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Outcomes from stroke rehabilitation in Veterans Affairs rehabilitation units: Detecting and correcting for selection bias

W. Bruce Vogel, PhD; Maude Rittman, PhD; Patrick Bradshaw, MS; Dan Nissen; Leigh Anderson, MD; Barbara Bates, MD; Cliff Marshall

Veterans Affairs Brain Rehabilitation Research Center, Malcom Randall Veterans Affairs Medical Center (VAMC), Gainesville, FL; Department of Health Policy and Epidemiology, University of Florida, FL; VAMC Denver, CO; VAMC Albany, NY; VHA Rehabilitation Strategic Health Group, VAMC, Memphis, TN

Abstract—This paper addresses the issue of statistical selection bias in multivariate models of functional gain estimated from observational data. Stroke patients from 20 high-volume Veterans Affairs Medical Centers (VAMCs) with acute and subacute inpatient rehabilitation treatment units were observed. Their gains in overall, motor, and cognitive functional status were measured with the use of the Functional Independence Measure (FIM). In estimating multivariate models of FIM gain during rehabilitation using these observational data, we found statistically significant evidence of selection bias, along with considerable differences in inferences between standard multivariate analyses and our selectivity-corrected models. Our results demonstrate the importance of detecting and correcting for statistical selection bias when one uses nonexperimental data to study gains in functional status.

Key words: *cerebrovascular accident, function recovery, rehabilitation, selection bias, treatment outcome.*

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Address all correspondence and requests for reprints to W. Bruce Vogel, PhD, Research Health Scientist, Rehabilitation Outcomes Research Center and Brain Rehabilitation Research Center (151B), VA Medical Center, 1601 SW Archer Road, Gainesville, FL 32608; 352-376-1611, ext. 5242; fax: 352-271-4540; email: bruce.vogel@med.va.gov.

INTRODUCTION

Numerous observational studies have examined the determinants of functional gain following stroke. They have also demonstrated that a significant proportion of improvements in functioning are determined by factors such as the patient's initial functional status, type of stroke, length of stay in rehabilitation, time since onset, and level of comorbidities [1–5]. A potential problem with such observational studies, however, is that stroke patients selected for rehabilitation are not a random sample of all stroke patients. Rather, clinical judgment is used to identify patients who are most likely to benefit from formal rehabilitative services. Such clinical judgment may be based on factors that are difficult to measure, such as the patient's cooperativeness, level of support at home, and motivation to recover. Because such patient selection is influenced by factors that are not measured and hence not included in a standard statistical model, bias can be introduced into models designed to explain functional gain for patients selected for rehabilitation.

Under such circumstances, standard statistical techniques applied to observational data on functional outcomes for stroke patients may produce incorrect or misleading inferences about those factors that determine functional gain. For example, patients selected for formal rehabilitative services may include those who are most likely to improve in their functional status. These patients

may improve with or without rehabilitation treatment. If standard statistical techniques are used, the results may overestimate the gains from rehabilitation programs. By contrast, if patients selected for formal rehabilitation services are those who in some unmeasured way are more difficult to rehabilitate, standard statistical techniques may understate the gains from rehabilitation by failing to account for the greater challenges posed by such patients. Randomized clinical trials avoid selection effects by randomly assigning patients to treatment and control groups before treatment. When researchers use secondary databases, randomization is not feasible, and hence, they must use other approaches to deal with potential biases stemming from selection effects.

The primary objective of this paper is to demonstrate the substantial impact of statistical selection bias in evaluating functional gain in stroke patients when observational data are used. We do this by comparing standard multivariate statistical analyses of functional gain to multivariate statistical analyses designed to detect and correct for selection bias. In this comparison, we demonstrate substantial differences in inferences between the two approaches.

It is important to understand that the term "selection bias" as used here is a purely statistical term. In this context, selection bias likely results from sound clinical decisions designed to target rehabilitation resources to those patients most in need. The term "selection bias" merely describes the nonrandom process that generates the data and is not a pejorative description of the quality of rehabilitative services or the ways in which rehabilitative services are distributed within the Veterans Affairs (VA).

It is also important to understand the population about which we seek to make inferences. Throughout this paper, we are seeking to model functional gain for those patients selected for rehabilitation on inpatient rehabilitation units. We are not seeking to extrapolate from the selected population to the general stroke population. We only study the selection process to gain insight into the process that generated the observational data. As we demonstrate later, accounting for the process that generated the observed data is critical in specifying a correct statistical model of rehabilitation outcomes for patients seen on VA inpatient rehabilitation units.

The remainder of the paper is divided into three major sections. The "Methods" section describes the VA's Functional Status Outcomes Database (FSOD), a key source of the sample for this research. This section also discusses the Functional Independence Measure (FIM) used as the measure of functional status [6]. Next, the statistical methods used to detect and correct for selection bias are presented. The "Results" section presents basic descriptive statistics, comparing those stroke patients who have received inpatient rehabilitation on acute and subacute rehabilitation units within the VA to those stroke patients in the VA who have not received rehabilitation on such units. Standard ordinary least squares (OLS) estimates of a multivariate model are then used to explore variations in the gains in functional status among patients admitted to inpatient rehabilitation units. These OLS results are then compared with results obtained after correcting for selection bias. The "Discussion" section reviews these results, discusses the limitations of our analyses, and presents the implications of this research for future rehabilitation research using the observational data.

METHODS

Sample

Considerable variation exists across different organizations and different studies in the diagnostic definition of stroke. In particular, different studies use different International Classification of Disease, 9th Revision, Clinical Modification (ICD-9-CM) codes to specify a diagnosis of stroke. Perhaps the most commonly used diagnostic criterion for a stroke involves ICD-9-CM codes 430 to 438 inclusive. Numerous studies, however, have suggested that such a broad definition may yield a significant overestimate of stroke incidence [7–9]. To avoid such overcounting, we used a definition of stroke developed by Reker et al. based on VA data and designed to achieve high sensitivity, while limiting the degradation of specificity [10]. Reker's stroke definition includes patients who have (1) admission or discharge diagnoses 430.xx to 432.xx, 434.xx, or 436xx (2) admission or discharge diagnoses V57.xx, and any secondary diagnosis from among 342.xx, 430.xx to 438.xx or (3) admission or discharge diagnoses 433.xx or 435.xx and any secondary diagnoses from among 342.xx, 430.xx to 432.xx, 434.xx, or 436.xx.

