Online Appendix:

Hospital Network Competition and Adverse Selection

Mark Shepard

August 2021

A Appendix: Data Construction and Summary Statistics

A.1 Hospitalization Dataset Construction

To estimate the hospital choice and prices model, I use the CommCare insurance claims data to construct a dataset of enrollees' inpatient hospitalizations at acute care hospitals in Massachusetts. Constructing hospital visits from claims data involves extensive cleaning. I base my procedure on a method used by the Health Care Cost Institute (Health Care Cost Institute, 2015; see also Cooper et al., 2019), modified to my setting and the nature of the CommCare insurer claims.

I start by flagging inpatient hospital facility claims, based on having a valid site of service code[1] plus either a valid revenue code for "room and board" services[2] or a valid DRG code. I further restrict to claims where the billing provider is a Massachusetts acute care hospital, which excludes out-of-state hospitals (relatively rare, but for which I do not have network information) and inpatient stays at skilled nursing facilities, psychiatric hospitals, and rehab hospitals (many of which are also for mental health/substance abuse, which is quite common in the CommCare data).[3] I do retain claims for several prominent specialty hospitals: New England Baptist (orthopedics), Mass Eye & Ear Infirmary, Dana Farber Cancer Institute, and Boston Children's Hospital. However, these are relatively uncommon (<1% of admissions combined).

Using this dataset of inpatient hospital facility claims, I define inpatient "episodes," which includes all consecutive days when a patient is hospitalized. This sometimes includes multiple adjacent admissions (typically when a patient is transferred), which I will subsequently split out. I group together all adjacent/overlapping inpatient hospital facility claims based on the admission and discharge dates on the claims.[4] Using this episode sample, I then add on *all* claims (including professional and ancillary

[1]The inpatient site of service codes are: (for the UB-04 bill type) U11, U12, U15, U16, U18, and (for CMS-1500 bill type) C21.

[2]Specifically, these include: all-inclusive codes 100-101; room and board codes 110-159, excluding the codes for hospice and rehabilitation; and ICU and CCU codes 200-219. I do not include newborn nursery codes, since all CommCare enrollees are adults.

[3]I define providers using a hand-constructed dataset made from the provider name, type, and location reported on the claims' provider file.

[4]These dates typically make sense and are consistent within claims for a hospitalization. But some hospitals appear to submit multiple adjacent-dated claims for each hospitalization (e.g., one claim per day, with admit date = discharge date). This procedure groups these together into a single admission. As a safeguard, I drop a tiny number of episodes (0.01%) where this extends the implied length of stay by more than 14 days.

services) that occurred on a day the patient was admitted.[5] I also include emergency department (ED) and ED observation visits that occur the day prior to admission.[6]

From this dataset of all claims for a hospitalization episode, I collapse the data to the hospitalization level. I calculate insurer payment and patient cost sharing amounts by summing across all claim lines – both total and separately for inpatient facility claims, professional services, and outpatient facility claims (typically ED visits). I define the principal diagnosis using the primary (first) diagnosis code associated with the main inpatient facility claims for the hospitalization.[7] For my model I categorize principal diagnoses into Clinical Classifications Software (CCS) codes – a useful grouping defined by the U.S. Agency for Healthcare Research and Quality (AHRQ) that collapses detailed ICD-9 codes into about 280 clinically meaningful categories. I define comorbidities using dummy variables for Elixhauser categories – based on whether an associated diagnosis code appears as a primary or secondary diagnosis on any of the claim lines for the hospitalization. I define the DRG using the value reported on the inpatient facility claims when available (86% of episodes).[8] These reported DRGs are mostly MS-DRGs version 25, though versions 23-24 and APR-DRGs also appear on the data. Since my goal is to have a consistent service unit measure for inpatient pricing (see Appendix C.2), I either map earlier-version MS-DRGs to version 25 (where the match is appropriate) or into a unique DRG category (to avoid a false overlap with version 25).[9] In the 14% of cases with no reported DRG, I leave the DRG as missing and instead use the CCS code of the principal diagnosis as the service unit for the hospital price model.

Finally, I limit the sample in several ways to facilitate estimation and exclude admissions where the data may be incorrect. Starting from a sample of 81,179 episodes, I exclude 1,780 (2.2% of the sample) where the episode included admissions at multiple different hospitals; in these cases (which are likely transfers), the patient choice is ambiguous. I further exclude 1,245 episodes (1.5% of the sample) where the total facility paid amount is <\$100 (most of these are \$0); these are likely either errors, denied claims, or corner cases where my data cleaning procedure fails to work properly. Next, I exclude 2,184 admissions from FY 2007 (for which I do not have network information), 5,552 episodes from FY 2014 (which is outside my sample period of interest), and 2 admissions that lack both DRG and principal diagnosis information. Finally, I exclude admissions where the patient zip code is missing/invalid (17 cases, 0.02% of the sample) or the patient used a hospital more than 100 miles away (305 cases, 0.39%

[5] I exclude a small number of claim lines (0.3%) added via this procedure that occur at non-acute hospitals. These are often claims for a post-acute/rehab stay that begins the day of discharge.

[6] Following HCCI, ED claims are identified by including a line with associated revenue codes (450-452, 456, 459, or 981) or procedure (HCPCS) codes for E&M services in the ED (99281-99292, 99466-99476). Observation stays are identified by revenue codes (760-762, or 769) or HCPCS procedure codes (99217-99220). I also use the ED claim line definition to flag whether a hospitalization was for an emergency, based on including an ED visit.

[7] The vast majority (about 90%) of hospitalizations have a single inpatient facility claim. In the remaining cases where there are multiple claims, I use the diagnosis associated with the highest total paid amounts on facility claims for the episode.

[8] In about 2% of cases, there are multiple reported DRGs. In these cases, I use the DRG associated with the inpatient claim with the highest total paid amounts.

[9] To do the mapping, I use the DRG code listed on claims when either: (1) the hospital-insurer pair pays using version 25, or (2) the hospital-insurer pair uses v23 or v24 and the DRG code definition is consistent between these versions and v25. In remaining cases, I map the DRG on the claims as a unique code, making sure it does not accidentally map to an existing v25 code. After doing this procedure, most admissions (about 74%) map to MS-DRG v25. Another 24% are version 24, and there are also a few from v23 (about 1%), APR-DRG (about 1%), and unknown values (0.3%).

of the sample). The latter is a standard restriction in empirical hospital choice models that lets me keep the choice set size manageable. The final hospitalization dataset includes 70,094 hospitalizations over the FY 2008-2013 period.

A.2 Outpatient Care Provider Use Dataset Construction

As described in Section II.B, I construct a dataset of whether enrollees have used certain hospitals or their affiliated community health centers (CHC) for outpatient care. Starting from the full claims data, I exclude inpatient and emergency department care, following a similar definition as in the hospitalization dataset. Emergency department care is defined in the same way as for the hospitalization file (see Appendix A.1 above). Inpatient care is flagged based on having either a valid inpatient site of service code, a valid revenue code for “room and board” services or a valid DRG code. This definition is slightly broader than for the hospitalization dataset in that it counts care as inpatient based on the site of service code alone. My goal is to be conservative and avoid including inpatient care in my outpatient care file. After excluding these inpatient/ED claims, I limit to outpatient and professional services using a flag given by the data provider.

I code the hospital or CHC (if any) at which the outpatient care was delivered using the name of the billing provider on the claims. This process involved hand-cleaning the names on the insurance provider file. By using the billing provider, I capture services delivered by physicians employed by a hospital or treating at a hospital-owned practice. This is intentional, since these physicians are closely associated with the hospital and are excluded from network in the change I study. I link CHCs to hospital systems (e.g., Partners) using an affiliation list provided by the Connector.

This procedure should capture care given directly by the vast majority of Partners physicians. This includes specialists treating at the Partners hospital campuses, primary care physicians treating at Partners CHCs, and PCPs/specialists treating with the main Partners-owned medical groups (Mass General Physicians Organization, Brigham & Women’s Physician Organization, Brigham Community Practices, Newton Wellesley-PHO, and North Shore Physicians Group). Statistics from Massachusetts’ Registration of Provider Organization (RPO) dataset for 2015 suggest that over 90% of Partners-contracting physicians are part of these medical groups.[10] The measure will not capture physicians who are clinically affiliated with Partners but are independently owned or part of another health system so do not bill with Partners. My analysis of a clinical affiliation dataset for another project suggests that the vast majority (at least 80%) of Partners-affiliated physicians are also formally owned by Partners Healthcare System.[11]

A.3 Plan Choice and Cost Dataset Construction

The plan choice and cost dataset is described in Section II.B. It includes a dataset of available plans, plan characteristics (including premium and network), and chosen options during fiscal 2008-2013. I

[10] See RPO data publicly available at https://www.mass.gov/service-details/ma-rpo-data.

[11] The affiliation dataset comes from Massachusetts Health Quality Partners (see http://www.mhqp.org/resources-professionals/massachusetts-provider-directory-mpd/) but was purchased under a project-specific agreement so cannot be used for this paper without additional fees.

also have data on fiscal 2014 choices, which I use for robustness checks on CeltiCare's network change (Section C.1). However, I do not use it for the plan choice model or cost model estimation because I lack full claims data for 2014.

This dataset is constructed at the level of instances of enrollees making a plan choice. I start from the full enrollment dataset provided by the exchange, which includes one observation per member-month of enrollment with information on their enrolled plan and income group and demographics. I then limit this to the two instances where enrollees make a plan choice: (1) when an individual newly enrolls in CommCare (or re-enrolls after a gap), and (2) at annual open enrollment when current enrollees can switch plans. I make several exclusions from this sample for various reasons. Starting from a preliminary sample of 2,148,834 choice instances, I exclude 684 observations with missing/invalid income group or location data, 966 observations who enroll in a plan that is supposed to be unavailable based on their location, and 9,691 observations in the 200-300% of poverty income group who choose a lower-cost sharing option that was available only in 2007-08. Finally, I exclude 142,108 observations in the 0-100% of poverty group who were passively auto enrolled into a plan upon joining the exchange, since they do not make active choices that my plan choice model seeks to capture. The auto enrollment policy ended after 2009 so is not relevant for the main period of my study (see Shepard and Wagner (2021) for research studying this policy). The final sample includes 1,684,203 plan choice instances made by 624,443 unique enrollees. Summary statistics are shown in Table A.1B.

Using administrative information from CommCare, I code the available plan choice set and the premiums and networks of each available plan. I define enrollee characteristics based on demographics on the enrollment file and information summarized from the linked claims data (e.g., medical conditions and HCC risk score). I use the available plan choice dataset along with enrollee characteristics to estimate the plan choice model described in Section V.A. The sample counts in the plan choice model estimates (Table A.11) differ slightly from those reported in Table A.1B because the plan choice model drops 3.5% of instances where individuals have only a single plan available.

Table A.1: Summary Statistics

Panel A: Hospitalization Dataset

Patient Characteristics

Variable		Mean
No. of Hospitalizations		70,094
Age		44.7
Male		48%
Emergency Department		65%
Principal	Mental Illness	14.9%
Diagnosis	Digestive	13.9%
	Circulatory	11.9%
	Injury / Poisoning	7.3%
	Respiratory	7.2%
	Cancer	6.8%
	Endocrine / Metabolic	6.3%
	Musculoskeletal	6.0%
	Pregnancy / Childbirth	5.4%
	All Other Diagnoses	20.4%

Chosen Hospital Statistics

Variable	Mean	Std. Dev.
Distance: Chosen Hosp. (miles)	12.7	15.1
All Hospitals (miles)	47.5	26.1
Hospital Category		
Academic Med. Ctr.	29%	---
Teaching Hospital	18%	---
All Others	53%	---
Partners Hospital	13%	---
Out-of-Network	8%	---
Past Use of Chosen Hospital (prior to this year)		
Any Use	43%	---
Inpatient Use	14%	---
Outpatient Use	42%	---
Total Cost to Insurer	$11,140	$14,017
Price (rel. to average)	1.019	0.274

Panel B: Plan Choice and Cost Dataset

Enrollee Characteristics

Variable	Mean	Std. Dev.
No. of Unique Enrollees	624,443	---
Age	39.9	14.0
Male	46.5%	---
Immigrant enrollee	5.6%	---
Income: <100% Poverty	46.8%	---
100-200% Poverty	39.4%	---
200-300% Poverty	13.7%	---
Past Use: Any Hospital	57.6%	---
Partners Hospitals	7.8%	---
Other 2012 Dropped Hosp.	5.3%	---
Risk Score: CommCare Score	1.001	0.924
HCC Risk Score	0.924	2.374
Choice Type: New Enrollee	29.5%	---
Re-Enrollee	13.7%	---
Current Enrollee	56.8%	---

Plan Statistics

Variable	Mean	Std. Dev.
No. of Choice Instances	1,684,203	---
Insurer Price (pre-subsidy)	$383.9	$69.6
Cons. Premium: Below Poverty	$0.0	$0.0
Above Poverty	$47.9	$46.1
Costs per Month: Total	$382.3	$1,484.5
Insurer Cost	$372.5	$1,478.6
Patient Cost Sharing	$9.7	$20.5
Hospital Network Utility	0.972	3.995
Share Covered Prev. Used Hosp.	0.740	0.420
Market Shares: BMC	35.7%	---
Network Health	34.4%	---
NHP	19.1%	---
CeltiCare	7.0%	---
Fallon	3.8%	---
Current Enr: Non-Switching	95.2%	---

NOTE: The table shows summary statistics for the hospitalization dataset (panel A) and the plan choice and cost dataset (panel B). These datasets are described Section II.B. The hospitalization dataset is used to estimate the inpatient price model and the hospital choice model (Appendix F.1). The plan choice and cost dataset is used to estimate the plan choice model (Section V.A). The unit of observation for each sample is the "choice instance" – an inpatient hospitalization in panel A and an instance of making a plan choice in panel B. The latter occurs either when joining the exchange (new/re-enrollees) or during annual open enrollment when people can switch plans (current enrollees). Hospital network utility is a measure that enters the plan choice model and is described in Appendix F.2. The sample counts in Panel B differ slightly from the counts in the plan demand estimates in Table A.11 because the latter excludes 3.5% of observations where there was only one available plan choice. These do not identify plan preferences but are included in the model analysis and simulations.

B Appendix: CommCare Premium and Network Variation

B.1 Prices, Subsidies, and Enrollee Premiums

My plan choice model (Section V.A) is identified based on variation in plan prices and enrollee premiums. This appendix provides additional description on the pricing and subsidy institutions that lead to this variation. The starting point is pre-subsidy prices set by annual insurer bidding. Insurers submit sealed price bids to the regulator several months before the start of the plan year. The regulator then amalgamates these prices and applies subsidies, which determines enrollees premiums that apply at the start of the next plan fiscal year (which begins in July of the preceding calendar year; e.g., FY 2012 starts in July 2011). Prices and premiums are fixed for the remainder of the fiscal year. (Whenever not specified, years in the discussion below refer to fiscal years.)

Figure A.1A shows average pre-subsidy prices in each CommCare fiscal year. (There are no points for 2008 because 2007 price bids were carried over to 2008 with an inflation update.) In 2007-2010, these prices represent enrollment-weighted averages across multiple pricing regions/cells. For 2007 and 2009, insurers could price separately by region, income group, and specified age-sex groups – with this more detailed pricing allowed because risk adjustment did not begin until 2010. In 2010, prices could be set at the region level (with five regions in the state). From 2011 on, insurers were required to set a single price for the whole state.

From pre-subsidy prices, subsidies were applied to generate post-subsidy "enrollee premiums." These vary substantially across income groups because of the application of different subsidies.[12] Average enrollee premiums are shown in Panel B of Figure A.1, with separate averages for below-poverty and above-poverty income groups. The below-poverty group (black line) is fully subsidized, paying $0 for any available plan in all years. Above-poverty groups receive large subsidies but pay higher premiums on the margin for higher-price plans. The specific subsidies vary by income group in four bins: 100-150%, 150-200%, 200-250% and 250-300% of poverty. In general, subsidies are designed to be progressive both in levels and in differences. Lower-income groups pay less for all plans, and premium differences are narrower for lower- vs. higher-income groups.

For instance, consider premiums in 2012. Figure A.1A shows the pre-subsidy prices, which vary by $87 per month across insurers – from a low of $360 for CeltiCare and Network Health to a high of $447 for BMC. For enrollee premiums, the below-poverty group pays $0 for any available plan. After subsidies, enrollees with incomes 100-150% of poverty pay premiums ranging from $0 for CeltiCare and Network Health up to $34 for BMC. Notice that subsidies substantially reduce both the level and difference in premiums between plans. Enrollees with incomes 150-200% of poverty pay premiums ranging from $39 for CeltiCare/Network Health up to $91 for BMC – a $52 difference. Enrollees with

[12] Two additional details are worth mentioning. First, while pre-subsidy prices could vary across age-sex groups in 2007-09, the exchange did not allow premiums to vary across these groups. Instead, they used a weighted-average composite bid across age groups to determine the pre-subsidy price for a given region x income group. Income-specific subsidies were then applied. Second, while insurers can only set prices at a region level (up to 2010) or statewide (2011+), sometimes post-subsidy premiums can vary across "service areas" within a region when the lowest-price plan is unavailable. When this occurs, the state adjusts subsidies so that the next cheapest plan has the targeted post-subsidy premium (e.g., $0 for 100-150% of FPL, $39 for 150-200% FPL). Plan availability can affect the level of plan premiums but does not affect premium differences across available plans. My demand model accounts for plan availability in the choice set definition.

incomes 200-250% of poverty pay premiums ranging from \$77 for CeltiCare/Network Health up to \$152 for BMC – a \$75 difference. Finally, enrollees with incomes 250-300% of poverty pay premiums ranging from \$116 for CeltiCare/Network Health up to \$197 for BMC – an \$81 difference. This example is representative of how subsidies affect both the level and difference in plan premiums in a progressive way.

B.2 Identifying Variation in Premiums

The subsidy schedule just described generates *within-plan* variation in premiums and premium changes that I use to identify premium coefficients in my plan demand model. Figure A.2 gives an example for Network Health in the Boston region from 2010-2013. Panel A shows the levels of enrollee premiums by income group in each year. Panel B subtracts the premium of the cheapest available plan to show premium differences (or "relative premiums"), which are the key statistics for identifying price-sensitivity in a discrete choice model.[13]

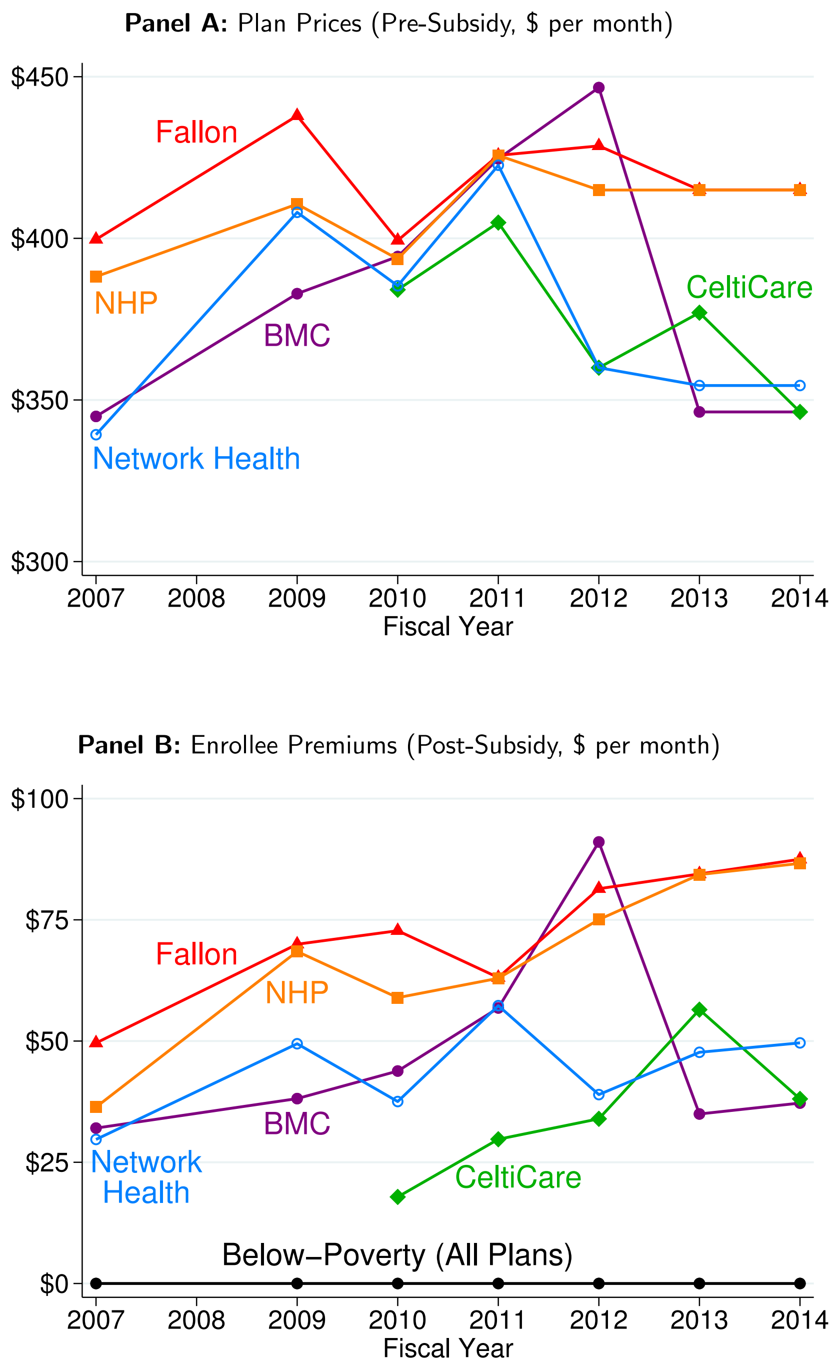
The plot shows how changes in Network Health's (and its competitors') pre-subsidy prices (Figure A.1A) translate through subsidies into *differential changes* across income groups in premiums for the same plan. For instance, Network Health's pre-subsidy price goes from being the lowest in 2010 to being second-lowest (after CeltiCare) in 2011. For enrollees, this results in a (post-subsidy) premium increase for all income groups 100-300% of the federal poverty level (FPL) but no premium change for enrollees below 100% of FPL (who still pay \$0). Further, the *amount* of the premium increase varies from +\$10.38 for 100-150% FPL enrollees up to +\$29.85 for 250-300% of FPL enrollees. Figure A.2 shows that across the four years shown, there is significant relative premium variation for Network Health, including both increases and decreases.

By comparing demand changes for the same plan across income groups – and especially relative to below-poverty enrollees who serve as a sort of "control group" for capturing unobserved quality – the model can infer a valid causal effect of premiums on demand. The difference-in-differences style logic and used of fixed effects is described in Section V.A. Here is how it works for the example shown in Figure A.2. First, the specification for plan utility (equation (9) in the text) includes plan-region-year dummies (ξ_{j,Reg_i,Yr_t}) that absorb variation due to insurer pricing (which occurs at the plan-region-year or plan-year level) and in particular, any year-specific demand shock for Network Health in the Boston region. Thus, premium (and network) coefficients will be identified only by comparing demand *for the same plan across people* within a given region-year cell. Second, plan utility includes plan-region-income group dummies (ξ_{j,Reg_i,Inc_i}) that absorb any *persistent demand differences across income groups* for Network Health in Boston. The only remaining premium variation not captured by the fixed effects comes from the (within-plan, within-region) *differential changes* in premiums by income group.

The full plan demand model is estimated using all plans, regions, and income groups over the six years from 2008-2013. As noted in Appendix B.1, premiums are set at the start of every fiscal year

[13]The cheapest premium is determined by the exchange's "price-linked" subsidies, which set subsidies so that the minimum post-subsidy price equals a target amount for each income group. In 2010-2012, the minimum premium for the five income groups shown are \$0, \$0, \$39, \$77, and \$116. In 2013, the min premium remains \$0 for the first two groups but rises to \$40, \$78, and \$118 for the next three groups.

