during the follow-up period; and average number of months of TCA receipt. The results from these analyses should be treated with extreme caution

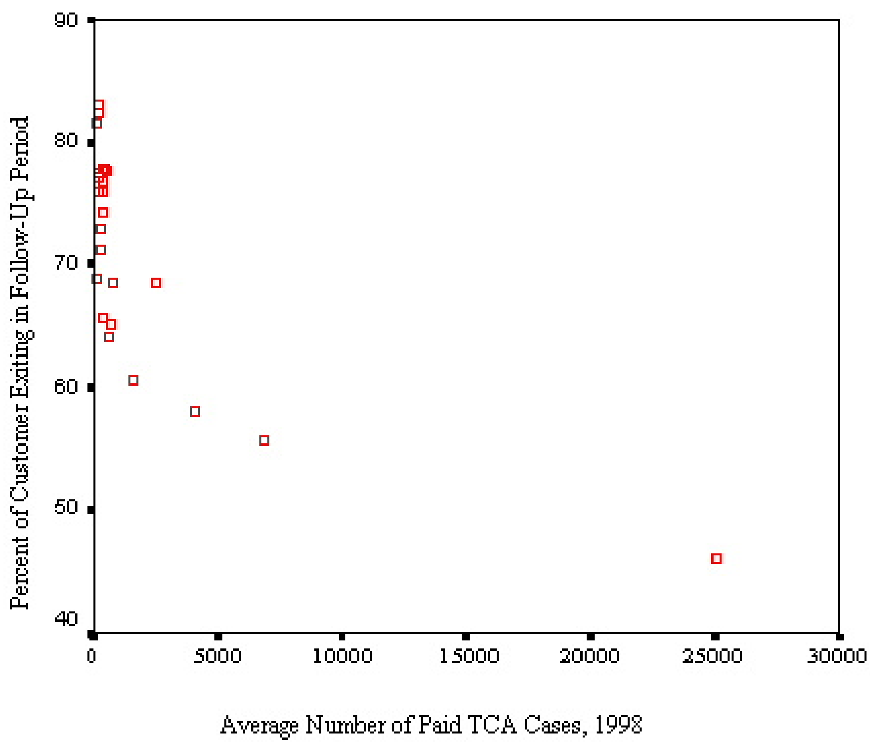
[45]To explore the possibility that the extremely large caseload in Baltimore City was alone producing this apparent relationship, we also graphed the data excluding Baltimore City. The relationship remains curvilinear for the remaining 23 counties.

because of the levels of analysis issue mentioned previously, the small number of cases, and the relatively large number of predictors in each model.

However, the results do provide some indication that the multivariate models are not able to capture the full complexity of relationships although some unexpected relationships remain. In particular, for the models of TCA outcomes, the amount of variance explained is generally higher in the jurisdictional level models (74% for average number of months of TCA receipt and 76% for percent of customers who exit) than in the individual level models (13% for number of months of TCA receipt and 12-28% for probability of exiting). For both of these outcomes, average caseload size, Perceived Culture Index score, and Economic Risk Score are statistically significant predictors. Large caseloads, low perceived culture and low economic risk are associated with a higher average number of months of TCA receipt. Similarly, small caseloads, higher perceived culture, and higher economic risk predict higher percentages of customers exiting TCA during the follow-up period.

Figure 1: Relationship between Caseload Size and Customer Outcomes





CONCLUDING THOUGHTS AND OBSERVATIONS

Hindsight is 20/20, as they say. Conducting this study has taught us many things, not least of which are the research findings themselves. Certainly we learned a great deal about what was occurring in Maryland s local welfare offices in terms of key assessment/service allocation practices, agency policies and the perspectives of supervisory and front-line staff about this new and still evolving thing called welfare reform . We also gained some knowledge about what predicts TANF outcomes in Maryland and acquired some insights into how agencies might most effectively allocate their resources. Of equal importance, however, is what we learned in the process of meeting the objectives of this ambitious, multi-year, multi-method study. Many of the lessons learned about how to execute a study of this size and scope primarily revolve around methodological issues; a few of the more important of these are highlighted below because they may be of some value to others who may be contemplating such a study.

Study Design

From a scientific perspective, definitively establishing the effect of agency processes and practices on client and county-level TANF outcomes requires the rigor and control inherent in experimental research designs. Indeed, research endeavors focused on similar questions (e.g., the GAIN studies) have traditionally attempted to control agency process and practice variables through study design in order to assess their independent effects on outcomes. When experimental control is not feasible, however, quasi-experimental designs and statistical methods can often offer sound alternatives for understanding causal relationships. In the current welfare environment where the need for timely information about reform implementation and impact is great, many practitioners and researchers rely on non-experimental methods. In this environment, our use of multivariate statistics was a reasonable approach to examining the research questions especially, so it seemed at the outset, given the amount and sources of data available to the research team through our long-standing partnership with the Maryland Department of Human Resources (DHR) and local Departments of Social Services (DSS). As researchers, our access to large quantities of high-quality, longitudinal administrative data and our access to and the promised cooperation of managerial and front-line staff across the entire state made a statistical methodology appealing. In retrospect, however, this choice was undermined by data and measurement limitations.

