Medicaid Program Choice, Inertia and Adverse Selection

James Marton[1]
Georgia State University

Aaron Yelowitz
University of Kentucky

Jeffery C. Talbert
University of Kentucky

Abstract: In 2012, Kentucky implemented Medicaid managed care statewide, and auto-assigned enrollees to one of three plans, allowing individuals to switch during an open enrollment window. Using administrative data, we find that the state's auto-assignment algorithm most heavily weighted cost-minimization and plan balancing, and placed little weight on the quality of the enrollee-plan match. Inertia contributed to the success of the cost-minimization strategy, as more than half of enrollees auto-assigned to even the lowest quality plans did not opt-out. High-cost enrollees were more likely to opt-out of their auto-assigned plan, creating adverse selection. The highest quality plan incurred the largest profit margin reduction due to adverse selection, as it attracted a disproportionate share of high-cost enrollees. The presence of such selection, and the extent to which it is exacerbated by differential degrees of inertia, raises concerns about the long run viability of the Medicaid managed care market in this context.

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[1] James Marton, Georgia State University, Department of Economics, P.O. Box 3992, Atlanta, GA 30302-3992; 404-413-0256 (p); 404-413-0145 (f); marton@gsu.edu.
Aaron Yelowitz (corresponding author), University of Kentucky, Department of Economics, 223B Gatton Business and Economics Building, Lexington, KY 40506-0034; 859-257-7634 (p); 859-323-1920 (f); aaron@uky.edu.
Jeffrey Talbert, University of Kentucky, College of Pharmacy, 789 South Limestone St., Lexington, KY 40536-0596; 859-323-7141 (p); Jeff.Talbert@uky.edu.

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1. Introduction

Between 2002 and 2014, the share of the Medicaid population enrolled in managed care grew from 58 percent to 77 percent (CMS, 2011; Mathematica Policy Research, 2016). By 2014, 61 percent of the 71.7 million Medicaid recipients nationwide were enrolled in comprehensive managed care plans, a sharp increase from the 56 percent just one year earlier (Mathematica Policy Research, 2015, 2016). As of July 2015, 48 states use managed care for at least some Medicaid recipients, 39 states contract with managed care organizations (MCOs) and 29 of them (including DC) use MCOs exclusively (Smith et al., 2015).

In many instances, consumers in a health insurance market face many choices between different plans. Even with a fully-binding individual mandate that compels health insurance coverage, offering choice between different health insurance plans during open enrollment periods – either through Medicaid MCOs, Qualified Health Plans (QHPs) in the Marketplace, in Medicare Part D, or elsewhere – raises the possibility of adverse selection and consequently economic losses for insurers. This has been seen recently in private Marketplace plans with major insurers – UnitedHealth Group, Humana Inc., and most recently Aetna – withdrawing completely, scaling back, or cancelling expansions, citing large losses on ACA plans (Matthews, 2016). Such adverse selection "death spirals" have been demonstrated in some other health insurance contexts (Cutler and Reber, 1998).

Compared with either Marketplace QHPs or Medicare Part D, analysis of coverage choices in Medicaid MCOs allows us to investigate the consequences of adverse selection in a completely new setting. In QHPs, consumers typically face multiple bronze, silver, gold and platinum plans, with different subsidized premiums, copayments or coinsurance rates, deductibles, out-of-pocket maximums, and network coverage. Given this complexity, recent work has argued for personalized decision support and smart defaults (Handel and Kolstad, 2015). In Medicare Part D – which only focuses on the prescription drug portion of the healthcare package for the elderly – recent work has noted that the financial complexity of the plans appears to lead to "choice inconsistencies" and little learning on the part of consumers (Abaluck and Gruber, 2011, 2016). In both contexts, the consumer must compare both financial implications (making a forecast of future distribution health care use) and benefit generosity across multiple plans. In contrast, the choice problem for Medicaid MCOs is simpler because the financial implications from different plans are minimal. Recipients with income under 150 percent of the FPL generally cannot be charged premiums for any plan. They also pay nominal amounts for drugs, and face more limited copayments for non-emergency use of emergency departments.[2] Thus, recipients should choose plans based on benefit quality and largely ignore the very small out-of-pocket cost differences.

Medicaid beneficiaries who are required to enroll in MCOs must be offered a choice of at least two plans (Smith et al., 2015), and those who do not select a plan are auto-enrolled in one. All but one of the 39 states with MCOs have an auto-enrollment process.[3] The median state typically auto-enrolls 45 percent of new recipients, defaulting them into a particular MCO (Smith et al., 2015). States typically include factors such as past provider relationships, geographic location, and continuity with other family members into their auto-assignment process. In addition, 23 of the 38 states with auto-assignment attempt to balance enrollments among plans, while 15 states consider plan capacity. Only 8 states' auto-

[2] For further discussion on cost sharing, see Marton (2007) and https://www.medicaid.gov/medicaid-chip-program-information/by-topics/cost-sharing/cost-sharing.html.
[3] North Dakota has one MCO, and thus no auto-enrollment (Smith et al 2015).

assignment algorithms account for quality rankings. Auto-assignment, and the likelihood of at least some degree of inertia from such defaults, has important implications for the impact of adverse selection on MCO profitability and, thus sustainability.

In this paper we examine the impact of auto-assignment, adverse selection, and health plan inertia on the functioning of the Medicaid managed care market in Kentucky, which introduced statewide Medicaid managed care in 2012.[4] The state auto-assigned enrollees to one of three plans then established a 90-day open enrollment period in which enrollees could switch. Using rich administrative data on all Medicaid enrollees in Kentucky, we analyze the impact of the auto-assignment algorithm selected by the state and enrollee responses to auto-assignment during open enrollment on the state's Medicaid budget, the quality of the match between enrollees and the plan within which they ultimately enroll, and the profitability of the plans.

Our analysis produces several strong conclusions. First, we find compelling evidence that the state's auto-assignment algorithm most heavily weighted cost considerations (i.e. lower capitation rates) and plan balancing, and placed relatively little weight on quality of the enrollee-plan match. That is, instead of acting like a "benevolent social planner" by maximizing quality of care, the algorithm largely attempted to minimize costs, in a sense acting like a "malevolent social planner" (from the point of view of the Medicaid clientele). For example, our simulation suggests that the algorithm selected by the state saved them over $31 million annually (approximately $200 per enrollee) as compared to the "benevolent social planner" algorithm. Second, from the state's perspective, the presence of inertia contributed to the success of their cost-minimization strategy. Even in the lowest quality plans, more than half of auto-assigned enrollees did not opt-out, and the percentage was greater in the highest quality plans.[5] Third, we observe a considerable degree of adverse selection which was exacerbated by lower levels of inertia among high cost enrollees. Although the share of enrollees that switched plans during open enrollment was small, the share of health care spending associated with those enrollees was large. Among individuals in the top 10 percent of the spending distribution, mobility across plans was dramatically higher regardless of initial plan assignment. Given that such high-cost individuals comprise nearly 50 percent of all spending, such movements have important implications for the financial well-being of the three plans. Our simulations suggest that the plan generally considered to be the highest quality incurred the largest reduction in profit margin due to adverse selection, as it attracted a disproportionate share of high-cost enrollees during open enrollment. The presence of such selection, and the extent to which it is exacerbated by differential degrees of inertia, raises concerns about the long run viability of the Medicaid managed care market in this context.

The rest of the paper is arranged as follows: Section 2 reviews the literature on inertia, with a focus on insurance markets, then Section 3 provides a brief institutional background on the transition to statewide Medicaid managed care in Kentucky. Section 4 describes conceptually the choices faced by enrollees, the state, and the MCOs. Section 5 lays out our empirical strategy and Section 6 describes the administrative data we use to implement this strategy. Our results, including a series of policy simulations, are presented in Section 7, and Section 8 concludes the paper.

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[4] Given this policy change, Kentucky is now part of a group states that enrolls virtually all recipients in MCOs (91 percent as of 2014). Other states with broad Medicaid managed care coverage include Tennessee, Hawaii, Kansas, New Jersey, Oregon and Delaware – all with 90 percent or more enrolled in MCOs (Smith et al. 2015).

[5] However, in our setting, there is relatively more mobility / less inertia than in other settings in which inertia is examined, such as retirement plan participation, Medicare Part D plan choice, etc.

2. Literature Review

There is an established inertia literature with studies on retirement plans (Madrian and Shea, 2001; Choi et al., 2002, 2004; Chetty et al., 2014; Messacar, 2014), organ donation (Johnson and Goldstein, 2003; Abadie and Gay, 2006), life insurance (Harris and Yelowitz, forthcoming), and income tax refunds (Jones, 2012). More closely related to this study, there has been evidence of inertia in health insurance decisions including Medicare Part D (Ketcham et al., 2012; Ericson, 2014; Ho, Hogan and Scott Morton, 2015; Polyakova, 2016), and private health insurance (Handel, 2013; Dahl and Forbes, 2016).

Although studies of inertia are widespread, there is significant diversity in magnitudes depending on the market environment. The degree of inertia has been found to depend on budget share and salience of the product. For example, in the case of employer-sponsored health insurance (significant budget share and relatively salient), Dahl and Forbes (2016) found that 22 percent of employees were inert (with an even smaller share in subsequent years), whereas in the case of employer-sponsored life insurance (small budget share) there was almost 100 percent inertia (Harris and Yelowitz, forthcoming). Even though these cases illustrate some patterns in inertia, the degree of inertia for Medicaid plan choice where the budget share is virtually zero remains unknown. In addition to the variation in magnitudes, there is also variation by market environment. In the context of Medicare Part D, Ketcham et al. (2012) show that those that were losing the most financially were less inert. Similarly, Dahl and Forbes (2016) find in the context of employer-sponsored health insurance that individuals with higher expected costs exhibited less inertia and were more likely to switch plans. In the case of mortgage refinancing, Andersen et al. (2015) find that more educated and higher-earning individuals have less inertia and less inattention.

These differences can have important implications for adverse selection in insurance markets inasmuch as inertia is correlated with expected cost. Strombom, Buchmueller and Feldstein (2002) analyze employer-sponsored health insurance for a large multi-location employer and find that younger, recently hired employees are more likely to respond to premium increases whereas older, incumbent employees in worse health are the least likely to switch leading to what they call “adverse retention.”[6] Additionally, Polyakova (2016) finds, in the context of Medicare Part D, that high frictions leading to inertia allow for an adversely-selected equilibrium that would otherwise lead to unraveling of the market. In yet another study, Handel (2013) analyzed the effects of a policy change that caused individuals to make an active choice regarding employer-sponsored health insurance. He finds that in the absence of inertia individuals made improved decisions, which substantially exacerbated adverse selection. Although Handel (2013) finds a negative relationship between inertia and adverse selection the study highlights that the reverse could be true in a different market environment and that the relationship can have potentially surprising welfare implications.

Given the Medicaid expansions under the Affordable Care Act and the widespread implementation of auto-enrollment/assignment, both the inertia and its interaction with adverse selection are relevant for policy makers. Handel and Kolstad (2015) illustrate how policy makers can use “smart defaults” to increase consumer welfare given that individuals exhibit inertia. At the same time, policy makers may use inertia to reduce overall costs. To our knowledge, ours is the first study to analyze inertia in Medicaid managed care from auto-assignment.

3. Institutional Background

[6] Royalty and Solomon (1999) similarly document this heterogeneity in price sensitivity.

