Determinants of Demand for HIV Testing: Evidence from California Outpatients Clinics

Dan Friesner[1], Peter Cashel-Cordo[2], Matthew Q. McPherson[1]

[1]*Gonzaga University*
[2]*University of Southern Indiana*

Abstract

This paper provides an initial empirical analysis of the impact of changing epidemiological, economic and sociological conditions on the amount of HIV testing in primary care, outpatient clinics. Particular attention is paid to examining whether changes in HIV/AIDS prevalence impact the amount of testing these clinics perform, and also how financial constraints impact this relationship. Using a sample of California clinics, we find that changing epidemiological conditions do impact the demand for HIV testing. Additionally, certain clinic characteristics, such as the type of practitioners providing care and the socio-economic characteristics of patients treated at each clinic also affect the demand for testing. However, we find little evidence supporting increased government or private grants, contracts and donations as a means of enhancing the demand for HIV testing.

Keywords: Demand for HIV Testing, Outpatient Clinics, HIV Prevention, and HIV Policy

Introduction

While the HIV/AIDS epidemic is taking its largest toll on societies in Southeast Asia and Sub-Saharan Africa, the US has also been significantly impacted by HIV/AIDS. According to the Centers for Disease Control and Prevention (CDC, 2004), in 2003 the cumulative number of AIDS cases in the US surpassed 900,000. Additionally, the cumulative number of HIV infections exceeded 200,000, with over 33,000 new infections during the year.

Within the US, the State of California has been especially hard-hit by the epidemic. As of 2003, California ranks second in the US with over 133,000 cumulative AIDS cases — nearly 15 percent of the nation's total. It also ranks second in the number of new AIDS cases with just over 5,900 — nearly 13 percent of the nation's total (CDC, 2004). Moreover, among new AIDS cases in 2003, California had the third highest proportion of new cases among the Hispanic population. Thus, not only has California been hard-hit by the disease, but also the impact has disproportionately affected its largest minority population.

Since there is no known cure for the disease, HIV testing is one of the most important actions an individual can take to prevent transmitting the disease or, once acquired, obtain life-prolonging treatment. Given the development of anti-retroviral which prevent rapid health deterioration due to the onset of AIDS, testing is important because it allows infected individuals to start treatment sooner, thus increasing both longevity and quality of life. Despite these facts, California ranks only ninth among US states in the percent of its population ever tested for HIV, and 33rd among states in the percentage of individuals between the ages of 18-64 who were tested for HIV in 2001 (CDC, 2004). Clearly, there is a need to increase both access to, and utilization of, HIV testing in California.

For most individuals in California, routine outpatient health care services (including testing for HIV and other sexually transmitted diseases) are provided by primary care outpatient clinics.

There are over 760 of these clinics in the State, all of which are not-for-profit institutions. While these clinics treat a significant number of middle and high-income patients (who are generally insured by private, third party payers), the majority of patients are both poor and of minority ethnic backgrounds (Appendix B). These clinics generally rely on government-sponsored insurers, grants and donations to cover expenses. Government-sponsored insurers, including Medicare, Medicaid and other local plans, often do not reimburse as generously as private, third party payers. Thus, while these clinics provide an initial point of access to health care, particularly for underserved populations, they may be limited in the extent of care that they can provide.

From a policy perspective, it is important to understand the role that these primary care outpatient clinics play in the fight against HIV/AIDS. More specifically, two questions appear especially relevant. First, as sociological, economic and epidemiological conditions change, there should be a corresponding change in the demand for HIV testing. If this is the case, what proportion of this demand is met by these primary care outpatient clinics? If there is a strong relationship between changing prevalence rates and the amount of testing in these clinics, then policy makers can reduce the spread of the disease by diverting resources towards primary care outpatient clinics.

Second, if these clinics play a significant role in providing HIV testing, how do financial constraints impact clinics' abilities to provide these services? Previous studies using California outpatient clinics (Friesner, 2003; Rosenman, Friesner & Stevens, 2005; Rosenman, Li & Friesner, 2000) have found evidence indicating that revenue considerations (particularly the ability to obtain grants and donations, as well as reliance on third-party payers) significantly impact the quantity and quality of services provided. Do specific types of revenue sources (reliance on grants and/or Medicaid funding, for example) have a disproportionate impact on the amount of HIV testing in these clinics? From a policy perspective, this is an important question because it not only identifies some possible methods of increasing HIV testing, but it also gives an indication about how resources should be allocated to maximize their effectiveness.

This paper provides an initial empirical analysis on the impact of changing epidemiological, economic and sociological conditions on the amount of HIV testing in California outpatient clinics. Particular attention is paid to examining whether changes in HIV/AIDS prevalence impact the amount of testing these clinics perform, and also how financial constraints impact this relationship.

The remainder of this paper proceeds in four steps. First, we present a brief literature review, which we use to develop our empirical methodology. Next, we present and discuss the data used in our analysis. The third section contains our empirical results. We conclude the paper by discussing the policy implications of our findings, as well as providing some suggestions for future research.

Literature Review

The study of socio-demographic determinants of HIV testing has been the subject of a significant amount of research. Several surveys of persons at risk of HIV infection have found that increased perception of risk leads to a greater demand for HIV testing. In a sample of 621 homeless women (Nyamathi, Stein and Swanson, 2000), increased intravenous drug use, unprotected sexual contact and other risky behaviors led to higher HIV testing. Extending the survey to include men, Stein & Nyamathi (2000) examine gender differences for HIV testing. While increased perception of risk increased the demand for HIV testing for both genders, men typically had a lower perception of risk despite reports of more risky behavior.

Boozer & Philipson (2000) address the issue of risk perception from a slightly different perception and find evidence in support of public testing for HIV. In this research, a blood test for HIV was administered as part of a longitudinal survey. This framework for the demand for information on HIV implies that because only individuals who are surprised by the results of the intervention respond to the results (in this case low-risk people who test HIV-positive or high-risk individuals who test HIV-negative) an information-intervention of this type may reach populations who would otherwise not seek testing.

A significant amount of research has also focused on the special considerations of injection drug users (IDU). For example, Harris (2006) examined the efficient allocation of resources to prevent HIV infection among IDUs in the context of the Prevention Point Philadelphia, a multi-site needle exchange program. At the optimal allocation of needles, the estimated cost per case of HIV averted was $2,800. This favorable cost-effectiveness ratio came primarily from the program's low marginal cost per distributed needle.