Data on all stroke patients within the VA come from the VA's discharge abstract system, the Patient Treatment File (PTF) for federal fiscal year 1998 (FY98). We obtained additional data for the same time period from

the VA's FSOD, a joint database effort by the VA and the Uniform Data System for Medical Rehabilitation (UDS_{MR}) [11]. Each of the VA's approximately 60 acute and subacute rehabilitation units nationwide is required to submit periodic functional assessments along with common discharge abstract data elements to the FSOD. Consequently, the FSOD contains information on all 2,000-plus patients who have undergone inpatient rehabilitation on VA acute and subacute rehabilitation units annually.

Only 615 (or 12.8 percent) of 4,823 VA patients who met our definition of stroke during FY98 received inpatient rehabilitation on an acute or subacute rehabilitation unit. Because we are interested in detecting and correcting for selection bias, we limited our sample to those facilities that had either an acute or subacute rehabilitation unit. In this way, we could observe stroke patients who had an opportunity to receive rehabilitation on a specialized inpatient rehabilitation treatment unit. We further limited our sample by including only those facilities that had at least 15 stroke patients discharged from their acute or subacute rehabilitation unit during FY98. This was done to ensure that each unit included in our sample had sufficient volume and expertise in rehabilitating stroke patients. Finally, we only included patients whose onset of stroke occurred within the past year. Because of these edits, our final sample consisted of 2,263 stroke patients, 439 (19.4 percent) of whom were treated on either an acute or subacute inpatient rehabilitation unit.

Because functional assessment data are only available on patients treated on inpatient rehabilitation units, we are unable to study functional gain in those stroke patients who were not seen on an acute or subacute rehabilitation unit. We know, however, that many of these patients had received rehabilitation services during their stays on general inpatient medical units within VA facilities. Consequently, while stroke patients found in the FSOD are known to have received formal rehabilitation services, those found in the PTF but not in the FSOD are a mixture of patients—some have received formal rehabilitation services and some have not.

This mixture of rehabilitation and nonrehabilitation patients would pose significant problems if we sought to evaluate the impact of rehabilitation by comparing non-FSOD patients to FSOD patients. However, this is not our purpose. Rather, we seek to discover whether the process whereby patients are chosen for rehabilitation on inpatient rehabilitation units introduces statistical bias into multivariate models of functional gain estimated on such a selected sample and designed to make inferences about the selected population. This issue is of significant practical importance, since we only observe FIM scores for patients in the FSOD.

Measures

The FIM is an 18-item, 7-level scale of independent performance in self-care, sphincter control, transfers, locomotion, communication, and social cognition [12]. Because scores on each item range from 1 to 7, the overall FIM score ranges from 18 (the lowest level of functioning) to 126 (the highest level of functioning). In addition to the overall FIM score, separate motor (13 items) and cognitive (5 items) subscales are commonly examined. The overall, motor, and cognitive FIM scales have been validated and tested for reliability and have been extensively used in observational studies of functional status [13–16].

Before being allowed to submit data to the FSOD, VA clinicians are required to pass a test of mastery of the FIM assessment tool. In addition, the data submitted to the FSOD are subjected to technical review for completeness, errors, and outlier values by the UDS_{MR}.

Statistical Analyses

How can we detect and control for unobserved patient selection effects and thereby remove this potential source of bias from our analysis? We have chosen to use a method developed by Heckman that has gained wide acceptance in the economics, health services research, and program evaluation literatures [17–20]. Heckman's method involves estimating two equations: (1) a probit selection equation that models the selection process of subjects and (2) a main regression equation that models the dependent variable of interest (in our case, the gain in FIM score during inpatient rehabilitation). The following is an explanation of Heckman's model for correcting for selection bias.

Let the regression equation of primary interest be

$$y = \beta' \mathbf{x} + \varepsilon \ . \tag{1}$$

Here, y is the relevant continuous dependent variable (in the present context, the FIM gain) and $\mathbf{x}$ is a column vector of independent variables. Let whether the subject "selected" for rehabilitation on an acute or subacute rehabilitation unit be represented by z^*, a latent continuous variable that is greater than zero when the individual

"selects." Let the vector **w** represent the independent variables that might influence z^*. We then have

$$z^* = \gamma' \mathbf{w} + u \ . \tag{2}$$

We only observe the FIM gain when the patient is on an acute or subacute rehabilitation unit. In algebraic terms, we only observe y when z^* is greater than zero. The conditional expectation of y given that y is observed is

$$\begin{aligned} E[y|y \text{ is observed}] &= E[y|z^* > 0] \\ &= E[y|u - \gamma' \mathbf{w}] \\ &= \beta' \mathbf{x} + E[\varepsilon|u - \gamma' \mathbf{w}] \ . \end{aligned} \tag{3}$$

If ε and u have a bivariate normal distribution with means μ_ε and μ_u, standard deviations σ_ε and σ_u, and correlation ρ, then

$$E[\varepsilon|u > a] = \mu_\varepsilon + \rho\sigma_\varepsilon \lambda(\alpha_u) \ , \tag{4}$$

where

$$\alpha_u = \frac{a - \mu_\varepsilon}{\sigma_u}$$

$$\lambda(\alpha_u) = \frac{\phi(\alpha_u)}{1 - \Phi(\alpha_u)} \ ,$$

and ø is the standard normal density, and Φ is the cumulative standard normal distribution.

