Check for updates

Steven D. Pizer
John A. Gardner

Is Fragmented Financing Bad for Your Health?

Americans finance health care through a variety of private insurance plans and public programs. This organizational fragmentation could threaten continuity of care and adversely affect outcomes. Using a large sample of veterans who were eligible for mixtures of Veterans Health Administration- and Medicare-financed care, we estimate a system of equations to account for simultaneity in the determination of financing configuration and the probability of hospitalization for an ambulatory care sensitive condition. We find that a change of one standard deviation in financing fragmentation increases the risk of an adverse outcome by one-fifth.

Health care financing in the U.S. is fragmented. Individual patients may pay for health services directly out of their own pockets, indirectly, through one (or sometimes more than one) of a multitude of private health insurance plans, or through one or more public programs. Even within a public program like Medicare, individuals can choose from a variety of health plans with different combinations of coverage and premiums, adjusting their plan choices when their tastes or circumstances change. This variety of health care financing choices has value to consumers (Danzon 1992), but it also has a cost because it makes continuity of care more difficult.

Continuity of care has been defined as a long-term relationship between a patient and a physician, regardless of the presence of any specific disease (Haggerty et al. 2003), and it is believed to be a critical determinant of quality in primary care (Starfield 1998). Continuity of care is associated with lower probability of hospitalization (Gill 1997; Mainous and Gill 1998), fewer visits to the emergency room (Gill, Mainous, and Nsereko 2000), and better immunization (Mark and Paramore 1996). Short or discontinuous relationships with providers could lead to lower quality of care because the provider's access to information about the patient's health is more limited than it would be in long, continuous relationships. When access to information is difficult, physicians may be more likely to choose treatments based on norms or past experience with other patients instead of treatments optimally tailored to an individual's particular condition and history. Frank and Zeckhauser (2007) use the colorful term "ready-to-wear" to characterize a treatment

Steven D. Pizer, Ph.D., *is associate director, Health Care Financing and Economics, U.S. Department of Veterans Affairs, and an associate professor of health policy and management, Boston University School of Public Health.* ***John A. Gardner, Ph.D.,*** *is an economist, Health Care Financing and Economics, U.S. Department of Veterans Affairs.* *This research was supported by a grant (no. ECI 03-199-2) from the Health Services Research and Development Service of the U.S. Department of Veterans Affairs and approved by the Institutional Review Board at the VA Boston Healthcare System.* *Address correspondence to Dr. Pizer at Health Care Financing and Economics, VA Boston Healthcare System, 150 South Huntington Ave. (152H), Boston, MA 02130. Email: pizer@bu.edu*

Inquiry 48: 109–122 (Summer 2011). © 2011 Excellus Health Plan, Inc.
ISSN 0046-9580 10.5034/inquiryjrnl_48.02.02
www.inquiryjournal.org

strategy that relies on norms, in contrast to "custom-made," which describes a treatment strategy that makes use of detailed, individual-specific information.

The goal of this paper is to assess empirically whether disruption in clinical relationships, resulting directly from fragmented financing, has a meaningful effect on health outcomes. We have chosen a very broad outcome: hospitalization for ambulatory care sensitive conditions (ACSC), which is a widely used and accepted measure that can be constructed easily from administrative data. To measure fragmentation, we focus on a population of low-income or disabled veterans who choose mixtures of services from private networks financed primarily by Medicare and the public network operated by the Veterans Health Administration (VA). We are able to observe all utilization for this population and, because the VA network and private networks have little overlap, we can infer with few errors discontinuity of care from fragmentation of financing.

Low-income or disabled veterans use combinations of Medicare and VA care for a variety of reasons. Low-income veterans can receive comprehensive health care from the VA at minimal financial cost, but large numbers regularly receive care from non-VA sources because VA services may not be available or may require patients to wait or to travel (Shen et al. 2003; Burgess and Fiore 1994; Prentice and Pizer 2008). Fleming et al. (1992) have documented the degree of dual use of VA and Medicare health services among veterans enrolled in Medicare. They describe an equilibrium that exists between VA and Medicare/Medicaid programs, mediated by eligibility requirements and financial controls on both sides. When Medicare or Medicaid eligibility rules tighten or out-of-pocket costs increase, more veterans turn to the VA for services. Fragmented financing between the VA and Medicare therefore can reduce out-of-pocket costs and improve convenience for individual veterans, but it may undermine the continuity of primary care.

Considerations like these apply to nonveterans as well. At a minimum, Americans may change health coverage when they graduate from college, change jobs, get married or divorced, move from place to place, or retire (Currie and Madrian 1999). If these changes in coverage were accompanied by disruptions in relationships with health care providers, fragmented financing could substantially undermine the quality of care. Cunningham and Kohn (2000) used data from the Community Tracking Study to show that about 17% of privately insured Americans changed health plans in the period 1996–1997. Those who switched plans were twice as likely as those who kept their plan to change their usual source of care (22.5% compared to 11.2%). When respondents switched from one HMO to another, the likelihood of changing their usual source of care increased further to 28.6%. One reason to change usual source of care is because the new plan does not include the previous provider in its network. Chernew et al. (2004) examined the degree of network overlap among HMOs in the same metropolitan statistical areas and found that a member switching from one HMO to another in the same market had about a 50% chance of having to change primary care physicians.

When measuring the effect of fragmented financing on outcomes, we face an endogeneity problem. Individuals in poor health will be more likely to have fragmented financing as well as bad outcomes. There are both institutional and individual reasons for this. Institutionally, those who are 65 or older or who receive Social Security Disability Income (SSDI) can qualify for Medicare. Individually, as health status deteriorates, demand for quantity and variety of services increases, making the use of multiple programs more attractive. We can use risk-adjustment techniques to mitigate this problem, but unobserved variation in health status will remain, causing naïve estimates of the effect of fragmentation on outcomes to be confounded with the effects of unobserved health. To address this problem, we need an instrumental variable that predicts fragmentation and is independent of unobserved individual health status.

