

LEAD Program Evaluation:

The Impact of LEAD on Housing, Employment and Income/Benefits

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Executive Summary

- **Background:** Seattle’s Law Enforcement Assisted Diversion (LEAD) program offers people suspected of low-level drug and prostitution offenses legal assistance and harm-reduction-oriented case management as an alternative to prosecution and incarceration.
- **Purpose:** This report describes findings for LEAD participants in terms of their housing, employment, and income/benefits both prior and subsequent to their referral to LEAD. Primary analyses also tested whether the number of contacts LEAD participants had with their case managers contributed to these findings. Additional, secondary analyses examined the associations between positive participant outcomes (i.e., attainment of housing, employment and income/benefits) and involvement in the criminal justice system (i.e., recidivism).
- **Findings:**
 - **Primary Analyses:** Participants were significantly more likely to obtain housing, employment and legitimate income in any given month subsequent to their LEAD referral (i.e., during the 18-month follow-up) compared to the month prior to their referral (i.e., baseline).
 - **Housing:**
 - LEAD participants were over twice as likely to be sheltered (e.g., permanent housing, temporary housing, emergency shelter, motel/hotel) versus unsheltered (e.g., sleeping on the streets, in abandoned buildings) during the follow-up. Further, each contact participants had with LEAD case managers was associated with a 2% increase in the likelihood of obtaining shelter during the follow-up.
 - Participants were 89% more likely to obtain permanent housing during the follow-up, and each contact they had with their LEAD case manager translated to a 5% higher likelihood of being housed during follow-up.
 - **Employment:** LEAD participants were 46% more likely to be on the employment continuum (i.e., in vocational training, employed in the legitimate market, retired) at follow-up versus baseline.
 - **Income/benefits:** LEAD participants were 33% more likely to have income/benefits at follow-up versus baseline.
 - **Secondary Analyses:** Additional analyses exploring the association between recidivism and obtaining housing, employment and income/benefits showed that housing and employment obtained during LEAD involvement was associated with less recidivism as measured by arrests during the 6-month follow-up.

- **Interpretation of findings:**
 - Prior reports showed Seattle's LEAD program reduces recidivism as well as utilization of and costs for the criminal justice and legal systems. The present report adds to these initial findings by showing that LEAD participants have a higher likelihood of attaining housing, improving employment outcomes, and obtaining legitimate income/benefits after their referral to the LEAD program.
 - Obtaining housing and employment is associated with less recidivism.
 - Interpretation of the present findings is limited by the fact that we did not have housing, employment and income data for the control group. Thus, the promising associations between LEAD participation and positive participant outcomes cannot be assumed to be causal. There could be other factors involved in producing the observed LEAD effects.
 - That said, the fact that increased contact with LEAD case managers predicted better housing outcomes increases our confidence that those effects may be attributable to LEAD.

- **Next Steps:** This report is one in a series being prepared by the University of Washington LEAD Evaluation Team over a two-year period. A final report will be released in the summer of 2016 and will document LEAD participants' perceptions of the LEAD program and its effect on their lives.

Introduction

Background

The US imprisons more of its population than any other country in the world, and incarceration rates, particularly among drug offenders, have increased exponentially since 2008.¹⁻³ Given that up to 3.5 million Americans experience homelessness in any given year,⁴ homelessness also represents a large and growing problem in America.^{5,6} Although the relationship between homelessness and criminal recidivism is not well understood, the two appear to be inexorably linked,⁵⁻⁷ with one representing a risk factor for the other.⁸⁻¹⁰ For example, the prevalence of homelessness among incarcerated offenders is 7.5 to 11.3 times that found in the general population.¹¹ Further, incarceration is disproportionately high among homeless individuals.⁵ For example, a recent study indicated that nearly one-quarter of homeless and marginally housed individuals had a history of incarceration.⁸ Collectively, studies have shown that people with unstable housing are more frequently arrested, are incarcerated longer, and are re-arrested at higher rates than people with stable housing.^{12,13}

Both homeless and incarcerated populations share certain characteristics that are noteworthy, including housing instability, unemployment, poverty, lack of job skills/training, and substance-use problems.^{6,11,14-18} Substance-use problems and ensuing drug offenses represent a particular challenge to policy makers because traditional policing efforts have not been found to improve public safety or decrease recidivism for drug offenders.^{3,19-21} Drug offenders instead often cycle through the criminal justice system with such frequency that this phenomenon is referred to as a “revolving door.”²²

A recent study has indicated that the standard approach of prosecution and incarceration may contribute to the revolving door phenomenon by decreasing opportunities to obtain housing, employment and legitimate income/benefits, thereby confining offenders to continued work in illegal markets.²³ These individuals thus lack the resources needed to stop the revolving door of homelessness and incarceration.⁸ Considering the numerous undesirable consequences of repeat drug offending at both the individual and societal level, there have been calls for innovative programs to engage repeat offenders and help them stop this detrimental cycle.²²

Over the past decade, studies have shown that case management, which entails connecting individuals with community services to help them meet their basic needs, is an essential component of programs that precipitate significant reductions in recidivism. For example, one study of a re-entry program offering case management (i.e., housing assistance, job training, financial assistance) to male offenders showed significant reductions in arrest rates.²⁴ Additionally, an evaluation of a pretrial diversion program featuring intensive, client-centered case management reported reduced arrest and incarceration rates.²⁵

Connecting individuals to services is a key component of case management; however, the nature of the relationship between clients and case managers also appears to be important to successful program outcomes. In a large-scale population-based study, Chinman and colleagues showed that a stronger therapeutic alliance between homeless clients and case managers was associated with fewer days of homelessness and better quality of life.²⁶ Taken together,

research to date highlights the importance of building a strong case management relationship and connecting individuals with services to maximally impact housing, employment and income/benefit outcomes for repeat offenders.

Seattle's LEAD Program

An understanding of this literature, the needs of this population, and potential viable solutions led to the development of Seattle's LEAD program. LEAD is a collaborative, prebooking diversion program that offers individuals suspected of low-level drug and prostitution offenses legal assistance and harm-reduction-oriented case management instead of prosecution and incarceration. The primary aim of LEAD is to reduce criminal recidivism. Secondary aims include reductions in criminal justice and legal system utilization and associated costs as well as improvements in outcomes directly impacting participants' lives, including housing, employment and legitimate income/benefits. Because LEAD is the first known prebooking diversion program of its kind in the United States, an evaluation is critically needed to inform key stakeholders, policy makers, and other interested parties of its impact.

For evaluation purposes, the implementation phase of this project occurred from October 2011 through January 2014. The Seattle Police Department's officer shifts were randomly divided into 'red- and greenlight' shifts. Offenders who were encountered during greenlight shifts were screened for project eligibility by officers on duty and, provided they met inclusion criteria and completed the intake process, they were offered LEAD at the point of arrest instead of undergoing standard criminal booking and prosecution. Additional participants were referred by officers as 'social contacts.' Social contacts were individuals who were eligible for LEAD but were recruited by officers outside of a criminal incident. Participants encountered during redlight shifts were randomized to the "system-as-usual" control group. As the original catchment area's potential participant population dwindled, additional control participants were recruited through an adjacent catchment area where they were encountered by the same officers who made referrals in the original LEAD catchment area. Only LEAD-eligible individuals were included in the control group. Participants were then referred to a LEAD case manager to complete an intake assessment. After completing the intake process, participants received legal assistance as well as case management through Evergreen Treatment Services' (ETS) REACH homeless outreach program.

The REACH Program

LEAD case managers are trained and supervised by ETS's REACH program. As part of ETS, which is a Western Washington-based nonprofit organization that delivers addiction treatment services, the REACH program provides outreach and harm-reduction-oriented case management to individuals experiencing homelessness and substance use disorders. The LEAD priority population that REACH serves includes a high percentage of individuals who have been repeatedly involved in the criminal justice system and are considered vulnerable and 'hard-to-reach.'

REACH is guided by the mission of "joining with individuals through outreach, relationship building, advocacy, and bridging gaps to reduce harm and support healing" (K. Craig, personal

communication, February 8, 2016). REACH espouses a trauma-informed, harm-reduction approach, which entails meeting participants 'where they are at' in their communities and in their own motivation to change. The program's case management model is highly individualized and uses a nonjudgmental, collaborative approach in which the client's own needs and priorities are the primary focus of attention. In this model, the goals are to engage and retain individuals in services by listening attentively to clients' needs and connecting them with appropriate community resources, such as housing placement, medical care, legal advocacy, job training, mental health counseling, and chemical dependency treatment.

To do this work, REACH employs a diverse and interdisciplinary team of professionals and paraprofessionals with backgrounds in nursing, social work, chemical dependency counseling and related disciplines. REACH case managers emphasize building and maintaining a trusting and supportive relationship with clients. Case management is provided on the streets, in clients' living situations, and onsite at REACH's home office. In the context of LEAD, case managers also have access to funds for the fulfillment of participants' basic needs (e.g., motel stays during cold weather, food, clothing, treatment). Overall, REACH's client-centered, theoretically grounded approach promotes self-efficacy and motivation to change by facilitating access to services and developing a flexible and compassionate outreach relationship.

Overall Program Evaluation Aims

The overall program evaluation was designed to assess the LEAD program in meeting the following objectives.