Substituting **Equation (4)** into **Equation (3)** yields

$$\begin{aligned} E[y|y \text{ is observed}] &= \beta' \mathbf{x} + \rho\sigma_\varepsilon \lambda(\alpha_u) \\ &= \beta' \mathbf{x} + \beta_\lambda \lambda(\alpha_u) \ , \end{aligned}$$

where

$$\alpha_u = \frac{-\gamma' \mathbf{w}}{\sigma_u} \qquad \lambda(\alpha_u) = \frac{\phi(\gamma' \mathbf{w}/\sigma_u)}{\Phi(\gamma' \mathbf{w}/\sigma_u)} \ .$$

The selectivity-corrected regression equation therefore is

$$y|z^* > 0 = \beta' \mathbf{x} + \beta_\lambda \lambda(\alpha_u) + v \ . \tag{5}$$

The selectivity-corrected regression equation differs from the standard regression equation by the inclusion of λ among the regressors. β_λ, the regression coefficient for λ, is the product of ρ and σ_ε and consequently will be the same sign as ρ, the correlation between ε and u.

The type of selectivity is reflected by ρ, since it represents the correlation between the disturbance in the selectivity equation and the disturbance in the primary equation. When the disturbances in the selectivity equation and the primary equation are positively correlated, those with greater likelihood of selection will have higher y values. Similarly, those with lesser likelihood of selection will have lower y values. The situation for negatively correlated disturbances (as evidenced by a negative β_λ) is analogous.

Equation (5) is the correct way to model FIM gain for patients seen on inpatient rehabilitation units. **Equation (5)** states that the FIM gain *given selection into a rehabilitation bed unit* is dependent upon the **x** variables and a variable (λ) that accounts for selection. By contrast, the OLS approach represented by **Equation (1)** alone states that the unconditional FIM gain is dependent upon the **x** variables alone. Clearly, **Equation (5)** is a richer formulation that accounts for the process by which patients are selected into rehabilitation bed units. Furthermore, use of OLS in place of Heckman's method is equivalent to omitting a relevant explanatory variable (λ) from the model. Under such circumstances, the OLS estimator may be biased and inconsistent.

Intuitively, one might expect that building a standard OLS multiple regression model based on patients seen in inpatient rehabilitation units would yield reasonable inferences about such patients. Heckman's method points out a major flaw in such intuition. In particular, failure to account for the process that generated the observed data can lead to biased and inconsistent results even when the population of interest is limited to the selected population.

It is also worthwhile to note that Heckman's method is a generalization of the OLS estimation. In particular, Heckman's method subsumes the OLS model as a special case. When no selection bias is present, i.e., when $\rho = 0$, Heckman's method reduces to the OLS model (since $\beta_\lambda = \rho\sigma_\varepsilon = 0$ in such a case). In this sense, one does not have to choose between Heckman's method and OLS. Running Heckman's method on the observational data tells us whether selection bias (as defined in Heckman's approach) is an issue. If no selection bias is present ($\rho = 0$), Heckman's method will produce the same regression coefficients as OLS.

It is important to be clear about what correcting for selection bias does and does not do. In correcting for selection bias, we are not imputing values for functional gain for the overall stroke population. Nor are we attempting to extrapolate our results to the overall stroke population based on a sample of inpatient rehabilitation

patients. Rather, we are accounting for the way in which the observational data were generated to make correct inferences about the selected population (i.e., patients seen in VA rehabilitation units).

Since the continuous z^* is unobservable, we estimate a probit equation for z that equals 1 when the individual exhibits selection (i.e., in the context of this study, is in the FSOD) and zero otherwise. Based on this probit equation, we calculated λ for each observation and used it as an additional regressor in the primary regression, where FIM gain is the dependent variable. The estimated coefficient for λ and its associated standard error provide information on the direction and significance of any selectivity bias.

While Heckman's original procedure estimated the probit and main regressions sequentially, we have chosen to estimate the two equations jointly using maximum likelihood estimation (MLE) to improve efficiency [21]. In the results section of this paper, we compare OLS estimates of the overall, motor, and cognitive FIM gain models to the estimates from Heckman's correction for selection bias. By examining the statistical significance, sign, and magnitude of ρ (the correlation between the disturbance terms in the selection and main equations), we can assess whether selection bias exists and the nature of its influence. Should selection bias be detected, we can determine the consequences of selection effects in rehabilitation by comparing the signs and significance of coefficients across the OLS and Heckman models.

RESULTS

Descriptive Results

Table 1 presents the descriptive statistics for our overall sample along with the statistics for the FSOD and non-FSOD subsamples. The FSOD subsample contains those stroke patients admitted to acute or subacute rehabilitation units while the non-FSOD subsample contains those stroke patients who were treated solely on regular

Table 1.
Descriptive statistics for VA stroke patients in FY98. Overall, FSOD, and non-FSOD patients.

Variables	Overall (SD)	FSOD (SD)	Non-FSOD (SD)
Gain in Overall FIM	—	22.80 (14.363)	—
Gain in Motor FIM	—	19.52 (12.543)	—
Gain in Cognitive FIM	—	3.28 (3.647)	—
Admission Overall FIM	—	72.91 (24.907)	—
Admission Motor FIM	—	49.09 (19.527)	—
Admission Cognitive FIM	—	23.82 (8.083)	—
Patient Age (yr)	67.49 (11.134)	66.95 (10.906)	67.618 (11.188)
Time Since Onset (days)	—	16.54 (27.422)	—
Rehab Length of Stay (days)	—	25.13 (17.729)	—
Rehab Length of Stay^2	—	945.11 (1593.820)	—
Charlson Index†	2.02 (1.927)	2.3622 (1.5015)	1.9413 (2.0083)
ICD-9 Code 430*	0.016	0.005	0.019
ICD-9 Code 431*	0.078	0.052	0.084

Table 1.
Descriptive statistics for VA stroke patients in FY98. Overall, FSOD, and non-FSOD patients. (Continued).

