Hospital Network Competition and Adverse Selection:

Evidence from the Massachusetts Health Insurance Exchange

Mark Shepard*

Harvard Kennedy School and NBER

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Abstract

I study the role of adverse selection when health insurers compete on an increasingly important benefit: coverage of the most prestigious (and expensive) "star" hospitals. Using data from Massachusetts' pioneer insurance exchange, I show evidence of substantial adverse selection through a channel theoretically distinct from standard selection on medical risk. Plans that cover star hospitals attract consumers with high costs because when sick, they tend to use the expensive star providers. This selection persists even with risk adjustment, which does not offset higher costs driven by hospital choices rather than medical risk. I show evidence of adverse selection through this mechanism using consumer choices across plans that differ in star hospital coverage and using switching choices after a plan drops the star hospitals from network. I then estimate a structural model of insurer competition to study the welfare and policy implications of selection. I find that adverse selection creates a strong incentive not to cover the star hospitals. Simple modifications to risk adjustment can preserve coverage, but I find that they do little to improve net welfare because of offsetting costs of greater use of the star hospitals. These results illustrate the challenge of addressing adverse selection in settings where it is linked to moral hazard.

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* Post-Doctoral Fellow in Aging and Health Care at NBER (2015-16) and Assistant Professor of Public Policy at Harvard Kennedy School (2016+). Email: Mark_Shepard@hks.harvard.edu. I thank my Ph.D. advisors David Cutler, Jeffrey Liebman, and Ariel Pakes for extensive comments and support in writing this paper. I thank the Massachusetts Health Connector (and particularly Michael Norton, Sam Osoro, Nicole Waickman, and Marissa Woltmann) for assistance in providing and interpreting the data. I also thank Katherine Baicker, Amitabh Chandra, Jeffrey Clemens, Keith Ericson, Amy Finkelstein, Jon Gruber, Kate Ho, Sonia Jaffe, Tim Layton, Robin Lee, Greg Lewis, Tom McGuire, Joe Newhouse, Daria Pelech, Amanda Starc, Karen Stockley, Rich Sweeney, Jacob Wallace, Tom Wollmann, Ali Yurukoglu, and participants in seminars at Boston College, the Boston Fed, CBO, Columbia, Chicago Booth, Duke Fuqua, Harvard, the NBER Summer Institute, Northwestern, U Penn, Princeton, Stanford GSB, UCLA, UCSD, and Washington University for helpful discussions and comments. I gratefully acknowledge data funding from Harvard's Lab for Economic Applications and Policy, and Ph.D. funding support from National Institute on Aging Grant No. T32-AG000186 (via the National Bureau of Economic Research), the Rumsfeld Foundation, and the National Science Foundation Graduate Research Fellowship.

Introduction

Public programs increasingly use regulated markets to provide health insurance to enrollees. These types of markets now cover more than 75 million people and cost over $300 billion in U.S. programs including the Affordable Care Act (ACA), Medicare Advantage, and Medicaid managed care. Markets can improve welfare by giving consumers choice and encouraging insurer competition. But a perennial concern in insurance markets is adverse selection. When high-cost types tend to prefer generous plans, insurers may have inefficient incentives to cut benefits to avoid attracting these customers. Selection is a particular concern in regulated markets because – to promote goals of equity and long-term insurance (Handel, Hendel, and Whinston 2013) – regulators typically restrict insurers from pricing on health status or most other observable variables. Instead, regulators use a tool called "risk adjustment" that transfers payments among insurers to compensate plans that attract observably sicker groups. They also regulate plan attributes, including cost sharing and covered services, to prevent a race to the bottom in these benefits.

A natural question is whether adverse selection still matters in these heavily regulated and risk-adjusted markets. In this paper, I address this question for an increasingly important benefit: insurers' networks of covered hospitals and other medical providers. Despite a large literature on selection, there is little direct evidence on whether plans with better networks face adverse selection.[1] This question is particularly important in regulated markets like the ACA exchanges, where networks are one of the few benefits on which insurers can flexibly compete.[2] The first years of the ACA have seen a proliferation of "narrow network" plans, which comprise almost half of exchange plans (McKinsey 2015).[3]

These plans have generated controversy, including calls for broader network requirements, partly because they tend to exclude the most prestigious academic hospitals.[4] These "star" hospitals are known as centers of advanced medical treatment and research but, partly as a result, are quite expensive (Ho 2009). By excluding them, insurers limit access to top providers but also reduce costs by steering patients to cheaper settings. However, insurers' incentives to balance this cost-quality tradeoff may also be influenced by adverse selection. Whether selection is involved is an important question for assessing the trend towards narrow networks and for the policy debate.

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[1] The literature has focused on selection between plans with higher vs. lower cost-sharing (e.g., deductibles) and between HMOs and traditional fee-for-service (FFS) plans (see Glied 2000 for a review). HMOs often have narrower networks than FFS plans but also differ in a variety of other managed care restrictions.

[2] The ACA heavily restricts covered services and cost-sharing rules. All plans must cover a broad set of "essential health benefits." Cost sharing generosity must fall within four tiers (bronze/silver/gold/platinum), and insurer flexibility is further limited by "cost-sharing subsidies" that limit cost sharing for enrollees below 250% of poverty.

[3] McKinsey defined narrow network plans as those excluding at least 30% of area hospitals. They documented a sharp increase in the share of narrow network plans relative to pre-ACA insurance markets.

[4] An article in *U.S. News & World Report* found that of that publication's top 18 ranked hospitals nationwide, 14 were covered by a minority of insurers on their state's exchange in 2014 (Richards 2013). This stands in contrast to employer-sponsored insurance, where star hospitals are often viewed as "must-cover" hospitals.

Using data from Massachusetts' pioneer insurance exchange, I show evidence of substantial adverse selection against plans that cover the state's top-ranked star hospitals. This selection occurs partly through a channel that is theoretically distinct from the usual selection mechanism and therefore poses a challenge for standard policy tools. Typically, economists equate adverse selection with *high-risk* (sicker) people selecting certain plans. But in addition to medical risk, some consumers may be more costly because for a given illness, they tend to *choose expensive providers*. This second dimension is likely to be important, since provider prices vary widely within areas (IOM 2013), and insurers typically cover the bulk of these price differences rather than passing them onto patients.[5] As a result, consumers who use star hospitals when sick are more costly than consumers who use less expensive alternatives. I find that in addition to classic selection on medical risk, plans that cover the star hospital face adverse selection on this alternate (provider choice) dimension of costs.

In some ways, the implications of this alternate selection channel are standard: inefficient sorting for consumers and incentives for insurers to avoid offering generous plans. For instance, some consumers might value access to a star hospital should they get seriously ill, but would be otherwise unlikely to use it. But to buy a plan covering it, they have to pool with people who regularly use star providers for all their health care needs. Plans covering star hospitals differentially attract these high users, forcing them to raise prices and further crowd out infrequent users. Depending on the market structure and type distribution, this process can either stabilize or lead to unravelling of star hospital coverage.

But selection on likelihood to use star providers is non-standard for at least three reasons. First, even excellent risk adjustment is unlikely to offset it, since provider choices are affected by many non-risk factors. For instance, patient preferences – e.g., existing relationships with providers, patient location, and value for quality vs. convenience – can be thought of as omitted variables in standard risk adjustment. Thus, adverse selection is likely to remain a concern even in markets with risk adjustment.

Second, the high costs of people who prefer star hospitals are not fixed but occur only when given the option to use these expensive hospitals at the insurer's expense. Stated differently, these individuals exhibit large *cost increases* – or moral hazard effects – when an insurer covers the star provider. What I find is that the people most likely to use star hospitals when covered (i.e. highest moral hazard) tend to select into plans that cover them. Thus, my findings are an example of "selection on moral hazard," an idea introduced by Einav et al. (2013).[6] My results suggest a natural mechanism for selection on moral hazard whenever insurers compete on coverage of specific benefits (e.g., a star hospital or an expensive

[5] The Massachusetts exchange requires plans to fully cover price differences by mandating equal copays for all in-network hospitals. However, insurers typically cover most price differences even in less regulated settings (see e.g., Gowrisankaran et al. (2015) who find that patients pay just 2-3% of price differences as coinsurance in their employer insurance setting).

[6] Similar to this paper, Einav et al. (2015) show that when moral hazard effects vary, risk adjustment cannot fully offset cost heterogeneity. They describe this as the missing "economic content of risk scores."

drug or treatment option). People with the strongest preference for the expensive benefit both use it more when sick and (anticipating this) purchase a plan that covers it.[7] Offsetting this selection channel would require charging fees related to how much enrollees use the expensive benefit – either via higher "tiered" copays at point of use, or via individually varying plan premiums (Bundorf et al. 2012).

A final difference from the standard analysis is that the selection is linked to a service (care at star hospitals) whose prices are not set competitively. Instead, these prices are partly driven by star hospitals' market power in negotiations with insurers. Because adverse selection reduces insurer incentives to cover star hospitals, it may have the side effect of disciplining star hospital prices in exchanges (relative to employer insurance settings where workers typically have fewer plan choices). Although I do not fully analyze hospital-insurer bargaining in this paper, this conceptual point has important implications for standard policy responses to selection. For instance, a mandate to cover the hospitals would be problematic because it would give star hospitals extreme power to raise prices.

To study these issues empirically, I use data from a market that was a key model for the ACA: Massachusetts' subsidized insurance exchange.[8] This exchange provides a nice setting for studying networks and selection. Exchange regulations required standardized cost sharing and covered services, which lets me compare plans that are nearly identical except for their provider network. Further, the state has a clear set of star academic hospitals: Mass. General and Brigham & Women's hospitals, the flagships of the Partners Healthcare System. *U.S. News & World Report* consistently ranks these as the top two hospitals in the state and among the top 10 hospitals in the nation. Consistent with past reports (e.g., Coakley 2013), I find that the star hospitals are extremely expensive – with severity-adjusted prices per admission almost twice the average of other hospitals and over $5,000 (or 33%) more than the average of other academic medical centers. Finally, the exchange has administrative enrollment and claims data for all consumers and plans over its entire history. These detailed data let me link plan choices, hospital choices, and costs to study the relationships driving adverse selection.

I start by testing for adverse selection against plans covering Partners using reduced form methods. I show that these plans attract a group who appear to strongly prefer Partners: people who have used Partners hospitals in the past for outpatient care, which includes doctor visits and other outpatient treatments. Compared to the average other enrollee, these past Partners patients are (1) 28% higher cost even after risk adjustment, (2) 80% more likely to select a plan that covers Partners, and (3) almost five times as likely to use the star hospitals for subsequent hospitalizations. These facts suggest that Partners

[7] This mechanism is embedded in the standard "option demand" model of provider networks and plan choices (Capps, Dranove, and Satterthwaite 2003; Town and Vistnes 2001) but to my knowledge has not been previously highlighted.
[8] This setting is distinct from Massachusetts' unsubsidized exchange, which Ericson and Starc (2013, 2014, 2015) have studied. The limited past work on the subsidized exchange by Chandra et al. (2011; 2014) has studied the effects of the individual mandate's introduction and of cost-sharing changes in 2008.

patients are loyal to their preferred hospitals and select plans partly based on their desire to continue using these providers. I find that this loyalty to previously used hospitals is true more broadly across all hospitals in my data, suggesting that it is a general phenomenon likely to drive plan choices in health insurance markets.[9] This loyalty in turn matters for costs when a patient is loyal to an expensive provider.

I next study how this selection played out in a case in 2012 when a large plan dropped Partners (both hospitals and affiliated physicians) as well as several other hospitals from its network. This type of network change provides a natural source of evidence that has rarely been available in past research. Consistent with the selection story, I find that high-cost Partners patients were far more likely to switch plans in response to this change. Nearly 40% of them switched plans in 2012, compared to a switching rate of less than 5% for enrollees who had not been patients at a dropped hospital. These switchers had high-cost even among past Partners patients, with risk-adjusted 2011 costs 80% higher than the average person who did not switch out of the plan. These findings suggest that many consumers are able to overcome well-known inertia in plan switching (see Handel 2013) in order to maintain access to their preferred doctors and hospitals. It further suggests that excluding a star hospital from network may be a powerful tool for insurers to reduce demand among their highest-cost consumers.

I also use the 2012 network change to show evidence of moral hazard from Partners coverage that is differentially large for past Partners patients. Using panel regressions with individual fixed effects, I find sharp cost reductions at the start of 2012 for Partners patients who stayed in the plan that dropped Partners. Cost reductions for all other stayers were much more modest. Thus, consistent with my model's prediction of "selection on moral hazard," the same group most likely to switch plans also experienced the largest cost reductions when they stayed with the plan that dropped the star hospitals.

The reduced form results suggest that adverse selection based on star hospital coverage is an important phenomenon. To further investigate the welfare and policy implications of this selection, I estimate a structural model of consumer preferences, insurer costs, and insurer competition. The model – which follows a structure used in past work (e.g., Capps et al. 2003; Ho 2009) – consists of three pieces: (1) a hospital demand system capturing hospital choices under different plan networks, (2) an insurance demand system capturing plan choice patterns, and (3) a cost model estimated from the insurance claims data. Relative to past work, the main innovation is to allow for detailed preference heterogeneity and use the individual-level data to capture the correlations among hospital choices, plan preferences, and costs – which are critical for adverse selection. In addition, I pay special attention to the identification of the

[9] It is less clear how much of this loyalty is driven by state dependence (a preference for hospitals used in the past) versus more durable preference heterogeneity. Both are valid channels for the short-run adverse selection results I find. But state dependence implies lower long-run welfare impacts of unraveling of Partners coverage, since patients need only incur a one-time cost of switching providers. Disentangling the roles of state dependence versus heterogeneity in loyalty to providers is an important question for future research.

premium and network coefficients in plan demand, using only within-plan variation to identify them. For premiums, I use variation driven by Massachusetts' income-varying subsidy rules. For networks, I use variation across consumers in how they value a given hospital network.

My demand estimates imply that individuals value both lower prices and better hospital networks (including star hospital coverage), though with significant heterogeneity in this tradeoff. Consistent with the reduced form evidence, I find that past patients of a hospital are particularly likely to use it again and to select plans that cover it. These effects are particularly strong for past patients of Partners hospitals. Thus, the demand estimates are consistent with significant selection based on coverage of the prestigious Partners hospitals. Applying the model to the 2012 network change discussed above, I find that selection explains between a third and half of the risk-adjusted cost reductions for the plan that dropped Partners.

I next use the model to study the competitive, welfare, and policy implications of network-based selection. I simulate equilibrium in a game where insurers first choose whether or not to cover the star Partners hospitals (holding fixed other hospital coverage) and then compete on prices. I model exchange policies similar to those in the ACA, which differ in several ways from those used in Massachusetts. The key limitation of these simulations is that they hold hospital prices fixed at their observed values, not modeling hospital-insurer price bargaining. At the star hospitals' observed high prices, I find a unique equilibrium in which all plans drop them from network. As in the reduced form results, a plan deviating to cover Partners loses money both through higher costs for its existing enrollees (moral hazard) and by attracting high-cost enrollees who particularly like Partners (adverse selection). I use the model to decompose the adverse selection into traditional selection on levels of cost and selection on moral hazard from covering Partners. Of the substantially higher risk-adjusted costs for the group that most values Partners, about 60% is driven by higher cost levels (i.e., even in a plan that does not cover Partners), and 40% is driven by larger cost increases when Partners is covered. Thus, both traditional selection and the theoretically distinct form of selection are quantitatively important in this market.

Finally, I use my model to analyze policy changes to address adverse selection. I find that modified risk adjustment and differential subsidies for higher price plans can reverse the unraveling of star hospital coverage. These policies give plans a greater incentive to cover these hospitals even though doing so requires raising prices and attracting high-cost enrollees. However, I highlight two tradeoffs. First, covering the star hospitals increase costs due to moral hazard. My model's estimates imply that past Partners patients have greater value of access than costs, but other enrollees on average do not. Because the latter group is much larger, I find a net decrease in social surplus when the government changes policy to encourage Partners coverage.

A second tradeoff of these policy changes is that they encourage both insurers and Partners hospitals to raise prices. My current model does not capture the higher Partners prices (which are held fixed by assumption). But I find important increases in insurance prices and markups, leading to a government-funded increase in insurer profits. This analysis aligns with recent work finding that adverse selection leads plans to reduce markups in imperfectly competitive markets (Mahoney and Weyl 2014; Starc 2014). Adverse selection gives insurers an incentive to keep prices low to attract low-cost consumers. Policies that offset this effect encourage plans to raise price markups. In exchanges, higher plan prices mean higher government subsidies, which are set based on these prices.

These results suggest that standard policies used to address adverse selection (e.g., risk adjustment and subsidies) are less effective at improving welfare with selection based on star hospital use. These policies compensate insurers for attracting high-cost enrollees but do not address the fundamental issue of efficiently sorting patients across hospitals. Policies that address this sorting challenge directly – e.g., higher "tiered" copays for high-price hospitals or payment incentives for doctors to steer patients to lower-cost hospitals – may be more effective and are a fruitful subject for future research.

The remainder of this paper is organized as follows. Section 1 outlines a simple model that captures the main intuition for network-based selection. Section 2 presents background on the Massachusetts exchange and hospital market and introduces the data. Section 3 shows reduced form results, and Sections 4-5 present the structural model and estimates. Section 6 analyzes the model's implications for adverse selection, and Section 7 presents the equilibrium and counterfactual policy simulations. The final section concludes.

1 Basic Theory

In this section, I present a simple model to illustrate how coverage of expensive star hospitals can lead to adverse selection, even with sophisticated risk adjustment in place. Adverse selection occurs when consumers with high value for generous insurance also tend to have high unobserved (or unpriced) costs. The literature has typically equated higher costs with greater *medical risk* – i.e., that higher-cost consumers are sicker. Key to my model is a second, conceptually different source of cost heterogeneity: *preferences* for using expensive providers when sick. While the model focuses on expensive star hospitals, the theory applies more broadly to preferences for any high-cost treatment option (e.g., branded vs. generic drugs, or high- vs. low-cost procedures). Because the insurer covers all or part of the excess cost of the expensive option, people who are more likely to use it are higher cost to the insurer. I show how this heterogeneity is likely to lead to adverse selection (conditional on medical risk) and analyze the equilibrium and policy implications it creates.

1.1 Simple Model

Consider a model where insurers compete on prices and a single generosity choice: whether to cover a star hospital, *S*, in its network. For simplicity, assume that the star hospital's price is a uniform τ_S per visit for all insurers.[10] All other "non-star" hospitals charge $\tau_{NS} < \tau_S$ per visit and are covered by all insurers. Importantly, insurers that cover *S* do not fully pass on its higher price to patients but instead cover the price differential. Here, for simplicity, I assume patient fees (copays) are zero.[11]

After seeing insurers' offerings, consumers choose a plan and when sick, choose among in-network hospitals. Consumers vary in two ways:

1. **Medical risk**, $r_{i,d}$, for various diagnoses $d = 1,...,D$
2. **Value for the star hospital**, $v_{i,d}^S$, for each diagnosis *d*

Medical risk equals a consumer's probability of being hospitalized for diagnosis *d*, which I model as an exogenous event. Value for the star hospital (or what I label "preferences") is consumers' diagnosis-specific WTP for the star hospital relative to the next best alternative. This value can be negative if a non-star hospital is preferred (e.g., because of greater convenience). Let $I_{i,d}^S$ indicate whether the consumer chooses the star hospital for diagnosis *d* if covered. Assume that consumers do not use the star hospital if out of network. Define individuals' overall risk as $r_i \equiv \sum_d r_{i,d}$, and the share of illnesses for which they choose the star hospital as $s_i \equiv \frac{1}{r_i}\sum_d r_{i,d} I_{i,d}^S$. Finally, $\Delta\tau \equiv \tau_S - \tau_{NS}$. Expected costs for consumer *i* in a plan that does <u>not</u> cover *S* equal:

$$C_i^{NoCover} = r_i \cdot \tau_{NS} \tag{1}$$

while costs in a plan that covers *S* equal:

$$\begin{aligned} C_i^{CoverS} &= r_i \cdot \tau_{NS} + r_i \cdot s_i \cdot \Delta\tau \\ &\equiv C_i^{NoCover} + \Delta C_i \end{aligned} \tag{2}$$

This formula shows the two sources of cost variation: illness risk (r_i) and likelihood to choose the star hospital when sick (s_i). Although these may be correlated – sicker people may be more likely to choose star hospitals – these are conceptually separate drivers of costs. A key distinction is that high-s_i types are more expensive only in plans that cover the star hospital they prefer. Preference for the star hospital therefore affects enrollees' *cost differences* (ΔC_i) across plans – often called the moral hazard effect of

[10] This and many other assumptions are made for presentational simplicity and are relaxed in the structural model.

[11] If they were non-zero, τ_S and τ_{NS} would equal the insurer's net cost (= hospital price – patient copay). The assumption that insurers cover part of the fee differential ensures that $\tau_S > \tau_{NS}$.

covering S.[12] This heterogeneity in cost differences has implications for the nature of selection and the effectiveness of risk adjustment, as I discuss below.

Prior to realizing health shocks, consumers choose among plans based on plans' prices and coverage of hospital S. Let the utility of a plan not covering S be normalized to zero. I assume that consumers' extra utility for a plan that covers S equals their *ex-ante* expected value of access to S, or:

$$U_i^{CoverS} = \sum_d r_{i,d} I_{i,d}^S v_{i,d}^S = r_i \cdot s_i \cdot \overline{v}_i^S \tag{3}$$

where $\overline{v}_i^S \equiv \frac{1}{r_i s_i} \sum_d r_{i,d} I_{i,d}^S$ is the consumer's average value for the star hospital conditional on use. The key feature of this assumption is that consumers' utility for a plan covering the star hospital is *linked to their likelihood of using it* $(= r_i \cdot s_i)$. This link – which is built into standard models, including the "option demand" model of Capps et al. (2003) – generates the correlation between demand and costs that drives adverse selection.

Following Massachusetts' rules, assume that each plan j sets a single premium P_j that cannot vary across consumers.[13] Although prices cannot vary, the exchange risk adjusts payments based on consumer observables Z_i so a plan in total receives $P_j + RA(Z_i)$ for consumer i.[14]The risk adjustment function is set to offset a consumer's expected extra costs, so $RA(Z_i) = E(C_{ij} \mid Z_i) - \overline{C}$ (where $\overline{C}$ is overall average cost). If risk adjustment captured costs perfectly, a plan's profit margin would be a constant $P_j - \overline{C}$ for all consumers. However, risk adjustment is unlikely to offset the higher costs of high-s_i types for two reasons. First, the standard risk adjusters in Z_i (typically age, sex, and medical diagnoses) are intended to capture medical risk, not hospital choices – though, in principle hospital choice predictors could be added. Second, and more fundamentally, a single risk adjustment value $RA(Z_i)$ cannot offset the heterogeneity in cross-plan cost differences (moral hazard) that occurs in this setting (a point demonstrated by Einav et al. 2015). Costs vary not only because of consumer heterogeneity but because of the *interaction* of consumer types with the hospitals a plan covers.

[12] In the health insurance literature, "moral hazard" typically refers to changes in enrollee's utilization in response to more generous insurance. Even though not "hidden action" in the contract theory sense, the term is applied because the change in action is not contracted on, often because of regulatory constraints.
[13] Assume that any subsidies are a flat amount so that consumer premium differences are equal to price differences.
[14] Risk adjustment methods vary, and in general, the exchange could also make risk adjustment a function of prices. This was done in Massachusetts so that $RA_i^{Mass} = (\varphi(Z_i) - 1) P_j$, where $\varphi(Z_i)$ was a risk score and the plan's total payment was $\varphi(Z_i) P_j$. The ACA's risk adjustment is closer to the simple model, since its transfer is based on an enrollee risk score and the average price in the market.

1.2 Implications for Market Equilibrium

This model has several implications for market equilibrium, which I discuss in turn. For simplicity, I continue to assume a setting where there are (at most) two types of otherwise identical plans: those that cover *S* and those that do not.