We use the distance between the patient's home and the nearest VA facility as an instrument to explain some of the variation in fragmented financing in this population and to identify the causal effect on outcomes.

We find that an increase of one standard deviation in the fragmentation of financing increases the probability of ACSC hospitalization by 21%. This effect is comparable in size to the effects of major chronic diseases such as arrhythmia, anemia, or peripheral vascular disease.

The remainder of the paper is organized in four sections. We present the statistical specifications for our models and discuss estimation and testing issues in the next section. In the third section, we describe our sources of data and how the sample was derived. The fourth and fifth sections present results and conclusions, respectively.

Statistical Specification

Our goal is to measure the effects on health outcomes of potential coordination failures arising from the fragmentation of health services financing. Our principal empirical challenge is that observed and unobserved health statuses simultaneously determine financing arrangements (through eligibility policies) and outcomes, so fragmented financing is endogenous with respect to the outcome. For example, a negative shock to unobserved health might simultaneously cause fragmentation and poor outcomes because demand for services and eligibility status both change. To isolate the effect of fragmentation on outcomes from other potentially confounding effects, we use an instrumental variables approach to identify exogenous components of fragmentation in a system of two equations where *f* denotes fragmentation, *h* denotes ACSC hospitalization, and *i, s,* and *t* index individuals, states, and time, respectively.

$$f_{it}=F(\alpha_0+\alpha_1 Dist_{it}+\alpha_2 Z_{it}+\alpha_3 DX_{it-1})+\varepsilon_{it}^{f} \quad (1)$$

$$h_{it}=H(\beta_0+\beta_1 f_{it}+\beta_2 \hat{\varepsilon}_{it}^{f}+\beta_3 Z_{it}+\beta_4 DX_{it-1}) + \varepsilon_{it}^{h} \quad (2)$$

Z_{it} = Demog_{it}, Priority_{it}, Beds, HMOpen, *t,* Division

The dependent variable in the outcome equation, equation 2, is an indicator variable for whether an individual had one or more ACSC hospitalizations in the current period. Independent variables include: "Demog," which represents a vector including age in years; a female indicator variable; the percentage of residents in the individual's zip code who are nonwhite; and per capita income in the individual's zip code. "Beds" denotes the number of acute care hospital beds per 1,000 residents and "HMOpen" reflects local Medicare Advantage HMO market penetration. Trends are captured by *t* and "Division" denotes a vector of indicator variables for the nine census divisions. "DX" denotes a vector of diagnosis-based comorbidity indicator variables that are measured in the prior period to avoid simultaneous determination with the outcome. "Priority" represents two indicator variables. The first is for VA priority status 1, 2, or 3, which correspond to veterans who have disabilities connected to their service in the military. These veterans generally have no copayments for VA care. The second indicator variable is for priority status 5, which corresponds to veterans with low incomes. These veterans have no copayments for inpatient or outpatient care, but they do have copayments for outpatient medications and extended care services. Demog, Priority, Beds, HMOpen, *t*, and Division are condensed into the vector *Z*.

Our belief that fragmented financing and ACSC hospitalization are simultaneously determined is reflected by the inclusion of the estimated residual from equation 1 as an independent variable in equation 2. This technique, known as a "control function" approach in the nonparametric literature (Newey, Powell, and Vella 1999) and referred to more recently as "two-stage residual inclusion" in a parametric context (Terza, Basu, and Rathouz 2008), is similar to the familiar Heckman two-step selection model (Heckman 1979). The necessary functional form assumption implicit in this approach is that the disturbance terms in both equations are additively separable from the functions *F*(.) and *H*(.). Given this assumption, we can use the estimated fragmented financing residual ($\hat{\varepsilon}_{it}^{f}$) in equation 2 to account for the endogenous components of *f,* leaving β_1 as an unbiased estimate of the effects of variation in *f* attributable to exogenous factors.

This system is identified by an exogenous instrument: the distance to the nearest VA facility (Dist). In equation 2, the fragmented financing residual is identified by the presence of the instrument in equation 1. Distance makes sense as an instrument because veterans who live farther away from VA facilities are less likely to use VA services and more likely to rely on other programs (Burgess and Difiore 1994; Borowsky and Cowper 1999). This variable is excluded from the outcome equation because we assume that it does not have effects on the outcome that are independent of its effects on financing. We defend this exclusion restriction by observing that all the veterans in our sample have access to a full range of services through both the VA and Medicare. VA care typically involves lower financial cost-sharing, but longer waiting times for appointments and more burdensome travel distances. Given these options, we believe distance principally affects the composition of financing rather than access to services.

We estimate both linear and nonlinear versions of this system. In the linear version, we use two-stage least squares and omit the estimated residual term. In the nonlinear version, we estimate equation 1 as a two-limit tobit and equation 2 as a probit. To help control for potential misspecification of functional forms, we use fourth-order polynomials in the fragmentation residual. Because the nonlinear system is estimated in two steps, the standard errors produced by statistical software are incorrect, failing to account for the stochastic nature of the estimated residual terms. We use bootstrapping with 400 iterations to calculate correct standard errors (Efron 1979).

Data and Sample

We chose to study a population of low-income or disabled veterans to minimize the likelihood that individuals in the sample would have private health insurance. This allows us to rely on administrative data from Medicare and the VA to obtain a reasonably comprehensive record of financing, utilization, and outcomes. With this goal in mind, we began with a 30% random sample of all veterans who had any use of VA-financed health services from FY1998 through FY2001 (October 1, 1997 to September 30, 2001). At the sampling stage, we excluded veterans determined by the VA to be in priority groups 7 or 8, which indicate that the veteran was not disabled and did not qualify as low income under the VA's means test. Once sampled, we also excluded those not eligible for Medicare, those living in nursing homes, those with any Medicaid enrollment, and those with missing priority status, means test values, age, or state of residence. In addition, we excluded those who had any enrollment in a Medicare HMO during the year because this study relies on hospital and physician visit utilization records for several key variables and utilization data are not available for HMO enrollees. Finally, we excluded about 560 records because the data indicated more than 90 physician visits in a six-month period (likely recording errors). These exclusions resulted in two files, as shown in Table 1, with a total sample size of 303,555. Note that the 2000 file is a little larger than the 1999 file due to increased Medicare eligibility.

