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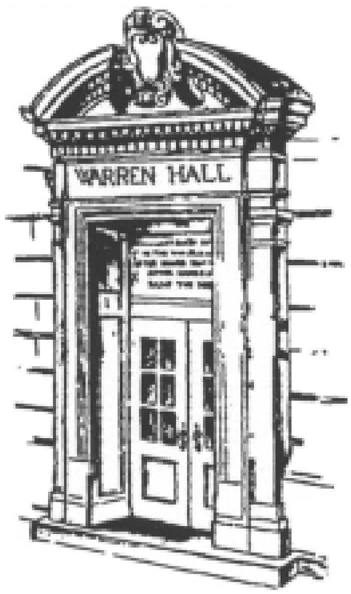

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Subsidized Vehicle Acquisition and Earned Income in the Transition from Welfare to Work

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Successful transition from welfare to work depends on the availability of supporting services such as reliable transportation and affordable childcare. Despite this recognition, few empirical studies analyze the impacts of reliable personal transportation programs on individuals in transition. This study examines the impacts on earned income of the "Good News Garage," a small-scale vehicle donation-and-sales program in Vermont. Using reduced-form random effects and censored regression models to account for the simultaneity of decisions to work and participate in welfare programs, we examine the impacts of this vehicle acquisition program for a small group of individuals. Our analyses indicate that the program results in a statistically significant increase in both earned income and the probability of employment.

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Introduction

Successful transition from welfare to work has been at the heart of the political debate over the last few years, particularly since the passage of the Personal Responsibility and Work Opportunity Reconciliation Act in 1996. Numerous studies have examined determinants of outcomes in this process [Seninger, 1999; London, 2000; Grogger, 2001; Lane and Stevens, 2001; and Loeb and Cochran, 2001]. A major finding is that successful outcomes in the transition to work depend in part on supporting services such as access to affordable childcare and transportation [Minton, 1999]. A study of welfare-to-work transportation issues [Multisystems, Inc., 2000] noted that fewer than seven percent of Temporary Assistance to Needy Families (TANF) recipients owned an automobile, and that existing transportation systems often did not provide sufficient services for welfare recipients seeking work. Public transportation routes (especially buses) provided inadequate services in geographic areas and for time schedules more common to individuals in transition. Moreover, few public transportation systems recognized the need for "trip chaining" in which workers link their daily commutes to daycare centers or school drop-offs and pick-ups.

These challenges are particularly acute in rural areas where population density is low and public transportation services are limited. About 38 percent of the nation's rural residents live in areas with no form of public transportation and an additional 28 percent of rural residents live in areas with very low levels of service provision [Dewees, 1998]. Small community size, dispersed residential areas, and low population density are often cited as barriers to the development of affordable and reliable transportation systems in rural areas [NADO, 1998]. As a result, the rural poor have less access to public transportation than their urban counterparts, but often must travel greater distances to commute to work, obtain essential services, and make needed purchases.

The lack of adequate transportation options to low-income citizens is, along with lack of child care and insufficient job readiness, one of the three reasons most frequently cited by governmental agencies for unemployment [Dewees, 1998; Ong, 2002].

For individuals in transition from welfare to work, access to reliable transportation has numerous potential benefits. First, transportation expands the number and scope of potential employment opportunities for those actively seeking work. Many previous studies have noted that employment opportunities are most frequent (or more lucrative) in locations spatially distant from where many welfare recipients reside, and that firms often undertake limited recruiting efforts in low-income or minority neighborhoods. In addition, entry-level jobs are often filled through processes that are influenced by proximity to the location of the position: walk-in applications, informal referrals, and other forms of face-to-face contact [Ong, 2002]. Reliable, accessible transportation supports job search efforts in a broader geographic area. A broader job search may also result in the individual finding a job with more desirable characteristics (higher wages or benefits, availability of child care, more convenient working hours, etc.), which can reduce job turnover. Moreover, the availability of transportation should facilitate participation in education and training programs designed to enhance an individual's work-related skills, thus enhancing the probability of employment.

The recognition that transportation services are often needed to facilitate workforce participation has led many state and local governments to explore alternatives to traditional public transportation that better meet the needs of current and former welfare recipients. These approaches include re-routing existing bus systems to better match the spatial and temporal needs of individuals in transition, organization of van and vanpool routes, increasing access to auto repair services, and donation-and-sales programs. The importance of these supporting services was underscored by the Transportation Equity Act for the 21st Century passed in 1998, which allocated $150 million per year through 2003 in Job Access and Reverse Commute grants to local governments.

Despite the recognition of transportation services as an important component of the transition from welfare to work, relatively few empirical studies exist on the impacts or effectiveness of the provision of supporting transportation services in the transition from welfare to work. Ong (2002) examined the impact of vehicle ownership on the probability that TANF recipients were employed, controlling for the endogeneity of the vehicle ownership decision, and other individual and community factors. This study found that vehicle ownership increased the probability of employment by nine percent. Another study found that recipients with a vehicle were nearly 10 times more likely to find a job than were recipients without a car [Cervero, Sandoval, and Landis, 1999]. However, the existing studies use data from Los Angeles and San Francisco, and the ability to generalize these findings to smaller metropolitan areas and other regions of the country has not been explored. Moreover, there are a growing number of public-private partnerships that seek to address the transportation issue by subsidizing vehicle acquisition by welfare recipients making the transition to work. The effectiveness of these programs has not yet been formally evaluated.