The introduction of the *Passport Health Plan* (Passport) in November 1997 marked Kentucky Medicaid's first major attempt to transition its enrollees into managed care coverage. Passport is a local non-profit MCO anchored by the University of Louisville hospital network. All Medicaid enrollees that live in the Louisville area (Region 3 in Figure 1) were required to enroll in Passport.[7,8]

No further attempt was made to expand Medicaid managed care (MMC) outside of Region 3 until 2011, when a very aggressive timeline was implemented for such an expansion. As described in Palmer et al., (2012), in April 2011 Kentucky sought bids from Managed Care Organizations (MCOs) to cover Medicaid enrollees outside of Region 3. In May 2011, they received bids from seven MCOs and selected three based on their likely performance and cost in July 2011: Coventry Cares of Kentucky (Coventry), WellCare of Kentucky (Wellcare), and Kentucky Spirit (Spirit).[9] Each plan negotiated regional capitation rates for a uniform set of demographic categories, which we refer to as capitation categories. In general, the highest capitation rates were negotiated by Wellcare and the lowest by Spirit. Table 1 lists the MCO with the lowest capitation rate for each capitation category-region bin. We see that Wellcare was never the lowest rate plan in any bin, Spirit was the lowest rate plan more often than Coventry across all regions, and that this was especially true in eastern Kentucky (Regions 7 and 8).

In November 2011, the state auto-assigned enrollees outside of Region 3 to either Wellcare, Coventry, or Spirit, then established a 90 day open enrollment period during which enrollees could switch plans.[10] According to Palmer et al. (2012), the state assigned more enrollees to plans with lower capitation rates, with Spirit receiving an initial assignment of over 200,000 members out of an approximate total of 550,000. Although we cannot directly observe the weights put on various factors, Palmer et al. (2012) provide the following qualitative description of Kentucky's auto-assignment algorithm:

> "*The auto-assignment algorithm accounted for the enrollees' historical physician relationships, consistency of household members assigned to the same plan, and load balancing across plans. When this was taken into account, preference was given to the plan with the lowest premium.*"

In the next section of the paper we discuss in more detail the varying objectives a state might have in the construction of such an algorithm.

There were many similarities and some differences between the three plans. In terms of cost, there were no premiums associated with any of the plans, as is typically the case in state Medicaid program. This shifts the focus more squarely to differences in MCO quality. In general, the plans offered a uniform set of services and did not "carve out" services such as behavioral health, dental, and pharmaceuticals. To the extent to which differences in capitation rates reflect differences in quality, we would regard Wellcare as generally being the highest quality plan and Spirit the worst. That being said, Table 1

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[7] Another local non-profit MCO, Kentucky Health Select (KHS), was simultaneously established in region 5. KHS served all Medicaid enrollees in the Lexington area (Region 5 in Figure 1). This MCO was anchored by the University of Kentucky hospital network. It ceased operation in 1999.

[8] Bartosch and Haber (2004) describe the introduction of Passport. Multiple studies have examined the impact of Passport on various outcomes; see Marton, Yelowitz, and Talbert (2014), Marton and Yelowitz (2015), Marton, Yelowitz, Shores, and Talbert (2015), and Marton, Palmer, Yelowitz, and Talbert (2016).

[9] All the new MCOs are run by for-profit, national companies which serve a large number of MMC beneficiaries in other states. Coventry (recently acquired by Aetna) covers MMC beneficiaries in 9 states, Centene (the company responsible for Kentucky Spirit) covers MMC beneficiaries in 18 states, and Wellcare covers MMC beneficiaries in 7 states (Palmer et al., 2012).

[10] Medicaid enrollees in region 3 continued to be covered by the Passport MCO.

illustrates that Spirit was not the lowest cost plan in every capitation category-region bin and it is also the case that Wellcare was not the highest cost plan in every bin.

Differences in MCO success in contracting with local providers both by MCOs and region would lead to differences in quality via access-to-care. As described in detail in Palmer et al. (2012), as of June 2012, 73 percent of hospitals in the state contracted with all three MCOs, 25 percent contracted with two MCOs, and 2 percent only contracted with one plan.[11] This report also states that subsequent actions by the MCOs with respect to their provider networks suggests that these numbers likely overstate the extent of actual overlap in the hospital networks across the three MCOs. Physician practices tended to participate in plans that their local hospital contracted with. One notable regional difference is that Spirit was not able to contract with Appalachian Regional Healthcare, a dominant provider in eastern Kentucky due to unsuccessful rate negotiations. Thus the quality of the Spirit plan could be viewed as lower than other MCOs in eastern Kentucky because enrollees would have trouble receiving services from the region's dominant provider. Spirit's difficulties in eastern Kentucky were widely reported in the press, so we would expect there to be greater awareness of differences in MCO provider network quality in that region, as compared to the rest of the state.[12]

4. Conceptual Framework

Here we describe a conceptual framework that discusses in a non-technical way the objective function, constraints, and choice parameters of the three economic agents of interest in our analysis: the state, the managed care plans (MCOs), and the enrollees. As mentioned in the previous section, the state contracted with MCOs and assigned enrollees to one of the three plans, then enrollees had a 90-day open enrollment period in which they could opt-out of their assigned plan and enroll in another. We work backwards through the choices faced by each agent.

Medicaid Enrollee Choice of MCO

Enrollees are informed by the state about which MCO (Wellcare, Coventry, or Spirit) they are auto-assigned to and then must decide during the open enrollment period whether to remain in that MCO or switch to one of the others. The plan information that is likely to be relevant to this choice would include premiums (costs) and plan quality (benefits). Because these are Medicaid plans, the premiums are zero. Therefore, from the enrollee's perspective, each plan has the same price and that price does not vary by the health status of the enrollee. The fact that these are Medicaid plans also implies that the covered services are essentially uniform across all three plans.[13] One difference in plan quality was the well-documented regional differences in provider networks. Due to difficulty in contracting with the

[11] Palmer et al. (2012) also mentioned that Spirit felt as though their lower capitation rates gave them less flexibility to reimburse providers at rates above the standard Kentucky Medicaid fee-for-service rates and thus hampered their ability to establish a broader provider network.
[12] Other quality metrics were harder for enrollees to access in 2011 during open enrollment. Standard plan quality metrics produced via HEDIS or CAHPS surveys were not available at that time. In addition, web-based provider directories for the MCOs were sometimes inaccessible or inaccurate. On the other hand, local providers may have encouraged their patients to switch to the MCOs they contracted with during open enrollment (Palmer et al., 2012). In addition, MCOs attempted to recruit profitable enrollees; for example, they employed marketing techniques such as diaper and stroller giveaways to attract profitable enrollees.
[13] In some of our subsequent analysis, we use differences in capitation rates within demographic-region cells as one proxy for differences in MCO quality.

major provider group in eastern Kentucky, Spirit had a narrower network in that region than the other MCOs.

Assuming enrollees are rational, utility maximizing decision-making agents with full information in a frictionless environment, we would expect that they would all choose to enroll in the highest quality plan. Thus if they were auto-assigned to the highest quality plan, they would not opt-out. Conversely, enrollees not assigned to the highest quality plan would opt-out and move to that plan. We just described the potential for regional differences in plan quality based on differences in provider networks, so the plan that is highest quality in western Kentucky may not be the highest quality in eastern Kentucky. In addition, it is reasonable to assume that enrollees may perceive there to be differences in match-specific quality across the three plans. For example, one enrollee might only be concerned with whether or not a given MCO includes a handful of specific providers, while another might not be concerned about any specific providers, but rather the overall size of each plan's network.

In this context, we define "inertia" to be when an enrollee remains in their auto-assigned plan, despite the fact that one of the other plans is objectively higher quality. Choi (2015) details many factors that could lead to inertia including transaction costs, perceived recommendation, cognitive dissonance, and ignorance. In the Medicaid context, the time cost of acquiring information about each MCO and the psychological cost of switching plans/thinking about health might deter individuals from changing plans.[14] Additionally, individuals could view the auto-assignment as implicit advice from the state regarding the best plan for them and consequently keep the default coverage (Benartzi, 2001; Brown, Farrell, and Weisbenner, 2012). Lastly, ignorance in this context implies that enrollees are unaware of the differences in plan quality and consequently do not switch to a higher quality plan. This could be a significant factor given the complexities of provider networks. A priori, the aforementioned factors should influence enrollees with higher expected costs (higher-stakes decision) less and result in lower levels of inertia. Outside of the initial auto-assignment, individuals might exhibit inertia – continue with the same plan – despite plan deficiencies due to status-quo bias. In this context, switching plans involves a level of uncertainty, which may be avoided by continuing with the same plan (Choi, 2015).

An alternative explanation for why individuals failed to switch plans is that the initial auto-assignment was optimal. If we underestimate the match-specific quality between the enrollee and their auto-assigned plan, then we would overestimate the effects of inertia.

State Choice of Auto-Assignment

Given the demographic-region bin capitation rates the negotiated with each MCO and perhaps some thoughts about how enrollees might respond, the state must decide how to auto-assign enrollees across plans. Smith et al. (2015) provides a nice description of potential considerations that may factor into such a decision:

> *"States' auto-enrollment algorithms also vary, but are usually designed to take into consideration previous plan or provider relationships, geographic location of the beneficiary, and/or plan enrollments of other family members. In addition, over half (23) of MCO states reported that their auto-enrollment algorithms were designed to balance enrollments among plans; 15 states considered plan capacity, and eight states took plan quality rankings into*

[14] Given that there are only three plan choices and minimal differences in premiums and cost sharing, this effect is likely mitigated relative to contexts where there are many options and large price differences.

consideration. Other states noted plans to move toward including quality rankings in their auto-assignment algorithms in the future."

We broadly think of these considerations as either regarding "plan balance" or "match-specific quality." All else equal, we would also expect that the state would prefer to pursue a "cost-minimization" strategy and assign enrollees to lower cost plans. Different states may put different weight on cost-minimization, plan balance, and match-specific quality and design their assignment algorithm accordingly.

MCO Capitation Rate Negotiation with the State

The first step in this entire process is the establishing of a contract between the state and the MCOs. Obviously, the MCOs are private firms seeking to maximize profits, so would prefer higher capitation rates than the cost-minimizing state would prefer. Capitation rates are negotiated for a uniform set of demographic categories separately by region, as described in the previous section. Competition in the MCO market dictates how much leverage each MCO brings to the negotiation. Federal regulations require states to offer Medicaid enrollees in managed care the choice between at least two plans.

5. Methods and Identification Strategy

We estimate models examining inertia from auto-assignment in the first year of open enrollment, and how adverse selection affects that inertia. We estimate linear probability models estimating inertia of the form:

$$(1) \qquad ENROLL_{ipr} = \beta_0 + \beta_1 ASSIGN_{ipr} + \beta_2 X_{ipr} + \delta_r + \varepsilon_{ipr}$$

where $ENROLL_{ipr}$ is an indicator for whether individual *i* in region *r* ultimately enrolled in plan *p* and $ASSIGN_{ipr}$ indicates whether that individual was initially assigned to that plan. As discussed, there are three plans (Wellcare, Coventry, and Spirit) that an individual could have been assigned to. The vector X_{ipr} includes 22 demographic categories on which capitation rates were based (combinations of age, gender, and eligibility category), as well as an indicator for non-white, while δ_r are dummy variables for regions within Kentucky (either West/Central/East). Although the data on individuals is gathered from different points in time (i.e. enrollment is as of March 2012, while assignment is as of November 2011), the regressions should be thought of as cross-sectional analyses. Standard errors are heteroscedasticity-robust.