In contrast, Heimer, Grau, Curtin, Khoshnood, & Singer (2007) sought to determine the extent of HIV testing among urban IDUs in order to assess the potential effectiveness of additional targeted testing programs for this population. Of the 1,543 IDUs in the sample, 93% had already been tested for HIV. The authors estimated the number of undetected infections among urban IDUs to be less than 40,000 in the United States. As a result, the authors concluded that expending scarce prevention money to expand testing of IDUs is unlikely to be productive. Given the national goals to identify previously undetected infections, the authors concluded that resources should be spent for proven HIV-prevention strategies including syringe exchange, drug treatment, and secondary prevention for those who are HIV positive.

Despite increased demand for HIV testing, most people diagnosed with AIDS were generally tested late in the course of their HIV infections while under acute medical care (Wortley et al., 1995). The demand for HIV testing varied according to risk group, race, and ethnicity. Intravenous drug users and heterosexual contact risk groups obtained the highest level of HIV testing during hospitalization. Additional evidence of late testing is found by Nakashima, Campsmith, Wolfe, Nakamura, Begley, & Teshale (2003). The authors interviewed 5,980 participants (from 16 different states) aged 18 and older with HIV or AIDS between May 2000 and February 2003. Participants were categorized in two groups: early testers (those who had their first positive test HIV test five or more years before the diagnosis of AIDS, or had gone five or more years with a diagnosis of AIDS after the first positive HIV test) or late testers (those who had their first positive HIV test one year or less before the diagnosis of AIDS). Among participants with AIDS, 24% where early testers and 45% were late testers. Late testers where more likely than early testers (1) to be 18-29 years old, (2) to be black or Hispanic, (3) to have acquired HIV through heterosexual contacts, (4) to have high school education or less, (5) to ever have been tested for HIV before the first positive result, (6) to have had confidential testing, (7) or to have received their first positive result from an HIV testing site or an acute or referral care setting. In addition, sixty five percent of late testers were tested for HIV because of illness, while the most common reason for testing among early testers was self-perceived risk (twenty nine percent).

Galvan, Bing & Bluthenthal (2000) found that racial and age differences exist once testing has been obtained. Young people and African Americans were less likely to return for results of their HIV tests. Age and race were also found to be a factor in accepting voluntary HIV testing. Hull, Bettinger, Gallaher, Keller, Wilson, & Mertz (1988) found that a higher percentage of African American males did not participate in HIV testing as compared to males from other ethnic groups. Kellerman et al. (2002), comparing the results from the HIV Testing Surveys, HITS1 and HITS2, found a decreasing proportion of people under the age of twenty-five years obtain HIV testing, whereas those over twenty-five years of age showed increased demand.

Two other patterns of HIV testing are of note. People engaging in higher risk behaviors have been found (Fernyak, Page-Shafer, Kellogg, McFarland, & Katz, 2002) to have higher demands for repeated testing. This is further evidence that higher perceptions of risk lead not only to increased HIV testing, but also repeat testing. However, in blind studies of anonymous testing, researchers found that the HIV prevalence rates are higher for people who have not had voluntary testing, regardless of risk group or socio-demographics (Weinstock et al., 2002).

Finally, there have been a number of studies which extend the traditional determinants of the demand for HIV testing to include the concepts of rational risk taking and the fear associated with a the possibility of a positive test. For example, Gritzman (2005) provided evidence indicating that individuals respond rationally to social and economic stimuli when it comes to taking risks. Therefore, viewing AIDS as a rational disease enriches our understanding of the behavioral underpinnings to the spread of AIDS and by extension, the determinants of demand for testing.

Caplin & Eliaz (2003) addressed the fear of a positive test as crucial to understanding the demand for testing. There are obviously strong health-based incentives to test for AIDS. However, the authors postulated that fear may override these incentives. They suggested decreasing the informativeness of a bad test result, thereby mitigating the fear of bad news. This would allow the health-based incentives to once again come to the forefront of the testing decision. The authors developed a model of AIDS transmission that acknowledges this form of fear. A mechanism is designed that not only encourages testing but also shows the spread of the disease through voluntary transmission. The authors showed that their model confirms that psychological interventions may slow the spread of AIDS, but conceded that much more work is needed in this area.

En totem, our literature review suggests three major hypotheses about the determinants of the demand for HIV testing. Stated in alternative form, these hypotheses can be characterized via the following statements:

Hypothesis 1: Higher levels of (perceived) risk should lead to an increased demand for HIV testing.

In this analysis, we measure perceived risk as an actual change in epidemiological conditions and outpatient clinics as the primary source for such tests. This assumes that individuals base their perceptions (at least partially) on some form of fact. Moreover, if people base their perceptions solely on fact, one would expect the demand for testing, on average, would change in direct proportion to changing epidemiological conditions. If fear, information uncertainty or other factors were used in the evaluation of risk perception, then this relationship would not be proportional, and (in extreme cases, for example, if individuals become fatalistic) possible inversely proportional.

Hypothesis 2: Enhanced clinic resources should lead to an increased demand for HIV testing.

Our second hypothesis implies that endowing the outpatient clinics with additional manpower and/or monetary resources should allow them to be more proactive in providing services to their constituents, and thus induce a greater quantity demanded for their services. The underlying assumption to Hypothesis 2 is that clinics are under-funded and/or understaffed, and do not use their market power to exploit their patients. Thus, if we fail to reject Hypothesis 2 (again, in its null form), researchers and policy-makers may want to re-examine the tactics and practices of these clinics, as they would not be fulfilling their core missions of community service.

Hypothesis 3: The demand for HIV testing should vary by the socio-economic characteristics of the community the clinic serves.

Our literature review implies that clinics serving poorer communities and those with higher minority populations should experience a lower demand for testing. One interesting corollary to this hypothesis (which we control for but, to our knowledge, has not been addressed in the literature) is the importance of distinguishing between the socio-economic characteristics of the entire community in which the clinic resides and those of the sub-population that utilize the clinic's services. This is especially true for clinics operating in urban and/or geographically dispersed communities, which may cater to specific minority group, or may share the responsibility for serving the greater community with a small number of other clinics.

Data

Our primary source of data comes from the California Office of Statewide Health Planning and Development (OSHPD). Each year, all primary care, outpatient clinics in the State are required to report revenue, expense and utilization data to OSHPD. These data are subsequently packaged and made available on the OSHPD website (http://www.oshpd.ca.gov). Our data come from these reports for the calendar year 2004. The complete set of data contains 804 clinics. After eliminating observations due to missing or mis-measured data, our sample consists of 706 observations. We eliminated 67 clinics because they were either not open for a full calendar year, or had a suspended operating license. Another 25 observations were eliminated because they provided mis-measured or unreliable data. Specifically, seven clinics reported having zero employees, four clinics reported zero operating revenue and five clinics reported negative prices for treating Medicare and Medi-Cal insured patients. We also eliminated nine firms for not treating at least 30 patients in a full year. Lastly, six observations were eliminated because they failed to report any information on the poverty status of their patients. Appendix A contains the names and definitions of all of the variables used in our analysis.