Variables	Overall (SD)	FSOD (SD)	Non-FSOD (SD)
ICD-9 Code 432†	0.038	0.011	0.044
ICD-9 Code 433	0.032	0.027	0.033
ICD-9 Code 434*	0.576	0.629	0.564
ICD-9 Code 435	0.021	0.009	0.024
ICD-9 Code 436*	0.216	0.253	0.207
Other Stroke Diagnoses	0.023	0.014	0.025
Source of Adm. Nurs. Hm.	0.020	0.009	0.023
Source of Adm. Outpatient	0.310	0.280	0.317
Source of Adm. Hospital†	0.075	0.112	0.066
Source of Adm. Direct	0.588	0.592	0.587
Charlson Index = 0†	0.230	0.134	0.253
Charlson Index = 1 or 2	0.430	0.417	0.433
Charlson Index = 3 or 4†	0.265	0.374	0.239
Charlson Index ≥ 5	0.076	0.075	0.076
Married†	0.508	0.431	0.526
Divorced*	0.233	0.276	0.223
Widowed	0.128	0.139	0.126
Never Married	0.075	0.089	0.071
Separated	0.057	0.066	0.055
VAMC Augusta	0.037	0.039	0.037
VAMC Baltimore	0.070	0.084	0.066
VAMC Bay Pines	0.051	0.034	0.055
VAMC Columbia	0.044	0.036	0.046
VAMC Danville†	0.014	0.034	0.009
VAMC Gulf Coast*	0.022	0.034	0.019
VAMC Hines	0.051	0.055	0.050
VAMC Houston	0.113	0.137	0.108
VAMC Indianapolis	0.042	0.052	0.040
VAMC Lexington	0.047	0.039	0.049
VAMC Little Rock	0.061	0.080	0.056
VAMC Minneapolis	0.041	0.052	0.038
VAMC Milwaukee†	0.026	0.048	0.020
VAMC New Mexico	0.033	0.034	0.032
VAMC Oklahoma City*	0.053	0.034	0.058
VAMC Portland	0.053	0.039	0.056
VAMC St. Louis	0.049	0.034	0.053
VAMC San Juan†	0.098	0.059	0.108
VAMC Tampa	0.042	0.041	0.042
VAMC Washington*	0.054	0.034	0.059
N	2263	439	1824

*Differences between FSOD and non-FSOD statistically significant at $\alpha = 0.05$.
†Differences between FSOD and non-FSOD statistically significant at $a = 0.01$.
SD = standard deviations.

inpatient units. Stroke patients admitted to acute or subacute rehabilitation units in the VA have higher levels of comorbidities (mean Charlson index = 2.36) compared to other VA stroke patients (mean Charlson index = 1.94). Also, some diagnostic differences between stroke patients admitted to VA rehabilitation units and those treated outside such units exist. For example, while 62.9 percent of FSOD patients were in ICD-9 code 434 (occlusion of the cerebral arteries), only 56.4 percent of non-FSOD patients had that diagnostic code. Similarly, 25.3 percent of FSOD patients fell into ICD-9 code 436 (acute ill-defined cerebrovascular disease), while only 20.7 percent of non-FSOD patients fell into the same category. By contrast, the FSOD contained a lower percentage of patients in ICD-9 codes 430 (subarachnoid hemorrhage), 431 (intracerebral hemorrhage), and 432 (other and unspecified intracranial hemorrhage).

We also observed considerable differences in the distribution of patients across facilities. For example, Veterans Affairs Medical Center (VAMC) San Juan contributes 5.9 percent of all FSOD patients and 10.8 percent of non-FSOD patients, indicating the VAMC San Juan sends a relatively small percentage of its stroke patients to its inpatient rehabilitation unit. Also, differences in marital status exist between the FSOD and non-FSOD subsamples, with 52.6 percent of the non-FSOD sample being married versus only 43.1 percent of the FSOD sample.

Finally, we observed a difference in the sources of admission to the hospital between FSOD and non-FSOD patients. The FSOD had a higher percentage of patients admitted from another hospital than did the non-FSOD.

Table 1 summarizes the differences between the FSOD and non-FSOD samples. A possibility remains, however, that *unobservable* (or imperfectly observed) differences exist between the samples that could bias our analyses. To address this issue, we turn to our multivariate analyses, where we compare the results from standard analyses to results corrected for selection bias.

Multivariate Results

Based on the literature, we modeled FIM gain as dependent upon—

- Initial functional status (as measured by the admission motor and cognitive FIM scores).
- Age.
- Time since stroke onset.
- Length of stay in rehabilitation (and its square).
- Diagnosis (as measured by three-digit ICD-9-CM categories).
- Comorbidities (as measured by categories of the Charlson index).
- Facility (as measured by dummy variables representing those VA medical centers in our sample, with VAMC Houston as the reference group).

To explore the existence and impact of selection bias, we compared standard models of OLS to models using Heckman's correction for overall, motor, and cognitive FIM gain. For the first stage probit selection model in Heckman's correction, we used the following variables as regressors: patient age, diagnosis, facility, source of admission (nursing home, outpatient, and hospital; direct admission as the reference group), and comorbidities. Both OLS and MLE selection (Heckman's) results are presented in **Tables 2–4**.

For the selection models, we find strong statistically significant selection effects for overall and motor FIM gains. The correlation between the disturbances in the first-stage probit and second-stage FIM gain regressions, ρ, is –0.96 for overall FIM gain and –0.95 for motor FIM gain. These strong negative correlations indicate that individuals who are more likely to be in the FSOD (i.e., who are more likely to receive rehabilitation on inpatient rehabilitation units) are *more* likely to have *lower* overall and motor FIM gains. Conversely, patients who are less likely to be treated on inpatient rehabilitation units are more likely to have higher overall and motor FIM gains.

The negative correlation between selection into inpatient rehabilitation units and the overall and motor FIM gains suggests that acute and subacute rehabilitation units in the VA are subject to adverse selection. In other words, the patients being selected for acute and subacute rehabilitation are more difficult to rehabilitate, as reflected by their lower FIM gains. This would be consistent with the notion that acute and subacute rehabilitation units in the VA are being used for the "tougher" patients.