Under certain assumptions, discussed extensively below, the estimated coefficient β_1 can be interpreted as inertia. That is, if initial assignment into plan *p* raises the likelihood of ultimately enrolling in that plan, then the defaults generated from auto-assignment affect actual behavior. We expect $\widehat{\beta_1} > 0$, which is interpreted as initial assignment increasing the likelihood of ultimately enrolling in the plan. As importantly, we investigate whether individual characteristics – such as high medical expense – affect the degree of inertia. In such specifications we estimate models of the form:

$$(2) \qquad ENROLL_{ipr} = \gamma_0 + \gamma_1 HIGH_{ipr} ASSIGN_{ipr} + \gamma_2 ASSIGN_{ipr} + \gamma_3 HIGH_{ipr} + \gamma_4 X_{ipr} + \delta_r + \varepsilon_{ipr}$$

where the specification is similar to before, and $HIGH_{ipr}$ is an indicator for whether individual *i* has high expected medical expenses, which is useful for determining adverse selection. In practice, we separate individuals based on their lagged actual medical expenses, where we create indicators for expenses in the 99th percentile or above, 95th to 99th percentile, 90th to 95th percentile, and 75th to 90th percentile (with the omitted category being "healthy" individuals with relatively modest expenses under the 75th percentile). Under the plausible assumption that the benefits of choosing the most appropriate plan is higher for unhealthy individuals (and the costs are the same), we would expect less inertia for high-cost individuals. Thus, one would expect the estimated interaction term $\widehat{\gamma_1} < 0$, since initial assignment is less "sticky" for high-cost enrollees. This movement, similar to Cutler and Reber (1998), provides evidence of adverse selection. As in equation (1), we expect that initial assignment to a plan to increase the likelihood of participation, or $\widehat{\gamma_2} > 0$.

As mentioned, a number of assumptions need to be examined for the interpretation of either $\widehat{\beta_1}$ or $\widehat{\gamma_2}$ to represent inertia (and consequently $\widehat{\gamma_1}$ to representing a reduction in inertia among unhealthy individuals). To a large extent, these assumptions have to do with how the auto-assignment algorithm assigned particular individuals to plans, how individuals valued that plan relative to the other two, and whether the frictions in switching plans was prohibitive. Although we address all of these issues below (after presentation of the main results), we outline the issues here. First, for the full sample, we do not want to assume that auto-assignment mimics random assignment. In particular, the algorithm may match individuals based on cost-considerations (i.e. capitation payments, which are a function of demographics, eligibility category and region), plan balancing (i.e. to preserve competition across plans and ensure a critical mass of consumers), overall plan quality, and patient-specific plan match (i.e., if the enrollee's primary care provider is in one plan but not the others, then the match-specific component for assigning to the first plan would be very high).

Of most concern for the interpretation of inertia is that the algorithm was sophisticated enough to assign the vast majority of individuals to the plan with the highest match-specific value, in which case one would observe lack of movement but this would not be inertia. We address these concerns by looking at individuals who were initially assigned to a plan in their region with the lowest capitation rate (in which case it is plausible to believe that cost-considerations were the over-riding factor) or by looking at new Medicaid enrollees, where there simply would not be sufficient utilization data to match the individual to a particular plan. Another lesser concern has to do with overall plan quality (which likely varies not only by plans, but by regions, given the nature of the provider networks). To the extent that one of the plans is generally better than the other(s) for most enrollees, assignment to the better plan again looks like inertia. However, one would not expect to see inertia for the other two plans.

Given these questions about the algorithm, we also examine explicitly whether cost factors influence initial assignment. We have capitation rates for Wellcare, Coventry, and Spirit for each of the 22 demographic categories and 7 regions we consider. To examine the state's initial auto-assignment choices, we estimate models of the form:

$$(3) \qquad ASSIGN_{ipr} = \theta_0 + \theta_1 CAPITATION\_MARKUP_{pr} + \theta_2 X_{ipr} + \delta_r + \varepsilon_{ipr}$$

where we predict assignment to plan *p* for individual *i* based on $CAPITATION\_MARKUP_{pr}$, the percentage markup for plan *p* in capitation rates over the lowest cost plan (where this variable equals zero for the least expensive plan within each of the 154 demographic-region cells), and the markup varies at the demographic-region level, not the individual levels. Standard errors are corrected for non-nested, two-way clustering by demographic category and region (Cameron, et al. 2011). If cost considerations are an important factor, then $\widehat{\theta_1} < 0$, meaning higher mark-ups decrease the likelihood of the state auto-assigning enrollees to that plan.

6. Data

Given that the MMC auto-assignment process started in November 2011, we pulled from the Kentucky Medicaid administrative database all records for each enrollee continuously enrolled between January 2010 and March 2012 not living in region 3 of the state.[15] This allows us to observe their pre-managed care (i.e. pre-period) Medicaid spending, their auto-assigned plan for 2012, and the plan they ended up being covered under during 2012. Approximately 370,000 unique enrollees satisfy these criteria. We then drop any enrollees that switch county of residence during this time, leaving us with approximately 300,000 unique enrollees.[16] We further restrict our attention to non-elderly adult enrollees with no Medicare coverage, bringing us down to approximately 180,000 unique enrollees. Finally, we drop those carved out of managed care coverage and those with missing values for demographic characteristics of interest. This leaves us with a final sample size of 160,263 unique enrollees.

Figures 2A and 2B illustrate the distribution of pre-period (January 2010-June 2011) Medicaid spending for our sample of 160,263 enrollees. Figure 2A presents the spending associated with each percentile of the spending distribution and illustrates the large amount of spending concentrated on the high end of the distribution. As can be seen, for much of the sample spending levels are under $5,000 for these 18 months; however, the highest percentiles exceed $25,000. Figure 2B presents similar information in a different way in order to more easily illustrate what share of all spending can be attributed to what share of enrollees. For example, it suggests that the top 5 percent of enrollees in terms of cost accounted for about 36 percent of all pre-period Medicaid spending, and the top 10 percent accounted for 50 percent. The key take away from these figures is that the actions of a small number of individuals at the top of the health care spending distribution is of critical importance for the financial stability of the three MCOs, even though they are a minor share of all capitated payments. Whether or not these enrollees remain in their auto-assigned plan and which plan they choose if they do opt-out clearly matters for the financial health of each plan.

The next several tables describe, both in terms of bodies and (more importantly) dollars, the distribution across plans in terms of auto-assignment and in terms of final plan choices. Table 2 takes our full sample of 160,263 unique enrollees and divides them in this fashion. Each row represents the enrollee's auto-assigned plan and we see that 22 percent were initially assigned to Wellcare, 39 percent to Coventry, and 39 percent to Spirit. Thus the state auto-assigned the highest shares to the two plans with the lowest capitation rates, as illustrated in Table 1. The columns represent the enrollee's final plan choice. Despite the fact that 39 percent were auto-assigned to Spirit, only 23 percent of the sample was ultimately covered by Spirit. Coventry ended up with 47 percent of the sample, and Wellcare ended up with 30 percent. The individual cells within the table illustrate each combination of auto-assigned and final plan. The diagonals represent those that did not opt-out of their auto-assigned plan and the off-diagonals show us which plan those that opted out ended up selecting. The most striking observations from this table are: first, those auto-assigned to Spirit were much less likely to stay in Spirit (57.3 percent) than those auto-assigned to Wellcare (95.0 percent) or Coventry (94.4 percent), which had a remarkable amount of stability. Second, very few of those opting out of Wellcare (0.5 percent) or Coventry (0.7 percent) actively selected the Spirit plan. We see much higher rates of switching into

[15] See Figure 1 for a map illustrating all 8 regions. We exclude those living in region 3 because, as mentioned, they were all covered by the Passport MCO during 2012 with no other MCO options.

[16] We exclude county movers for several reasons. First, non-movers can arguably better understand the health care networks around them and make more informed comparison across plans, potentially leading to less inertia. Second, one may think that moving is related to other changes in income, family structure, etc., and we would like to hold as many of those factors as constant as possible.

Wellcare and Coventry. To the extent "low-cost" and "low-quality" are interchangeable, one might interpret these results as suggesting that a significant share of Medicaid enrollees recognized that Spirit was a lower quality plan and behaved accordingly (i.e. opting-out if auto-assigned to Spirit or choosing not to move into Spirit upon opting out of Wellcare or Coventry).

Tables 3A and 3B explore this further by presenting similar tabulations for the subset of enrollees that account for the top 50 percent of pre-period spending (i.e. the 16,027 "high-cost" enrollees that comprise 10 percent of Medicaid enrollment) and the remaining "low-cost" enrollees (i.e., the 144,236 who comprise 90 percent of enrollment). These tables suggest that high-cost enrollees are more likely than low-cost enrollees to opt-out of their auto-assigned plan. For example, 58.8 percent of low-cost enrollees auto-assigned to Spirit remained in Spirit, while only 44.2 percent of high-cost enrollees auto-assigned to Spirit remained there. Although this is a relatively small sample, their decision matter greatly for MCO financial sustainability. The pattern we observed of very few enrollees actively opting in to Spirit and more actively opting in to the other plans is also present when we focus on high-cost enrollees. One difference is the active opt in (off-diagonal) probabilities are uniformly higher among the high-cost enrollees. The idea that a greater fraction of high-cost enrollees would move makes sense, since the net benefits of choosing a plan with a good patient-plan specific match is higher for the less healthy. Thus, in the aggregate, both capitation rates and revealed-preference behavior amongst those with the greatest stakes in making an informed choice suggest that Spirit was, on average, lower quality. It should come as no surprise then that low-cost users – the bottom 90 percent – tend to exhibit greater inertia. About 5 percent opt-out of Wellcare or Coventry, and about 40 percent out of Spirit. For those who are relatively healthy, the benefits of searching for a new plan are likely lower.

Table 4 is similar to Table 2, but rather than focusing on counts of enrollees it instead gives counts of the pre-period (January 2010-June 2011) health care spending associated with each enrollee. Our sample of 160,263 enrollees generated $750,249,362 in Medicaid spending between January 2010 and June 2011. A comparison with Table 2 shows that the state auto-assignment shares of enrollees and dollars were pretty similar, with Wellcare, Coventry, and Spirit assigned 22, 39, and 39 percent of the enrollees, respectively, and 21, 40, and 39 percent of the dollars. If we instead look at shares based on final plan enrollment, we see that while the share of enrollees in Spirit fell from 39 to 23 percent, the share of dollars fell from 39 to 20 percent. This suggests negative selection (from the insurer's perspective) out of Spirit into the other plans. Wellcare ended up with 30 percent of the enrollees and 30 percent of the dollars, while Coventry ended up with 47 percent of the enrollees but 50 percent of the dollars. Thus we observe less inertia for dollars than bodies, again consistent with high-cost users in all plans being more mobile, but rarely choosing Spirit as their outcome.