We measure the amount of HIV testing within a clinic with two, related variables. The first, HIV, is a truncated variable that gives a value of zero if the clinic performed no HIV tests and the quantity of HIV tests performed otherwise. (The technical definition for this variable is the quantity of procedures performed under CPT codes 86701-86703 and 87390-87391).

Because approximately half of the clinics did not perform any HIV tests, we also created a dummy variable (HIVDV) that gives a value of one if the clinic performed HIV tests, and zero otherwise.

The data allow for the construction of a number of variables describing the operating characteristics of these clinics. For example, the data contain a dummy variable identifying clinics located in rural areas (as defined by OSHPD). The data also include the total number of full time equivalent employees (FTEs) who have direct patient contact. This data is further disaggregated by the type of FTE (e.g., physician, dentist, physician's assistant, nurse family practitioner, etc.) as well as the method by which FTEs are compensated (e.g., salary, contract, or volunteer).

We construct a number of variables describing the populations served by each clinic. Information was collected on the total number of patients receiving treatment at each clinic. This data is also disaggregated by race (white, black and all other races), ethnicity (Hispanic versus non-Hispanic), age (patients aged 65 and older versus all other ages) and gender. Patient level data are also decomposed by income level (below 100 percent of the poverty level, between 100-200 percent of the poverty level, above 200 percent of the poverty level, and non-reporters). To ease exposition and reduce the possibility of heteroskedasticity in our empirical analysis, we express each patient sub-group as a proportion of the total number of patients.

As noted earlier, financial concerns may influence a clinic's ability to offer HIV testing. Because these clinics are not-for-profit, and because many clinics treat a disproportionate number of disadvantaged individuals, government and philanthropic sources of revenue are vital to a clinic's ability to cover its operating expenses. Our data allow us to measure several of these potential revenue sources. First, we collect information on grant and contract monies from Federal, local (state, county and other local agencies) and private sources. We also identified the dollar value of donations to each clinic. Lastly, we measured the average price per patient encounter that Medicare and Medi-Cal (California's Medicaid program) reimburse clinics. Because both Medicare and Medi-Cal have both traditional and managed care programs, we provide two separate prices for each insurance program. Two comments are in order here. First, a patient encounter is the appropriate measure of output for prices, because a particular patient may visit a clinic multiple times during the year, making the number of patient encounters at least as large as the number of patients. Because price is, by definition, average revenue per unit of use, the number of encounters is the appropriate measure. For a more detailed discussion of this issue, see Rosenman et al. (2000) and Rosenman et al. (2005). Second, all Medicare and Medi-Cal programs (whether managed care or otherwise) reimburse for services in a manner consistent with prospective payment. As a result, clinics do not have the ability to significantly manipulate the average reimbursement per encounter they receive for treating Medicare and Medi-Cal-insured patients (Friesner, 2003).

Because not all clinics treat all types of Medicare and Medi-Cal patients, nor do all clinics have access to all four grant/contract and donation sources, we also create a series of dummy variables that identify whether a particular clinic has access to a particular revenue source. Finally, to reduce the potential for heteroskedasticity, we take the natural logarithm of our grant/contract and donation variables.

From our literature review, we expect demographic, economic and epidemiological conditions outside of a clinic's control to impact HIV testing decisions; therefore, county level information was collected on these characteristics. Data on the spread of HIV/AIDS was collected from the California HIV Cumulative Surveillance Reports, which are published monthly (and by county) by the California Department of Health Services, Office of AIDS. These reports are available on the web at CADHS. These reports contain information about the cumulative number of AIDS cases (both currently living and total), AIDS-related deaths, and total HIV cases per county.

We use this data to construct three variables, which we believe adequately measure the current state of the disease in each county between December 31, 2003 and December 31, 2004: the change in the cumulative number of living AIDS cases in a county; the change in the cumulative number of AIDS deaths; and the change in the cumulative number of HIV infections. We use the change in these cumulative data to capture the extent of the epidemic during 2004. Additionally, each of these variables provides information (in a manner consistent with the static, marginal nature of our analysis) about the history, potential growth and potential decline of the epidemic. In particular, the number of new HIV infections represents the potential growth of the epidemic, while the number of AIDS deaths in 2004 represents potential decline. Since there is usually a large incubation period between HIV infection and the onset of AIDS, the number of living AIDS cases also provides some information about the history of the epidemic in a particular county.

As a measure of economic prosperity within a county, we collected data on average weekly wages per county (in 2004) from the California Economic Development Department. This weekly measure was subsequently multiplied by 52 to arrive at an average yearly income variable. Demographic data were obtained from the US Census Bureau. In addition to the total population per county, we collected data on race, Hispanic origin, sex and age. Consistent with our clinic-specific demographics, we express each of our demographic variables as a proportion of the total population to reduce the potential for heteroskedasticity.

Appendix B contains some basic descriptive statistics for non-truncated variables used in our analysis. Table 1 presents descriptive statistics for non-zero observations of our truncated variables. The following are characteristics of the average (mean) clinic. Approximately half (350 out of 706) of the clinics provide HIV testing. Of these 350 clinics that do provide testing, 378.98 tests are performed annually. These clinics have approximately 5.2 full time staff who provide services to patients. Of these FTEs, thirty-eight percent are physicians and twenty-four percent are nurse practitioners. The majority of the staff are employed on a salary basis, as opposed to a contract or a volunteer basis. Seventy percent of patients are white, while just under fifty percent are Hispanic. In our data, Hispanic is treated as an ethnicity, as opposed to a race. As a result, a large proportion of patients classified as white are also likely to be Hispanic. Nearly sixty percent of patients are below the poverty line, and nearly two-thirds of patients are female.

Table 1
Conditional Descriptive Statistics

Variable	Mean	SD	No. of Observations
HIV	378.98	513.17	350
LFEDGT	12.16	1.53	426
LLOCALGT	11.53	1.66	421
LPVTGT	10.53	2.01	332
LDONATE	10.09	2.49	373
PCARE	83.15	108.08	477
PMCARE	234.63	693.52	84
PCAL	111.63	86.80	623
PMCAL	430.28	2787.57	390

The revenue variables indicate that clinics utilize a wide variety of sources to obtain funds. With the exception of managed Medicare, each revenue source is utilized by between one half and two-thirds of the clinics, on average. Clinics appear to be highly reliant on traditional Medicare and Medi-Cal reimbursement, as well as Federal grant and contract funds. Not surprisingly, among clinics receiving positive funds, clinics receive a larger amount of funds from Federal sources than from local or private sources. Reimbursement for traditional Medi-Cal patients is also more generous than Medicare, at the mean.