The objective of this paper is to examine the impacts of a small-scale vehicle donation-and-sales program in Vermont on the earned income of individuals in transition. Using two types of econometric models to control for other factors influencing these outcomes, we show that this pilot program likely increases earned income and the probability of employment. We also explore the information necessary for a more complete evaluation of program impacts.

The “Good News Garage” Vehicle Donation-and-Sales Program

As noted above, access to reliable and affordable transportation often constitutes a barrier for those seeking to make the transition from welfare to work. This barrier is particularly important in Vermont, a predominantly rural state. Over 60 percent of its population lives in rural areas. Of an estimated 231,000 households in the state, about 7 percent own no automobile, and more than 30 percent of households have only one. There are only a few towns in Vermont with a public transportation system, and inter-city public transportation is available for only a limited number of towns and cities. Even for existing services, the frequency of intermediate stops, particularly those along the interstate highways, has declined as services are increasingly made into limited stop expresses serving major cities [KFH Group, 1998]. This lack of transportation has likely had negative effects on economic development and employment. In some areas of the Northeast Kingdom, the most isolated part of Vermont, the unemployment rate is as high as 6.2 percent, about twice the state average [Woods, 1998].

However, even in larger urban centers such as Burlington where public transportation is available, the public transportation system does not provide all low-income people with the mobility required to take available jobs. First, many jobs are not at locations on the bus routes. Second, the public transportation system does not offer the non-peak (evening, night and week-end) service hours required to meet the scheduling demand of many entry-level, lower skilled jobs [Kaplan, 1997; 1998]. As of the mid-1990s, there was growing evidence that access to adequate transportation was essential to help many low-income residents of the state retain their jobs or make the transition from welfare to work. This need provided the underlying rationale for the creation of the Good News Garage (GNG) in Burlington in 1996.

The objective of GNG is to facilitate ownership of functional vehicles by low-income individuals, with a focus on helping them find or retain employment. Under the program, GNG acquires vehicles from donors, repairs or refurbishes the vehicles, and sells them at minimal cost to individuals meeting specific criteria. Only individuals with an income less than 150 percent of the poverty level may acquire vehicles, and priority is given to applicants who need transportation to retain a current job or participate in a job training program. Typically, an applicant will contribute $400 to $800 to cover some of the costs of repair or refurbishing, vehicle registration, and taxes. Since the first car was donated in 1996, GNG has provided over 1,000 donated cars to low-income Vermont residents.

In addition to the donation of vehicles, the GNG program has been supported by grants from various charity organizations and state government agencies. Since the program's inception, many vehicles have been acquired by low-income individuals referred from the State of Vermont's Department of Prevention, Assistance, Transaction and Health Access (PATH)[2]. Given the objectives of GNG to enhance job retention and the transition to employment, PATH contracted directly with GNG in 1998 to provide vehicles to individuals identified by the department as likely to benefit from vehicle ownership. Under the contract, PATH provides core funding for GNG and $400 per car to PATH recipients. From 1998 to 2000, more than 40 individuals received vehicles under the contract with PATH.

Anecdotal evidence suggests that the collaboration of GNG and PATH has been successful in helping individuals make the transition from welfare to work [Wolkomir and Wolkomir, 1999]. However, no formal studies have been conducted to document the magnitude of the benefits of

[2] Until recently, this agency was known as the Department of Social Welfare. PATH administers the Vermont's welfare programs.

GNG program to its participants or to the State of Vermont. The objective of this paper is to analyze the impact of vehicle acquisition through GNG on a variable of interest to both GNG and PATH: earned income by program participants. Information about whether there is an increase in earned income provides GNG with an opportunity to examine the effectiveness of its program, and PATH with the opportunity to evaluate its policy of supporting the transition from welfare to work through GNG. Moreover, increases in earned income also imply reductions in welfare payments, and thus imply the potential for cost savings to the state of Vermont.

Methods

A variety of methods are available to evaluate the impact of a program or a policy on valued outcomes. The choice of the most appropriate method is determined by (1) the purpose for which the evaluation is required, (2) the practical limitations placed on the evaluation process, and (3) the environment in which the evaluation is to be undertaken. For example, a rapid assessment of the short-term benefits of a newly introduced program can be conducted in order to decide whether this program is to be continued. Alternatively, a more comprehensive analysis designed to produce generalizable results often should be used to determine whether a program is to be expanded. Thus, it is important that the decision maker distinguish between the characteristics of these available methods, understand their technical advantages and disadvantages, and recognize the ethical and political implications involved in their use [Hogwood and Dunn, 1984]. Based on Garasky and Barnow [Garasky and Barnow, 1992], we describe the three broad approaches available to evaluate the impacts of programs.