Figure A.1: CommCare Plan Prices and Enrollee Premiums



NOTE: The graphs show average pre-subsidy insurer prices (Panel A) and post-subsidy enrollee premiums (Panel B) for each insurer's plan in the CommCare market, by fiscal year. The five plans are shown in different colors and labeled. Values shown are averages for the plan's actual enrollees; underlying premiums and (in some years) prices vary by income group and region. The premiums in Panel B are shown separately for enrollees above-poverty (colored series) – who pay a subsidized amount related to the pre-subsidy price – and for below-poverty enrollees who are fully subsidized ($0 premium for all plans). I use the fact that subsidies imply different enrollee premiums for the same plans for identification of price sensitivity in my plan choice model.

Table A.2: Distribution of Changes in Plan Relative Premiums

	Premium Decreases					Premium Increases				
	Share with	Distribution of Changes				Share with	Distribution of Changes			
	Decreases	Mean	Std Dev	Min	Max	Increases	Mean	Std Dev	Min	Max
All Years and Incomes	22%	-$31.0	$22.8	-$103.4	-$0.2	56%	$16.4	$15.9	$1.0	$103.4
By Income Group										
100-150% poverty	15%	-$22.5	$11.1	-$34.0	-$0.4	56%	$10.7	$8.6	$1.0	$35.1
150-200% poverty	22%	-$27.4	$20.5	-$57.1	-$0.2	55%	$15.3	$13.7	$2.0	$68.8
200-250% poverty	30%	-$42.2	$25.6	-$103.4	-$1.4	59%	$25.3	$20.8	$1.9	$103.4
250-300% poverty	35%	-$37.3	$29.7	-$103.4	-$0.6	55%	$28.2	$22.0	$1.6	$103.4
By Year										
2008-2009	18%	-$18.2	$17.9	-$53.7	-$2.6	30%	$43.1	$23.8	$5.6	$103.4
2009-2010	27%	-$34.6	$23.5	-$103.4	-$1.4	41%	$12.7	$10.0	$1.2	$60.9
2010-2011	5%	-$4.5	$5.4	-$25.9	-$0.2	86%	$11.1	$7.8	$1.3	$35.0
2011-2012	29%	-$18.4	$7.3	-$29.9	-$10.4	55%	$23.8	$13.7	$8.8	$81.0
2012-2013	27%	-$51.6	$18.4	-$81.0	-$1.0	70%	$8.2	$5.7	$1.0	$29.0

NOTE: The table shows statistics on the distribution of changes in (post-subsidy) enrollee premiums for each plan relative to the previous year. The underlying dataset includes one observation per plan x income group x service area x year cell (where service areas are the sub-region geographic level at which plan availability is determined) for the 2009-2013 period, excluding the income group 0-100% of poverty for whom all plans are $0 in all years. Statistics are calculated weighting by the number of enrollees in each cell. The variable of interest is the change in the plan's relative premium versus the previous year (for the same income group and service area). Relative premiums are defined as the plan's premium minus the cheapest available plan's premium; this nets out across-the-board shifts due to subsidy changes. The table shows the distribution separately for relative premium decreases and increases, along with the share of each. The remaining share of observations are cases with no change in the relative premium.

and are locked in for 12 months. Premiums for a given plan vary across income groups in all years and across regions prior to 2011. Table A.2 shows the distribution of relative premium changes for a plan between adjacent years, separately for premium decreases and increases (following the presentation in Figure A.23). The average relative premium decrease in the data is $31.0 per month, while the average premium increase is $16.4 per month. There is a substantial range of changes, with increases/decreases as large as $103 and as small as $1 or less. The table also shows how the distribution varies across income groups and years.

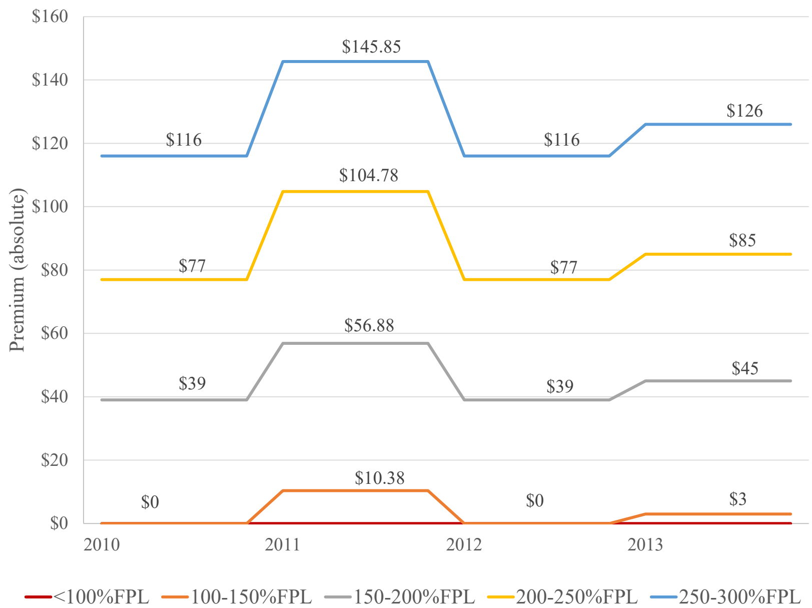
B.3 Hospital Networks

CommCare insurers have flexibility to set their covered hospital and medical provider network, subject to minimum network adequacy rules that were rarely binding. Figure A.3 shows information on plans' share of hospitals covered (weighted by hospital beds), and Table A.3 reports their coverage of the Partners Healthcare System hospitals. Through 2011, there were three broad-network plans: BMC HealthNet Plan, Neighborhood Health Plan (NHP), and Network Health. All of these covered about 80% of hospitals, and NHP and Network Health both covered most Partners hospitals. BMC did not cover Partners because it is owned by the rival Boston Medical Center hospital, but it otherwise has a broad network. Fallon is a regional plan based in central Massachusetts (and only available there in later years), so it does not cover Partners hospitals and its statewide coverage is low.

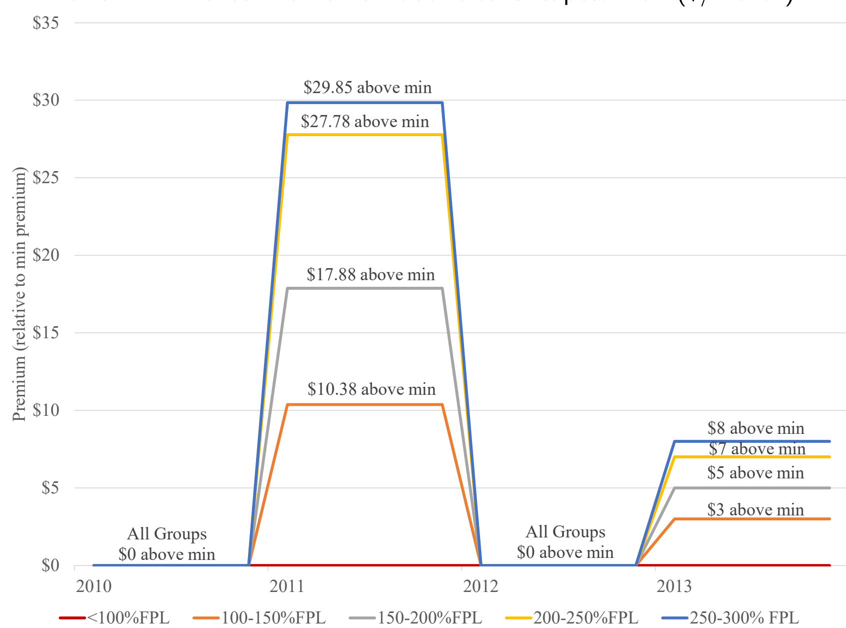
CeltiCare is a new plan that enters the state in 2010 with a narrow network that covers less than

Figure A.2: Identifying Premium Variation Example: Network Health (Boston region), 2010-13

Panel A: Enrollee Premium Levels by Income ($/month)

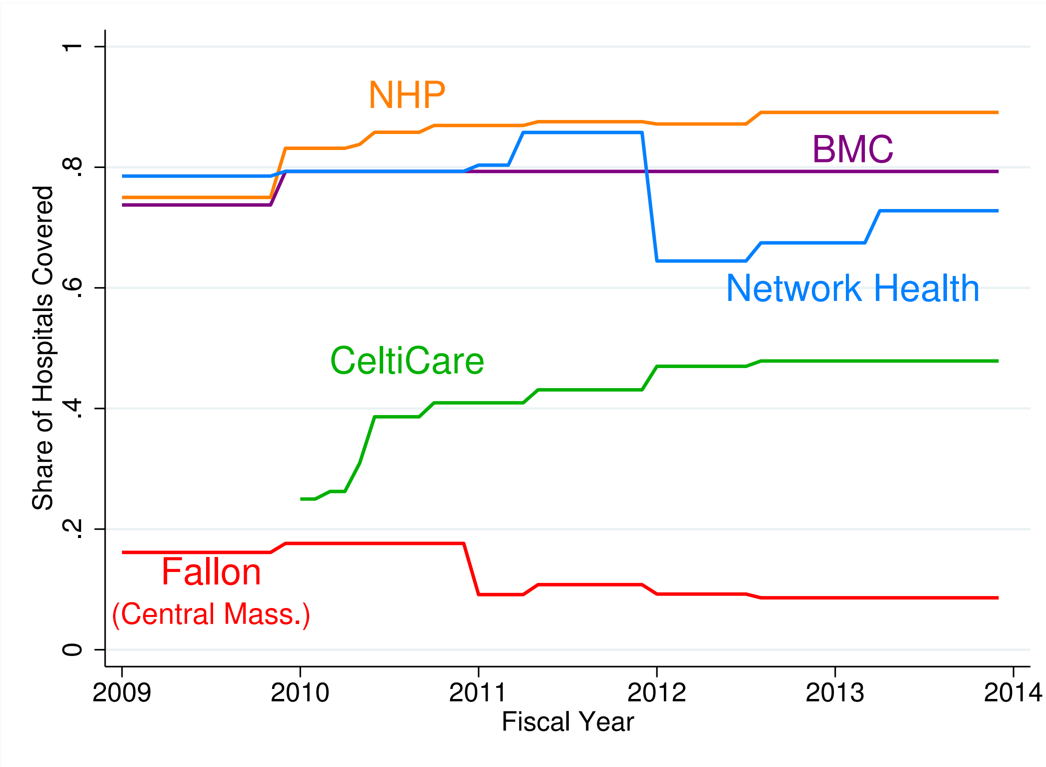


Panel B: Enrollee Premiums Relative to Cheapest Plan ($/month)



NOTE: The graphs shows the example of Network Health's (post-subsidy) enrollee premiums by income group over the 2010-2013 CommCare years. "FPL" refers to the federal poverty level. Pre-subsidy prices (and enrollee premiums) vary at the regional level in 2010, and the graph shows premiums specifically for the Boston region. Both are constant statewide in 2011-2013. Panel A shows the level of the premium for Network Health in dollars per month. Panel B shows the plan's "relative" premium, equal to the difference between its premium and the premium of the cheapest plan. The graph shows that different subsidies by income group translate a single pre-subsidy price into variation across income groups in the plan's post-subsidy relative premium.

Figure A.3: Hospital Coverage in Massachusetts Exchange Plans



NOTE: The graph shows the shares of Massachusetts hospitals covered by each CommCare plan, where shares are weighted by hospital bed size in 2011. Fallon's hospital coverage share is much lower than other plans largely because it mainly operates in central Massachusetts and therefore does not have a statewide network.

half of hospitals but surprisingly, does cover Partners hospitals until 2014. It suffered from severe adverse selection after Network Health dropped Partners in 2012, and it subsequently decided to drop Partners in 2014. In testimony to the Mass. Health Policy Commission, CeltiCare's CEO wrote: "For the contract year 2012, Network Health Plan removed Partners hospital system and their PCPs from their covered network. As a result, the CeltiCare membership with a Partners PCP increased 57.9%. CeltiCare's members with a Partner's PCP were a higher acuity population and sought treatment at high cost facilities. . . . A mutual decision was made to terminate the relationship with BWH [Brigham & Women's] and MGH PCPs as of July 1, 2013." (Note that July 1, 2013, is the start of fiscal year 2014 for the purposes of the CommCare market.)

Network Health's dropping of Partners and several other hospitals in 2012 is evident in Figure A.3 as the large fall in its hospital coverage share. It subsequently adds a few additional hospitals later in 2012-13, but it never restores coverage of Partners including after the ACA begins in 2014. Indeed, after its success in CommCare, it also dropped Partners in its (much larger) Medicaid managed care plan as of 2014. These changes left NHP as the only managed care plan that covers Partners in either Medicaid or the ACA "ConnectorCare" program that offers additional subsidies to low-income people in Massachusetts' ACA exchange.

Table A.3: Coverage of Partners Hospitals by Exchange Plans

Plan	Hospitals	2009	2010	2011	2012	2013	*2014 (ACA)*
Boston Medical Center Plan (BMC)	MGH & Brigham	No	No	No	No	No	*No*
	Others	2/5	1/5	1/5	1/5	1/5	*0/5*
Network Health	MGH & Brigham	Yes	Yes	Yes	No	No	*No*
	Others	5/5	5/5	5/5	2/5	2/5	*0/5*
Neighborhood Health Plan (NHP)	MGH & Brigham	Yes	Yes	Yes	Yes	Yes	*Yes*
	Others	2/5	4/5	4/5	4/5	5/5	*5/5*
CeltiCare *(new in 2010)*	MGH & Brigham	---	Yes	Yes	Yes	Yes	*No*
	Others		3/5	3/5	3/5	3/5	*0/5*
Fallon *(mainly central MA)*	MGH & Brigham	No	No	No	No	No	*No*
	Others	0/5	0/5	0/5	1/5	0/5	*1/5*

NOTE: The table shows network coverage of the Partners hospitals by each CommCare plan over time. For each plan, the first line shows coverage of the two star academic hospitals – Mass. General Hospital (MGH) and Brigham & Women's Hospital – which are always bundled together. The next line shows how many of the five Partners community hospitals are covered in network.

C Appendix: Robustness and Additional Analyses

C.1 Robustness Analyses on Adverse Selection Findings

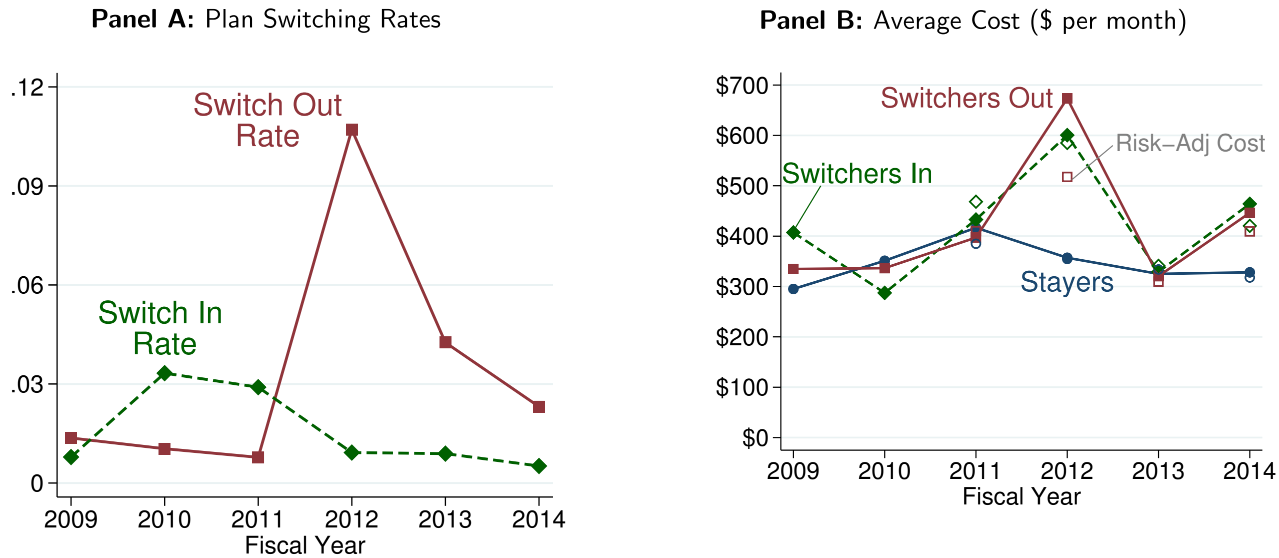
The evidence in the body text (Section III) focuses on plan switching patterns for Network Health's current enrollees at the end of 2011. This section implements three analyses to check the robustness of these findings: (1) studying switching by zero-premium enrollees, for whom there is no concurrent change in Network Health's premium that could affect results; (2) examining new enrollee choices, which are not subject to inertia; and (3) showing similar evidence from CeltiCare's 2014 exclusion of Partners from its network.

(1) Plan Switching for Zero-Premium Enrollees

The selection changes for Network Health in 2012 reflect a combination of its narrower network and lower premium, which are part of the same strategic bundle. However, a natural question is whether the results are *entirely* driven by the lower premium, rather than the network shift. The CommCare setting provides an easy way to test this by examining switching patterns for below-poverty enrollees for whom all plans are free (both before and after 2012). Importantly, existing below-poverty enrollees were not subject to the limited choice policy (which applied only to new enrollees) so could switch freely.

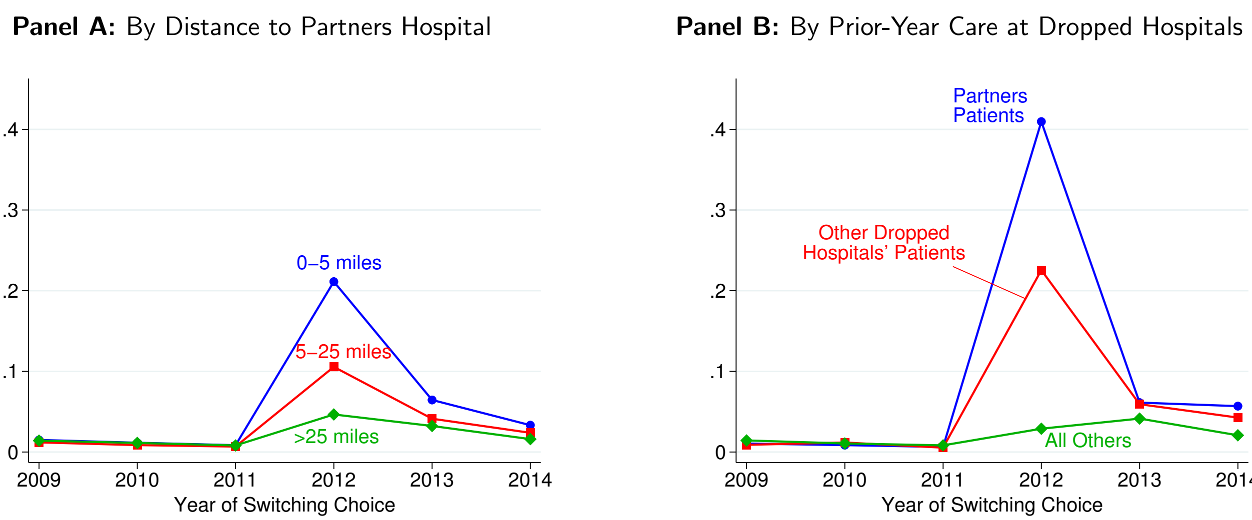
Appendix Figures A.4-A.5 replicate Figures 2-3 with the sample limited to below-poverty enrollees. Both switching out and cost patterns for stayers/switchers out are quite similar to the full sample. The one meaningful difference is instructive: there is no spike in low-cost below-poverty enrollees *switching into* Network Health in 2012, consistent with the lack of a premium incentive to do so. This suggests that the network and premium changes work together in driving selection incentives: the narrower network pushes out high-cost enrollees who care about provider choice, while the lower premium pulls in low-cost enrollees who are price-sensitive. These findings suggest that adverse selection on networks is likely relevant in settings without premiums (e.g., Medicaid managed care) but may be more muted.

Figure A.4: Plan Switching and Selection for Network Health: Zero-Premium Enrollees



NOTE: These figures show switching and selection patterns for *zero-premium* (below-poverty) Network Health over time and especially around its 2012 network narrowing. The graphs are exactly analogous to Figure 2 in the main text but with the sample limited to below-poverty enrollees who do not pay premiums. See the caption to Figure 2 for additional information.

Figure A.5: Plan Switching Out Rates for Network Health: Zero-Premium Enrollees



NOTE: These figures show switching out patterns for *zero-premium* Network Health enrollees around its 2012 dropping of Partners and several other hospitals. They are exactly analogous to Figure 2 in the main text but with the sample limited to below-poverty enrollees who do not pay premiums. See the caption for Figure 2 for additional information.

(2) Evidence from New Enrollee Choices

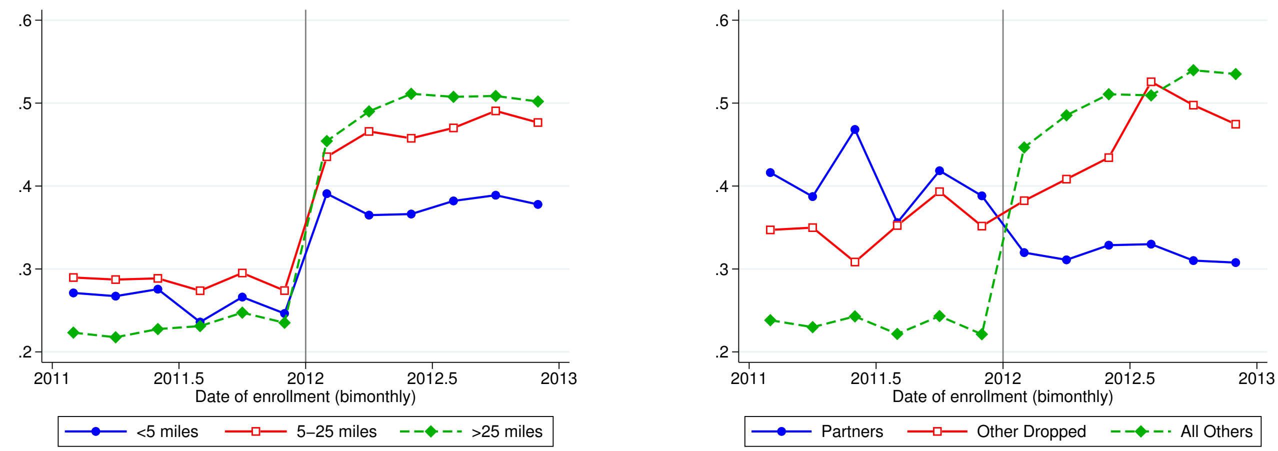
While switching behavior provides the cleanest evidence of adverse selection, another important channel is changing plan demand among "new enrollees" entering the exchange. I briefly provide evidence of similar selection patterns among this group; their choices also enter the plan demand estimates in the structural model. A challenge with studying new enrollees is that, because they newly join the market, I often lack data on their costs and provider use *prior to* the network change (and outcomes after the change could be directly influenced by it). Therefore, when I study cost/utilization variables, I restrict to the subset of "re-enrollees" who have a prior CommCare enrollment spell that ended before 2012. I use this prior spell to measure provider use and costs. In addition, because of the 2012 limited choice policy for below-poverty new/re-enrollees (see Section II.C), I limit the analysis to above-poverty enrollees who have unrestricted choice.