(a) Selection on two dimensions of costs: Adverse selection occurs if plans that cover the star hospital tend to attract enrollees with high risk-adjusted costs. This selection can occur through two cost dimensions: unobserved risk and the cost difference from covering *S*. To see this formally, assume that the exchange risk adjusts based on costs in plans not covering *S*, and define $e_i \equiv C_i^0 - RA(Z_i)$ as the error in this prediction. Define average risk-adjusted costs in plan *j* as $AC_j = E\left(C_{ij} - RA(Z_i) \mid i \text{ chooses } j\right)$. For any price difference ΔP between types of plans, $\Delta AC \equiv AC_{CoverS} - AC_{NoCoverS}$ equals:

$$\Delta AC = \underbrace{\overline{\Delta C}}_{\text{(1) Cost Difference for Avg. Person}} + \underbrace{\left(\overline{e}^{CoverS} - \overline{e}^{NoCoverS}\right)}_{\text{(2) Selection on Unobs. Risk}} + \underbrace{E\left(\Delta C_i - \overline{\Delta C} \mid U_i^{CoverS} \geq \Delta P\right)}_{\text{(3) Selection on Cost Difference}} \tag{4}$$

where $\overline{e}^{CoverS}$ and $\overline{e}^{NoCoverS}$ are average risk adjustment errors for each plan type. Equation (4) separates out three components of average cost differences between plans. First, term (1) captures that plans covering *S* have higher costs even for an average person (i.e., no adverse selection) because of the moral hazard effect of covering *S*. Term (2) captures traditional selection on unobserved risk. Without additional assumptions, the sign of this term is ambiguous. Whether people who like the star hospital are unobservably sicker or healthier is driven by context-specific factors that are not obvious *a priori*. Finally, term (3) captures *selection on cost differences* (or selection on moral hazard). Unlike unobserved risk, there is a simple theoretical reason to expect a positive sign (adverse selection) for this term. The people who select plans covering *S* are those with $U_i^{CoverS} = r_i \cdot s_i \cdot \overline{v}_i^S \geq \Delta P$. Meanwhile, the cost difference is $\Delta C_i = r_i \cdot s_i \cdot \Delta\tau$. Because use of the star hospital ($= r_i \cdot s_i$) appears in both terms, it seems likely that these will be positively correlated. Intuitively, propensity to use the star hospital drives both plan preferences and the cost difference between plans.

(b) Inefficient sorting across plans: To sort consumers efficiently between plans, it is optimal for premium differences, ΔP, to equal *individual-specific* cost differences, ΔC_i. In a model with homogenous cost differences ($\Delta C_i = \overline{\Delta C}$ for all *i*), this optimum would be attainable. The goal of risk adjustment in such a model is to eliminate selection on unobserved risk, so that in competitive equilibrium, $\Delta P = \Delta AC = \overline{\Delta C}$. This is the basic intuition underlying traditional risk adjustment.

With heterogeneity in ΔC_i, first-best sorting is unattainable with homogenous premium differences between plans – a point that has been emphasized by Bundorf et al. (2012). It is optimal to choose a plan covering *S* if and only if $U_i^{CoverS} \geq \Delta C_i$, which simplifies to $\overline{v}_i^S \geq \Delta\tau$.[15] But consumers choose it if $r_i s_i \overline{v}_i^S \geq \Delta P$. The discrepancy between these conditions leads to both errors of over- and under-purchase of plans covering the star hospital.

Even if the first-best is unattainable, it is interesting to ask how selection affects prices relative to a second-best optimal single premium difference. The second best is defined by the condition $\Delta P = E\left(\Delta C_i \mid U_i^{CoverS} = \Delta P\right)$, which equates price to the marginal enrollees' cost difference. Equation (4) shows that in a competitive equilibrium with $\Delta P = \Delta AC$, adverse selection on both unobserved risk and moral hazard pushes ΔP above this optimum. The intuition for unobserved risk is standard. For selection on moral hazard, the intuition is that the marginal type uses the star hospital less than the average person in the *S*-covering plan. The need to pool with these high-ΔC_i types discourages some people for whom access to *S* would be efficient.

(c) Star hospital coverage and market power: Adverse selection (through either channel) has a natural effect on insurers' incentives to cover the star hospital, and in turn on its market power in price negotiations. To study these issues, suppose that instead of perfect competition, there is an imperfectly competitive insurance market where each insurer bargains with the star hospital over its payment rate, τ_S, and inclusion in network. Assume that the star and non-star hospitals have marginal costs of mc_S and mc_{NS}, and that because of hospital competition $\tau_{NS} = mc_{NS}$. I do not specify a full bargaining model for the determination of τ_S but note that in standard models (e.g., Nash bargaining), a key determinant is an insurer's change in profits from shifting from not covering to covering *S* at a given τ_S, or:

$$\Delta\pi_j\left(\tau_S\right) = \left[\Delta P_j - \Delta AC_j\left(\tau_S\right)\right] \cdot Q_j^{CoverS} + \left[P_j^{NoCover} - AC_j^{NoCover}\right] \cdot \Delta Q_j \tag{5}$$

where all of these terms are equilibrium values, which incorporate the shift in plan prices when plan *j* adds *S* to its network.[16] Adverse selection implies a larger increase in average costs (ΔAC_j) when a plan covers *S*. This makes covering the star hospital less profitable at any given payment rate τ_S.

This lower insurer profitability in turn affects the payment rate the star hospital can extract. Intuitively, adverse selection improves the insurer's *threat point* (profits if it excludes *S*) in a bargaining

[15] These conditions would be different if $\Delta\tau$ includes a markup above hospital marginal cost differences, an issue I return to below.
[16] Depending on the timing of the game, this condition may implicitly include the equilibrium pricing response of other insurers' in the definition of quantities and average costs.

game. Two possible outcomes can result. If the star hospital's high prices reflect high markups, adverse selection can discipline these markups and lead to lower τ_S without any plans dropping it from network. Alternatively, if the star hospital's high payment rates reflect high marginal costs, insurers may find it profitable to drop *S* even at $\tau_S = mc_S$, resulting in less equilibrium coverage of the star hospital.

Thus, adverse selection can have important implications for both equilibrium coverage and prices of star hospitals. For tractability in my structural model, I will only consider the coverage channel – I hold hospital prices fixed and simulate insurers' decision to cover/exclude the star hospital. However, readers should keep in mind the broader conceptual point that adverse selection in insurance markets can discipline star hospitals' market power. This point is an important caveat to the typical logic that popular hospitals for which consumers have high "willingness to pay" have the strongest market power (see e.g., Ho 2009). In markets where insurers compete (as opposed to most employer insurance settings), a hospital's market power is related to insurers' *profitability* of covering it. Profitability depends both on how much covering the hospital increases a plan's demand (roughly analogous to willingness to pay) but also on *which* consumers it attracts. If covering it attracts high-cost, unprofitable consumers, that hospital may have significantly less leverage to negotiate high prices.

2 Massachusetts Exchange Background and Data

I study the subsidized Massachusetts health insurance exchange – called Commonwealth Care, or CommCare. Created in Massachusetts' 2006 health reform, it operated from November 2006 to December 2013, after which it shifted form to comply with ACA rules. Like the ACA exchanges, CommCare offered subsidized coverage to low-income people (0-300% of poverty) not eligible for employer-sponsored insurance or other public programs.[17] CommCare enrollees could choose among competing private plans in a centralized marketplace. Over the 2010-2013 period I focus on, the exchange had five competing insurers and averaged 170,000 enrollees. This size makes it comparable to a very large employer plan but still small relative to Massachusetts' overall population of 6.6 million.

CommCare is a nice setting to study the selection implications of provider networks (and star hospital coverage in particular) for several reasons. First, the exchange standardized essentially all benefits *other than* networks. By rule, all plans had the same patient cost-sharing rules and covered

[17] A separate market called "CommChoice" offered unsubsidized plans for all others (see Ericson and Starc 2013, 2015). In the ACA, the unsubsidized and subsidized populations are combined into a single exchange, while people below 138% of poverty are eligible for Medicaid.

services.[18] This structure – which is more standardized than the ACA but similar to Medicaid managed care programs – lets me study plans that differ in network but are nearly identical on other dimensions.

Second, like the ACA, CommCare used sophisticated policies to counteract adverse selection. In addition to subsidies and a mandate to encourage broad participation in the market, it also employed risk adjustment based on enrollee observables.[19] Specifically, the exchange used demographics and past diagnoses to assign each enrollee a "risk score," intended to predict their relative costliness. Risk scores multiplied the plan's price (P_j), so a plan would receive $RA_i \cdot P_j$ for someone with risk score RA_i. While there is debate on how well risk adjustment has worked in other settings (see Brown et al. 2014; Newhouse et al. 2015), the methods used by CommCare are state-of-the-art.[20] Notably, however, these methods do not incorporate predictors of provider choices (e.g., past provider utilization).

I discuss two more reasons CommCare is a nice setting for this study in the next subsections.

2.1 Star Hospitals: Partners Healthcare

Massachusetts includes a clear pair of star academic hospitals: Massachusetts General Hospital (MGH) and Brigham & Women's Hospital, the flagship hospitals of the Partners Healthcare System.[21] These hospitals fit what Ho (2009) called "star hospitals" – prestigious hospitals that use their reputations to bargain for high prices. *U.S. News & World Report's* "Best Hospitals" issue perennially ranks them as the top two hospitals statewide and among the top 10 nationwide. This position has given them the perception of "must-cover" hospitals that can command high prices. These high prices have been repeatedly documented (see Allen et al. 2008; Coakley 2013; CHIA 2014) and have sparked anti-trust investigations by federal and state authorities.

The two Partners hospitals also have very high prices in the CommCare market. Table 1 shows price estimates for the 10 most expensive general acute care hospitals. The first column shows raw average payments per admission, while the next column reports estimates of severity-adjusted prices from my model (see Section 5.1). On both measures, the Brigham and MGH are the two most expensive hospitals by a substantial margin. For the average-severity patient, these hospitals have prices of about \$20,000, compared to \$15,900 for the next most expensive hospital and about \$11,000 for the average

[18] There was an exception to this rule in two cases: (1) prescription drug formularies (for above-poverty enrollees only), subject to minimum standards, and (2) a few "extra benefits" like gym memberships.
[19] CommCare also had a reinsurance program, which covered 75% of any enrollee's costs exceeding \$150,000 per year. This very high cutoff meant reinsurance played a minor role, covering just 0.03% of enrollees and 1% of costs.
[20] One limitation was that CommCare (like Medicare, but unlike the ACA) used *prospective* risk adjustment, which uses only *past years'* diagnoses. As a result, new enrollees receive risk scores based only on age and sex. In practice, I find that the selection results hold robustly even in the subsample with diagnosis-based risk scores.
[21] As of 2012, Partners also included five community hospitals in Eastern Massachusetts and more than 1,100 primary care physicians (BCBS of Massachusetts Foundation 2013).

hospital. Column (3) shows that they also attract patients of above-average severity (a diagnosis-based measure normalized to have mean 1.0), but most of their higher payments are driven by prices.

Several considerations are relevant for interpreting the Partners hospitals' high prices. First, a natural question is whether these prices reflect high costs and/or high margins. Column (4) of Table 1 shows estimates of hospitals' average costs per (severity-adjusted) patient from state hospital cost reports for 2012 (CHIA 2014). While this measure is imperfect,[22] it gives a sense of relative costs across hospitals. Within this high-price list, the Brigham and MGH have the highest costs (and rank near the top of the full list). However, costs only partly explain their high prices. Using the difference between my price estimates and the state's cost estimates as a proxy for margins, the Brigham and MGH also have the highest margins of any hospital.

Second, it is important to consider whether the star hospitals also have better quality. My structural model allows for (and finds) them to be higher quality based on hospital demand estimates. However, these estimates cannot distinguish between clinical quality and other drivers of demand, such as better amenities or (possibly incorrect) perceptions. Indeed, the outside evidence on star hospitals' clinical superiority is mixed.[23] Although beyond the scope of this paper, studying whether (and for whom) star hospitals have better clinical quality is an important topic for future work.

Finally, as non-profit academic hospitals, Partners' high prices partly support medical teaching and research. To the extent that these activities generate positive externalities, downward pressure on their prices may have social costs. The key empirical question is "where the money comes from" if prices fall – to what extent is it items like research, medical staffing, or fancy new buildings? There is little evidence on this question specifically for star hospitals, so this is another avenue for future research.

2.2 Variation in Insurers' Hospital Coverage

A final advantage of the CommCare market is its significant network variation across plans and over time. Figure 1 shows the share of statewide hospitals (weighted by bed size) covered by the five CommCare plans. The table below shows coverage of the Partners hospitals. The three largest plans – Boston Medical Center HealthNet (BMC), Network Health, and Neighborhood Health Plan (NHP) – all operate statewide and cover a relatively broad 70-90% of hospitals up to 2011. Fallon operates mainly in Central Mass., so has limited statewide coverage. The one truly limited network statewide plan is CeltiCare, which entered in 2010 with a low-price plan that covered less than half of hospitals.

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[22] In particular, it is based on costs across all patients, not just CommCare enrollees. It is also a measure of average costs (which includes some fixed costs), rather than marginal costs per patient.

[23] On the one hand, the *U.S. News* rankings indicate a *reputation* for superiority, at least for the sickest patients. Further, some past work has found that top teaching hospitals deliver lower mortality for heart attack patients (Chandra et al. 2013; Doyle et al. 2012). However, MGH and Brigham do not uniformly score higher on process-based measures of clinical quality (CHIA 2015).

My empirical work exploits a major network shift at the start of fiscal year 2012,[24] spurred by an exchange policy change. The background for this change is as follows. Because of federal rules, enrollees earning less than 100% of poverty receive full premium subsidies (i.e., all plans are free). Prior to 2012, this group also had full choice among plans, just like higher-income, premium-paying enrollees. Starting in 2012, new enrollees in the below-poverty group were limited to choosing one of the two cheapest plans. This policy encouraged greater plan price competition to be one of these two lowest-price plans.

In response, CeltiCare and Network Health cut prices sharply – by 11% and 15%, respectively – to become the two cheapest plans in 2012. While CeltiCare already had a low-cost structure, Network Health needed to reduce costs to make this price cut feasible. To do so, Network Health shifted to a narrower network by dropping the Partners hospitals (and associated physicians), plus several other less prestigious hospitals. Figure 1 shows that this narrowing was the single largest network change in the exchange's history, with Network Health's statewide hospital coverage falling by 18% points.[25]

I use these 2012 changes as a natural experiment to study the cost and selection implications of dropping the star hospitals. In Section 3, I show evidence of both individual-level cost reductions and selection of high-cost types away from Network Health. Figure 2 shows evidence that the combined effect of these two forces led to immediate and substantial changes in costs and hospital use patterns. After holding relatively steady, Network Health's costs fell by 21% from 2011-2012, while costs in all other plans rose by 6%. The share of Network Health's hospitalized patients using a Partners facility fell by two-thirds, from 20% to 6%.[26] The enrollees who shifted away from Network Health tended to be the patients most likely to use Partners. As a result, the Partners use share in all other plans rose sharply in 2012, despite no changes in their coverage of Partners.

After seeing sharply higher costs in 2012-2013, CeltiCare also dropped Partners' physicians and subsequently its hospitals in fiscal 2014, explicitly citing adverse selection as a rationale.[27] Meanwhile, NHP retained Partners but had special reason to do so: Partners acquired NHP in fiscal year 2013. Thus, at the start of the ACA in 2014, only one plan covered Partners and that through a vertical relationship.

[24] CommCare's fiscal year runs from July to June, so fiscal 2012 started in July 2011.

[25] Dropping Partners accounted for almost 90% of this (bed-weighted) coverage reduction. The non-Partners hospitals dropped included one less prestigious academic medical center (Tufts Hospital), one teaching hospital (St. Vincent's in Worcester), and six community hospitals. The plan did retain two small and isolated Partners hospitals on the islands of Nantucket and Martha's Vineyard but dropped all other Partners hospitals.

[26] This fall led to a 15% decline in the plan's costs per hospital admission, a drop entirely accounted for by less use of Partners. The Partners use share did not fall all the way to zero because patients can get coverage for out-of-network hospitals in an emergency or if the insurer gives prior authorization.

[27] In testimony to the Massachusetts Health Policy Commission (HPC 2013), CeltiCare's CEO wrote: "For the contract year 2012, Network Health Plan removed Partners hospital system and their PCPs [primary care physicians] 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."

2.3 Data: Plan Choices and Insurance Claims

To study these issues, I use a comprehensive administrative dataset on plan enrollment and insurance claims for all CommCare plans and enrollees from fiscal 2007-2013.[28] For each (de-identified) enrollee, I observe demographics, plan enrollment history, and claims for health care services while enrolled in the market. The claims include information on patient diagnoses, services provided, the identity of the provider, and the actual amounts the insurer paid for the care.

I use the raw data to construct two datasets for reduced form analysis and model estimation. The first is for hospital choices and costs. From the claims, I pull out all inpatient stays at general acute care hospitals in Massachusetts during fiscal years 2008-2013 – the period over which I have data from the exchange on plans' hospital networks. I add on hospital characteristics from the American Hospital Association (AHA) Annual Survey and define patient travel distance using the driving distance from the patient's home zip code centroid to each hospital.[29] For each hospitalization, I sum up the insurer's total payment while the patient was admitted (including both hospital facility fees and physician professional service fees) and use this to estimate the hospital price model described in Section 5.1.

The second dataset is for insurance plan choices and costs. Using the enrollment data, I construct a dataset of available plan choices, plan characteristics (including premium and network), and chosen options during fiscal 2008-2013. I consider plan choices made at two distinct times: (1) when an individual initially enrolls in CommCare or re-enrolls after a gap in coverage, and (2) at annual open enrollment when current enrollees can switch plans. A key difference between these two situations is their default choice. New and re-enrollees must make an active choice to receive any coverage,[30] while non-responsive current enrollees are defaulted to their current plan. Consistent with past work, I find this default to be quite important. Finally, for each enrollee x choice instance, I observe both costs for the remainder of the year (from claims data) and the enrollee's risk score.

The tables in Appendix A show summary statistics for both the hospital and plan choice samples. The data include 611,455 unique enrollees making a total of 1,588,889 plan choices and experiencing 74,383 hospital admissions. The average age is 39.6, and just under half of enrollees earn less than poverty and therefore are fully subsidized. There is substantial flow of enrollees into an out of the market. In steady state, about 11,000 people per month (or 6.5% of the market) newly enroll or re-enroll in CommCare, and a comparable number exit. This churn gives me a significant population of active choosers from which to estimate plan demand.

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[28] The data was obtained via a data use agreement with the Massachusetts Health Connector, the exchange regulator. To protect enrollees' privacy, the data was purged of all identifying variables.

[29] I thank Amanda Starc and Keith Ericson for sharing this data.

[30] This rule had one exception. Prior to fiscal 2010, the exchange auto-assigned plans to the poorest new enrollees who failed to make an active choice. I exclude these passive enrollees from the plan choice estimation dataset.

3 Reduced Form Evidence of Adverse Selection

In this section, I present reduced form evidence of adverse selection against plans that cover the star hospitals in the Massachusetts exchange. I also show evidence of the key mechanism in my model: that variation in preferences for using star hospitals is an important non-risk dimension of heterogeneity that can drive costs and selection.

To do so, I first show that certain patients are much more likely than others to use a star hospital when sick. This propensity is predictable based on past use of outpatient care at a star hospital or another hospital in the same system (Partners Healthcare). I show that this past Partners patient group has high costs conditional on observable risk, consistently across the entire risk distribution. I also show that these high-cost patients drive adverse selection, as they are more likely to actively choose plans that cover Partners. These facts emerge both in cross-sectional regressions (following the literature on testing for selection) and based on switching choices after a plan dropped Partners from network in 2012.

Finally, I provide evidence that these Partners patients' high costs are driven at least partly by a causal effect of having access to the star hospitals (i.e., moral hazard). Using panel data on costs for stayers in the plan that dropped Partners, I show that past Partners patients experienced sharp cost reductions that were much larger than for other enrollees. Thus, the same group most likely to switch plans also experienced the largest cost reductions when they did not switch – consistent with my model's prediction of "selection on moral hazard."

3.1 Star Hospital Patients and Adverse Selection

I start by testing for adverse selection by asking whether individuals with high risk-adjusted costs tend to select plans that cover Partners. I use a method similar to the positive correlation test of Chiappori & Salanie (2000), and specifically the "unused observables" approach of Finkelstein & Poterba (2014). Starting with data on plan choices, costs, and other outcomes over the subsequent year, this method runs regressions of the form:

$$Y_{it} = X_{it}\alpha + Z_{it}\beta + \varepsilon_{it} \tag{6}$$

where Y_{it} are various outcomes for individual *i* in year *t*, X_{it} are factors on which insurer prices can vary, and Z_{it} are other "unused" observables that insurers cannot price based on. During the 2011-13 period I analyze, the only factors in X_{it} were risk scores (used to risk-adjust payments) and income group.[31] In

[31] Risk adjustment started in 2010, but my dataset is missing risk scores from part of 2010. Technically, insurers set a single price for all income groups, but because of subsidies, post-subsidy premiums vary across income groups. I include income groups in X_{it} to capture any effects of these varying premiums.

addition, because I run the regression across multiple years, I interact the income groups with year dummies. All standard errors are clustered at the individual level.

My goal is to use unused observables in Z_{it} that capture people's propensity to use the star hospitals. This serves both as a test of adverse selection and of the specific mechanism of selection driven by the patients most likely to use the star hospitals. To do so, I use a variable based on past utilization: whether an individual has previously received *outpatient care* from physicians affiliated with a star hospital or another Partners hospital (which are part of the same referral network). This measure includes both physician visits at Partners-owned practices and treatments in the outpatient wing of Partners' hospitals. For the analysis below, I define past Partners patients as individuals with any outpatient claims billed to a Partners hospital prior to the timing of a given plan choice.[32]

This measure's main limitation is that past use is only observable while patients were enrolled in the exchange. Because of this limitation, I exclude from the sample first-time new enrollees. For the final sample, outpatient care occurs regularly enough that I observe some outpatient care use for the vast majority (87%) of individuals. In particular, 12% of the full sample (and 20% of those in the Boston region) have past use at a Partners hospital.

The idea of this variable as a predictor of star hospital use is simple. When choosing a hospital, patients are likely to go to one where they have past experience or have a relationship with its affiliated physicians. However, two caveats may be helpful in interpreting this variable.

First, past outpatient use of Partners providers is not an exogenous characteristic but an outcome for a separate (but related) care choice. As such, its predictive power may work through two channels. First, using a Partners physician may *cause* patients to use the star hospitals for inpatient care – e.g., through physician referral patterns (see Baker et al. (2015)). Second, similar underlying factors may influence both decisions – e.g., distance and perceptions of Partners' quality. Separating these two channels – a version of the classic state-dependence vs. heterogeneity problem – is empirically challenging, and I have not been able to do so given the variation in my data. Importantly, *both* channels imply that these patients will have a special affinity for using the star hospitals, at least in the short run.[33] Both therefore provide variation needed to test for my adverse selection mechanism.

[32] This captures visits to Partners-owned physician practices via the "facility fee" billed to the owning hospital. This measure also includes emergency room visits, since some people obtain their regular outpatient care in this way. However, the measure is essentially unchanged if ER use is removed – the two measures have 98% overlap.

[33] The two channels differ in their long-run welfare implications. State dependence implies that the welfare loss from losing access to a star hospital would fade over time, as relationships with new providers formed. Heterogeneity, by contrast, would imply a more durable welfare loss. It would be interesting in future work to disentangle these two channels. Doing so would require exogenous changes in patient-physician relationships – e.g., if patients moved locations or were randomly assigned to primary care providers when joining a new plan.