Table 5 presents our descriptive statistics stratified by auto-assigned plan (left panel) and then by enrolled plan (right panel). The first two rows report enrollee counts and shares as in Table 2. The next several rows report the percentage of enrollees that fall within a given range of pre-period (January 2010-June 2011) Medicaid spending. In the right tail of the expense distribution (99^{th}-100^{th} percentile, 95^{th}-99^{th} percentile, 90^{th}-95^{th} percentile), more enrollees were initially assigned to Coventry.[17] Under perfect balancing, we would expect each plan to have 1 percent of enrollees in the 99^{th}-100^{th} percentile, 4 percent of enrollees in the 95^{th}-99^{th} percentile, and so forth. While the state assigned slightly lower shares of high-cost enrollees to Wellcare as compared to Coventry or Spirit (left panel), a larger share

[17] For the 75-90^{th} and the 99-100^{th} percentiles, the difference in assignment rates between Wellcare and Coventry and Wellcare and Spirit were both statistically significant at the 5 percent level. For the 90-95^{th} and the 95-99^{th} percentiles, the difference in assignment rates between each pair of plans was statistically significant at the 5 percent level.

ended up being covered by Wellcare as compared to Spirit (right panel).[18] This echoes what we observed in the previous tables in terms of the movement of dollars across plans.

We next report averages for gender, race, and age. The allocation of females is pretty uniform in terms of auto-assignment and enrollment, with each plan having approximately 52-53 percent female enrollees. In terms of race, the allocation of non-whites via auto-assignment is also very uniform, though it appears as though some non-whites then opted out of Wellcare and Coventry and in to Spirit. In terms of age, we see a relatively younger age profile among those auto-assigned to Wellcare and Coventry as compared to Spirit. The right panel suggests that older enrollees appeared to shift away from Spirit into Wellcare and Coventry and younger enrollees tended to do the opposite.

We see differences in auto-assigned shares of enrollees by eligibility category, with Spirit receiving a higher share of Supplemental Security Income (SSI) recipients (often thought of as high-cost) and a somewhat lower share of Children's Health Insurance Program (CHIP) recipients (often thought of as low-cost). In terms of final plan coverage though, we see that Spirit ended up with the lowest share of SSI recipients. We also see differences in auto-assigned shares of enrollees by region, with Wellcare and Coventry being assigned more enrollees from western Kentucky and fewer enrollees from eastern Kentucky than Spirit. Opt-outs on the part of enrollees led to a very different regional distribution in terms of final coverage though, as Spirit ended up receiving the smallest share of enrollees in eastern Kentucky. Overall, Table 5 suggests that the state tended to auto-assign enrollees with characteristics associated with relatively high medical costs (older, eligible for Medicaid via SSI, and residing in eastern Kentucky) to the Spirit plan more often than the other plans. These enrollees however tended to opt-out of Spirit (and opt in to Wellcare), as Spirit ended up with the lowest shares of individuals in these categories among the three plans in terms of final plan enrollment.

Given the regional differences suggested in Table 5, Table 6 further stratifies the sample by three broad regions of residence (rather than the narrower regions used to set capitation rates). In all three regions, Wellcare's initial share was roughly 22 percent, while Coventry obtained a large share of initial enrollment in the western part of Kentucky and Spirit in the eastern part of Kentucky (and both had equal shares in central Kentucky). In all regions, Wellcare generally started off with the healthiest distribution of assignment. We also see that those assigned to each plan in eastern Kentucky are more likely to fall at the top of the spending distribution as compared with the other two regions. This reinforces the fact that the health of eastern Kentucky residents is worse than those in the rest of the state.

Comparing auto-assignment to enrollment rates in the west and central regions, there was some exit from Spirit – roughly 10 percentage points – and those individuals disproportionately move to Wellcare. Overall, in those two regions, Spirit's distribution of expensive enrollees falls for the most part, Wellcare's increases, and Coventry's remains quite similar to initial assignment. After such movements, again, the health risk distribution of Wellcare and Coventry look quite similar, and more expensive than Spirit's. Table 6 shows much more pronounced responses in eastern Kentucky. This is likely tied to the fact that Spirit had considerably more trouble contracting with eastern Kentucky providers as compared to the other plans and as compared to itself in other parts of the state. Although Spirit started off with

[18] For the 90-95th and the 99-100th percentiles, the difference in final enrollment between Wellcare and Spirit and Coventry and Spirit were both statistically significant at the 1 percent level. For the 75-90th and the 95-99th percentile the differences in final enrollment between each pair of plans was statistically significant at the 5 percent level.

the greatest share of enrollees (consistent with Table 1 where Spirit was reported as having the lowest capitation rate in 17 of the 22 demographic groups in the eastern region), it's total share fell by 26 percentage points. Those who left were somewhat more likely to move to Coventry than Wellcare. As evidenced by the health risk distribution, Spirit appeared to retain a healthier risk pool.

7. Results

Basic Inertia Results and Adverse Selection Results

Table 7 provides the first pass at examining inertia, by estimating equation (1).[19] In the full sample, it is clear that initial assignment matters for enrollment. Assignment to Wellcare increases the likelihood of enrollment in Wellcare by 84 percentage points, assignment in Coventry raises enrollment by 78 percentage points, and assignment in Spirit raises enrollment by 57 percentage points. Note that the first two estimates – for Wellcare and Coventry – are lower than the off-diagonal in Table 2, because of mobility from the other "not Wellcare" or "not Coventry" bins. When one breaks out the results by region, a more nuanced picture emerges. Inertia is not all that much different across plans in the western and central parts of the state (although fewer individuals clearly stay in Spirit). However, in the eastern part of the state, there was less overall inertia, and substantially less inertia in Spirit. Assignment to Spirit raises participation in Spirit by 37 percentage points, much lower than in the west region (62 percentage points) or the central region (74 percentage points). Given the well-known and public difficulties of Spirit in eastern Kentucky, one might surmise that more individuals exerted effort to leave what they viewed as an inferior plan.

Our test for adverse selection is illustrated in Table 8. What we see is that is that "inertia" might be viewed as "rational inattention." Those with the greatest incentive to shop around – the highest expense individuals – stuck far less to initial assignment than healthier individuals. For example, in the full sample, assignment to Wellcare raised participation in Wellcare by 85 percentage points for low-cost individuals, but only by 77 percentage points for high-cost individuals (top 10 percent of expenses). Assignment to Coventry raised participation by 80 percentage points for low-cost individuals, but only by 70 percentage points for high-cost ones. And assignment to Spirit raised participation by 61 percentage points for the healthy, but only 44 percentage points for the unhealthy. The pattern is also monotonic: exits are most pronounced for the top 10 percent of the expense distribution (although very similar within that 10 percent), and are less pronounced but still sizable for the next 15 percent of the spending distribution. Results for the west and central regions largely mirror the full sample. Results in eastern Kentucky follow the same pattern as well, but that panel shows very low inertia for high expense individuals in Spirit. Initial assignment to Spirit is associated with a 41 percentage point increase for healthy individuals, but just a 26 percentage point increase for high-cost ones.

Robustness Checks

The principal concern with both the inertia regressions and adverse selection regressions is the interpretation of the coefficients. Lack of mobility could stem from inertia – as we have defined it – or could indicate a good match between the patient and provider. If lack of mobility represents the former, we could expect that if the state had instead auto-assigned the enrollee to a different plan, they would have largely "stuck" in that plan. However, if immobility stems from good individual matches, auto-assigning the enrollee to a different plan would then lead to significant mobility.

To address this, we first exploit the fact that we have capitation rates for all three plans. Table 9 examines the impact of higher capitation mark-ups on assignment to the three plans. For both Coventry

[19] Results are nearly identical from including a full set of demographic category-region interactions.

and Spirit, higher percentage mark-ups – above the lowest cost plan for a particular demographic-region bin – lead to significantly fewer plan auto-assignments. The effect is large for these two plans; a capitation rate that is 10 percent above the lowest baseline rate leads to a decline in auto-assignment of 6.1 percentage points for Coventry and 4.7 percentage points for Spirit. Conditional on not being the lowest plan, the average Spirit mark-up was 7.9 percent, and the average Coventry mark-up was 8.4 percent. Wellcare was never the lowest cost plan, and the average mark-up was 11.8 percent. However, the effect of Wellcare's mark-up on auto-assignment is both insignificant and much smaller in magnitude, perhaps consistent with notion that the state assigned recipients to that plan for either plan balancing or quality considerations.

From this, we conclude that for individuals assigned to the lowest-cost plan – along with the ample anecdotal evidence from Palmer et al. (2012) – cost considerations rather than quality of the individual match were likely to be the overriding consideration. Next, we re-estimate the baseline inertia regressions and adverse selection regressions, restricting the sample to the 43 percent of individuals (69,099 out of 160,263) who were assigned to a low-cost plan.[20] As such, we estimate such mobility regressions for Coventry and Spirit only and the sample consists people who were initially assigned to one of these two plans; the same covariates are included as before. Identification is achieved because there is variation within capitation category-region bins with respect to whether Coventry or Spirit is the lowest cost plan.[21]

What we observe in the first half of the Table 10 is that assignment to Coventry (relative to "not Coventry" – which is assignment to Spirit instead of assignment to both Spirit and Wellcare) raises participation by 74 percentage points, very similar to the 78 percentage point increase in Table 7. For those auto-assigned to Spirit, participation is increased by 63 percentage points, relative to the baseline estimate of 57 percentage points. Thus, estimates of inertia – where cost-considerations rather than quality-of-match must be the overriding concern – are essentially the same magnitude as for the full sample. Given this similarity in coefficients to the baseline, it is difficult to believe that patient-specific match quality is an important factor in explaining lack of mobility. The second half of the table also re-estimates the adverse selection regressions, conditional on being assigned to the lowest-cost plan. Much like before, we find significant evidence of adverse selection, and again the magnitudes are very similar to the full sample. For Coventry, those in the top 10 percent of health expenses are 9.9 percentage points more mobile than those in the bottom 75 percent. This compares with a 10.1 percentage point estimate in the full sample (Table 8). For Spirit, individuals in the top 10 percent of expenses are 14.9 percentage points more mobile, compared with a baseline estimate of 17.1 percentage points. The similarity again provides reassurance that immobility – and differences in immobility due to adverse selection – are not arising due to good patient-plan match quality.

Next, we perform a second test motivated by Handel (2013). In his analysis of health plan inertia within a large employer, he examines a sample of employees enrolled over several years (t-1 to t+1) in order to model expected costs and choices, meaning he has medical data for the health insurance choice at t=0. Importantly, he notes that new employees do not have medical histories, making it more difficult to model expected expenses. Lack of utilization history – either for employees in an individual firm or for enrollees in Medicaid – makes it far more difficult to match based on expected medical expenses. We

[20] Although it is plausible that cost considerations were the overriding factor in assignment, some individuals may have been assigned to such plans due to patient-plan match. However, we suspect this is far less important this sub-sample than for the full sample.

[21] The plan assigned, by definition, is the lowest cost one in a demographic category-region cell. Therefore, standard errors are corrected for non-nested, two-way clustering by demographic category and region (Cameron, et al. 2011).

therefore examine an entirely new sample of 13,169 individuals who were <u>not</u> enrolled in Medicaid at any time between January 2010 and June 2011. Instead, such individuals signed up for the program between July 2011 and November 2011 (and remain enrolled through March 2012). We can only estimate the baseline inertia regressions, not the adverse selection regressions, due to this restriction on medical histories. However, assignment to plans for these baseline regressions should not be related to the patient-specific quality of match. In addition, we can estimate these regressions for auto-assignment for all three plans. Table 11 presents the results, for the full sample as well as broken out by region. For each plan, as well as region, the patterns are quite similar to the full sample. The coefficients for Wellcare and Coventry are within 4 percentage points for all regions compared to the baseline estimates in Table 7. For example, assignment to Wellcare raises participation by 87 percentage points (versus 84 percentage points in Table 8). The coefficients for Spirit are similar, especially in the west and central regions. Among new enrollees, there is greater immobility from Spirit assignment in eastern Kentucky – with assignment raising participation by 52 percentage points (versus 37 percentage points in Table7).