Appendix Figure A.6 shows evidence of changing demand for Network Health in 2012 that is correlated with markers of provider demand – just as in the switching findings in Figure 2 in the main paper. Each point on the graphs represents Network Health's market share for the group of new enrollees joining the exchange in a given bimonthly period. Panel A breaks out market shares by enrollee distance to the nearest Partners hospital. While demand increases in 2012 for all groups – reflecting the plan's premium decrease – the jump is much smaller for people living within 5 miles of a Partners hospital. Panel B shows even starker results breaking out demand among re-enrollees based on use of the dropped hospitals during their prior spell. While market shares for the "all others" group (who did not use Partners or another dropped hospital) more than doubles from about 25% in 2011 to over 50% in late 2012, shares for Partners patients decline in 2012. Shares for other dropped hospitals' patients increase but by much less than for the "all others" group.

These results show that the impact of the network change on plan demand was not limited to plan switching but also had a major effect on new enrollee choices. Appendix Figure A.7 shows that these demand shifts were correlated with proxies for costs in a way suggesting more favorable selection. Following the change, the plan's new enrollees' average risk score falls and its re-enrollees' prior-spell average cost decreases – implying that older and higher-cost enrollees select away from the plan. Although this evidence is more limited than for switching, it again is consistent with the basic adverse selection story.

Figure A.6: Network Health's New Enrollee Market Share around 2012 Change

Panel A: By Distance to Partners | **Panel B:** By Prior Provider Use



NOTE: These figures show evidence of changes in new enrollees' demand for Network Health in 2012 that are correlated with valuation for the Partners and other dropped hospitals. Each point on the figures is the market share who choose Network Health among above-poverty new enrollees joining the exchange in a given (bimonthly) period. The sample is restricted to above-poverty enrollees who are not subject to the 2012+ limited choice policy. Panel A divides enrollees by proximity to the nearest Partners hospital. Panel B divides enrollees by use of the dropped hospitals during a prior enrollment spell, with the sample limited to re-enrollees with a previous spell. In both panels, market shares increase in 2012 for groups least likely to value the dropped hospitals (reflecting Network Health's premium decrease) but increase much less or decline for groups more likely to value the hospitals.

Figure A.7: Changing Risk Selection for Network Health among New Enrollees

Panel A: Average Risk Score (all new enrollees) | **Panel B:** Prior-Spell Costs ($/month, re-enr. only)

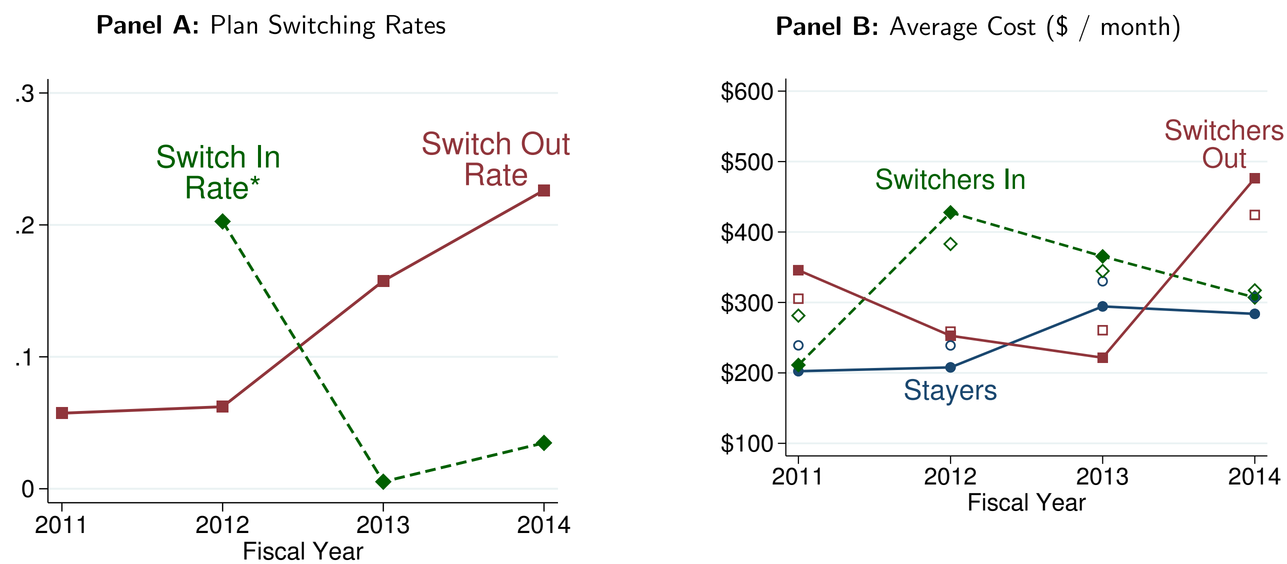
NOTE: These figures show evidence that shifts in new enrollee demand for Network Health at its 2012 network narrowing were correlated with proxies for cost in a way suggesting more favorable selection. Each point on the figures shows an average value for above-poverty new enrollees joining in a given bimonthly period who select Network Health (blue series) and all other plans (red series). The sample is restricted to above-poverty enrollees who are not subject to the 2012+ limited choice policy. Panel A shows average CommCare risk score (for all new enrollees). The average risk of Network Health's enrollees fell at the start of 2012 while that of other plans rose, suggesting a shift of high-risk enrollees from Network Health to other plans. Panel B shows prior-spell average costs (in $ per month) with the sample limited to re-enrollees who have a prior CommCare enrollment spell. The average cost of Network Health's enrollees falls at the start of 2012, while that of other plans is relatively flat.

(3) Evidence from CeltiCare 2014 Dropping of Partners

The analysis so far relies on a single network change for Network Health in 2012. It is reasonable to ask whether this is a fluke. To provide evidence, I examine the only other CommCare network change involving the star Partners system: when CeltiCare drops Partners at the start of fiscal year 2014. This change is at the tail end of my data period, limiting the analyses I can do (e.g., the claims data for 2014 are incomplete). Nonetheless, to provide an additional source of evidence, I replicate the analyses of the figures above for CeltiCare.

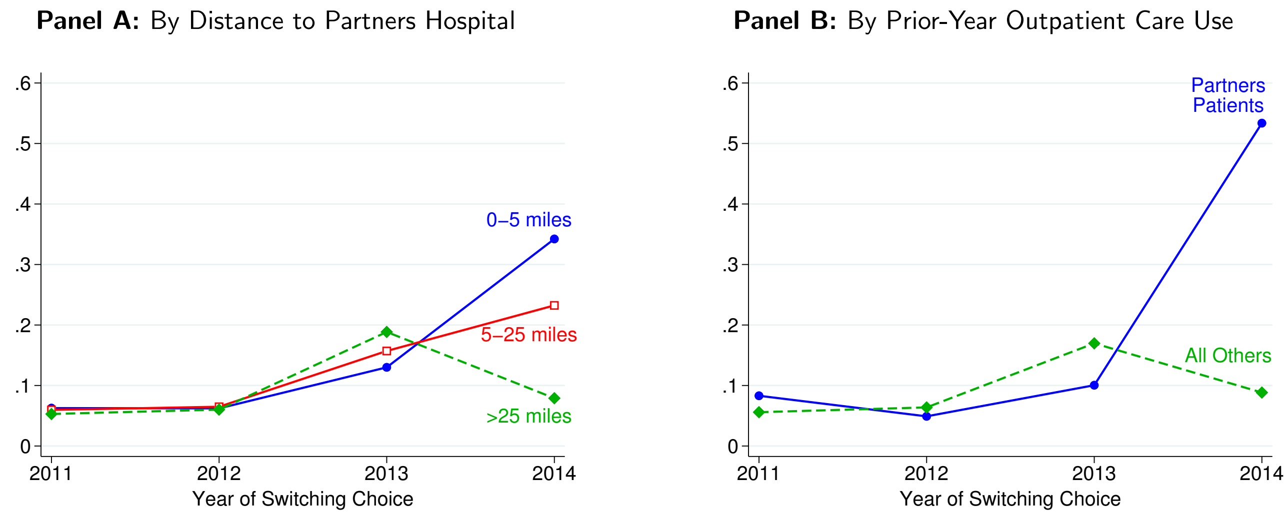
The results are shown in Appendix Figures A.8-A.10. All of the main selection findings carry over to CeltiCare in 2014. Specifically: (1) CeltiCare experiences a high switching out rate in 2014, with switchers out having high raw and risk-adjusted costs; (2) switching rates are strongly correlated with proximity to Partners and prior-year use of Partners, and (3) CeltiCare's demand among new enrollees shows similar patterns (falling for Partners patients and people living nearby a Partners hospital, while rising for others). Together, these results suggest that Network Health's 2012 experience was not an idiosyncratic event but representative of generalizable patterns of selection based on star hospital coverage.

Figure A.8: Plan Switching and Selection for CeltiCare (Drops Partners in 2014)



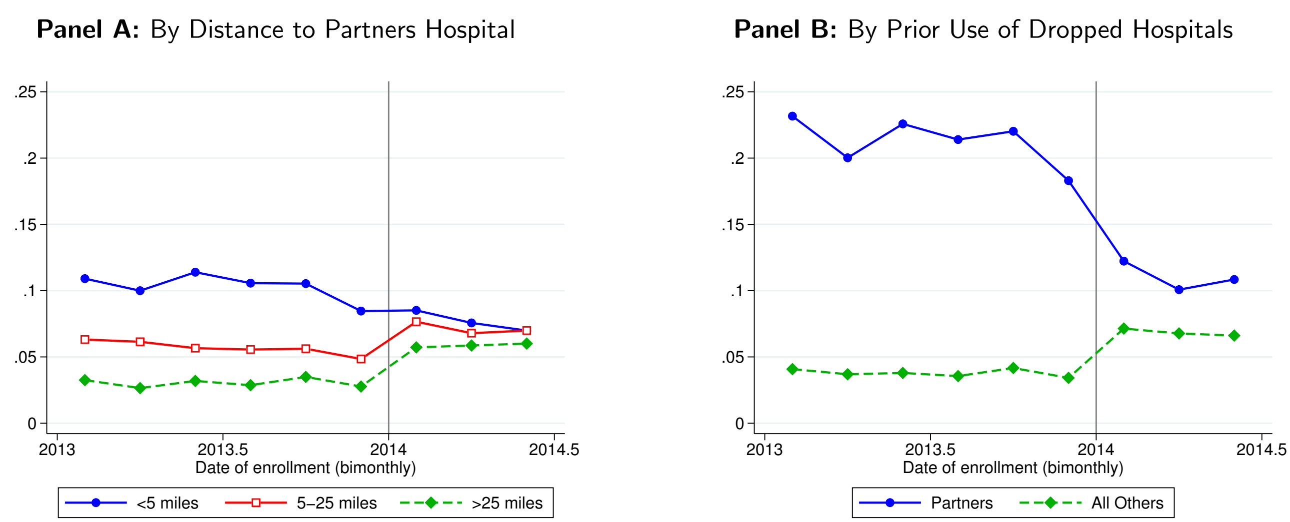
* Panel A excludes the 2011 switching in rate for CeltiCare to avoid blowing up the y-scale.
NOTE: These figures show switching rates for CeltiCare (Panel A) and average prior-year costs for CeltiCare enrollees (Panel B, in $ per month) in each year's open enrollment. CeltiCare drops the Partners Healthcare system from its network in 2014. These plots are analogous to Figure 3 in the main text and Appendix Figure A.12, which show switching and selection for Network Health. See the notes to those figures for additional description. The current figure shows that similar adverse selection patterns occur for CeltiCare when it excludes Partners from network.

Figure A.9: Switching Out Rates for CeltiCare (Drops Partners in 2014), by Enrollee Characteristics



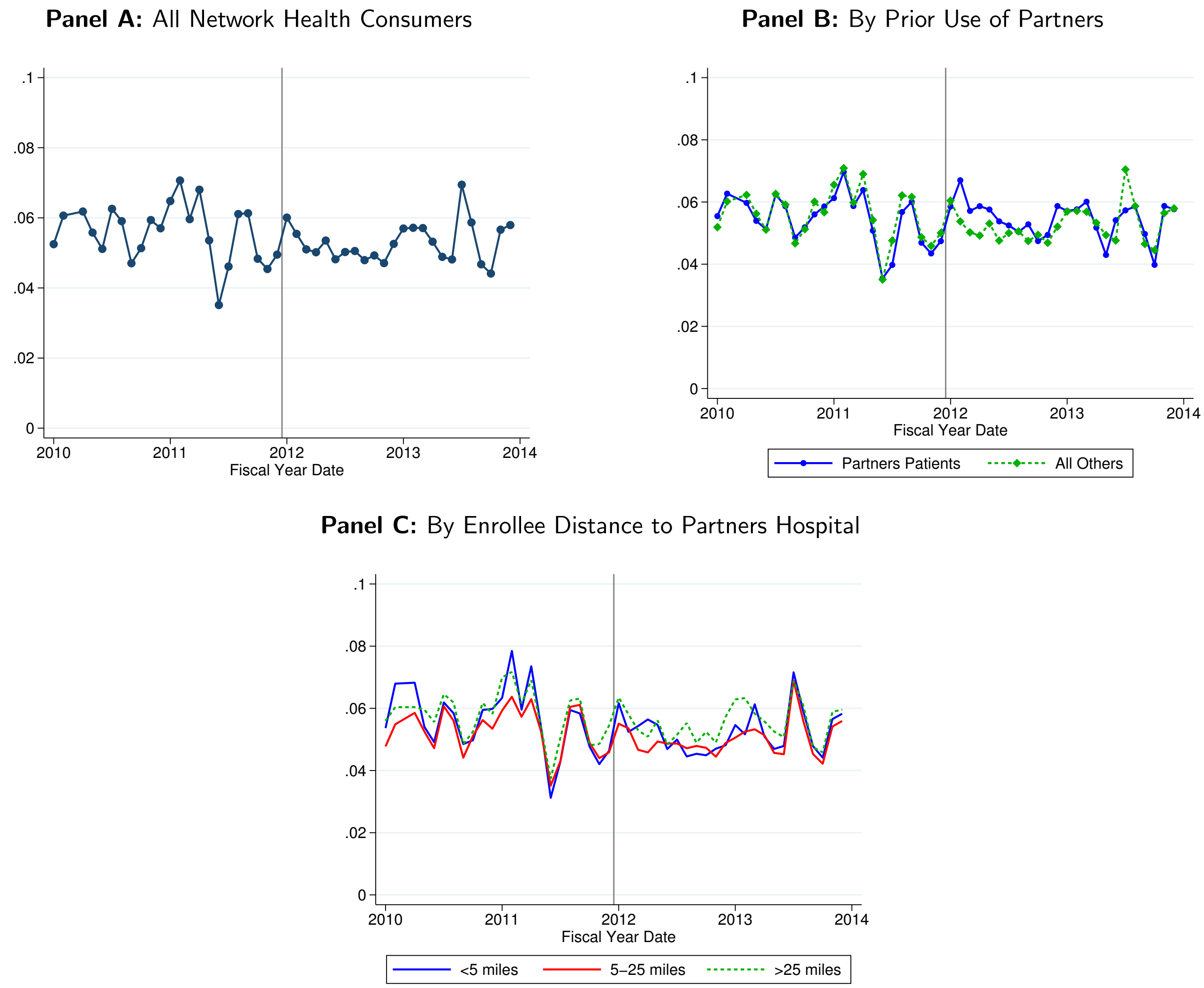
NOTE: These figures show switching out rates for CeltiCare enrollees by variables likely to correlate with demand for Partners, which is dropped from the plan's network in 2014. Panel A shows switching rates by enrollee distance to the nearest Partners hospital; Panel B shows switching rates by prior-year use of Partners for (non-emergency room) outpatient care. These plots are analogous to Figure 2 in the main text, which shows switching for Network Health. See the note to that figure for additional description.

Figure A.10: CeltiCare's Market Share among New Enrollees (Drops Partners in 2014)



NOTE: These figures show evidence of changes in new enrollees' demand for CeltiCare in 2014 (when it drops Partners from network) that are correlated with valuation for Partners providers. (The plots are analogous to Figure A.6 in the main text, which studies Network Health's network change in 2012.) Each point on the figures is the share who choose CeltiCare among above-poverty new enrollees joining the exchange in a given (bimonthly) period. The sample is restricted to above-poverty enrollees who are not subject to the 2012+ limited choice policy. Panel A divides enrollees by proximity to the nearest Partners hospital. Panel B divides enrollees by use of the Partners hospitals during a prior enrollment spell (with the sample limited to re-enrollees who have a prior spell). The slightly "early" decline in the market share for Partners patients (in the final period of 2013) reflects the fact that the network change was announced prior to its enactment at the start of fiscal year 2014.

Figure A.11: Monthly Rate of Exiting the Exchange, Network Health Enrollees



NOTE: The figure provides evidence on a key assumption in the plan choice model: that Network Health's network narrowing in 2012 does not affect whether consumers participate in the exchange (no "extensive margin" response). The figure plots the share of Network Health's existing enrollees who exit the exchange in each month from 2010-2013. If the network narrowing in 2012 led to an extensive margin response, we would expect to see a jump upward in the exit rate at the start of 2012. There is little evidence of this either for Network Health enrollees overall (panel A) or when broken down by factors that strongly predicted plan switching: Partners patients vs. others (panel B) or enrollee distance to a Partners hospital (panel C).

C.2 Additional Analyses on Reduced Form Switching and Selection Patterns

This appendix shows additional facts about plan switching and selection into and out of Network Health and runs robustness checks on the excess switching rate logits shown in Section III.B.

1. Switching Rates In and Out of Network Health Figure A.12 shows switching rates for Network Health in each year from 2009-2014. I define the "switching out rate" for a plan-year (e.g., Network Health in 2012) as the number of people who switched out divided by the total who could have switched out. The "switching in rate" is defined as the number of switchers *into* the plan divided by the same denominator, which allows for comparing the two figures in levels. At the start of 2012 when its narrower network (and lower price) took effect, the plan experienced a spike in switching – to 11.3% for switching out and 7.6% for switching in. While low in absolute terms (consistent with the presence of inertia), these rates are more than double those of adjacent years.[14] This is consistent with the shift to a narrower network and lower price spurring significant changes in plan choices (i.e., ΔD_i), which is necessary for selection incentives to be relevant.

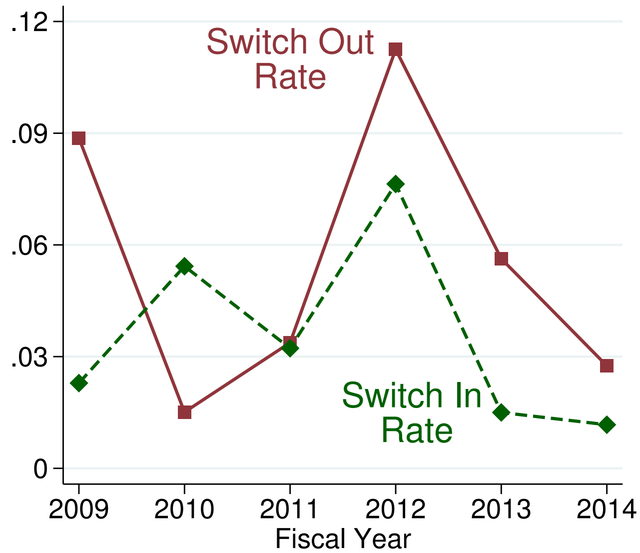
2. Breakdown of Costs of Switchers and Stayers by Group Appendix Table A.4 shows evidence that the groups most likely to switch out of Network Health in 2012 also have high costs, implying adverse selection. Among all continuing 2011 Network Health enrollees (switchers plus stayers), both raw and risk-adjusted costs are higher for the groups most likely to switch out – people living nearby Partners and patients of Partners or the other dropped hospitals. The highest-cost group are Partners patients, with risk-adjusted costs of \$564 per month, or 63% above average. Of course, this analysis does not explain *why* the switching groups had high costs, a question that matters for interpreting the findings. I discuss this issue in Section IV.

3. Robustness Check on Logit Regressions for Switching Patterns Figure A.13 shows a robustness check on Figure 4 in the body text. It shows estimates from a multivariate version of the logit regression in equation (5), with distance, observed sickness (quantile of the CommCare risk score), and unobserved sickness (ratio of HCC risk score to the CommCare risk score) all included as covariates in the same specification. The results are estimates of the odds ratio for excess switching in 2012 (= $\exp(\beta_g)$ in equation (5)). The results confirm that distance, observed risk, and unobserved risk all separately predict plan switching in 2012 in a multivariate specification.

Figure A.14 shows another robustness check on these logit regressions. It replicates the top three panels of Figure 4 in the body text, separately for prior-year Partners patients (red triangles) and people who were not patients of a dropped hospital (blue circles). Distance, sickness, and unobserved sickness continue to predict plan switching in 2012 within each subgroup, though the sickness gradient is stronger for the Partners patients and the distance gradient is somewhat stronger for non-patients.

[14]Switching out rates were also high in 2009, reflecting unusually large increases in Network Health's enrollee premiums from 2008-09.

Figure A.12: Plan Switching Rates In and Out of Network Health (around 2012 network change)



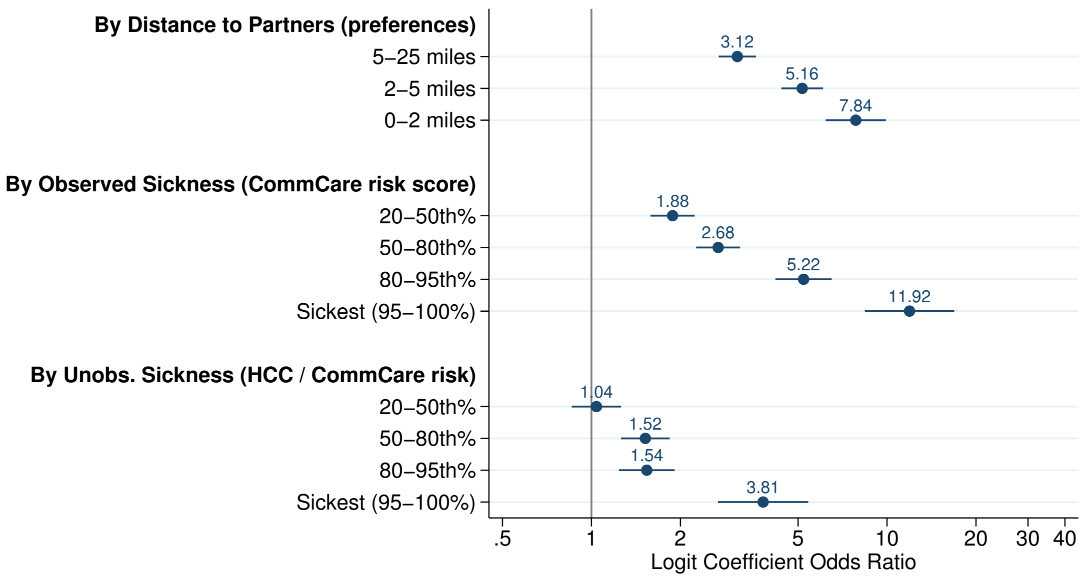
NOTE: The figure shows switching patterns for Network Health over time and especially around its 2012 network narrowing. It plots the rate of switching in and out of Network Health at each year's open enrollment. These rates are defined as the number of switchers in/out divided by the same denominator – the number of continuous market enrollees in Network Health at the end of the prior year – so their levels are comparable.