We followed detailed methods described in Gardner, Hendricks, and Wolfsfeld (2008) for cleaning and linking Medicare files with VA files. For analytic purposes, we divided the two years of data into four six-month periods (1999-a, 1999-b, 2000-a, and 2000-b). We excluded 2000-b from our analysis due to concern that the data might not have been complete at the time of extraction by the Centers for Medicare and Medicaid Services (CMS) because of lags in Medicaid claims processing. Consequently, we had two six-month outcome periods for analysis (1999-b and 2000-a), with 1999-a used exclusively for lagged values. Individuals were included in each outcome period only if they survived to the end of the period.

Our model relies on the fractions of physician visits financed by different payers to measure the fragmentation of financing. We calculated this fragmentation measure on an annual basis, so we had to exclude those who had zero physician visits during the year. This reduced our sample by almost 8,000 in each year (5%). The final sample was 287,681 (Table 1).

Table 1. Derivation of sample

Sample after excluding:	1999	2000	Total
	186,494	209,018	395,512
Nursing home residents	184,691	207,215	391,906
Missing data	179,181	200,184	379,365
Died in six-month period [a]	173,252	193,778	367,030
Enrolled in Medicare HMO	144,934	159,182	304,116
Current or lagged utilization > 90	144,658	158,897	303,555
Fragmentation measure could not be calculated [b]	136,721	150,960	287,681

[a] Six-month periods for analysis were the second six months in 1999 and the first six months in 2000. Lagged utilization was measured in the first six months of 1999 for the 1999 groups and in the second six months of 1999 for the 2000 groups.
[b] Those with utilization = 0 in the current year were excluded from our sample because our measure of fragmentation could not be constructed for them.

Our sample was 98% male, with an average age in 2000 of 71 (Table 2). Most had access to VA services with minimal copays, with 27% receiving high priority status due to service-connected disability and 57% due to low income and assets. The average percent nonwhite in the zip code of residence was 22%, and the average per capita income in the zip code was $19,208. The unadjusted six-month probability of ACSC hospitalization was 4.3%, and the mean number of visits to the doctor was about seven. Tabulations of the data by period show that the average proportion of physician visits that occurred in the VA was 58% in 1999-b and 54% in 2000-a (data not shown). Approximately 27% of the sample relied exclusively on the VA for physician visits in both periods, while the percentage that relied exclusively on Medicare grew from 11% to 16%.

Variable Definitions

Fragmented financing. To answer our empirical question we need a measure of fragmentation of health care financing. This is not a standard concept with a widely accepted definition, so we followed an approach similar to that used in the study of the effects of ethnic fragmentation on economic growth (e.g., Alesina and La Ferrara 2005). We began by categorizing all physician visits as either VA- or Medicare-financed. In our preferred specification, the degree of fragmentation was defined as one minus the maximum of the percentages of physician visits covered by VA or Medicare financing. This variable ranged from zero to .5 by construction, with zero indicating that all of an individual's physician visits were financed by either the VA or Medicare. The mean was .11. If an individual had no physician visits during the period, fragmentation was coded as missing. We present results using this measure because they are easiest to interpret. To check robustness, we obtained similar results with an alternative measure defined as one minus the sum of squared shares of physician visits (results from alternative specifications are available from the authors).

Outpatient physician visits can be counted in VA data by identifying outpatient encounters with appointment types that correspond to physician services. Although there are data available on all types of appointments, the VA focuses on 49 types to monitor how quickly facilities are providing appointments to patients. These 49 clinic appointment types are used because they are: 1) appointment types with high volumes, 2) appointment types that cover 93% of office-based patient-provider interactions in the VA (versus other services, such as labs or telephone consultations), and 3) appointment types that represent all major subspecialties of medicine (e.g., mental health, orthopedics) (Baar 2005).

We counted physician visits in Medicare data by relying on codes for type of service (physician) and place of service (home, office, outpatient hospital, ER, clinic, and several others). To determine the number of visits covered by each claim (almost always one visit), we followed methods described by Gardner, Hendricks, and Wolfsfeld (2008). Constructed this way, a few observations had physician visit numbers that were not credible. We excluded observations with more

Table 2. Sample statistics ($N = 287{,}681$)