- *Specific aim 1* is to test the relative effectiveness of the LEAD program compared to the 'system-as-usual' control condition in reducing criminal recidivism (i.e., arrests and charges).
- *Specific aim 2* is to test the effectiveness of the LEAD program compared to the 'system-as-usual' control condition in reducing publicly funded legal and criminal justice service utilization and associated costs (i.e., prosecution, public defense, jail, prison) subsequent to evaluation entry.
- *Specific aim 3* is to test within-subjects differences on housing, employment and income variables subsequent to LEAD program entry.
- *Specific aim 4* is to explore LEAD participants' perceptions of the program in their own words.

Findings from specific aims 1 and 2 were released in reports in March 2015 and June 2015, respectively. The current report (specific aim 3) reviews housing, employment and income/benefits outcomes for LEAD participants subsequent to LEAD involvement. A final report documenting qualitative findings for specific aim 4 will be released in Summer 2016.

Purpose and Methods

Design

This report documents changes for LEAD participants on housing, employment and income/benefit outcomes after their entry into the LEAD program. Because data were only available for LEAD participants, the design is a single-arm, within-subjects analysis of outcomes for the one month prior to the LEAD program referral (baseline) and for any given month of the 18 months subsequent to the LEAD program referral (follow-up).

Participants

Participants were adults who were suspected of low-level drug or prostitution offenses and were offered and diverted to LEAD instead of booking and prosecution as usual. Based on whether law enforcement contact was made during a red- or greenlight shift and whether it occurred in the LEAD catchment area, participants were either assigned to the LEAD ($n = 203$) or control (i.e., booking as usual; $n = 115$) conditions. At the time of referral, 146 of the LEAD participants were under arrest, and 57 were suspected of qualifying criminal activity but were referred outside of an alleged criminal incident as social contacts. Because the data for the current report were collected by REACH case managers in the course of their work with LEAD participants, only LEAD participants--not control participants--were included in the present analyses. Further, housing, employment and income data were available for a smaller subset of the original, intent-to-treat sample; thus, 176 participants made up the sample featured in the present report.

All LEAD participants were suspected of recent violations of the uniform controlled substances act (VUCSA) and/or prostitution offenses and were deemed eligible for the program by SPD officers. SPD considered individuals ineligible if they met any of the following criteria:

- The amount of drugs involved exceeded 3 grams, except where an individual was arrested for delivery of or possession with intent to deliver marijuana or possession, delivery or possession with intent to deliver prescription controlled substances (pills).
- The individual did not appear amenable to diversion.
- The suspected drug activity involved delivery or possession with intent to deliver (PWI), and there was reason to believe the suspect was dealing for profit above a subsistence income.
- The individual appeared to exploit minors or others in a drug dealing enterprise.
- The individual was suspected of promoting prostitution.
- The individual had a disqualifying criminal history as follows:
 - Without time limitation: Any conviction for murder 1 or 2, arson 1 or 2, robbery 1, assault 1, kidnapping, Violation of the Uniform Firearms Act (VUFA) 1, any sex offense, or attempt of any of these crimes.
 - Within the past 10 years: Any conviction for a domestic violence offense, robbery 2, assault 2 or 3, burglary 1 or 2, or VUFA 2.

- The individual was already involved in King County Drug Diversion Court or Mental Health Court. This exclusion criterion served to ensure the LEAD program was not combined with other models of intervention and case management.

Measures

The evaluation team obtained all necessary IRB exemptions and data sharing agreements from the appropriate entities for the purposes of conducting these analyses. Demographic data were obtained via SPD and REACH case management records. Case management contacts were defined as any phone or in-person communications between a REACH case manager and a LEAD participant lasting at least 5 minutes. Contact data were logged by case managers and stored in the REACH database (AGENCY Software, Seattle, WA).

Baseline housing, employment and income/benefit statuses were based on participants' retrospective self-report to REACH case managers at their intake into the LEAD program. Ongoing housing, employment and income/benefit data were obtained by REACH case managers throughout their work with clients and were documented in the REACH database.

Housing outcomes entered into the REACH database at any given time point were coded using the federal definition of homelessness (i.e., lacking a fixed, regular and adequate nighttime residence; having a primary nighttime dwelling that is not a regular sleeping accommodation; living in a supervised shelter or transitional housing; exiting an institution that served as temporary residence when the individual had previously resided in a shelter or place not meant for human habitation; or facing imminent loss of housing when no subsequent residence is identified and insufficient resources/support networks exist.²⁷ For the housed versus unhoused outcome, this variable was recoded, where 1 = permanent housing and 0 = homelessness for any given month during the baseline and 18-month follow-up period. For the sheltered versus unsheltered outcome, this variable was recoded, where 1 = sheltered and either housed or homeless (e.g., permanent housing, temporary housing, emergency shelter, motel/hotel) and 0 = unsheltered homeless (e.g., sleeping on the streets, in abandoned buildings).

Employment outcomes for any given time point included being in vocational training/internship; in legitimate, paid employment; retired from legitimate employment; unemployed; and unable to work. Participants were classified as 'unable to work' based on formal legal and medical determination. Employment data were recoded for the employed versus unemployed outcome, such that 1 = part or full time legitimate employment and 0 = all others. Employment data were recoded for the employment continuum versus nonemployment continuum outcome, where 1 = being in vocational training/internship; in legitimate, paid employment; or retired from legitimate employment, and 0 = unemployed or unable to work.

Income/benefits outcomes for any given time point included AFDC/TANF; Aged, blind, or disabled (ABD) funding; supplemental security income (SSI); social security disability insurance (SSDI); income from legitimate full or part time employment; pensions; unemployment

compensation; veterans benefits; or no legitimate income. Income/benefits data were recoded, such that 1 = any legitimate income/benefits and 0 = no legitimate income/benefits.

Data Analysis Plan

Using SPSS 19 and Stata 13, descriptive analyses were conducted to describe the sample, ascertain the nature of the data distributions, and detect potential outliers.

Primary analyses. Population-averaged generalized estimating equations²⁸ (GEEs) were used in primary analyses. GEEs model marginal effects and may be used to accommodate alternative distributions (e.g., binomial) and correlated data (e.g., data collected on the same participant over time). In this evaluation, GEEs were used to test the relative prediction of housing, income and employment outcomes by: a) *time* (0=baseline, 1=follow-up), which accounted for overall, pre- to post referral longitudinal effects; b) *case management contacts*; and c) the two-way *time x case management contacts* interaction. The interaction effect reflects changes on the outcomes over time as a function of the intensity of a participant's exposure to case management.

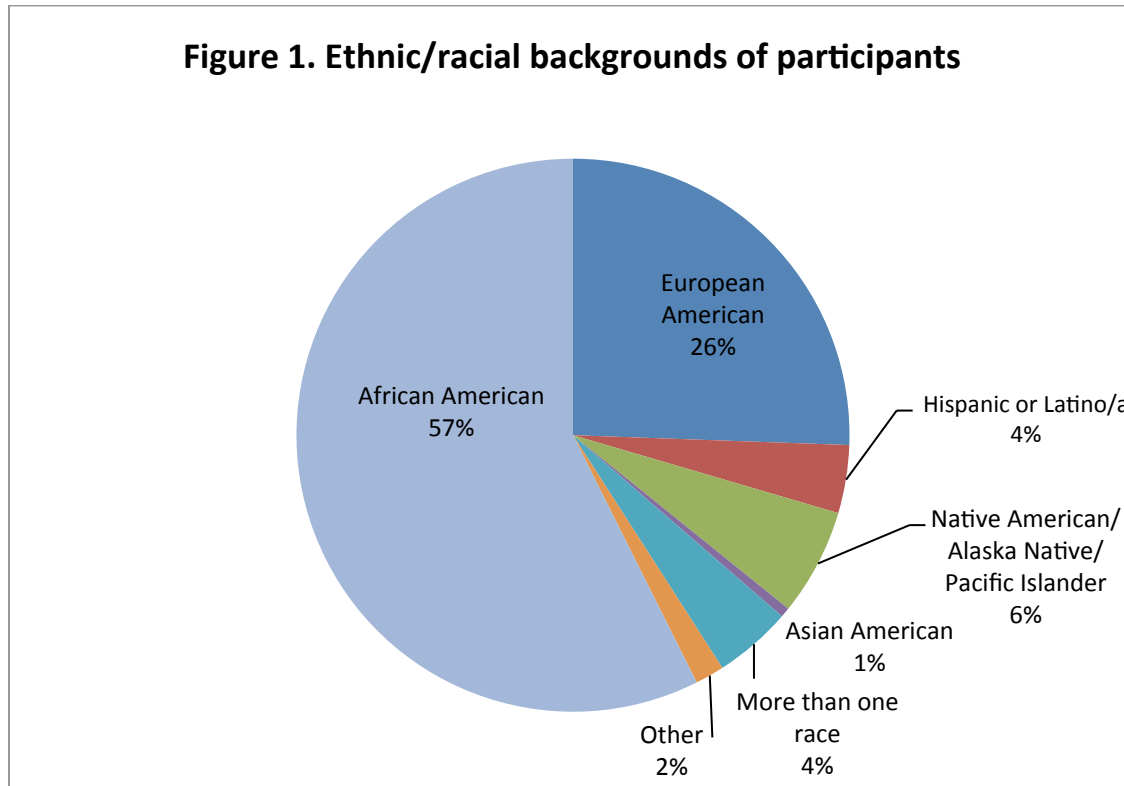
Because outcomes were dichotomous, we specified Bernoulli distributions with the logit link. We assumed an exchangeable correlation structure to accommodate repeated measures on one individual, which served as the sole clustering variable.²⁹ To enhance model interpretability, resulting effect sizes were exponentiated and reported as odds ratios (*ORs*), where *ORs* < 1 indicate an inverse association, *ORs* = 1 indicate no association, and *ORs* > 1 indicate a positive association. Alphas were set to $p = .05$, indicating statistically significant results. Confidence intervals were set to 95%. Two sets of models were used. The first set of models included main effects of covariates (i.e., age, gender, race/ethnicity and death during the study), time and case management contacts. The second set of models included the time x case management contact interactions, to test whether there were differential pre- to post referral effects as a function of participants' exposure to LEAD case management. The best-fitting model was determined by the lowest quasilielihood under the independence model information criterion (QICu) score, with lower scores indicating the more parsimonious model.²⁹

Secondary analyses. Additional analyses were conducted linking the housing, income and employment data from the current report to recidivism data from the initial March 2015 report. Given the well-documented associations between housing status and involvement in the criminal justice system,^{5,8,9} we tested months participants spent in housing, were engaged on the employment continuum, and had legitimate income/benefit sources during the 6-month follow-up as correlates of recidivism (arrest, charges) during the 6-month follow-up. Associations were tested using logistic regression models that controlled for baseline recidivism, demographic characteristics and death. Alphas were set to $p = .05$, indicating statistically significant results. Confidence intervals were set to 95%.