Table A.4: Analysis of Costs for Network Health Enrollees in 2011 (Stayers and Switchers)

Enrollee Group	All Network Health Enrollees in 2011 (Switchers + Stayers)			Switching Out Choices		Risk Adj. Cost Among Switchers Out	
	Raw Cost	Risk Adj. Cost	Share of Enrollees	Switching Rate	Share of Switchers	2011	2012
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All Enrollee Groups	$366	$346	100%	11%	100%	$508	$452
By Prior-Year Care							
Partners Hospitals	$701	$564	18%	45%	67%	$572	$475
Other Dropped Hospitals	$487	$386	8%	24%	17%	$375	$372
All Other Enrollees	$273	$274	74%	3%	16%	$333	$422
By Distance to Partners Hospital							
0-5 miles	$383	$363	23%	22%	46%	$469	$478
5-25 miles	$371	$354	36%	12%	36%	$512	$399
> 25 miles	$353	$329	41%	5%	18%	$583	$497

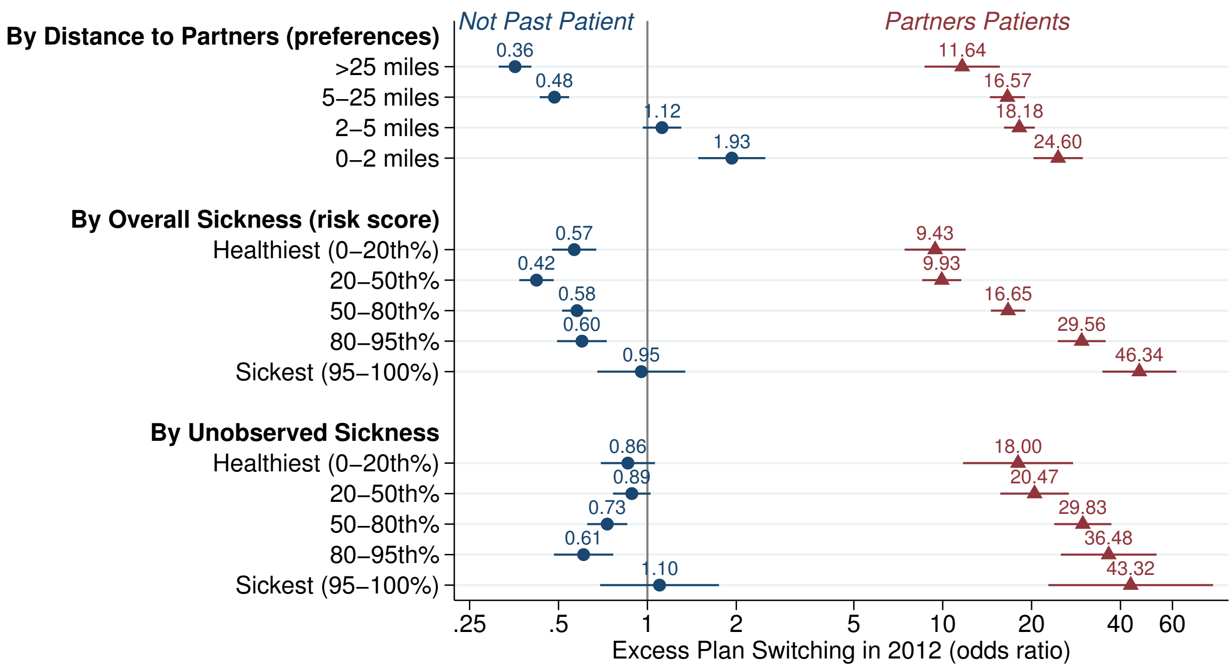
NOTE: The table shows statistics about continuing enrollees in Network Health in 2011, including both individuals who stick with the plan in 2012 ("stayers") and those who switch to another plan in 2012 ("switchers out") when the network changes. The top row (highlighted in gray) shows overall average statistics, and the following panels show subgroup averages by prior-year outpatient care use and by enrollee distance to the nearest Partners hospital. Columns (1)-(3) show statistics (raw cost, risk adjusted costs, and the share each group represents) for all switchers and stayers together. Columns (4)-(5) show switching rates and shares of switchers each subgroup represents. Columns (6)-(7) show average risk-adjusted costs for 2011 and 2012 conditional on switching out.

Figure A.13: Excess Switching Out Rates in 2012: Multivariate Logit Estimates



NOTE: The figure shows odds ratios corresponding to $\exp(\beta_g)$ from estimates of switching multivariate logit regression specification (5). The results come from a single logit regression with distance, observed sickness, and unobserved sickness as covariates. Distance is defined as enrollee distance to the nearest Partners hospital (with an omitted group of 25+ miles). Observed sickness is defined as quantiles of the (prior-year) CommCare risk score (with 0-20th% as the omitted group), which is the measure used for actual risk adjustment. Unobserved sickness is defined as the ratio of of the HCC risk score to CommCare's risk score, both measures for the prior year.

Figure A.14: Excess Switching Out Rates in 2012: Separately by Past Patient Status



NOTE: The figure shows odds ratios corresponding to $\exp(\beta_g)$ from estimates of switching multivariate logit regression specification (5). The results come from a single logit regression with distance, observed sickness, and unobserved sickness as covariates. Distance is defined as enrollee distance to the nearest Partners hospital (with an omitted group of 25+ miles). Observed sickness is defined as quantiles of the (prior-year) CommCare risk score (with 0-20th% as the omitted group), which is the measure used for actual risk adjustment. Unobserved sickness is defined as the ratio of of the HCC risk score to CommCare's risk score, both measures for the prior year.

D Appendix: Understanding Demand for Star Providers

D.1 Decomposition of Role of Sickness vs. Preferences in Demand

To quantify the role of sickness versus preference measures in explaining demand for the star Partners hospitals, I implement a decomposition method suggested by Shorrocks (2013); see also Shorrocks (1982). The method, which is also known as a "Shapley-Shorrocks decomposition," quantifies the role of covariates in explaining variation in an outcome variable.[15] This role is quantified by the marginal contribution of a covariate (or group of covariates) to the $R^2$of a regression – i.e., how much the R^2 increases when a covariate is added. To account for complementarity among covariates (which means that the ordering in which covariates enter matters), it calculates the Shapley value of this contribution – essentially averaging over the marginal contribution to R^2 for every possible covariate ordering. I implement the method using the add-on Stata command "shapley2".

I implement the decomposition for two metrics of demand (Y_i) for Partners: (1) switching plans in 2012, and (2) being a Partners patient in 2011. I restrict the sample to the 2012 current enrollee sample enrolled in Network Health at the end of 2011. I run logit regressions of the form:

$$Y_i = logit\left(\alpha + X_i^{Dist}\beta_1 + X_i^{Sickness}\beta_2\ [+X_i^{ProvRelat}\beta_3]\right)$$

where X_i^{Dist} is a vector of covariates for distance to the nearest Partners hospital (10 deciles up to 35 miles away, plus a dummy for 35+ miles) and to the nearest other dropped hospital (similar variables); $X_i^{Sickness}$ is a vector of sickness covariates, including "observed" and "unobserved" risk; and $X_i^{ProvRelat}$ are dummies for being a patient of Partners and of another dropped hospital during 2011 (only included when Y_i = switching plans). Observed risk covariates include age groups and deciles of the CommCare risk score, plus an extra category for the top 5%. I consider two versions of unobserved risk. A simpler version includes quantiles of the HCC risk score (deciles + top 5% dummy) and dummies for nine chronic illnesses. A richer version includes these variables plus variables for prior-year (2011) utilization of care (e.g., quantity of care, number of office visits, any hospitalization) and subsequent-year (2012) HCC risk score quantiles and diagnosis variables, which can capture the role of future health shocks.[16] The bottom of Table A.5 reports the number of variables for each group of covariates.

Table A.5 reports results of the decomposition for four covariate specifications: (1) distance + observed risk only, (2) adding the simpler unobserved risk covariates, (3) adding the richer unobserved risk covariates, and (4) adding provider relationships. The first panel shows results for the demand measure (Y_i) of switching out of Network Health in 2012; the second panel shows results for being a Partners patient in 2011. In each panel, the top row lists the overall explained variation (McFadden's pseudo-R^2) and the contribution of each set of covariates to this R^2 (these by construction add up to

[15] The method is sometimes used to quantify the contribution of factors to explaining distributional inequality (e.g., in income or wealth). It is distinct from the better known Oaxaca-Blinder decomposition, which decomposes the role of factors in explaining inequality *between two groups* (e.g., the black-white income gap).

[16] Although subsequent-year variables are potentially endogenous to the switching choice, this very rich specification allows me to capture any future health shocks that emerge during 2012 and that agents might have known when making switching decisions.

the total).[17] As noted above, the covariate contribution represents the average marginal increase in the psuedo-R^2 when this group of covariates is added to the specification (i.e., the Shapley value of their contribution).

The results in Table A.5 suggest that while preferences and sickness both matter, preferences are quantitatively more important in explaining demand variation. Even in the richest specification for sickness (column 3, which includes 64 sickness covariates), distance accounts for 56% of the explained variation in switching plans and 69% of the explained variation in being a Partners patient, with sickness variables accounting for the remainder. There is also substantial unobserved variation, as indicated by the pseudo-R^2 of 0.147-0.285. Although this unexplained variation may reflect either unobserved preferences or sickness, unobserved preferences are likely more important. Distance is just one driver of preferences, while sickness is relatively well measured in claims data. Moreover, column 4 shows that adding provider relationship dummies (just two variables) more than doubles the R^2 to 0.336, and these dummies account for more variation than all of the distance and sickness variables combined.

D.2 Role of State Dependence vs. Heterogeneity

Why do some individuals exhibit high demand for the star providers, as exhibited in their willingness to switch plans to retain access? What role do state dependence and heterogeneity play? This issue is relevant for interpreting the short- vs. long-term patient welfare losses from the narrower networks. While the data do not provide a good way to precisely decompose the precise contribution of each channel, this section presents evidence suggesting that both are involved.

Start by noting that the fact that people switch plans does *not* distinguish state dependence from heterogeneity. While switching out of Network Health in 2012 – which involves an administrative hassle and often paying a higher premium[18] – suggests a desire to keep one's hospital/doctor, there are two reasons people may have this preference. First, they may be "matched" to their provider based on *persistent heterogeneity* in factors that make the provider more attractive: good care for their condition, greater convenience, or other factors. Alternatively, they may simply not want to switch providers, especially if they have a good relationship or are in the middle of an active treatment regime. These explanations are examples of state dependence because they arise from *past treatment history*. Notice that they may be still be quite important to patients and even clinically meaningful in the sense that breaking the relationship harms a patient's health (see Sabety, 2020). But their key feature is that they are rooted in past history that might have been different and whose importance may fade over time.

To examine these mechanisms, I dig deeper into who switches plans in response to Network Health's 2012 network change. As in Section III.A, this section limits the sample to current Network Health

[17] I use the psuedo-R^2 because this is a logit regression, but I have found that results are nearly identical if I instead run a linear probability model and use the traditional R^2.

[18] Below-poverty enrollees could switch to any plan and still pay zero premium, but above-poverty enrollees faced a choice of two plans that covered Partners: (1) NHP, whose premium was $21-51 per month higher than Network Health (depending on income), or (2) CeltiCare, which cost the same as Network Health but had a much narrower network in other ways (see Appendix Figure A.3) and a worse reputation (as indicated in the plan demand estimates in Table A.11). Interestingly, switching rates for below- and above-poverty enrollees were quite similar.

Table A.5: Role of Sickness vs. Preferences in Explaining Demand for Star Hospitals

	Observed Risk Only		Add Unobs. Risk		Additional Risk Covars.		With Provider Relationships	
	(1)		(2)		(3)		(4)	
Demand Measure #1: Switching Out of Network Health in 2012								
Explained Variation (McFadden's Pseudo-R^2)	**0.106**		**0.130**		**0.147**		**0.336**	
Contribution to Pseudo-R^2								
Distance to dropped hospitals (preference)	0.083	*[79%]*	0.083	*[64%]*	0.083	*[56%]*	0.054	*[16%]*
Sickness: Observed (in risk adjustment)	0.022	*[21%]*	0.013	*[10%]*	0.012	*[8%]*	0.011	*[3%]*
Unobserved (not in risk adj.)	---		0.035	*[27%]*	0.052	*[35%]*	0.038	*[11%]*
Patient of dropped hospitals	---		---		---		0.234	*[69%]*
Demand Measure #2: Being a Partners Patient in 2011								
Explained Variation (McFadden's Pseudo-R^2)	**0.204**		**0.276**		**0.285**		---	
Contribution to Pseudo-R^2								
Distance to dropped hospitals (preference)	0.192	*[94%]*	0.196	*[71%]*	0.197	*[69%]*		
Sickness: Observed (in risk adjustment)	0.012	*[6%]*	0.007	*[3%]*	0.007	*[2%]*		
Unobserved (not in risk adj.)	---		0.073	*[26%]*	0.080	*[28%]*		
Covariates Included								
Distance to Partners, other dropped hosp. (n = 20)	X		X		X		X	
Prior-Year Patient of Dropped Hospitals (n = 2)							X	
Sickness covariates								
Age groups (n = 9)	X		X		X		X	
CommCare risk score bins (n = 10)	X		X		X		X	
HCC risk score bins (n = 10)			X		X		X	
Diagnoses dummies (n = 9)			X		X		X	
Prior-Year Utilization variables (n = 5)					X		X	
Subsequent-year risk score & diagnoses (n = 21)					X		X	
Number of Observations	41,917		41,917		41,917		41,917	

NOTE: The table reports results of the Shorrocks decomposition of the contribution of distance and sickness covariates to explained variation (the pseudo-R^2) in two demand outcomes: (1) switching out of Network Health in 2012 when it drops Partners (top panel), and (2) being a Partners patient in 2011 (middle panel). See the appendix text for a detailed description of the method for this decomposition. The sample is restricted to current enrollees in Network Health as of the end of 2011, just as in the reduced form analysis in the paper.

enrollees at the end of 2011 and runs regressions to analyze who switches out of the plan at the start of 2012.

Evidence of Heterogeneity

Table A.6 shows (binary) logit regressions, with the outcome variable in columns (1)-(2) an indicator for switching out of Network Health. The x-variables are various characteristics that may predict heterogeneous value for the Partners hospitals or other dropped providers: distance (i.e., convenience), medical conditions, and demographics. To aid interpretation, I report odds ratios (which equal e^{β} of the underlying logit coefficients, β).

Column (1) shows results *without* controlling for prior provider use. This model therefore sheds light on whether there is "matching" on characteristics associated with provider demand in a history-unconditional sense. The estimates indicate strong evidence of this matching. One clear factor is convenience: individuals are more likely to switch out if they live closer to a Partners hospital or another dropped hospital, with odds >7x higher for people living within 2 miles and gradually declining with further distance. A second set of factors are medical risk and conditions. These matter because the star hospitals are known for their advanced care for the sickest patients – the explicit criteria on which the *U.S. News* rankings are based. Switching rises with age (consistent with age as a risk factor) and with observed medical conditions. Having any chronic or acute illness increases switching odds by 68% and 42%, respectively. On top of these, there are sizable further effects of having a risk score in the top 5% (+45%) and having cancer (+110%). Cancer is notable because Brigham & Women's Hospital is clinically integrated with Dana Farber Cancer Institute, the region's top cancer hospital, making it difficult to get care at Dana Farber without access to Brigham's facilities.

These differences imply that in an unconditional sense, provider preferences revealed in plan switching reflect real heterogeneity in value for the star hospitals. However, it is important to interpret these findings with care. While they indicate that there *is* real sorting on persistent determinants of provider demand (i.e., heterogeneity), they do *not* rule out state dependence – or even suggest that it is unimportant. It is a mistake to think of this as an "either/or" story; rather a "both/and" approach is more appropriate. Indeed, heterogeneity and state dependence are likely deeply intertwined. Individuals may *initially* sort into becoming a Partners patient based on real heterogeneity (e.g., convenience or sickness) but remain loyal to Partners because of a mix of heterogeneity and state dependence (e.g., a switching cost or the relationship's value). Columns (2)-(3) of Table A.6 indicate support for both stories. Column (3) reports a logit for the outcome of being a Partners patient in 2011 and finds that there is strong sorting based on convenience and medical conditions. Column (2) shows that even after controlling for being a Partners patient in 2011 – which is by far the strongest predictor of switching, with an odds ratio of 23.25 – convenience still predicts switching. Age, high risk score, cancer, and cardiovascular disease also predict higher switching. But interestingly, acute illness and pregnancy during 2011 have odds ratios significantly below one (0.64 and 0.46), indicating these groups are less likely to switch (conditional on other covariates). This suggests forward looking behavior as individuals care less about provider access once they have recovered from temporary conditions.

Overall, this evidence is most consistent with a role for *both* heterogeneity and state dependence.

Table A.6: Heterogeneity in Likelihood to Switch Out after 2012 Network Narrowing

Variable	Outcome: Switch Out of Network Health				Outcome: Being a Partners Patient	
	Unconditional		Controlling for Patient Status			
	(1)		(2)		(3)	
	Odds Ratio	*(S.E.)*	*Odds Ratio*	*(S.E.)*	*Odds Ratio*	*(S.E.)*
Distance to Partners Hospital						
0-2 miles	7.24	(0.45)	2.17	(0.16)	40.61	(2.94)
2-5 miles	4.83	(0.24)	1.96	(0.12)	22.93	(1.44)
5-10 miles	2.68	(0.15)	1.29	(0.08)	13.45	(0.86)
10-20 miles	2.40	(0.15)	1.25	(0.08)	8.53	(0.59)
20-30 miles	1.25	(0.08)	1.09	(0.07)	3.14	(0.23)
> 30 miles	*(omitted = 1.0)*		*(omitted = 1.0)*		*(omitted = 1.0)*	
Medical Risk and Conditions (during 2011)						
Age (years/10)	1.21	(0.02)	1.23	(0.02)	1.04	(0.01)
Any Chronic Illness	1.68	(0.07)	1.01	(0.05)	2.26	(0.09)
Any Acute Illness	1.42	(0.06)	0.64	(0.03)	3.34	(0.16)
Risk Score in top 5%	1.45	(0.10)	1.17	(0.09)	1.59	(0.10)
Cancer	2.10	(0.17)	1.64	(0.15)	2.56	(0.21)
Cardiovascular	1.51	(0.12)	1.26	(0.11)	1.55	(0.12)
Diabetes	1.05	(0.06)	1.08	(0.07)	0.95	(0.05)
Lung Disease	1.18	(0.08)	1.07	(0.08)	1.19	(0.08)
Mental Health	1.04	(0.06)	1.04	(0.06)	1.08	(0.05)
Pregnancy	0.63	(0.19)	0.46	(0.15)	1.53	(0.33)
Patient at Dropped Providers during 2011						
Partners Provider	---		23.25	(1.14)	---	
Other Dropped Provider	---		12.24	(0.71)	---	
Observations	41,917		41,917		41,917	
Pseudo-R^2	0.105		0.305		0.232	

* Statistical difference from an odds ratio of 1.0 is indicated with ** (1% level) and * (5% level).

NOTE: The table reports estimates of binary logit regressions for the outcome of switching out of Network Health in 2012 (columns 1-2) and being a Partners patient for outpatient care in 2011 (column 3). The sample consists of current enrollees in Network Health as of the end of 2011 who choose whether or not to switch plans at the start of 2012. The table reports logit odds ratios, equal to e^{β} of the underlying logit coefficients β. Distance is defined as driving distance to the closest Partners hospital. All medical conditions are defined based on diagnoses on 2011 claims. Any chronic and acute illnesses are defined based on a categorization shared with me by Kaushik Ghosh and David Cutler. The specific illnesses are based on a categorization of diagnoses entering the HCC risk score model. The top 5% risk score category is based on CommCare's risk score as calculated from 2011 claims data. In addition to the variables shown above, the model includes controls for gender and income group.

Importantly, this suggests that patients likely suffer real utility losses both in the short and long run if they lose access to their preferred providers. Someone who has cancer or lives nearby a Partners hospital loses out from the narrower network, even after they switch to a new provider. As long as provider sorting is partly based on persistent factors (either initially or dynamically), there are long-run welfare implications. Of course, state dependence also matters because it *amplifies* how much patients care today about keeping their doctor, relative to the long run.

Evidence of State Dependence

The findings so far are suggestive that state dependence is relevant. To provide stronger evidence, I examine the role of of a more detailed treatment history variable: the *recency* of the latest visit to a physician of Partners or another dropped provider. The model I have in mind is one where a patient's loyalty is determined by the strength of the patient-doctor relationship. That relationship, in turn, is strongest when recently renewed through an in-person office visit and decays gradually as time elapses without an interaction. Of course, the main concern in testing this story is that visit recency correlates with illness – sicker people get care more frequently – so I will do my best to control for sickness in the analysis.

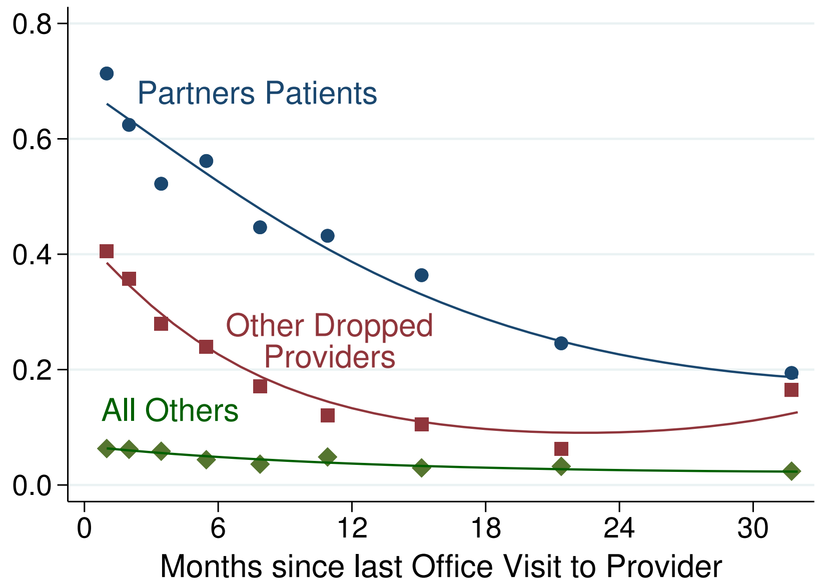
Figure A.15 shows how probability of switching out of Network Health at the start of 2012 varies with months elapsed since the patient's last office visit to Partners or another dropped hospital's physician. The sample is split among Partners patients (blue), patients of other providers dropped by Network Health in 2012 (red), and as a control group, patients of all other providers who are not dropped (green).[19] The plot shows binned predicted probabilities from logit regressions (separately by patient group) after controlling for a detailed set of demographic, health status, and distance-to-provider variables (see figure notes), along with quadratic best-fit curves. Appendix Table A.7 reports the numerical estimates and shows robustness to the controls included.

For patients of Partners or another dropped provider, there is a steep relationship between visit recency and the likelihood of switching out of Network Health in 2012. Among patients who visited Partners in the past 1-2 months, 62-71% switch plans – an extremely high rate for insurance choice where inertia is the norm. This declines to 52-56% for patients with a visit 3-6 months prior, 43-45% for patients with a visit 7-12 months prior, and gradually down to 19% for patients whose most recent visit is 25+ months prior (the final plotted bin). There is a similar pattern for patients of other dropped providers, albeit at a lower level of switching. For all other patients, switching is only modestly related to visit recency.

These results in Figure A.15 suggest that consumers' willingness to switch plans to keep their provider is influenced not just by the existence of a relationship but by how recently it has been renewed. They are strongly consistent with history (i.e., state dependence) mattering for provider preferences, and particularly so for the star hospitals. While not perfect evidence – visit recency is

[19]The analysis excludes about 19% of individuals do not have any observed physician visits prior to the start of 2012. Among the remaining sample, 13% have a prior Partners visit and 4% have a prior visit to another dropped hospital's physician, with a small number of overlaps (0.3%) classified as Partners patients. The x-variable is defined as months since the last visit to the provider in the indicated system (Partners or other dropped) – i.e., it does not count more recent visits to other providers.