Data and Measurement Issues

From the outset, we were aware that qualitative and quantitative methods were necessary to appropriately address our research questions, even though, broadly speaking, it is always challenging to effectively combine these two types of data and to quantify qualitative data. In retrospect, we suspect that a great deal of important information about local practices and assessment processes was likely lost by reducing these complex phenomena to the variables demanded by traditional statistical techniques. Through the process of distilling rich data into a more diluted and perhaps less valid form, we suspect we may have also lost predictive ability. If our predictors were not valid measures then we would not expect to observe any impact on outcomes because we may have failed to capture a critical component of the relationship under examination.

Related to this point is the question of how best to measure and document the behaviors and human interactions that comprise agency processes and practices. Measurement difficulty is compounded by the also complex task of identifying the most salient dimensions for study. Established theory typically guides variable selection and measurement development. In our enthusiasm to investigate factors associated with outcomes under welfare reform, however, we failed to appreciate, up front, that our study was being undertaken during a unique and dynamic time in welfare programming when the research objectives and methodology for meeting them were relatively unique. Therefore, theoretical and procedural guidance was scarce. The practical lesson here is that the researchers partnership with DHR and DSS granted us unfettered access to invaluable sources of data, but availability of data does not guarantee that one will have or be able to create the most appropriate or psychometrically sound measures.

Procedures

In addition to the measurement issues, there were data collection issues that may also be germane to other complicated TANF-era, state-level studies such as this one. At the start of this multi-year study, we appreciated that a county-administered, state-supervised State operating in the devolved TANF policy environment certainly had many programmatic benefits; what we perhaps did not appreciate quite so fully was that it also presents many research challenges, especially in a multi-year research investigation. Change is constant, and keeping abreast of such change is extremely challenging. Documenting these changes (e.g., to assessment practices or customer pathways) would have required several in-depth data collection points throughout the study; it would not have been possible to carry out a study like that, however, within the funds available for these projects.

Concluding Thoughts

As Richard Nathan, a notable veteran of implementation research, has noted, public policies operate in complex, noisy environments in which a great many factors are operating (Nathan, 2000, p197). Such was certainly true with regard to welfare reform in Maryland during the three year period covered by this study. The data collected during the first year of the study provided valuable insight into how welfare was being implemented across Maryland s jurisdictions. They illustrated that the changes associated with reform went far beyond the client assessment process in which we were initially interested. Indeed, no aspect of agency process, practice or culture appeared to be unaffected by PRWORA. The qualitative data collected through site visits, observations, and interviews provide a rich picture of a unique moment in public welfare history.

In retrospect, however, while the dynamic nature of the environment was well-suited to our process study, it was not ideal for the second phase which attempted to examine how individual, agency and jurisdictional factors affected welfare reform outcomes. The noise in the system, noted by Nathan (2000), limited the utility of the quantitative analyses. Deferring the study until the system had reached equilibrium most likely would have made the conduct of the quantitative study easier and the results more consistent with theoretical expectations. Measurement issues aside, we must wonder how study results might have been different had we waited until reform-induced local practices in customer assessment and service patterns became more fixed and, perhaps, until sufficient time had elapsed for even the most skeptical staff (and perhaps customers) to have become convinced that, this time, welfare reform is, indeed, here to stay.

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APPENDIX A
BIVARIATE CORRELATIONS: INDIVIDUAL, AGENCY, AND JURISDICTIONAL VARIABLES AND CUSTOMER OUTCOMES

This appendix presents bivariate correlation analyses of (individual, agency, and jurisdictional) predictor variables and customer outcomes. Each set of predictor variables is presented in a separate table and briefly summarized below.

Table A-1 presents correlations among individual customer characteristics and customer outcomes. Focusing on cash assistance outcomes post-certification, race and child-only case status stand out as relatively highly correlated with both total months of receipt in the one year follow up period and exiting cash assistance during the follow-up period. Being African-American appears to increase total months of receipt (r =.15) and decrease likelihood of exiting (r = -.12). Child-only case status also appears to increase total months of receipt (r = .24) and decrease likelihood of exiting (r = -.23).

With regard to employment outcomes, work history, age, and disability exemption status exhibit notable correlation coefficients. Recent work history appears to increase the number of quarters employed (r = .46) and total follow-up earnings among those who are employed (r = .33). Age is inversely correlated with the number of quarters employed (r = -.14) but positively correlated with earnings (r = .25). This suggests that, in general, older customers within the sample may be less likely to work, but among those who do, earnings are relatively high. Logically, the presence of a disability exemption appears to decrease both employment (r = -.14) and earnings (r = -.08).

Table A-2 presents the correlations among agency characteristics and customer outcomes. These variables show virtually no relationship with employment and earnings outcomes and only small relationships with cash assistance outcomes. TCA caseload size and the proportion of the caseload considered long-term (two highly correlated variables themselves) are both positively correlated with total months of cash assistance receipt (r = .23 and r = .21 respectively) and inversely correlated with exiting cash assistance (r = -.20 and r = -.18 respectively) during the follow-up period. In other words, customers served by agencies with large overall TCA caseloads and high proportions of long-term recipients within the caseload appear less likely to exit cash assistance during the follow-up period.