Variable	Mean	Standard deviation	Minimum	Maximum
Fragmentation	.113	.154	.000	.500
ACSC hospitalization	.043	.203	.000	1.000
Outpatient utilization	7.042	7.514	.000	90.000
Fragmentation tobit residual	.133	.158	−.485	.754
Distance to VA (miles)	17.088	18.224	.000	848.642
Observation in 2000-a	.525	.499	.000	1.000
Hospital beds per 1,000	2.941	.647	1.450	5.120
Medicare Advantage penetration	.153	.112	.001	.397
Percent nonwhite in zip code	21.8	23.1	.000	100
Per capita income in zip code (000s$)	19.208	7.029	1.269	162.075
VA priority status 1–3	.274	.446	.000	1.000
VA priority status 5	.569	.495	.000	1.000
Female	.024	.152	.000	1.000
Age in years	70.95	10.178	22	108
AIDS	.003	.056	.000	1.000
Alcohol abuse	.028	.164	.000	1.000
Blood loss anemia	.005	.070	.000	1.000
Arrhythmias	.099	.299	.000	1.000
Congestive heart failure	.088	.283	.000	1.000
Chronic pulmonary disease	.174	.379	.000	1.000
Coagulopathy	.018	.132	.000	1.000
Deficiency anemias	.066	.249	.000	1.000
Depression	.057	.232	.000	1.000
Diabetes	.206	.405	.000	1.000
Drug abuse	.011	.104	.000	1.000
Fluid and electrolyte disorders	.037	.188	.000	1.000
Hypertension	.433	.495	.000	1.000
Hypothyroidism	.033	.179	.000	1.000
Liver disease	.010	.099	.000	1.000
Metastatic cancer	.008	.089	.000	1.000
Obesity	.047	.211	.000	1.000
Other neurological disorders	.042	.201	.000	1.000
Paralysis	.013	.112	.000	1.000
Peptic ulcer	.020	.140	.000	1.000
Peripheral vascular disorders	.081	.272	.000	1.000
Psychoses	.072	.259	.000	1.000
Pulmonary circulation disorders	.006	.078	.000	1.000
Renal failure	.027	.162	.000	1.000
Rheumatoid arthritis	.020	.139	.000	1.000
Tumor without metastases	.117	.321	.000	1.000
Valvular disease	.037	.188	.000	1.000
Weight loss	.006	.076	.000	1.000

than 90 visits in a six-month period (less than .2% of the sample).

ACSC hospitalization. We used methodology developed by the Agency for Healthcare Research and Quality (AHRQ) to identify hospitalizations for ambulatory care sensitive conditions (AHRQ 2001). AHRQ specifies diagnosis and procedure codes to define qualifying inpatient admissions. We used 13 of the 16 defined types of admissions, excluding those featuring pediatric diagnoses. Selected types of admissions included uncontrolled diabetes, complications of diabetes, congestive heart failure, asthma, chronic obstructive pulmonary disorder, and bacterial pneumonia. Inpatient admissions were screened as potential ACSC hospitalizations if they generated a claim in Medicare administrative files or a utilization record in VA files. We coded these events in our four six-month time periods using the admission date to locate each event in time.

Distance to the VA. We used a database developed by the VA Planning Systems

Support Group (PSSG) that contains distances from each zip code to the nearest VA facility, by type of facility. This database is available to authorized individuals for download on the PSSG website.

Diagnosis groups. Using California inpatient hospitalization data, Elixhauser et al. (1998) defined an extensive list of comorbidities and examined the effect of these comorbidities on hospital length of stay, hospital charges, and mortality. Conditions were defined as comorbid if they were not related to the primary reason for hospitalization and were likely to be significant contributors to hospital resource use and mortality. Thirty comorbidities significantly predicted increases in hospital length of stay, cost, and mortality. These potentially important risk adjusters include a wide variety of physical and mental conditions such as diabetes, neurological disorders, chronic pulmonary disease, depression, alcohol abuse, and drug abuse.

We used the *International Classification of Diseases, ninth revision* (ICD-9-CM), diagnosis codes listed in Elixhauser et al. (1998) to define 30 comorbidity indicator variables to risk adjust the outcomes in our models. For all veterans in our samples, we extracted diagnosis codes from all inpatient and outpatient encounters financed by the VA or Medicare. We created four sets of comorbidity indicators based on the diagnosis codes extracted from the same four six-month periods defined previously. We used lagged comorbidity indicators to estimate each equation to avoid simultaneous determination of outcomes and risk-adjustment variables.

Additional variables. We extracted each individual's age and sex from VA administrative records, as well as his or her VA priority status. Priority status is a function of a veteran's service-connected disability rating and score on the VA means test. To control for race, we linked individuals to the percentage of residents in their zip code who were nonwhite in the 2000 census. We chose this approach to race because the individual-level race data in VA records are known to be incomplete and unreliable (VIReC, 2004). We included per capita income in the zip code of residence, also extracted from the 2000 census. To control for geographic differences in hospital capacity we included the number of acute care hospital beds per thousand residents in 1996 by hospital referral region as reported by the Dartmouth Atlas of Healthcare (Dartmouth, 2010). We also included state-level Medicare Advantage HMO market penetration from the July 1999 State County Plan market penetration file, downloaded from the CMS website (www.cms.hhs.gov). Finally, we included indicator variables for the nine census divisions to control for remaining regional differences in practice patterns or unobserved health status.

Results

The fragmented financing model specified by equation 1 was estimated by two-limit tobit, producing the results reported in Table 3. The estimated effect of our identifying variable indicates that veterans living farther away from VA facilities had financing that is more fragmented. This effect is consistent with the fact that low-income veterans typically rely fairly heavily on VA care, but will use it less if it is far away. The estimate is highly statistically significant with an F-statistic of 353, well beyond the standard threshold for detecting weak instruments (Staiger and Stock 1997).

Other results from the fragmented financing model indicate that older veterans had more fragmented financing, while those residing in zip codes with more nonwhites or higher per capita income had less. Again, these results are consistent with the idea that reliance on VA care is fairly heavy in this sample, so increased use of non-VA services tends to be correlated with more fragmented financing. Older veterans are more likely to have higher utilization, making some non-VA options more attractive. Veterans living in zip codes with high percentages of nonwhites may be less likely to have employer-sponsored Medicare supplements, making non-VA options less affordable. Local non-VA practice pattern variation might affect fragmentation too, which would be consistent with the estimates indicating that a larger number of hospital beds per 1,000 residents was associated with higher fragmentation and