The county level demographics also corroborate our earlier assertion that these clinics treat a disproportionate number of disadvantaged individuals within a particular county. Mean yearly income per county is approximately $42,700 — a value much higher than the poverty level. The proportions of black, Hispanic and female residents in each county are also lower than the mean proportions of patients that an average clinic treats.

Lastly, the descriptive statistics for our epidemiological variables provide some insight into the extent of the epidemic in California. During 2004, an average of 314 individuals in a given county was living with AIDS, and approximately 47 people per county died of AIDS. Approximately 1,234 people per county, on average, were HIV-positive in 2004. Clearly, these statistics imply both a growing epidemic as well as the need for policies designed to curb the spread of the disease and provide palliative care for those already infected.

Empirical Methodology

Our empirical methodology operates under a number of assumptions, which are all consistent with the economic and epidemiological literatures. Perhaps most importantly, we assume clinics are the primary source of care for disadvantaged individuals within their communities. From an economic standpoint this implies clinics have a high degree of monopoly power over this segment of society. At the very least, these firms can be considered as monopolistic competitors, meaning they hold power over a segment of the market for health care in the short run. Given the time frame of our analysis, this less stringent assumption is also sufficient to justify our empirical approach.

As such, clinics base operating decisions by assessing the demand curve for their services. The implication of this assumption is that issues of endogeneity arising from estimating a demand curve without also controlling for factors affecting the supply curve for clinic services are irrelevant, since these firms essentially do not face a supply curve for their services.

Given our literature review and data constraints, we postulate a reduced form, linear in coefficients and variables equation to explain the demand for HIV testing, which we estimate using regression analysis techniques. The advantages of this approach are that it is both parsimonious and also allows the signs and significance of each individual coefficient estimate to test each of the hypotheses identified in our literature review.

The Probit Model

A crucial econometric issue is how to specify the dependent variable for our regression analysis, and consequently the regression technique to estimate our equation. We have two dependent variables, both of which express similar information, but in different ways. Our HIVDV variable is a binary indicator of whether or not a clinic offers HIV testing. We examine whether epidemiologic, clinic-specific and socio-economic factors influence the demand for testing by estimating a standard Probit model (Greene, 2000) (see Figure 1):

$$P(HIVDV=1 \mid W,X,Y,Z) = \beta_0 + \sum_{j=1}^{3} \beta^{j} W^{j} + \sum_{j=1}^{11} \beta^{j+3} X^{j} + \sum_{j=1}^{6} \beta^{j+14} Y^{j} + \sum_{j=1}^{16} \beta^{j+20} Z^{j} \qquad (1a)$$

$$P(HIVDV = 0 \mid W, X, Y, Z) = 1 - P(HIVDV = 1 \mid W, X, Y, Z) \qquad (1b)$$

where: P() denotes the cumulative normal distribution function;
W denotes an nx3 vector of county-level HIV/AIDS variables;
X denotes an nx11 vector of clinic-specific demographic variables;
Y denotes an nx6 vector of county-specific demographic variables;
Z denotes an nx16 vector of clinic financial variables; and
n denotes the sample size.

Figure 1
Standard Probit Model (Greene, 2000)

One other technical note about the probit model deserves mentioning. Because the model is estimated via maximum likelihood (an inherently non-linear procedure), the coefficient estimates in the probit model cannot be directly interpreted as marginal effects, as is the case in other regression procedures such as ordinary least squares (OLS). However, the probit model does facilitate the construction of marginal effects, which are directly dependent on these coefficient estimates. As such, when interpreting the results of the probit model, we give primary emphasis to interpreting the signs, magnitudes and significance of the marginal effects, as opposed to the coefficient estimates.

The signs and significance of our marginal effects (and their underlying parameter estimates) can be used to test Hypotheses 1 – 3. For example, if the marginal effects for our HIV/AIDS variables are significantly different from zero, then we would reject Hypothesis 1 (in its null form). Moreover, the magnitudes of these marginal effects (if significant) allow us to gain additional information about how epidemiological conditions impact whether clinics perform HIV tests. Similar analysis of the clinic-specific and socio-economic marginal effects can be used to test Hypotheses 2 and 3, respectively.

The Tobit Model
The HIV variable takes this a step further by identifying the number of tests provided, and zero otherwise. Thus, HIV is essentially a variable that is either censored or truncated (on the left side of the distribution) at zero. The crucial issue is how to interpret the values of HIV at the censoring or truncation point. One approach is to assume that the zero values are determined simultaneously with the positive values. Our HIV variable is actually a count variable. This implies that the distribution is censored, and can be estimated with a standard Tobit model (Greene 2000). In the context of our study, this model can be expressed as:

$$HIV^* = \beta_0 + \sum_{j=1}^{3} \beta^j W^j + \sum_{j=1}^{11} \beta^{j+3} X^j + \sum_{j=1}^{6} \beta^{j+14} Y^j + \sum_{j=1}^{16} \beta^{j+20} Z^j + \varepsilon \quad (2)$$

where: HIV* is the value for HIV in the absence of censoring (i.e., if demand could be positive, zero or negative) which could, if observed, be estimated using standard ordinary least squares (OLS) techniques;
HIV = max(0, HIV*) is the observed (and censored) vector of HIV values;
ε is a normally distributed error term with a mean of zero and a constant variance;
and the remaining variables are defined identically to the probit model.

Figure 2
Tobit Model (Greene, 2000)

As with the probit model, the Tobit model is estimated by defining and subsequently maximizing the (cumulative) log likelihood function for a censored (at HIV = 0) normal distribution. When testing Hypotheses 1 – 3, this also forces us to calculate and interpret marginal effects, as opposed to simply interpreting the model's coefficient estimates.