Second, past use of Partners should not be interpreted as a marker *only* of preference and not medical risk. Indeed, compared to other enrollees, past Partners patients are somewhat older (mean age of 42.7 versus 41.0) and sicker on observable risk score (mean of 1.29 versus 0.96, implying 33% higher predicted costs). Given the star hospitals' reputations for treating the sickest patients, it would not be surprising if this group were also unobservably sicker – the relevant criterion in a market with risk adjustment. What I argue is that even if they are sicker, a substantial portion of their costs are driven by their tendency to choose Partners' high-price providers.[34] I provide additional evidence for this below.

The first four columns of Table 2 show regression estimates of hospital use and cost outcomes, controlling for observable risk. To remove the effect of differential plan enrollment between groups, I limit the sample to plans that cover Partners and also interact the income group x year dummies with plan dummies (though results are similar without these adjustments). Column 1 shows that past Partners patients are substantially more likely to use a star hospital (MGH or Brigham & Women's) when hospitalized. The average difference of 32.2% points represents a nearly *five-fold* increase over the mean rate of 6.6% for other enrollees. As a result of these hospital choices, past Partners patients' prices per admission are $3,143 (or 29%) higher than for other enrollees (column 2).[35] Thus, this group has high costs at least partly because they choose high-price hospitals when sick.

Comparing these risk-adjusted coefficients to the raw differences (reported at the bottom of the table) shows that controlling for risk scores narrows this difference only slightly. By contrast, column 3 shows that controlling for risk scores essentially eliminates the difference in hospitalization rates between the groups. This is consistent with risk adjustment being more effective at offsetting Partners patients' higher medical risk (proxied by hospitalization rate) than at offsetting differences due to hospital choices.

Finally, column 4 shows that past Partners patients have overall risk-adjusted annual costs $1,137 (or 28%) higher than the mean for other enrollees. Risk adjustment is not completely ineffective: it narrows the groups' unadjusted cost difference of $3,286 by about two-thirds. But this still leaves a substantial gap that can lead to adverse selection after risk adjustment.

Figure 3 shows the same results visually using binned scatter plots. For each bin of risk scores (on the x-axis), the figures show average outcomes for past Partners patients (red triangles) versus all others (blue circles), along with best-fit lines for each group. The graphs show that the different hospital choices, costs, and plan choices of Partners patients are substantial and occur across the whole distribution of

[34] Clearly, it would be nicer to have a simple measure that separates preferences from medical risk. Unfortunately, I have not been able to find one. Distance is a candidate, but as I show below, it also seems to correlate with unobserved medical risk – perhaps because of the type of people who live in the central city near the star hospitals. Instead, I rely on my structural model to separate preferences from medical risk.
[35] The results are similar if I analyze raw cost per admission instead of my severity-adjusted price measure.

medical risk, not just the sick. This is consistent with the idea that propensity to use high-cost providers is an independent driver of higher costs at any level of medical risk.

The final issue in the unused unobservables test is whether the Partners patients are also more likely to select plans that cover Partners. The typical method would be to run a version of regression (1) with a dummy for having chosen a plan covering Partners as the outcome variable. However, a concern with this method here is reverse causality. It is possible that people choose a plan covering Partners (for unrelated reasons) and then use the star hospitals simply because they are available. These people would have higher costs and would likely remain in the same plan over time due to inertia, but a durable preference for Partners would not be the reason. To address this concern, I take two approaches.

First, I restrict attention to "re-enrollees" who make an active plan choice upon rejoining the exchange after having been away (e.g., due to income fluctuations that made them ineligible). For this group, past Partners use is defined based on data from their previous coverage spell. Column 5 of Table 2 shows that past Partners patients are 29.8% points more likely to actively choose a plan covering Partners – an 80% increase vs. the mean for all others.[36] Thus, this approach suggests substantial adverse selection: the same group has high costs and is more likely to choose a plan covering Partners.

My second approach is to consider plan switching choices after an insurer changes its coverage of Partners. I present these results in the next subsection, after discussing some robustness checks.

A key question in interpreting these findings is whether past Partners patients simply have higher unobserved risk, not higher costs because of their provider choices. Both of these channels would imply adverse selection (and would have similar effects on insurer incentives), but only the latter would be evidence of the new theoretical mechanism. Appendix Table B.1 shows several robustness regressions showing that the cost results above persist in different subgroups and with additional controls. In particular, past Partners patients are still higher cost if the sample is limited to those with the highest-quality, diagnosis-based risk adjustment;[37] if the sample is limited to re-enrollees; if past Partners use is defined only based on physician office visits (not other forms of outpatient care); and if additional controls for past use of any hospital or any academic medical center are included. These checks provide additional evidence that the effects are not simply driven by unobserved risk. Ultimately, the best evidence for this comes from the evidence on differential moral hazard presented below.

Two final points are helpful in interpreting these findings. First, the predictive power of outpatient care use for future hospital choices is not limited to star hospitals, but holds more generally. In

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[36] This effect is almost as large as the effect for the full sample (not restricting to re-enrollees) of 33.2% points. It is also robust to limiting the sample to re-enrollees with longer breaks from the exchange. Even among enrollees with breaks of more than two years, the effect for past Partners patients is 21% points.

[37] Diagnoses were unavailable for newer enrollees without sufficient past claims data, so risk adjustment was based on age and sex only. While this is an important concern with risk adjustment in health insurance exchanges, the adverse selection channel I identify appears largely orthogonal to this limitation.

Section 4.1, I show that past outpatient use of a given hospital enters as a strong predictor of choosing that hospital in a formal discrete choice model (even after controlling for variables like distance). This result holds even if the sample is limited to non-Partners hospitals. Thus, patient loyalty to specific providers seems to be a general fact. However, this loyalty only matters for costs and adverse selection if the provider (like the star hospitals) has high prices.

Second, an additional way to test my model would be to use enrollee distance to the star hospitals as a proxy for their preferences. Distance is in many ways conceptually cleaner than past use, and its continuity lets me do a "dose response" type test. Appendix Figure B.1 shows binned scatter plots (analogous to Figure 3) of distance to the closest star hospital versus various outcomes, after controlling for risk score. Living near a star hospital is a strong predictor of choosing one of them for inpatient care, though not as strong as past use. Consistent with my model, nearby enrollees also have higher prices (and costs) per hospital admission. However, surprisingly, the hospitalization rate is *lower* for enrollees near the star hospitals, suggesting that this group is unobservably healthier (perhaps because of the types of low-income people who live in central Boston). The net implication is that risk-adjusted costs are approximately flat with distance. Thus, although nearby enrollees are significantly more likely to choose a plan covering Partners (not shown), this group does not contribute to adverse selection. This analysis is a reminder that multiple sources of unobserved heterogeneity can sometimes offset, weakening adverse selection or even creating advantageous selection (Cutler, Finkelstein, and McGarry 2008; Fang, Keane, and Silverman 2008; Finkelstein and McGarry 2006).

3.2 Adverse Selection Evidence from Plan Network Changes in 2012

A second way to test for adverse selection is to study plan network changes. This lets me disentangle star hospital coverage from any other plan differences (e.g., better reputation or customer service), to provide more direct evidence on the demand, cost, and selection effects of covering the star hospitals. Of course, the key assumption is that any other simultaneous plan changes are not driving the results I find.

I focus on changes in 2012 that were both the largest in CommCare's history and the only time when the star hospitals were dropped. As discussed in Section 2.2, this change occurred after the exchange introduced new incentives rewarding the lowest-price plans. In response, Network Health cut its price by about 15% and, to cut costs, excluded the Partners system (both its hospitals and doctors) and several other hospitals from its network. Other plans also changed prices but did not make significant network changes at the time.

I start by studying plan choice patterns, again using past Partners use as a proxy for preference for the star hospitals. Figure 4 shows the share of current Network Health enrollees who switched plans just before the start of each plan year. The average switching rate is usually very low (about 5%), but it spikes in 2012 to just over 10%. All of this spike is driven by patients of the hospitals Network Health dropped – switching rates actually fell slightly for everyone else. Almost 40% of past Partners patients switched away from Network Health in 2012, a more than *seven-fold* increase from adjacent years. This huge increase suggests that many patients are willing to overcome inertia and switch plans to retain access to their preferred providers.[38] Most of these switchers moved to CeltiCare and Neighborhood Health Plan, the two remaining plans covering Partners. Switching rates also spiked for past patients of the other dropped hospitals, but only to 18% (about half as much as for Partners patients). This is consistent with willingness to switch plans to retain access to a provider being a general phenomenon, but one whose effects are stronger for star hospitals.

Because the Partners patients are a high-cost group, these switching patterns had important cost implications. Table 3 shows statistics on unadjusted and risk-adjusted costs for Network Health between 2011 and 2012. Overall, its per-member-month costs fell by 21% (or 15% after risk adjustment), a huge decline in the health insurance industry where costs rarely fall. However, for the fixed population of "stayers" enrolled in Network Health in both years, costs fell by just 6%. The remainder of the cost change came through selective entry and exiting from the plan. The most expensive group was those who switched away from Network Health in 2012 – their 2011 risk-adjusted costs were $6,109 per year, almost 40% above the plan's average and 60% above the average stayer.[39]

The bottom panel of the table breaks down costs for switchers and stayers into past Partners patients (as of the start of 2012) and all others. It makes clear that Partners patients drove the high costs among switchers away from Network Health. They represented 68% of all switchers and had risk-adjusted costs of $6,853 in 2011 (54% above the plan average), whereas all other switchers had below-average costs. In comparison, the Partners patients who stayed with Network Health were somewhat less expensive – only $5,662 (after risk adjustment) in 2011. Thus, even among the Partners patients, dropping Partners selectively induced the highest-cost patients to switch plans.

A second notable finding in Table 3 is that cost changes varied substantially among stayers in Network Health. The 6% overall cost fall for stayers reflected a 26% decline for Partners patients versus a small increase for all other enrollees. These heterogeneous changes are consistent with the model's prediction of differential cost effects of dropping a star hospital on the patients most likely to use it. I explore this finding further in the following subsection.

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[38] One factor behind this high switching rate may be that Partners itself encouraged its patients to switch plans. By chance, I observed this occur during a tour of Brigham & Women's Hospital in late 2013 when a Medicaid managed care plan was about to drop Partners. The finance department was calling patients to let them know they needed to switch plans to maintain access to their Brigham & Women's providers.

[39] In addition to the switchers, the group exiting the market had high costs. While the reasons are unclear, exiting enrollees appear to be high-cost in other years and plans as well, not just in Network Health in 2011-12.

3.3 Heterogeneity and Selection on Moral Hazard

One of the key predictions of my model is selection on cost changes (or the moral hazard effect) from covering the star hospitals. To test this prediction, I ask whether past Partners patients – the group most likely to switch away from Network Health – also experienced the largest cost reductions when they stayed with Network Health. Of course, stayers and switchers are different people, so it is not possible to measure both cost effects and switching rates for literally the same individuals. But finding that the same characteristic predicts both outcomes would be suggestive evidence of selection on moral hazard.

I use the panel structure of my data to analyze within-person cost changes over time using regressions with individual fixed effects. I first restrict the sample to individuals who were in the market in both 2011 and 2012. Then I run the fixed-effect regressions with dummy variables for each two-month period in 2011-12, interacted with whether a person was in Network Health or another plan. I take these estimated coefficients, add back the group mean cost, and plot the results in Figure 5. The results can be thought of as estimates of average within-person cost changes over time, correcting for the fact that the panel is unbalanced due to enrollee entry and exit from the market. The left graphs in Figure 5 show results split by the plan an individual was in during 2011 (regardless of their 2012 plan), while the right graphs show results limited to stayers who did not switch plans during this period.

Panel A shows evidence of sharp and significant cost reductions overall for Network Health when it dropped Partners from network at the start of 2012. The results for other plans shows little change at the start of 2012, suggesting that there were not any important market-wide shocks at this time. These results hold both for all enrollees in Network Health in 2011 (left graph) and when attention is restricted to stayers (right graph). Panel B shows that these cost reductions were concentrated among past Partners patients (defined as of the end of 2011), consistent with the theory. Among stayers, past Partners patients show an average cost drop of more than $2,000 per year, compared to a much more modest drop for all other enrollees. The analogous numbers for Partners patients in other plans (dotted green lines) shows little evidence of a systematic fall in costs at this time.[40]

4 Structural Model: Hospital and Insurance Plan Demand

The reduced form evidence suggests that consumers select into plans covering the star Partners hospitals based on their preference for using those hospitals. Understanding the competitive and welfare implications of this selection requires estimating a structural model that can capture this correlation. In this section, I present and estimate the hospital and insurance demand portion of this model. I follow a

[40] This fact alleviates concerns that the fall in costs for Partners patients is driven primarily by mean reversion, since Partners patients (by construction) are more likely to have used a hospital in 2011.

method introduced by Capps et al. (2003) to capture how different consumers value plans' hospital networks. I first estimate a hospital demand model that captures how patients weigh different factors (e.g., distance, hospital characteristics) when selecting hospitals. This hospital demand model generates an expected "network utility" metric capturing the attractiveness of each plan's network to a specific consumer. I then estimate an insurance plan demand model, including network utility as a covariate. If patients choose plans based on their hospital networks, the coefficient on network utility should be positive. Because of the importance of past Partners users in the reduced form results, I allow preferences in both the hospital and plan demand models to vary based on which hospitals an individual has previously used. This section proceeds by estimating hospital demand (Section 4.1) and deriving network utility (Section 4.2). I then present and estimate plan demand (Section 4.3-4.4).

4.1 Hospital Demand

I use the micro-data on inpatient hospital use to estimate a multinomial logit model capturing how patients choose hospitals. My method and specification are similar to much past work (e.g., Town & Vistnes 2001; Gaynor & Vogt 2003; Ho 2006). The main covariates are distance and hospital characteristics, and I allow preferences to vary with patient observables. I do not include patient fees as a covariate, since CommCare's copays are constant across in-network hospitals and therefore drop out.[41] In addition, I do not include an outside option, since I am focusing on patients sick enough to need hospital care and Massachusetts is a relatively complete hospital market.[42]

My model differs from past work in two main ways. First, based on the reduced form results, I allow hospital preferences to vary with whether a patient has used the hospital in the past (either for inpatient or outpatient care).[43] Although its interpretation is not obvious – it captures both heterogeneity and state dependence – I include past hospital use because of its importance as a channel for adverse selection. Second, because I observe a non-trivial number of out-of-network hospitalizations covered by plans, I include out-of-network hospitals in the choice set. This captures the fact that patients can sometimes get plan authorization to see an out-of-network provider. To capture the associated hassle costs, I estimate a plan-specific out-of-network cost in the hospital choice model.[44] This specification generalizes previous work that disallows out-of-network admissions, which is equivalent to assuming an infinite hassle cost.

[41] Recent work by Ho & Pakes (2014) also finds that hospital price matters for referral patterns in plans where doctors are paid by capitation. Unlike their California setting, CommCare insurers pay doctors almost exclusively fee-for-service, with capitation accounting for less than 5% of physician service fees.
[42] The only significant exception is spillover of patients in Southeastern Mass. to hospitals in Providence, RI.
[43] To rule out immediate readmissions, I require that the past use occurred more than 60 days beforehand.
[44] Patients can also use any hospital in an emergency (without needing plan authorization) but may need to be transferred once stabilized, creating a different type of hassle. I allow for an interaction between emergency status and the out-of-network cost but find little evidence that the cost is lower in emergencies.

Consider an admission at time t for individual i (in plan j) who has principal diagnosis d. I specify the following model for the latent utility for hospital h:

$$u_{i,d,t,j,h} = \underbrace{\delta\left(Z_{i,d,t}\right) Dist_{i,h}}_{\text{Distance}} + \underbrace{\gamma\left(Z_{i,d,t}\right) X_h + \eta_h}_{\text{Hospital Characteristics}} + \underbrace{\lambda \cdot PastUse_{i,h}}_{\text{Past Use Dummy}} - \underbrace{\kappa_j \cdot 1\left\{h \notin N_{j,t}\right\}}_{\text{Out-of-Network Hassle Cost}} + \varepsilon_{i,d,t,h} \tag{7}$$

where $Dist_{i,h}$ is patient travel distance (and distance-squared), X_h are observed hospital characteristics, η_h is an unobserved characteristic (captured by hospital dummies), $PastUse_{i,h}$ are past use indicators, and $1\left\{h \notin N_{j,t}\right\}$ is an out-of-network dummy (and κ_j the hassle cost). I allow coefficients on distance and characteristics to vary with patient observables $Z_{i,d,t}$ to allow for preference heterogeneity. Finally, $\varepsilon_{i,d,t,j,h}$ is an i.i.d. Type 1 extreme value error that generates the logit demand form.

Because all of the covariates are observed, I estimate the model by maximum likelihood. Table 4 shows the results. Consistent with previous papers' estimates, patients have a disutility of traveling to more distant hospitals, with the estimates implying that an extra 10 miles distance reduces a hospital's share by 31% on average. The model estimates a sizeable hassle cost for out-of-network hospitals that reduces their shares by 63% on average.[45] The table shows the largest hospital service x diagnosis interactions; the remaining coefficients are almost all significantly positive.

Two sets of coefficients have implications for adverse selection. First, teaching hospitals and particularly the largest academic medical centers (including the two star Partners hospitals) attract the sickest patients – where severity is based on an index of the costliness of a patient's diagnoses defined in Section 5.1. A one standard deviation increase in severity (a change of 0.3) increases the likelihood of using an academic medical center by 47%. Second, the past use dummies are very strong predictors of future hospital choices. For instance, patients who have previously used a hospital for outpatient care choose the same hospital in future admissions about 40% of the time. The model implies that this 40% share is an almost five-fold increase above what would be expected otherwise.

The model fit is quite good, particularly when past hospital use variables are included. Calculating hospital shares at the service area-plan-year level,[46] the model explains 74% of the variance in shares, despite the absence of any year-specific interactions in the model. This indicates that conditional on network, hospital use patterns are fairly stable in the market over time. The left half of Table 4 shows estimates and fit from a simpler model (with only distance, out-of-network cost, and hospital dummies) for comparison. This simple model can also pick up 64% of the variance in shares.

[45] A 63% reduction from being out of network may seem low. However, it is consistent with a basic statistic from the data: only 25% of hospital choices are out of network but 8% of admissions are at out-of-network facilities.
[46] Service areas are subregions defined by the exchange as the areas at which plans can choose whether or not to offer coverage. The five regions are divided into 38 service areas.

Most of the increase in fit from moving to the more complex model comes by adding the previous use covariates.

One concern with the out-of-network costs is that they are based on the network of a patient's chosen plan. Plan selection on observables (such as distance and past use) is okay, but if there is selection on unobservable hospital tastes, the out-of-network cost will be biased upward. This problem could be addressed econometrically by estimating the plan and hospital demand models jointly, allowing for unobserved hospital tastes to enter into plan choices (see Crawford & Yurukoglu 2012; Lee 2013). I have not implemented this method because of its computational complexity. One suggestion that any bias may not be too severe is that the model credibly matches hospital use patterns around Network Health's 2012 change in network (see Section 5.4). Nonetheless, the absence of plan selection on unobserved hospital preferences is a limitation of the model.

4.2 Hospital Network Utility

To generate a measure of network utility for plan demand, I follow the method of Capps et al. (2003). I define network utility based on the expected utility metric from the hospital demand system. Conditional on needing to be hospitalized, a consumer's utility of access to network $N_{j,t}$ in plan *j* is:

$$HospEU_{i,d,t,j}\left(N_{j,t}\right) \equiv E\max_{h}\left\{\hat{u}_{i,d,t,j,h}\left(N_{j,t}\right)+\varepsilon_{i,d,t,j,h}\right\} = \log\left(\sum_{h}\exp\left(\hat{u}_{i,d,t,j,h}\left(N_{j,t}\right)\right)\right) \tag{8}$$

where $\hat{u}_{i,d,t,j,h}\left(N_{j,t}\right) \equiv u_{i,d,t,j,h} - \varepsilon_{i,d,t,j,h}$. At the time of plan choice, however, consumers do not know their hospital needs. Instead, they have expectations of their hospital use frequency for each diagnosis *d* over the coming year, which I denote $freq_{i,d,t}$. Given this expectation, the *ex-ante* expected network utility is:

$$NetworkUtil_{i,j,t}\left(N_{j,t}\right) \equiv \sum_{d} freq_{i,d,t} \cdot HospEU_{i,d,t,j}\left(N_{j,t}\right) \tag{9}$$

This network utility in (9) is what I include in plan demand. To calculate it, I first use my data to estimate a Poisson regression of the annual number of hospitalizations for each diagnosis on individuals' age and demographics.[47] I use the predicted values from these regressions for $freq_{i,d,t}$. Next, I calculate the value of $HospEU_{i,d,t,j}\left(N_{j,t}\right)$ for each plan and diagnosis, using the individual's location and demographics at the time of plan choice.[48] Finally, I input these values into equation (9) to calculate

[47] I choose not to use diagnoses in this regression because past diagnoses are unavailable for new enrollees. I plan to explore a robustness check in which for current enrollees I use past diagnoses and for new enrollees, I use a separate model including chronic disease diagnoses observed in the subsequent plan year.

[48] The two hospitalization variables that remain to be filled in are severity and emergency status. For emergency status, I use the average emergency probability for each diagnosis to take an average of the values of *EU* for each

network utility. 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.

4.3 Plan Demand Model

I next estimate plan demand to capture how plan premiums and hospital networks influence consumers' choices. These estimates are important for capturing the extent of both market power (which is based on the price elasticity of demand) and adverse selection (which is based on the correlation between demand and cost). The demand estimates also generate a revealed-preference welfare measure capturing how individuals trade off generous networks against lower prices when choosing plans.

I use the dataset described in Section 2 to estimate a multinomial logit plan choice model for both new and current enrollees (allowing inertia for the latter, as I discuss below). I treat individuals' timing of entry/exit from the exchange as exogenous and model just their choices among exchange plans.[49] For new/re-enrollee i making a choice at time t, the model for utility of plan j is:

$$U_{ijt} = \underbrace{\alpha(Z_i) \cdot Prem_{j,t,Reg_i,Inc_i}}_{\text{Plan Premium}} + \underbrace{Network_{ijt}}_{\text{Hospital Network Vars.}} + \underbrace{\xi_{ijt}}_{\text{Unobs. Quality}} + \underbrace{\varepsilon_{ijt}^{Plan}}_{\text{Logit Error}} \tag{10}$$

where:

$$Network_{ijt} = \beta_1(Z_i) \cdot NetworkUtil_{ijt} + \beta_2(Z_i) \cdot CoverPastUsed_{ijt}$$
$$\xi_{ijt} = \xi_{j,Reg_i,Inc_i} + \xi_{j,t,Reg_i}$$

and ε_{ijt}^{Plan} is an i.i.d. Type 1 extreme value error that gives demand its logit form. Plan utility depends on three sets of plan attributes: premiums, networks, and unobserved quality. Premiums – which vary across plans and within-plan across years, regions, and income groups – are observed, and I include them directly. Hospital networks are more difficult because while observed, the value of a given network varies across individuals. To capture this heterogeneity, I include two terms: the consumer-specific network utility measure (see Section 4.2) and a direct variable for whether the plan covers a consumer's previously used hospitals (or the share covered if there are multiple). Of course, these two variables are related, since past use entered hospital demand and therefore influenced network utility. However, the direct variables may predict demand beyond their impact on hospital network utility for several reasons. First, they may capture loyalty to doctors, who in Massachusetts are often hospital-affiliated and covered/dropped along

possibility. For severity, I regress severity in the hospitalizations data on age-gender groups and emergency status and use the predicted value from this regression for each individual.

[49] Because exogenous factors like income and job status determine exchange eligibility and generous subsidies incentivize participation, this assumption seems reasonable. This assumption implies that in my model, changes in plan prices and networks do not induce people to substitute into/out of the market. Although it would be nice to weaken this assumption, I do not have sufficient data on people choosing the outside option (largely uninsurance) to estimate a model incorporating it as a choice.

with the hospital.[50] Second, it may be picking up error in hospital demand or the sickness frequency prediction. Finally, it may matter simply because plan and hospital choices are driven by different things. People may choose plans based on whether it covers their regular provider but hospitals based on many other factors (e.g., which hospital is closest in an emergency).