Does the existence of this selection bias have implications for our multivariate models? In other words, having detected strong selection bias, does this selection bias change our conclusions regarding those factors that influence FIM gain? We now turn our attention to answering these questions by comparing the results from our selectivity models with standard OLS results.

Previous research has demonstrated that higher FIM scores of patients upon admission to rehabilitation are associated with lower gain in FIM scores during rehabilitation [7].

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Table 2.
Regression results for gain in overall functional independence measure (FIM).

Independent Variables	Ordinary Least Squares (SE)	MLE Selection Correction (SE)
Admission Cognitive FIM	0.229814* (0.093970)	0.09946 (0.087210)
Admission Motor FIM	–0.216515† (0.043062)	–0.352007† (0.054524)
Patient Age (yr)	–0.171536† (0.058637)	–0.129258 (0.071924)
Time Since Onset (days)	–0.067594† (0.025192)	–0.061930† (0.022368)
Rehab Length of Stay (days)	0.432681† (0.097521)	0.410643† (0.091502)
Rehab Length of Stay^2	–0.002971† (0.001034)	–0.002829† (0.000875)
ICD-9 Code 430	–17.90544 (9.298962)	–9.311613 (10.0041)
ICD-9 Code 431	–0.639973 (2.795788)	5.348577 (3.395972)
ICD-9 Code 432	5.146904 (5.957256)	13.7972* (6.647452)
ICD-9 Code 433	4.225049 (3.768668)	9.770032* (4.592573)
ICD-9 Code 435	–1.678532 (6.447219)	9.117716 (7.081086)
ICD-9 Code 436	–0.779786 (1.584283)	–0.477491 (1.98568)
Other Stroke Diagnoses	6.234619 (5.392445)	12.70192* (6.187025)
VAMC Baltimore	5.482162 (2.834059)	7.745254* (3.615514)
VAMC Little Rock	0.995733 (2.742881)	–3.16642 (3.55222)
VAMC San Juan	10.0736† (3.016902)	17.43318† (3.771805)
VAMC Hines	4.456154 (3.067766)	5.527881 (3.904341)
VAMC Indianapolis	14.78286† (3.110346)	13.2843† (3.979803)
VAMC Minneapolis	12.43952† (3.115633)	10.10735* (4.039284)
VAMC Milwaukee	6.010006 (3.248794)	–1.71626 (4.414755)
VAMC Portland	7.03095* (3.477779)	12.61655† (4.343738)
VAMC Tampa	3.206588 (3.453723)	6.016549 (4.402857)
VAMC Augusta	11.65071† (3.47273)	11.39082† (4.410248)
VAMC Lexington	12.0396† (3.662885)	18.41489† (4.451063)

Table 2.
Regression results for gain in overall functional independence measure (FIM). (Continued).

Independent Variables	Ordinary Least Squares (SE)	MLE Selection Correction (SE)
VAMC Columbia	8.154348* (3.636208)	10.26314* (4.316598)
VAMC Danville	10.02327* (4.005261)	1.823794 (5.421722)
VAMC Gulf Coast HCS	3.865084 (3.958948)	–0.77046 (5.277729)
VAMC St. Louis	6.635006 (3.617581)	15.60998† (4.601961)
VAMC Bay Pines	15.9907† (3.660603)	21.1286† (4.374662)
VAMC New Mexico HCS	12.06868† (3.824153)	11.02179* (4.72072)
VAMC Oklahoma City	–3.32038 (3.674273)	5.078876 (4.815009)
VAMC Washington	–0.1792 (3.758133)	10.46125* (4.753265)
Charlson Index = 1 or 2	1.349956 (1.951137)	–6.083499* (2.526383)
Charlson Index = 3 or 4	–2.400145 (2.080995)	–14.54427† (2.904379)
Charlson Index ≥ 5	3.783069 (2.914275)	–4.189065 (3.744788)
Constant	26.3507† (5.883751)	67.82736† (8.897517)
Rho	—	–0.9604402† (0.0194282)
Wald χ^2	—	251.03†
F statistic	5.34†	—
Adj. R^2	0.2576	—
N selected	439	439
N total	—	2263

*Statistically significant at $\alpha = 0.05$ †Statistically significant at $\alpha = 0.01$ SE = standard errors

This is confirmed in our findings in the sense that higher initial motor FIM scores are associated with lower overall and motor FIM gain. However, compared to the conventional approach, we found a much larger absolute effect after correcting for selection bias. For the overall FIM gain, the OLS analysis suggested that a one-point increase in motor FIM score of patients at admission is associated with a decrease in expected overall FIM gain of approximately 0.22. By contrast, after correcting for selection bias, we found that a one-point increase in motor FIM score at admission is associated with a decrease in expected overall FIM gain of approximately 0.35, a 59 percent change from the OLS estimate. Similarly, after correcting for selection bias, we found that a one-point increase in admission motor FIM score is associated with a 0.38 decrease in expected motor FIM gain. This contrasts sharply with the 0.26 decrease estimated by the conventional OLS approach.

Previous research has also found that length of stay in rehabilitation is positively related to overall, motor, and cognitive FIM gains. Our results are consistent with the literature. The coefficients for both length of stay and length-of-stay squared were statistically significant in both the OLS and selectivity-corrected models and suggest an approximately linear relationship between overall

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Table 3.
Regression results for gain in motor functional independence measure (FIM).