The FIP Perceptions and Job Satisfaction index scores are both inversely correlated with total months of cash assistance receipt during the 12 month follow-up period (r = -.18 and r = -.17 respectively) and positively correlated with exiting cash assistance (r = .15 and r = .14 respectively). These results seem to suggest that customers served by agencies in which workers have positive perceptions of welfare reform and are relatively satisfied with their work environments were more likely to exit cash assistance during the follow-up period.

Assessment approach exhibits a small, inverse correlation with total months of cash assistance receipt during the follow-up period (r = -.13) and a small, positive correlation with exiting cash assistance (r = .12). Specifically, customers served by agencies using a one-on-one approach to customer assessment may have been less likely to exit cash assistance during the follow-up period. Multiple pathways exhibits a small, positive correlation with total months of cash assistance receipt (r = .16) and a small, inverse correlation with exiting cash assistance (r = -.13), indicating that customers served by agencies with more customer pathways were less likely to exit cash assistance.

Table A-3 presents the correlations among jurisdictional characteristics and customer outcomes. Like agency characteristics, jurisdictional characteristics exhibit virtually no relationship with employment and earnings outcomes and only small relationships with cash assistance outcomes. In general, customers residing within economically and/or socio-demographically at-risk jurisdictions and were less likely to exit cash assistance during the follow-up period. Two jurisdictional variables   per capita income and percentage of residents with a Bachelors degree   stand out as exhibiting relatively small correlations with cash assistance outcomes.

Table A-1:Correlations among Customer Characteristics and Customer Outcomes

	Customer Outcomes			
	Cash Assistance Receipt	Exit Cash Assistance	Quarters Employed	Earnings
Customer Characteristics				
Age	.08**	-.09**	-.14**	.25**
Race	.15**	-.12**	.05**	.01
Marital Status	.08**	-.05**	.03**	-.13**
Welfare History	.10**	-.08**	-.02**	-.17**
Work History	-.10**	.09**	.46**	.33**
Disability Exemption	.01	.00	-.14**	-.08**
Pregnancy Exemption	.03**	-.01	-.03**	-.09**
Child < 1 Exemption	-.02**	.03**	.01	-.03**
Child Only Exemption	.24**	-.23**	-.05**	.34**
Child < 5 in Assistance Unit	-.02**	.02**	-.05**	-.08**
Number of Children in Assistance Unit	.02**	-.02**	.00	-.03**

Table A-2: Correlations among Agency Characteristics and Customer Outcomes

	Customer Outcomes			
Agency Characteristics	**Cash Assistance Receipt**	**Exit Cash Assistance**	**Quarters Employed**	**Earnings**
Index of FIP Perceptions	-.18**	.15**	.08**	.02**
Index of Job Satisfaction	-.17**	.14**	.08**	.01
TCA Caseload (1998)	.23**	-.20**	-.06**	-.03**
% of Caseload > 60 months receipt	.21**	-.18**	-.06**	-.04**
Assessment Approach	-.13**	.12**	.03**	.03**
Multiple Pathways	.16**	-.13**	-.08**	-.03**
Orientation	-.08**	.07**	-.04**	.04**
Reliance on Vendors	.09**	-.08**	-.05**	-.01
Standardized Testing	-.08**	.08**	-.01	.02**

Table A-3: Correlations among Jurisdictional Characteristics and Customer Outcomes

	Customer Outcomes			
Jurisdictional Characteristics	**Cash Assistance Receipt**	**Exit Cash Assistance**	**Quarters Employed**	**Earnings**
Population Density	.22**	-.19**	-.05**	-.03**
Crime Rate	.24**	-.07**	-.03**	-.20**
Owner-Occupied Units	-.23**	.20**	.07**	.03**
Property Crime Rate	.17**	-.14**	-.10**	.00
% of Population on TCA	.22**	-.19**	-.05**	-.03**
% Female-Headed HH with Children < 5	.22**	-.19**	-.06**	-.04**
Child Abuse/Neglect Investigation Rate	.19**	-.04**	-.04**	-.17**
Total Population	.19**	-.10**	.03**	-.15**
Total Population % Change	-.21**	.18**	.05**	.03**
Drug Arrest Rate	.20**	-.18**	-.04**	-.04**
% White	-.23**	.19**	.08**	.04**
% Black	.23**	-.19**	-.08**	-.04**
% Non-Marital Births	.21**	-.18**	-.05**	-.05**
Poverty Rate	.19**	-.17**	-.04**	-.04**
Late or No Prenatal Care	.22**	-.18**	-.06**	-.05**
Per Capita Income	-.03**	.03**	.00	.07**
% with Bachelors Degree	-.08**	.07**	.00	.06**
Male Unemployment Rate	.17**	-.16**	-.05**	-.05**
Unemployment Rate	.16**	-.14**	-.03**	-.05**
Median Household Income	-.12**	.11**	.01**	.06**
% Substandard Housing	.16**	-.13**	-.08**	-.06**
Infant Mortality Rate	.22**	-.19**	-.08**	-02**