The third set of covariates in plan demand (ξ_{ijt}) are plan dummies capturing unobserved quality – e.g., customer service and plan reputation.[51] To aid identification of the premium coefficient (see discussion below), I allow these to vary at a detailed region-year and region-income group level.

Preference heterogeneity enters this model in two ways. First, I allow observed heterogeneity by income, age, and gender groups for the premium coefficient and by income group for network utility. Second, the network variables also incorporate heterogeneity, since (for the same plan) they vary by consumer location, sickness, and past relationships with providers. This heterogeneity is useful for capturing substitution patterns and adverse selection.

Current Enrollees and Inertia: The model so far has applied to new/re-enrollees, who I can be sure are making active choices. A final issue is how to treat current enrollees, who can switch plans at annual open enrollment but are defaulted into their current plan if they take no action. There is growing evidence that defaults and inertia matter in health insurance (Ericson 2012; Handel 2013), and consistent with this, I find that fewer than 5% of enrollees switch plans each year. However, how to interpret this low switching rate is less clear. It may reflect a combination of true inertia/switching costs (a form of state dependence) and preference heterogeneity causing optimal choices to be serially correlated.[52]

While I am not able to fully separate these factors, I want the model to capture switching behavior because of its implications for selection. To do so, I take a reduced form approach. In addition to the terms in equation (10), current enrollees' utility includes a dummy for their current plan. I allow the coefficients on this dummy to vary with observed demographics and (based on the evidence in Section 3) whether the plan has just dropped a previously used hospital. These inertia coefficients can be interpreted as either switching costs or reduced form coefficients capturing the likelihood of consumers being passive/inattentive in their switching choice, and I report statistics for both interpretations.[53]

Including current plan dummies ensures that the model will match average switching rates for each group with a separate coefficient. However, the coefficients themselves will pick up both true inertia

[50] Though I do have information on physician networks and utilization, I have not yet modeled physician demand or network utility because of its complexity.
[51] Past work has found reputation to be an important driver of demand in the Medigap insurance market (Starc 2011), and based on my discussions with market participants, reputation is also important in CommCare.
[52] This low switching rate does not appear to only reflect heterogeneity. Enrollees who enter the exchange just after prices have changed end up with very different market shares overall than enrollees who entered just before the price change. This group-level share difference is strongly suggestive the true state dependence is involved.
[53] In Appendix B, I show how this maps into a particular two-step model of inattention, where the first step models whether an enrollee is passive or active and a second step models plan choice conditional on being active.

and any unobserved heterogeneity driving choice persistence. For matching static adverse selection, it is not clear that it is critical to distinguish these factors. Where the two specifications will primarily differ is in their implications for dynamic competition, which I do not study in my counterfactuals. However, in interpreting the inertia estimates, readers should keep in mind that these coefficients are also picking up unobserved heterogeneity.[54]

Identification and Estimation: I estimate the model using a micro-data method of moments estimator similar to Berry et al. (2004). A key difference in my setting is that the main plan attributes – premium and network utility – vary across individuals even for the same product in the same market and year. As a result (under assumptions discussed below), I can estimate the premium and network coefficients consistently from the micro-data alone, without needing instruments.

To identify the premium coefficients, I use within-plan variation induced by CommCare's subsidies. The key variation is that higher price plans have higher premiums for above-poverty enrollees but the same premium (always $0) for fully subsidized below-poverty enrollees. This structure also creates differential premium changes across years, which I use for identification. Consider an example from Network Health's premiums in the Boston region in 2010-2011. In 2010, Network Health was the cheapest plan for all groups. In 2011, its relative price increased but while above-poverty groups' premiums increased as a result, below-poverty premiums were unchanged (still $0).

I use these differential premium changes for identification by absorbing all other premium variation with a detailed set of plan dummies. Recall that because of regulation, premiums vary only across plans, years, regions and income groups. The first set of dummies (ξ_{j,Reg_i,Inc_i}) absorb any persistent demand differences for plan j across income groups (within a region). The second set of dummies (ξ_{j,t,Reg_i}) absorb demand differences across regions and over time. The remaining variation is from within-region differential premium changes across income groups. Because I allow a separate premium coefficient for each above-poverty group, the main identification comes from comparing demand changes for each above-poverty income group to those of below-poverty enrollees.

This identification strategy is a nonlinear version of the standard difference-in-differences approach. Thus, the key assumption is that any changes in unobserved plan quality evolve in parallel for low- and high-income enrollees. This assumption seems reasonable because all groups have access to a plan under the same brand name, with the same provider network and member services. However, to test its validity, I employ the standard parallel trends test for difference-in-differences. This test compares trends for the outcome (market shares) around price changes for the treatment group (above-poverty)

[54] In a future revision, I plan to do a robustness check with a demand model that includes time-invariant unobserved heterogeneity through random coefficients on premiums and plan dummies. I will use the choice patterns of re-enrollees to separately identify the random coefficient variances from the switching costs.

versus the control group (below-poverty). Figure 6 shows this test, plotting average market shares for new enrollees in each month around price changes, separately for price cuts (top graph) and price increases (bottom graph).[55] Consistent with the parallel trends assumption, market share trends are flat and parallel for both groups at all times except when prices change. At price changes, price-paying groups' shares jump sharply in the expected direction, while zero-price groups' shares are essentially unchanged.

The detailed plan dummies are also helpful for proper identification of the network utility coefficients. The potential identification threat is that plans with better networks also have better unobserved quality. However, with the plan dummies, the network utility coefficients are identified from *within-plan* variation across individuals in the same region and year. A key source of variation is enrollees' location relative to covered hospitals, since this strongly predicts hospital utility.

I estimate the model using moments similar to those used in Berry et al. (2004).[56] For plan dummies, I match observed market shares for the relevant plan and enrollee group. For plan characteristics (whose coefficients vary with observed demographics), I match the average interaction between the characteristic and the demographic among chosen plans in the data. Appendix C shows the formulas for these moments.

4.4 Plan Demand Estimates

The demand estimates are shown in Table 5. Premiums (in dollars per month) enter negatively and significantly for all income groups. (I normalize the average premium coefficient to -1.0, so the remaining coefficients can be interpreted as dollar values for an average enrollee.) Premium sensitivity decreases monotonically with income, with the highest-income group's coefficient less than half as large as the lowest-income group's. Premium sensitivity also decreases with age, although much less sharply. Overall, these estimates imply that new enrollees are quite premium sensitive. A \$1 increase in monthly premium decreases the average plan's market share among premium-paying enrollees by 3.0%.[57]

Enrollees place positive and significant value on both measures of hospital network quality. Recall that network utility was normalized so that 1.0 was the average utility change for Boston-area enrollees when Network Health dropped Partners in 2012. Thus, for an average Boston enrollee with no

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[55] The analysis is restricted to fiscal years 2008-2011. I drop 2007 because above-poverty enrollees did not start enrolling in the market until mid-way through 2007. I drop 2012+ because below-poverty new enrollees become subject to a limited choice policy that required them to choose lower-price plans.

[56] I use method of moments rather than maximum likelihood for two reasons. First, my network utility covariates are not observed, and I employ a standard error correction that is valid for method of moments. Second, in future revisions, I plan to include random coefficients, for which simulated method of moments is more appropriate.

[57] Because prices are subsidized, there are two ways to convert this semi-elasticity into an elasticity. Relative to consumers' relatively low premiums (which average about \$45 for premium payers), the elasticity averages a relatively modest -1.35. However, relative to insurers' full prices (about \$400 on average) – the statistic relevant for insurers' markups – the demand elasticity is -11.9.

previous Partners use, the estimates indicate a modest \$6-8 monthly value of Partners access. This positive but modest average value of broader networks is consistent with the findings of Ho (2006), who estimated a similar model for employer-sponsored insurance. However, this average masks significant heterogeneity both in the network utility of Partners and in the marginal utility of money. In addition, I estimate substantial coefficients on the direct measure of whether a plan covers an enrollee's previously-used hospitals. For non-Partners hospitals, I estimate an additional value of \$5.41 per month and for Partners hospitals, the total effect is \$17.04 per month.

As expected, I find substantial inertia in consumers' plan switching decisions. Rationalizing observed switching rates requires an average switching cost of \$96.8 per month, or equivalently, an average 94.6% probability of passively choosing.[58] Though large, these estimates are actually a bit smaller than the average switching costs found in an employer insurance setting by Handel (2013) of \$2,032 per year (or \$169 per month). What is most interesting for selection on networks is that estimated inertia decreases when a plan drops an enrollee's past used hospital from network. For dropped non-Partners hospitals, enrollees are 19% points less likely to be passive and for Partners hospitals, they are 43% points less likely to be passive. A possible explanation is that when an enrollee's regular provider is being dropped, the provider contacts the patient and encourages them to switch plans. Whatever the reason, this inertia reduction exacerbates adverse selection, consistent with the findings of Handel (2013). Here, the inertia reduction is particularly important because it occurs precisely among some of a plan's most expensive consumers, past patients of the Partners hospitals.

5 Structural Model: Insurer Cost and Profit Functions

The adverse selection implications of hospital networks depend on the interaction between demand and costs. In this section, I specify a model for insurer costs and (combining this with demand) derive the insurer profit function. The goal is to capture insurer incentives to cover or exclude high-price star hospitals like those in the Partners system. These incentives depend both on how covering Partners affects individual-level costs and how it affects plan selection by individuals of different costliness.

I start by modeling how individual-level costs would vary in plans with different hospital networks. Section 5.1 describes how I model insurer costs for hospital care, which uses my hospital demand model and a set of estimated hospital prices. Section 5.2 then presents my model for non-hospital costs. In Section 5.3, I aggregate this individual-level cost model up to the insurer level (using plan

[58] While these estimates are also picking up unobserved heterogeneity, a simple calculation suggests that the passive probability would still be about 90% with a realistic degree of heterogeneity (based on the 55% rate at which re-enrollees choose the same plan as they had before). If there were 55% persistence among current enrollees who were active choosers, 91% of people must have been making passive choices to explain a 96% non-switching rate.

demand to predict plan choices) and derive the insurer profit function. Finally, Section 5.4 considers model fit and analyzes the 2012 change when Network Health dropped Partners.

5.1 Hospital Prices and Insurer Costs for Hospital Care

To model insurer costs for inpatient hospital care, I start from an individual-level model. I condition on each person's set of observed hospitalizations (and their diagnoses) and ask how hospital choices and costs would have changed if the patient had been in a different plan with a different hospital network. An advantage of this approach is that it lets me capture the correlation between hospital use and enrollee attributes (which determine plan selection) in a rich, nonparametric way.[59] Nonetheless, this approach assumes networks do not affect the *number* of hospitalizations, only the hospitals chosen when sick.[60]

I first estimate the prices insurers pay to hospitals for inpatient care using the payment data in the insurer claims. Because actual payment rules are unknown (and likely quite complicated), there is a need for simplification. I follow past work (e.g., Gowrisankaran et al. 2015) in estimating *average* payment factors that capture proportional differences across hospital-insurer pairs.[61] I estimate a Poisson regression (also known as a generalized linear model with a log link) of the form:

$$E\left[Payment_{i,j,h,t,a} \mid Diag_{ita}, Z_{ita} \right] = \exp\left(\rho_{j,h,t} + Diag_{ita}\lambda + Z_{ita}\gamma \right) \tag{11}$$

where *a* indexes the admission, $Diag_{ita}$ is the principal diagnosis, and Z_{ita} is other patient covariates.[62] The key term is $\rho_{j,h,t}$, which is a coefficient that captures average payment differences across hospitals, insurers, and years.[63] This effect is assumed to be proportional across all types of admissions, which is surely not exactly right but should capture a valid average effect. Appendix C discusses additional details on the hospital price estimation.

I use the estimates of (11) to define hospital prices as $\hat{P}_{j,h,t} \equiv \exp\left(\hat{\rho}_{j,h,t}\right)$ and an admission-specific severity measure as $\hat{\omega}_{i,t,a} \equiv \exp\left(Diag_{ita}\hat{\lambda} + Z_{ita}\hat{\gamma}\right)$. I scale $\hat{\omega}_{i,t,a}$ so that its mean is 1.0 and divide

[59] The potential danger is over-fitting. Because I have a large sample and consider only insurer actions that affect a large set of individuals (prices and coverage of Partners), over-fitting is less of a concern for my purposes.

[60] This assumption is likely a good first approximation but is not perfect. Recent evidence from Gruber and McKnight (2014) finds small reductions in the number of hospitalizations in limited network plans. If applicable in my setting, my model will somewhat understate the cost savings from plans' limiting their networks.

[61] Following convention, I refer to these payment factors as "prices," although they are distinct from the actual negotiated prices. These payment factors capture both price differences and service quantity differences across hospitals (conditional on diagnosis) since both affect insurers' payment differences across hospitals.

[62] For the principal diagnosis, I use the Clinical Classification Software (CCS) dummies defined by the U.S. government's Agency for Healthcare Research and Quality. The additional covariates include age, gender, income, and Elixhauser comorbidity dummies for the secondary diagnoses.

[63] As discussed in Appendix C, I specify a restricted model for $\rho_{j,h,t}$ to avoid over-fitting for hospital-insurer-year cells with small samples. I allow for flexible hospital-insurer and insurer-year dummies, separately by in- and out-of-network status, plus a separate insurer-year factor for each of the six largest hospital systems.

$\hat{P}_{j,h,t}$ by the same factor, so it can be interpreted as the hospital price for a patient of average severity. The average prices and severities for the 10 most expensive hospitals are shown in Table 1.

I use these severities and prices to model how hospital costs would differ in counterfactual plans and networks. As discussed above, I condition on each individual's observed admissions (or lack thereof) and severities $(\hat{\omega}_{i,t,a})$ and use hospital demand to predict how these admissions shift across hospitals. The hospital costs for individual *i* in year *t* in plan *j* (with network N_{jt}) is:

$$c_{ijt}^{Hosp}\left(N_{jt}\right)=\sum_{a=1}^{NAdmits_{it}}\hat{\omega}_{i,t,a}\cdot\left(\sum_{h}\hat{P}_{j,h,t}\cdot s_{i,d,t,j,h}^{Hosp}\left(N_{jt}\right)\right) \tag{12}$$

For most hospitals, I use only the plans' observed networks so hold hospital prices fixed at the estimated values. However, for Partners hospitals, I also consider adding/dropping them and therefore need a counterfactual price model. For this, I use a simple average of prices paid by insurers that actually covered (excluded) the Partners hospital in a given year. The main limitation of this approach is that it does not capture insurer-hospital bargaining dynamics, something I have not yet modeled.[64]

5.2 Non-Hospital Costs

I complete the cost model by considering all costs other than inpatient hospital care. Unfortunately, I do not have a provider choice model for non-hospital care through which I could define costs analogously to my hospital cost model. Instead, I take a reduced form approach. I calculate monthly non-inpatient costs for each enrollee-year and use them to estimate the following Poisson regression model:

$$E\left(NonHospCost_{it}\mid Z_{it}\right)=\exp\left(\eta_{j(i),Reg(i),t}+Z_{it}\mu\right) \tag{13}$$

where Z_{it} are detailed enrollee diagnoses and demographics.[65] I use these estimates to define a region-year-specific plan effect $\hat{C}_{j,Reg,t}\equiv\exp\left(\hat{\eta}_{j,Reg,t}\right)$, an enrollee severity $\hat{\varsigma}_{it}\equiv\exp\left(Z_{it}\hat{\mu}\right)$, and an enrollee residual $\hat{\nu}_{it}\equiv NonHospCost_{it}/\left(\hat{C}_{j(i),Reg(i),t}\cdot\hat{\varsigma}_{it}\right)$. If an enrollee switches to plan *k*, I assume that his severity and residual are unchanged but that the plan effect switches to the counterfactual plan, so the enrollee's new cost is $\hat{C}_{k,Reg,t}\cdot\hat{\varsigma}_{it}\cdot\hat{\nu}_{it}$. This reduced form approach is clearly an approximation. However, the $\hat{C}_{j,Reg,t}$ estimates should capture a valid average plan effect on costs absent unobserved cost-based selection into plans. Given that I have documented unobserved selection based on the exchange's risk adjustment, this

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[64] Two facts suggest this approach may be a reasonable approximation in this setting. First, within-year price variation across insurers for the main Partners hospitals is small in practice – standard deviations for Brigham and Mass. General are just \$359 and \$846, respectively. Second, when Network Health drops Partners, I see little change over the next two years in Partners prices paid by the plans that still cover it.

[65] For diagnoses, I use the Hierarchical Condition Categories (HCC) defined by Medicare for its risk adjustment. I use HCCs observed in the *current* plan year so I can include diagnoses for new enrollees.

assumption is clearly imperfect.[66] If there is residual selection, I will understate costs for plans attracting residually healthier enrollees and overstate costs in the opposite case.[67] This will affect my estimates of the *level* of non-inpatient costs at observed networks but not the cost *difference* from network changes, which I specify separately next.

Networks may affect non-inpatient costs both through outpatient hospital care and through secondary effects on services like drugs and post-acute care. For the effect of adding/dropping Partners, I again specify a reduced form adjustment.[68] I first use the hospital cost model to calculate inpatient costs with and without the network change. I then assume that a plan's non-inpatient costs change in proportion to the *regional average* change in inpatient costs.[69] The final non-inpatient cost model is:

$$c_{ijt}^{NonHosp}\left(N_{jt}\right)=\underbrace{\hat{C}_{j,Reg,t}}_{\text{Plan Effect}}\cdot\underbrace{\left(\hat{\varsigma}_{it}\cdot\hat{v}_{it}\right)}_{\text{Ind. Severity and Residual}}\cdot\underbrace{\left(1+\lambda\cdot\%\Delta HospCost_{j,Reg,t}\left(N_{jt}\right)\right)}_{\text{Network Cost Adjustment}} \quad (14)$$

Based on a risk-adjusted regression at the plan-region-year level, I find that each 10% increase in inpatient costs is typically associated with a 3.8% increase in non-inpatient costs and therefore set $\lambda=0.38$. However, I can do robustness checks with alternate values of λ.

5.3 Total Costs and Insurer Profits

With a model for both individual-level inpatient hospital and other costs, I sum them to define total costs, $c_{ijt}^{Total}\left(N_{jt}\right)$. I also include in total costs a measure of variable plan administrative costs (e.g., for claims processing) based on plan financial reports to the exchange.[70] The final model step is to aggregate costs and revenue up to the plan level using the demand function. The annual profit function for plan *j* is:

$$\pi_{jt}=\sum_i\left(\varphi_{it}P_{jt}-c_{ijt}^{Total}\left(N_{jt}\right)\right)\cdot D_{ijt}\left(\mathbf{Prem},\mathbf{N}\right) \quad (15)$$

where P_{jt} is the plan's price, φ_{it} is the exchange's risk adjustment score for enrollee *i*, and $D_{ijt}(.)$ is the enrollee's demand for plan *j*. Demand is in units of member-months and is the product of two terms:

$$D_{ij}\left(\mathbf{Prem},\mathbf{N}\right)=nMon_i\cdot S_{ij}\left(\mathbf{Prem},\mathbf{N}\right)$$

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[66] The covariates in (11) will do somewhat better than the exchange risk adjustment because they include concurrently observed diagnoses, which allows for including diagnoses for new enrollees.

[67] To address this potential bias, I plan in a future revision to instrument for plan enrollment using the *timing* when an enrollee entered the exchange. Because of inertia, enrollees who enter just before a price change will have different plan shares at a later date *t* than enrollees who enter just after the price change. Assuming that entry timing does not independently affect costs and that attrition is independent of unobserved costs, then entry timing in the exchange is a valid instrument for current plan enrollment.

[68] Past structural work on hospital networks has generally either ignored non-inpatient costs or assumed that they did not change with the hospital network. My reduced form method, though imperfect, improves on the past literature.

[69] A limitation with this method is that it does not capture *differential* percent changes for the people most likely to use Partners.

[70] To do so, I estimate a regression of plan's reported administrative costs on their total enrollment. I find an almost perfect linear fit with a coefficient of about $30 per member-month, which I use for the model.

The first is the number of months an individual is enrolled in the exchange during the year. Many enrollees enter or leave in the middle of the year (e.g., because of a change in jobs that affects their eligibility), and I assume this enrollment churn is exogenous and hold $nMon_i$ fixed as observed. The second term is consumer *i*'s predicted share for plan *j* from the logit demand system.

5.4 Model Fit and Analysis of 2012 Network Health Change

Appendix Figure D.1 shows the model fit for plans' average monthly medical costs per enrollee. The model averages are calculated using the model's cost and demand functions (as in (15)), creating two potential sources of errors versus the costs in the data. Nonetheless, the fit is quite good, with an R^2 at a plan-year level of 0.926. Importantly, the model captures very well the large fall in costs for Network Health in 2012 when it dropped Partners. The largest errors are predicting too high costs for CeltiCare in 2010 and 2011 (when it was a new plan and had very low enrollment), although the model does capture its large cost increase in 2012 after Network Health dropped Partners.

I next consider in more detail how well the model matches the cost and demand patterns for Network Health in 2012. Appendix D shows a series of figures and tables with values from the data compared to those predicted by the model. The model captures the variations in switching rates among Network Health's current enrollees quite well. Past Partners' patients switching rate is matched almost perfectly – since the model's interaction of switching costs with dropping Partners is largely identified from the 2012 change. It also captures the intermediate level of switching for patients of other dropped hospitals. The next table shows how the model matches the cost change from 2011 to 2012. For the average costs and cost changes, the model matches almost perfectly. Breaking it into enrollee subgroups, the model captures the basic pattern that enrollees who left the plan in 2011 were much more expensive and that the cost decrease for stayers was smaller than the overall decrease, though it slightly underestimates the former and overestimates the latter.

The final set of figures analyze how the hospital model captures changes in admission shares and costs at Partners and other dropped hospitals.[71] In all cases, the fit is quite good. In particular, the model matches the striking fact that Partners admissions fell for Network Health, rose at other plans, and barely changed overall. It also matches Network Health's and other plans' costs per hospital admission in levels and trends (including the 15% drop for Network Health in 2012).[72]

[71] To focus on the hospital demand and cost model's ability to fit patterns, these figures condition on people's actual plans, rather predicting plan shares using the plan demand model.

[72] I have found that including the past hospital use variables in the hospital demand system are important to matching these patterns so well. Without these covariates, for instance, the model cannot match the sharp rise in Partners admissions for plans other than Network Health in 2012.

Finally, I use the model to decompose how much of the 15% decline in Network Health's risk-adjusted costs was due to selection versus "real" cost reductions. One indication that selection played a large role is that costs declined just 6% on a fixed population of stayers in the plan in both 2011 and 2012 (see Table 3). However, this statistic does not capture the full effect of real cost cuts, which would also have applied to the people who switched plans had they not left. Instead, I use the model to decompose how changes in plan selection versus changes in the cost function affected costs. Formally, I can decompose the 2011-2012 change in costs into:[73]

$$Cost_{2012} - Cost_{2011} = \underbrace{\sum_i \left(c_{ij,2012} - c_{ij,2011}\right) \cdot D_{ij,2012}}_{\text{Cost Function Change}} + \underbrace{\sum_i \left(D_{ij,2012} - D_{ij,2011}\right) \cdot c_{ij,2011}}_{\text{Selection}}$$

where $j = \text{Network Health}$. Based on this decomposition, I find that selection explains 50% of Network Health's reduction in costs, with the rest due to a lower cost function for a fixed population. Notice that this decomposition calculates the cost function effect with 2012 shares and the selection effect with 2011 costs. If instead, I calculate the cost function effect with 2011 shares, the cost reductions are larger, and selection explains 36% of the decline. This difference implies that many of the people whose costs would have declined the most selected out of Network Health in 2012. Selection attenuated the cost-reducing effects of a change in networks. Either way, however, selection was important, explaining between 36-50% of Network Health's cost reduction.