The theoretically preferred approach is to use the classical experimental approach to investigate the causal relationships influencing program outcomes. This approach, relying on well-known survey and statistical techniques, requires the random assignment of eligible clients to one or more treatment (or program) groups and a non-treatment (or control) group, prior to the introduction of the interventions. This random assignment reduces bias due to initial selection differences and enables the isolation of program-specific effects from other effects. The outcomes of participants who received the program's interventions are compared to those who did not receive them. Because all groups are subject to similar influences, any differences in outcomes can be justifiably attributed to the program [Blalock, 1990; Hoaglin, 1982]. This approach has been used in national evaluation projects of welfare-to-work strategies [Manpower Demonstration Research Corporation, 1997; 1998]. However, because of cost and time considerations, the use of the experimental method is likely to be more limited [Hogwood and Dunn, 1984]. Finally, due to the practical difficulties and political implications attached to conducting experiments in social contexts, the experimental approach cannot always be realistically implemented [Mark, Henry, and Julnes, 2000]. The second approach, referred to as the quasi-experimental approach, addresses some of the practical and political difficulties previously mentioned. It relies on the establishment of non-random treatment and control groups, and compares the outcomes of the program participants to statistically constructed comparison groups of individuals who have not received the program's intervention. Thus, instead of random selection, individuals with similar characteristics are assigned to a comparison group, and one of the main challenges is to be able to guarantee comparison groups with characteristics similar to those of the treatment groups [Hogwood and Dunn, 1984]. After statistically controlling for differences between groups, the impacts of the program effect are derived from observing differences in outcomes between the groups [Heckman and Hotz, 1989]. Finally, the third approach is to develop an econometric time series or other similar statistical model. Under this approach, it is common to use data on outcomes of interest collected regularly over time (e.g., weekly, monthly, or quarterly) both before and after the introduction of the program. Data on other variables influencing the observed outcomes are used to isolate the impact of the program intervention. The predicted outcomes with and without the intervention are compared to provide an empirical estimate of the impact of the intervention [Mark, Henry, and Julnes, 2000].

The situation faced by the GNG is similar to that of many non-profit organizations, in which human and financial resources for formal assessment of program impacts are limited. As a result, no explicit evaluation strategy was formulated when the program began. The organization's interest in assessing its impacts arose primarily from a desire—but not a formal requirement—to demonstrate to state government funding sources that the program had been successful. Thus, the GNG was not required and did not establish experimental treatment groups to evaluate the impacts of its program. In part because no experimental design was established at the start of the agreement between GNG and PATH, no information is available on welfare recipients who did not receive vehicles[3]. This circumstance implies that the statistical methods often used in quasi-experimental approaches may result in biased indicators of the program's impacts due to sample selection (We discuss this issue in greater detail subsequently). Using the available information on program participants from PATH's administrative databases, we develop two types of econometric models to examine the impacts of the GNG program on individuals referred by PATH. This general empirical approach has been used to examine the outcomes of a variety of changes to welfare programs [Seninger, 1998; London, 2000; Klattiwer et al., 2000; Lane and Stevens, 2001; Loeb and Corcoran, 2001]. Our analysis explores determinants of the variable of interest, earned income, during the 12 months before and after the acquisition of a vehicle through GNG, controlling for other factors likely to have an impact.

Model Description

According to economic theory, individuals make choices to maximize their utility subject to a set of constraints [Becker, 1964; Grogger and Michalopoulos, 1999]. Thus, an individual's choices to participate in the labor force or receive welfare payments will depend on both individual personal (or behavioral) characteristics, and local or regional factors influencing the availability of employment options or social services. Increasing the availability of transportation or reducing its cost should have the effect of increasing workforce participation and reducing welfare support payments, all other things being equal. However, earned income and support payments are simultaneously determined: the motivation and need to earn depends in part on what payments are available from social service agencies, whereas eligibility for support payments is in part determined by an applicant's income and program administrative requirements. Moreover, the principal effect of a vehicle donation program is hypothesized to occur through increases in earned income, because the purpose of vehicle acquisition is to enhance the ability to find and retain employment. Thus, we would expect vehicle acquisition to have a positive impact on earned income.

[3] Data collection for this project relied on efforts by GNG program administrators, who met with limited success in convincing welfare agency staff of the need for information about non-participants due to issues of confidentiality.

The observed level of earned income depends on the solution to the utility maximization problem, which involves a number of simultaneous decisions, as captured by a simultaneous system of equations. Because we do not have data on all dimensions of the household's decision making processes, we do not estimate the complete simultaneous system, but instead, a "reduced-form" system, given by:

$$EI_{it} = f^{EI}(VEHICLE_{it}, X_{kit}),$$

where *EI* is the amount of earned income, *VEHICLE* indicates whether the individual has acquired a vehicle through the program as of the current month, and X_{kit} are other independent variables influencing earned income, such as individual and community characteristics. The subscript *i* indicates the ith individual, *t* indicates time (month in this case), and *k* indicates the set of explanatory (independent) variables. The use of reduced forms implies that the estimated coefficients for the variables included in the model account for both the direct effects of an independent variable on EI and the indirect effects of that variable on the other dependent variables in the system. In other words, in this equation, the coefficients for the variables other than vehicle acquisition include both their direct effects on EI <u>and</u> the indirect effects of those variables on other decision variables[4]. By assumption, the impact of vehicle acquisition is direct only, arising primarily through broader job search possibilities, greater incentives to work (e.g., higher wages) and fewer disincentives (lower commuting costs).