Heckman's Two-Step Estimator
Alternatively, it may be the case that the zero values are determined prior to the positive values. This means that there may exist some process determining whether there is zero or positive demand for HIV testing. If positive demand exists, the quantity of testing is subsequently determined through a second process. This phenomenon is often referred to as incidental truncation, and it is generally necessary to employ Heckman's two-step estimation procedure to estimate the regression equation of interest (Greene, 2000). The first step in this procedure is to estimate the determinants of whether or not a clinic experiences a demand for HIV testing using a probit model, as defined above. The predicted probabilities from this regression (in the form of an Inverse Mills Ratio) are calculated and used as an instrument in the second step (which is conducted using OLS) to control for the potential effects of the incidental truncation. The Inverse Mills Ratio is the standard normal probability density function (evaluated at some point, usually the sample mean values) divided by the standard normal cumulative density function (again, evaluated at the sample mean values). In general, the first step's regression results should always have at least as many regressors as the second step regression (Wooldridge, 2000). In our case, we use the

exact same number of regressors in each step, although in many studies it is common to add additional regressors to the first step's estimation (all of which must be relevant, exogenous determinants of the dependent variable) in order to reduce the effects of multicollinearity. We use the same number of regressors because it is a more parsimonious approach. We also ran several variations of this first step estimation procedure where additional regressors were added, and there were no significant changes in the second step results. Our two-step estimation procedure can be characterized as follows Figure 3):

Step 1: Estimate the probit model defined above and save the Inverse Mills Ratio, or IMR.

Step 2: Use OLS to estimate the following:

$$HIV^* = \beta_0 + \sum_{j=1}^{3} \beta^j W^j + \sum_{j=1}^{11} \beta^{j+3} X^j + \sum_{j=1}^{6} \beta^{j+14} Y^j + \sum_{j=1}^{16} \beta^{j+20} Z^j + \varepsilon \qquad (3)$$

where: HIV' is the subset of non-zero HIV values; and the remaining variables are identical to those postulated in the Probit model.

Figure 3
Heckman's Two-Step Estimator

The question of interest is whether the data are censored or incidentally truncated. To check, we employ Hausman's (1978) specification test. The test operates under the null hypothesis of incidental truncation; that is, that the zeros and positive values are determined simultaneously. In this case, both the Tobit and incidental truncation models provide consistent estimates, but the Tobit model's estimates are more efficient. In this case, we place more emphasis on the Tobit results. Rejection of the null implies that the zero and positive values are determined sequentially, in which case the incidental truncation estimates are consistent, but the Tobit results are not. The test is distributed as chi-square, with degrees of freedom equal to the number of intercept and slope parameters.

A final issue concerns the transformations of our independent variables. Adding proportional variables that are both mutually exclusive and collectively exhaustive (e.g., the proportion of male and female patients) as independent variables in a regression will necessarily create perfect multicollinearity with the equation's intercept. A common approach (which we utilize here) is to drop one of the multicollinear regressors from the regression (Greene, 2000). As such, all coefficient estimates are measured relative to the omitted category.

Empirical Results

Appendices C and D contain our empirical results. Appendix C contains the results from our probit model. The chi-square test for overall model fit is highly significant, indicating that the model does an acceptable job of predicting our dependent variable. Our primary focus (Hypothesis 1) is whether changing epidemiological conditions within a community induce changes in the demand for HIV testing in the primary care clinics serving these communities. Our results indicate that this is the case. Specifically, the mean marginal effect for our SDAIDS variable (the number of AIDS deaths in a county in 2004) is –4.786, and significant at the one percent level. This indicates that, for each additional person dying of AIDS per county in 2004, the likelihood of a positive demand for HIV testing in these clinics falls by 4.8 percent, holding all other specified regressors constant. From an economic-epidemiological perspective this makes sense; a higher number of AIDS deaths, holding HIV conditions constant, leaves fewer people in the population from which someone can acquire the disease. Thus, there is a lower need for HIV testing.

It is also interesting to note that our other two HIV-related explanatory variables are not statistically significant determinants of HIV-related testing. This indicates that efforts designed to increase testing in these clinics will not be successful unless it is solely targeted at the number of AIDS deaths, and not the number of HIV infections or living AIDS cases.

Our results also identify a number of other variables that impact the likelihood of HIV testing, implying rejection of Hypotheses 2 and 3 as well. First, the types of practitioners staffing these clinics influence the likelihood of increased testing. Increasing the proportion of physicians, physician's assistants and family nurse practitioners all increase the likelihood of clinic HIV testing. All categories of providers are statistically significant, and the magnitude of the marginal impact of family nurse practitioners is greatest.

The (mean) marginal effect of an increase in low-income patients also has a positive and significant impact on the likelihood of HIV testing. This indicates that low-income people are utilizing these clinics for one of their intended purposes — an access point for HIV testing. Demographics within the clinic and county also impact the likelihood of HIV testing. A higher proportion of a clinic's patients that are black, Hispanic, or age 65 or older all significantly reduce the likelihood of HIV testing. Higher proportions of female patients, however, significantly increase the likelihood of HIV testing. This also has policy implications: racial and ethnic minorities are not utilizing these clinics as an access point for testing.

Our county-level economic and demographic variables indicate the need to control for the distributional consequences of socio-economic factors influencing HIV testing. The county income variable is positive and statistically significantly different from zero (at the ten percent level), implying that increases in income throughout the county also increase the demand for HIV testing. The implication is that mid and high-income individuals are also utilizing these clinics as an access point for testing. Increases in the elderly and Hispanic communities in a clinic's county also increase the likelihood of HIV testing. One interpretation of this finding is that clinics in these communities are providing services to a specific component of the racial and ethnic communities within a county. As such, policies designed to increase HIV testing at these clinics should not be directed at these communities as a whole, but at the components of this population who regularly use these clinics for other health care services.

Lastly, three clinic-level financial variables impact the likelihood of HIV testing. Clinics providing services to non-managed care Medicare patients, on average, experience a higher likelihood of HIV testing. However, the average reimbursement for these services has no significant impact. Concomitantly, a clinic's receipt of donations has a mixed, but highly significant impact on HIV testing. If a clinic receives donations it has a higher likelihood of providing HIV testing. However, increasing the level of donations has a negative and significant mean effect.

Appendix D, Panel A contains our Tobit and incidental truncation regression results for HIV testing variable. The Hausman specification test yielded a value of 9.68, which is statistically insignificant from zero at a five percent significance level. As such, we give primary emphasis to the Tobit results. The chi-square statistic indicates that the Tobit model does explain a significant portion of variation in the quantity of HIV testing. The disturbance term (which measures the amount of censoring in the model) is also statistically significant, which supports the rationale for adjusting the estimation technique to control for the censoring of the dependent variable.

The mean marginal effect of the number of AIDS deaths in the Tobit model is negative and statistically significant. The number of HIV infections in 2004 is also statistically insignificant from zero. The number of living cases of AIDS is now positive and significant (at the five percent level). This implies that changes in the number AIDS deaths are negatively associated with both the likelihood and quantity of HIV tests provided. The number of living AIDS cases, however, does not impact whether HIV testing services are offered, but it does positively impact the quantity of services provided.