6 Model Analysis: Heterogeneity in Value and Cost of Partners

Having estimated the model of insurance and hospital demand, I use the estimates to study heterogeneity in consumers' costs and value of Partners coverage. For simplicity, I focus on current enrollees in the exchange at the start of 2012, when Network Health dropped Partners. I define utility for Partners based on the difference in plan utility for Network Health, excluding switching costs (U_{ijt} in equation (10)), with and without Partners covered. I convert utilities into dollar values by dividing by each individual's marginal utility of money (the negative of their premium coefficient).[74] I calculate costs based on the cost function for Network Health with and without Partners.

Table 6 shows these estimates for all current enrollees in the exchange at the start of 2012.[75] The rows are sorted by the measure of Partners value. About 80% of enrollees have relatively little value for Partners coverage, with a monthly value of $4.30 or less – quite small compared to the typical variation in plan premiums of $20-60 per month. But value for Partners rises sharply in the top 10-20% of enrollees,

[73] Because this decomposition requires observing individuals in both years, I restrict the sample accordingly.
[74] I exclude below-poverty enrollees from this calculation because I cannot estimate their premium coefficient.
[75] I focus on current enrollees because their past hospital use (a key model covariate) is more likely to be observed.

with the top 5% valuing Partners at $46.80 per month. For these enrollees, almost all of whom are past Partners patients, Partners coverage plays a determinative role in their plan choices.

The remainder of Table 6 shows how these differences in value for Partners correlate with costs. I distinguish between two sources of adverse selection discussed in the theory: selection on unobserved risk and selection driven by use of Partners' high-price care. Columns (2)-(3) suggest that unobserved risk is important. Even without Partners covered, people in the top decile of Partners value have risk-adjusted monthly costs of about $350, which is $50 (or 17%) higher than those who value Partners the least. Column (5) indicates that selection on use of Partners is also important. The ΔC from covering Partners rises from $8.0 (2.7%) for the lowest-value group to $48.5 (10.0% of a larger base) for the highest-value group. Combining both types of selection, the people in the top decile of Partners values are $84 (or 27%) more expensive (after risk adjustment) in a plan covering Partners than people with below-median values. Of this $84 difference, about 60% is due to selection on unobserved risk and the remainder due to differential use of the Partners system.

A final insight from Table 6 is that for each group, the estimated consumer value from access to Partners falls short of the increase in insurer costs. Even aside from adverse selection, this fact gives insurers a strong incentive to drop Partners. However, this does not prove that the welfare effect of covering Partners is negative for all groups. Part of plans' higher costs represent markups to the Partners hospitals, which may be used for socially valuable purposes like teaching and research. To account for these markups, I draw on a Massachusetts government estimate of the per-admission costs of Partners (CHIA 2014).[76] Based on these estimates, the cost per admission at the two star Partners hospitals in 2012 were about $12,500 (MGH) and $13,800 (Brigham), implying margins of about 30-35% relative to my estimated prices. Column (7) shows the net cost increase, subtracting the change in Partners net revenue for inpatient care from insurer costs.[77] After doing so, the net cost increase for people in the top decile of Partners values is substantially lower. Their value for Partners coverage now exceeds the estimate of net costs. However, value still falls short of net costs for people in the bottom 90% of Partners valuations.

7 Equilibrium and Analysis of Policy Solutions

This section uses the demand and cost estimates to simulate equilibrium in a model of insurance competition. I use this to examine the impact of different policies used to address adverse selection in

[76] The measure is of hospitals' "inpatient cost per case mix adjusted discharge". The calculation, which is based on hospitals' cost reports to the state, is intended to be a comprehensive measure of average hospital costs (including fixed costs of facilities), excluding physician compensation and graduate medical education costs.
[77] Note that this values each $1 of Partners net revenue as $1 of social value. This calculation is imperfect because it excludes Partners markups for non-inpatient care and reductions in net revenue for non-Partners hospitals. The latter, however, are likely to be small; non-star hospitals often have low or negative margins (Katherine Ho 2009).

insurance exchanges. In general, insurer competition on prices and hospital networks is extremely complicated and subject to multiple equilibria.[78] To make progress, I focus on a static model where insurers compete only on price and coverage of the expensive Partners hospitals, holding hospital-insurer prices and other aspects of the network fixed. Although stylized, this model goes beyond most past empirical work on selection, which studies pricing holding fixed product characteristics.[79]

7.1 Equilibrium Simulations: Method and Results

Consider a model of insurance market equilibrium for a particular year (e.g., 2012) in the Massachusetts exchange. As in Massachusetts, I assume that each insurer offers a single plan with exchange-specified consumer cost sharing and covered service rules.[80] I condition on the plan's past history, including past network coverage and the set of current enrollees entering the year. I also hold fixed (at observed values) each plan's network and payment rates for all non-Partners hospitals. Before the year, the exchange announces policies (e.g., subsidy and risk adjustment rules). Insurers then compete in the following game:

Insurer Competition:	1. Insurers choose whether to cover Partners hospitals
	2. Insurers set plan prices
Consumer Demand:	3. Consumers choose plans
	4. Sick consumers choose providers (based on plan network)

I assume that insurers observe networks from stage 1 when setting prices and that they have full information on all demand and cost functions.

Insurers make choices to maximize profits, following the model for demand, costs and profits estimated in Sections 4-5. However, there is one additional simulation issue: how to incorporate dynamics arising because of enrollee inertia. When a plan lowers its price and attracts more enrollees today, it increases its future demand because some enrollees will passively stick with the plan in following years. This can lead to an invest-then-harvest equilibrium in which plans cycle between low and high prices. I choose not to specify a fully dynamic model, which would be both complicated and unrealistic unless it modeled uncertainty about policy changes (which occurred frequently in Massachusetts). Instead, I take a simple static approach that approximates a dynamic model. I assume that enrolling someone today increases future profits in proportion to the person's future duration in the market and the current profit

[78] For an innovative model incorporating hospital-insurer bargaining and network formation in a dynamic equilibrium framework, see Lee and Fong (2013).

[79] For example, see Einav, Finkelstein and Cullen (2010), Starc (2014), and Handel, Hendel, and Whinston (2013). One recent paper by Einav, Jenkins and Levin (2012) does consider the effect of selection on product design in consumer credit markets but does so in a setting with a monopolist firm.

[80] In the ACA, insurers can offer multiple plans with varying networks across four tiers of cost-sharing generosity. Unfortunately, my data (in which all plans have the same cost sharing) do not make it possible to model cost-sharing differentiation. However, in future analysis, I could study equilibrium when insurers can offer two plans that vary in whether they cover Partners.

margin on the individual. This "future profit effect" gives insurers an added incentive to keep prices low and helps offset the lower price elasticity of demand due to inertia. Appendix E shows the modified pricing first-order conditions and lays out additional details for the simulation method.

In full-information Nash equilibrium, each insurer sets prices in step 2 to satisfy its first-order conditions given all other insurers' prices and networks. In step 1, they choose Partners coverage knowing the pricing equilibrium that will prevail for each network possibility. For Partners coverage, I assume a binary choice: either sticking with their actual coverage of Partners or adding/dropping all of the Partners hospitals. I do not model the vertical relationship between Partners and Neighborhood Health Plan (NHP) but allow it to flexibly cover/drop Partners.[81] Nash equilibrium occurs at a set of networks **N** if no insurer wishes to unilaterally deviate: $\pi_j\left(N_j, \mathbf{N}_{-j}\right) \geq \pi_j\left(\tilde{N}_j, \mathbf{N}_{-j}\right)\ \forall \tilde{N}_j, j$. While there is no guarantee of a unique equilibrium, I do not find multiplicity in my main results.

Table 7 shows equilibrium insurer choices for several simulations.[82] The top panel shows equilibrium under the actual Massachusetts subsidy and pricing policies in 2011, comparing these to the observed prices and networks.[83] The model's prices match extremely well. But this occurs largely because Massachusetts had a narrow allowed price range, and all plans bid at or near the range's min or max.[84] Nonetheless, the model captures well which insurers priced near the min versus the max. For networks, the model predicts just one plan (CeltiCare) willing to cover Partners, while in reality Network Health and NHP also covered Partners in 2011. However, Network Health did drop Partners in 2012, and Partners announced intentions to buy NHP in August 2011, a factor that I do not model. It is interesting that the model can rationalize CeltiCare's surprising decision (as the low-price plan) to cover Partners. In the model, CeltiCare is willing to do so because of the binding price floor. Without a price floor, CeltiCare instead cuts its price and drops Partners.

Because many of Massachusetts' distinct rules did not continue under the ACA, I perform the rest of the analysis using rules closer to those in the ACA. Specifically, I include only the 100-300% poverty population (those below poverty generally get Medicaid in the ACA), set subsidies as a flat amount for all

[81] To simplify, I also hold fixed the observed choice of Fallon (which is not available in most of the Boston area) not to cover Partners.

[82] To speed computing time, all of the simulations I report here have been conducted on a 10% random sample of enrollees. I will perform the simulations on the full sample in future revisions.

[83] While I would like to perform a similar model fit test for other years, data limitations and policy complexities make this difficult. Prior to 2010, the pricing process was much more complicated and involved some negotiation with the exchange. In 2010, I am missing the risk adjustment scores. And in 2012-13, the exchange introduced a limited choice policy that creates auction-like dynamics that I have not yet modeled.

[84] Massachusetts used maximum prices to lower costs given that it fully subsidizes below-poverty enrollees for any plan they choose. Minimum prices were imposed by federal actuarial soundness rules, which are designed to prevent insurers from pricing so low that they are unable to pay for the required medical benefits.

plans, and do not impose minimum or maximum prices.[85] Panel B of Table 7 shows the simulation results. Under ACA-like policies, the model predicts that all plans drop Partners, and this result is robust across all the simulation years, 2011-2013. When an insurer deviates to cover Partners, its costs go up for all of its enrollees, and it particularly attracts the enrollees who most value Partners and whose risk-adjusted costs are high. But by raising its price to compensate, it reduces demand among a large number of lower-cost enrollees. As a result, total profits go down when a plan covers Partners.

7.2 Social Welfare Function

To analyze the welfare effects of alternate policies, I need a social welfare function, which is not obvious to define in this setting. My starting point is a social surplus approach, in which welfare equals consumer plan value (plan utility divided by marginal utility of money[86]) minus insurer costs. But I make several adjustments. First, I choose to exclude the switching cost, treating them as pure inattention. Recall that I estimated that switching costs were much lower when a plan dropped a consumer's hospital, and I do not want the welfare analysis to be driven by this difference.[87] Once I exclude switching costs, however, the standard inclusive value formula for expected utility in a logit model does not apply. Instead, I define expected plan value for consumer *i* as:

$$ConsValue_i = \tfrac{1}{-\alpha_i} \sum_j \hat{s}_{ij}^{Plan} \cdot \hat{U}_{ij}$$

where α_i is the premium coefficient, $\hat{s}_{ij}^{Plan}$ is the model's predicted share for consumer *i* choosing plan *j*, and $\hat{U}_{ij}$ is plan utility excluding switching costs and the logit error.

A second adjustment to social welfare is that I allow for an excess cost of government subsidies, to reflect the distortionary cost of tax financing. As a baseline, I assume an excess cost of government funds (ECF) of 30%, but I also consider an ECF of zero as in a textbook social surplus calculation. Finally, I add to social welfare an estimate of the markup of Partners' hospital prices above cost, based on the Massachusetts government estimate (discussed above in Section 6). As a starting point, I value each dollar of markup as $1 of social welfare, although alternate assumptions are possible. How to value these

[85] The main remaining differences with the ACA are the lack of higher-income unsubsidized enrollees (who represent about 20% of ACA enrollees) and the absence of plans across four cost-sharing generosity tiers (platinum, gold, silver, and bronze). There is not much I can do to incorporate these factors, since I do not have data on higher income people or a way or estimating preferences for different levels of cost sharing. Therefore, the simulations should be seen as illustrative of the economic forces involved, not a prediction of what will occur in the ACA.

[86] The marginal utility of money is the negative of the premium coefficient in the plan demand system. I do not need to worry about the premium coefficient for the below-poverty group (which I could not estimate) because they are excluded from the ACA-like population.

[87] I have also done the welfare analysis with switching costs included. The results are qualitatively similar, but past Partners' patients value of coverage is higher because of the switching cost interaction. However, this difference is not enough to change the net result of the welfare calculation.

markups depends on the social value of the hospital activities they fund, including teaching, research, and uncompensated care.

7.3 Policy Counterfactuals

In this section, I examine two policies to offset adverse selection and encourage coverage of the Partners hospitals: modified risk adjustment and subsidies. I examine how plans' prices and Partners coverage decisions change under alternate policies, continuing to hold Partners' hospital prices fixed.

The first policy modifies risk adjustment by increasing how much it compensates for high-risk types and reducing it for low risks – a form of the "over-payment" that Glazer & McGuire (2000) find to be optimal for risk adjustment. The logic for over-payment is that plans covering Partners attract consumers who are both observably and unobservably high-cost. The modified risk adjustment over-pays based on observed risk to compensate for the high unobserved risk of enrollees in plans covering Partners. To implement this, I multiply all risk scores above the mean by a factor $(1+\phi)$, divide all below-mean risk scores by the same factor, and renormalize the distribution to be mean 1.0. The potential downside of this policy is that insurers have incentives to avoid covering people with low observed risk (e.g., young people). If low risks are more price sensitive (as I found for young people in the plan demand estimates), insurers will respond by raising prices and markups.

The top of Table 8 shows the simulation results for modified risk adjustment. A ϕ of 50% is sufficient to reverse the unravelling, with NHP choosing to cover Partners. The change increases consumer surplus (by \$5.4 per member-month), insurer profits (by \$6.9), and Partners net revenue (by \$1.1). However, the largest change is in government subsidy costs, which increase by \$14.4 per member-month (or 4.4%). Government costs increase because subsidies are set based on the lowest plan's price, which rises from \$365 to \$381.[88] The low-price plan (CeltiCare) tends to selects low-risk people, and the modified risk adjustment penalizes it more for doing so. In addition, it has less incentive to keep markups low to attract the healthy, as discussed above. Therefore, CeltiCare raises its price. The cost of higher subsidies depends on whether there is an excess marginal cost of government funds (ECF). If there is no excess cost (ECF = 0), this is a pure transfer, and social surplus changes only slightly. With a more typical ECF of 30% (the final column in Table 8), social surplus falls more substantially.

I consider a second policy to address adverse selection: differentially subsidizing high-price plans. Rather than a fixed subsidy S_0 for all plans, a plan's subsidy equals $S_0 + \sigma \cdot \left(P_j - \min_k P_k\right)$, which

[88] These simulations follow the Massachusetts rule of setting subsidies so that the cheapest plan's premium equals a pre-specified affordable amount. The ACA sets subsidies based on the second-cheapest silver-tier plan, which I do not follow because I do not have plans across multiple generosity tiers. Note that the increase in the lowest plan price is slightly larger than the increase in subsidies because the risk adjustment is not perfectly budget neutral.

is linked to its price P_j. I call this policy "marginal subsidies" because a plan's subsidy increases on the margin as it raises its price. Marginal subsidies decrease plans' incentive to compete on prices and therefore increase the incentive to raise quality (here, Partners coverage) – as shown by the classic analysis of Dorfman & Steiner (1954). Marginal subsidies also decrease the inefficiently high premiums a plan covering Partners charges because of selection. The downside is that plans have greater incentive to markup prices, regardless of whether they cover Partners.

The bottom part of Table 8 shows the simulations for marginal subsidies. Although conceptually different, subsidies have similar qualitative effects as risk adjustment. Marginal subsidy rates exceeding 25% induce BMC plan and at 50%, also NHP to cover Partners. Consumer surplus, insurer profit, and Partners net revenue increase at the expense of higher government spending. Relative to risk adjustment, however, consumer surplus increases less and insurer profits increase more. A key difference is the pattern of price increases across plans. With risk adjustment, the low-price plan raises its price, while all higher-price plans raise prices relatively little, since they benefit from the greater compensation for their relatively sick consumers. However, with subsidies, all plans increase their prices in tandem. As a result, insurer profits increase a bit more, and social surplus falls a bit more.

This analysis points to a more general tradeoff involved with mitigating adverse selection in settings with imperfect competition, as shown in recent work by Starc (2014) and Mahoney & Weyl (2014). When sicker people differentially choose higher-price plans, insurers have an incentive to keep prices low to avoid the sick. If risk adjustment or subsidies offset this effect, insurers raise price markups. In insurance exchanges, higher markups may be a greater public policy concern than in typical markets, since government subsidies are linked to prices. Higher markups raise government costs, which create a direct efficiency cost because of the excess cost of tax-financed public funds.

An important limitation of this analysis is that I have throughout held fixed the prices of Partners hospitals. This may be sensible for the relatively small CommCare exchange (covering about 3% of Massachusetts' population), and indeed, I found that Partners did not change its prices much after Network Health dropped it in 2012. However, if plans in a broader array of markets dropped Partners, Partners would be forced to respond. Analyzing this response would require modeling hospital-insurer bargaining, something I have not yet done because of its complexity. However, part of the logic in such a model seems clear. Adverse selection that discourages plans from covering Partners should pressure Partners to lower its prices – while policies that offset selection should reduce this pressure. These effects are qualitatively similar to the effects on insurer prices discussed above.

With Partners, however, the welfare effects of higher prices are more complicated. Higher prices at star academic hospitals partly fund activities like teaching and medical research. Whether the government should subsidize plans to cover Partners depends on the social value of these activities. The above analysis has valued these at cost, but the true social value may be higher or lower. How to assess high star hospital prices is beyond the scope of this paper but an important topic for future research.

8 Conclusion

As health insurance programs like the ACA increasingly use exchanges to provide coverage, an important question is how well insurance competition will work. A key part of that question is whether adverse selection is still a concern, despite exchange regulations and risk adjustment used to combat it. This paper has shown evidence from the Massachusetts exchange that there is meaningful residual selection against plans covering expensive star hospitals. Studying a 2012 case where a large plan dropped the star Partners hospitals, I find that selection explains between 35-50% of the plan's cost reductions. The selection is driven by people who strongly prefer the star hospitals and are willing to switch plans to maintain access to them. I find that this group has high risk-adjusted costs both because of greater unobserved risk and because conditional on medical risk, they are more likely to use the high-price hospitals. Improved risk adjustment can mitigate the selection on unobserved risk, but existing risk adjustment methods are not designed to address selection on use of high-price providers.

In many ways, the implications of this adverse selection are standard. Plans have disincentive to cover star hospitals. And when they do, their costs (and therefore prices) are increased in a way that sub-optimally allocates consumers across plans. For example, some people who would like to use star providers only for a severe disease like cancer must pay higher premiums that reflect the costs of people who use high-price providers for all their health care. This inability of a single premium to efficiently sort people with heterogeneous costs across plans is related to a point made in a different context by Bundorf et al. (2012). I show that this problem is also related to adverse selection, which gives plans an incentive to exclude star hospitals from network.

This inefficiency is fundamentally related to a sorting challenge: which patients should get access to the expensive services star academic hospitals provide? In standard markets, prices at the point of use create the sorting mechanism – only those willing and able to pay get access. In health insurance, plans cover all or most of hospitals' prices. Instead, people choose their hospital access when they choose plans. This system can lead to a type of moral hazard – when a plan covers star hospitals, its enrollees switch to using these high-price facilities rather than lower-price alternatives. Policies that reduce this moral hazard may also mitigate the adverse selection I find. Examples include tiered patient copays (higher fees for more expensive providers) and supply-side incentives for doctors to steer patients to lower-price facilities (e.g., partial capitation; see Song, et al. 2011; Ho and Pakes 2014). How best to sort patients across hospitals of varying costs is an important question for future research.

A key driver of the selection I find is the high prices of star hospitals. Researchers are increasingly recognizing the importance of provider prices in driving both cost increases and variations across providers (IOM 2013). This study contributes an additional finding: providers with high prices create adverse selection against plans covering them.

This selection has implications for the health insurance exchanges in the ACA. It calls into question the efficiency of the sharp rise in limited network plans in the ACA's first year (McKinsey 2014). Narrow network plans (covering less than 70% of area hospitals) represented almost half of exchange plans and about 70% of the lowest-price plans. These plans, which are particularly likely to exclude academic hospitals, may grow because of favorable selection at the expense of broad network plans. This pressure on insurers may lead star providers to respond by cutting their prices and costs. It may also add to incentives for these providers to merge with or create an insurer – as Partners did with NHP in Massachusetts and as hospitals elsewhere have done or are considering.

The policy implications of my adverse selection findings, however, are less clear. On the one hand, selection against plans covering star hospitals suggests a benefit to subsidizing these plans, through modifications to risk adjustment or subsidies. However, as I showed in simulations, these policies reduce incentives for both insurers and the star providers to lower prices, worsening pre-existing market power. A key question for assessing this tradeoff is what high prices at star academic hospitals fund. If high prices fund valuable teaching, medical research, and uncompensated care for the poor, then pressure to reduce prices may be a public policy concern. If high prices fund higher physician salaries and fancier medical facilities, the policy calculus of subsidizing them would be different. Optimal policy also depends on whether there are more efficient means of subsidizing these activities than through the insurance system. These issues are important questions for future research.