Results

Overall Sample Description

Participants in this phase of the project ($N = 176$) had an average age of 42.62 ($SD = 11.01$) years and were predominantly male (39.20% female; $n = 69$). The racial and ethnic diversity of the overall sample is shown in Figure 1.



Comparing Arrest Diversion and Social Contact Participants

Of the baseline demographic and outcome variables (i.e., housing status, employment, income/benefits), the arrest diversion and social contact groups significantly differed on participant age ($p = .02$) and housing status (i.e., housed versus unhoused; $p = .01$; other $ps > .18$). Specifically, arrest diversion participants were younger ($M = 41.36$, $SD = 10.94$) than social contact participants ($M = 45.55$, $SD = 10.71$) and more likely to be housed than social contact participants (24% versus 6%, respectively). Thus, age was included, along with other demographic variables, as a covariate in all analyses, and group was included as a covariate in the housed status analyses.

Pre- and Post-referral Descriptive Statistics of Outcomes by Group

Descriptive statistics for raw, unadjusted housing, income and employment outcomes were calculated prior and subsequent to referral to LEAD (see Table 1).

Table 1. Unadjusted descriptive statistics for primary outcomes

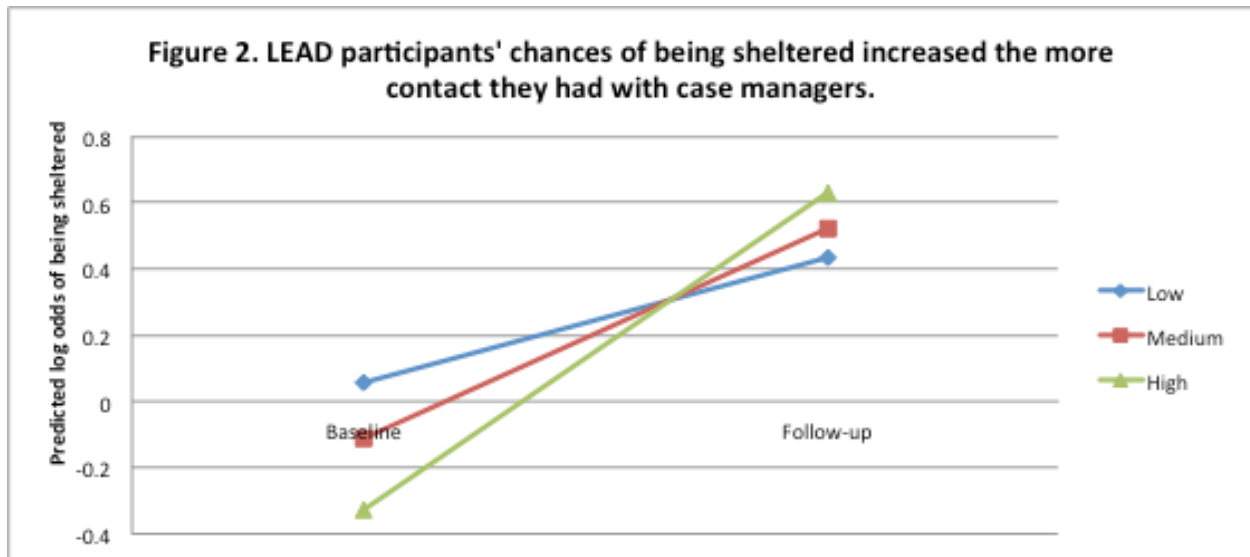
Outcome Measures	Pre-LEAD referral	Post-LEAD referral
Housing		
Sheltered versus unsheltered	48.30%	65.83%
Housed versus unhoused	17.61%	28.49%
Employment		
Employed versus not employed	7.43%	9.03%
On employment continuum versus not on employment continuum	8.57%	11.83%
Income		
Having legitimate income/benefits versus not	51.76%	57.45%

Note: This table features unadjusted values. Postreferral values are comprised of the percentage of individuals fitting that category averaged over each month of the 18-month follow-up period.

Primary Analyses

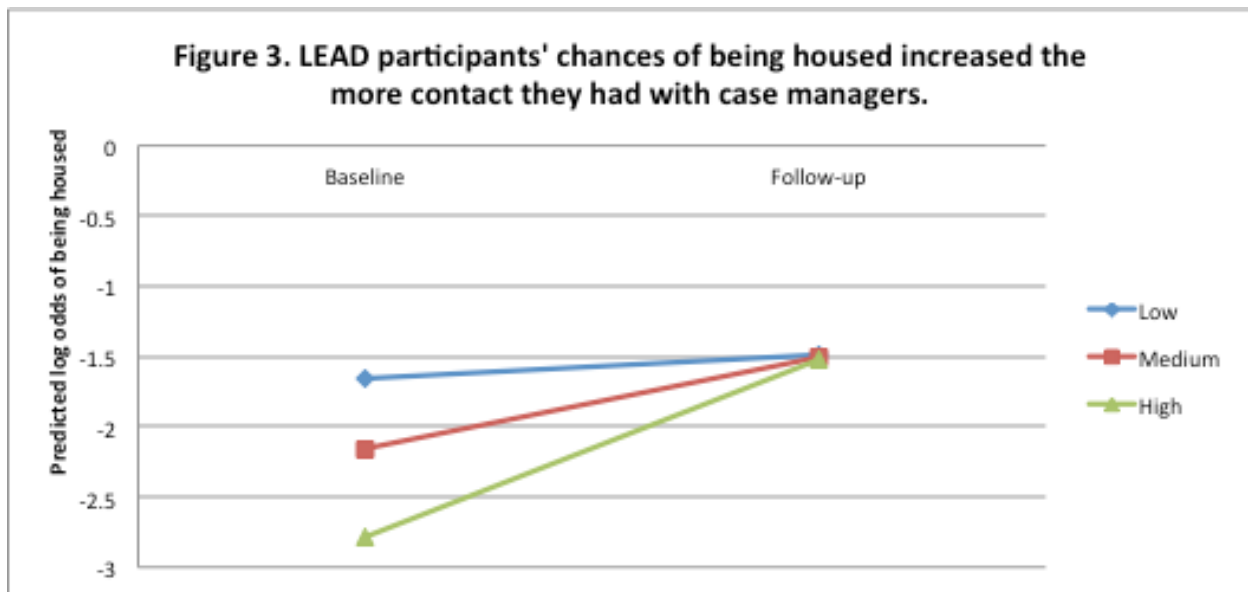
Housing status. The model for sheltered status was significant, Wald $X^2(6, N = 176) = 39.51$, $p < .001$, QICu = 4221. After controlling for sociodemographic variables, LEAD participants were over twice as likely to have been sheltered in any given month during the follow-up versus baseline ($OR = 2.08$, robust $SE = .25$, $p < .001$).

The interaction model was also significant, Wald $X^2(7, N = 176) = 43.93$, $p < .001$, QICu = 4215, and showed that each contact with a case manager was associated with a 2% higher likelihood of being sheltered in any given month during the follow up compared to baseline ($OR = 1.02$, robust $SE = .01$, $p < .001$). See Figure 2 below for the relationship of contact with case managers and sheltered status from baseline to follow-up. See Appendix A for full output.



Note: For the purposes of graphing, number of contacts was split using the interquartile range, where a low number of contacts is less than the 25th percentile, medium is between the 25th and 75th percentiles, and high is greater than the 75th percentile.

The model for housing status was likewise significant, Wald $\chi^2(7, N = 176) = 36.70, p < .001$, QICu = 3823. After controlling for demographic variables and social contacts/arrest diversion study entry, LEAD participants were 89% more likely to have been housed at some point during the follow-up versus baseline ($OR = 1.89$, robust $SE = .24, p < .001$). The interaction model was also significant, Wald $\chi^2(8, N = 176) = 33.96, p < .001$, QICu = 3802, and showed that each contact with a case manager was associated with a 5% higher likelihood of being housed during the follow-up compared to baseline ($OR = 1.05$, robust $SE = .01, p < .001$). See Figure 3 below for the relationship of contact with case managers and housing status from baseline to follow-up. See Appendix A for full output.



Note: For the purposes of graphing, number of contacts was split using the interquartile range, where a low number of contacts is less than the 25th percentile, medium is between the 25th and 75th percentiles, and high is greater than the 75th percentile.