Independent Variables	Ordinary Least Squares (SE)	MLE Selection Correction (SE)
Admission Cognitive FIM	0.472406† (0.080951)	0.438777† (0.073164)
Admission Motor FIM	–0.255357† (0.037095)	–0.381101† (0.050471)
Patient Age (yr)	–0.149467† (0.050513)	–0.107160 (0.060938)
Time Since Onset (days)	–0.060504† (0.021702)	–0.057606† (0.019339)
Rehab Length of Stay (days)	0.342774† (0.084010)	0.311501† (0.081484)
Rehab Length of Stay^2	–0.002305† (0.000891)	–0.002162† (0.000786)
ICD-9 Code 430	–15.31273 (8.010635)	–8.711038 (8.287691)
ICD-9 Code 431	–1.037047 (2.408444)	3.989046 (2.884997)
ICD-9 Code 432	2.077686 (5.131906)	10.41895 (5.658342)
ICD-9 Code 433	2.983949 (3.246537)	7.201344 (3.90995)
ICD-9 Code 435	–2.566987 (5.553987)	6.606501 (6.045845)
ICD-9 Code 436	–1.437442 (1.364788)	–1.216532 (1.682637)
Other Stroke Diagnoses	5.923304 (4.645347)	11.18932* (5.263595)
VAMC Baltimore	4.851* (2.441413)	6.48823* (3.052303)
VAMC Little Rock	0.187816 (2.362867)	–3.12884 (3.003852)
VAMC San Juan	8.843664† (2.598924)	14.66261† (3.202318)
VAMC Hines	3.600195 (2.642742)	4.335229 (3.305046)
VAMC Indianapolis	11.42616† (2.679422)	10.5073† (3.361298)
VAMC Minneapolis	9.782894† (2.683977)	8.048358* (3.405383)
VAMC Milwaukee	3.415734 (2.798689)	–2.69927 (3.721578)
VAMC Portland	4.989511 (2.99595)	9.160072* (3.663954)
VAMC Tampa	2.360293 (2.975226)	4.358504 (3.736424)
VAMC Augusta	8.182172† (2.9916)	7.84734* (3.731256)

Table 3.
Regression results for gain in motor functional independence measure (FIM). (Continued).

Independent Variables	Ordinary Least Squares (SE)	MLE Selection Correction (SE)
VAMC Lexington	9.52274† (3.15541)	14.15123† (3.778323)
VAMC Columbia	6.164438* (3.132429)	8.461983* (3.672306)
VAMC Danville	7.997694* (3.450351)	1.020354 (4.598998)
VAMC Gulf Coast HCS	3.947563 (3.410454)	0.200641 (4.414806)
VAMC St. Louis	4.239491 (3.116382)	11.23054† (3.862993)
VAMC Bay Pines	12.91339† (3.153444)	17.44242† (3.749876)
VAMC New Mexico HCS	9.31731† (3.294335)	8.832106* (3.992091)
VAMC Oklahoma City	–3.90422 (3.16522)	1.972118 (3.99375)
VAMC Washington	–0.30318 (3.237462)	8.699091* (4.100867)
Charlson Index = 1 or 2	0.863608 (1.680816)	-4.822897* (2.124423)
Charlson Index = 3 or 4	–2.668016 (1.792683)	–12.28332† (2.466681)
Charlson Index ≥ 5	2.941754 (2.510516)	–3.009804 (3.14776)
Constant	21.32134† (5.068585)	53.98579† (7.652042)
Rho	—	–0.9506704† (0.0235457)
Wald χ^2	—	267.15†
F statistic	5.8100†	—
Adj. R^2	0.2775	—
N selected	439	439
N total	—	2263

*Statistically significant at $\alpha = 0.05$ †Statistically significant at $\alpha = 0.01$ SE = standard errors

FIM gain and length of stay. However, correcting for selection bias had little effect on the relationship between length of stay and overall FIM gain.

Numerous patient and facility variables that were not statistically significant in the OLS models became statistically significant in the selectivity-corrected models:

1. In the selectivity-corrected models, we were able to detect differences in overall FIM gain across diagnostic categories. For example, ICD-9-CM codes 432 and 433 were seen to have higher overall FIM gain than the reference group (ICD-9-CM code 434) in the selectivity model. The coefficients for these variables were not statistically significant in the OLS model.
2. For the overall and motor FIM gain models, we discovered statistically significant effects of comorbidities only after correcting for selection bias. For our overall and motor FIM gain results, higher levels of comorbidties were associated with lower FIM gain (reference group: Charlson index = 0).

Table 4.
Regression results for gain in cognitive functional independence measure (FIM).

Independent Variables	Ordinary Least Squares (SE)	MLE Selection Correction (SE)
Admission Cognitive FIM	–0.242591† (0.022501)	–0.242169† (0.021635)
Admission Motor FIM	0.038841† (0.010311)	0.038268† (0.009878)
Patient Age (yr)	–0.0220691 (0.014041)	–0.018665 (0.013867)
Time Since Onset (days)	–0.007090 (0.006032)	–0.006690 (0.005801)
Rehab Length of Stay (days)	0.089906† (0.023351)	0.088435† (0.022368)
Rehab Length of Stay^2	–0.000665† (0.000247)	–0.000647† (0.000237)
ICD-9 Code 430	–2.592715 (2.226667)	–2.083746 (2.172539)
ICD-9 Code 431	0.397073 (0.669460)	0.669045 (0.682373)
ICD-9 Code 432	3.069218* (1.426485)	3.758912† (1.464639)
ICD-9 Code 433	1.241099 (0.90242)	1.42371 (0.889546)
ICD-9 Code 435	0.888455 (1.543808)	1.49046 (1.560081)
ICD-9 Code 436	0.657655 (0.379361)	0.681740 (0.370393)
Other Stroke Diagnoses	0.311315 (1.291239)	0.800794 (1.303204)
VAMC Baltimore	0.631162 (0.678625)	0.54908 (0.663773)
VAMC Little Rock	0.807917 (0.656792)	0.551191 (0.6719)
VAMC San Juan	1.229933 (0.722407)	1.51595* (0.736013)
VAMC Hines	0.855959 (0.734587)	0.825197 (0.717037)
VAMC Indianapolis	3.356702† (0.744783)	3.21496† (0.735739)
VAMC Minneapolis	2.656621† (0.746049)	2.480806† (0.741227)
VAMC Milwaukee	2.594272† (0.777934)	2.056643* (0.870219)
VAMC Portland	2.041439* (0.832766)	2.171466† (0.817564)
VAMC Tampa	0.846295 (0.827005)	0.820616 (0.806499)
VAMC Augusta	3.468537† (0.831557)	3.382529† (0.813596)

Table 4.
Regression results for gain in cognitive functional independence measure (FIM). (Continued).