[4] For example, the number of pre-school children in a household may influence both earned income directly (by influencing the desire and ability to work) and indirectly through its impact on monthly welfare benefits (which also then influence the desire to work). In our models, both of these effects are captured by the pre-school children variable.

Two characteristics of the data influence the choice of the empirical model to be estimated. First, we have multiple observations through time for a set of individuals. This implies that a specification should allow for the effects to differ by individual due to factors that are constant through time but not directly observable [Balestra, 1996]. Second, a substantial portion of the observations for earned income are censored, with about 52 percent of these observations equal to zero. This implies that an empirical model should account for the impact of censoring on the estimated coefficients. To account for both the panel nature and censoring of the data, we adopt the approach of estimating two separate model formulations: a Random Effects Model to account individual effects, and a Censored Regression Model, also referred to as a Tobit Model, to address censoring in the data.

The Random Effects Model (REM)

In our case, the REM can be specified as:

$$EI_{it} = \alpha_{it}^{EI} VEHICLE_{it} + \sum_{r=0}^{R} \beta_{ikt}^{EI} X_{kit} + \gamma_{i}^{EI} + \varepsilon_{it}^{EI} \quad ,$$

where the *i* indicates the ith individual, *t* indicates time (month in this case), *k* indicates the set of explanatory (independent) variables, EI_{it} and $VEHICLE_{it}$ are as defined previously, the β_{kit} are coefficients to be estimated, the X_{kit} are explanatory variables, γ_i are random effects specific to each individual, and ε_{it} are random error terms. Under the assumptions of this model, we have:

$$\gamma_{\mathrm{i}} \sim iid\ N(0,\sigma_{i}^{2});\, E(\gamma_{\mathrm{i}} \mid X_{kit}, \varepsilon_{it}) = 0\,;\, \varepsilon_{it} \sim iid\ N(0,\sigma_{\varepsilon}^{2}).$$

This model specification explicitly recognizes the potential for effects to differ by individual. In contrast to the classical regression model, the REM treats these effects as random, but individual-specific instead of summarizing them in the error term ε. The coefficients are estimated using the method of Feasible Generalized Least Squares (FGLS), corrected for first-order autocorrelation. As noted above, the use of reduced-form equations implies that the β coefficients indicate the impact of the *X* variables on *EI* directly, and indirectly through impacts on the other dependent variables in the system.

The Censored Regression Model (CRM)

The formulation of the CRM is given in terms of an index function for the variable of interest, *EI**. If we let *Y** represent the index function for these variables, *Y* the observed values of *EI*, and *X* the exogenous variables, the formulation of the censored regression model is:

$$
\begin{aligned}
&Y_t^* = \beta' X_t + \varepsilon_t, \\
&Y_t = 0, \text{ if } Y_t^* \le Y_0, \\
&Y_t = Y_t^*, \text{ if } Y_t^* > Y_0,
\end{aligned}
$$

where β is a vector of coefficients, ε is an error term assumed to be normally distributed with mean 0 and variance σ^2, and Y_0 is a minimum threshold, or the value at which the data are censored. The CRM assumes that Y^* is the solution to an individual's utility maximization problem, but conditional on Y^* being above the limit Y_0. In this case, $Y_0=0$. Thus, the CRM can be defined as:

$$
\begin{aligned}
\mathrm{Y_t} &= 0, \quad \text{if } \mathrm{Y_t^*} \le 0. \\
&= \mathrm{Y_t^*}, \ \text{ if } \mathrm{Y_t^*} > 0.
\end{aligned}
$$

The expected value of the observed value *Y* is:

$$E[Y] = X\beta\Phi\left(\frac{X\beta}{\sigma}\right) + \sigma\phi\left(\frac{X\beta}{\sigma}\right),$$

[Tobin, 1958], where X and β are as defined previously, Φ is the cumulative normal distribution, σ is the standard error of the error term, and ϕ is the normal probability density function. The marginal effect of an explanatory variable x_k on the expected value of Y is:

$$\frac{\partial E[Y]}{\partial x_{ki}} = \Phi\left(\frac{X\beta}{\sigma}\right)\beta_k,$$

[Greene, 1993]. Note that the effect of a unit increase in the X is not equal to the estimated coefficient β (as it is in the classical regression model), and now depends on the level of the X variables. (As a result of this dependence on X values, marginal effects are typically evaluated at the mean of the X.) The value $\Phi\left(\frac{X\beta}{\sigma}\right)$ is termed a "scaling factor" and is always less than one. Thus, the effect of a one-unit change in a variable x_k on the observed value of Y will always be less than β_k. Moreover, the impact of a variable X can be decomposed into two separate effects, one on the probability that a non-zero (non-censored) value is observed, and the other on the observed Y given that it is above zero [McDonald and Moffitt, 1980]. In our context, this latter relationship can be used to estimate the impact of vehicle acquisition on the probability that earned income is greater than zero.