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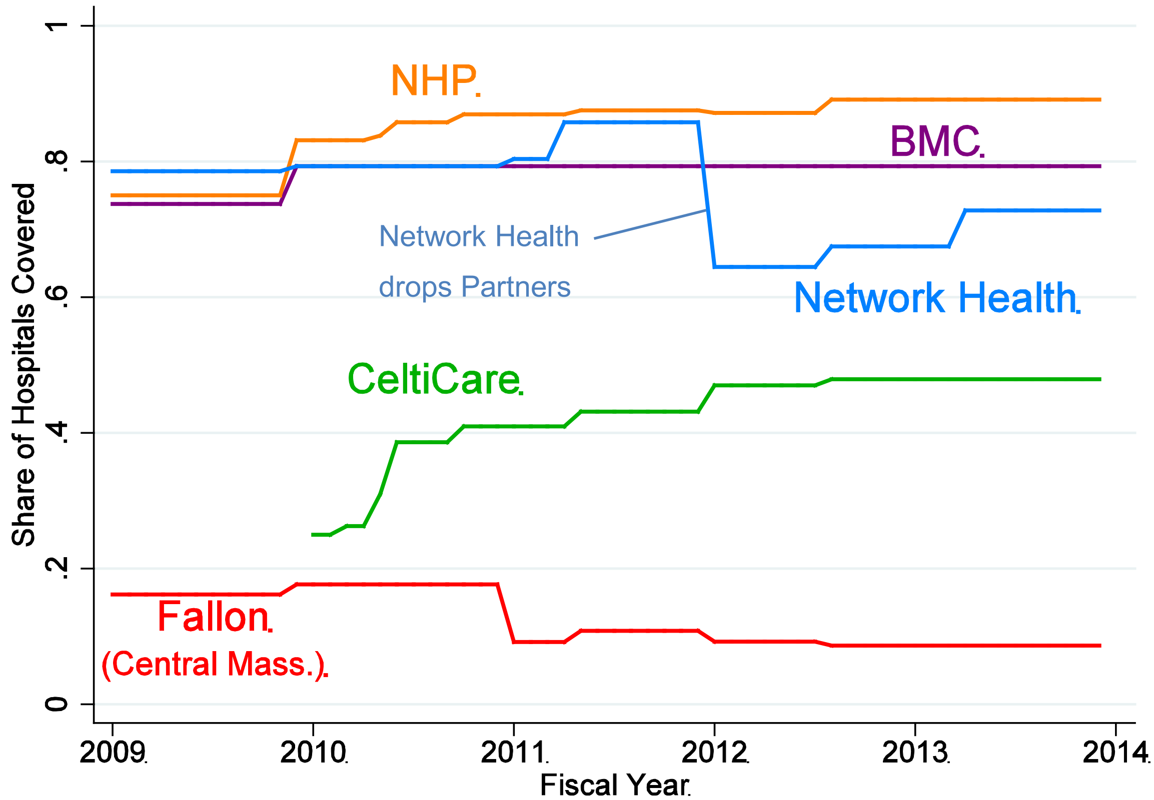
Table 1. Hospital Price Estimates: Most Expensive Hospitals

	Hospital	System	CommCare Data			State Report
			Average Payment (per patient)	Hospital Price Model		Costs per Case-Mix Adj. Discharge
				Price (severity-adj.)	Avg. Severity	
			(1)	(2)	(3)	(4)
1	Brigham & Women's	Partners	\$23,278	\$20,474	1.12	\$13,801
2	Mass. General (MGH)	Partners	\$21,428	\$19,550	1.09	\$12,498
3	Boston Med. Ctr. (BMC)	---	\$16,850	\$15,919	1.05	\$12,188
4	Charlton Memorial	Southcoast	\$14,411	\$14,210	1.03	\$8,795
5	Umass Med. Ctr.	UMass	\$14,941	\$14,111	1.07	\$9,900
6	Tufts Med. Ctr.	Tufts/NEQCA	\$15,328	\$14,038	1.10	\$9,185
7	Baystate Med. Ctr.	Baystate	\$13,715	\$12,223	1.11	\$8,298
8	St. Luke's	Southcoast	\$11,786	\$12,113	0.97	\$8,795
9	Beth Israel Deaconess	CareGroup	\$12,971	\$11,787	1.08	\$9,534
10	Tobey Hospital	Southcoast	\$11,427	\$11,777	0.97	\$8,795
	All Other Hospitals	---	*\$8,267*	*\$8,549*	*0.96*	---

NOTE: These tables show most expensive general acute hospitals in my Massachusetts exchange (CommCare) data, ranked by the hospital price measure in column (2). All measures are averages over in-network hospital admissions for CommCare enrollees from fiscal years 2008-2013. Column (1) shows the raw average insurer payment, winsorized at \$150,000 per admission to remove extreme outliers. Columns (2)-(3) shows the output of a severity-adjusted price model described in Section 5.1. Column (2) is the average severity-adjusted price, and column (3) is the hospital's average patient severity, a measure normalized to have mean 1.0. Column (4) shows data from a state report (CHIA 2014) on average costs per case-mix adjusted discharge. This data is not perfectly comparable – it is based on all admissions, not just CommCare – but gives a sense of relative costs across hospitals. For the three hospitals in the Southcoast system, this cost measure is only available at the system level, which is what I report.

Figure 1. Hospital Network Coverage in Exchange Plans

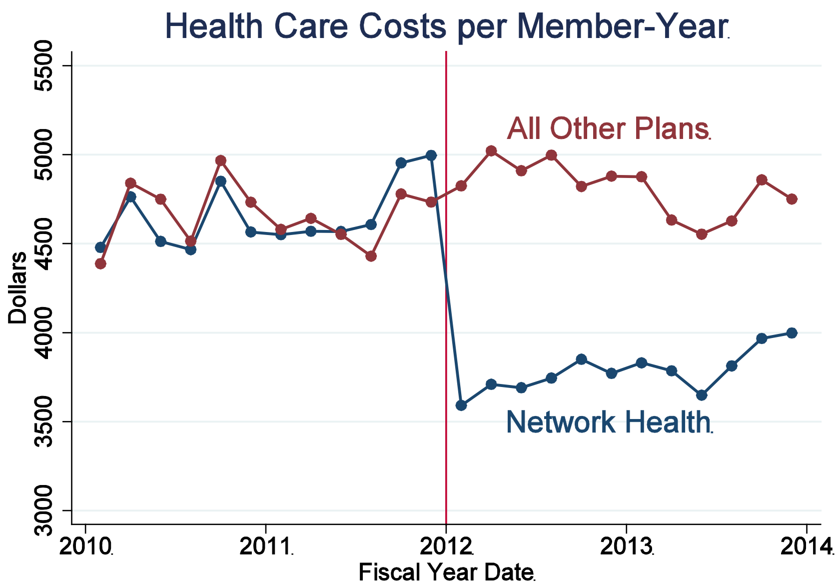


Coverage of Partners Hospitals

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 graph shows the shares of Massachusetts hospitals covered by each CommCare plan, where shares are weighted by hospital bed size in 2011. The table shows coverage of the Partners hospitals, separately for the two star academic medical centers – Mass. General Hospital (MGH) and Brigham & Women's Hospital – and for the number covered among the five Partners community hospitals.

Figure 2. Costs and Hospital Use around 2012 Network Health Changes



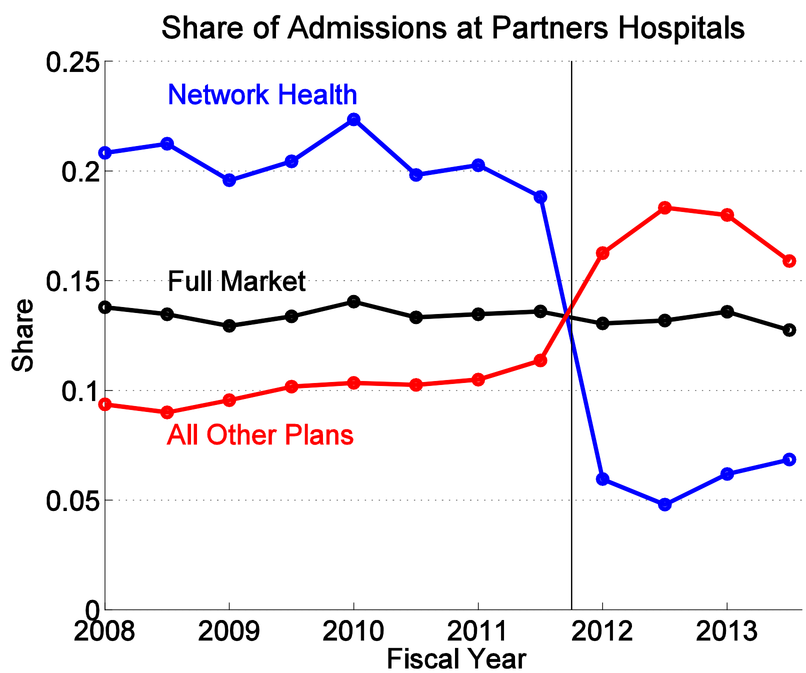


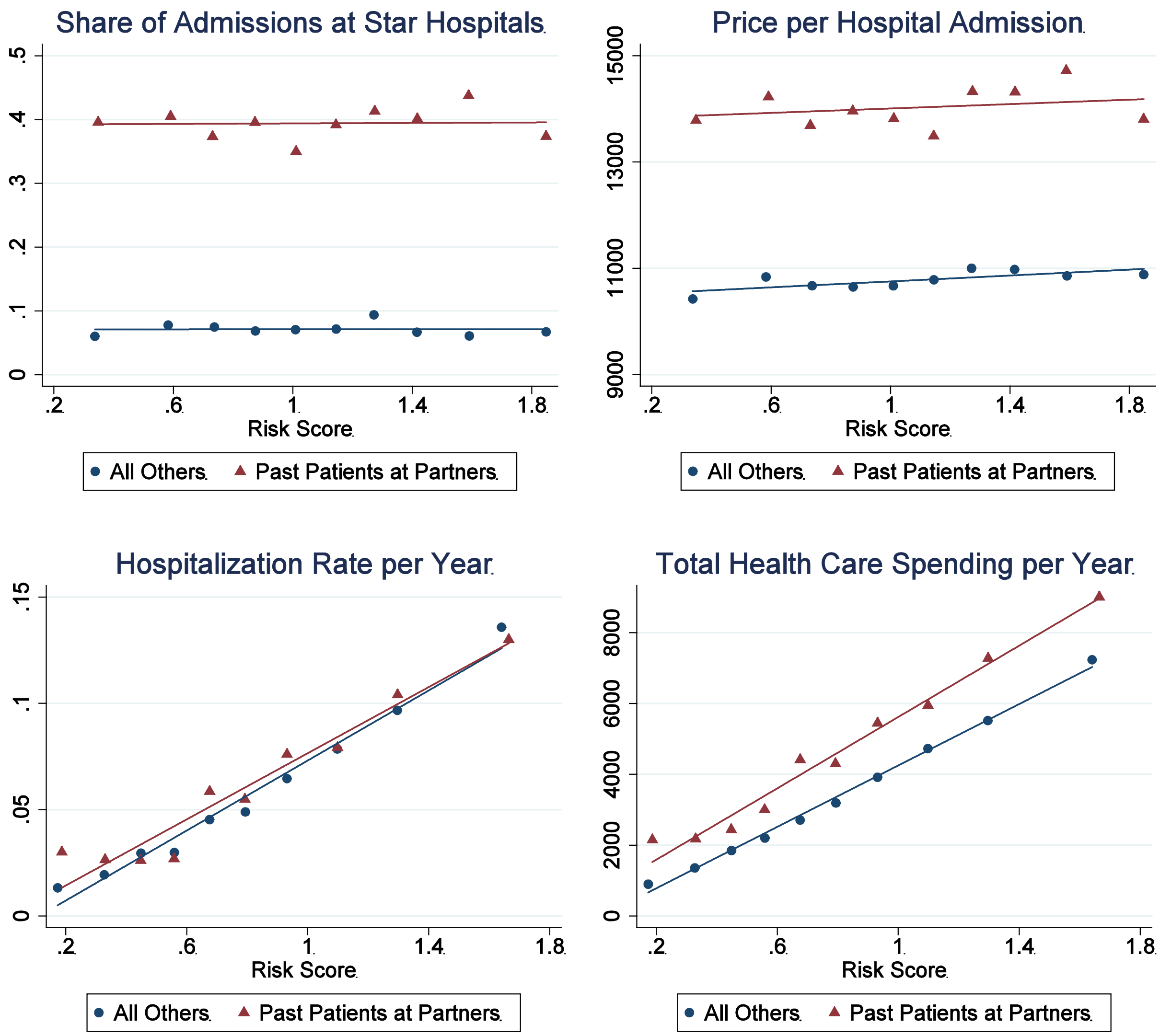
Table 2. Test of Adverse Selection Mechanism: Past Patients at Partners Hospitals

	Dependent Variable:				
	Hospital Use and Cost (Plans Covering Partners Only)				Plan Choice
	Share of Admissions at Star Hospital	Price per Admission ($)	Hospitalization Rate (annual)	Total Cost per Year ($)	Actively Choose Plan Covering Partners
	(1)	(2)	(3)	(4)	(5)
Past Patient at Partners Facility	0.322**	3,143.0**	0.0039	1,137.3**	0.298**
	(0.010)	(126.8)	(0.0034)	(96.3)	(0.004)
Control Variables					
Risk Score	0.007**	99.2**	0.0953**	4,788.7**	-0.004**
	(0.002)	(22.3)	(0.0040)	(159.0)	(0.001)
Plan x Year x Income Grp FE	X	X	X	X	---
Year x Income Grp FE	---	---	---	---	X
Observations	10,505	10,505	270,198	270,198	172,874
R-Squared	0.184	0.127	0.029	0.117	0.181
Dependent Var. Means:					
Past Patient at Partners Facility	0.398	14,125	0.111	7,318	0.661
All Others	0.066	10,770	0.072	4,032	0.376
[Difference]	*[0.332]*	*[3,355]*	*[0.039]*	*[3,286]*	*[0.285]*

** p<0.01, * p<0.05

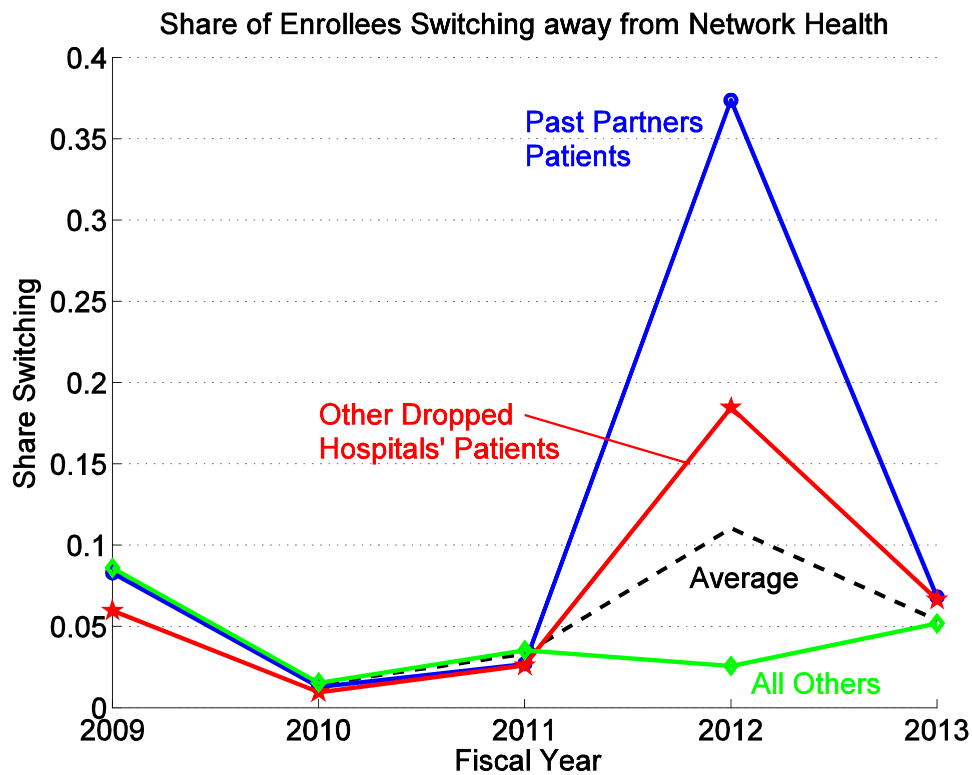
NOTE: The table shows regression results from the unused observables test for adverse selection, as described in Section 3.1. The bottom section shows raw means of the dependent variables, to show how controlling for risk affects the between-group differences. The data are at the individual x plan choice instance level for the 2011-2013 period during which I have full risk adjustment data. Cost and hospital use outcomes are defined as averages over the subsequent year. "Past Patient at Partners Facility" is a dummy for whether an individual has been observed using a Partners facility for outpatient care prior to the given plan choice instance. The sample excludes new enrollees into the exchange, for whom past utilization data is not observed. Columns (1)-(4) limit the sample to plans covering Partners to examine a sample who all have access to the star hospitals. Column (5) limits the sample to individuals making active plan choices when re-enrolling in the exchange after a gap in coverage. Regressions in columns (4) and (5) are weighted by the number of months each individual was enrolled during the year. All standard errors (in parentheses) are clustered at the individual level.

Figure 3. Hospital Use and Cost Differences: Past Patients at Partners vs. Others



NOTE: The figures show binned scatter plots, analogous to the adverse selection test regression results in Table 2. The figures compare outcomes for past Partners patients (in red triangles) to all other enrollees (blue circles), within bins of medical risk score (the x-axis). The solid lines are best-fit lines for each group. The underlying sample and data setup are identical to Table 2. Data are at the individual x plan choice instance level for the 2011-2013 period during which I have full risk adjustment data. Cost and hospital use outcomes are defined as averages over the subsequent year. "Past Patients at Partners" is a dummy for whether an individual is observed using a Partners facility for outpatient care prior to the given plan choice instance. The sample excludes new enrollees in the exchange (for whom past utilization data is not observed) and is limited to people in plans that cover Partners.

Figure 4. Plan Switching after Network Health Dropped Partners in 2012



NOTE: This figure shows the share of enrollees in Network Health plan who switch to another plan at the start of each fiscal year (when all exchange enrollees are given an opportunity to switch plans). The black dashed lines show the average switching rate for all enrollees; the colored solid lines decompose this average into subgroups. In most years, switching rates are quite low, but in 2012, switching spiked after Network Health dropped the star Partners hospitals and eight other less prestigious hospitals. The graph shows a large switching spike among past patients of Partners (in blue) and a smaller spike among patients of the other dropped hospitals (in red). There was little change in switching rates among all other enrollees (in green). These results suggest that many patients are willing to switch plans to keep access to their regular hospital provider. As I show elsewhere, the past Partners patients were a particularly high-cost group, so these switching patterns contributed to favorable selection for Network Health when it dropped Partners.

Table 3. Analysis of Costs for Network Health Enrollees, 2011-12

Enrollee Group	**Avg. Costs**			**Risk-Adjusted Avg. Costs**			**Group**
	2011	**2012**	**%Δ**	**2011**	**2012**	**%Δ**	**Size***
All Enrollees	**$4,631**	**$3,676**	**-21%**	**$4,439**	**$3,761**	**-15%**	**---**
Stayers	$3,877	$3,641	-6%	$3,807	$3,596	-6%	36,768
Left Plan in 2012							
Switched Plans	$8,045	*[$7,391]*	---	$6,109	*[$5,106]*	---	4,640
Exited Market	$5,634	---	---	$5,511	---	---	22,617
Joined Plan in 2012							
Switched Plans	*[$3,391]*	$3,461	---	*[$3,641]*	$3,706	---	15,062
Entered Market	---	$3,781	---	---	$4,007	---	51,109

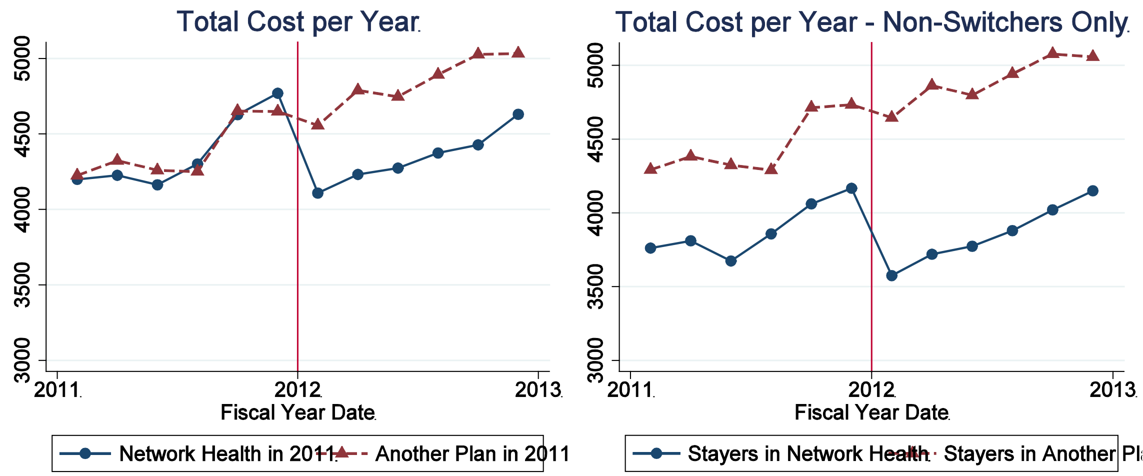
Breakdown by Partners Patient Status

Enrollee Group	**Avg. Costs**			**Risk-Adjusted Avg. Costs**			**Group**
	2011	**2012**	**%Δ**	**2011**	**2012**	**%Δ**	**Size***
Stayers							
Partners Patients	$6,396	$4,765	-26%	$5,662	$3,983	-30%	5,308
All Others	$3,406	$3,467	2%	$3,414	$3,523	3%	31,460
Switched from Network Health in 2012							
Partners Patients	$9,337	*[$8,082]*	---	$6,853	*[$5,259]*	---	3,169
All Others	$4,834	*[$5,882]*	---	$4,017	*[$4,695]*	---	1,471
Exited Market in 2012							
Partners Patients	$10,280	---	---	$7,770	---	---	3,150
All Others	$4,865	---	---	$5,002	---	---	19,467

* Number of enrollees during the relevant year they were enrolled in Network Health.

Figure 5. Treatment Effects on Per-Member Costs

Panel A: Overall Effects



Panel B: Heterogeneity in Effects

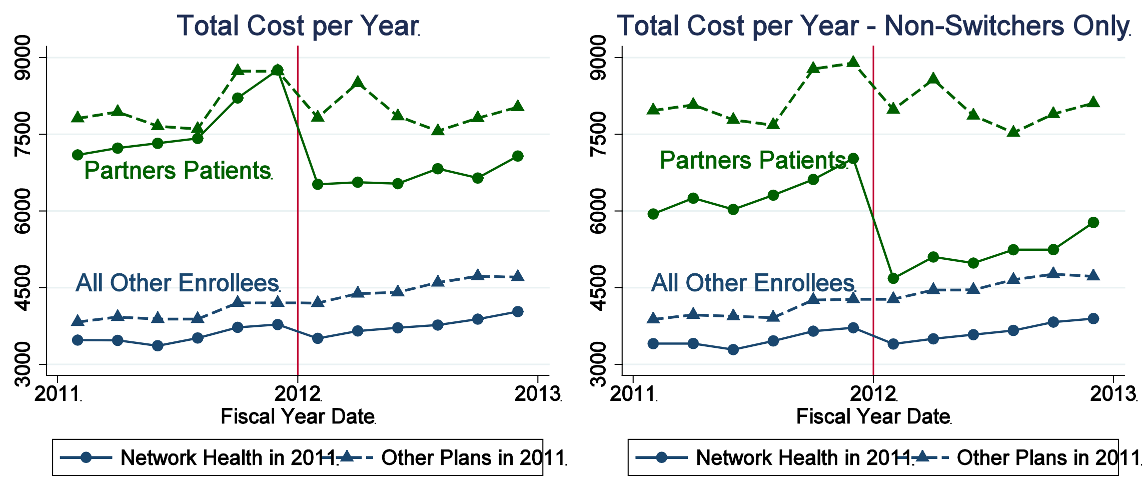
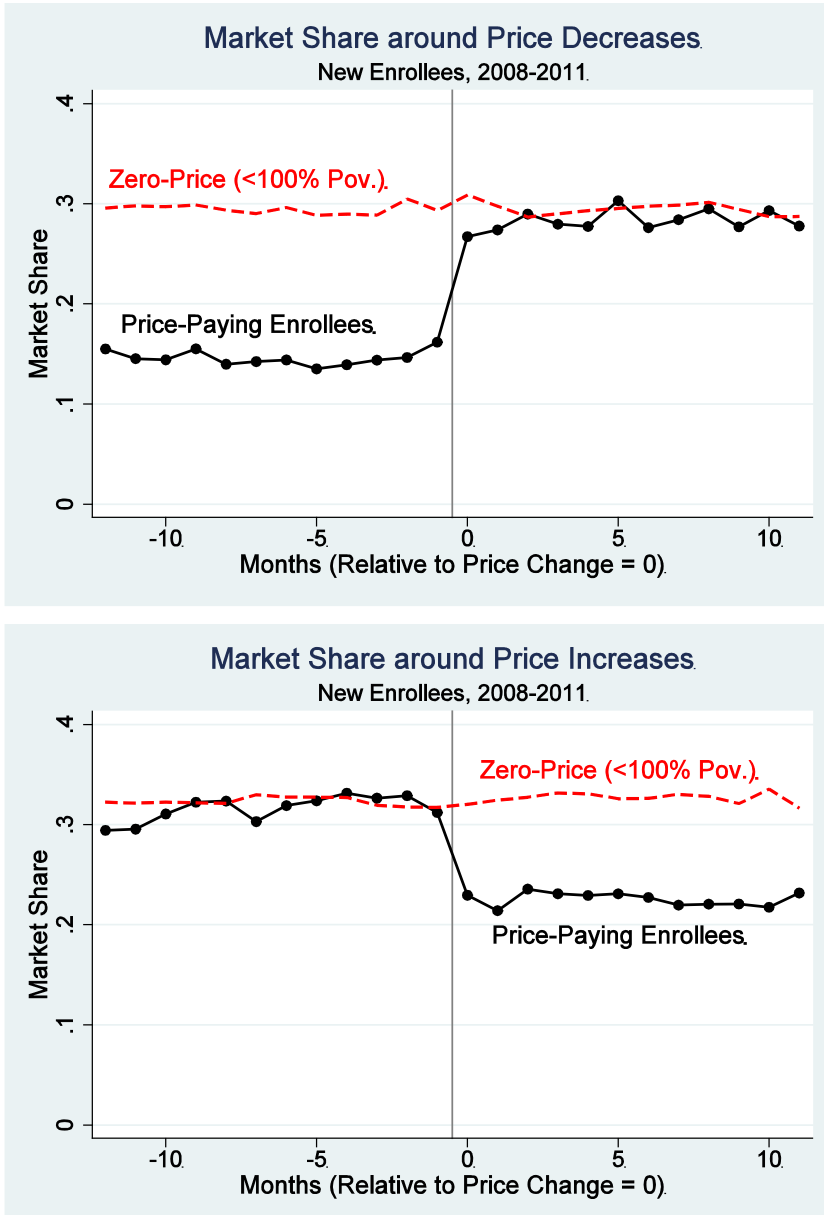


Figure 6. Premium Identification and Test of Parallel Trends Assumption



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 (top figure) or increased their prices (bottom figure). Each point represents the shares 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 2007 because above-poverty enrollees did become eligible for the market until mid-way through the year and 2012+ because below-poverty new enrollees became subject to a limited choice policy that required them to choose lower-price plans.