The proportion of a clinic's staff that is a nurse family practitioner positively and significantly increases the amount of HIV testing. Interestingly, the proportion of staff that is physicians or physician's assistants is not statistically significant determinants of the dependent variable. This indicates that certain types of staff within a clinic may be more successful than others at increasing HIV testing and awareness.

The economic and demographic variables also significantly impact the quantity of HIV testing. An increase in both the quantity of low-income patients visiting the clinic, as well as increasing the average income level in the county a clinic serves, increases the amount of HIV testing clinics perform. Increases in the proportion of black, Hispanic and elderly patients currently receiving other health care services from the clinics, on average, reduce the quantity of HIV tests, while increases in the entire Hispanic community within a community significantly increase the number of HIV tests. The proportion of white patients receiving other services from the clinics is a positive and significant determinant of the quantity of HIV testing in the Tobit model. Additionally, the mean marginal effect of the elderly population in a county is not significant in the Tobit regression.

The results in Appendix D (Panel A) show that providing a positive number of Medicare services has a positive and statistically significant mean impact on the quantity of HIV testing. However, donations are not statistically significant determinants of the quantity of HIV tests. Instead, Federal and local government grants influence the quantity of tests performed. In particular, receiving Federal grants and contracts has a negative and significant mean marginal effect on the quantity of testing, but increases in the level of Federal funding have a positive and significant impact. Additionally, the ability to receive local government grants and contracts has a negative and significant impact on HIV testing. Thus, simply giving money to these outpatient clinics will not necessarily increase the amount of HIV testing. Instead, policies should also be concerned with the level of funding provided to these clinics for such a purpose.

The results from Heckman's two-step sample selection model (Appendix D, Panel B) closely mimic those from the Tobit model, with only a few minor exceptions. As such, the policy implications of the Tobit model are, by and large, supported by the sample selection model. Consistent with the Tobit model, the sample selection equation's chi-square statistic and F-test are highly significant, indicating a reasonable fit of the dependent variable. The Inverse Mills Ratio coefficient estimate is also statistically different from zero (at a .05 significance level), implying a need to control for the truncation of the dependent variable.

As mentioned above, the signs and significance of the sample selection model closely mimic the Tobit model, with three exceptions. First, the proportion of black patients visiting these clinics is no longer statistically significant, nor is the proportion of a county's population that is white. Third, the Federal grant and contract variables are no longer statistically significant. The latter finding is particularly important because it casts doubt on whether Federal grant and contract monies are effective at increasing the amount of HIV testing in these clinics.

These discrepancies may also be due to the fact that the incidental truncation model's results are not only less efficient than those of the Tobit model, but also could be distorted by multicolinearity between the IMR and the second step regressors, both of which lead to inflated standard error estimates and lower levels of statistical significance.

Conclusions and Policy Implications

The main goal of our paper was to empirically determine what factors were significantly responsible for increasing or reducing the likelihood and quantity of HIV testing performed in outpatient, community clinics. Since outpatient clinics are a primary access point for health care not only in California, but also in communities across the US, an understanding of these factors is an essential tool for constructing policies that are effective in controlling the US HIV/AIDS epidemic.

Our findings indicate several factors that may be useful at increasing HIV testing. First, our results show that HIV testing is responsive to the change in the AIDS population, but not the HIV-infected population. That is, people appear to want testing only when they see an increase in the number of people living with AIDS (which increases the potential for infection, and thus the need for testing) and a reduction in the number of AIDS deaths (which has a similar impact). As a result, policies promoting HIV testing may want to focus on these epidemiological factors, as opposed to HIV prevalence statistics.

Second, certain types of medical staff are positively associated with a higher amount and likelihood of HIV testing. Nurse practitioners, and to a lesser extent, physicians and physician's assistants, are most effective at increasing HIV testing. This implies that HIV prevention and awareness policies should include these types of staff as an integral part of any such policy implemented at the level of the outpatient clinic.

Third, demographics play a crucial role in the demand for HIV testing. While this finding is not new, what we do find to extend this literature is that clinics play a unique role in HIV prevention by being able to target policies at specific sub-components of a population, most notably poor women and minorities. What makes this finding especially useful for policy makers is that these groups are extremely high-risk components of the population, and thus most in need of effective policy intervention.

Lastly, we do find evidence that outside sources of funding may be effective at increasing HIV testing in outpatient clinics. However, our results here are quite mixed. Some sources of funds increase the likelihood that a clinic offers HIV testing, but do not significantly impact the amount of HIV testing. Other sources of funds are only marginally significant determinants of funding, depending on how one estimates the demand for HIV testing. Thus, simply "throwing money at the problem" may not be an effective means of combating the epidemic.

While our results present some intriguing findings, they should also be viewed with caution. Our study only looks at California outpatient clinics in a single year. Future studies analyzing health care providers who have different operating characteristics, operate at different points in time, serve different socio-economic segments of the population, and who face different epidemiological conditions may find disparate results. We view this study as an initial step to spark discussion and future research about the effectiveness of these health care providers as a focal point in combating the spread of the HIV/AIDS epidemic.

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Author Information

Dan Friesner
Gonzaga University

Peter Cashel-Cordo
University of Southern Indiana

Matthew Q. McPherson*
Gonzaga University
502 E. Boone Ave.
Spokane WA 99258-0009
E-Mail: McPherson@jepson.gonzaga.edu
Ph.: 509-323-7034

* corresponding author

Appendix A

Variable Names and Definitions

Variable	Definition
Clinic-Level HIV Testing Variables	
HIVDV	Dummy variable identifying whether an outpatient clinic provided HIV testing in 2004
HIV	Number of HIV tests performed at an outpatient clinic
Clinic-Level Demographic Variables	
RURAL	Dummy variable identifying outpatient clinics in rural areas
FTE	Number of full time equivalent staff devoted to treating patients
MD	Proportion of a clinic's FTEs that are physicians
PA	Proportion of a clinic's FTEs that are physician assistants
NFP	Proportion of a clinic's FTEs that are family nurse practitioners
DENT	Proportion of a clinic's FTEs that are Dentists
OTH	Proportion of a clinic's FTEs that are not included in the above four categories
SALARY	Proportion of a clinic's FTEs that are on salary
CONT	Proportion of a clinic's FTEs that are paid contractually
VOLUN	Proportion of a clinic's FTEs that are volunteers
TOTPAT	Total number of patients visiting an outpatient clinic
WHITEPT	Proportion of a clinic's patients that are white
BLACKPT	Proportion of a clinic's patients that are black
HISPPT	Proportion of a clinic's patients that are Hispanic
LOWPOVPT	Proportion of a clinic's patients that are below 100 percent of the poverty level
MIDPOVPT	Proportion of a clinic's patients that are between 100 and 200 percent of the poverty level
UPPOVPT	Proportion of a clinic's patients that are above 200 percent of the poverty level
OTHPOVPT	Proportion of a clinic's patients that do not report income information
ELDERPT	Proportion of a clinic's patients that are age 65 and older
FEMALEPT	Proportion of a clinic's patients that are female
Clinic-Level Financial Variables	
LPVTGT	Dummy variable identifying whether a clinic received Federal grant or contract funds
FEDDV	Variable giving the natural log of Federal grant and contract money, and zero if the clinic did not receive these funds
LFEDGT	Dummy variable identifying whether a clinic received state, county or local grant or contract funds
LOCALDV	Variable giving the natural log of state, county and local grant and contract money, and zero if the clinic did not receive these funds
LLOCALGT	Dummy variable identifying whether a clinic received private grant or contract funds
PVTDV	Variable giving the natural log of private grants and contract money, and zero if the clinic did not receive these funds
DONATEDV	Dummy variable identifying whether a clinic received donations
LDONATE	Variable giving the log of donations, and zero if the clinic did not receive these funds