As noted earlier, our sample contains observations on those individuals who participated in the program (received a vehicle), and no information is available on other welfare recipients who did not participate. Thus, the estimated model coefficients may be subject to sample selection bias. The sample selection problem arises because individuals often "self-select" into programs, so that participants are those who are more likely to benefit (or benefit more than) those who don't participate. This implies that direct comparisons of outcomes for participants and non-participants (or before and after participation for participants only) will tend to overstate the benefits of program participation, because part of the observed difference is due to selection effects [Greene, 2000].

To make the issue more concrete, it is helpful to specify a generic program evaluation model and explore the implications of sample selection. Following Greene (2000), we can specify this model as:

$$Y_i = \beta' X_i + \alpha C_i + \varepsilon_i,$$

where *Y* is the variable of interest (e.g., earned income), *B'X* represents the impact of other factors influencing *Y*, *C* represents a dummy variable for program participation (equals one if individual participates and 0 if not) and *α* represents the impact of program participation on *Y*. The objective of the estimation is to obtain an unbiased (consistent) estimator of the parameter *α*. Assume also that C is determined by the group of individuals eligible for participation in the program, according to the following equation:

$$C_i^* = \gamma' W_i + u_i,$$

where *C** is a latent variable implying that the participation outcome *C* observed is determined as:

$$C_i = \begin{cases} 1, \text{if } C_i^* > 0 \\ 0, \text{otherwise} \end{cases}.$$

Let ρ be the correlation between the error terms ε and u, and σ_ε and σ_u be the standard deviations of ε and u, respectively. A positive value for ρ implies that individuals with a higher likelihood of participating in the program are also likely to have higher incomes even without participation in the program. The expected value of Y for program participants is given by:

$$E[Y_i \mid C_i = 1] = \beta' X_i + \alpha + E[\varepsilon_i \mid C_i = 1].$$

It can be shown that this expression is equal to:

$$E[Y_i \mid C_i = 1] = \beta' X_i + \alpha + \rho\sigma_\varepsilon \lambda(\theta),$$

where $\lambda(\theta)$ is a function of γ'W, the normal probability density function, and the normal cumulative distribution function. If $\rho \neq 0$, then the omission of the last term in this expression results in biased estimation of the coefficient α. In fact, Greene (2000) has shown that if $\rho > 0$, estimates of α that do not account for sample selection will be biased upwards, which implies that the impact of program participation will be overstated. The difference in the expected value of Y for participants and non-participants is given by:

$$E[Y_i \mid C_i = 1] - E[Y_i \mid C_i = 0] = \alpha + \rho\sigma_\varepsilon \lambda^*(\theta),$$

where $\lambda^*(\theta)$ is again a function of γ'W. Thus, this difference depends on both program participation (with effect α) and selection effects (the second term), if $\rho \neq 0$. Typically, a two-stage estimation procedure using data from participants and non-participants is used to account for the participation decision, e.g., [Heckman (1979)]. Models estimated with data only from participants are subject to the same potential for upward bias when $\rho > 0$.

In the case of the GNG participants, the sample selection process differs somewhat from that described above. Although individuals must apply to participate in the program, PATH administrators and case managers play a fundamental role in determining which individuals apply. Because nearly all individuals who apply are accepted for the program[5], administrators and case managers have an influential role in which individuals ultimately participate. The factors that case managers use to encourage or facilitate application are not known with certainty. However, it is likely that individuals with greater ability and willingness to work or undertake training apply, given that these characteristics are prerequisites for vehicle recipients to benefit from car ownership. In addition, applicants were required to have sufficient financial resources (often hundreds of dollars) to cover the difference between the costs of repairs made by GNG and payment by PATH. Both of these factors tend to suggest that individuals participating in the program would have higher incomes in the absence of the program (i.e., that $\rho > 0$ and estimates of program impact may be overstated). The presence of time limits for some welfare recipients may also influence who applies. Case managers may encourage those closer to the expiration of their time limits to apply. This may involve either those who are more prepared (with higher income earning potential) or those who have had more difficulty finding employment previously (who may have lower skills and less income earning potential). Thus, the overall effect of time limits on selection bias is uncertain.

[5] Although nearly all individuals will ultimately received a vehicle, the length of time waiting is determined by the individual's characteristics, based on criteria developed by GNG.

The net result of these various factors influencing application is likely to be some degree of upward bias in our estimated parameters for program impacts due to the factors mentioned above. However, one additional characteristic of the data will tend to offset this bias to an unknown degree. Data on earned income used in our estimations are subject to partial truncation from above, that is, for some (but not all) individuals, income data are not observed when an individual is earning sufficient income so that PATH support payments are not received. This type of truncation tends to result in downward bias in estimated coefficients under OLS [Greene, 2000]. Although this type of truncation can be corrected for when the truncation is complete, this is not attempted here because the truncation is partial. Also, it is worth noting that increases in measured earned income can underestimate the impact on purchasing power, if acquisition of the vehicle permits participants to reduce expenses on housing, food, and other necessities.