Figure A.15: Switching Rate Out of Network Health, by Recency of Last Provider Visit



NOTE: The plot shows how plan switching rates out of Network Health in 2012 relate to the recency of a physician office visit with the indicated provider. Individuals are categorized into Partners patients (blue circles), patients of another dropped hospital (red squares), and all other patients (green diamonds) based on prior physician office visits in the claims data. Individuals with no prior office visits in the data are excluded, and a small number (0.3%) of overlaps between Partners and other dropped providers' patients are classified as Partners patients. The x-axis is recency (as of the start of 2012) of the latest physician office visit to the indicated provider (e.g., Partners for the Partners patients). The numbers shown are predicted probabilities for recency bins from logit regressions, controlling for demographics (age, gender, income group), medical risk variables (chronic condition dummies and vigintiles HCC risk score), and distance to Partners and other dropped hospitals. Separate regressions are run for each patient group, and predicted probabilities are evaluated at the mean of control variables. The lines are quadratic best-fit curves.

not randomly assigned – the patterns are difficult to explain with other stories. The results control for detailed medical risk variables (along with demographics and distance), suggesting that recency is not merely proxying for sickness. Results are also not sensitive to which controls are included (see Appendix Table A.7). Moreover, the patterns are only present based on recency of visits to the dropped providers, not to other providers. Thus, the most likely explanation is that past experience with a provider matters – and matters more so when that experience is recent.

Table A.7: Switching Rate Out of Network Health, by Recency of Last Provider Visit (Estimates)

Recency of Latest Visit to Provider	Probability Switch Out of Network Health in 2012					
	Raw Probabilities (no controls)		Medical Risk Controls		Medical Risk and Distance Controls	
	(1)		(2)		(3)	
	Prob.	*(S.E.)*	*Prob.*	*(S.E.)*	*Prob.*	*(S.E.)*
Partners Patients						
1 month	0.730	(0.016)	0.726	(0.016)	0.713	(0.017)
2 months	0.651	(0.020)	0.641	(0.021)	0.624	(0.022)
3-4 months	0.545	(0.019)	0.541	(0.020)	0.522	(0.021)
5-6 months	0.565	(0.027)	0.572	(0.028)	0.562	(0.029)
7-9 months	0.448	(0.026)	0.455	(0.027)	0.447	(0.028)
10-12 months	0.433	(0.033)	0.449	(0.034)	0.432	(0.034)
13-18 months	0.339	(0.026)	0.349	(0.027)	0.364	(0.028)
19-24 months	0.226	(0.022)	0.229	(0.023)	0.246	(0.025)
>24 months	0.186	(0.016)	0.180	(0.016)	0.194	(0.017)
Other Dropped Providers' Patients						
1 month	0.469	(0.036)	0.446	(0.038)	0.405	(0.039)
2 months	0.375	(0.043)	0.367	(0.045)	0.357	(0.047)
3-4 months	0.292	(0.031)	0.304	(0.034)	0.279	(0.034)
5-6 months	0.290	(0.055)	0.273	(0.056)	0.240	(0.054)
7-9 months	0.183	(0.038)	0.179	(0.039)	0.171	(0.039)
10-12 months	0.137	(0.040)	0.112	(0.036)	0.120	(0.039)
13-18 months	0.123	(0.031)	0.112	(0.030)	0.105	(0.029)
19-24 months	0.071	(0.028)	0.066	(0.027)	0.062	(0.026)
>24 months	0.213	(0.031)	0.192	(0.031)	0.165	(0.029)
All Other Patients						
1 month	0.084	(0.003)	0.076	(0.003)	0.063	(0.003)
2 months	0.081	(0.004)	0.076	(0.004)	0.062	(0.003)
3-4 months	0.075	(0.004)	0.072	(0.004)	0.059	(0.003)
5-6 months	0.055	(0.005)	0.054	(0.005)	0.044	(0.004)
7-9 months	0.047	(0.004)	0.046	(0.004)	0.036	(0.004)
10-12 months	0.060	(0.006)	0.061	(0.007)	0.049	(0.005)
13-18 months	0.038	(0.005)	0.040	(0.006)	0.030	(0.004)
19-24 months	0.041	(0.007)	0.044	(0.008)	0.032	(0.006)
>24 months	0.031	(0.005)	0.033	(0.005)	0.024	(0.004)

NOTE: The table reports estimates corresponding to Figure A.15 in the text. Individuals are categorized into Partners patients (top panel), patients of another dropped hospital (middle panel), and all other patients (bottom panel) based on prior physician office visits in the claims data. Individuals with no prior office visits (about 19%) in the data are excluded. Among the remaining sample, 13% have a prior Partners visit and 4% have a prior visit to another dropped hospital's physician, with a small number of overlaps (0.3%) classified as Partners patients. The table shows rates of switching out of Network Health in 2012 by recency (as of the start of 2012) of the latest physician office visit to the indicated provider (e.g., Partners for the Partners patients). The numbers shown are predicted probabilities for bins of recency (using Stata's "margins" command) from logit regressions with various controls, evaluated at control variable means. Column (1) has no control variables; column (2) controls for demographics (age, gender, income group) and medical risk variables (chronic condition dummies and ventiles of HCC risk score); column (3) additionally controls for distance to Partners and other dropped providers, using the distance categories in Table A.6. Separate regressions are run for each patient group.

E Appendix: Cost Decomposition Details and Analyses

This appendix describes additional details of the method for decomposing medical spending, as summarized in Section IV.A, and also presents additional analyses related to the findings in Section IV.

E.1 Cost Decomposition Method Details

As discussed in Section IV.A, I decompose costs into prices vs. quantities, and quantities into risk-predictable quantity and a residual. The method involves four key steps:

1. Defining the unit of medical services (s)
2. Estimating the "quantity" of each medical service (Q_s) based on typical amounts paid for the service across all insurers and years
3. Calculating total quantity and average price for an enrollee
4. Estimating Risk-Predictable Quantity

The following subsections describe how this is operationalized separately for outpatient and inpatient care. The next subsection reports some summary statistics on the share of cost variation accounted for by price versus quantity.

Outpatient Care

The most natural unit of service (s) for outpatient care are procedure codes, since the vast majority of care is paid for on a fee-for-service basis based on these. This definition, however, means that I exclude outpatient care that is paid for via other methods like capitation. In practice, non-FFS payments are not very common in the claims data.[20] I also exclude outpatient emergency department care to avoid double-counting, since these are included in the inpatient costs when there is an inpatient admission. Therefore, my outpatient cost decomposition reflects non-emergency department outpatient care.

I define a unit of service, s, based on HCPCS procedure codes (as used by Medicare and most private insurers, including CommCare) interacted with the type of bill/provider. HCPCS codes are detailed service units; an example code is 99213, a 15-minute physician office visit with an established patient. The type of bill/provider captures the distinction between bills for facility costs vs. professional services, as well as high-level provider categories (e.g., medical, behavioral health, and dental care) for which a given procedure may mean something slightly different. Following Medicare rules, a procedure delivered in a "facility" (e.g., a hospital or nursing home) is billed in two parts, with one payment for facility costs and one payment to the physician for professional services. I treat these bills as separate "services" and use each one's average price to calculate price-standardized utilization.

Given this definition of s, I define quantity Q_s as the mean insurer-paid amount ($Paid_{a_{it},s}$ in the notation of Section IV.A) for the service across all insurers and years of the claims data. Price is

[20] Public reports indicate very little capitation payment by CommCare insurers. This is consistent with my analysis of the claims data, for which just 0.4% of claim lines for outpatient care (representing 0.6% of spending) have flags indicating capitation contracts. I exclude these claims from the outpatient cost decomposition.

defined as the residual multiplicative factor that accounts for observed spending: $P_{a_{it},s} \equiv Paid_{a_{it},s}/Q_s$. This ensures that price measures are centered around 1.0. It also means that total quantity is a form of price-standardized utilization, which adds up services used valued at constant prices across insurers and years.

Let A_{it}^{OP} be the set of outpatient services used by person i in year t, and let a_{it} index each instance of utilization. With these definitions (and following Section IV.A), total quantity of outpatient care for an enrollee equals

$$Q_{i,t}^{OP} = \sum_{a_{it} \in A_{it}^{OP}} Q_{s(a_{it})} = \sum_{a_{it} \in A_{it}^{OP}} \overline{Paid}_{s(a_{it})}. \tag{1}$$

Average price equals the residual factor explaining costs, which is also a (quantity-weighted) average of prices across all services used by the individual:

$$P_{i,t}^{OP} \equiv \frac{C_{i,t}^{OP}}{Q_{i,t}^{OP}} = \sum_{a_{it} \in A_{it}^{OP}} \left(\frac{Q_{s(a_{it})}}{Q_{it}^{OP}} \right) \cdot P_{a_{it},s}. \tag{2}$$

Inpatient Care

For inpatient care, the most natural service unit is the diagnosis-related group (DRG), which is the standard measure used in hospital price analyses (e.g., Cooper et al., 2019) and is the method of payment for about 90% of hospitalizations in my data. Nonetheless, because not all admissions are DRG-paid and because even DRG payment allows exceptions due to outlier adjustments, I estimate a pricing model that allows quantity to vary within a DRG or diagnosis based on other patient severity observables. Essentially, this method defines the quantity associated with each hospital admission in a continuous way based on a projection of spending onto DRG/diagnosis categories and other patient observables.

Consider a particular admission a – for enrollee i in plan j in year t for DRG (or diagnosis) d at hospital h.[21] I regress log insurer payments ($\log(Paid_{a,i,j,t,d,h})$) on insurer-hospital dummies $\alpha_{h,j,N}$ that can vary with the network status ($N \in \{0, 1\}$), year dummies (β_t), DRG/diagnosis fixed effects (γ_d), and patient severity factors ($Z_{a,i,t}$) comprised of gender x age groups (in 5-year bins), income groups, and Elixhauser comorbidities:[22]

$$\log\left(Paid_{a,i,j,t,d,h}\right) = \alpha_{h,j,N} + \beta_t + \gamma_d + Z_{a,i,t}\delta + u_{a,i,j,d,t} \tag{3}$$

Using estimates of (3), I define the quantity unit as the component of payment arising from DRG/diagnosis,

[21] When the DRG is unavailable, I use the single-level Clinical Classification Software (CCS) category of the principal diagnosis. CCS codes are a categorization defined by the U.S. Agency for Healthcare Research and Quality (AHRQ). As an alternative, I considered using DRG grouper software to impute the DRG for admissions where it is not listed. I found, however, that the claims data often did not include all necessary information to impute DRGs, making this method unreliable. The main missing information was ICD-9 procedure codes for the inpatient facility bill, which is required by Medicare DRG grouper software.

[22] This regression specification is quite similar to that of Cooper et al. (2019). To avoid over-fitting, I pool $\alpha_{h,j,Netw}$ cells with fewer than 11 observations into an "other hospitals" group, still separately by insurer and network status. This pooling only applies to about 0.5% of admissions – primarily for out-of-network care and small hospitals, and I ensure it does not affect the star hospitals.

severity, and the residual, converting the estimate to spending levels:

$$\widetilde{Q}_{a,i,t} \equiv \exp\left(\hat{\gamma}_d + Z_{a,i,t}\hat{\delta} + \hat{u}_{a,i,j,d,t}\right) \tag{4}$$

The residual ($\hat{u}$) seems most natural to treat as quantity, since it likely reflects outlier adjustments and unmeasured add-on services. The remainder of (3) is defined as price:

$$\widetilde{P}_{a,i,j,h,t} \equiv \exp\left(\hat{\alpha}_{h,j,N(h,t)} + \hat{\beta}_t\right) \tag{5}$$

where I rescale the (non-identified) constant multiplier between price and quantity so that $\widetilde{P}_{j,h,t}$ has mean of 1.0 across the full sample (which means that $\widetilde{Q}$ is denominated in dollars). Given these definitions of price and quantity, I apply the same idea as in equations (1) and (2) for outpatient care to define inpatient quantity for i in year t as $Q_{i,t}^{IP} \equiv \sum_{a \in Admit(i,t)} \widetilde{Q}_{a,i,t}$, and price as $P_{i,t}^{IP} \equiv C_{i,t}^{IP}/Q_{i,t}^{IP}$.

Combined Inpatient and Outpatient Costs

Inpatient and outpatient care estimates can be analyzed separately or combined to form a decomposition for total costs in the sample. If combined, total quantity equals the sum of the two:

$$Q_{i,t}^{Tot} \equiv Q_{i,t}^{IP} + Q_{i,t}^{OP} \tag{6}$$

Price is defined as the remaining factor needed to account for costs (which as noted above equals a weighted average of service-level prices):

$$P_{i,t}^{Tot} = \frac{C_{i,t}^{IP} + C_{i,t}^{OP}}{Q_{i,t}^{Tot}} \tag{7}$$

Estimating Risk-Predictable Quantity

After pulling out quantity, I project it (separately for outpatient and inpatient care) onto medical risk observables (Z_{it}) to estimate "risk-predictable quantity." To deal with the combination of zeros and skewed distribution of Q_{it}, I estimate a two-part model, with a logit for the probability of positive quantity and log-linear regression for quantity conditional on positive. Specifically, the two parts are: (1) the logit model: $Pr\left(Q_{it} > 0\right) = Logit\left(Z_{it}\theta_1\right)$, and (2) the log-linear model: $\log Q_{it} | Q_{it} > 0 = Z_{it}\theta_2 + \varepsilon_{it}$. These models are estimated using the Stata command "twopm". The command uses the estimates to output predicted quantity as:

$$\hat{Q}_{it}^{risk} = E\left[Q_{it}|Z_{it}\right] = Logit\left(Z_{it}\hat{\theta}_1\right) \cdot \exp\left(Z_{it}\hat{\theta}_2\right) \cdot E\left(e^{\varepsilon}\right)$$

where $Logit\left(.\right) = \frac{\exp(.)}{1+\exp(.)}$ and the $E\left(e^{\varepsilon}\right)$ is the "Duan smearing" correction so that the mean of $\hat{Q}_{it}$ more closely matches Q_{it}, a method that works better than using the standard log-normal factor $\exp\left(\sigma_{\varepsilon}^2/2\right)$.[23]

[23] See the documentation for Stata's "twopm" command for additional details.

I do this projection first using only variables included in the exchange's (retrospective) risk adjustment, including age and a flexible 11-part spline for the CommCare risk score. This generates what I call "observed risk": $\hat{Q}_{it}^{risk,obs} = f\left(Z_{it}^{obs};\hat{\theta}\right)$. I then do the decomposition for these variables plus a broader set of risk variables from the claims, including concurrent diagnoses and a spline of the concurrent HCC risk score. This generates my overall measure of risk-predictable quantity: $\hat{Q}_{it}^{risk} = f\left(Z_{it}^{obs}, Z_{it}^{other};\hat{\theta}\right)$. I then define "residual quantity" as the remaining factor explaining observed quantity: $\hat{Q}_{it}^{resid} \equiv Q_{it}/\hat{Q}_{it}^{risk}$.

Summary of Decomposition

Putting everything together, individual-level costs equal the product of three factors: $C_{it} = \hat{Q}_{it}^{risk} \cdot \hat{Q}_{it}^{resid} \cdot P_{it}$. This relationship also holds at a group level for (appropriately weighted) averages:

$$\overline{C}_{g,t} = \overline{Q}_{g,t}^{risk} \times \overline{Q}_{g,t}^{resid} \times \overline{P}_{g,t} \tag{8}$$

where $\overline{P}_{g,t}$ is average prices weighted by enrollee quantity (Q_{it}), and $\overline{Q}_{g,t}^{resid}$ is the average residual weighted by risk-predicted quantities ($\hat{Q}_{it}^{risk}$). This equation lets me decompose the share of group cost differences (e.g., stayers vs. switchers in 2012) that are driven by (1) risk-predictable quantity, (2) residual quantity, and (3) provider prices. Its multiplicative form suggests decomposing log differences for each factor, which are additive:

$$\Delta \log\left(\overline{C}\right) = \Delta \log\left(\overline{Q}^{risk}\right) + \Delta \log\left(\overline{Q}^{resid}\right) + \Delta \log\left(\overline{P}\right)$$

This allows me to quantify the share of log cost differences explained by these three factors, as shown in Table 2.

E.2 Summary Statistics on Price-Quantity Estimates

Appendix Table A.8 shows summary statistics from the decomposition. Panel A shows statistics about the mean and standard deviation of medical costs and the quantity and price decomposition estimates. In addition to quantity in dollars per month, I show statistics for quantity relative to the sample mean, to make the units more comparable to the price variable. Panel B shows the relationship of quantity and price to the HCC medical risk score. For both analyses, the unit of analysis is the enrollee-year (reflecting the insurance contract period), and the sample is limited to 2011-2013, the years around the network change. All results are similar if I instead restrict the analysis to Network Health in 2011 (the key plan-year for the selection analysis).

Panel A shows that there is substantial cost variation across enrollees, with both quantity and price contributing. For total costs covered by the decomposition (column 1), its mean is \$228.2 per month (which, is 61% of overall average costs of \$375). Its standard deviation of \$780 is more than three times as large, reflecting the skewed nature of medical spending. Most of this variation comes from quantity, whose coefficient of variation is 3.15. But price also varies meaningfully, with a standard deviation of 34% across enrollees (coefficient of variation = 0.33). Interestingly, price and quantity are largely orthogonal, with a correlation of -0.02. The same basic patterns hold separately for outpatient and inpatient costs in columns (2)-(3).

Panel B shows the relationship of this quantity/price variation to the HCC enrollee risk scores, using simple regressions of quantity/price on risk score and a constant. (The HCC risk score is a concurrent measure used by the ACA and capture more information about risk than the retrospective CommCare risk score, especially for new enrollees.) This relationship is important for selection incentives: the better risk scores capture predictable cost variation, the more likely they will neutralize selection incentives. The table shows that while risk scores strongly predict quantity of care (scaled relative to the sample mean) – with a regression coefficient of 0.408 (s.e. = 0.007) – they hardly predict price variation at all (coeff. = -0.0004, s.e. = 0.0001). Similarly, the R^2 is about 26% for quantity versus <0.1% for price. The pattern is similar for outpatient quantity. Risk score is slightly better at predicting inpatient prices, with a coefficient of 0.002 and R^2 of 1.3%, but these are still an order of magnitude smaller than the analogs for inpatient quantity.

Overall, Table A.8 suggests that while utilization is the main driver of cost heterogeneity, the price dimension of costs – reflecting enrollees' use of higher-price providers – is also relevant. Moreover, the price dimension is not well captured by risk adjustment, consistent with it being driven by a different source of heterogeneity than the sickness measures that enter risk adjustment. This suggests that both (residual) quantity and price variation may be important for insurer selection incentives.

Table A.8: Price vs. Quantity Medical Cost Decomposition

Variable	Statistic	Total Costs (1)	Outpatient Costs (2)	Inpatient Costs (3)
A. Cost Decomposition Summary				
Costs in Decomp.	Mean	$228.2	$163.6	$64.7
($ per month)	*[S.D.]*	*[$779.5]*	*[$388.7]*	*[$609.2]*
Quantity of Care	Mean	$228.6	$165.9	$62.7
($ per month)	*[S.D.]*	*[$720.9]*	*[$395.8]*	*[$536.2]*
Quantity (relative	Mean	1.00	1.00	1.00
to mean)	*[S.D.]*	*[3.15]*	*[8.55]*	*[2.39]*
Price Factor	Mean	1.02	1.02	1.00
	[S.D.]	*[0.34]*	*[0.34]*	*[0.26]*
B. Regression of Quantity/Price on Risk Score				
Quantity (relative	Regr. Coeff	0.408	0.912	0.217
to mean)	(s.e.)	(0.007)	(0.024)	(0.004)
	[R^2]	*[26.0%]*	*[17.7%]*	*[12.9%]*
Price Factor	Regr. Coeff	-0.0004	-0.0010	0.0022
	(s.e.)	(0.0001)	(0.0001)	(0.0001)
	[R^2]	*[0.00%]*	*[0.02%]*	*[1.27%]*

NOTE: The table shows a summary of the decomposition of medical costs into price versus quantity. Panel A shows means and standard deviations across enrollees for costs included in the decomposition (in $ per member-month), for quantity (in $ per month) and quantity relative to the sample mean, and for price (see text for its definition). Panel B shows estimates of regressions of quantity/price (y-variable) on an enrollee's HCC risk score. For both panels, the columns show results separately for (1) total costs in the decomposition (outpatient + inpatient costs), (2) outpatient costs, and (3) inpatient costs. Observations are at the enrollee-year level (with outcomes averaged to per-month values) and are weighted by number of months a person is enrolled during the year. The sample is limited to fiscal years 2011-2013, the years surrounding the key network change.

E.3 Switchers vs. Stayers Costs: Additional Analyses

Table 2 in the body text quantifies the contribution to switcher-stayer cost differences of overall quantity, risk-predictable quantity, residual quantity, and provider prices. These differences shed light on the role of the two cost dimensions, medical risk and provider costs/choices, to cost differences driving adverse selection. This appendix discusses additional analyses that illustrate how switchers and stayers differ in different components of the cost decomposition.

Descriptive Plots of Stayers vs. Switchers Cost Differences Figures A.16 and A.17 show descriptive plots on the distribution of components of the cost decomposition for stayers vs. switchers out of Network Health in 2012. In most panels, the left figure shows the overall measure's distribution for stayers (red) vs. switchers (blue), while the right panel shows a bin scatter of the mean by decile of enrollee HCC risk score, to illustrate the risk-conditional distribution. Each panel shows a different variable relevant to the cost decomposition: total medical spending included in the decomposition (panel A), total quantity of care (panel B), risk-predictable quantity of care (panel C) using all risk variables, inpatient prices (panel D), outpatient prices (panel E), and share of utilization that occurs at Partners providers (panel F). (In panel F, I do not show the overall distribution, which is bimodal and hard to see, but instead show risk bin scatters separately for inpatient and outpatient costs.)

The figures indicate that switchers are higher cost on nearly all metrics. Switchers' overall higher costs (panel A) are evident in the raw distributions, with stayers having a much higher density peak at low spending levels. The left figure of panel A shows that the differences are consistent across the risk distribution and close to constant in percentage terms (note the log scale of the axes). In particular, switchers' costs are higher than stayers regardless of whether they are healthy or sick. Panel B shows that a similar pattern holds for overall quantity of care, which drives the majority of cost differences. Panel C shows that risk-predictable quantity captures much of the differences, but there is still a gap as indicated by the higher residual quantity for switchers (see Table 2). Some of this residual quantity may reflect effects of provider treatment intensity.

Figure A.17 show that prices and provider use is also relevant. Panel A shows that switchers have almost 30% higher inpatient care prices, which is entirely driven by their much higher likelihood to choose Partners hospitals (panel F1). Panel B shows, by contrast, that switchers and stayers have similar outpatient care prices. Even though switchers are much more likely to choose Partners for outpatient care (panel F2), I estimate that Partners outpatient prices are not high, leading to the result of similar outpatient prices.