Table 3. Fragmented financing two-limit tobit model estimates

Variable	Coefficient	Standard error	*t*-statistic	*P*-value
Distance to VA	.001	.000	18.790	.000
Observation in 2000-a	.023	.001	17.990	.000
Hospital beds per 1,000	.009	.001	6.970	.000
Medicare Advantage penetration	−.051	.008	−6.150	.000
Percent nonwhite in zip code	−.138	.003	−43.580	.000
Per capita income in zip code	−.001	.000	−9.590	.000
VA priority status 1–3	.033	.002	16.540	.000
VA priority status 5	.017	.002	9.220	.000
Female	−.003	.004	−.840	.402
Age in years	.003	.000	35.990	.000
AIDS	−.006	.012	−.520	.604
Alcohol abuse	−.005	.004	−1.150	.252
Blood loss anemia	.000	.009	.030	.979
Arrhythmias	.023	.002	10.810	.000
Congestive heart failure	.024	.002	10.410	.000
Chronic pulmonary disease	.035	.002	20.990	.000
Coagulopathy	.019	.005	4.220	.000
Deficiency anemias	.010	.003	3.790	.000
Depression	.028	.003	10.040	.000
Diabetes	.022	.002	14.080	.000
Drug abuse	.048	.007	7.300	.000
Fluid and electrolyte disorders	.007	.003	1.980	.048
Hypertension	.047	.001	34.950	.000
Hypothyroidism	.030	.003	8.880	.000
Liver disease	.015	.006	2.350	.019
Metastatic cancer	−.015	.007	−2.150	.032
Obesity	.005	.003	1.740	.082
Other neurological disorders	.037	.003	12.110	.000
Paralysis	.020	.006	3.610	.000
Peptic ulcer	.024	.004	5.580	.000
Peripheral vascular disorders	.019	.002	8.220	.000
Psychoses	.011	.003	4.250	.000
Pulmonary circulation disorders	.008	.008	1.070	.284
Renal failure	.022	.004	5.790	.000
Rheumatoid arthritis	.033	.004	7.680	.000
Tumor without metastases	.024	.002	12.340	.000
Valvular disease	.026	.003	8.070	.000
Weight loss	−.049	.008	−5.830	.000
N = 287,681				
Pseudo R-squared =.042				

Note: Estimates omitted for intercept and eight indicator variables for census divisions.

higher Medicare Advantage market penetration was associated with lower fragmentation.

Of 28 diagnosis groups, 21 had significant and positive effects on the level of financing fragmentation. This is expected because individuals with more complex and acute needs for services are more likely to seek care from multiple sources, taking advantage of differences in covered services, provider networks, and convenience to optimize their care. The same reasoning applies to the VA priority status variables and (because higher-income individuals tend to be healthier) to per capita income. The trend indicates that fragmentation increased for this sample over time.

The next pair of models are ACSC hospitalization models corresponding to equation 2. The first version (Table 4) was estimated by two-stage least squares and the second version (Table 5) combined estimates from the two-limit tobit and an ACSC hospitalization probit. Results from the linear model indicate that fragmentation was strongly associated with higher probability of ACSC hospitalization, with a one-standard deviation increase in fragmentation leading

Table 4. Two-stage least squares ACSC hospitalization estimates

Variable	Coefficient	Standard error	*t*-statistic	*P*-value
Fragmentation	.181	.078	2.330	.020
Observation in 2000-a	.008	.001	8.190	.000
Hospital beds per 1,000	.004	.001	4.690	.000
Medicare Advantage penetration	.016	.005	2.960	.003
Percent nonwhite in zip code	.017	.005	3.450	.001
Per capita income in zip code	.000	.000	.480	.633
VA priority status 1–3	−.034	.002	−20.570	.000
VA priority status 5	−.038	.001	−30.220	.000
Female	−.003	.002	−1.160	.245
Age in years	.000	.000	3.630	.000
AIDS	.015	.007	2.310	.021
Alcohol abuse	−.001	.002	−.240	.814
Blood loss anemia	−.004	.005	−.800	.421
Arrhythmias	.012	.001	8.150	.000
Congestive heart failure	.075	.002	46.210	.000
Chronic pulmonary disease	.053	.001	36.270	.000
Coagulopathy	.005	.003	1.680	.093
Deficiency anemias	.014	.002	8.620	.000
Depression	.007	.002	3.810	.000
Diabetes	.022	.001	19.640	.000
Drug abuse	.002	.004	.470	.639
Fluid and electrolyte disorders	.036	.002	17.180	.000
Hypertension	−.008	.002	−4.790	.000
Hypothyroidism	−.001	.002	−.450	.652
Liver disease	−.007	.004	−1.750	.081
Metastatic cancer	.023	.004	5.100	.000
Obesity	−.006	.002	−3.370	.001
Other neurological disorders	.006	.002	2.910	.004
Paralysis	.014	.003	4.140	.000
Peptic ulcer	.005	.003	1.750	.081
Peripheral vascular disorders	.012	.001	8.450	.000
Psychoses	−.002	.002	−1.380	.167
Pulmonary circulation disorders	.071	.005	14.670	.000
Renal failure	.042	.002	17.570	.000
Rheumatoid arthritis	−.001	.003	−.330	.738
Tumor without metastases	−.001	.001	−.440	.659
Valvular disease	.006	.002	2.740	.006
Weight loss	.027	.005	5.260	.000
N = 287,681				
R-squared = .039				
Exogeneity of fragmentation rejected by two-stage residual inclusion test (t = −2.2; P = .03)				

Note: Estimates omitted for constant term and eight indicator variables for census divisions.

to a 2.9-percentage-point (67%) increase in probability. As a formal test of the endogeneity of fragmentation, we included the residual from the linear first-stage equation in an alternative specification of the second stage (Terza, Basu, and Rathouz 2008). If the estimated coefficient on the residual is significantly different from zero then exogeneity of fragmentation is rejected. This test produced a t-statistic of −2.2 (P = .03), rejecting exogeneity of fragmentation. Other estimates show that ACSC hospitalization rates rose over time and were higher for older people and in areas with more nonwhites, more hospital beds, and higher Medicare Advantage penetration. ACSC hospitalization rates were lower for high-priority veterans. Of the diagnosis groups, 16 of 28 were significantly associated with higher risk while only two were significantly associated with lower risk. These results are generally consistent with the idea that clinical complexity (age, diagnoses) intensifies risk, while access to care (priority status, white race) reduces risk.