In summary, it is important to distinguish between lack of mobility due to inertia and quality-of-match. These robustness checks suggest quite strongly that almost all of the immobility is due to inertia. Thus, we proceed forward with policy implications assuming that the estimated coefficients would apply to those who were not auto-assigned to a particular plan.

Policy Implications

Our empirical results above establish several stylized facts. First, the auto-assignment default did lead to inertia in all three plans but the level varied substantially based on overall plan quality. Second, those with the greatest incentive to switch did so – individuals with high health expenses had substantially higher mobility in all three plans. Third, a substantial number of enrollees – 43 percent – were auto-assigned to plans with the lowest of three capitation rates; for this group, where cost-considerations rather than good patient-plan match were very likely the critical consideration in the state's algorithm. We observe nearly identical mobility rates as for the full sample, and nearly identical adverse selection behavior. From this robustness check, we infer that immobility due to good initial patient-plan matches is unlikely to be a major explanation for our results. Thus, in deriving policy implications below, we will assume that the mobility rates based on initial plan assignment can be extrapolated to other Medicaid enrollees who were not assigned to that same plan. For instance, we would assume that had 100 people who had actually been initially assigned to Wellcare (i.e., where the baseline inertia results show 84 additional people would enroll in Wellcare based) instead been assigned to Spirit, then 57 would remain in Spirit.

Given these findings, we conduct a policy simulation that proceeds in several steps. Our conceptual model posited that the state's objective is to minimize costs, subject to (roughly) balancing enrollments across plans. As noted previously, for each of 22 demographic cells and 7 regions (154 cells), we obtained the first-year capitation rates for each of the three plans. As an initial (and unrealistic) benchmark, we ask: *What would monthly capitation payments from the state to MCOs have been if the state simply assigned each enrollee to the <u>lowest capitation plan</u>, and enrollees were prohibited from switching plans?* Table 1 showed that such a cost-minimization strategy involves assigning individuals to only Spirit and Coventry, not Wellcare. In the aggregate Figure 3 shows such a strategy for our sample of 160,263 individuals results in $53.2 million in monthly capitation payments. Assuming that capitation rates for each of the 154 demographic-region cells are perfect proxies for the overall quality of each plan (for that particular cell), we could also ask: *What would monthly capitation payments from the state to MCOs have been if the state assigned each enrollee to the <u>highest quality plan</u>, and enrollees were again* *prohibited from switching plans?* That is, the highest capitation rate plan reflects the highest quality or most comprehensive plan. If all individuals in our sample were assigned to the highest quality plan (and prohibited from moving), monthly capitation payments would be $59.8 million.

Those two endpoints, of course, are unrealistic because individuals were able to switch plans, and such capitation payments could only be achieved with complete inertia. We therefore ask two parallel questions: *With observed mobility rates and transitions across plans, what would be the aggregate state capitation payment if the state initially assigned each individual to the <u>lowest cost plan</u> or the <u>highest quality (highest cost) plan</u>?* For each of the 154 demographic-region cells, we assume that the observed mobility rates based on initial assignment generalize to all individuals in that cell; this assumption is supported by the robustness checks.[22] If we assume the state pursues a cost-minimization strategy – thus assigning all individuals to only Spirit or Coventry depending on the capitation rates in the 154 cells – and that the enrollees then stay in that plan or move to one of the other two plans based on observed behavior for those who were actually assigned to that low-cost plan, total capitation payments would be $55.3 million. Although the state controls initial assignment, the estimated coefficients in Table 7 show a great deal of movement out of Spirit, which was often the low-cost plan. If the state pursued a "quality maximization" strategy by assigning individuals to the high-cost plan, total monthly capitation payments would be $59.6 million, very close to $59.8 million where mobility was prohibited. This is unsurprising, since the level of inertia reported in Table 7 (especially for Wellcare) was quite high, and Wellcare was often the high-cost plan. If quality-maximization had been the goal, one would observe very little movement of enrollees (presumably because only a small fraction of enrollees would have had a better patient-plan match to pursue).

Given these theoretical extremes based on hypothetical state auto-assignment strategies, our next question is: *Relative to the $55.3 million and $59.6 million endpoints, what were the monthly capitation payments from the state to the MCOs based on the state's <u>actual assignment algorithm</u> and the <u>observed mobility</u> of enrollees?* The state initially allocated 22 percent of individuals to Wellcare, and 39 percent of individuals each to Coventry and Spirit. Capitation payments based on this initial assignment would have resulted in $56.0 million in expenditure per month. After allowing for the actual switching observed during open enrollment, which typically resulted in enrollees moving to higher quality (higher capitation) rate plans, expenditure was $56.9 million.

Thus, the state's actual behavior appears to be much closer to a cost-minimization strategy than a quality-maximization strategy. Had the state assigned all individuals to the lowest cost plan, and then individuals moved according to the actual mobility patterns for those in the low-cost plans, Wellcare would have ended up with roughly 13 percent of enrollees, Coventry with 51 percent, and Spirit with the remaining 36 percent. Such an allocation would have undermined the state's "plan balancing" objective, which suggests steps were taken to auto-assign more individuals in Wellcare and fewer in Coventry to achieve this balance. Taking into consideration the desire to better balance enrollments (which raises capitation payments by increasing Wellcare's auto-assigned share), it appears that the state's actual objective was to minimize costs.

The above analysis focuses on the state's perspective. Yet Table 8 demonstrated substantial adverse selection: high-cost individuals were far more mobile than low-cost individuals. From the MCO's perspective, movement of unprofitable enrollees out of their plan (capitation rate minus expected cost) raises profits, as does retaining (or attracting) profitable ones. To the extent that there were differential movements of unprofitable enrollees, then some plans would likely experience losses. MCOs may have

[22] Transition rates for each of the 154 demographic-region cells are also computed by white/non-white.

tried to cherry-pick profitable enrollees away from other plans. In the Kentucky context, some providers enticed enrollees to join their plan by offering such incentives as free diapers and free strollers (Palmer, et al., 2012).[23] The impact of the actual capitation rates and medical expenses, combined with the demonstrated adverse selection, allows for an analysis of profitability. One important caveat should be kept in mind: the three plans – depending on the region – offered very different access to care, potentially creating differing amounts of subsequent utilization apart from underlying health status. Thus, we do not use actual expenditure of enrollees in the first plan year, but the pre-determined average monthly expenditure of each enrollee between January 2010 and June 2011. Table 12 examines MCO profitability under two scenarios: first, under the actual initial auto-assignment of enrollees to plans by the state, and second, after open enrollment was completed. As mentioned, total capitation payments would have been $56.0 million based on initial assignment and $56.9 million after observed enrollee movement across plans. The table shows that the allocation of payments across three plans changed dramatically between initial assignment and the end of open enrollment, due to enrollee mobility and differing capitation rates received by each plan. Both Wellcare's and Coventry's share of payments rose by about 10 percentage points, while Spirit's share fell by about 20 percentage points.

Based on the average monthly costs between January 2010 and June 2011, aggregate expected MCO expenditures would be $41.7 million, and therefore lead to very high profit margins for all plans. It is important to note that capitation rates would include not only the continuously enrolled individuals, but the expected costs of more recently enrolled ones. It would also include administrative costs estimated to be between 8 to 11 percent (Palmer et al., 2012), rising prices due to health care inflation, and expected savings due to the switch from FFS to managed care. We scale-up this cost measure by a factor of 1.34 ($56.0 million in capitation payments divided by $41.7 million in medical expense) under the assumption that the capitation rates computed in the aggregate will be actuarially fair. After this adjustment to costs, the profit margin implied by auto-assignment was +11 percent for Wellcare, -6 percent for Coventry, and +1 percent for Spirit. The impact of adverse selection from open enrollment is noticeable. After open enrollment, profit margins were +5 percent for Wellcare, -3 percent for Coventry, and +7 percent for Spirit.[24] This is a result of many more high-risk patients leaving Spirit, raising its overall profit margin, and migrating to Wellcare. Coventry continued to lose money, although its loss margin narrowed. The analysis lends credence to Coventry's claim that its losses were attributable to its sicker membership (Palmer et al., 2012).

The calculations therefore demonstrate the importance of adverse selection – even in the presence of inertia – in changing profit margins – payments and quality varied by plan, and higher risks within the 154 capitation-region cells tended to respond more to quality. Thus, the competing goals of preserving competition and plan choice, along with the strong incentives for Medicaid enrollees to opt into expensive plans, creates losses (or narrows profit margins) for some MCOs. Interestingly, although Coventry lost money, the migration of adversely selected individuals did not contribute to those losses. Rather, the sizable profit margins for WellCare were narrowed due to adverse selection, while margins for Spirit increased due to exits of unhealthy individuals. To the extent that these kinds of patterns persist over time, one can imagine that some plans would be unsustainable.

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[23] In a different context, Duggan (2000) showed that in response to change in financial incentives from Medicaid's "Disproportionate Share Hospital" program, private hospitals cream-skimmed newly profitable Medicaid patients, but did not recruit or attract the far-less-profitable uninsured patients.

[24] Palmer et al. (2012) compute medical loss ratios (MLR), which obviously are different than using lagged costs, but the ordering is the same as here. WellCare and Spirit essentially broke even in 2012:Q1, while Coventry had considerable losses. Spirit's MLR was 104.3 percent, Wellcare's was 103.9 percent and Coventry's was 120.7 percent.

8. Conclusions

In this paper we examine the impact of auto-assignment, adverse selection, and health plan inertia on the functioning of the Medicaid managed care market in Kentucky. We find compelling evidence that the state's auto-assignment algorithm most heavily weighted on cost and plan balancing, and placed relatively little weight on the quality of the enrollee-plan match. The presence of inertia contributed to the success of the state's cost-minimization strategy, as more than half of enrollees auto-assigned to even the lowest quality plans (Spirit) did not opt out. We also observe a considerable degree of adverse selection which was exacerbated by lower levels of inertia among high cost enrollees. High cost enrollees were much more likely to opt out of their auto-assigned plan. Our simulations suggest that the highest quality plan (Wellcare) incurred the largest profit margin reduction due to adverse selection, as it attracted a number of high cost enrollees during open enrollment. The presence of such selection, and the extent to which it is exacerbated by differential degrees of inertia, raises concerns about the long run viability of the Medicaid managed care market in this context.

The fact that the state "nudged" enrollees into lower reimbursement rate plans through the auto-assignment process stands in contrast to much of the behavioral economics literature on this topic.[25] In most cases, the focus is on "smart defaults" or nudging individuals toward beneficial outcomes, such as retirement plan participation or health insurance policies providing the most appropriate level of coverage and / or cost sharing for that individual. To the extent to which lower capitation rates were associated with lower quality, the state was actually "nudging" enrollees towards lower quality plans.