Variable	Definition
CAREDV	Dummy variable identifying whether a clinic treated (non-managed care) Medicare patients
PCARE	Variable that gives the average price the clinic received for treating (non-managed care) Medicare patient encounters, and zero if the clinic did not treat these patients
MCAREDV	Dummy variable identifying whether a clinic treated managed care Medicare Patients
PMCARE	Variable that gives the average price the clinic received for treating managed care Medicare patient encounters, and zero if the clinic did not treat these patients
CALDV	Dummy variable identifying whether a clinic treated (non-managed care) MediCal Patients
PCAL	Variable that gives the average price the clinic received for treating (non-managed care) MediCal patient encounters, and zero if the clinic did not treat these patients
MCALDV	Dummy variable identifying whether a clinic treated managed care MediCal patients
PMCAL	Variable that gives the average price the clinic received for treating managed care MediCal patient encounters, and zero if the clinic did not treat these patients
County-Level Demographic and Financial Variables	
WAGE	Average yearly income per county
PWHITE	Proportion of a county's population that is white
PBLACK	Proportion of a county's population that is black
PHISP	ion Proportion of county's population that is Hispanic
PELDER	Proportion of a county's population that is age 65 and older
PFEMALE	Proportion of a county's population that is female
County-Level Epidemiological Variables	
CTACASE3	Total number of AIDS cases in a county between 1981 and 2003
CLACASE3	Total number of living AIDS cases in a county between 1981 and 2003
CADEATH3	Total number of AIDS deaths in a county between 1981 and 2003
CTACASE4	Total number of AIDS cases in a county between 1981 and 2004
CLACASE4	Total number of living AIDS cases in a county between 1981 and 2004
CADEATH4	Total number of AIDS deaths in a county between 1981 and 2004
CHCASE3	Total number of HIV cases between 1981 and 2003
CHCASE4	Total number of HIV cases between 1981 and 2004
SAIDS	Change in the number of living AIDS cases in a county between 2004 and 2003
SDAIDS	Change in the number of AIDS deaths in a county between 2004 and 2003
SHIV	Change in the total number of HIV cases between 2004 and 2003

Appendix B

Unconditional Descriptive Statistics

Variable	Mean	Standard Deviation
Clinic-Level HIV Testing Variables		
HIVDV	0.496	0.500
Clinic-Level Demographic Variables		
RURAL	0.052	0.223
FTE	5.249	8.642
MD	0.378	0.305
PA	0.101	0.188
NFP	0.236	0.304
DENT	0.098	0.222
OTH	0.187	0.256
SALARY	0.815	0.314
CONT	0.121	0.243
VOLUN	0.064	0.218
TOTPAT	4659.760	4866.900
WHITEPT	0.704	0.293
BLACKPT	0.075	0.129
HISPPT	0.478	0.316
LOWPOVPT	0.591	0.281
MIDPOVPT	0.186	0.165
UPPOVPT	0.071	0.141
OTHPOVPT	0.152	0.269
ELDERPT	0.071	0.152
FEMALEPT	0.647	0.171
Clinic-Level Financial Variables		
FEDDV	0.603	0.490
LOCALDV	0.596	0.491
PVTDV	0.470	0.499
DONATEDV	0.528	0.500
CAREDV	0.676	0.468
MCAREDV	0.119	0.324
CALDV	0.882	0.322
MCALDV	0.552	0.498
County-Level Demographic and Financial Variables		
WAGE	41752.800	10384.700
PWHITE	0.783	0.103
PBLACK	0.062	0.038

Appendix B (continued)
Unconditional Descriptive Statistics

PHISP	0.324	0.142
PELDER	0.111	0.020
PFEMALE	0.499	0.014
County-Level Epidemiological Variables		
CTACASE3	14249.200	18823.800
CLACASE3	5761.250	7480.500
CADEATH3	8487.990	11368.000
CTACASE4	14610.700	19414.700
CLACASE4	6075.760	7987.000
CADEATH4	8534.910	11455.500
CHCASE3	2632.450	3147.770
CHCASE4	3866.700	4995.630
SAIDS	314.511	516.445
SDAIDS	46.921	92.960
SHIV	1234.250	1903.970
Number of observations		706

Appendix C

Bivariate Probit Model (Dependent Variable: HIVDV)

Variable	Coefficient	T-Ratio	Marginal Effect	T-Ratio
Constant	-7.430**	-2.176	-2.956**	-2.176
County Epidemiology				
SAIDS	0.002	1.228	0.001	1.228
SDAIDS	-0.020***	-4.788	-0.008***	-4.786
SHIV	0.000	0.569	0.000	0.569
Clinic Demographics				
RURAL	0.201	0.758	0.080	0.759
MD	0.427*	1.806	0.170*	1.808
PA	0.621*	1.853	0.247*	1.853
NFP	0.862***	3.195	0.343***	3.196
VOLUN	-0.104	-0.283	-0.041	-0.283
LOWPOVPT	1.186***	5.146	0.472***	5.148
WHITEPT	0.315	1.277	0.125	1.276
BLACKPT	-1.147**	-2.165	-0.456**	-2.164
HISPPT	-0.592**	-2.200	-0.236**	-2.200
ELDERPT	-2.373***	-3.096	-0.944***	-3.101
FEMALEPT	0.951**	2.271	0.378**	2.270
County Demographics				
WAGE	0.000*	1.774	0.000*	1.773
PWHITE	0.603	0.330	0.240	0.330
PBLACK	2.027	0.582	0.807	0.582
PHISP	2.804***	3.114	1.116***	3.114
PELDER	9.665*	1.722	3.846*	1.722
PFEMALE	3.069	0.614	1.221	0.614
Clinic Financial Variables				
FEDDV	-1.109*	-1.649	-0.441*	-1.649
LFEDGT	0.136**	2.446	0.054**	2.447
LOCALDV	-0.347	-0.630	-0.138	-0.630
LLOCALGT	0.013	0.275	0.005	0.275
PVTDV	-0.338	-0.689	-0.135	-0.689
LPVTGT	0.018	0.412	0.007	0.412
DONATEDV	1.654***	4.649	0.658***	4.643
LDONATE	-0.113***	-3.367	-0.045***	-3.364
CAREDV	0.937***	5.197	0.373***	5.201
PCARE	0.000	0.486	0.000	0.486
CALDV	-0.373	-1.411	-0.149	-1.411
PCAL	0.000	0.233	0.000	0.233
MCAREDV	0.256	0.891	0.102	0.893