Independent Variables	Ordinary Least Squares (SE)	MLE Selection Correction (SE)
VAMC Lexington	2.516856† (0.87709)	2.640579† (0.862831)
VAMC Columbia	1.98991* (0.870702)	2.099503* (0.850003)
VAMC Danville	2.025579* (0.959073)	1.495812 (1.023429)
VAMC Gulf Coast HCS	–0.08248 (0.947983)	–0.39997 (0.956637)
VAMC St. Louis	2.395515† (0.866242)	2.668967† (0.872176)
VAMC Bay Pines	3.077305† (0.876544)	3.351499† (0.877211)
VAMC New Mexico HCS	2.751371† (0.915706)	2.587917† (0.899715)
VAMC Oklahoma City	0.583835 (0.879817)	0.832941 (0.88136)
VAMC Washington	0.123986 (0.899897)	0.490563 (0.918206)
Charlson Index = 1 or 2	0.486347 (0.467206)	0.179628 (0.515636)
Charlson Index = 3 or 4	0.267871 (0.498301)	–0.310697 (0.662550)
Charlson Index ≥ 5	0.841315 (0.697832)	0.519794 (0.726771)
Constant	5.029356† (1.408884)	6.667099† (1.890271)
Rho	—	–0.3774575 (0.2584083)
Wald χ^2	—	277.79†
F statistic	7.44†	—
Adj. R^2	0.3396	—
N selected	439	439
N total	—	2263

*Statistically significant at $\alpha = 0.05$ †Statistically significant at $\alpha = 0.01$ SE = standard errors

3. After other covariates were controlled, the facility variables in the overall, motor, and cognitive FIM gain equations when compared to VAMC Houston, the reference facility, showed that—
   a. VAMCs Baltimore, St. Louis, and Washington had higher overall FIM gains.
   b. VAMCs Portland, St. Louis, and Washington had higher motor FIM gains.
   c. VAMC San Juan had higher cognitive FIM gains.

The selectivity-corrected results did not support several statistically significant findings from the OLS models. In particular, the OLS results suggested that a higher initial cognitive FIM score was associated with higher overall FIM gain. Also, the OLS results suggested that increasing patient age is associated with reduced overall and motor FIM gain. Neither of these findings, however, appeared in the selectivity-corrected results.

Finally, **Table 5** presents the results for the first-stage probit selection models that explain variations in the probability of receiving services on an acute or subacute rehabilitation unit. Because we estimated the probit selection equation and the FIM gain equation using a joint maximum likelihood approach, the results differ slightly across the overall, motor, and cognitive FIM gain analyses. All three analyses yielded consistent findings, however:

1. Patients in ICD-9-CM codes 430, 431, 432, 435, and "other stroke diagnoses" were less likely than patients in ICD-9 code 434 (the reference group) to be admitted to acute or subacute rehabilitation units (i.e., to appear in the FSOD).
2. Stroke patients admitted to a medical center from a nursing home were less likely than direct admissions (the reference group) to be treated on an acute or subacute rehabilitation unit.
3. Patients who were not married (i.e., who were divorced, widowed, never married, or separated) were more likely than married patients to be treated on an acute or subacute rehabilitation unit.
4. Patients with higher levels of comorbidities (as measured by categories of the Charlson index) were more likely to be treated on an acute or subacute rehabilitation unit.

Table 5.
Selection regression results for inclusion in the functional status outcomes database.

Variable	Overall FIM Gain (SE)	Motor FIM Gain (SE)	Cognitive FIM Gain (SE)
Patient Age (yr)	–0.001315 (0.002961)	–0.001303 (0.002969)	–0.001501 (0.003084)
ICD-9 Code 430	–0.708887* (0.351760)	–0.725812* (0.352882)	–0.756431* (0.354062)
ICD-9 Code 431	–0.306196* (0.130494)	–0.305431* (0.130625)	–0.372047† (0.134342)
ICD-9 Code 432	–0.712916† (0.230602)	–0.709560† (0.229929)	–0.762299† (0.232427)
ICD-9 Code 433	–0.231406 (0.182339)	–0.244110 (0.183348)	–0.270438 (0.187968)
ICD-9 Code 435	–0.718709† (0.269478)	–0.707124† (0.268527)	–0.679167* (0.270187)
ICD-9 Code 436	–0.015439 (0.081285)	–0.017805 (0.081456)	0.000402 (0.083045)
Other Stroke Diagnoses	–0.667891† (0.244448)	–0.666863† (0.244643)	–0.648591† (0.246639)
VAMC Baltimore	0.024954 (0.150023)	0.029893 (0.150603)	–0.07974 (0.160527)
VAMC Little Rock	0.211524 (0.153928)	0.212726 (0.154619)	0.13194 (0.164483)
VAMC San Juan	–0.3276* (0.15212)	–0.32358* (0.152576)	–0.36086* (0.161577)
VAMC Hines	–0.08332 (0.168323)	–0.07692 (0.168738)	–0.11412 (0.177799)
VAMC Indianapolis	0.080676 (0.17274)	0.09992 (0.173148)	0.026288 (0.182063)
VAMC Minneapolis	0.09051 (0.174268)	0.103592 (0.174726)	0.021455 (0.183484)
VAMC Milwaukee	0.519479† (0.194582)	0.534503† (0.195411)	0.44622* (0.205517)
VAMC Portland	–0.20226 (0.171204)	–0.2085 (0.171592)	–0.28726 (0.176213)

Table 5.
Selection regression results for inclusion in the functional status outcomes database. (Continued).