Table 5. ACSC hospitalization probit estimates

Variable	Coefficient	Standard error[a]	*Z*-statistic	*P*-value	Marginal effect[b]
Fragmentation	.815	.382	2.140	.033	.058
Fragmentation residual	−.320	.386	−.830	.407	−.023
$(\text{F residual})^2$	.143	.548	.260	.794	.010
$(\text{F residual})^3$	−6.162	2.069	−2.980	.003	−.435
$(\text{F residual})^4$	8.784	2.476	3.550	.000	.620
Observation in 2000-a	.090	.012	7.430	.000	.006
Hospital beds per 1,000	.046	.010	4.450	.000	.003
Medicare Advantage penetration	.179	.071	2.510	.012	.013
Percent nonwhite in zip code	.172	.063	2.720	.006	.012
Per capita income in zip code	.000	.001	−.360	.723	.000
VA priority status 1–3	−.302	.018	−16.610	.000	−.019
VA priority status 5	−.360	.013	−27.850	.000	−.027
Female	−.060	.033	−1.850	.064	−.004
Age in years	.006	.001	5.680	.000	.000
AIDS	.225	.079	2.840	.004	.020
Alcohol abuse	.024	.027	.890	.372	.002
Blood loss anemia	−.064	.048	−1.320	.187	−.004
Arrhythmias	.091	.016	5.580	.000	.007
Congestive heart failure	.456	.016	28.790	.000	.046
Chronic pulmonary disease	.472	.017	28.410	.000	.045
Coagulopathy	.035	.028	1.250	.213	.003
Deficiency anemias	.098	.016	6.130	.000	.008
Depression	.065	.022	3.000	.003	.005
Diabetes	.231	.013	17.860	.000	.019
Drug abuse	.028	.047	.610	.544	.002
Fluid and electrolyte disorders	.186	.019	9.870	.000	.015
Hypertension	−.066	.020	−3.330	.001	−.005
Hypothyroidism	−.010	.025	−.400	.688	−.001
Liver disease	−.052	.045	−1.150	.250	−.003
Metastatic cancer	.187	.042	4.450	.000	.016
Obesity	−.059	.022	−2.690	.007	−.004
Other neurological disorders	.069	.026	2.690	.007	.005
Paralysis	.154	.038	4.090	.000	.013
Peptic ulcer	.046	.031	1.510	.132	.003
Peripheral vascular disorders	.095	.017	5.570	.000	.007
Psychoses	−.030	.018	−1.610	.107	−.002
Pulmonary circulation disorders	.278	.038	7.360	.000	.025
Renal failure	.254	.022	11.320	.000	.022
Rheumatoid arthritis	−.007	.032	−.230	.818	−.001
Tumor without metastases	−.006	.016	−.390	.699	.000
Valvular disease	.042	.023	1.830	.068	.003
Weight loss	.136	.050	2.720	.006	.011
$N = 287{,}681$					

Note: Estimates omitted for constant term and eight indicator variables for census divisions.
[a] Bootstrapped standard errors calculated with 400 replications.
[b] Marginal effects for indicator variable (D_j) calculated as $\Pr(\text{mean}|D_j=1) - \Pr(\text{mean}|D_j=0)$.

Results from the nonlinear model typically have the same signs as the linear versions, but effect sizes are different in some cases. In particular, the estimated marginal effect of the exogenous component of fragmentation was .058, implying that a one-standard deviation increase in fragmentation would lead to a .92-percentage-point increase in probability, which is 21% of the observed rate. This is a large effect, comparable to the binary effects of arrhythmia, anemia, or peripheral vascular disease. The direction of the effect is consistent with our hypothesis that fragmented financing leads to coordination failure and lower quality care.

Although these results are consistent with our fragmented financing and coordination failure hypothesis, it is also possible that our

findings do not reflect coordination failure at all, but rather arise from some unmeasured factor that is correlated with fragmented financing and ACSC hospitalization. The natural candidate for this kind of omitted variable bias would be access to inpatient hospital care. This variable ought to be correlated with ACSC hospitalization because areas with good access to hospital care might have high ACSC hospitalization rates. On the other hand, our results relate to the exogenous component of fragmented financing, identified by variation in distance to VA facilities. While this identifying instrument is strongly related to individual-level fragmented financing, it is not obvious that it should be related to access to hospital care in general. As a test, we estimated a regression model adapted from equation 2 with hospitalization for trauma as the dependent variable (see Prentice and Pizer 2007 for ICD-9 codes). We chose hospitalizations for trauma because, unlike ACSC hospitalizations, these events are very unlikely to reflect coordination failures and disruptions in continuity of care. In contrast to the ACSC hospitalization result, we found no significant relationship between fragmented financing and hospitalization for trauma (Table 6). Thus, the exogenous component of fragmentation increased the probability of ACSC hospitalization while having no effect on the risk of hospitalization for trauma. This suggests that our finding with respect to ACSC hospitalization was not driven by local differences in access to hospital care, although it is also possible that hospitalizations for trauma are not sufficiently sensitive to these differences.

Conclusion

We used a two-stage residual inclusion model to estimate the effects of fragmented financing on ACSC hospitalization, controlling for health status, demographics, and simultaneous determination of financing and outcome. We found that fragmented financing has a statistically significant effect on the probability of ACSC hospitalization and that the magnitude of this effect is relatively large—comparable to the effects of serious health conditions like arrhythmia, anemia, and peripheral vascular disease. It is not possible to directly compare our results to previous studies in the literature on continuity of care, but some information is available. The most relevant published estimates come from Gill and Mainous (1998) and Mainous and Gill (1998). The first of these studies described the relationship between hospitalization and an index of single-provider continuity of care among Delaware Medicaid patients. It found a strong relationship, with high-continuity groups having hospitalization odds ratios of .56 (all causes) and .54 (chronic ambulatory care sensitive conditions). The second study demonstrated that continuity at a site of care does not appear to have the beneficial effects of single-provider continuity. These studies differ from ours in population, analytic methods, and definitions of fragmentation and outcomes, but the magnitude of their estimates is consistent with our own.