Table 4. Hospital Demand Estimates

VARIABLE	Simple Model Coeff.	Simple Model Std. Error	Full Model Coeff.	Full Model Std. Error
Distance to Hospital:				
Distance in Miles (avg. coeff.)	-0.189***	(0.001)	-0.144***	(0.001)
Distance^2 (avg. coeff.)	0.0013***	(0.0000)	0.0009***	(1e-5)
Distance Interactions:				
x Income > Poverty			-0.006***	(0.0006)
x Age / 10			-0.003***	(0.0002)
x Severity Weight			-0.002	(0.0011)
x Emergency			-0.015***	(0.0006)
Out-of-Network Disutility				
Out-of-Network x BMC	-1.327***	(0.016)	-1.117***	(0.034)
Out-of-Network x CeltiCare	*(same for all plans)*		-1.464***	(0.058)
Out-of-Network x Fallon			-1.583***	(0.059)
Out-of-Network x NHP			-0.543***	(0.049)
Out-of-Network x Network			-1.011***	(0.036)
Out-of-Network x Emergency			0.010	(0.034)
Past Use of this Hospital *(>60 days before)*				
Inpatient Care			1.417***	(0.020)
Outpatient Care			2.202***	(0.013)
Hospital Characteristics				
Hospital Dummies	Yes		Yes	
Severity x Academic Med. Ctr. (avg).			2.076***	(0.044)
Severity x Teaching Hosp			1.026***	(0.045)
Diagnoses x Hospital Services (largest coeffs.):				
Mental: Psych. Services			1.844***	(0.040)
Pregnancy: Obstetrics Services			1.122***	(0.076)
Injury: Level 1 Trauma Center			0.805***	(0.037)
Cancer: Oncology Services			0.704***	(0.084)
Model Statistics:				
Pseudo-R^2 (McFadden's)	0.463		0.569	
R^2 in Shares (Area-Plan-Yr Level)	0.643		0.742	
Num. Choice Instances	74,383		74,383	

Std. Errors in parentheses. * = 5% sign., ** = 1% sign., *** = 0.1% sign.

NOTE: The table shows estimates for the multinomial logit hospital choice model described in Section 4.1. The left columns show a simple model, while the right columns show the full model used for all further analyses. The logit coefficients shown are interpretable as entering the latent utility function describing hospital choice. Past use variables are dummies for whether a patient has used each specific hospital at least 60 days before the current admission. Severity is an estimated summary measure of costs described in Section 5.1. In addition to the variables shown, the model includes: distance interacted with exchange region, detailed income group (by 50% of poverty), and gender; severity interacted with separate dummies for each academic medical center; and five additional diagnosis x hospital service interactions (circulatory diagnosis interacted with cath lab, interventional cardiology, and heart surgery services; pregnancy diagnosis x NICU; and musculoskeletal diagnosis x arthritis services).

Table 5. Insurance Plan Demand Estimates

VARIABLE	Coeff.	Std. Error	
Premium: Avg. Coeff. (*normalized*)	**-1.000*** **	**(0.025)**	
x 0-100% Poverty -- *Omitted (no prems.)*	---		
x 100-150% Poverty	-1.340***	(0.038)	
x 150-200% Poverty	-0.935***	(0.024)	
x 200-250% Poverty	-0.712***	(0.015)	
x 250-300% Poverty	-0.656***	(0.016)	
x Age/5 (average effect)	0.029***	(0.002)	
Hospital Network			
Network Utility x <100% Poverty	6.355***	(0.885)	
Network Utility x 100-150% Poverty	7.371***	(0.939)	
Network Utility x 150-200% Poverty	7.453***	(0.962)	
Network Utility x 200-250% Poverty	7.736***	(1.270)	
Network Utility x 250-300% Poverty	8.541***	(1.878)	
Past-Used Hospitals Covered (share)	5.411***	(0.836)	
x Past-Used Partners Hospitals	11.631***	(0.773)	
Switching and Inertia			Passive Prob.
Average Inertia Coefficient	96.810***	(0.230)	94.6%
x Drops Past-Used Hospital (Non-Partners)	-29.905***	(1.142)	75.2%
x Drops Past-Used Hospital (Partners)	-51.048***	(0.962)	51.8%
Plan Brand Effects (average)			
BMC HealthNet (normalized)	0.000	---	
CeltiCare	-23.088***	(0.890)	
Fallon	14.021***	(1.023)	
Neighborhood Health Plan	-2.199***	(0.251)	
Network Health	-3.822***	(0.337)	
Model Statistics			
R^2 in Share (Area-Income-Year)	0.963		
Model w/ Only Avg. Plan Dummies	0.866		
No. Choice Instances	1,588,889		
No. Unique Individuals	611,455		

* = 5% sign., ** = 1% sign., *** = 0.1% sign.

NOTE: This table shows estimates for the multinomial logit plan choice model described in Section 4.3. Premium is the monthly plan price, which typically varies by $20-60 across plans. (In addition to the interactions shown, the full model contains interactions with 5-year age groups and gender.) I normalize the average consumer's premium coefficient to -1.0, so all other coefficients are interpretable as dollar values. Network utility is the consumer-specific expected utility measure for a plan's hospital network, derived in Section 4.2. Past-used hospitals coverage is the share of an enrollee's previously used hospitals that a plan covers, with a separate interaction for the star Partners hospitals. Switching and inertia are coefficients on a dummy variable for the current plan. The coefficients are interpretable as "switching costs" in dollars per month; the passive probabilities are the implied share of enrollees who passively stick with their current plan. The plan brand effects are coefficients on dummies for each plan. I show average values; the full model contains region-year- and region-income group-specific plan dummies.

Table 6. Model Estimates: Relationship between Value and Cost of Partners Coverage

Consumer Value of Partners Covg.		**Costs to Insurer (per month)**					
		Not Covering Partners		**Covering Partners**			
Percentiles	Avg. Value ($/month) (1)	Unadjusted Cost (2)	Risk Adj. Cost (3)	Risk Adj. Cost (4)	ΔCost (5)	%Δ (6)	ΔCost - Partners Hospital Mkup. (7)
0-50%	$0.5	$300.0	$301.2	$309.2	$8.0	2.7%	$7.0
50-70%	$2.2	$269.6	$294.5	$308.6	$14.0	5.2%	$10.6
70-79%	$4.3	$264.3	$292.7	$310.8	$18.1	6.8%	$12.4
80-89%	$8.8	$300.1	$311.8	$335.3	$23.5	7.8%	$14.0
90-95%	$23.6	$455.7	$360.4	$398.3	$37.9	8.3%	$21.1
96-100%	$46.8	$482.3	$340.1	$388.6	$48.5	10.0%	$23.3
Average	***$5.7***	***$308.8***	***$305.6***	***$321.2***	***$15.6***	***5.0%***	***$10.6***

NOTE: This table shows the estimated model's implication for the relationship between enrollees' costs and their value coverage of the star Partners hospitals – the key relationship driving adverse selection. Consumers are sorted into percentiles of Partners value, and each row shows average values and costs for people in the relevant percentiles. All values and costs are calculated for current enrollees in 2012 based on the value and cost if Partners were added to Network Health plan's network. Value of Partners is defined as the extra plan utility (excluding switching costs) if Partners is covered, divided the marginal utility of money – based on plan utility estimates shown in Table 4. Because I cannot estimate marginal utilities for below-poverty enrollees, they are excluded. Costs are defined using the estimated cost function without Partners covered (columns 2-3) and with it covered (columns 4-7), both based on the plan cost model in Section 5.3. Column 7 subtracts from the increase in cost an estimate of how much of these higher costs are funding higher markups for Partners. The table shows that most enrollees value Partners coverage little, but the top 10-20% values Partners substantially. The table also decomposes two different reasons people with high values for Partners are high-cost. First, they have higher risk adjusted costs even if Partners is not covered, which suggests they are unobservably sicker. Second, they have a larger increase in costs when Partners is covered (column 5) because they use Partners hospitals more often.

Table 7. Simulation Results

Equilibrium Simulation Results

Panel A: Mass. Exchange Population & Policies (2011)

			Insurance Plan				
Source	Year	Variable	BMC	Fallon	Network Hlth	NHP	CeltiCare
Observed	2011	Partners Covg.	No	No	Yes	Yes	Yes
		Price*	$424.6	$425.7	$422.6	$425.7	$404.9
Simulated	2011	Partners Covg.	No	No	No	No	Yes
		Price*	$425.7	$425.7	$425.7	$425.7	$404.9

** Exchange imposed maximum price of $425.7 and minimum price of $404.9*

Panel B: ACA-Like Population & Policies

			Insurance Plan				
Source	Year	Variable	BMC	Fallon	Network Hlth	NHP	CeltiCare
Simulated	2011	Partners Covg.	No	No	No	No	No
		Price	$407.2	$409.3	$389.4	$402.5	$318.8
Simulated	2012	Partners Covg.	No	No	No	No	No
		Price	$427.5	$464.5	$371.0	$417.6	$365.0
Simulated	2013	Partners Covg.	No	No	No	No	No
		Price	$437.2	$476.8	$432.9	$461.8	$419.4

NOTE: These tables show equilibrium results for the insurance market simulations described in Section 7.1. In the game, insurers first simultaneously choose whether or not to cover the Partners hospitals (holding fixed other hospital coverage) and then simultaneously choose their plan's price. The tables show their equilibrium choices of Partners coverage and price. Panel A shows simulations using the Massachusetts exchange's actual enrollee population and policies for 2011 – including required minimum and maximum prices – and compares simulated coverage and prices to the observed values. I do this comparison only for 2011 because of complications with analyzing other years. As discussed in Section 7.1, the model matches prices well but predicts even more dropping of Partners than actually occurred (although Network Health dropped Partners the following year). Panel B conducts simulations with a population and policies closer to those in the ACA exchanges. Specifically, I exclude enrollees below poverty (who get Medicaid in the ACA), set subsidies as a flat amount for all plans (versus Massachusetts' higher subsidies for higher-price plans), and do not impose minimum and maximum prices. In these simulations, no insurer chooses to cover Partners partly because doing so attracts enrollees with high risk-adjusted costs and therefore lowers profits.

Table 8. Counterfactual Policy Simulations

Risk Adjustment

Over-Adjustment Factor	Plan Statistics			Welfare Analysis (per member-month)					
	Covering Partners	Minimum Price	Avg. Price Other Plans	ΔCons. Surplus	Insurer Profit	Partners Net Rev.	Govt. Costs	ΔSocial Surplus ECF = 0	ΔSocial Surplus ECF=0.3
None	None	$365.0	$420.1	$0.0	$26.5	$0.6	$322.7	$0.0	$0.0
25%	None	$374.5	$420.9	$4.1	$30.0	$0.6	$330.7	-$0.4	-$2.8
50%	NHP Only	$381.3	$426.4	$5.4	$33.4	$1.7	$337.1	-$1.0	-$5.3

Marginal Subsidies

Marginal Subsidy Rate	Plan Statistics			Welfare Analysis (per member-month)					
	Covering Partners	Minimum Price	Avg. Price Other Plans	ΔCons. Surplus	Insurer Profit	Partners Net Rev.	Govt. Costs	ΔSocial Surplus ECF = 0	ΔSocial Surplus ECF=0.3
None	None	$365.0	$420.1	$0.0	$26.5	$0.6	$322.7	$0.0	$0.0
15%	None	$368.8	$427.6	$0.7	$33.4	$0.6	$331.1	-$0.8	-$3.3
25%	BMC Only	$372.1	$435.9	$0.7	$39.5	$1.0	$338.8	-$1.9	-$6.8
50%	BMC + NHP	$384.5	$469.4	$2.5	$65.5	$2.4	$370.2	-$4.1	-$18.4

NOTE: This table shows results of simulations of counterfactual policies to address the adverse selection, as discussed in Section 7.3. The top table shows simulations that modify risk adjustment by over-paying by the listed "over-adjustment factor" for people with above-average risk scores (and under-paying by the same factor for below-average risks). The bottom table shows simulations with "marginal subsidies" that narrow price differences across plans by the listed marginal subsidy rate. All simulations are for the ACA-like population and policies in 2012, so the baseline results (in the top row of each table) are the same as the 2012 equilibrium in Table 6. Each table lists which plans cover Partners, the minimum plan price, and average price of all other plans. They also list welfare statistics in units of dollars per member-month: the change in consumer surplus (with the baseline normalized to $0), insurer profit, Partners' net inpatient hospital revenue, and government subsidy costs. The final columns show the change in social surplus, with an excess government cost of funds (ECF) of either 0 or 0.3. The latter values each $1 of government subsidies as incurring a social cost of $1.3 because of the excess burden of tax financing.

Appendix A. Sample Summary Statistics

Appendix Table A.1

Hospital Choice Sample

Patient Characteristics

Variable		Mean
No. of Hospitalizations		74,383
Age		44.6
Male		49%
Emergency Department		56%
Diagnoses	Mental Illness	16.7%
	Digestive	13.5%
	Circulatory	12.6%
	Injury / Poisoning	7.1%
	Respiratory	7.0%
	Cancer	6.4%
	Endocrine / Metabolic	6.0%
	Musculoskeletal	5.6%
	Genitourinary	5.1%
	Pregnancy / Childbirth	5.0%
	All Others	14.9%

Chosen Hospital Statistics

Variable	Mean	Std. Dev.
Distance: Chosen Hosp. (miles)	14.1	16.3
All Hospitals (miles)	48.4	25.9
Hospital Category		
Academic Med. Ctr.	29%	---
Teaching Hospital	19%	---
All Others	52%	---
Partners Hospital	14%	---
Out-of-Network	8%	---
Past Used Hospital (>60 days before)		
Any Use	54%	---
Inpatient Use	19%	---
Outpatient Use	51%	---
Total Cost to Insurer	$11,369	$15,711
Price (estimated)	$10,981	$4,112
Patient Severity (estimated)	1.000	0.310

Plan Choice Sample

Enrollee Characteristics

Variable	Mean	Std. Dev.
No. of Enrollees	611,455	---
Age	39.6	13.8
Male	46.5%	---
Income: <100% Poverty	47.1%	---
100-200% Poverty	39.6%	---
200-300% Poverty	13.3%	---
Past Hospital User	44.3%	---
Partners Hospitals	7.4%	---
Other Hospitals	40.3%	---
Risk Adjustment Score	0.99	0.90
Choice Type: New Enrollee	29.5%	---
Re-Enrollee	13.5%	---
Current Enrollee	57.1%	---

Plan Choice Statistics

Variable	Mean	Std. Dev.
No. of Choice Instances	1,588,889	---
Insurer Price	$380.7	$69.5
Cons. Premium: Below Poverty	$0.0	$0.0
Above Poverty	$47.3	$45.7
Costs per Month: Total	$371.5	$1,480
Hospital Inpatient	$81.5	$1,048
Non-Inpatient	$290.0	$873
Current Enr: Non-Switching	95.8%	---
Market Shares: BMC	35.5%	---
Network Health	34.7%	---
NHP	19.2%	---
CeltiCare	6.9%	---
Fallon	3.8%	---

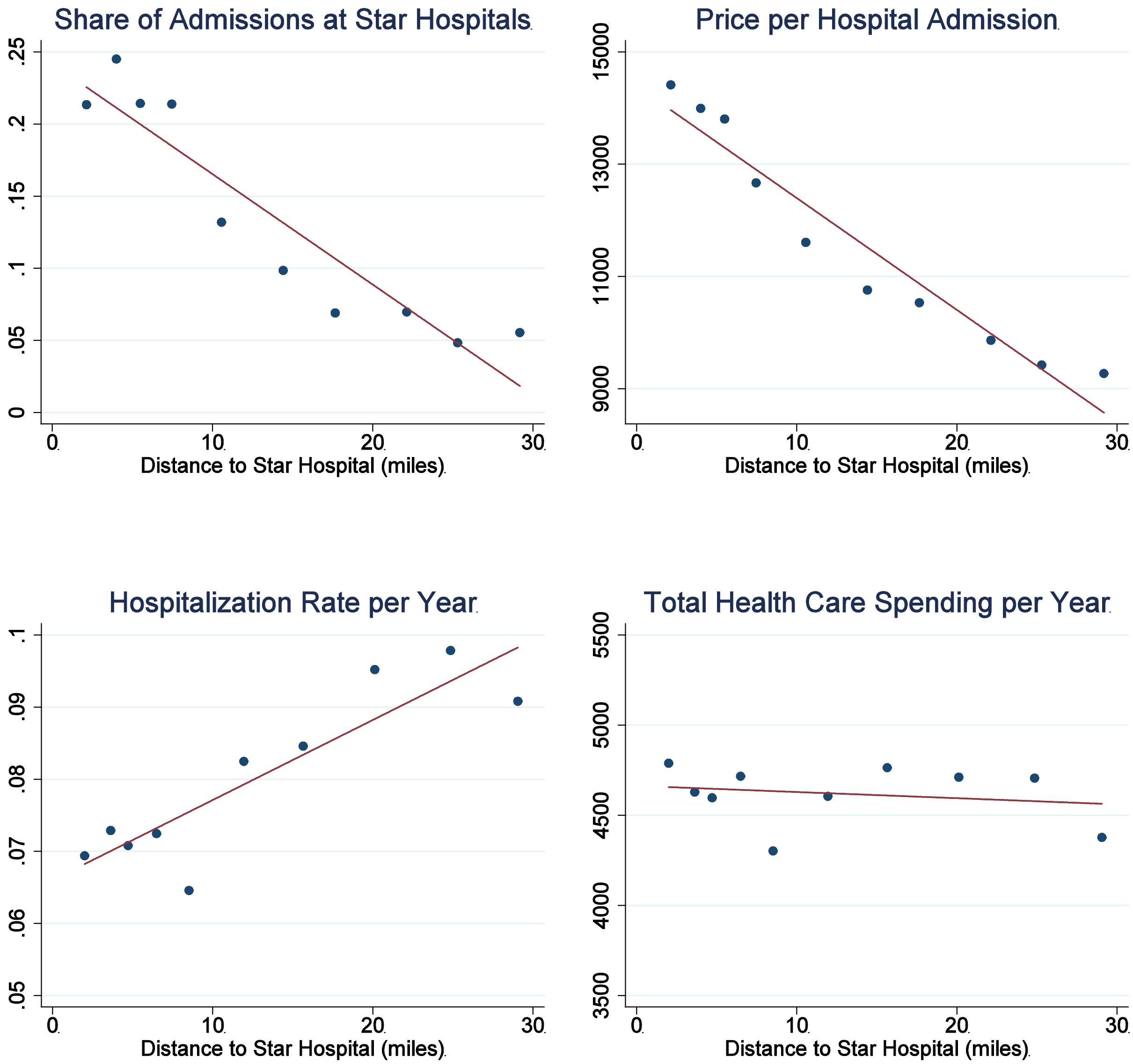
Appendix B. Robustness Tests for Reduced Form Analysis

Appendix Table B.1

	Dependent Variable: Total Cost per Year ($)				
	Baseline Regression	Sample: Dx-Based Risk Adj. Only	Sample: Re-Enrollees Only	Past Doctor Visits Only	Other Past Hospital Use Controls
	(1)	(2)	(3)	(4)	(5)
Past Patient at Partners	1,137.3**	908.2**	1,067.0**	1,304.6**	915.4**
	(96.3)	(108.0)	(162.8)	(160.0)	(93.5)
Other Past Use Variables:					
Any Academic Med. Ctr.					237.1**
					(68.9)
Any Hospital					360.6**
					(73.7)
Control Variables					
Risk Score	4,788.7**	4,561.6**	4,585.6**	4,799.4**	4,752.0**
	(159.0)	(171.0)	(302.4)	(159.4)	(162.9)
Plan x Year x Income Grp FE	X	X	X	X	X
Observations	270,198	172,520	71,303	270,198	270,198
R-Squared	0.117	0.132	0.103	0.117	0.117
Dependent Var. Means:					
Past Patient at Partners	7,318	7,216	6,929	8,088	7,318
All Others	4,032	3,966	4,392	4,321	4,032
[Difference]	*[3,286]*	*[3,250]*	*[2,537]*	*[3,767]*	*[3,286]*

** p<0.01, * p<0.05

Appendix Figure B.1



Appendix C. Demand and Cost Model and Estimation Details

C.1. Insurance Plan Demand Estimation Details

I estimate the plan demand model parameters by matching moments that fall into two categories. First, for plan dummies, I match market shares for the appropriate region/year/income group *g*. These market shares uniquely identify plan mean utilities, which in my case are equivalent to the plan dummies.[89] The formula for these market share moments is:

$$G^{(1)}_{j,g}\left(\theta\right)=\tfrac{1}{N}\sum_{i,j,t}1\{i,t\in g\}\cdot\left[1\{y_{it}=j\}-Pr\left(y_{it}=j\,|\,\theta\right)\right]$$

where θ is the parameter vector, $1\{y_{it}=j\}$ is an indicator for whether individual *i* chose plan *j* at time *t*, and $Pr\left(y_{it}=j\,|\,\theta\right)$ is the predicted choice share from the logit model.

Second, for the coefficients for premium, network utility, and other observed characteristics (which are interacted with observed enrollee attributes), I match the average values for chosen plans in the data to those in the model. Specifically, the moments for characteristic $X^{(k)}$ (e.g., premium) interacted with enrollee attribute $Z^{(r)}$ (e.g., income) are:

$$G^{(2)}_{k,r}\left(\theta\right)=\tfrac{1}{N}\sum_{i,j,t}X^{(k)}_{ijt}Z^{(r)}_{it}\cdot\left[1\{y_{it}=j\}-Pr\left(y_{it}=j\,|\,\theta\right)\right]$$

Another way of interpreting these is as matching the *covariance* between plan characteristics and household attributes. In the case of observing the full market, these moments are equivalent to the micro BLP covariance moments. These moments are also equivalent to first-order conditions from the associated maximum likelihood problem.

Stacking all of the moments into a vector $G\left(\theta\right)$, the MSM estimator searches for the parameter θ that minimizes the weighted sum of squared moments, $G\left(\theta\right)'\cdot W\cdot G\left(\theta\right)$. Because the system is just-identified (equal number of parameters and moments), I am able to match the moments exactly, making the solution invariant to the choice of *W*. I calculate standard errors using the standard GMM sandwich formula. To account for the fact that network utility variable is derived from the hospital demand estimates, I am planning to implement an adjustment following the lecture notes of Pakes (2013). However, I have not yet implemented this adjustment in the current draft.