Employment status. The model predicting being employed versus not employed was significant, Wald $\chi^2(6, N = 176) = 18.56, p = .005$, QICu = 1871. There were, however, no significant changes in employment over time or as a function of case management contacts ($ps > .14$). Similarly, the interaction effect was not significant ($p = .89$) in the full model, Wald $\chi^2(7, N = 176) = 19.49, p = .007$, QICu = 1873.

The model predicting being on the employment continuum (i.e., legitimately employed, in vocational training, or retired from legitimate employment) was significant, Wald $\chi^2(6, N = 176) = 14.03, p = .029$, QICu = 2261. After controlling for demographic variables, LEAD participants were 46% more likely to have been on the employment continuum at some point during the follow-up versus at baseline ($OR = 1.46$, robust $SE = .22, p = .013$). The interaction model was, however, not significant ($p > .05$, QICu = 2263). Case management contact was not a significant predictor in either model ($ps > .51$).

Income/benefits. The main effects model for having legitimate income/benefits was significant, Wald $\chi^2(6, N = 176) = 21.60, p = .001$, QICu = 4327. After controlling for demographic variables, LEAD participants were 33% more likely to have received legitimate income/benefits during the follow-up versus at baseline ($OR = 1.33$, robust $SE = .12, p = .002$). The interaction model was significant, Wald $\chi^2(7, N = 176) = 22.09, p = .003$, QICu = 4332;

however, neither case management contacts nor the time x case management interaction were significant predictors in either model ($ps > .28$).

Associations between Housing, Employment and Income/Benefits and Recidivism Outcomes

The omnibus model for likelihood of arrest was significant, $\chi^2(8, N = 176) = 24.24, p = .002$. After controlling for baseline recidivism and demographic variables, the number of months housed ($OR = .83, SE = .07, p = .01$) and the number of months spent on the employment continuum ($OR = .68, SE = .12, p = .02$) were significant predictors of recidivism. For each additional month housed, participants were 17% less likely to have been arrested during the 6-month follow-up. For each additional month spent on the employment continuum (i.e., in job training, legitimately employed or retired), participants were 33% less likely to have been arrested.

This pattern held even after warrant arrests were removed, $\chi^2(8, N = 176) = 22.92, p = .004$. For each additional month housed, participants were 17% less likely to have been arrested during the 6-month follow-up ($OR = .83, SE = .08, p = .045$). For each additional month spent on the continuum to employment (i.e., in job training, legitimately employed or retired), participants were 41% less likely to have been arrested ($OR = .59, SE = .15, p = .041$).

The omnibus models for overall charges and felony charges were not significant ($ps > .05$).

Discussion

This report documents housing, employment, and income/benefits outcomes subsequent to individuals' referral to LEAD as well as the potential additive effects of the amount of contact with LEAD case managers. Secondary analyses tested associations between participants' outcomes (i.e., housing, employment and income/benefits) and recidivism (i.e., arrests, charges) following LEAD referrals. Overall, findings indicated that participants' housing, employment, and income/benefits outcomes improved subsequent to LEAD program involvement. Moreover, obtaining housing and employment was related to reduced recidivism, as measured by arrests.

Housing Outcomes

Housing analyses tested LEAD participants' likelihood of being sheltered (versus unsheltered) and housed (versus unhoused) at baseline versus any given month in the year and a half after their LEAD referral. Findings indicated that participants were twice as likely to have been sheltered, and were 89% more likely to have obtained permanent housing after their LEAD referral.

Given that approximately 82% of the current sample was homeless at baseline, achieving better housing outcomes was a key goal of LEAD case managers. This goal appears to have been fulfilled, with a 62% increase in participants housed over the course of the study. This outcome is particularly impressive when considering Seattle's limited housing stock and the state of emergency regarding homelessness declared by both the City of Seattle and King County in November 2015.³⁰ The present findings are also in line with those of other studies, which have shown that both the amount of contact and the perceived therapeutic alliance established

during homeless outreach and case management are essential predictors of positive housing outcomes.^{26,31,32}

Additionally, each contact—via phone or in person—that participants had with case managers was associated with an additional 2% higher likelihood of being sheltered and a 5% higher likelihood of being housed subsequent to LEAD referral. The fact that housing outcomes improved as a function of the number of contacts with case managers increases our confidence that REACH case management is a key factor in predicting LEAD participants' positive housing outcomes. That said, the current evaluation design does not comprise a control group and thus precludes causal attributions for this association. This means that other factors (e.g., participants' own motivation for change) may have accounted for the number of case management contacts and are thus responsible for the observed effects. Further study is needed to understand the nature of the relationship between case management contacts and housing outcomes and to provide definitive recommendations regarding an ideal number of case management contacts.

It is notable that LEAD was associated with improved shelter and housing outcomes despite various systemic challenges. First, Seattle and King County have experienced recent, dramatic increases in homelessness, which have placed considerable stress on local resources for this population. Second, overall housing stock is insufficient, and there are limited housing options for substance-involved individuals with criminal histories. Third, LEAD entailed neither housing 'set asides' nor preferential access to housing for LEAD participants,¹ which makes it difficult to compare LEAD with programs that do have priority access to housing stock. Instead, the present findings show what can be accomplished within the existing system with the benefit of additional legal assistance, case management, and monies to support case management efforts (e.g., for treatment, emergency shelter, rent assistance).

Employment Outcomes

The raw percentages of employed LEAD participants were low: 7.4% and 9% of LEAD participants had full- or part-time employment prior and subsequent to their LEAD referrals, respectively. Although this percentage increased slightly over the course of the study, this increase was not statistically significant. When we expanded this analysis to include individuals who fell along the legitimate employment continuum (i.e., participating in vocational training/internships, being employed, being retired from legitimate employment), however, LEAD participants were 46% more likely to be on the employment continuum subsequent to their LEAD referral. The overall numbers of people joining the employment continuum increased from 9% to 12% or by 33%. This finding echoes those of other studies in the literature, which have indicated that criminal justice diversion and case management programs can help individuals make positive steps towards legitimate employment.^{33,34}

Joining the employment continuum is a more realistic outcome to consider for the LEAD priority population than achievement of full or part time employment alone. First, 82% of LEAD

¹ This "nondisplacement" principle of LEAD stemmed from the understanding that the program was meant to achieve community-wide gains in public order and safety if taken to scale. If LEAD participants had gained access to services with a wait list, thus driving other similarly situated people further down or off the wait list, the net impact on the community might have been neutral or negative, even though results for individuals in LEAD were positive.

participants were homeless. Considering the vulnerability of this priority population, many individuals were ineligible to work due to chronic physical or mental health disabilities. Further, as repeated drug and prostitution offenders, LEAD participants had been working in illegal markets and regularly cycling in and out of the street-to-jail-to-street revolving door for some time. Taken together, these population characteristics likely complicated and slowed participants' complete reintegration into mainstream, legitimate employment. Thus, participants' significant movement along the employment continuum is both realistic and highly encouraging.

We did not observe effects of case management contacts on employment outcomes. In retrospect, this lack of a significant finding is not surprising given the various factors influencing whether a person is ready, willing and/or able to engage along the employment continuum.^{14,35-}

³⁸ Many of these factors, including the severity of existing disabilities, income status, client motivation, job readiness and availability of suitable positions, are outside of a case manager's control. This evaluation also featured a follow-up period of 18 months. Such a relatively short period of time may be adequate for simpler and more achievable goals, such as obtaining shelter and housing. It may not, however, be adequate for case managers to help participants fully achieve such multistep, complex tasks as attaining and maintaining full time employment. For example, employment attainment trajectories may involve case managers helping LEAD participants obtain housing (most employers require a permanent address), secure a state-issued identity card, complete vocational training, acquire appropriate interview attire, attend interviews, complete hiring paperwork, find transportation to work, and perform adequately on the job.

Income/benefits Outcomes

LEAD participants were 33% more likely to be connected to income/benefits subsequent to their LEAD involvement. Sources of income/benefits included income stemming from legitimate employment (e.g., wages, unemployment benefits, military pensions) as well as income from state and federal sources (e.g., ABD, SSI, SSDI, TANF). We did not, however, observe a significant association between number of contacts with case managers and income/benefits outcomes. Similar to employment, however, there are many mediating factors that determine an individual's ability to secure income and benefits that are not within a case manager's immediate control. Thus, the further outcomes move away from those that case managers can directly influence, the less of a direct effect we may expect to see.

Associations Between Recidivism and Participants' Housing, Employment and Income/Benefits Status

Additional, secondary analyses showed that housing and employment obtained during participants' LEAD involvement was associated with significantly less recidivism as measured by arrests. In other words, housing and employment appear to serve as independently predictive and protective factors against arrests. This finding corresponds to existing literature showing that employment and housing is associated with reduced risk of recidivism.^{39,40}

Limitations

The limitations of this evaluation should be noted. First, administrative datasets often feature missing data and clerical errors. That being said, considerable effort was made by the evaluation team to follow up with administrative sources and ensure we obtained complete and accurate data. Second, specific features of the geographical location of this work likely influenced key characteristics of Seattle's LEAD program and the resulting evaluation. For example, 82% of LEAD participants in this evaluation were homeless, which certainly influenced the nature of the participants' needs and the resulting approaches used for case management and legal assistance. Thus, the present findings may not easily generalize to other communities where the LEAD priority population and existing systems (e.g., case management services, housing stock, criminal justice system) may differ.