Variable	Coefficient	T-Ratio	Marginal Effect	T-Ratio
PMCARE	-0.002	-0.671	-0.001	-0.673
MCALDV	0.063	0.398	0.025	0.398
PMCAL	0.000	-0.156	0.000	-0.156
Number of Observations			706	
Log-Likelihood Function				-353.621
Restricted Log-Likelihood Function				-489.336
Chi-Square Test Statistic				271.431***
Degrees of Freedom				36
* significant at the 0.10 level				
** significant at the 0.05 level				
*** significant at the 0.01 level				

NOTE: All estimated marginal effects are evaluated at sample mean values.

Appendix D

Parameter Estimates (Dependent Variable: HIV)

Panel A: Tobit Model			Panel B: Sample Selection Model
Variable	**Coefficient**	**Marginal Effect**	**Coefficient**
Constant	-3438.800**	-1249.896**	-4312.790
	(-2.245)	(-2.214)	(-1.243)
County Epidemiology Variables			
SAIDS	1.760**	0.640**	2.070*
	(2.386)	(2.361)	(1.660)
SDAIDS	-8.745***	-3.179***	-11.834***
	(-5.359)	(-4.973)	(-2.593)
SHIV	-0.086	-0.031	-0.032
	(-0.479)	(-0.479)	(-0.112)
Clinic Demographics			
RURAL	10.763	3.912	31.408
	(0.089)	(0.089)	(0.156)
MD	14.267	5.186	-31.810
	(0.131)	(0.131)	(-0.145)
PA	222.306	80.801	198.224
	(1.488)	(1.479)	(0.705)
NFP	423.484***	153.923***	493.311*
	(3.594)	(3.495)	(1.853)
VOLUN	-54.701	-19.882	-0.327
	(-0.318)	(-0.318)	(-0.001)
LOWPOVPT	405.379***	147.342***	592.901*
	(3.718)	(3.478)	(1.735)
WHITEPT	239.435**	87.027**	297.015*
	(2.166)	(2.117)	(1.627)
BLACKPT	-414.442*	-150.637*	-684.000
	(-1.694)	(-1.665)	(-1.425)
HISPPT	-491.618***	-178.688***	-650.566***
	(-4.116)	(-3.929)	(-2.900)
ELDERPT	-1647.590***	-598.849***	-2774.980***
	(-3.876)	(-3.926)	(-3.083)
FEMALEPT	574.007***	208.634***	803.256**
	(3.310)	(2.920)	(2.203)
County Demographics			
WAGE	0.010*	0.004*	0.013
	(1.758)	(1.738)	(1.328)
PWHITE	62.178	22.600	180.209
	(0.078)	(0.078)	(0.137)
PBLACK	1378.750	501.132	2265.980

Panel A: Tobit Model			Panel B: Sample Selection Model
Variable	Coefficient	Marginal Effect	Coefficient
	(0.911)	(0.909)	(0.914)
PHISP	1111.720***	404.077***	1496.510*
	(2.898)	(2.831)	(1.774)
Appendix D (Continued)			
PELDER	2185.930	794.516	2004.970
	(0.882)	(0.882)	(0.440)
PFEMALE	2451.460	891.029	2094.250
	(1.051)	(1.048)	(0.420)
Clinic Financial Variables			
FEDDV	-512.963*	-186.446*	-744.491
	(-1.736)	(-1.726)	(-1.372)
LFEDGT	57.180**	20.783**	80.666
	(2.351)	(2.321)	(1.620)
LOCALDV	-477.668*	-173.617*	-669.273*
	(-1.994)	(-1.927)	(-1.648)
LLOCALGT	30.997	11.267	43.790
	(1.452)	(1.450)	(1.251)
PVTDV	-97.883	-35.577	-165.759
	(-0.489)	(-0.489)	(-0.518)
LPVTGT	14.357	5.218	24.408
	(0.783)	(0.781)	(0.848)
DONATEDV	169.036	61.439	386.161
	(1.237)	(1.241)	(1.016)
LDONATE	2.184	0.794	-9.498
	(0.168)	(0.168)	(-0.324)
CAREDV	476.461***	173.179***	654.224***
	(6.339)	(5.461)	(2.937)
PCARE	-0.124	-0.045	-0.013
	(-0.513)	(-0.510)	(-0.36)
CALDV	-129.802	-47.179	-150.400
	(-1.073)	(-1.069)	(-0.698)
PCAL	-0.001	0.000	-0.156
	(-0.002)	(-0.002)	(-0.263)
MCAREDV	-14.786	-5.374	-43.869
	(-0.113)	(-0.113)	(-0.192)
PMCARE	-0.768	-0.279	-0.736
	(-0.587)	(-0.602)	(-0.320)
MCALDV	58.219	21.161	65.841
	(0.829)	(0.844)	(0.574)
PMCAL	-0.191	-0.070	-0.226
	(-0.885)	(-0.946)	(-0.791)

Notes: T Ratios are in parentheses. *, **, and *** represent 1, 5, and 10 percent significance, respectively. **For Panel A** - Inverse Mills Ratio: 856.634** (2.240). Observations: 350. Log-Likelihood Function: -2588.493. Restricted Log-Likelihood Function: -2680.343. Chi-Square Statistic:

183.700*** (Degrees of Freedom: 36). Pseudo R-Square: 0.336. Pseudo Adjusted R-Square: 0.258. Degrees of Freedom (37, 312) F-Statistic: 4.270***. **For Panel B** - Disturbance Term: 519.219 *** (25.251). Observations: 706. Log-Likelihood Function: -2846.256. Restricted Log-Likelihood Function: -2997.821. Chi-Square Statistic: 303.130***. Degrees of Freedom: 36. Estimated marginal effects evaluated at sample mean.