Another point of contrast between our work and others is that we tend to see less inertia in our setting of Medicaid managed care plan choice than is observed in other settings. Even in the most extreme example – the poorly functioning Spirit MCO in eastern Kentucky, which did not have a contract with the dominant health care provider group – 25 out of 100 high-cost users auto-assigned to Spirit still elected not to opt out. In our view, large or small, what we ultimately care about is relating initial assignment – and the stickiness of it – with longer-term health outcomes. We view initial assignment and longer-run enrollment as mostly affecting access for an individual through provider networks, which is unquantified in this paper other than indirectly through regional variation. To the extent that cost savings alone dictates the state's auto-assignment choices, Table 1 shows there are clear regression discontinuities to exploit in future work. For example, a 24-year-old male in region 1 would have been more likely to have been assigned to the lowest-cost Spirit plan, while a 25-year-old male in that same region would have been more likely to have been assigned to Coventry. Such initial assignment would tend to "stick", along with the "bundle" of plan characteristics that go along with each MCO, principally access to care and provider networks.

One of the key themes of this paper is whether auto-assignment, and the inertia arising from those default plan choices, can overcome the adverse selection problem. Although the state clearly saves money in capitation payments due to auto-assignment to low-cost plans, this does not address the financial concerns of the MCOs. Our empirical estimates suggest far greater levels of inertia among low-cost individuals. The fact that cost sharing is near zero for all plans from the enrollee's perspective suggests that enrollees should migrate to the highest quality plan. And even though there are some

[25] Thaler and Sunstein (2008) do provide some discussion of bad nudges.

differences in patient-specific match quality, this would for the most part suggest movement toward one plan (in the Kentucky context, Wellcare). The fact that high-cost enrollees tended to exit the lower quality plans to a far greater extent than low-cost enrollees suggests that the adverse selection problem was exacerbated. This is illustrated by examining the change in profit margins between auto-assignment and eventual enrollment. Profit margins decreased for the high-quality plan, and increased for the lower-quality plans. Ultimately, policymakers face an important tradeoff, given that they must offer choice across MCOs: inertia can save the state government money in the short run, but looks to affect the long-run viability of the most generous MCOs.

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Figure 1. Map of Kentucky Medicaid Regions

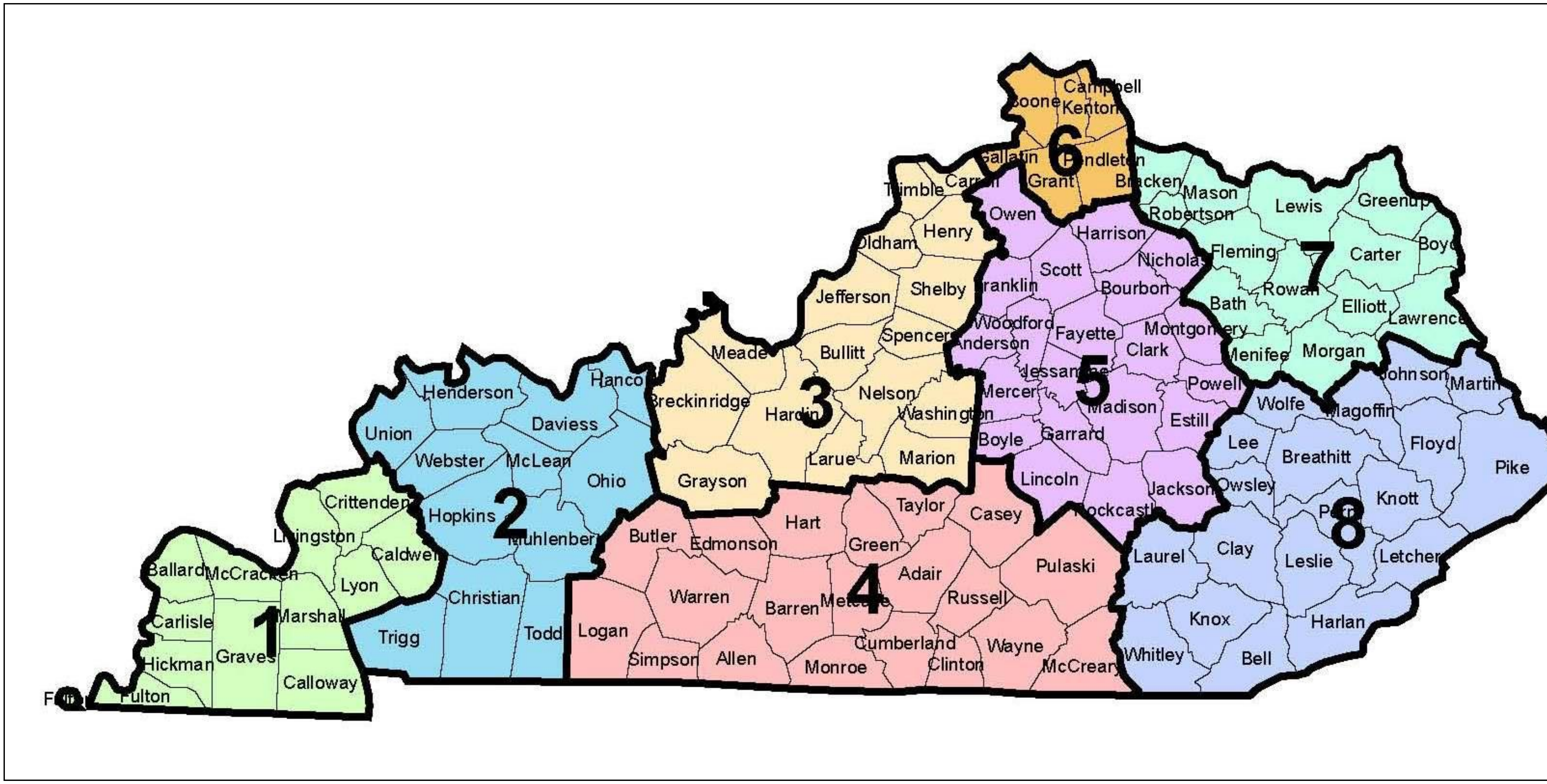
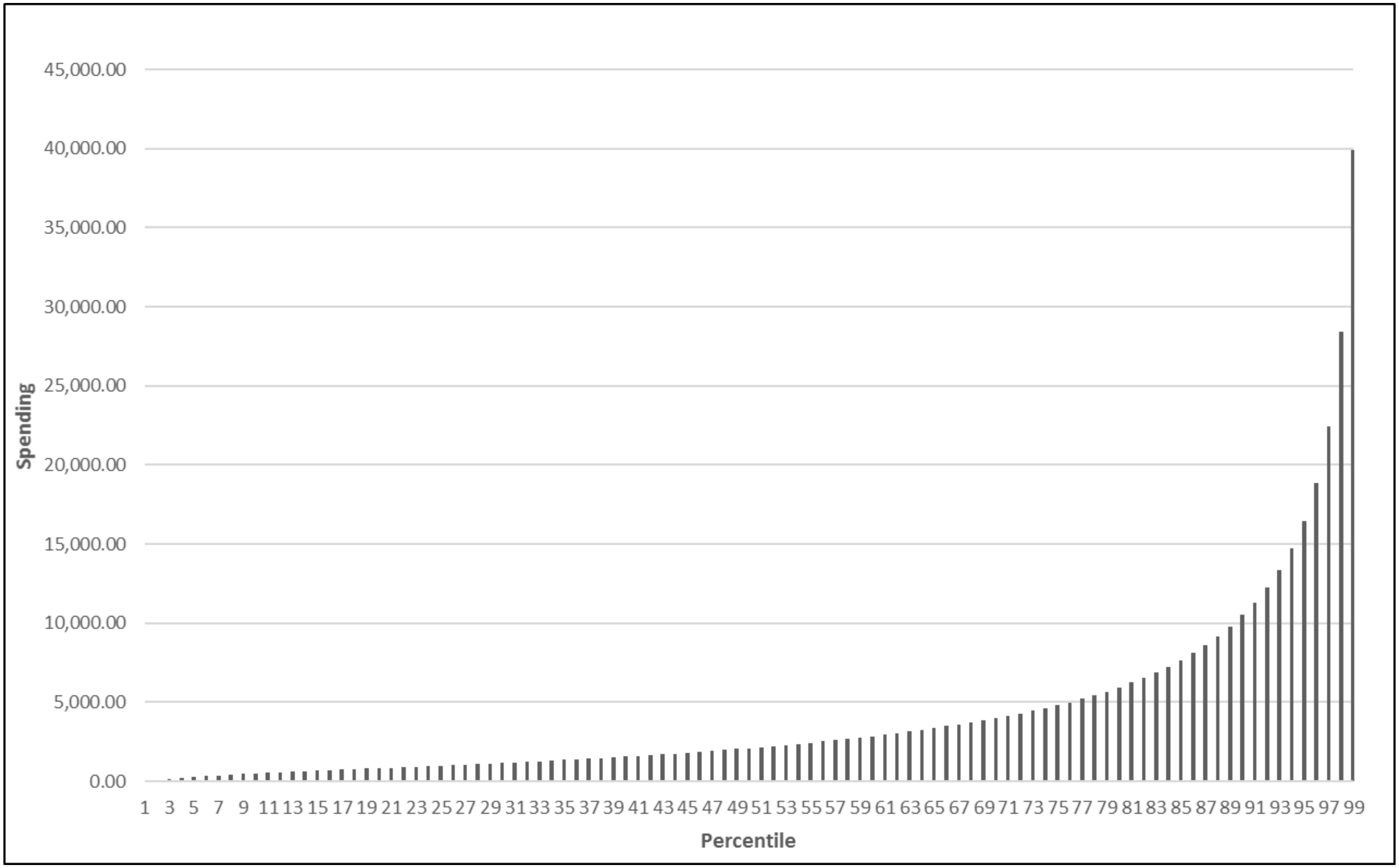
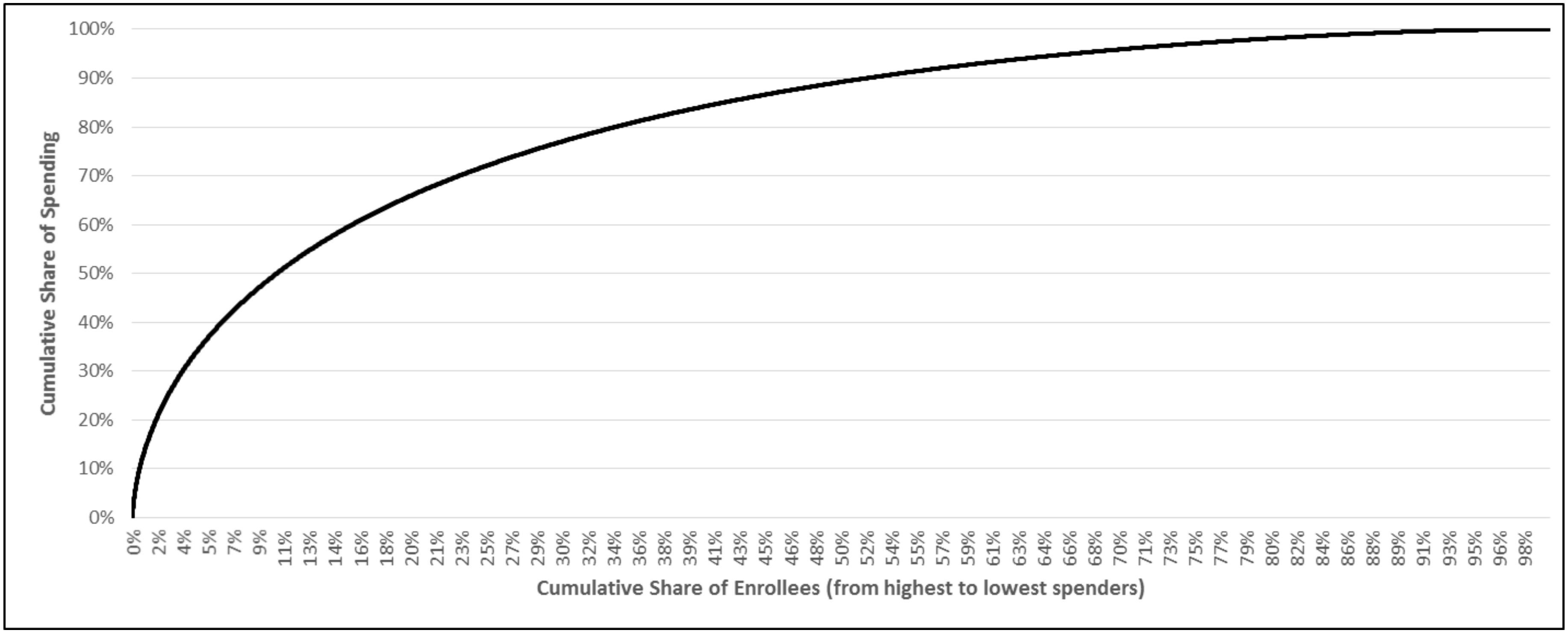