Because we lack a control group for these particular analyses, the present evaluation design is not sufficient to demonstrate causality of the observed effects. In other words, we cannot be sure the changes we have observed are due to the LEAD program versus other confounding factors or statistical phenomena, such as regression to the mean. Thus, causal conclusions cannot be drawn based on these findings. Fortunately, we can conclude that all effects are moving in a positive direction, and thus, LEAD does not appear to have iatrogenic or negative effects for participants. Further, our confidence that the observed effects are attributable at least in part to LEAD is increased by the fact that the number of contacts with case managers predicted positive housing outcomes above and beyond what we would expect due to statistical regression to the mean.

Conclusions and Future Directions

Findings indicated improvements for LEAD participants across housing, employment, and income/benefit outcomes. Case management appears to play a significant role in ameliorating housing outcomes. Secondary analyses showed that better housing and employment outcomes are associated with reduced recidivism among LEAD participants. Further study of LEAD programs is necessary to understand whether these effects are generalizable to other communities and to draw causal conclusions as to the programmatic components that are driving the observed LEAD effects. Further, future studies should include assessment and analysis of other relevant participant outcomes to elucidate LEAD's impact on various aspects of participants' lives. Because these individuals and their communities are particularly impacted by substance use, we are consulting with REACH on data collection protocols to assess new LEAD participants' substance use at baseline and allow for future evaluation of the effects of LEAD on substance use and substance-related harm.²

Taken together, the findings from our three reports to date suggest positive findings for LEAD and collectively indicate that LEAD is slowing the street-to-jail-to-street revolving door for low-level drug and prostitution recidivating offenders. This report is one in a series being

² When LEAD was designed, its stated goal was to reduce recidivism of individual participants. Reducing substance use and substance-related harm were not explicitly stated goals. As a result, the original evaluation consultants engaged by the LEAD Policy Coordinating Group prior to the program's launch suggested methods needed to assess LEAD's effect on recidivism. The original evaluation consultants were not retained to conduct the current evaluation and were subsequently replaced by the current authorship team. Moving forward, we are consulting with the LEAD Policy Coordinating Group and REACH to establish substance-use assessment protocols for new LEAD participants that will allow future analysis of the effects of LEAD on substance use and substance-related harm.

prepared by the University of Washington LEAD Evaluation Team. The next and final report, which we plan to release in Summer 2016, will explore LEAD participants' perceptions of the program in their own words.

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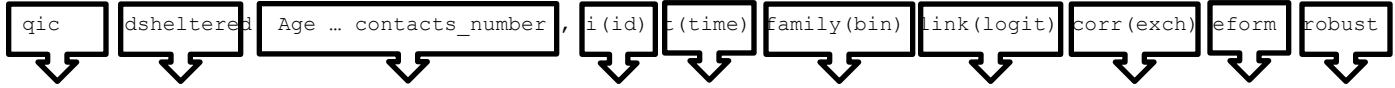
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Appendix A: Analysis Output

Key for abbreviations used in this output



Analysis type: generalized estimating equations with QICu test of model parsimony/fit

Outcome: d=dichotomous sheltered = outcome type

Covariates/primary predictors: t=time contacts_number= number of case management contacts txcontacts_number = interaction effect

Case identifier (participant identifier ID number) within ID

Time point as a unique type (binomial)

Distribution type (binomial)

Link function (logit)

Correlation structure for panel data (exchangeable)

Requests exponentiated coefficients (ORs)

Robust standard errors to account for correlated data structure

Primary analyses

```
. gic dsheltered Age reEthGrp Gender Died t contacts_number if include==1, i(Client_ID) t(time)
fam(bin) link(logit) corr(exch) robust reform
```

Iteration 1: tolerance = 6.567e-14

```
GEE population-averaged model
Group variable: Client_ID
Link: logit
Family: binomial
Correlation: independent
Scale parameter: 1
Pearson chi2(3287): 3286.58
Dispersion (Pearson): .9998716
Number of obs = 3287
Number of groups = 176
Obs per group: min = 3
                avg = 18.7
                max = 19
Wald chi2(6) = 50.05
Prob > chi2 = 0.0000
Deviance = 4204.65
Dispersion = 1.279176
```

dsheltered	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]
Age	1.005058	.0038429	1.32	0.187	.9975541 1.012618
reEthGrp	1.04215	.0593434	0.73	0.468	.9320945 1.1652
Gender	.7056628	.0608479	-4.04	0.000	.5959363 .8355927
Died	1.370062	.229892	1.88	0.061	.9860777 1.903571
t	2.089565	.3266443	4.71	0.000	1.538136 2.838685
contacts_number	1.004872	.0020531	2.38	0.017	1.000856 1.008904
_cons	.7566102	.1807105	-1.17	0.243	.4737719 1.208301

```
Iteration 1: tolerance = .07320543
Iteration 2: tolerance = .01382931
Iteration 3: tolerance = .00331801
Iteration 4: tolerance = .0005853
Iteration 5: tolerance = .0001375
Iteration 6: tolerance = .00002691
Iteration 7: tolerance = 6.067e-06
Iteration 8: tolerance = 1.259e-06
Iteration 9: tolerance = 2.742e-07
```

```
GEE population-averaged model
Group variable: Client_ID
Link: logit
Family: binomial
Correlation: exchangeable
Scale parameter: 1
Number of obs = 3287
Number of groups = 176
Obs per group: min = 3
                avg = 18.7
                max = 19
Wald chi2(6) = 39.51
Prob > chi2 = 0.0000
```

(Std. Err. adjusted for clustering on Client_ID)

| Robust

dsheltered	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
Age	1.006172	.0141849	0.44	0.663	.9787505	1.034361
reEthGrp	1.053863	.2269067	0.24	0.807	.6910542	1.607148
Gender	.6612762	.2099359	-1.30	0.193	.354937	1.232011
Died	1.254462	.5943718	0.48	0.632	.4956248	3.175134
t	2.079075	.2478541	6.14	0.000	1.645869	2.626304
contacts_number	1.002769	.0068408	0.41	0.685	.9894506	1.016267
_cons	.7708743	.5631298	-0.36	0.722	.184151	3.226956

QIC and QIC_u

```

Corr =          exch
Family =         bin
Link =          logit
p =             7
Trace =         73.265
QIC =          4353.047
QIC_u =        4220.517

```

```

. gic dsheltered Age reEthGrp Gender Died t contacts_number txcontacts_number if include==1,
i(Client_ID) t(time) fam(bin) link
> (logit) corr(exch) robust eform

```

Iteration 1: tolerance = 6.741e-14

```

GEE population-averaged model
Group variable:          Client_ID
Link:                   logit
Family:                 binomial
Correlation:            independent
Scale parameter:        1
Wald chi2(7)            = 55.92
Prob > chi2             = 0.0000

Pearson chi2(3287):     3287.77
Dispersion (Pearson):  1.000233
Deviance                = 4197.64
Dispersion              = 1.277043

```

dsheltered	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
Age	1.005079	.003844	1.32	0.185	.9975727	1.012641
reEthGrp	1.041748	.0593576	0.72	0.473	.9316706	1.164832
Gender	.7049413	.0608486	-4.05	0.000	.5952229	.8348843
Died	1.368318	.2296272	1.87	0.062	.9847838	1.901224
t	1.261022	.3134189	0.93	0.351	.7747505	2.052501
contacts_number	.9835599	.0084478	-1.93	0.054	.9671411	1.000257
txcontacts_number	1.023068	.0090423	2.58	0.010	1.005498	1.040945
_cons	1.217427	.3658469	0.65	0.513	.6755384	2.193997

```

Iteration 1: tolerance = .07847544
Iteration 2: tolerance = .01199298
Iteration 3: tolerance = .00202913
Iteration 4: tolerance = .00082846
Iteration 5: tolerance = .00013771
Iteration 6: tolerance = .00006402
Iteration 7: tolerance = .00001555
Iteration 8: tolerance = 5.458e-06
Iteration 9: tolerance = 1.537e-06
Iteration 10: tolerance = 4.915e-07

```

```

GEE population-averaged model
Group variable:          Client_ID
Link:                   logit
Family:                 binomial
Correlation:            exchangeable
Wald chi2(7)            = 43.93
Number of obs          = 3287
Number of groups       = 176
Obs per group: min     = 3
                    avg = 18.7
                    max = 19

```

Scale parameter: 1 Prob > chi2 = 0.0000

(Std. Err. adjusted for clustering on Client_ID)

	Odds Ratio	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
Age	1.006227	.0142321	0.44	0.661	.9787155	1.034511
reEthGrp	1.045478	.2259723	0.21	0.837	.6844382	1.596967
Gender	.6651334	.2130229	-1.27	0.203	.3550533	1.246017
Died	1.249776	.5959637	0.47	0.640	.4908298	3.182241
t	1.248178	.2145253	1.29	0.197	.89121	1.748128
contacts_number	.9848146	.0090115	-1.67	0.094	.9673098	1.002636
txcontacts_number	1.023268	.0073278	3.21	0.001	1.009006	1.037731
_cons	1.174034	.8598203	0.22	0.827	.2794415	4.932535

QIC and QIC_u

```

Corr =          excl
Family =         bin
Link =          logit
p =             8
Trace =         76.115
QIC =          4351.152
QIC_u =         4214.923

```

```

. qic dhoused Age reEthGrp Gender Died TxSbGrp t contacts_number if include==1, i(Client_ID)
t(tim
> e) fam(bin) link(logit) corr(exch) robust eform