To further confirm these results, additional research should examine whether other quality of care measures are also affected by fragmented financing. Such measures might include receipt of recommended screening tests, immunizations, and regular examinations for those with particular chronic conditions. Measurements of self-care like medication adherence rates might also be affected by fragmented financing and might help explain variation in ACSC hospitalization rates. We plan to investigate these relationships in future work.

An objection to our model could be that distance to the VA might not be truly exogenous. This would be the case if, for example, individuals who become ill move their residences to be closer to VA hospitals or clinics. To the extent this occurs, sicker individuals would have shorter distances to the VA and less fragmentation, leading our results to be biased towards zero. Our estimates may be conservative for this reason.

Another important limitation of this study is that our results might not be generalizable to the entire population. Our sample consisted of low-income and disabled veterans who had some contact with the VA and who had one or more physician visits. This is a group that has relatively high demand for health services and may be particularly vulnerable

Table 6. Hospitalization for trauma probit estimates

Variable	Coefficient	Standard error	*Z*-statistic	*P*-value
Fragmentation	−1.011	.806	−1.250	.209
Fragmentation residual	1.134	.795	1.430	.154
$(\text{F residual})^2$	2.558	.976	2.620	.009
$(\text{F residual})^3$	−8.291	3.270	−2.540	.011
$(\text{F residual})^4$	8.450	3.842	2.200	.028
Observation in 2000-a	.042	.025	1.660	.096
Hospital beds per 1,000	.007	.020	.330	.742
Medicare Advantage penetration	−.030	.133	−.230	.821
Percent nonwhite in zip code	−.120	.130	−.930	.354
Per capita income in zip code	.003	.002	1.540	.123
VA priority status 1–3	−.164	.037	−4.490	.000
VA priority status 5	−.250	.027	−9.170	.000
Female	.183	.051	3.620	.000
Age in years	.012	.002	5.350	.000
AIDS	−.050	.200	−.250	.804
Alcohol abuse	.121	.050	2.410	.016
Blood loss anemia	.075	.109	.690	.490
Arrhythmias	.034	.036	.950	.342
Congestive heart failure	.026	.034	.770	.441
Chronic pulmonary disease	.092	.037	2.520	.012
Coagulopathy	.072	.059	1.220	.222
Deficiency anemias	.127	.031	4.180	.000
Depression	.159	.039	4.050	.000
Diabetes	.059	.030	1.970	.049
Drug abuse	.284	.086	3.300	.001
Fluid and electrolyte disorders	.136	.037	3.680	.000
Hypertension	−.014	.042	−.320	.747
Hypothyroidism	.067	.053	1.270	.205
Liver disease	.299	.069	4.350	.000
Metastatic cancer	−.027	.093	−.290	.769
Obesity	−.051	.047	−1.100	.273
Other neurological disorders	.254	.046	5.540	.000
Paralysis	.366	.051	7.220	.000
Peptic ulcer	.045	.058	.770	.439
Peripheral vascular disorders	.083	.030	2.800	.005
Psychoses	.043	.036	1.200	.229
Pulmonary circulation disorders	.230	.085	2.700	.007
Renal failure	.041	.060	.690	.491
Rheumatoid arthritis	.070	.064	1.090	.276
Tumor without metastases	.070	.033	2.140	.033
Valvular disease	.067	.052	1.290	.196
Weight loss	.041	.094	.430	.664
N = 287,681				

Notes: Estimates omitted for constant term and eight indicator variables for census divisions.
Bootstrapped standard errors calculated with 400 replications.

to access problems posed by bureaucratic boundaries between programs. In contrast, those who do not use health services clearly are not vulnerable to disruptions in continuity of care. Furthermore, a transition from one HMO or preferred provider organization (PPO) to another in the commercial market might not have the same disruptive effects as those measured here, particularly if provider networks happen to overlap. Nevertheless, the size of the effect detected in this study suggests that fragmented financing is a serious problem, at least for those who use health services regularly and rely on financing arrangements that feature restrictive provider networks.

Returning to the issue that motivated this study: Does fragmented financing meaningfully disrupt continuity of care? Our results suggest that fragmented financing increases

the risk of coordination failures that result in ACSC hospitalizations, so the effect on quality of care is important for individual patients. Beyond this, there is a financial impact as well because potentially avoidable hospitalizations are costly. We can begin to get an idea of the financial cost with some fairly simple calculations. In 1999 and 2000, the average Medicare payment for an ACSC hospitalization in our sample was $5,249. If the average degree of fragmentation in our sample was reduced by one standard deviation, the average six-month probability of ACSC hospitalization would have declined from 4.3% to 3.2%, which translates into $96 per person per year ($48 per six-month period). This is equivalent to a 3% reduction in total Medicare hospital spending per beneficiary in 2000, a financially significant effect, suggesting that fragmented financing has substantial costs that have not previously been considered.

Given these human and financial costs, policy initiatives to reduce fragmented financing are warranted. For veterans, such initiatives include the ongoing expansion of community-based outpatient clinics and efforts to reduce the number of days between appointment requests and scheduled visits. For all Americans, integration of electronic medical records between providers in different networks might reduce coordination failures and improve outcomes. Finally, as health insurance reform legislation is implemented over the next few years, some individuals will obtain coverage through regional insurance exchanges instead of through employer-based groups. These arrangements may be more stable through time, leading to fewer disruptions in patient-provider relationships.