Data[6]

The GNG program does not formally monitor the outcomes for individuals receiving vehicles. As a result, the data used for this study were provided by PATH, which collects basic socio-economic information about its payment recipients over time. The availability of information from PATH records is limited to data used in program administration. Thus, data are unavailable on some variables that would be of interest to examine the outcomes of the GNG program, such as information on the individual's family background or psychosocial status [Klattiwer et al., 2000]. Nevertheless, our data include many variables commonly used in previous studies [Moffit, 1992; Ong, 2002]. Out of the thirty-eight program participants who had received a car at least one year prior to the start of the study, basic socio-economic information was available

[6] We gratefully acknowledge the contribution of Mark Schroeter to facilitating the data collection from PATH records, and the data entry by University of Vermont graduate student Wan Fei.

for thirty-four individuals. Although this is not a large number of observational units, it represents the entire population for which sufficient data are available to make inferences about the impacts of this program. Moreover, for each individual, up to 25 monthly observations are available, dramatically expanding the effective number of data points.

Independent Variables

For these 34 individuals, information was available on the age, sex, education (years of formal schooling), location at which the individual resides, the number of children in the household, the ages of any children, and whether the individual is a single parent (Table 1). These variables are hypothesized to affect an individual's ability to earn income. All but two of the program participants were female, so an analysis of the impacts of gender on *EI* is not possible. Because public transportation is more limited in the Northeast Kingdom, the models include a binary variable equal to one if the individual resided in that region, or zero otherwise. The number of pre-school age children in the individual's household are also included in the model, as this is likely to affect both earned income (by lowering ability to work).

In addition, PATH defines three specific categories of welfare payment recipients. An individual is assigned to a category when applying for support from PATH. These categories, referred to as group I, II, or III, are based on (a) the time at which an individual started to receive welfare payments, and (b) the existence or not of work requirements. An individual who started to receive welfare payments before July 1, 1994 was classified as Group I. Groups II and III include these individuals who became welfare recipients after that date, but Group III includes these individuals with work requirements. For the econometric analyses, a binary variable equal to 1 for individuals in Group III and 0 otherwise is specified to reflect differences in work requirements for welfare payment recipients.

Other time-dependent factors influencing *EI* are controlled for in two ways. First, the initial observation for the 34 individuals varies from mid-1997 to late 1998. These staggered starting dates imply that trends in variables that are not directly included in the model but that influence job prospects (e.g., economic conditions) and level of benefits (e.g., state and federal budget conditions) are not common to all observational units. In addition, if the totality of PATH programs is effective in preparing individuals in making the transition from welfare to work, we might expect to see increases in earned income and decreases in payments over time, independent of the acquisition of the vehicle through GNG. To control for these latter effects, a trend variable is included in the model for each individual. An overall trend variable also is included to examine the trends in economic conditions and the level of benefits.

Finally, a binary variable indicating when the individual received the vehicle from the GNG program is specified. This variable is 0 for the 12 months prior to receipt of the vehicle and for the month in which the vehicle was acquired. Thereafter, the variable has the value one. This is the key variable of interest, given that other variables control for a number of factors affecting earned income. The sign and magnitude of the α coefficients for this variable in each equation provide an estimate of the impact of the GNG program. We hypothesize that the sign of this coefficient in the earned income equation should be positive.

Dependent Variable

Data on earned income were collected for the 25-month period starting 12 months before acquisition of the vehicle and ending 12 months after acquisition (Table 2). This variable is commonly used in studies to examine the impacts of changes to welfare programs [Manpower Demonstration Research Corporation, 1998; Lane and Stevens, 2001]. Earned income is the monthly income earned by these individuals as reported to PATH, which includes (1) gross earned income, (2) net self-employment income, and (3) unearned income. These income categories are defined by PATH and recorded on benefits application forms. The number of observations on payments and income during the 25 months differs for the 34 individuals. This is because PATH records include data only for those months during which an individual received payments. When individuals find work or benefits are terminated, information often is unavailable. Although payments in these months are known to be zero, the amount of earned income for individuals in months without payments is unknown. As noted earlier our estimates will tend to understate the impact of the program on earned income, because the total earned income is underreported.

Model Results and Discussion

A comparison of the mean values for earned income before and after receipt of the vehicle provides a starting point for discussion of the impacts of the GNG program. Mean earned income was about $220 per month higher after receipt of the vehicle, roughly two and a half times higher than the amount earned prior to receipt of the vehicle (Table 2). This provides circumstantial evidence that the program is having an impact, and that the magnitude of the impact is reasonably large. In addition, support payments by PATH were lower after receipt of the vehicle, about $157 per month. Some of this reduction is undoubtedly due to administrative rules unrelated to earned income, but a part is likely due to increases in earned income. On the basis of these comparisons alone, the GNG program would seem beneficial to both participants and to the PATH budget. These descriptive results complement the econometric modeling efforts, to which we now turn.