```

Iteration 1: tolerance = 2.217e-11

```

GEE population-averaged model
Group variable:          Client_ID
Link:                   logit
Family:                 binomial
Correlation:            independent
Wald chi2(7)           = 113.41
Scale parameter:       1
Prob > chi2            = 0.0000

Pearson chi2(3287):     3344.48
Deviance               = 3772.99
Dispersion (Pearson):  1.017486
Dispersion             = 1.147851

```

	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
dhoused						
Age	1.027583	.0043394	6.44	0.000	1.019113	1.036124
reEthGrp	.7721077	.0481137	-4.15	0.000	.6833379	.8724093
Gender	.898736	.0827759	-1.16	0.246	.7502989	1.07654
Died	1.163846	.1895691	0.93	0.352	.845766	1.60155
TxSbGrp	1.868499	.1772735	6.59	0.000	1.551441	2.250352
t	1.898937	.3880648	3.14	0.002	1.272213	2.834401
contacts_number	.9937413	.0022499	-2.77	0.006	.9893413	.9981608
_cons	.0816158	.0248214	-8.24	0.000	.0449679	.148131

```

Iteration 1: tolerance = .20523242
Iteration 2: tolerance = .01682038
Iteration 3: tolerance = .00445555
Iteration 4: tolerance = .00069221
Iteration 5: tolerance = .00006518
Iteration 6: tolerance = .00002024
Iteration 7: tolerance = 1.347e-06
Iteration 8: tolerance = 5.265e-07

```



```

GEE population-averaged model      Number of obs      =      3287
Group variable:                    Client_ID           Number of groups   =      176
Link:                              logit              Obs per group: min =      3
Family:                            binomial           avg                =     18.7
Correlation:                       exchangeable       max                =      19
                                      Wald chi2(7)      =     36.70
Scale parameter:                   1                 Prob > chi2       =     0.0000

```

(Std. Err. adjusted for clustering on Client_ID)

```

-----+-----
          |              Robust
          | Odds Ratio  Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
      Age |  1.027529   .0165709    1.68  0.092   .9955585   1.060526
reEthGrp |  .7620567   .1814025   -1.14  0.254   .4779302   1.215095
  Gender |  .8710026   .2876841   -0.42  0.676   .4559062   1.664039
    Died |  1.318378   .7318231    0.50  0.619   .4441644   3.913239
TxSbGrp |  1.343767   .4634255    0.86  0.392   .683549    2.641668
      t |  1.888952   .2442628    4.92  0.000   1.466057    2.433834
contacts_number |  1.002144   .0084416    0.25  0.799   .9857342   1.018826
      _cons |  .090044   .0742976   -2.92  0.004   .0178693   .4537353
-----+-----

```

QIC and QIC_u

```

-----
Corr =          exch
Family =        bin
Link =          logit
p =            8
Trace =         96.215
QIC =          3999.661
QIC_u =         3823.232
-----

```

```

. qic dhoused Age reEthGrp Gender Died TxSbGrp t contacts_number txcontacts_number if include==1,
> i(Client_ID) t(time) fam(bin) link(logit) corr(exch) robust eform

```

Iteration 1: tolerance = 6.881e-13

```

GEE population-averaged model      Number of obs      =      3287
Group variable:                    Client_ID           Number of groups   =      176
Link:                              logit              Obs per group: min =      3
Family:                            binomial           avg                =     18.7
Correlation:                       independent       max                =      19
                                      Wald chi2(8)      =     114.78
Scale parameter:                   1                 Prob > chi2       =     0.0000

```

```

Pearson chi2(3287):                3325.64           Deviance           =     3762.56
Dispersion (Pearson):              1.011756         Dispersion         =     1.14468

```

```

-----+-----
          |              Robust
          | Odds Ratio  Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
      Age |  1.027668   .0043411    6.46  0.000   1.019194   1.036212
reEthGrp |  .7715287   .0481256   -4.16  0.000   .6827422   .8718614
  Gender |  .8978951   .0827747   -1.17  0.243   .7494721   1.075711
    Died |  1.165068   .1898619    0.94  0.348   .8465206   1.603484
TxSbGrp |  1.869697   .1776399    6.59  0.000   1.552025   2.252392
      t |  .8284745   .2679885   -0.58  0.561   .4394799   1.561778
contacts_number |  .9475423   .0165083   -3.09  0.002   .9157328   .9804567
txcontacts_number |  1.050068   .0184354    2.78  0.005   1.01455    1.08683
      _cons |  .1817139   .0703702   -4.40  0.000   .0850654   .3881711
-----+-----

```

```

Iteration 1: tolerance = .20047132
Iteration 2: tolerance = .03206022
Iteration 3: tolerance = .00331681
Iteration 4: tolerance = .00014459

```

Iteration 5: tolerance = .00004303
 Iteration 6: tolerance = 2.572e-06
 Iteration 7: tolerance = 5.401e-07

```
GEE population-averaged model
Group variable:      Client_ID
Link:                logit
Family:              binomial
Correlation:         exchangeable

Number of obs      =      3287
Number of groups   =       176
Obs per group: min =         3
                  avg =      18.7
                  max =        19

Wald chi2(8)      =      33.96
Prob > chi2       =      0.0000
```

(Std. Err. adjusted for clustering on Client_ID)

	Odds Ratio	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
dhoused						
Age	1.016433	.0167207	0.99	0.322	.9841836	1.049739
reEthGrp	.8459414	.2118144	-0.67	0.504	.5178557	1.381885
Gender	.9617023	.324652	-0.12	0.908	.4962398	1.863759
Died	1.259143	.6877876	0.42	0.673	.4316375	3.673084
TxSbGrp	1.400699	.496634	0.95	0.342	.6991039	2.806391
t	.866046	.1222359	-1.02	0.308	.6567502	1.142041
contacts_number	.9556347	.0128106	-3.39	0.001	.9308535	.9810757
txcontacts_number	1.045332	.0097721	4.74	0.000	1.026354	1.064662
_cons	.2620723	.2196451	-1.60	0.110	.0507016	1.35463

QIC and QIC_u

```
Corr =      exch
Family =     bin
Link =      logit
p =         9
Trace =     99.626
QIC =      3982.883
QIC_u =    3801.631
```

```
. qic employed Age reEthGrp Gender Died t contacts_number if include==1,
> i(Client_ID) t(time) fam(bin) link(logit) corr(exch) robust eform
```

Iteration 1: tolerance = 1.556e-11

```
GEE population-averaged model
> 3323
Group variable:      Client_ID
> 176
Link:                logit
> 6
Family:              binomial
> 18.9
Correlation:         independent
> 19

Wald chi2(6)      =      11
Prob > chi2       =      0.

> 6.02
Scale parameter:   1
> 0000
```

```
Pearson chi2(3323):      3190.18      Deviance      =      1850.75
Dispersion (Pearson):   .9600299      Dispersion     =      .5569503
```

	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
employed						
Age	.965192	.0063071	-5.42	0.000	.9529091	.9776333
reEthGrp	1.485465	.1417824	4.15	0.000	1.232022	1.791046

```

Gender | 5.542965 .9947291 9.54 0.000 3.899305 7.87947
Died | .0673952 .0678419 -2.68 0.007 .009371 .4846995
t | 1.259666 .3788828 0.77 0.443 .6986037 2.271329
contacts_number | 1.008603 .0033476 2.58 0.010 1.002063 1.015185
_cons | .0407806 .0176256 -7.40 0.000 .0174808 .0951365
-----

```

```

Iteration 1: tolerance = .12638868
Iteration 2: tolerance = .02549085
Iteration 3: tolerance = .00163697
Iteration 4: tolerance = .00003672
Iteration 5: tolerance = 5.528e-06
Iteration 6: tolerance = 7.185e-07

```

```

GEE population-averaged model
Group variable: Client_ID Number of obs = 3323
Link: logit Number of groups = 176
Family: binomial Obs per group: min = 6
Correlation: exchangeable avg = 18.9
max = 19
Wald chi2(6) = 18.56
Prob > chi2 = 0.0050
Scale parameter: 1

```

(Std. Err. adjusted for clustering on Client_ID)

```

-----
employed | Odds Ratio Robust Std. Err. z P>|z| [95% Conf. Interval]
-----+-----
Age | .9602728 .0271553 -1.43 0.152 .9084974 1.014999
reEthGrp | 1.323081 .4827561 0.77 0.443 .6471516 2.704995
Gender | 8.206686 7.201811 2.40 0.016 1.469577 45.8293
Died | .104982 .104393 -2.27 0.023 .0149516 .7371247
t | 1.258215 .1970998 1.47 0.143 .9255799 1.710393
contacts_number | 1.010044 .0158691 0.64 0.525 .9794148 1.04163
_cons | .0434965 .0536631 -2.54 0.011 .0038752 .4882149
-----

```

QIC and QIC_u

```

-----
Corr =      exch
Family =      bin
Link =      logit
p =          7
Trace =      99.867
QIC =      2057.204
QIC_u =      1871.471
-----

```

```

. qic employed Age reEthGrp Gender Died t contacts_number txcontacts_number if include==1,
i(Clien
> t_ID) t(time) fam(bin) link(logit) corr(exch) robust eform

```

Iteration 1: tolerance = 1.556e-11

```

GEE population-averaged model
Group variable: Client_ID Number of obs = 3323
Link: logit Number of groups = 176
Family: binomial Obs per group: min = 6
Correlation: independent avg = 18.9
max = 19
Wald chi2(7) = 116.03
Prob > chi2 = 0.0000
Scale parameter: 1

```

```

Pearson chi2(3323): 3189.83 Deviance = 1850.74
Dispersion (Pearson): .9599257 Dispersion = .5569476