Figure 2A: Pre-Period (Jan 2010-June 2011) Spending Percentiles 1-99



Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.
Notes: The 100th spending percentile is omitted because it is so large ($1,191,661) that it throws off the scaling of the figure.

Figure 2B: Pre-Period (Jan 2010-June 2011) Spending Curve



Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.
Notes: This suggests that a very small percentage of enrollees in our sample account for a very large percentage of pre-period (January 2010-June 2011) spending. For example, the top 5 percent of spenders accounted for about 36 percent of total pre-period spending.

Figure 3: Monthly Cost of Simulated State Auto-Assignment Choices

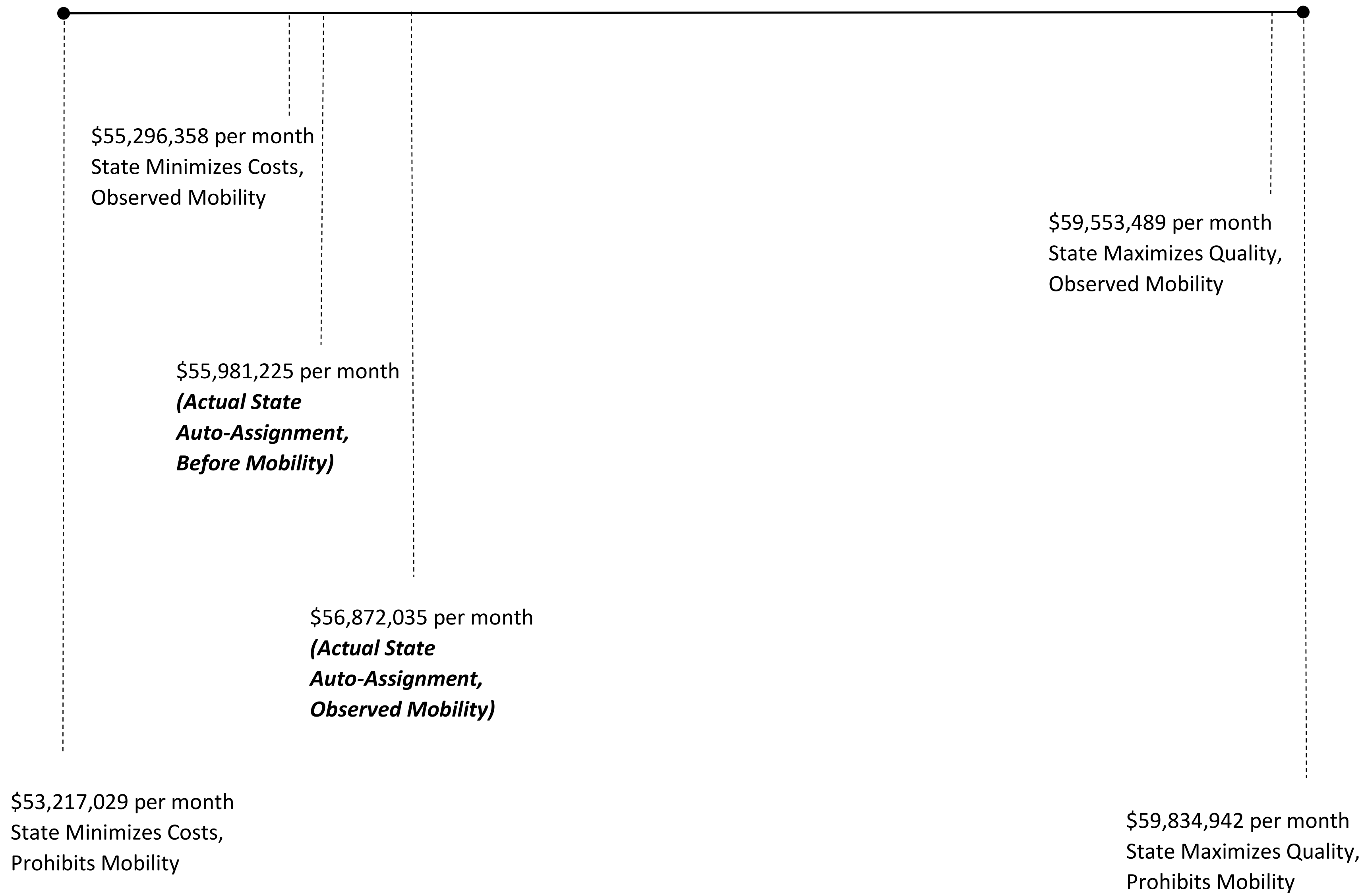


Table 1: Lowest Capitation Plan by Region and Capitation Category

Capitation Category		Region						
Group	**Age**	**1 – west**	**2 – west**	**4 - central**	**5 - central**	**6 - central**	**7 - east**	**8 - east**
Families and Children	Child (age 1 through 5)	SPIRIT	SPIRIT	SPIRIT	COVENTRY	SPIRIT	COVENTRY	COVENTRY
Families and Children	Child (age 6 through 12)	SPIRIT	COVENTRY	COVENTRY	SPIRIT	SPIRIT	SPIRIT	COVENTRY
Families and Children	Child (age 13 through 18) - Female	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT
Families and Children	Child (age 13 through 18) - Male	COVENTRY	COVENTRY	COVENTRY	COVENTRY	SPIRIT	SPIRIT	SPIRIT
Families and Children	Adult (age 19 through 24) - Female	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT
Families and Children	Adult (age 19 through 24) - Male	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT
Families and Children	Adult (age 25 through 39) - Female	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT
Families and Children	Adult (age 25 through 39) - Male	COVENTRY	SPIRIT	SPIRIT	SPIRIT	COVENTRY	SPIRIT	SPIRIT
Families and Children	Adult (age 40 or older) - Female	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT
Families and Children	Adult (age 40 or older) - Male	COVENTRY	COVENTRY	SPIRIT	COVENTRY	COVENTRY	SPIRIT	SPIRIT
SSI Adults without Medicare	Adult (age 19 through 24) - Female	COVENTRY	COVENTRY	COVENTRY	SPIRIT	SPIRIT	COVENTRY	SPIRIT
SSI Adults without Medicare	Adult (age 19 through 24) - Male	COVENTRY	SPIRIT	SPIRIT	COVENTRY	COVENTRY	COVENTRY	SPIRIT
SSI Adults without Medicare	Adult (age 25 through 44) - Female	COVENTRY	SPIRIT	COVENTRY	SPIRIT	SPIRIT	COVENTRY	SPIRIT
SSI Adults without Medicare	Adult (age 25 through 44) - Male	SPIRIT	SPIRIT	SPIRIT	COVENTRY	COVENTRY	SPIRIT	SPIRIT
SSI Adults without Medicare	Adult (age 45 or older) - Female	SPIRIT	COVENTRY	SPIRIT	SPIRIT	SPIRIT	SPIRIT	SPIRIT
SSI Adults without Medicare	Adult (age 45 or older) - Male	SPIRIT	COVENTRY	SPIRIT	SPIRIT	COVENTRY	SPIRIT	SPIRIT
SSI Children	Child (age 1 through 5)	SPIRIT	SPIRIT	SPIRIT	COVENTRY	COVENTRY	SPIRIT	COVENTRY
SSI Children	Child (age 6 through 18)	COVENTRY	COVENTRY	COVENTRY	SPIRIT	SPIRIT	SPIRIT	SPIRIT
Foster Care	Child (age 1 through 5)	SPIRIT	SPIRIT	SPIRIT	COVENTRY	COVENTRY	COVENTRY	COVENTRY
Foster Care	Child (age 6 through 12)	SPIRIT	COVENTRY	COVENTRY	SPIRIT	SPIRIT	SPIRIT	SPIRIT
Foster Care	Child (age 13 through older) - Female	SPIRIT	SPIRIT	COVENTRY	COVENTRY	COVENTRY	SPIRIT	COVENTRY
Foster Care	Child (age 13 through older) - Male	COVENTRY	COVENTRY	SPIRIT	SPIRIT	COVENTRY	SPIRIT	SPIRIT
	unweighted count spirit (out of 22)	*14*	*13*	*15*	*14*	*13*	*17*	*17*

Source: Palmer, Howell, Costich, and Kenney (2012), Appendix B.

Table 2: Plan Assignments and Choices by Enrollee

	enrolled Wellcare	enrolled Coventry	enrolled Spirit		
assigned Wellcare	**33,939**	1,618	172	35,729	*22%*
	95.0%	*4.5%*	*0.5%*		
assigned Coventry	3,056	**58,658**	416	62,130	*39%*
	4.9%	***94.4%***	*0.7%*		
assigned Spirit	11,047	15,576	**35,781**	62,404	*39%*
	17.7%	*25.0%*	***57.3%***		
	48,042	75,852	36,369	160,263	
	30%	*47%*	*23%*		

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.
Notes: Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "enrolled plan" refers to the plan the enrollee ended up being covered under. Thus if an enrollee remained in their assigned plan it would also be their enrolled plan. If an enrollee opted out of their assigned plan and switched to one of the others then they would be different. The percentages within each cell refer to the percent of the enrollees assigned to a given plan then enroll in each of the three plans. For example, 95 percent of those assigned to Wellcare enrolled in Wellcare, 4.5 percent of those assigned to Wellcare enrolled in Coventry, and .05 percent of those assigned to Wellcare enrolled in Spirit.