Analysis of Residual Quantity The estimates in Table 2 indicate that residual quantity (not predictable by medical risk variables) accounts for a meaningful share of the higher costs of switchers out of Network Health relative to stayers. This residual quantity is challenging to interpret because it might reflect either further unobserved medical risk (the standard cost channel) or provider effects on treatment intensity (the second channel). To provide suggestive evidence on this issue, Table A.9 analyzes whether residual quantity is associated with provider use, proxied by being a patient of Partners or another dropped hospital. Because patients may sort on unobserved medical risk, columns (2)

Table A.9: Analysis of Residual Quantity and Partners Use

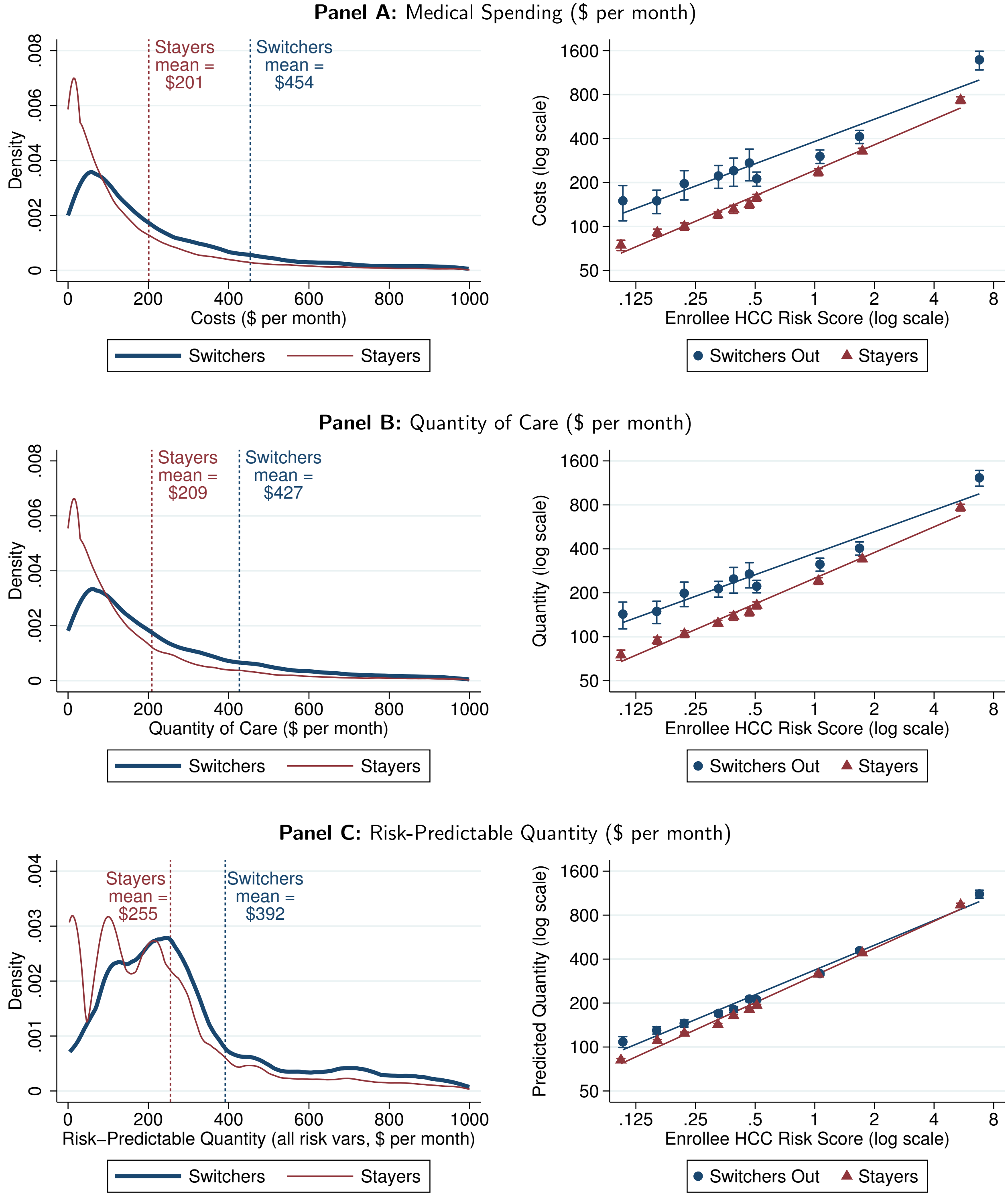
	Outcome: Residual Quantity			
	Outpatient Care		**Inpatient Care**	
	OLS (1)	Distance IV (2)	OLS (3)	Distance IV (4)
Partners Patient	0.292	0.158	0.299	0.147
	(0.020)	(0.046)	(0.066)	(0.149)
Other Dropped Hospital Patient	0.221	0.034	0.134	0.346
	(0.023)	(0.069)	(0.070)	(0.213)
Constant	0.770	0.823	0.758	0.779
	(0.007)	(0.019)	(0.030)	(0.061)
First-Stage F-Stats.				
Partners Patient	---	219.3	---	41.0
Other Dropped Patient	---	107.0	---	26.6
Num. Obs.	41,917	41,917	41,917	41,917

NOTE: The table shows estimates of a regression of residual quantity on dummies for being a Partners patient or patient of another hospital dropped by Network Health in 2012. The sample is all current Network Health enrollees at the end of 2011 (same as for Table 2 in the main text), and the residual quantity measure is for 2011 and is defined by the price-quantity decomposition in Section IV.A. Columns (1)-(2) show estimates for outpatient costs, while columns (3)-(4) show inpatient costs. Columns (1) and (3) show OLS estimates, while columns (2) and (4) instrument for patient status using distance to the relevant hospitals. If distance is orthogonal to unobserved medical risk, these IV estimates reflect causal provider impacts on quantity of care.

and (4) instrument for patient status using distance to the relevant provider. If distance is orthogonal to unobserved medical risk, then these IV estimates represent causal provider impacts on quantity.

The IV estimates suggest that Partners patients have about 15% points higher residual quantity of outpatient care (significant at the 1% level) and a non-significant 15% higher residual quantity for inpatient care (where the estimates are much noisier). These estimates are about 20% of the average for other enrollees (captured by the regression constant). The IV estimates are about half of the OLS estimates, suggesting that high residual quantity reflects a mixture of unobserved medical risk and Partners provider impacts on quantity.

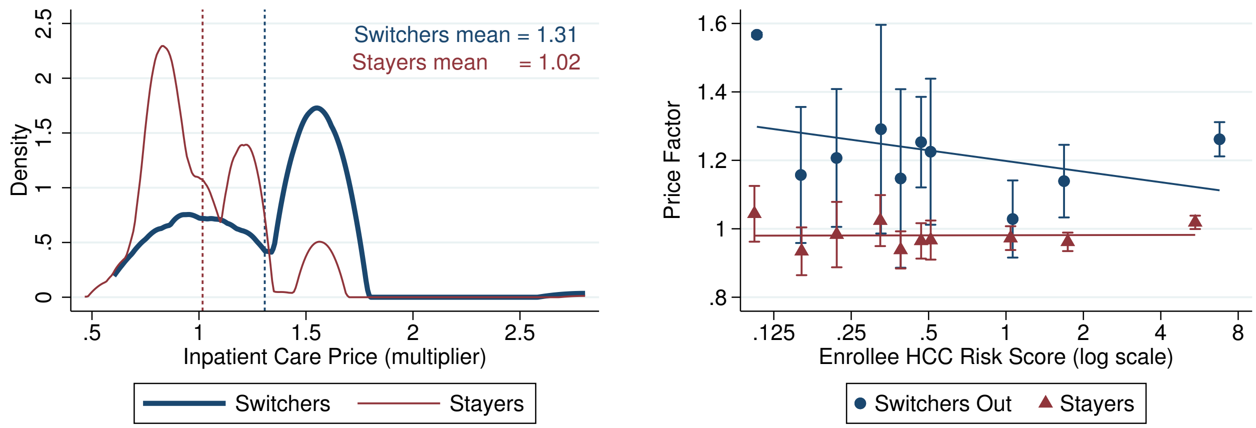
Figure A.16: Switcher vs. Stayer Cost Decomposition: Distributions and Bin Scatters by Risk Score



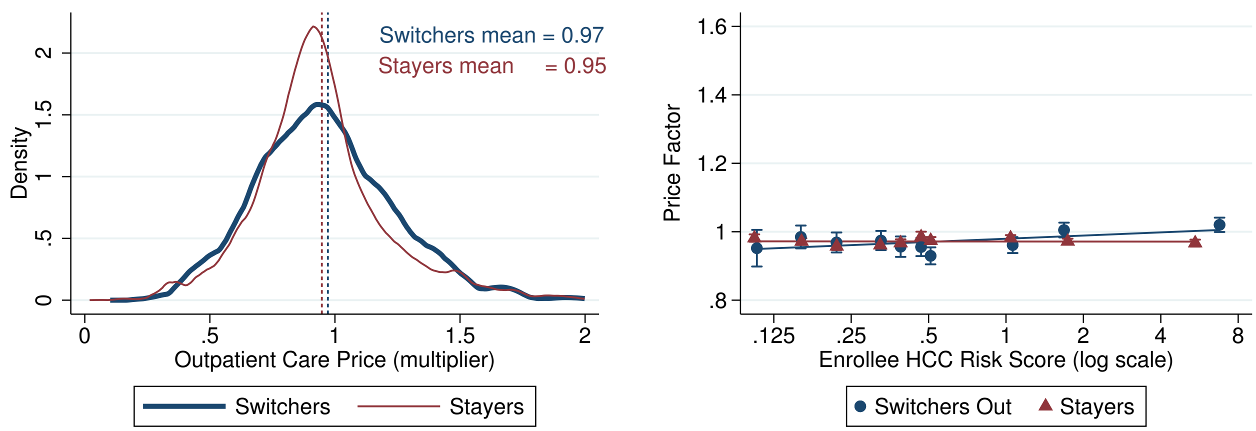
NOTE: The figures show the distribution and risk score-conditional distributions of cost components for switchers vs. stayers in Network Health in 2012. In each panel, the left figure shows the distribution (kernel densities) for switchers, while the right figure shows a bin scatter of means by decile of the HCC risk score (with confidence intervals shown in bars) to illustrate the risk-conditional distribution.

Figure A.17: Switcher vs. Stayer Cost Decomposition: Distributions and Risk Bin Scatters (cont'd)

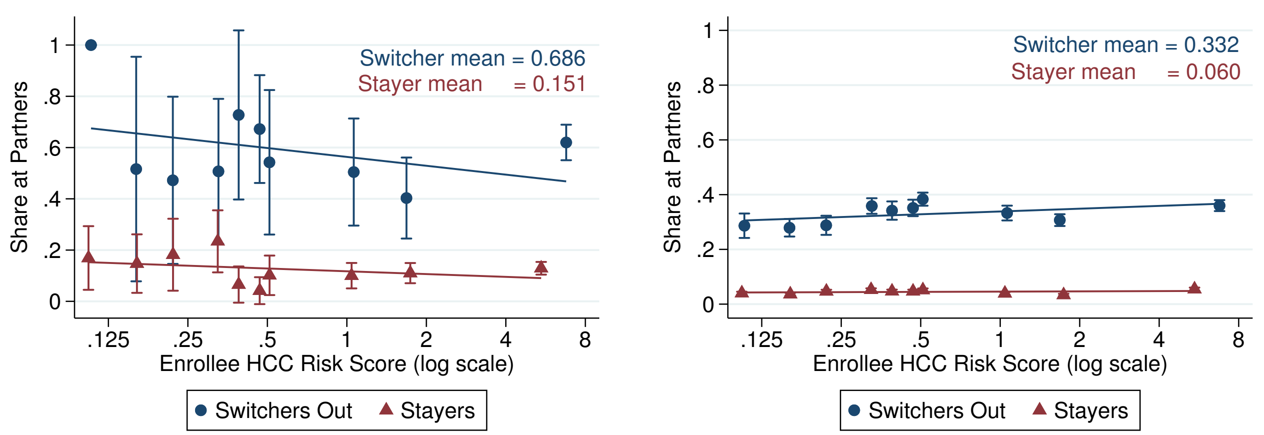
Panel D: Inpatient Prices (multiplicative factor)



Panel E: Outpatient Prices (multiplicative factor)



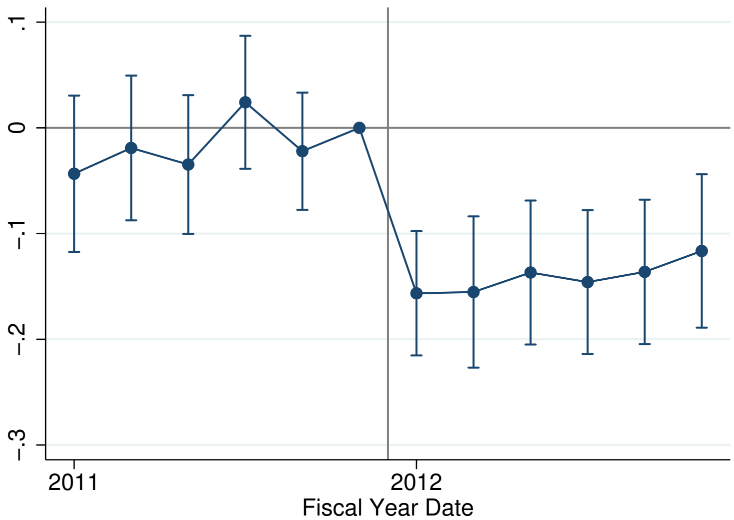
Panel F1: Share at Partners: Inpatient Care **Panel F2:** Share at Partners: Outpatient Care



NOTE: The figures show the distribution and risk score-conditional distributions of cost components for switchers vs. stayers in Network Health in 2012. In panels D-E, the left figure shows kernel densities for switchers, while the right figure shows a bin scatter of means by decile of the HCC risk score (with confidence intervals shown in bars) to illustrate the risk-conditional distribution. Panel F shows bin scatters for inpatient (F1) and outpatient (F2) shares at Partners.

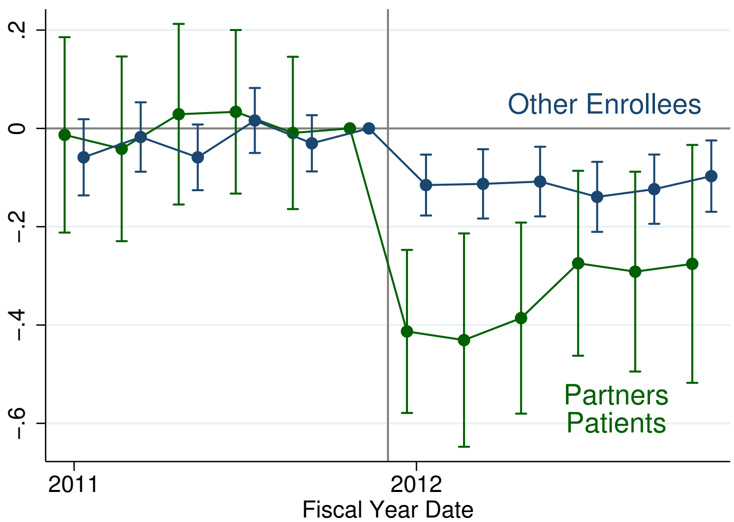
E.4 Additional Estimates of Causal Cost Effects (Moral Hazard)

Figure A.18: Event Study: Cost Reductions after 2012 Network Change



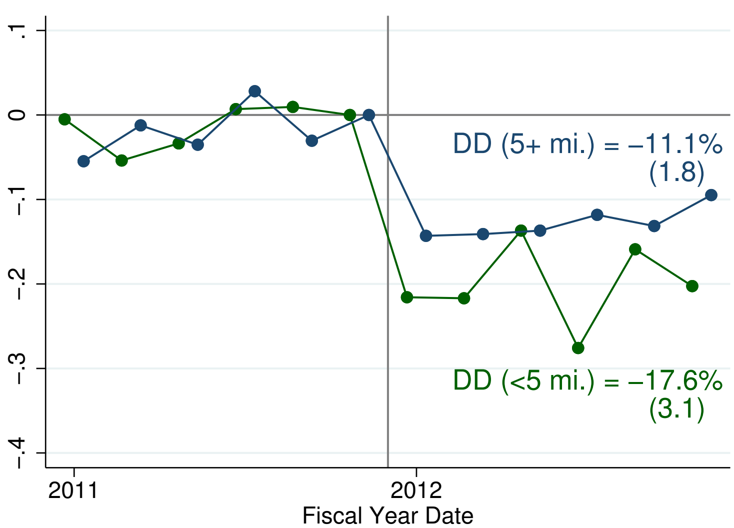
NOTE: The figure shows coefficient estimates (and 95% confidence intervals) of $\hat{\gamma}$ from the event study version of regression (8) in Section IV.C (and corresponding to Panel A of Figure 5). Estimates are from a Poisson regression with individual fixed effects and capture the cost differences between stayers in Network Health from 2011-12 versus stayers in other plans (control group), relative to the omitted period (the final bimonthly period of 2011). Poisson coefficients are roughly interpretable as percent differences; more precisely the percent difference is $\exp(\gamma) - 1$. The figure confirms the presence of parallel pre-trends and a sharp and persistent fall in costs of about 10-15% during 2012.

Figure A.19: Event Study: Cost Reductions after 2012 Network Change, by Partners Patients



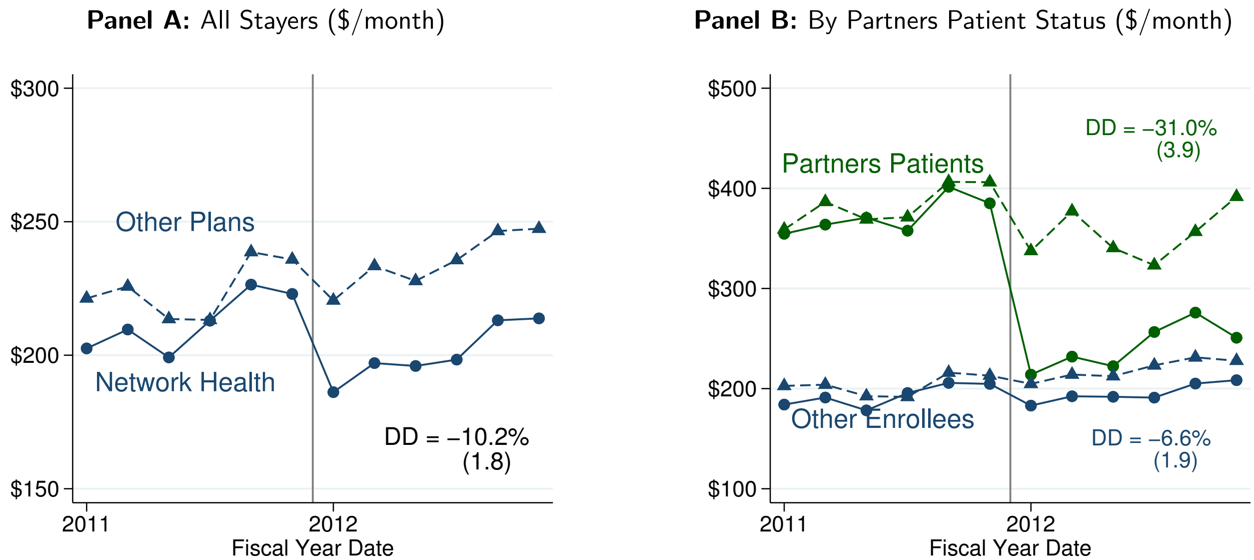
NOTE: The figure shows coefficient estimates (and 95% confidence intervals) of $\hat{\gamma}$ from the event study version of regression (8) in Section IV.C, with separate interactions for γ with Partners patients (green series) versus other enrollees (blue), corresponding to Panel B of Figure 5. See note to Figure A.18 for additional information on the setup and interpretation of coefficients. This figure confirms the presence of parallel pre-trends for both groups and a share cost reduction in 2012 that is much larger for Partners patients.

Figure A.20: Cost Reductions after 2012 Network Change, by Distance to Partners Hospital



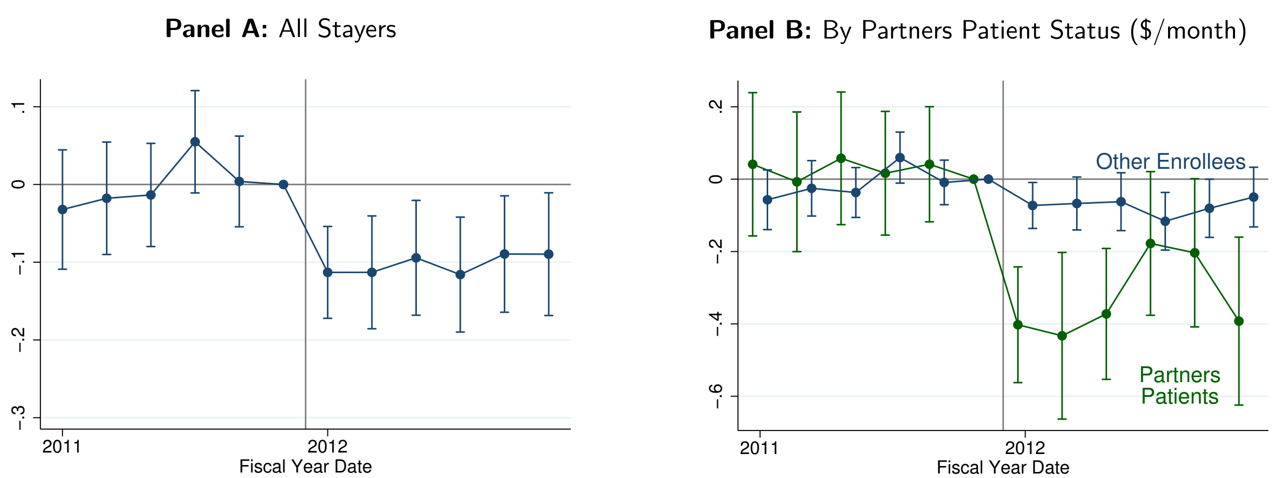
NOTE: The figure shows coefficient estimates (and 95% confidence intervals) of $\hat{\gamma}$ from the event study version of regression (8) in Section IV.C, with separate interactions for γ with people living within 5 miles of a Partners hospital (green series) versus those living 5+ miles away (blue). See note to Figure A.18 for additional information on the setup and interpretation of coefficients. Confidence intervals are suppressed because they are sufficiently wide to make it difficult to see the two series. The overall DD coefficients and their confidence intervals are reported. These are suggestive of a larger cost reduction for people living within 5 miles of a Partners hospital, but note that the difference is not statistically significant.

Figure A.21: Reductions in Quantity for Stayers after 2012 Network Change



NOTE: These graphs show estimates from quantity regressions with individual fixed effects corresponding to the event study version of equation (8). The sample is "stayers" continuously enrolled in Network Health or other plans between 2011 and 2012, when Network Health narrows its network. The regression is exactly analogous to Figure 5 in the text, but with a dependent variable of quantity of care (in $ per month), rather than total costs. Quantity is defined in the price-quantity decomposition discussed in Section IV.A and Appendix E.1. The levels of quantity are below the levels of total costs because quantity is only defined for care included in the price-quantity decomposition, which covers about two-thirds of costs.

Figure A.22: Quantity Reductions for Stayers after 2012 Network Change: Event Study



NOTE: The figure shows coefficient estimates (and 95% confidence intervals) of $\hat{\gamma}$ from the event study version of regression (8) in Section IV.C, with a dependent variable of quantity of care. Panel B has separate interactions for γ with Partners patients (green series) versus other enrollees (blue). This figure confirms the presence of parallel pre-trends for both groups and a quantity reduction in 2012 that is much larger for Partners patients.

F Appendix: Structural Model and Estimation Details

F.1 Hospital Choice Model

I use the inpatient hospitalization dataset (see Appendix A.1) to estimate a multinomial logit choice model. I distinguish patients' utility for different hospitals from the barriers their plan's network creates. The utility of patient i with diagnosis d for hospital h at time t is:

$$U_{i,d,t,h}^{Hosp} = \underbrace{\gamma_1 (Z_{i,d,t}) \cdot Dist_{i,h}}_{\text{Distance}} + \underbrace{\gamma_2 (Z_{i,d,t}) \cdot X_h + \gamma_3 \cdot PastPatient_{i,h,t}}_{\text{Hospital characteristics x Patient observables}} + \underbrace{\eta_h}_{\text{Hospital dummy}} + \underbrace{\epsilon_{i,d,t,h}}_{\text{Logit error}} \tag{9}$$

The function governing patient choices (and entering the logit equation) equals this utility minus a hassle cost of going out of network:

$$u_{i,j,d,t,h}^{Hosp} = U_{i,d,t,h}^{Hosp} - \kappa_j (Z_{i,t}) \cdot 1 \{h \notin N_{j,t}\} \tag{10}$$

The specification in (9) is similar to past work (e.g., Town and Vistnes, 2001; Gaynor and Vogt, 2003; Ho, 2006). While this past work (if it measures networks at all) simply excludes out-of-network hospitals from the choice set, I include these hospitals and instead estimate an out-of-network hassle cost $\kappa_j (Z_{i,t})$, which can vary by insurer and patient severity and emergency status. I choose this approach because of the observation that a non-trivial share of patients (about 8%) use out of network hospitals, both for emergencies and non-emergencies. This can occur when the insurer gives prior authorization to go out of network, a barrier that is reasonably represented as a hassle cost. Notice that my approach is a generalization of the standard practice of excluding out-of-network hospitals from the choice set; my model's predictions converge to the standard approach as $\kappa \to \infty$.