```

```

-----
employed | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]
-----+-----
Age | .9651927 .0063071 -5.42 0.000 .9529099 .9776339
reEthGrp | 1.485459 .1417815 4.15 0.000 1.232017 1.791037

```

Gender		5.542969	.994729	9.54	0.000	3.89931	7.879474
Died		.0673963	.067843	-2.68	0.007	.0093711	.4847072
t		1.215398	.5853597	0.41	0.685	.4728935	3.123734
contacts_number		1.007152	.0157317	0.46	0.648	.9767858	1.038462
txcontacts_number		1.001507	.0159833	0.09	0.925	.9706648	1.033328
_cons		.042198	.0237063	-5.63	0.000	.0140313	.1269072

Iteration 1: tolerance = .15829
Iteration 2: tolerance = .02657027
Iteration 3: tolerance = .00164058
Iteration 4: tolerance = .00048231
Iteration 5: tolerance = .00003658
Iteration 6: tolerance = 5.406e-06
Iteration 7: tolerance = 4.594e-07

GEE population-averaged model
Group variable: Client_ID
Link: logit
Family: binomial
Correlation: exchangeable
Scale parameter: 1

Number of obs = 3323
Number of groups = 176
Obs per group: min = 6
avg = 18.9
max = 19
Wald chi2(7) = 19.49
Prob > chi2 = 0.0068

(Std. Err. adjusted for clustering on Client_ID)

	Odds Ratio	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
Age	.9602364	.0270505	-1.44	0.150	.9086555	1.014745
reEthGrp	1.328144	.4824041	0.78	0.435	.6517402	2.706548
Gender	8.120708	6.96926	2.44	0.015	1.510378	43.66186
Died	.1111601	.1108473	-2.20	0.028	.015745	.7847931
t	1.228539	.3385433	0.75	0.455	.7158579	2.10839
contacts_number	1.008	.0200402	0.40	0.689	.9694776	1.048054
txcontacts_number	1.000988	.0068942	0.14	0.886	.9875668	1.014592
_cons	.0458041	.0572597	-2.47	0.014	.003952	.5308729

QIC and QIC_u

Corr = exch
Family = bin
Link = logit
p = 8
Trace = 100.375
QIC = 2057.869
QIC_u = 1873.118

```
. qic employmentpath Age reEthGrp Gender Died t contacts_number if include==1, i(Client_ID)
t(time)
> ) fam(bin) link(logit) corr(exch) robust eform
```

Iteration 1: tolerance = 2.138e-13

GEE population-averaged model
Group variable: Client_ID
Link: logit
Family: binomial
Correlation: independent
Scale parameter: 1

Number of obs = 3323
Number of groups = 176
Obs per group: min = 6
avg = 18.9
max = 19
Wald chi2(6) = 118.54
Prob > chi2 = 0.0000

Pearson chi2(3323): 3223.12
Deviance = 2223.82
Dispersion (Pearson): .9699419
Dispersion = .6692193

employmentpath	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
Age	.9669292	.0056383	-5.77	0.000	.9559412	.9780435
reEthGrp	1.363536	.116634	3.63	0.000	1.153073	1.612415
Gender	4.194338	.6292662	9.56	0.000	3.125789	5.628168
Died	.2035582	.1041321	-3.11	0.002	.0746876	.55479
t	1.429118	.4006374	1.27	0.203	.8249791	2.475671
contacts_number	1.007125	.0030009	2.38	0.017	1.001261	1.013024
_cons	.0680841	.0265655	-6.89	0.000	.0316898	.1462759

Iteration 1: tolerance = 1.0925738
Iteration 2: tolerance = .44537486
Iteration 3: tolerance = .25302544
Iteration 4: tolerance = .01161685
Iteration 5: tolerance = .0003632
Iteration 6: tolerance = .00008009
Iteration 7: tolerance = 2.976e-06
Iteration 8: tolerance = 1.928e-07

GEE population-averaged model
Group variable: Client_ID Number of obs = 3323
Link: logit Number of groups = 176
Family: binomial Obs per group: min = 6
Correlation: exchangeable avg = 18.9
max = 19
Wald chi2(6) = 14.03
Scale parameter: 1 Prob > chi2 = 0.0293

(Std. Err. adjusted for clustering on Client_ID)

employmentpath	Odds Ratio	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
Age	.9622265	.021895	-1.69	0.091	.9202559	1.006111
reEthGrp	1.221131	.3846112	0.63	0.526	.6586658	2.263911
Gender	6.394073	3.71943	3.19	0.001	2.04472	19.99499
Died	.9192846	.9348925	-0.08	0.934	.1252554	6.746888
t	1.457666	.2211492	2.48	0.013	1.082726	1.962446
contacts_number	1.008021	.0123355	0.65	0.514	.9841315	1.03249
_cons	.0680509	.0651343	-2.81	0.005	.0104259	.4441751

QIC and QIC_u

Corr = exch
Family = bin
Link = logit
p = 7
Trace = 81.401
QIC = 2409.628
QIC_u = 2260.827

```
. qic employmentpath Age reEthGrp Gender Died t contacts_number txcontacts_number if include==1,
i
> (Client_ID) t(time) fam(bin) link(logit) corr(exch) robust eform
```

Iteration 1: tolerance = 8.993e-13

GEE population-averaged model
Group variable: Client_ID Number of obs = 3323
Link: logit Number of groups = 176
Family: binomial Obs per group: min = 6
Correlation: independent avg = 18.9
max = 19

```

Scale parameter:          1      Wald chi2(7)      =      118.59
                             Prob > chi2      =      0.0000

Pearson chi2(3323):      3223.36      Deviance      =      2223.79
Dispersion (Pearson):    .9700144      Dispersion      =      .6692108

```

```

-----
employmentpath | Odds Ratio   Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
      Age |      .9669306   .0056382    -5.77   0.000      .9559428      .9780447
    reEthGrp |      1.363534   .1166333     3.63   0.000      1.153072      1.612411
      Gender |      4.194328   .6292625     9.56   0.000      3.125786      5.62815
      Died |      .2035662   .1041359    -3.11   0.002      .0746907      .5548105
         t |      1.347827   .5995905     0.67   0.502      .5636001      3.223275
contacts_number |      1.004696   .0148277     0.32   0.751      .9760501      1.034182
txcontacts_number |      1.00252    .015087     0.17   0.867      .9733817      1.03253
      _cons |      .0720149   .0368288    -5.14   0.000      .026431      .1962146
-----

```

```

Iteration 1: tolerance = 1.0636059
Iteration 2: tolerance = .44276926
Iteration 3: tolerance = .24713603
Iteration 4: tolerance = .00950001
Iteration 5: tolerance = .00037574
Iteration 6: tolerance = .00005536
Iteration 7: tolerance = 3.449e-06
Iteration 8: tolerance = 1.244e-07

```

```

GEE population-averaged model
Group variable:      Client_ID      Number of obs      =      3323
Link:                logit          Number of groups   =      176
Family:              binomial        Obs per group: min =      6
Correlation:         exchangeable     avg                =      18.9
                                           max                =      19
                                           Wald chi2(7)       =      13.98
Scale parameter:     1              Prob > chi2        =      0.0515

```

(Std. Err. adjusted for clustering on Client_ID)

```

-----
employmentpath | Odds Ratio   Robust Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
      Age |      .9622353   .0218021    -1.70   0.089      .9204388      1.00593
    reEthGrp |      1.22379    .3869852     0.64   0.523      .6584777      2.27443
      Gender |      6.480529    3.771941     3.21   0.001      2.070977      20.27896
      Died |      .903193    .9103588    -0.10   0.920      .1252638      6.512315
         t |      1.407254    .3140728     1.53   0.126      .9086576      2.179439
contacts_number |      1.00483    .0180363     0.27   0.788      .970094      1.04081
txcontacts_number |      1.001525    .0068884     0.22   0.825      .9881145      1.015117
      _cons |      .0720976    .0704904    -2.69   0.007      .0106095      .4899445
-----

```

QIC and QIC_u

```

-----
Corr =      exch
Family =     bin
Link =      logit
p =         8
Trace =     85.246
QIC =      2417.708
QIC_u =     2263.216
-----

```

```

. qic d_income Age reEthGrp Gender Died t contacts_number if include==1, i(Client_ID) t(time)
fam(
> bin) link(logit) corr(exch) robust eform

```

```

Iteration 1: tolerance = 6.741e-13

```

```

GEE population-averaged model
Group variable:      Client_ID      Number of obs      =      3338
Link:                logit          Number of groups   =      176
Family:              binomial       Obs per group: min =      18
Correlation:         independent     avg                =     19.0
Scale parameter:    1                max                =      19
Wald chi2(6)        =     231.45
Prob > chi2         =     0.0000

Pearson chi2(3338):      3392.79      Deviance           =     4306.47
Dispersion (Pearson):  1.016414    Dispersion         =     1.290134

```

```

-----
      d_income | Odds Ratio   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
      Age |      1.05441   .0041219    13.55  0.000    1.046362    1.06252
    reEthGrp |      .7201798   .0406838    -5.81  0.000    .6446968    .8045005
      Gender |      .6258397   .0531937    -5.51  0.000    .5298032    .7392845
      Died |      .8923293   .1387254    -0.73  0.464    .6579511    1.210199
          t |      1.283302   .210286     1.52  0.128    .9307829    1.769333
contacts_number |      1.004211   .002019     2.09  0.037    1.000262    1.008177
      _cons |      .2567375   .0625232    -5.58  0.000    .159293    .4137919
-----