[89] A difference in my setting from the standard BLP approach is that I treat the plan dummies as parameters, with associated standard errors, since both they and the characteristics coefficients are estimated from a dataset of the same size (the full market data). In previous applications including Berry, Levinsohn, and Pakes (2004), the micro data came from a sample, while the market shares came from aggregate data on the whole market.

C.2. Inattention Interpretation of Plan Inertia Coefficients

For current enrollees, I included in the logit demand model a dummy variable for their current plan, so their full demand utility was:

$$U_{ijt}^{Curr} = \hat{U}_{ijt} + \underbrace{\chi(Z_i)\cdot 1\{j = CurrPlan\}}_{\text{Switching Cost / Inertia}} + \varepsilon_{ijt}^{Plan} \tag{16}$$

where $\hat{U}_{ijt}$ is the plan utility for new enrollees (defined in Section 4.3), excluding the ε_{ijt}^{Plan}. In this equation, $\chi(Z_i)$ is interpreted as a switching cost – an extra utility for the current plan needed to rationalize the low level of plan switching. The plan demand estimates in Table 4 reports these switching costs but also an alternate interpretation based on an inattention model. I show here how I derive the inattention/passive probability reported in Table 4.

Consider a two-step model in which the first step models whether enrollees make an active choice, and the second step models plan choice conditional on being active. The second step is standard and follows the logit model for new enrollees (or current enrollees excluding switching cost):

$$Pr(y_{it} = j \mid Active) = \frac{\exp(\hat{U}_{ijt})}{\sum_k \exp(\hat{U}_{ikt})}$$

The first step is a reduced form model of being passive:

$$Pr_{it}(Passive) = \frac{\exp(\hat{U}_{i,j_{curr},t} + \tilde{\chi}_i)}{\exp(\hat{U}_{i,j_{curr},t} + \tilde{\chi}_i) + \exp(I_{i,Active,t})} \quad \text{where } I_{i,Active,t} = \log\left(\sum_k \exp(\hat{U}_{ikt})\right)$$

Notice that it is the choice probability from a two-choice logit model, where the utility of being passive is the current plan utility plus a reduced-form inertia coefficient $\tilde{\chi}_i$ (which is different from the switching cost χ). The utility of being active is $I_{i,Active,t}$, which is the inclusive value (or expected utility) from the second-stage active choice model.

I claim that if $\tilde{\chi}_i = \log(\exp(\chi(Z_i)) - 1)$, the switching cost and inattention models have identical predictions for choice probabilities. For the current plan, the inattention model predicts a probability that it is chosen of $Pr_{it}(Passive) + (1 - Pr_{it}(Passive)) \cdot Pr(y_{it} = j_{curr} \mid Active)$, which simplifies to:

$$Pr(y_{it} = j_{curr}) = \frac{\exp(\hat{U}_{i,j_{curr},t} + \chi(Z_i))}{\exp(\hat{U}_{i,j_{curr},t} + \chi(Z_i)) + \sum_{k \neq j_{curr}} \exp(\hat{U}_{ikt})}$$

This equals the current plan's choice probability in the switching cost model in (15). Further, the inattention model's probability of switching to another plan j is $(1 - Pr_{it}(Passive)) \cdot Pr(y_{it} = j \mid Active)$, which simplifies to:

$$Pr\left(y_{it}=j\right)=\frac{\exp\left(\hat{U}_{i,j,t}\right)}{\exp\left(\hat{U}_{i,j_{curr},t}+\chi\left(Z_i\right)\right)+\sum_{k\neq j_{curr}}\exp\left(\hat{U}_{ikt}\right)}$$

which is again equivalent to the choice probability from the switching cost model in (15).

Hence, these two models have equivalent predictions for choice probabilities. The plan demand results in Table 4 report both the average switching costs $\chi(Z_i)$ and the passive probability $Pr_{it}(Passive)$, as defined by the equation above.

C.3. Details of Hospital Price Model

As discussed in Section 5.1, I estimate a risk-adjusted hospital price model. Recall that I estimate a Poisson regression (also known as a generalized linear model with a log link) of the form:

$$E\left[Payment_{i,j,h,t,a} \mid Diag_{ita}, Z_{ita}\right]=\exp\left(\rho_{j,h,t}+Diag_{ita}\lambda+Z_{ita}\gamma\right)$$

For the principal diagnosis ($Diag_{ita}$), I use the Clinical Classification Software (CCS) dummies defined by the U.S. government's Agency for Healthcare Research and Quality. The additional covariates (Z_{ita}) include age, gender, income, and Elixhauser comorbidity dummies for the secondary diagnoses.

I specify a restricted model for $\rho_{j,h,t}$ to avoid over-fitting for hospital-insurer-year cells with small samples. Specifically, I start from the model:

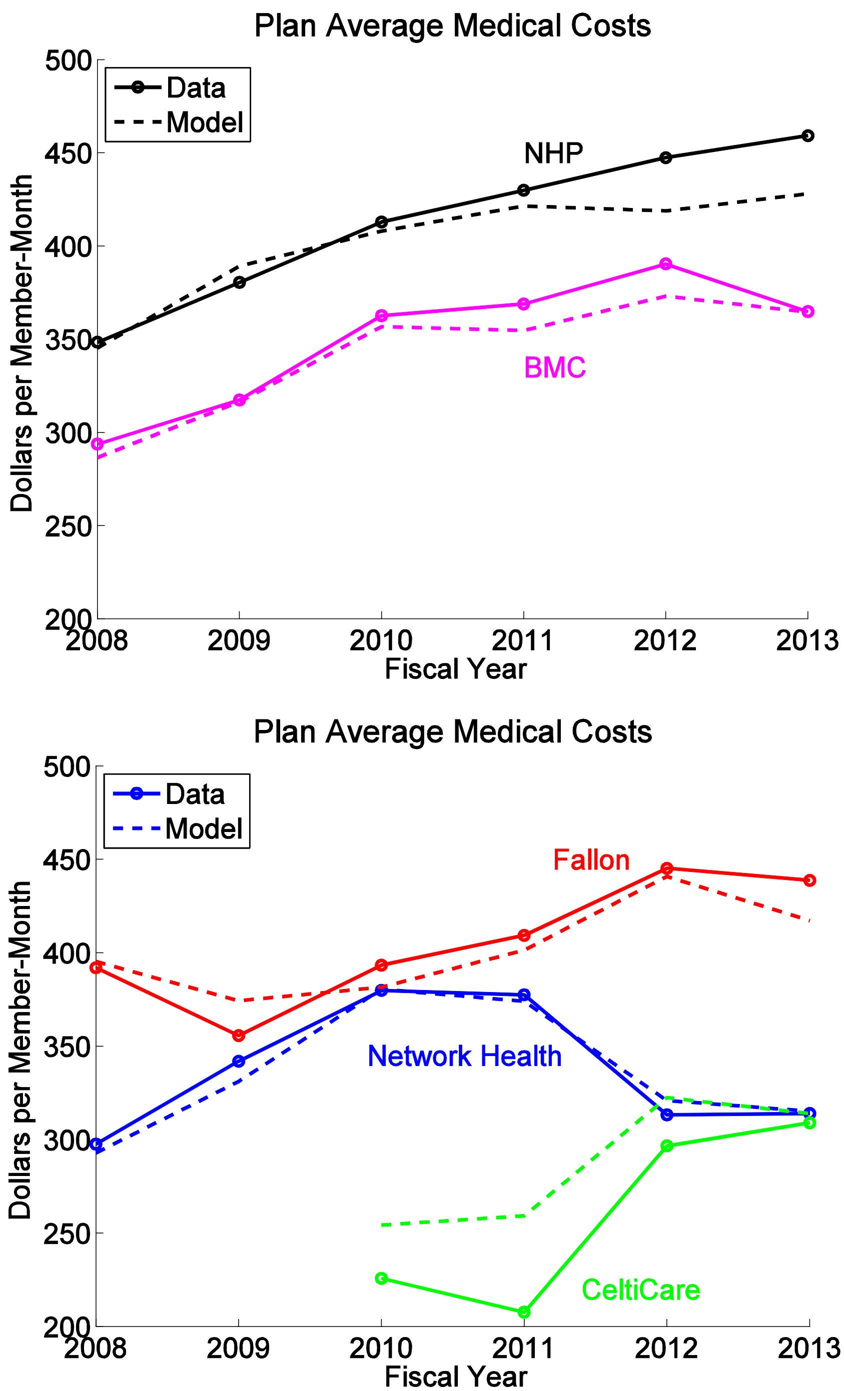
$$\rho_{j,h,t}=\rho_{j,h,NetwStat(h,t)}+\rho_{j,Sys(h),t}+\rho_{j,t,NetwStat(h,t)}$$

The first term, $\rho_{j,h,NetwStat(h,t)}$, is a coefficient on hospital-insurer-network status (i.e., in or out of network) dummies that is constant across years. I include this term for all cells with at least 50 observations; otherwise, I set it to zero. The second term, $\rho_{j,Sys(h),t}$, is a coefficient on insurer-hospital system-year dummies for the top six hospital systems. This allows for a separate hospital price paths over time for each of the largest systems (including Partners). I do not include this term for hospitals in smaller systems or when the large system is out-of-network, with the exception that I always include these dummies for Partners regardless of whether it is in-network. The final term, $\rho_{j,t,NetwStat(h,t)}$, is a residual that allows for a separate effect for each plan, year, and network status. This captures the average insurer-specific price path for all smaller hospitals not included in one of the six largest systems.

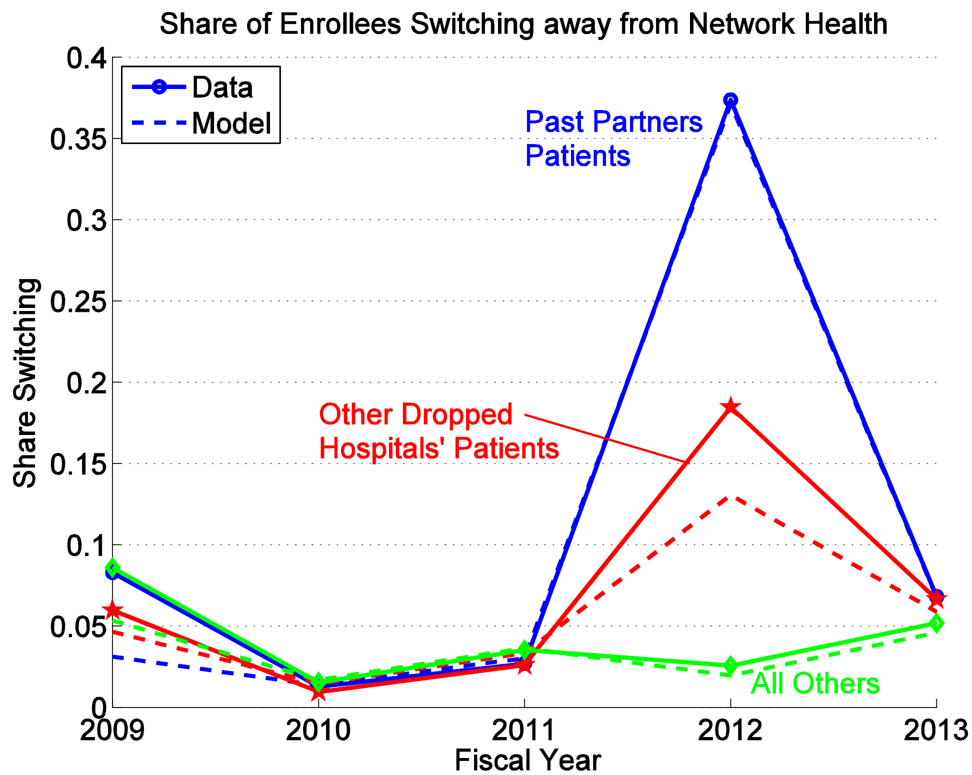
Appendix D. Model Fit Tables and Figures

This appendix shows tables and figures that display the model's ability to match the reduced form patterns around Network Health's dropping of the Partners hospitals in 2012, as discussed in Section 5.4.

Appendix Figure D.1. Model Fit for Plan Average Medical Costs



Appendix Figure D.2. Plan Switching Patterns

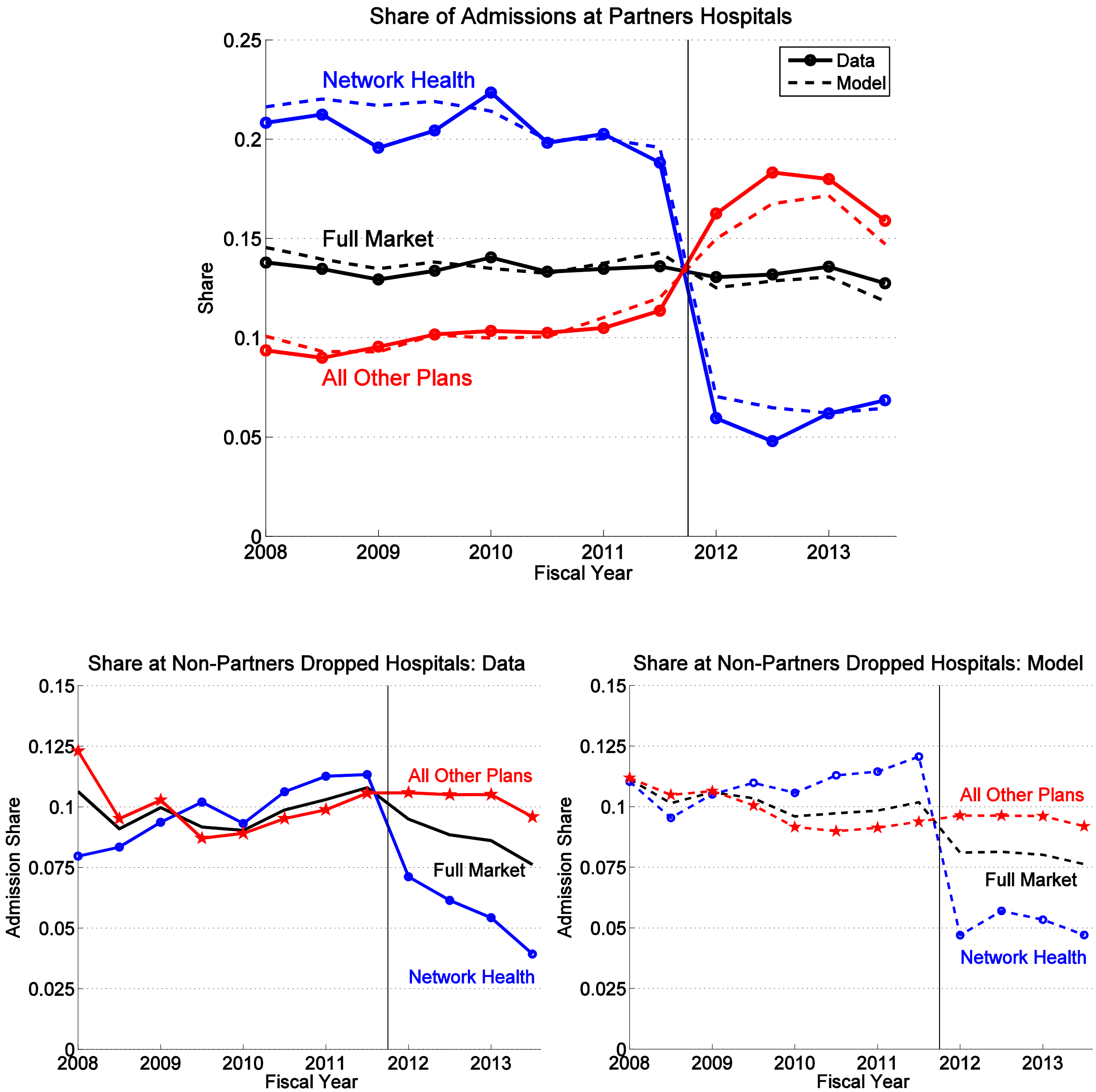


Appendix Table D.1. Cost Changes for Network Health

Network Health: Average Costs 2011-12

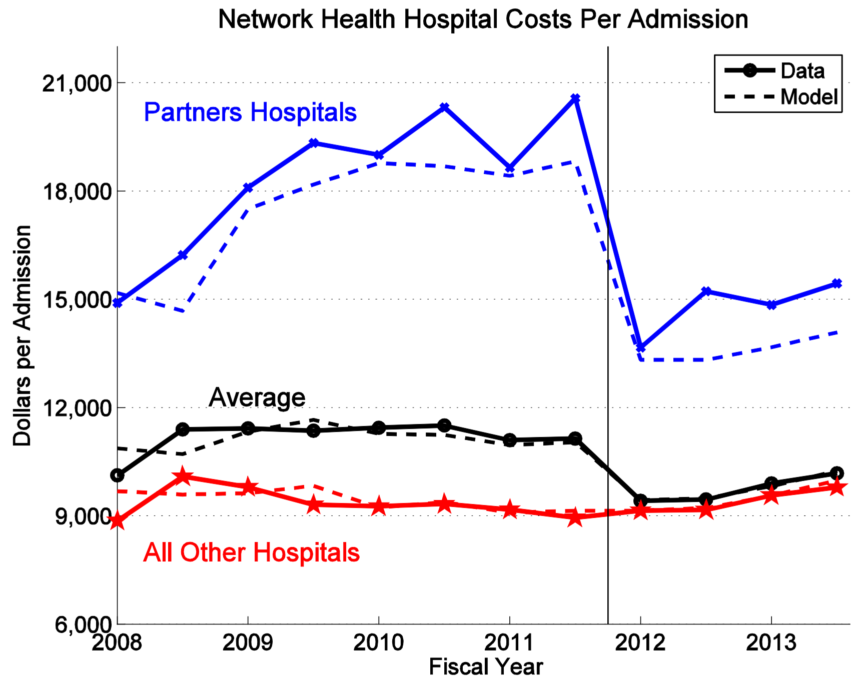
Enrollee Group	Data				Model			
	2011	2012	%Δ	Risk Adj. %Δ	2011	2012	%Δ	Risk Adj. %Δ
All Enrollees	**$378**	**$313**	**-17%**	**-15%**	**$374**	**$310**	**-17%**	**-16%**
Stayers (in plan both years)	$317	$305	-4%	-5%	$334	$312	-7%	-9%
2011 Only Enrollees	$476	---	---		$435	---	---	
2012 Only Enrollees	---	$310	---		---	$302	---	

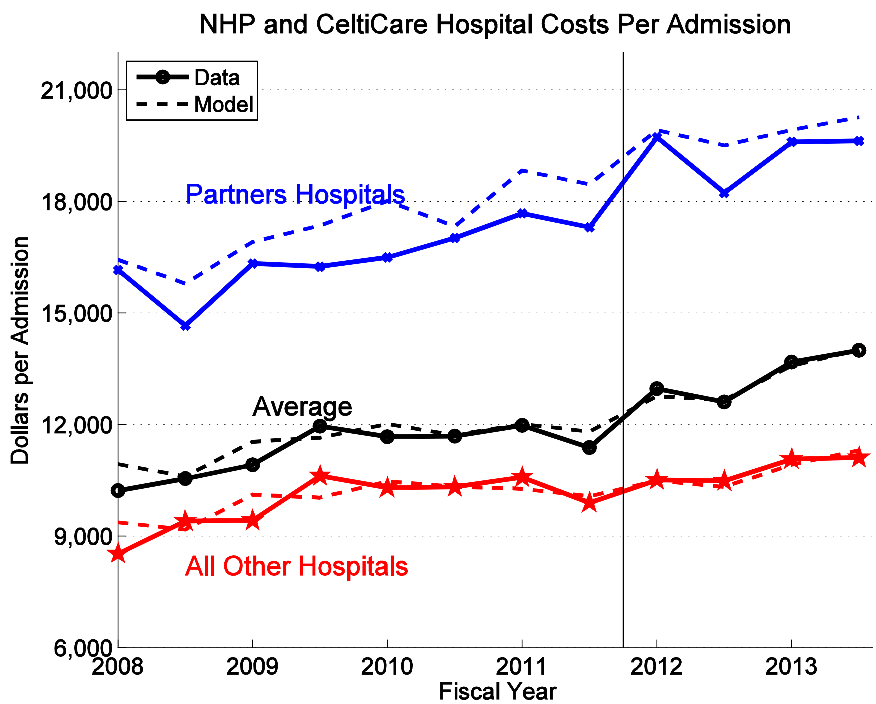
Appendix Figure D.3. Admission Shares at Hospitals Dropped by Network Health in 2012



NOTE: These figures show the share of hospital admissions at hospitals that Network Health plan dropped from its network in 2012. The dashed lines show the model's prediction for the same statistics. These are calculated holding fixed each individual's observed plan, not reassigning plan choices using the plan demand model.

Appendix Table D.4. Changes in Cost per Hospital Admission around 2012 Network Changes





NOTE: These figures show average costs per hospital admission for two sets of plans: Network Health (top figure), which dropped the star Partners hospitals in 2012, and NHP and CeltiCare (bottom figure), which continued to cover them. The dashed lines show the model's prediction for the same statistics. These are calculated holding fixed each individual's observed plan, not reassigning plan choices using the plan demand model.

Appendix E. Simulation Method Details

This appendix details the simple approach I use to incorporate a future profit effect in a static pricing model for my simulations in Section 7. Note that in a dynamic model, an insurer's pricing FOC includes a term capturing the effect of changing today's price on future profits on consumer *i*. I model this "future profit effect" as the product of the change in future demand $(\partial D_{ij}^{Fut} / \partial P_j)$ times an expected profit margin M_{ij}^{Fut}, which is unaffected by today's price. For the change in future demand, a lower price increases demand today and therefore increases the number of inertial enrollees in the future. To simplify, I take future market enrollment $(nMon_{i,t+k})$ as given and assume an exogenous, constant inertia probability η at each year's switching choice, which I set at 89%.[90] Given these assumptions:

$$\frac{\partial D_{ij}^{Fut}}{\partial P_j} = \frac{\partial S_{ij}}{\partial P_j} \cdot \left(\sum_{k \geq 1} \eta^k \cdot nMon_{i,t+k} \right) \tag{17}$$

where $\partial S_{ij} / \partial P_j$ is the effect of price on current year's choice share.

Finally, I need to specify insurers' future profit margins. Although imperfect, I simply assume that insurers expect M_{ij}^{Fut} to equal current margins at the enrollee level – which assumes that prices and costs grow in parallel for each enrollee. Notice that I still treat M_{ij}^{Fut} as a constant in the pricing FOC but plug in the equilibrium margin ($= \varphi_i P_j^* - c_{ij}(N_j)$) for it at the end.

Combining these assumptions and defining the term in parentheses in (16) as $nFutMon_i$, the pricing FOC for insurer *j* is:

$$\begin{aligned} 0 &= \frac{\partial \pi_j}{\partial P_j} + \sum_i M_{ij}^{Fut} \cdot \frac{\partial D_{ij}^{Fut}}{\partial P_j} \\ &= \sum_i \varphi_i \cdot nMon_i \cdot S_{ij}(.) + \sum_i \left(\varphi_i P_j - c_{ij} \right) \left(nMon_i + nFutMon_i \right) \cdot \frac{\partial S_{ij}}{\partial P_j} \end{aligned} \tag{18}$$

Accounting for future profits adds the $nFutMon_i$ term to the FOC, which increases the incentive to lower prices (just like a steeper demand curve). This effect is likely to have a significant impact. Months in the current year $(nMon_i)$ average 6.2, and future months $(nFutMon_i)$ average 6.8. So the future profit effect works like a more than doubling of the demand slope.

[90] I use 89% rather than the 95% inertia probability reported in the plan demand estimates based on a rough correction for unobserved heterogeneity. Looking at re-enrollees (people who leave the market and return later), people tend to actively choose the same plan as during their prior spell about 55% of the time. For an inertia probability of ρ the overall non-switching probability is $\rho + (1-\rho) \cdot Pr_j^{Active}$. Plugging in $Pr_i^{Active} = 55\%$, $\rho = 89\%$ is required to rationalize a 95% overall non-switching probability.