In addition to hospital dummies, the utility covariates in (9) include patient travel distance and patient observables interacted with hospital characteristics to allow patient preferences and substitution patterns to differ. The distance variables include distance (in miles) and distance-squared (with separate coefficients for patients living in each of five regions of the state) and distance interacted with patient age, gender, income group, emergency status, and severity (the $\widetilde{Q}_{a,i,t}$ metric from the price decomposition; see equation (4)). The patient observable x hospital characteristics variables are: (1) patient diagnosis category (using the top-level CCS category) interacted with hospital's service offerings (e.g., cancer patient x hospital has oncology services); (2) hospital academic type (top academic medical center, teaching hospital, community hospital) interacted with patient severity, diagnosis category, and whether the patient is a past Partners patient; and (3) whether patient i has previously used hospital h or its doctors (separate dummies for inpatient and outpatient care) prior to the current plan year (and at least 30 days prior to the admission, to avoid any mechanical relationship).

Including past provider use variables differs from past work, which has often not had panel data or outpatient claims to measure it. Including past use allows me to capture relationships between patients and a hospital's physicians, which is a key source of heterogeneity in hospital choices. However, this coefficient's interpretation is complicated because it picks up both state dependence and heterogeneity. To deal with this issue, I assume is that these relationships are fixed in the short run – e.g., the one-year horizon in my counterfactuals – so past use variables are held fixed in all simulations. Of course, it would be nice to model the process through which these patient-provider relationships form. But doing so would introduce complicated dynamics into an already complex model. Instead, I treat these relationships as exogenous, which is sensible in the short run (but less ideal over longer horizons).

Estimates Because all covariates are observed, I estimate the model by maximum likelihood. Table A.10 shows the results. Consistent with previous papers' estimates, patients dislike traveling to more distant hospitals, with each extra mile of distance reducing a hospital's share by 7.6% on average. The model estimates a sizeable hassle cost for out-of-network hospitals that reduces their shares by 58% on average. Two sets of coefficients have implications for the main selection findings of the paper. First, teaching hospitals and academic medical centers (AMCs) tend to attract sicker patients, both measured by patient severity and by particular diagnoses (e.g., cancer). Moreover, AMCs and teaching hospitals are particularly attractive to past Partners patients. Second, past care use is a very strong predictor of future hospital choices. Patients choose a hospital where they have a relationship about 40% of the time, about twice as high as would be expected based on other covariates.

F.2 Hospital Network Utility

To generate a measure of network utility for plan demand, I follow the method of Capps et al. (2003). Consider a consumer i who is deciding among various plans j (with networks $N_{j,t}$) at time t. I define network utility of each plan based on the expected utility metric from the hospital demand system. Conditional on needing to be hospitalized for diagnosis d with emergency status $e \in \{0,1\}$, at time t, a consumer's utility of access to network $N_{j,t}$ in plan j is:

$$\begin{aligned} EU_{i,d,e,t,j}\left(N_{j,t}\right) &= E\left[\max\left\{\hat{u}_{i,d,e,t,j,h}\left(N_{j,t}\right) + \varepsilon_{i,d,e,t,h}\right\}\right] \\ &= \log\left(\sum_h \exp\left(\hat{u}_{i,d,e,t,j,h}\left(N_{j,t}\right)\right)\right) \end{aligned} \tag{11}$$

where $\hat{u}_{i,d,e,t,j,h}\left(N_{j,t}\right)$ is the utility function from (10) excluding the logit error term. (Note that I explicitly include emergency status e in the subscripts here; in equation (9) it was implicitly part of $Z_{i,d,t}$.) Many covariates that enter hospital utility are known at the time of plan choice (e.g., distance, past patient status, and demographics). However, other variables are not realized until later: notably diagnosis, emergency status, and severity. I assume that consumers have expectations over these variables based on observed patterns in the data. Consumers have expectations for their hospital use frequency for each diagnosis d and emergency status $e \in \{0,1\}$ over the coming year, which I denote $freq_{i,d,e,t}$. I estimate these frequencies using a Poisson regression of the number of hospitalizations in the data (for a given $\{d,e\}$ combination) on age-sex and income groups.[24] I use the predicted values from these regressions for $freq_{i,d,e,t}$. For patient severity, I use the average observed severity in the hospitalization data for the $\{d,e\}$ and age-sex group cell.

[24] I choose not to use diagnoses in this regression because past diagnoses are unavailable for new enrollees.

Table A.10: Hospital Choice Model Estimates

Variable	Coeff.	Std. Error
Distance to Hospital (miles):		
Distance (base coeff.: Boston)	-0.2320	(0.0052)
x Region = Central Mass.	0.0889	(0.0057)
x Region = Northern Mass.	0.0561	(0.0058)
x Region = Southern Mass.	0.1030	(0.0052)
x Region = Western Mass.	0.1452	(0.0058)
Distance^2 (avg. coeff.)	0.0012	(0.00002)
Distance x 1{Income > Poverty} (avg.)	-0.0080	(0.0009)
x Age / 10	-0.0031	(0.0003)
x Male	0.0063	(0.0009)
x Admission Severity	0.0021	(0.0006)
x Emergency	-0.0203	(0.0009)
Past Patient of this Hospital		
Inpatient Care	0.9958	(0.0390)
Outpatient Care	1.8195	(0.0200)
Hospital x Patient Characteristics		
Academic Med. Ctr. x Severity	0.4300	(0.0377)
Teaching Hospital x Severity	0.2261	(0.0336)
AMC x Past Partners Patient	0.3224	(0.0569)
Teaching x Past Partners Patient	0.3508	(0.0647)
AMC/Teaching x Diagnoses	Yes	
Selected Coeffs: AMC x Cancer	1.3257	(0.0666)
AMC x Injury	1.0210	(0.0953)
AMC x Musculosk.	0.4308	(0.0903)
AMC x Mental	-1.4726	(0.0626)
Diagnosis x Hospital Specialty Services	Yes	
Hospital Dummy Variables	Yes	
Out-of-Network Disutility		
Out-of-Network x Plan = BMC	-1.8590	(0.0517)
x Plan = CeltiCare	-2.3100	(0.0732)
x Plan = Fallon	-1.8027	(0.0748)
x Plan = NHP	-0.9391	(0.0652)
x Plan = Network	-1.8405	(0.0495)
Out-of-Network x Emergency	0.9084	(0.0433)
Model Stats: Number of Admissions	70,094	
Number of Individuals	47,958	
Pseudo-R^2	0.578	

NOTE: The table shows estimates for the multinomial logit hospital choice model. The coefficients shown are interpretable as entering the utility function describing hospital choice. Past use variables are dummies for whether a patient has previously used each specific hospital (before the current plan year and at least 30 days before the current admission). Severity is an estimated summary measure ($\widetilde{Q}_{a,i,t}$) from the inpatient price model described in Appendix C; it is standardized (mean 0, SD 1) before entering as a covariate in this model. In addition to the variables shown, the model includes: distance interacted with detailed income group (0-100% poverty and by 50% of poverty from 100-300%); distance-squared interacted with region; interactions between academic medical center (AMC) and teaching hospital status and diagnoses; and seven diagnosis x hospital specialty service interactions (cancer x oncology services; cardiovascular diagnosis x cath lab, x interventional cardiology, and x heart surgery services; pregnancy x obstetrics services and x NICU; musculoskeletal diagnosis x arthritis services; and injury diagnosis x level 1 trauma center).

Given these expectations, the *ex-ante* expected network utility is:

$$NetworkUtil_{i,j,t}\left(N_{j,t}\right)=\sum_{d,e} freq_{i,d,e,t}\cdot EU_{i,d,e,t,j}\left(N_{j,t}\right) \tag{12}$$

The network utility in (12) is what I include in plan demand. Because network utility does not have natural units, I normalize it so that 1.0 is the average decrease in utility for Boston-region residents when Network Health dropped Partners in 2012.

F.3 Plan Choice Model Details

The plan choice model is described in Section V.A. This appendix describes additional model details. Table A.11 below shows a summary of estimates, and Table A.12 lists the full set of coefficients on plan attributes (premium, network value, and inertia) that enter the model, including interaction terms with enrollee observables.

The model is a standard multinomial logit choice model that allows for preference heterogeneity across consumers based on observables. The choice utility specification, as reported in equation (9) is:

$$U_{i,j,t}^{Plan}=\underbrace{\alpha\left(Z_{it}\right)\cdot Prem_{i,j,t}}_{\text{Subsidized Premium}}+\underbrace{V\left(N_{j,t};Z_{it},\beta\right)}_{\text{Network Value}}+\underbrace{\delta\left(Z_{it}\right)\cdot 1\{CurrPlan_{i,j,t}\}}_{\text{Inertia (current enrollees)}}+\underbrace{\xi_{j,t}\left(Z_{it}\right)}_{\text{Plan dummies}}+\epsilon_{i,j,t}^{Plan}$$

where $Prem_{i,j,t}$ is the enrollee's subsidized premium, $V\left(N_{j,t};Z_{it},\beta\right)$ is consumer value of the provider network, $1\{CurrPlan_{i,j,t}\}$ is a dummy for current enrollees' current plan (capturing inertia), $\xi_{j,t}\left(Z_{it}\right)$ are plan dummy variables capturing unobserved quality, and $\epsilon_{i,j,t}^{Plan}$ is the type 1 extreme value error that gives shares their logit form. Coefficients on these plan characteristics are allowed to vary with consumer observables, Z_{it}. The text of Section V.A discusses each of these variables. Here are some additional details about each and the consumer observables their coefficients can vary with:

1. Subsidized Premiums These are observed and included directly. Premium coefficients, $\alpha\left(Z_{it}\right)$, are allowed to vary with: (1) income groups (100-150%, 150-200%, 200-250%, and 250-300% of poverty), (2) quantile of the HCC risk score (quintiles, plus an extra group for the highest 5% risk enrollees), (3) dummies for having any chronic illness and for cancer, (4) age-sex groups, and (5) immigrant status. The full list of interactions and estimates is shown in Table A.12.

Notice that unlike a standard market, premiums vary not just across plans and years (j,t) but also across consumers for a given plan-year. As discussed in the body text, insurers (who each operate a single plan) are limited to setting pre-subsidy premiums at either the plan-year-region level (from 2007-2010) or at the plan-year level (from 2011-2013). Thus, pre-subsidy premiums vary only at the plan-region-year level. The exchange applies a subsidy schedule that varies across income groups and that also affects prices differences across plans. Subsidies are set so that the lowest-price plan always costs a targeted "affordable" amount by income – e.g., in 2009-2012 this amount is $0 per month for enrollees with incomes below 150% of poverty, $39 for 150-200% of poverty, $77 for 200-250% of poverty, and $116 for 250-300% of poverty. Subsidies for higher-price plans follow a schedule that also varies across income groups and leads to variation in *premium differences* for the same plans across incomes. For enrollees in the 0-100% of poverty group, *all plans* are subsidized to be \$0 – i.e., there are no premium differences. For enrollees in the 100-300% of poverty groups, higher-price plans cost more than the cheapest plan, but the gap between plans is adjusted in a "progressive" way so that premium gaps are smaller for lower-income groups and larger for higher-income groups. Appendix B.1 includes some examples of how this variation plays out.

2. Network Valuation Networks are observed and modeled using two sets of variables. The first is the "network utility" measure from the hospital choice model, described in Appendix F.2 above. The second are variables for whether the plan covers the hospitals with which the consumer has past outpatient relationships (or the share covered if there are multiple). These variables are all observed and vary across consumers and years, so identification comes from the relationship between this panel variation and consumer plan choices.

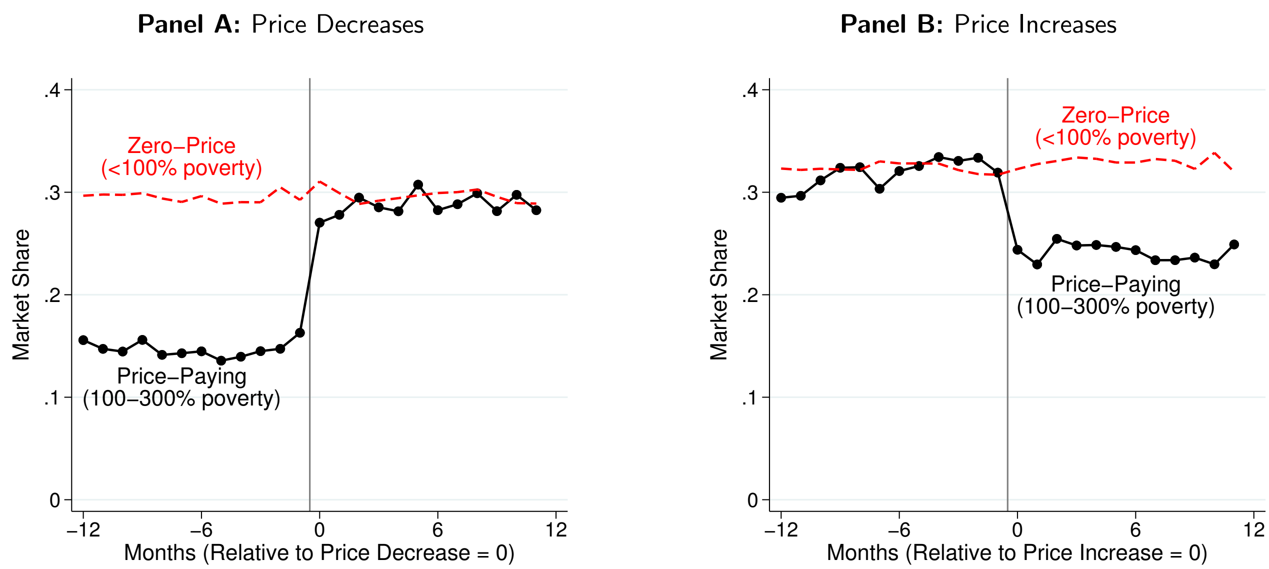
Coefficients on network utility are allowed to vary by: (1) income groups, (2) HCC risk score quantiles, and (3) dummies for having any chronic illness and for cancer. I do not vary coefficients with age-sex groups because the illness probabilities used to define network utility already vary by age-sex groups. Coefficients on coverage of hospitals with which a consumer has relationships are allowed to vary with these same three sets of characteristics, and I also further interact these coefficients with whether the hospital is a Partners hospital to allow for special loyalty to the star hospitals.

3. Inertia (current enrollees) To capture inertia, which is well known to affect health insurance choices, I include a dummy for current enrollees' current plan. Coefficients, $\delta(Z_{it})$, are allowed to vary with the the same observables as premium coefficients: (1) income groups, (2) HCC risk score quantiles, (3) chronic illness and cancer dummies, (4) age-sex groups, and (5) immigrant status. Including a lagged plan dummy allows for capturing inertia in a simple way, but the estimates may pick up both true inertia and persistent unobserved preference heterogeneity. Column (1) of Table A.11 shows a robustness check that includes only new/re-enrollees (for whom inertia is not relevant) and finds that remaining coefficient estimates are quite similar as in the full specification with current enrollees (column 2).

4. Plan dummy variables (unobserved quality) I include a large number of plan dummy variables and interactions to capture unobserved plan quality (e.g., insurer reputation) and to ensure proper identification of the premium coefficient. For each plan, I include separate dummies at the region-income group and region-year level, as well as interactions with age-sex groups and risk score deciles to allow unobserved quality to vary with medical risk. The CommCare program includes five regions (Boston, Central MA, Northern MA, Southern MA, and Western MA) and five income groups at which prices vary (0-100%, 150-200%, 200-250%, and 250-300% of poverty). After omitting empty cells where a plan is not available, there are 251 plan dummy variables/interactions in total. These are not all reported in Table A.12 due to space constraints but will be available in data output in the replication packet.

Discussion of Identification The specification of plan dummies is intended to aid in identifying the premium coefficients using only *within-plan* variation across income groups due to subsidies. Specifically, the plan-region-year dummies soak up any quality variation correlated with insurer pricing, which occurs at the plan-region-year level (or plan-year level from 2011-forward). The plan-region-income group dummies soak up any persistent plan preference differences across income groups within a region. The only remaining variation in premiums not soaked up by these dummies are *within-plan differences in premium changes* across income groups. Appendix B.2 and Figure A.2 show examples of this; see that section for further discussion.

Figure A.23: Premium Coefficient Identification: Market Shares around Price Changes



NOTE: These graphs show the source of identification for the premium coefficients in plan demand and test the key parallel trends assumption for the difference-in-differences approach. Each graph shows average monthly plan market shares among new enrollees for plans that at time 0 decreased their prices (panel A) or increased their prices (panel B). Each point represents an average market share for an independent set of new enrollees. The identification comes from comparing demand changes for above-poverty price-paying enrollees (for whom premium changes at time 0) versus below-poverty zero-price enrollees (for whom premiums are unchanged at $0). Consistent with the parallel trends assumption, trends in shares are flat and parallel for both groups at times other than the premium change but change sharply for price-payers only at the price change. The sample is limited to fiscal years 2008-2011. I drop 2012+ because below-poverty new enrollees became subject to a limited choice policy that required them to choose lower-price plans. In the demand estimates, I keep this sample but limit the choice set for this group accordingly.

Table A.11: Insurance Plan Choice Model Estimates

Variable	(1) New/Re-Enr. Only Coeff.	(1) New/Re-Enr. Only Std. Error	(2) All Enrollees Coeff.	(2) All Enrollees Std. Error
Enrollee Premium (per $10/month): Avg. Coeff.	**-0.454**	**(0.004)**	**-0.506**	**(0.003)**
Base Coeffs by Income: 100-150% poverty	**-0.734**	**(0.010)**	**-0.774**	**(0.008)**
150-200% povery	**-0.506**	**(0.009)**	**-0.564**	**(0.008)**
200-250% poverty	**-0.415**	**(0.008)**	**-0.451**	**(0.007)**
250-300% poverty	**-0.392**	**(0.009)**	**-0.424**	**(0.007)**
x High Risk Score (>80th pctile)	0.084	(0.009)	0.089	(0.008)
x Any Chronic Illness	0.018	(0.003)	0.018	(0.003)
x Cancer	0.041	(0.005)	0.037	(0.004)
x Age ≥45 years	0.111	(0.011)	0.094	(0.010)
Provider Network				
Network Utility (avg. coeff.)	**0.506**	**(0.005)**	**0.463**	**(0.005)**
x Income >100% poverty.	0.097	(0.008)	0.059	(0.007)
x High Risk Score (>80th pctile)	-0.252	(0.014)	-0.239	(0.013)
x Any Chronic Illness	0.135	(0.006)	0.129	(0.005)
x Cancer	0.040	(0.011)	0.033	(0.010)
Share Prev Used Hosp. Covered (avg. coeff.)	**0.249**	**(0.013)**	**0.291**	**(0.012)**
x Income >100% poverty.	0.217	(0.026)	-0.011	(0.022)
x High Risk Score (>80th pctile)	0.277	(0.044)	0.262	(0.037)
x Any Chronic Illness	0.203	(0.027)	0.164	(0.022)
x Cancer	0.129	(0.053)	0.188	(0.041)
x Prev. Used Partners Hospitals	0.625	(0.023)	0.982	(0.021)
Inertia: Current Plan Dummy (avg. coeff.)	---		**4.413**	**(0.007)**
x Income >100% poverty.	---		-1.059	(0.013)
x High Risk Score (>80th pctile)	---		-0.136	(0.032)
x Any Chronic Illness	---		-0.153	(0.013)
x Age ≥45 years	---		-0.079	(0.020)
Avg. Plan Dummies: BMC HealthNet	*(normalized = 0)*		*(normalized = 0)*	
CeltiCare	-1.055	(0.029)	-1.082	(0.025)
Fallon	-0.049	(0.040)	0.058	(0.034)
Neighborhood Health Plan (NHP)	-0.090	(0.016)	-0.037	(0.015)
Network Health	-0.001	(0.013)	-0.119	(0.012)
Model Stats: Pseudo-R^2	0.181		0.575	
No. Choice Instances	690,365		1,613,003	
No. Unique Enrollees	526,665		611,070	

NOTE: This table shows estimates for the multinomial logit plan choice model described in Section V.A. Column (1) includes just new and re-enrollees who make active choices (so do not have inertia terms). Column (2) shows the main model that includes all enrollees, with inertia variables for current enrollees. Premium is the amount paid by consumers after subsidies, in $10 per month; this varies by about $20-60 across plans. Network utility is the consumer-specific expected utility measure for a plan's hospital network, defined in Appendix D.2. Share previously used hospitals covered is the share of an enrollee's previously used hospitals that a plan covers, with a separate interaction for the star Partners hospitals. For most covariates, I report the average coefficient across all enrollees, as well as selected interactions terms with consumer observables. The model allows for more interactions than those shown. For premium and inertia, it includes interactions with: (1) income groups, (2) risk score quantiles (quintiles with a separate category for the 95-100 percentiles), (3) diagnosis indicators (chronic disease, cancer), (4) demographics (5-year age-sex groups and immigrant status). The provider network measures are interacted with all of these except demographics. Plan dummies are interacted with region-year dummies, region-income dummies, and risk score quantiles and demographics.