The Random Effects Model

The reduced-form random effects model of earned income is summarized in Table 3. The explanatory power of the models (as indicated by the adjusted R-squared values) is consistent with that commonly reported for panel data models. In the earned income equation, the binary variable for acquisition of the vehicle from GNG is statistically significant at the 1% level. The coefficient on this variable indicates that earned income after receipt of the vehicle was, on average, $127 per month higher than earned income before receipt of the vehicle. The positive value indicates that vehicle acquisition is having a desirable effect on job acquisition and retention by individuals in the program, and its magnitude is roughly consistent with the difference in mean earned income before and after vehicle acquisition. However, the combined effects of sample selection bias and the underreporting of earned income noted earlier probably imply that the impact of program participation is somewhat smaller than $127 per month. The overall trend variable is statistically significant and negative, indicating that the general trend in earned income among participants is down by about $46 per month. This is offset to a certain degree by the effect of trends for individuals, which has a positive effect of about $50 per month. The number of pre-school children in the household has a large negative effect (as expected) on earned income, and is also significant at the 5% level. Locational factors, age, education, PATH group, and being a single parent all had statistically insignificant effects on earned income.

The Censored Regression Model for Earned Income

In the censored regression model, all of the coefficients except for those for education and the dummy variables for location, and PATH Group III are statistically significant at the 5% level and have logically consistent signs (Table 3). The individual trend variable, and age have a positive effect on earned income, whereas number of pre-school age children, being a single parent, age squared and the overall trend have a negative effect on earned income. The censoring sigma is highly significant, indicating that censoring is an important effect for earned income. The marginal effect of vehicle acquisition is an increase in earned income of $124 per month (Table 3), somewhat less than the estimated value in the REM estimation but of the same order of magnitude. As for the REM, this result may overstate the impact of vehicle acquisition on earned income.

The decomposition of the CRM coefficients proposed by MacDonald and Moffit [1980] provides insights into the effect of the dependent variables on the probability of an individual having non-zero earned income (Table 3). Vehicle acquisition had a large positive impact on the probability of non-zero earned income. Individuals were 19 percent more likely to have earned income after vehicle acquisition. This is a somewhat larger effect than found for a study in Los Angeles, where vehicle ownership by welfare recipients was found to increase the probability of employment by nine percent [Ong, 2002]. An additional year age increased this probability eight percent and the individual trend increased the probability 6 percent per month. The overall trend, the number of pre-school children, and being a single parent household decreased the probability of non-zero earned income by 5, 25 and 14 percent, respectively. Thus, the CRM indicates that vehicle acquisition through GNG has significant positive effects on both the level of earned income and the probability of paid employment.

The descriptive analyses and econometric models both suggest that the GNG program has a positive impact on earned income, although the exact magnitude of the impact is uncertain due to lack of non-participant data. The magnitude of the estimated effects (even if somewhat overstated) suggests that the impact of the program is large relative to the mean earned income prior to vehicle acquisition. Moreover, the impact on earned income is likely to be large enough to reduce PATH payments to program participants. Payments under the "Reach Up" program are reduced \$0.75 for every dollar of earned income over \$150 and less than the maximum qualifying income. Thus, for every \$100 increase in earned income, PATH payments under Reach Up are reduced by \$75, all other things being equal. If the impact of the GNG program on earned income is roughly \$100 per month, the \$400 cost of the vehicle to PATH could be recovered through reductions in Reach Up payments in just over five months. (The cost of the vehicle to the individual would be recovered in four to eight months depending on the specific car.)

In addition to the caveats about bias in the estimated coefficients, a number of other comments on the results are in order. First, the reported results provide an indication of only the mean response of individuals to program participation. The experience of individuals will vary. Some individuals experienced little or no increase in earned income after vehicle acquisition, whereas others demonstrated much greater increases. Our results do not explain these differences, and therefore provide relatively few insights about how to make the GNG program more effective. Second, our results do not indicate the full range of costs and benefits from vehicle acquisition through GNG. The focus on earned income ignores other potential economic benefits for individuals (such as reductions in living expenses) and non-economic (e.g., psychological) benefits. A more thorough evaluation of the GNG-PATH collaboration requires examination of the additional measures. Further study of the program's impacts can also benefit from the use of non-participant data (to correct for sample selection bias) and the larger sample sizes that will become possible as the cumulative number of participants increases over time. The incorporation of additional variables on employment history and other personal characteristics could help to make the GNG program more effective.

Summary

This paper examines the impacts of a small-scale vehicle donation-and-sales program on individuals in transition from welfare to work. The challenges faced by the Good News Garage in assessing the impacts of its program on individuals in transition are similar to those faced by many not-for-profit organizations: no *a priori* formal evaluation structure, limited access to necessary data, and—perhaps most importantly—limited staff resources for assessment efforts. Given the practical limitations of resource constraints and the lack of information on non-program participants, we rely on an econometric analysis of program participants to examine the impacts of the GNG program on individuals referred by PATH. The use of data only from participants implies the potential for upward bias in our estimates of program impact, but these are likely offset to a certain extent due to partial truncation of the dependent variable.