```

```

Iteration 1: tolerance = .19709543
Iteration 2: tolerance = .01501042
Iteration 3: tolerance = .00493148
Iteration 4: tolerance = .00041922
Iteration 5: tolerance = .00018174
Iteration 6: tolerance = .00002399
Iteration 7: tolerance = 7.231e-06
Iteration 8: tolerance = 1.188e-06
Iteration 9: tolerance = 3.012e-07

```

```

GEE population-averaged model
Group variable:      Client_ID      Number of obs      =      3338
Link:                logit          Number of groups   =      176
Family:              binomial       Obs per group: min =      18
Correlation:         exchangeable   avg                =     19.0
Scale parameter:    1                max                =      19
Wald chi2(6)        =     21.60
Prob > chi2         =     0.0014

```

(Std. Err. adjusted for clustering on Client_ID)

```

-----
      d_income | Robust Odds Ratio   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
      Age |      1.056536   .0177347     3.28  0.001    1.022342    1.091873
    reEthGrp |      .67787    .1592577    -1.65  0.098    .4277269    1.074302
      Gender |      .6632276   .2230023    -1.22  0.222    .3431281    1.281944
      Died |      .716222    .4365778    -0.55  0.584    .2168663    2.365392
          t |      1.330762   .1197888     3.17  0.002    1.115525    1.587528
contacts_number |      1.001602   .0079514     0.20  0.840    .986138    1.017308
      _cons |      .2560845   .1887893    -1.85  0.065    .0603761    1.08618
-----

```

QIC and QIC_u

```

-----
Corr =          exch
Family =         bin
Link =          logit
p =              7
Trace =         99.047
QIC =          4511.362
QIC_u =         4327.267
-----

```

```

. qic d_income Age reEthGrp Gender Died t contacts_number txcontacts_number if include==1,
i(Client)

```

```
> t_ID) t(time) fam(bin) link(logit) corr(exch) robust eform
```

```
Iteration 1: tolerance = 3.949e-13
```

```
GEE population-averaged model
Group variable:      Client_ID      Number of obs      =      3338
Link:                logit          Number of groups   =      176
Family:              binomial        Obs per group: min =      18
Correlation:         independent      avg                =     19.0
Scale parameter:    1                max                =      19
Wald chi2(7)        =     231.86
Prob > chi2         =     0.0000

Pearson chi2(3338):      3392.93      Deviance           =     4305.98
Dispersion (Pearson):  1.016456    Dispersion         =     1.289989
```

d_income	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
Age	1.05442	.0041222	13.55	0.000	1.046371	1.06253
reEthGrp	.7201523	.0406834	-5.81	0.000	.6446702	.8044724
Gender	.62573	.0531882	-5.52	0.000	.529704	.7391638
Died	.8927664	.138806	-0.73	0.466	.6582552	1.210825
t	1.117646	.2876345	0.43	0.666	.674903	1.850834
contacts_number	.998393	.0085549	-0.19	0.851	.9817657	1.015302
txcontacts_number	1.006159	.0088603	0.70	0.486	.9889422	1.023675
_cons	.292594	.0898969	-4.00	0.000	.1602291	.5343053

```
Iteration 1: tolerance = .21640148
Iteration 2: tolerance = .01861824
Iteration 3: tolerance = .0088202
Iteration 4: tolerance = .00110106
Iteration 5: tolerance = .00047854
Iteration 6: tolerance = .00007863
Iteration 7: tolerance = .00002694
Iteration 8: tolerance = 5.220e-06
Iteration 9: tolerance = 1.564e-06
Iteration 10: tolerance = 3.344e-07
```

```
GEE population-averaged model
Group variable:      Client_ID      Number of obs      =      3338
Link:                logit          Number of groups   =      176
Family:              binomial        Obs per group: min =      18
Correlation:         exchangeable    avg                =     19.0
Scale parameter:    1                max                =      19
Wald chi2(7)        =     22.09
Prob > chi2         =     0.0025
```

(Std. Err. adjusted for clustering on Client_ID)

d_income	Odds Ratio	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
Age	1.057014	.0180636	3.24	0.001	1.022196	1.093017
reEthGrp	.6673578	.1589182	-1.70	0.089	.4184674	1.06428
Gender	.6675479	.2269162	-1.19	0.234	.3428766	1.299652
Died	.7066382	.4298465	-0.57	0.568	.214493	2.32799
t	1.161906	.1476405	1.18	0.238	.9057555	1.490497
contacts_number	.9949732	.0089586	-0.56	0.576	.9775687	1.012688
txcontacts_number	1.005979	.0055659	1.08	0.281	.9951288	1.016947
_cons	.2983638	.2210347	-1.63	0.103	.0698484	1.274487

QIC and QIC_u

```
Corr =      exch
Family =     bin
Link =      logit
p =        8
Trace =    100.896
```


QIC = 4517.593
 QIC_u = 4331.801

Secondary analyses

logistic dpostarresttot6 dprearresttot6 reEthGrp Died Gender Age fu6_incomemo fu6_housedmo
 fu6_employmentpathmo, or

Logistic regression Number of obs = 176
 LR chi2(8) = 24.24
 Prob > chi2 = 0.0021
 Pseudo R2 = 0.1045
 Log likelihood = -103.79436

dpostarresttot6	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
dprearresttot6	2.037231	.7329022	1.98	0.048	1.006508	4.123477
reEthGrp	.5758409	.153921	-2.06	0.039	.3410188	.9723592
Died	.6701924	.4912991	-0.55	0.585	.1592971	2.819624
Gender	1.360886	.5280627	0.79	0.427	.6361087	2.91147
Age	.9913533	.0178873	-0.48	0.630	.9569075	1.027039
fu6_incomemo	1.007277	.0607965	0.12	0.904	.8948964	1.133771
fu6_housedmo	.8282983	.0708764	-2.20	0.028	.7004071	.9795419
fu6_employmentpathmo	.6759141	.1158121	-2.29	0.022	.4831093	.9456657
_cons	2.212062	1.852901	0.95	0.343	.4283521	11.42335

. logistic dwpostarrest6 dwprearrest6 reEthGrp Died Gender Age fu6_incomemo fu6_housedmo fu6_employmentpathmo, or

Logistic regression Number of obs = 176
 LR chi2(8) = 22.92
 Prob > chi2 = 0.0035
 Pseudo R2 = 0.1064
 Log likelihood = -96.219073

dwpostarrest6	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
dwprearrest6	1.839091	.7331828	1.53	0.126	.8418956	4.017429
reEthGrp	.5746563	.1608483	-1.98	0.048	.332012	.9946322
Died	.4790478	.3998218	-0.88	0.378	.0933149	2.459274
Gender	1.443567	.5843754	0.91	0.364	.6529189	3.191647
Age	1.000858	.0189336	0.05	0.964	.9644282	1.038663
fu6_incomemo	1.004087	.0633391	0.06	0.948	.8873121	1.13623
fu6_housedmo	.8316587	.0763416	-2.01	0.045	.6947196	.9955904
fu6_employmentpathmo	.5903784	.1525002	-2.04	0.041	.355842	.9794984
_cons	1.167799	1.017767	0.18	0.859	.2116041	6.444838

. logistic dpostcrime6_tot dprecrime6_tot reEthGrp Died Gender Age fu6_incomemo fu6_housedmo
 > fu6_employmentpathmo, or

Logistic regression Number of obs = 176
 LR chi2(8) = 7.48
 Prob > chi2 = 0.4856
 Pseudo R2 = 0.0366
 Log likelihood = -98.391185

dpostcrime6_tot	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
dprecrime6_tot	2.153892	.8389657	1.97	0.049	1.003855	4.621434
reEthGrp	.6971475	.1916792	-1.31	0.189	.4067136	1.19498
Died	1.059312	.7672641	0.08	0.937	.2561502	4.380793
Gender	1.207777	.4918772	0.46	0.643	.5436605	2.683154
Age	1.00401	.0186995	0.21	0.830	.9680205	1.041337
fu6_incomemo	1.002502	.0630669	0.04	0.968	.8862102	1.134055
fu6_housedmo	.9350532	.0779717	-0.81	0.421	.7940663	1.101072
fu6_employmentpathmo	.9297929	.1054397	-0.64	0.521	.7444901	1.161217
_cons	.4902335	.4382952	-0.80	0.425	.084993	2.827633

```
. logistic dpostfelonycharge6_tot dprefelonycharge6_tot reEthGrp Died Gender Age fu6_income
fu6_housed fu6_employmentpath, or
```

```
Logistic regression                                Number of obs   =          176
                                                    LR chi2(8)      =          15.32
                                                    Prob > chi2     =          0.0532
Log likelihood = -50.426755                       Pseudo R2       =          0.1319
```

dpostfelonycharge6_tot	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]
dprefelonycharge6_tot	2.349346	1.805953	1.11	0.267	.5207443 10.59911
reEthGrp	.4186286	.1825915	-2.00	0.046	.1780589 .9842241
Died	2.416419	2.208981	0.97	0.334	.4027564 14.4978
Gender	2.320975	1.449299	1.35	0.178	.6825749 7.892065
Age	.9956924	.0267366	-0.16	0.872	.9446448 1.049499
fu6_income	1.026323	.605601	0.04	0.965	.3228621 3.262506
fu6_housed	.0932402	.1033629	-2.14	0.032	.0106167 .8188722
fu6_employmentpath	.231206	.33338	-1.02	0.310	.0136974 3.902668
_cons	.5359406	.6765428	-0.49	0.621	.0451446 6.362503