Notes

All opinions expressed are those of the authors and do not necessarily reflect the official position of the U.S. Department of Veterans Affairs or Boston University. The authors wish to thank two anonymous referees, Partha Deb, Jane Ruseski, and participants at the American Society of Health Economists and Allied Social Science Association conferences for helpful comments on an earlier version of this paper. The authors have no potential conflicts of interest to disclose.

References

Agency for Healthcare Research and Quality (AHRQ). 2001. Quality Indicators-Guide to Prevention Quality Indicators: Hospital Admission for Ambulatory Care Sensitive Conditions. AHRQ Pub No. 02-R0203. Rockville, Md.: Agency for Healthcare Research and Quality.

Alesina, A., and E. La Ferrara. 2005. Ethnic Diversity and Economic Performance. *Journal of Economic Literature* 43(3):762–800.

Baar, B. 2005. New Patient Monitor: Data Definitions. Salt Lake City, Utah: Veterans Health Administration Support Services Center.

Borowsky, S. J., and D. C. Cowper. 1999. Dual Use of VA and Non-VA Primary Care. *Journal of General Internal Medicine* 14(5):274–280.

Burgess, J. F. Jr., and D. A. DeFiore. 1994. The Effect of Distance to VA Facilities on the Choice and Level of Utilization of VA Outpatient Services. *Social Science & Medicine* 39(1):95–104.

Chernew, M. E., W. P. Wodchis, D. P. Scanlon, et al. 2004. Overlap in HMO Physician Networks. *Health Affairs* 23(2):91–101.

Cunningham, P. J., and L. Kohn. 2000. Health Plan Switching: Choice or Circumstance? *Health Affairs* 19(3):158–164.

Currie, J., and B. C. Madrian. 1999. Health, Health Insurance and the Labor Market. In *Handbook of Labor Economics,* Vol. 3, O. Ashenfelter and D. Card, eds. Amsterdam: Elsevier Science.

Danzon, P. M. 1992. Hidden Overhead Costs: Is Canada's System Really Less Expensive? *Health Affairs* 11(1):21–43.

Dartmouth Atlas of Healthcare. 2010. Acute Care Hospital Beds per 1,000 Residents. 1996 database downloaded from www.dartmouthatlas.org. Accessed December 23, 2010.

Efron, B. 1979. Bootstrap Methods: Another Look at the Jackknife. *The Annals of Statistics* 7(1):1–26.

Elixhauser, A., C. Steiner, D. R. Harris, et al. 1998. Comorbidity Measures for Use With Administrative Data. *Medical Care* 36(1):8–27.

Fleming, C., E. S. Fisher, C. Chang, et al. 1992. Studying Outcomes and Hospital Utilization in

the Elderly: The Advantages of a Merged Database for Medicare and Veterans Affairs Hospitals. *Medical Care* 30(5):377–391.

Frank, R. G., and R. J. Zeckhauser. 2007. Custom-made Versus Ready-to-wear Treatments: Behavioral Propensities in Physicians' Choices. *Journal of Health Economics* 26:1101–1127.

Gardner, J. A., A. M. Hendricks, and L. Wolfsfeld. 2008. Analyzing Medicaid Utilization and Expenditures: A Guide for VA Researchers. HCFE Data Brief 2008-01. www.hcfe.research.va.gov.

Gill, J. M. 1997. Can Hospitalization Be Avoided by Having a Regular Source of Care? *Family Medicine* 9:166–171.

Gill, J. M., and A. G. Mainous. 1998. The Role of Provider Continuity in Preventing Hospitalizations. *Archives of Family Medicine* 7:352–357.

Gill, J. M., A. G. Mainous, and M. Nsereko. 2000. The Effect of Continuity of Care on Emergency Department Use. *Archives of Family Medicine* 9:333–338.

Haggerty, J., R. Reid, K. Freeman, et al. 2003. Continuity of Care: A Multidisciplinary Review. *British Medical Journal* 327:1219–1221.

Heckman, J. J. 1979. Sample Selection Bias as a Specification Error. *Econometrica* 47:153–161.

Mainous, A. G., and M. Gill. 1998. The Importance of Continuity of Care in the Likelihood of Future Hospitalization: Is Site of Care Equivalent to Primary Clinician? *American Journal of Public Health* 88:1539–1541.

Mark, T. I., and C. Paramore. 1996. Pneumococcal Pneumonia and Influenza Vaccination Access to and Use by U.S. Hispanic Medicare Beneficiaries. *American Journal of Public Health* 86:1545–1550.

Newey, W. K., J. L. Powell, and F. Vella. 1999. Nonparametric Estimation of Triangular Simultaneous Equations Models. *Econometrica* 67(3):565–603.

Prentice, J. C., and S. D. Pizer. 2008. Waiting Times and Ambulatory Care Sensitive Condition Hospitalizations. *Health Services and Outcomes Research Methodology* 8(1):1–18.

Shen, Y., A. Hendricks, S. Zhang, and L. Kazis. 2003. VHA Enrollees' Health Care Coverage and Use of Care. *Medical Care Research and Review* 60(2):253–267.

Staiger, D., and J. Stock. 1997. Instrumental Variables Regression with Weak Instruments. *Econometrica* 65:557–586.

Starfield, B. 1998. *Primary Care: Balancing Health Needs, Service, and Technology*. New York: Oxford University Press.

Terza, J. V., A. Basu, and P. J. Rathouz. 2008. Two-stage Residual Inclusion Estimation: Addressing Endogeneity in Health Econometric Modeling. *Journal of Health Economics* 27: 531–543.

VIReC Data Issues Brief, March 2004. Hines, Ill.: VA Information Resource Center. http://www.virec.research.va.gov/References/DataIssuesBrief/DIB_Arch_2004.htm. Accessed January 28, 2008.