Variable	Overall FIM Gain (SE)	Motor FIM Gain (SE)	Cognitive FIM Gain (SE)
VAMC Tampa	–0.0599 (0.184348)	–0.05906 (0.184933)	–0.12333 (0.1922)
VAMC Augusta	0.061578 (0.187628)	0.066946 (0.188406)	–0.00547 (0.196385)
VAMC Lexington	–0.05853 (0.172045)	–0.06488 (0.172666)	–0.17254 (0.179608)
VAMC Columbia	–0.20021 (0.179922)	–0.17914 (0.179887)	–0.30271 (0.189437)
VAMC Danville	0.613216† (0.235998)	0.599766* (0.236688)	0.606353* (0.246211)
VAMC Gulf Coast HCS	0.251445 (0.219834)	0.251833 (0.219297)	0.200317 (0.226337)
VAMC St. Louis	–0.29771 (0.181506)	–0.29354 (0.181919)	–0.40805* (0.191966)
VAMC Bay Pines	–0.34603 (0.180357)	–0.34329 (0.181202)	–0.42928* (0.191321)
VAMC New Mexico HCS	0.09123 (0.197371)	0.100915 (0.19728)	0.102366 (0.203347)
VAMC Oklahoma City	–0.29546 (0.17436)	–0.30563 (0.174748)	–0.35678* (0.176801)
VAMC Washington	–0.48959† (0.176495)	–0.47301† (0.176575)	–0.57181† (0.182155)
Admitted from Nursing Home	–0.7473056† (0.2018678)	–0.637975† (0.202495)	–0.624270* (0.284906)
Admitted from Outpatient	–0.058882 (0.062061)	–0.050205 (0.063565)	–0.097979 (0.089634)
Admitted from Hospital	0.152506 (0.090227)	0.160322 (0.091385)	0.367750† (0.117434)
Divorced	0.180191† (0.056383)	0.185466† (0.058098)	0.220680† (0.079569)
Widowed	0.227785† (0.068946)	0.237737† (0.071102)	0.213346* (0.09821)
Never Married	0.269487† (0.086706)	0.283889† (0.088389)	0.308653* (0.122129)
Separated	0.194391* (0.098111)	0.158422 (0.101768)	0.292475* (0.135303)
Charlson Index = 1 or 2	0.335201† (0.089985)	0.342069† (0.090218)	0.354209† (0.091262)
Charlson Index = 3 or 4	0.683986† (0.096992)	0.686658† (0.097263)	0.672521† (0.098694)
Charlson Index ≥ 5	0.412396† (0.13813)	0.417228† (0.138315)	0.391401* (0.141262)
Constant	–1.10093† (0.231004)	–1.116053† (0.2322338)	–1.055608† (0.2476704)

Note: These probit models were estimated jointly with FIM gain equations with use of maximum likelihood methods. Consequently, Wald χ^2 and sample sizes for respective MLE selection equations in previous tables also apply to these results.

*Statistically significant at $\alpha = 0.05$
†Statistically significant at $\alpha = 0.01$
SE = standard errors

DISCUSSION

The results just presented demonstrate the importance of detecting and correcting for selection bias when one uses observational data, where clinical judgment and patient preferences determine treatment patterns. We found evidence of (1) strong selection bias in those patients who have received rehabilitation in acute or subacute rehabilitation units in the VA and (2) significant effects of such selection bias on the results obtained from standard OLS multiple regressions. Moreover, failure to correct for selection bias can obscure important influences and lead to incorrect conclusions about those factors that exert a statistically significant influence on gains in functional status. (We emphasize again that the models presented in **Tables 2** to **4** refer to those patients seen on VA inpatient rehabilitation units. They do not represent an attempt to extrapolate beyond this selected population to the general stroke population.)

We should also note that Heckman's approach to correcting for selection bias is not without shortcomings. For example, some research has shown that Heckman's approach is sensitive to departures from the assumption of joint normality among the disturbances, although some simulation studies have found small departures from normality to be relatively benign [22,23]. In addition, some researchers have criticized the uncritical use of Heckman's sequential selectivity approach when many selectivity contexts involve the joint determination of z^* and y [24]. Finally, Heckman's approach models a simple dichotomous selection process (in this case, treatment on a rehabilitation unit versus no treatment on a rehabilitation unit) when the actual selection process extends over multiple levels (e.g., VA versus non-VA care, rehabilitation versus no rehabilitation, rehabilitation in a rehabilitation unit versus rehabilitation elsewhere). For our purposes, we have chosen to use Heckman's approach because of (1) its widespread acceptance and numerous applications in other areas and (2) the exploratory nature of our study of how selectivity may influence rehabilitation outcomes. We hope that our work will spawn the development and application of statistical methods designed to accommodate the particular characteristics of the rehabilitation environment.

Finally, it should be noted that our findings on selection bias are largely irrelevant in randomized clinical trials. Only when (1) independent clinical judgment and/or patient preferences result in a nonrandom distribution of patients across treatment regimes, (2) the factors underlying such distribution are either unmeasured or imperfectly measured, and (3) those factors have a significant influence on the outcome of interest, does correcting for selection bias become an important consideration.

CONCLUSIONS

The major conclusions of our research are as follows:

1. Multivariate models of rehabilitation outcomes with the use of the VA's Functional Status Outcomes Database are subject to statistical selection bias.
2. This selection bias has a major impact on the conclusions derived from multivariate models of functional gain.
3. Failure to correct for such selection bias can lead to erroneous conclusions about—
   a. Which factors influence functional gain.
   b. The magnitudes of those influences.

Although this study was limited to a single database, we believe that researchers should be cautious whenever they use observational data to study rehabilitation outcomes. The kinds of clinical decisions that generated the selection bias observed in this research are likely similar to the kinds of clinical decisions routinely made about poststroke rehabilitation. Given our documentation of the influence of selection bias on multivariate studies of rehabilitation outcomes, we believe that the issue of selection bias should be addressed in all multivariate studies of rehabilitation outcomes where observational data and lack of random assignment are present. Fortunately, general statistical software packages such as SAS and Stata (as well as more specialized packages such as LIMDEP) now provide procedures that enable researchers to explore Heckman's method as a matter of course.

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