Table A.12: Plan Choice Model: Full List of Coefficient Estimates

Variable	Coeff.	Std. Error
Enrollee Premium (per $10/month)		
Base Coeffs: 100-150% FPL	**-0.774**	**(0.008)**
150-200% FPL	**-0.564**	**(0.008)**
200-250% FPL	**-0.451**	**(0.007)**
250-300% FPL	**-0.424**	**(0.007)**
x Risk Score: 20-40th pctile	0.014	(0.008)
40-60th pctile	0.027	(0.009)
60-80th pctile	0.038	(0.008)
80-95th pctile	0.075	(0.008)
95-100th pctile	0.129	(0.009)
x Any Chronic Illness	0.018	(0.003)
x Cancer	0.037	(0.004)
x Age-Sex Grp: Male 19-24	(omitted)	
Male 25-29	0.014	(0.009)
Male 30-34	0.033	(0.009)
Male 35-39	0.060	(0.012)
Male 40-44	0.066	(0.011)
Male 45-49	0.079	(0.011)
Male 50-54	0.088	(0.011)
Male 55-59	0.084	(0.011)
Male 60+	0.099	(0.011)
Female 19-2	-0.008	(0.009)
Female 25-2	0.044	(0.011)
Female 30-3	0.070	(0.011)
Female 35-3	0.089	(0.012)
Female 40-4	0.095	(0.011)
Female 45-4	0.085	(0.011)
Female 50-5	0.089	(0.011)
Female 55-5	0.094	(0.011)
Female 60+	0.130	(0.011)
x Immigrant enrollee	-0.259	(0.010)

Variable	Coeff.	Std. Error
Network Utility: Base Coeff.	**0.551**	**(0.012)**
x Income: 100-150% FPL	0.086	(0.009)
150-200% FPL	0.053	(0.010)
200-250% FPL	0.019	(0.011)
250-300% FPL	0.029	(0.015)
x Risk Score: 20-40th pctile	-0.244	(0.012)
40-60th pctile	-0.243	(0.012)
60-80th pctile	-0.303	(0.012)
80-95th pctile	-0.243	(0.014)
95-100th pctile	-0.229	(0.018)
x Any Chronic Illness	0.129	(0.005)
x Cancer	0.033	(0.010)
Share Prev. Used Hosp Covere	**0.052**	**(0.029)**
x Income: 100-150% FPL	-0.162	(0.027)
150-200% FPL	0.127	(0.029)
200-250% FPL	0.026	(0.034)
250-300% FPL	0.117	(0.044)
x Risk Score: 20-40th pctile	0.121	(0.032)
40-60th pctile	0.080	(0.034)
60-80th pctile	0.171	(0.035)
80-95th pctile	0.241	(0.039)
95-100th pctile	0.323	(0.059)
x Any Chronic Illness	0.164	(0.022)
x Cancer	0.188	(0.041)
x Prev. Used Partners Covere	0.735	(0.058)
x Income: 100-150% FPL	0.051	(0.053)
150-200% FPL	-0.358	(0.054)
200-250% FPL	-0.245	(0.061)
250-300% FPL	-0.357	(0.075)
x Risk Score: 20-40th pct	0.272	(0.066)
40-60th pcti	0.482	(0.068)
60-80th pcti	0.685	(0.070)
80-95th pcti	0.466	(0.073)
95-100th pc	0.526	(0.093)
x Any Chronic Illness	-0.086	(0.044)
x Cancer	0.185	(0.062)

Variable	Coeff.	Std. Error
Inertia (Current Plan Dummy)	**5.435**	**(0.027)**
x Income: 100-150% FPL	-0.872	(0.016)
150-200% FPI	-1.023	(0.017)
200-250% FPI	-1.419	(0.018)
250-300% FPI	-1.372	(0.023)
x Risk Score: 20-40th pctile	-0.107	(0.033)
40-60th pctile	-0.113	(0.036)
60-80th pctile	-0.184	(0.033)
80-95th pctile	-0.118	(0.032)
95-100th pctile	-0.188	(0.040)
x Any Chronic Illness	-0.153	(0.013)
x Cancer	-0.079	(0.020)
x Age-Sex Grp: Male 19-24	(omitted)	
Male 25-29	-0.072	(0.037)
Male 30-34	-0.125	(0.040)
Male 35-39	-0.129	(0.048)
Male 40-44	-0.149	(0.047)
Male 45-49	-0.154	(0.046)
Male 50-54	-0.206	(0.045)
Male 55-59	-0.249	(0.046)
Male 60+	-0.251	(0.046)
Female 19-2	-0.136	(0.034)
Female 25-2	-0.258	(0.044)
Female 30-3	-0.350	(0.046)
Female 35-3	-0.301	(0.049)
Female 40-4	-0.278	(0.047)
Female 45-4	-0.336	(0.045)
Female 50-5	-0.357	(0.044)
Female 55-5	-0.430	(0.043)
Female 60+	-0.344	(0.043)
x Immigrant enrollee	-0.408	(0.025)

F.4 Cost Model Estimates

The insurer cost model is described in Section V.B and is based on the reduced form analysis in Section IV.C. Table A.13 shows estimates of the key piece of the model: how costs change at the enrollee level due to the narrower network adopted by Network Health in 2012. The estimating equation is:

$$E\left(C_{i,j,t}\right) = \exp\left(\alpha_i + \beta_t\left(Z_i\right) + \gamma\left(Z_i\right) \cdot 1_{\{j=NH,t\geq 2012\}}\right) \tag{13}$$

where $C_{i,j,t}$ is insurer cost on individual i at time t, α_i is an enrollee fixed effect (which is divided out and not estimated), $\beta_t(.)$ are time fixed effects that capture trends for the control group, and Z_i are enrollee characteristics on which time trends and causal effects may vary. Regression (13) is estimated by maximum likelihood (using "xtpoisson, fe" in Stata), with cluster-robust standard errors at the i level. The coefficients of interest are $\gamma(Z_i)$, which capture the differential cost change for Network Health stayers in 2012.

Table A.13 shows the estimates of $\hat{\gamma}(Z_i)$, the key coefficients of interest. Recall that the implied (multiplicative) effect on costs equals $dC_i = \exp(\hat{\gamma}(Z_i))$, and the percent change is $dC_i - 1$. Columns (1)-(3) report models with increasing flexibility in the Z_i with which γ is allowed to vary. Column (3) is the full model that is used for the final cost analysis in Sections V.C-V.D.

Role of Price vs. Quantity Changes My cost model's approach can also be used to decompose the cost effects into price vs. quantity, providing further insight on the role of each. Recall that using the decomposition in Section IV.A, cost equals quantity times price. Therefore, as long as expected quantity is positive under both networks, $dC_i = dQ_i \cdot dP_i$.[25] I can estimate regression (8) using quantity as the outcome variable to get an estimate of $d\hat{Q}_i = \exp(\hat{\gamma}_Q(Z_i))$. The implied effect on prices is $d\hat{P}_i = d\hat{C}_i / d\hat{Q}_i = \exp(\hat{\gamma}_C(Z_i) - \hat{\gamma}_Q(Z_i))$.

Appendix Figures A.21 and A.22 show the DD estimates and event study coefficients with quantity as the outcome variable, analogous to the cost results in Figure 5 of the main text. As with costs, pre-trends are parallel, and there is a sharp quantity reduction at the start of 2012. The quantity reductions are larger in both levels and percentages for Partners patient stayers than other stayers.

Table A.13, columns (4)-(6) report estimates of the price-quantity decomposition. Column (4) shows estimates for the subset of costs (inpatient and outpatient care) included in the decomposition; the estimates are quite similar to those for total costs. Interestingly, column (5) shows that most of the cost reductions represent a fall in *quantity* of care, with price reductions explaining a minority. While the average $\hat{\gamma}_C = -0.137$ (s.e. $= 0.021$) corresponding to a 12.8% cost reduction, the average $\hat{\gamma}_Q = -0.105$ (s.e. $= 0.020$) which is a 10% fall. Thus, quantity reductions account for about three-quarters of the fall in costs, while price reductions account for just one-quarter. The interactions with patient status also reveal interesting patterns. Both quantity and price reductions are largest for Partners patients (even controlling for other health measures), but quantity reductions still explain

[25] To see this use the notation of Section I to write $C_i(n) = Q_i(n) P_i(n)$ under network n (where 0 = narrower, 1 = broader). For a narrowing of the network, $dC_i = C_i(0)/C_i(1) = (Q_i(0)/Q_i(1))(P_i(0)/P_i(1)) \equiv dQ_i dP_i$. Notice that this decomposition only works if *expected* quantity is positive under both networks (though *ex-post* realized quantity may be negative for some people), which is required for price to be well-defined. This seems like a reasonable assumptions for most people.

more than three quarters of the cost fall. For patients of other dropped hospitals, quantity falls but price increases, consistent with them substituting to higher-price providers.

Table A.13: Cost Model Estimates: Change in Cost with Narrower Network

Network Health x Post	Effect on Insurer Cost			Decomposition: Costs	Decomposition: Quantity	*Price*
	(1)	(2)	(3)	(4)	(5)	(6)
Average Effect	**-0.133*** **	**-0.125*** **	**-0.136*** **	**-0.137*** **	**-0.105*** **	***-0.032***
	(0.018)	**(0.018)**	**(0.018)**	**(0.021)**	**(0.020)**	
Full Specification						
Constant	-0.133***	-0.089***	-0.236*	-0.367*	-0.387**	*0.020*
	(0.018)	(0.020)	(0.119)	(0.142)	(0.131)	
Patient of: Partners		-0.277***	-0.235***	-0.294***	-0.246***	*-0.048*
		(0.054)	(0.062)	(0.078)	(0.069)	
Other Dropped Hosp.		-0.071	-0.068	-0.076	-0.153*	*0.077*
		(0.070)	(0.070)	(0.073)	(0.074)	
Dist. to Partners: 0-2 miles *(omitted)*						
2-5 miles			0.004	0.029	0.030	*-0.001*
			(0.094)	(0.099)	(0.087)	
5-10 miles			0.072	0.124	0.099	*0.024*
			(0.098)	(0.102)	(0.090)	
10-20 miles			0.017	0.069	0.104	*-0.036*
			(0.097)	(0.106)	(0.094)	
20-30 miles			0.133	0.126	0.165	*-0.039*
			(0.099)	(0.104)	(0.092)	
>30 miles			0.032	0.095	0.148	*-0.053*
			(0.095)	(0.104)	(0.090)	
Other Interactions (summary)						
Age >= 45			0.084	0.214	0.233	*-0.019*
			(0.094)	(0.123)	(0.122)	
Risk score 40-80th%			-0.048	-0.039	-0.008	*-0.031*
			(0.074)	(0.094)	(0.089)	
Risk score >80th%			-0.039	-0.035	0.006	*-0.041*
			(0.067)	(0.086)	(0.080)	
Chronic illness			0.051	0.024	0.008	*0.016*
			(0.046)	(0.051)	(0.049)	
Cancer			-0.134**	-0.143**	-0.135*	*-0.008*
			(0.050)	(0.055)	(0.054)	
Number of Obs.		1,131,878			1,110,587	
Number of Individuals		128,496			125,572	

NOTE: The table reports estimates of cost changes due to Network Health's network narrowing in 2012, following the Poisson regression equation in (13). The estimates are of the $\gamma(Z_i)$ terms, which are approximately equal to percent effects on costs. More precisely, the multiplicative effect of the narrower network is $\exp(\gamma(Z_i))$, and the percent changes is $\exp(\gamma(Z_i)) - 1$. Columns (1)-(3) show estimates on total insurer costs for models with increasingly rich interactions. Column (4) shows the same specification as (3) but with a dependent variable of (inpatient/outpatient) costs covered by the price-quantity decomposition presented in Appendix E. Column (5) show estimates for changes in quantity, and (6) shows implied changes in prices.

F.5 Robustness Checks on WTP and Cost of Star Hospital Coverage

This appendix presents several modifications of ΔWTP and $\Delta Cost$ of Network Health's broader 2011 network that covers the star Partners hospitals in order to check the robustness of the finding in the body text (see Figure 6B) that ΔWTP is below $\Delta Cost$. See section V.D for the definition of these variables. Figure A.24 replicates Figure 6B with several modified versions of these curves. In all cases, the baseline ΔWTP and $\Delta Cost$ curves are shown in green and black respectively with point markers. The modified curves are shown in curves without point markers. These modifications are:

1. Counting only quantity of care reductions in $\Delta Cost$ (Panel A): This defines $\Delta Cost$ based only on changes in *quantity* of care (price-standardized utilization) due the broader network, not the effect of higher prices. This will tend to produce smaller estimates of $\Delta Cost$. Quantity reductions are estimated using the method in Appendix F.4 and specifically the estimates in column (5) of Table A.13. Figure A.24A shows both a high and low estimate of $\Delta Quantity$ calculated under different assumptions. The low estimate (gray curve) takes the estimates of proportional reductions in $\Delta Quantity$ and applies them to quantity of care *included in the cost decomposition* (inpatient and outpatient costs). This assumes that the one-third of costs not included in the decomposition do not change with the broader network, which likely generates a conservatively low estimate of $\Delta Quantity$.[26] Nonetheless, this low estimate of $\Delta Quantity$ is still substantially larger than ΔWTP by a factor of 2-3x. The high estimate (dark blue curve) assumes that the proportional reductions in $\Delta Quantity$ apply to total costs. This generates estimates quite similar to the baseline $\Delta Cost$ curve.

2. Recalculating $\Delta Cost$ using lower Partners prices (Panel B): This panel redefines the incremental costs of the broader network using Partners prices that are counterfactually lower, which generates a lower estimate of $\Delta Cost$. These lower prices could either reflect changes in hospital-insurer bargaining due to adverse selection or a lower social cost of care reflecting Partners' price markups.[27] To see how this works, note that $C_{ij}(1) = C_{ij}^{Partners}(1) + C_{ij}^{Other}(1)$, where the two terms reflect costs incurred at Partners and all other providers. Then $\Delta Cost_{ij} = C_{ij}(1) - C_{ij}(0)$. The modification recalculates $C_{ij}^{ALT}(1) = (1-\phi)\, C_{ij}^{Partners}(1) + C_{ij}^{Other}(1)$, where ϕ is a Partners price reduction factor. It then defines $\Delta Cost_{ij}^{ALT} = C_{ij}^{ALT}(1) - C_{ij}(0)$.[28] I consider price reductions (ϕ) of 10%, 25%, and 50%, reflecting a range of possible price reductions and/or markups.[29] Even with a 50% price reduction (an

[26]The decomposition excludes items like prescription drugs, inpatient rehab, and some inpatient/outpatient costs that are paid in non-standard ways (see Appendix E). It seems likely that if included inpatient/outpatient costs fall substantially, these would also fall at least somewhat since their provision is also linked to the high-cost excluded Partners system. For instance, Partners owns a network of rehab hospitals (Spaulding Rehab), and costs may fall as patients substitute to other providers. Of course, it is also possible that non-included quantity of care moves in the opposite direction as included quantity (i.e., the two are substitutes), but this seems less likely. Against this possibility, the proportional reduction in total costs and included costs are quite similar – both are about 13-14% (see Table A.13, columns (3) vs. (4) – which is consistent with the two moving in the same direction.

[27]The social value of these markups would depend on how the money is spent, which is an important but unclear issue. If used to increase hospital amenities (e.g., nicer buildings) or physician/administrator salaries, the social value might be less than dollar-for-dollar. If used to fund research and teaching, the social value might be more than dollar-for-dollar.

[28]This effectively assumes no change in Partners out-of-network prices under the narrower network that excludes it. This is conservative in that it will produce smaller estimates of $\Delta Cost^{ALT}$ than if I assumed $C_{ij}(0)$ also decreased.

[29]For context, a very rough calculation using state data on hospital costs per risk-adjusted discharge (CHIA, CHIA) suggests that the inpatient CommCare prices for MGH and Brigham & Women's (BWH) are marked up by about 20-30%

extreme upper bound), the $\Delta Cost^{ALT}$ curve is still above WTP throughout the distribution.

3. Recalculating ΔWTP based on social marginal utility of money (Panel C): This recalculates ΔWTP using a social marginal utility of money, which is a simple way to include a notion of equity in the welfare analysis. Note that baseline WTP is defined in equation (10) as the utility of the broader network (ΔV_i) divided by the marginal utility of money ($-\alpha(Z_i)$, the negative premium coefficient). We can define alternate $\Delta WTP^{ALT} = \Delta V_i / (-\widetilde{\alpha})$, where $-\widetilde{\alpha}$ is a uniform social marginal utility of money (e.g., reflecting a cost of redistribution).[30] I consider two possible values for $\widetilde{\alpha}$: (1) the average $\alpha(Z_i)$ among CommCare consumers and (2) the 99th percentile $\alpha(Z_i)$ (i.e., close to the smallest in absolute value) which reflects the estimates for the highest-income (near 300% of poverty) and oldest (over age 60) consumers. The former does not affect ΔWTP much. The latter closes only a small part of the gap, with $\Delta Cost$ still 1.5-2.5x as large as ΔWTP^{ALT}. Note, however, that if I combine this high-end ΔWTP^{ALT} with the smallest version of $\Delta Cost^{ALT}$ with 50% lower Partners prices (from panel C), the two are approximately equal. This illustrates the extreme modifications to WTP and costs that would be required to overturn the basic finding that WTP for the broader network falls short of costs.

4. Counting only lower inpatient prices from steering patients in $\Delta Cost$ (Panel D): This panel recalculates $\Delta Cost$ by assuming that the entire cost impact of the narrow network operates through *lower inpatient hospital prices* (due to exclusion of high-price hospitals from network and associated steering to lower-price hospitals). All other cost variables – inpatient quantity, outpatient quantity and prices, and all other spending – are assumed unchanged. I estimate changes in inpatient prices by taking observed 2011 Network Health hospital admissions, re-predicting choices using the hospital choice model with the 2012 network exclusions applied, and applying the plan's hospital price estimates for 2012.[31] This modification makes a much more substantial difference, so that $\Delta Cost^{IP}$ is now less than ΔWTP across the whole distribution (it is about half as large as ΔWTP). A major reason is that inpatient costs are only about 20-25% of overall spending. Therefore, although inpatient costs fall by about 15% among the highest-WTP types (and 5-10% among lower-WTP types), the fall in *total* spending is only 1-5%. Although this is much smaller than the main estimates of $\Delta Cost$ (which includes changes in quantity and outpatient costs), a 1-4% spending reduction is consistent with the

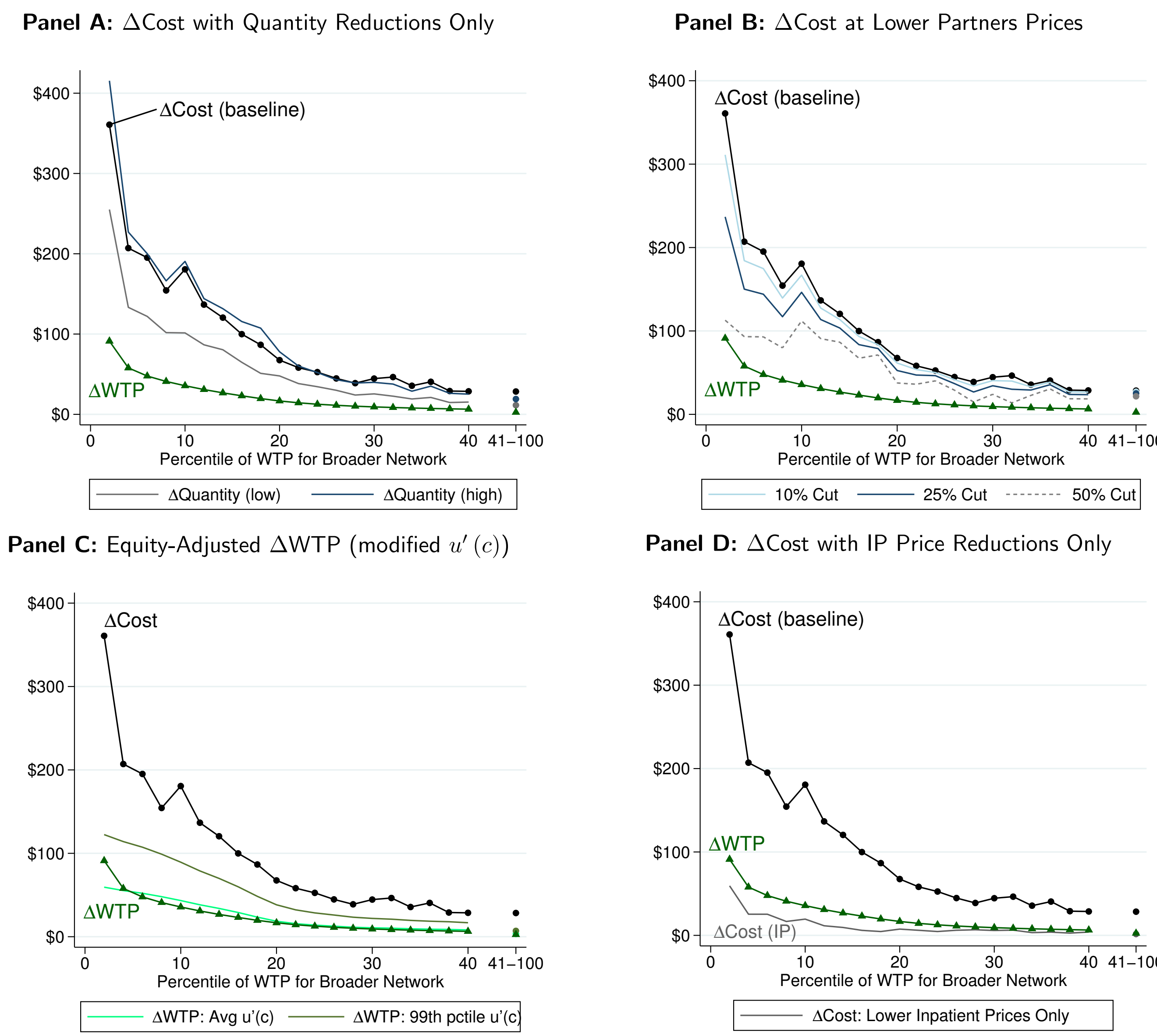
relative to costs, while prices for the other five Partners hospitals are at or below costs. Outpatient care cost and markup data are not available, though the fact that Partners' outpatient care prices are not very high suggests they might be lower. Thus, 25% represents a high-end estimate of Partners' markup that assumes that the 20-30% inpatient markups for MGH and BWH apply to all care at Partners providers. Of course, hospital costs are known to be quite difficult to define and measure, so these figures should be taken to be very rough. Nonetheless, a 50% Partners price reduction is an extreme upper bound that would likely require Partners not just to cut markups (which are not "free," since markups are used to cross-subsidize other Partners activities) but also to make radical changes to how it delivers care.

[30] Note that a fully consistent cost-benefit analysis of the policy problem would need to explain why the government does not redistribute to CommCare enrollees (e.g., via lower premiums or cash checks) up to the point that their marginal utility of money equals the social cost of redistribution. This exercise is meant as illustrative, not a fully consistent policy analysis of equity and redistribution.

[31] I use 2012 hospital prices because Network Health's out-of-network prices paid to Partners are much lower than its in-network 2011 prices. Its prices for all other hospitals do not change much from 2011-12.

estimates in Table A.13 that overall *prices* of care fall by about 3%.[32] Thus, this analysis suggests that most consumers *would be* willing to pay for star hospital coverage if the only incremental costs were via higher inpatient prices.

Figure A.24: Robustness Analysis: ΔWTP and $\Delta Cost$ of Broader Network



NOTE: These figures replicate Figure 6 in the body text with various modifications to $\Delta Cost$ and ΔWTP. See the note to Figure 6 and the text of Appendix F.5 for additional information describing the definition of these curves.

[32]Thus, this is consistent with the entire price reduction occurring through inpatient care, with no fall in outpatient prices. This makes sense given the finding that Partner hospitals' inpatient prices are quite high but their outpatient prices are similar to the state average.

References

Capps, Cory, David Dranove, and Mark Satterthwaite, "Competition and market power in option demand markets," *RAND Journal of Economics*, 2003, pp. 737–763.

(CHIA) Massachusetts Center for Health Information and Analysis, "Massachusetts Hospital Profiles: Data through Fiscal Year 2012," Technical Report, https://www.chiamass.gov/hospital-profiles/ 2014.

Cooper, Zack, Stuart V Craig, Martin Gaynor, and John Van Reenen, "The price ain't right? Hospital prices and health spending on the privately insured," *The Quarterly Journal of Economics*, 2019, *134* (1), 51–107.

Gaynor, M and WB Vogt, "Competition among Hospitals.," *The Rand Journal of Economics*, 2003, *34* (4), 764–785.

Health Care Cost Institute, "2014 Health Care Cost and Utilization Report: Analytic Methodology," 2015.

Ho, Katherine, "The welfare effects of restricted hospital choice in the US medical care market," *Journal of Applied Econometrics*, 2006, *21* (7), 1039–1079.

Sabety, Adrienne, "The Value of Relationships in Health Care," Technical Report, Working Paper 2020.

Shepard, Mark and Myles Wagner, "Reducing Ordeals through Automatic Enrollment: Evidence from a Health Insurance Exchange," Technical Report, Working paper 2021.

Shorrocks, Anthony F, "Inequality decomposition by factor components," *Econometrica*, 1982, pp. 193–211.

_ , "Decomposition procedures for distributional analysis: a unified framework based on the Shapley value," *Journal of Economic Inequality*, 2013, *11* (1), 99.

Town, Robert and Gregory Vistnes, "Hospital competition in HMO networks," *Journal of health economics*, 2001, *20* (5), 733–753.