The analysis focuses on the impacts of the subsidized vehicle acquisition program on a variable of interest to state welfare policy makers and program administrators: earned income. Using two alternative econometric model specifications to control for other factors influencing these outcomes, we find that the program results in statistically significant increases in earned income. Moreover, vehicle acquisition through the program results in an increase in the probability of employment. These results provide evidence that the program is achieving success in assisting individuals to find and retain employment during their transition from welfare to work. In addition, there exists the potential for a reduction in welfare payments due to the increase in earned income. It appears likely that the State of Vermont recovers the amount per vehicle it provides to the GNG program in less than six months. A more accurate assessment of the impact on earned income after vehicle acquisition would require data collection from welfare recipients not participating in the program. Additional information on the characteristics of participants and non-participants could help to make the GNG program more effective.

Table 1. Characteristics of N=34 GNG Program Participants

Characteristics at Time of Vehicle Acquisition	Mean	Median	St. Dev	Valid N
Number of Children	1.8	2.0	0.7	34
Number of Pre-school Children	0.6	1.0	0.6	34
Age, years	31.4	28.0	7.9	34
Education, years	12.5	12.0	1.4	34
Single Parent Household (1=Yes, 0=No)	0.76	1.0	--	34
Located in Northeast Kingdom (1=Yes, 0=No)	0.59	1.0	--	34
In PATH Group III (1=Yes, 0=No)	0.79	1.0	--	34

Table 2. Earned Income and Aggregate Support Payments by PATH, N=34 GNG Program Participants

PATH Support Payments and Earned Income	Mean	Median	St. Dev	Valid N
Earned Income, $/month				
Before Vehicle Acquisition	141.9	0.0	316.0	394
After Vehicle Acquisition	361.4	179.0	424.0	302
Overall	237.2	0.0	382.4	696
Difference, Before and After	219.5	179.0	--	--
PATH Support Payments, $/month				
Before Vehicle Acquisition	723.8	780.7	405.0	442
After Vehicle Acquisition	567.2	533.1	440.6	408
Overall	648.6	716.0	429.4	850
Difference, Before and After	-156.6	-247.6	--	--

Table 3. Results of Random Effects and Censored Regression Model of Effects of Vehicle Acquisition on Earned Income

	Random Effects Model			Censored Regression Model						
	Coefficient	s.e.	t-stat	Coefficient	s.e.	t-stat	Marginal Effect[1]	s.e.	t-stat	Effect on Prob[EI]> 0[2]
Independent Variables										
Constant	2032.5	1244.4	1.63	807.3	732.1	1.10	371.6	339.2	1.10	
Vehicle acquisition from GNG[3]	126.5	43.1	2.93	270.2	92.4	2.92	124.3	42.6	2.92	0.19
Individual Trend	56.0	20.3	2.77	87.1	12.5	6.97	40.1	5.8	6.92	0.06
Overall Trend	-48.3	19.9	-2.46	-72.2	10.4	-6.93	-33.2	4.9	-6.83	-0.05
Number of Pre-school Children	-242.7	99.7	-2.43	-348.4	55.4	-6.29	-160.4	25.8	-6.21	-0.25
Single parent household (1=Yes, 0=No)	-42.4	78.4	-0.54	-201.6	61.6	-3.27	-92.8	28.2	-3.29	-0.14
Age, years	-12.6	63.5	-0.20	108.7	38.6	2.82	50.0	17.5	2.85	0.08
Age squared	-0.1	0.9	-0.10	-2.0	0.6	-3.68	-0.9	0.3	-3.74	0.00
Education, years	-18.4	39.2	-0.47	-39.5	21.2	-1.86	-18.2	9.8	-1.86	-0.03
Located in Northeast Kingdom (1=Yes, 0=No)	-47.7	102.0	-0.47	-10.9	57.9	-0.19	-5.0	26.6	-0.19	-0.01
In PATH Group III (1=Yes, 0=No)	-10.8	125.0	-0.09	-95.5	69.4	-1.38	-44.0	31.9	-1.38	-0.07
Model Characteristics										
Number of observations	662			696						
Degrees of freedom	651			685						
Adjusted R^2 (OLS)	0.14			0.22						
Log likelihood	-4617.5			-5036.3						
Hausman test for random effects										
LM test vs.OLS	246.10			--						
Probability	0.00			--						
Censoring sigma[4] (Probability)	--			559.3 (0.00)						

[1] The marginal effect of the independent variable *x* on the dependent variable (EI) is $\dfrac{\partial E[Y]}{\partial x_{ki}} = \Phi\left(\dfrac{\overline{X}\beta}{\sigma}\right)\beta_k$.

[2] Based on the decomposition procedure in MacDonald and Moffit (1980), this indicates impact of a one-unit change in the independent variable on the probability that the individual will have non-zero earned income, evaluated at the mean of the data. As an example, each additional pre-school child reduces the probability of earned income by 25 percent.

[3] Binary variable that has the value zero for the twelve months prior to the acquisition of the vehicle from GNG and during the month of acquisition. Variable has the value 1 in subsequent months.

[4] The censoring sigma indicates the estimated value of the σ coefficient in the equation for the expected value of Y^*

$$E[Y^*] = XB + \sigma \frac{\phi(XB/\sigma)}{\Phi(XB/\sigma)}$$

and the probability that it is significantly different from zero (i.e., that there is statistically significant censoring in the sample).

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