Table 3A: Plan Assignments and Choices by High Cost Enrollees

	enrolled Wellcare	enrolled Coventry	enrolled Spirit		
assigned Wellcare	3,007	*212*	22	3,241	*20%*
	92.8%	*6.5%*	*0.7%*		
assigned Coventry	475	*6,071*	63	6,609	*41%*
	7.2%	***91.9%***	*1.0%*		
assigned Spirit	1,531	*1,915*	2,731	6,177	*39%*
	24.8%	*31.0%*	***44.2%***		
	5,013	8,198	2,816	16,027	
	31%	*51%*	*18%*		

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.
Notes: Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "enrolled plan" refers to the plan the enrollee ended up being covered under. Thus if an enrollee remained in their assigned plan it would also be their enrolled plan. If an enrollee opted out of their assigned plan and switched to one of the others then they would be different. By high cost enrollees we mean those that are in the top 10 percent of spending in the pre-period (January 2010-June 2011). The percentages within each cell refer to the percent of the enrollees assigned to a given plan then enroll in each of the three plans. For example, 92.8 percent of the high cost enrollees assigned to Wellcare enrolled in Wellcare, 6.5 percent of them assigned to Wellcare enrolled in Coventry, and .07 percent of them assigned to Wellcare enrolled in Spirit.

Table 3B: Plan Assignments and Choices by Low Cost Enrollees

	enrolled Wellcare	enrolled Coventry	enrolled Spirit		
assigned Wellcare	30,932	1,406	150	32,488	*23%*
	95.2%	*4.3%*	*0.5%*		
assigned Coventry	2,581	52,587	353	55,521	*38%*
	4.6%	***94.7%***	*0.6%*		
assigned Spirit	9,516	13,661	33,050	56,227	*39%*
	16.9%	*24.3%*	***58.8%***		
	43,029	67,654	33,553	144,236	
	30%	*47%*	*23%*		

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.
Notes: Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "enrolled plan" refers to the plan the enrollee ended up being covered under. Thus if an enrollee remained in their assigned plan it would also be their enrolled plan. If an enrollee opted out of their assigned plan and switched to one of the others then they would be different. By non-high cost enrollees we mean those that are in the bottom 90 percent of spending in the pre-period (January 2010-June 2011). The percentages within each cell refer to the percent of the enrollees assigned to a given plan then enroll in each of the three plans. For example, 95.2 percent of the non-high cost enrollees assigned to Wellcare enrolled in Wellcare, 4.3 percent of them assigned to Wellcare enrolled in Coventry, and .05 percent of them assigned to Wellcare enrolled in Spirit.

Table 4: Plan Assignments and Choices by Pre-Period (January 2010-June 2011) Spending

	enrolled Wellcare	enrolled Coventry	enrolled Spirit		
assigned Wellcare	**$145.8m**	$8.8m	$943.4m	$155.5m	*21%*
	93.8%	*5.6%*	*0.6%*		
assigned Coventry	$18.9m	**$279.8**	$3.4m	$302.2m	*40%*
	6.2%	***92.6%***	*1.1%*		
assigned Spirit	$63.6m	$84.9	**$144.1m**	$292.6m	*39%*
	21.7%	*29.0%*	***49.2%***		
	$228.3m	$373.5m	$148.5m	$750.2m	
	30%	*50%*	*20%*		

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.
Notes: Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "enrolled plan" refers to the plan the enrollee ended up being covered under. Thus if an enrollee remained in their assigned plan it would also be their enrolled plan. If an enrollee opted out of their assigned plan and switched to one of the others then they would be different. The percentages within each cell refer to the percent of aggregate pre-period (January 2010-June 2011) spending associated with all enrollees assigned to a given plan then enroll in each of the three plans. For example, the pre-period spending of all enrollees assigned to Wellcare that remained with Wellcare represents 93.8 percent of the aggregate pre-period spending associated with all enrollees assigned to Wellcare, the pre-period spending of all enrollees assigned to Wellcare that switched to Coventry represents 5.6 percent of the aggregate pre-period spending associated with all enrollees assigned to Wellcare, and the pre-period spending of all enrollees assigned to Wellcare that switched to Spirit represents 0.6 percent of the aggregate pre-period spending associated with all enrollees assigned to Wellcare.

Table 5: Descriptive Statistics by Plan Assignment and Plan Enrollment

	auto-assigned plan			*enrolled plan*		
	assigned Wellcare	**assigned Coventry**	**assigned Spirit**	**enrolled Wellcare**	**enrolled Coventry**	**enrolled Spirit**
# enrollees	35,729	62,130	62,404	48,042	75,852	36,369
% enrollees	22%	39%	39%	30%	47%	23%
% 99-100th percentile	0.85%	1.08%	1.01%	1.02%	1.07%	0.84%
% 95-99th percentile	3.56%	4.31%	3.94%	4.15%	4.38%	3.02%
% 90-95th percentile	4.66%	5.25%	4.95%	5.27%	5.36%	3.89%
% 75-90th percentile	14.46%	15.11%	15.19%	15.31%	15.73%	13.06%
% female	52.48%	53.28%	53.26%	53.16%	53.51%	52.13%
% nonwhite	8.21%	9.07%	8.54%	7.67%	7.99%	11.40%
% age 18 and under	71.74%	71.94%	67.77%	69.69%	69.46%	72.74%
% age 19-29	5.21%	5.22%	5.20%	5.22%	5.31%	5.00%
% age 30-39	6.73%	6.80%	7.24%	6.99%	7.26%	6.28%
% age 40-49	7.39%	7.56%	8.81%	8.13%	8.36%	7.11%
% age 50-59	7.24%	6.83%	8.86%	8.12%	7.71%	7.18%
% age 60-64	1.69%	1.65%	2.12%	1.85%	1.91%	1.70%
% region west	15.04%	17.64%	12.76%	17.46%	14.03%	14.48%
% region central	44.22%	45.42%	45.20%	38.72%	42.65%	58.48%
% region east	40.74%	36.95%	42.04%	43.83%	43.32%	27.03%
% eligibility KCHIP	14.23%	13.49%	12.82%	13.55%	12.92%	14.19%
% eligibility AFDC	26.66%	26.95%	26.12%	27.07%	27.55%	23.83%
% eligiblity SOBRA	34.25%	34.83%	32.02%	32.76%	32.75%	36.53%
% eligibility FOSTER	2.09%	2.47%	2.21%	2.06%	2.31%	2.54%
% eligibility SSI	22.77%	22.25%	26.83%	24.55%	24.48%	22.92%

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.

Notes: Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "enrolled plan" refers to the plan the enrollee ended up being covered under. Thus if an enrollee remained in their assigned plan it would also be their enrolled plan. If an enrollee opted out of their assigned plan and switched to one of the others then they would be different.

Table 6: Descriptive Statistics by Plan Assignment and Plan Enrollment - Stratified by Region

	west			*central*			*east*		
	assigned Wellcare	**assigned Coventry**	**assigned Spirit**	**assigned Wellcare**	**assigned Coventry**	**assigned Spirit**	**assigned Wellcare**	**assigned Coventry**	**assigned Spirit**
# enrollees	5,374	10,958	7,963	15,799	28,218	28,206	14,556	22,954	26,235
% enrollees	22%	45%	33%	22%	39%	39%	23%	36%	41%
% 99-100th percentile	0.63%	0.86%	0.90%	0.78%	0.95%	0.89%	1.00%	1.34%	1.17%
% 95-99th percentile	2.88%	3.12%	3.20%	3.54%	3.96%	3.68%	3.83%	5.32%	4.44%
% 90-95th percentile	3.13%	3.93%	3.65%	4.29%	4.49%	4.34%	5.63%	6.80%	6.00%
% 75-90th percentile	11.54%	11.49%	11.70%	13.15%	13.51%	13.68%	16.96%	18.82%	17.88%

	west			*central*			*east*		
	enrolled Wellcare	**enrolled Coventry**	**enrolled Spirit**	**enrolled Wellcare**	**enrolled Coventry**	**enrolled Spirit**	**enrolled Wellcare**	**enrolled Coventry**	**enrolled Spirit**
# enrollees	8,386	10,641	5,268	18,601	32,352	21,270	21,055	32,859	9,831
% enrollees	35%	44%	22%	26%	45%	29%	33%	52%	15%
% 99-100th percentile	0.85%	0.81%	0.82%	0.90%	0.90%	0.87%	1.19%	1.32%	0.76%
% 95-99th percentile	3.29%	3.20%	2.56%	3.87%	4.07%	3.18%	4.74%	5.05%	2.92%
% 90-95th percentile	3.71%	3.77%	3.38%	4.60%	4.65%	3.80%	6.47%	6.58%	4.34%
% 75-90th percentile	12.09%	11.57%	10.74%	13.37%	13.97%	12.90%	18.30%	18.82%	14.67%

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.
Notes: Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "enrolled plan" refers to the plan the enrollee ended up being covered under. Thus if an enrollee remained in their assigned plan it would also be their enrolled plan. If an enrollee opted out of their assigned plan and switched to one of the others then they would be different. It should also be noted the Louisville region of Kentucky is not included in this table because it is excluded from our analysis due to a lack of Medicaid plan choices.

Table 7: Baseline Inertia Regression Results

	all regions			West only			Central only			East only		
	Wellcare Assigned, Wellcare Enrolled	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*	*Wellcare Assigned, Wellcare Enrolled*	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*	*Wellcare Assigned, Wellcare Enrolled*	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*	*Wellcare Assigned, Wellcare Enrolled*	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*
Assigned												
Beta	0.836	0.776	0.572	0.766	0.768	0.616	0.898	0.858	0.741	0.794	0.681	0.368
s.e	0.001	0.001	0.002	0.004	0.004	0.006	0.002	0.002	0.003	0.003	0.003	0.003
sample size	*160,263*	*160,263*	*160,263*	*24,295*	*24,295*	*24,295*	*72,223*	*72,223*	*72,223*	*63,745*	*63,745*	*63,745*

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.

Notes: Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "enrolled plan" refers to the plan the enrollee ended up being covered under. Each of these regression coefficients is statistically significant at the 1 percent level, so p-values are not reported in the table.

Table 8: Baseline Adverse Selection Regressions

	all regions			West only			Central only			East only		
	Wellcare Assigned, Wellcare Enrolled	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*	*Wellcare Assigned, Wellcare Enrolled*	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*	*Wellcare Assigned, Wellcare Enrolled*	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*	*Wellcare Assigned, Wellcare Enrolled*	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*
assigned * top 90 percentile spending												
beta	-0.078	-0.101	-0.171	-0.079	-0.095	-0.124	-0.057	-0.077	-0.121	-0.092	-0.090	-0.158
s.e	0.006	0.006	0.006	0.018	0.018	0.021	0.008	0.007	0.010	0.009	0.009	0.009
assigned * 75th percentile spending												
beta	-0.046	-0.072	-0.121	-0.063	-0.061	-0.080	-0.028	-0.049	-0.067	-0.050	-0.063	-0.109
s.e	0.004	0.005	0.005	0.015	0.014	0.018	0.006	0.006	0.008	0.007	0.007	0.008
assigned												
beta	0.851	0.797	0.607	0.779	0.783	0.635	0.907	0.872	0.761	0.813	0.704	0.405
s.e	0.002	0.002	0.002	0.005	0.005	0.006	0.002	0.002	0.003	0.003	0.003	0.004
sample size	*160,263*	*160,263*	*160,263*	*24,295*	*24,295*	*24,295*	*72,223*	*72,223*	*72,223*	*63,745*	*63,745*	*63,745*

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.

Notes: Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "enrolled plan" refers to the plan the enrollee ended up being covered under. Each of these regression coefficients is statistically significant at the 1 percent level, so p-values are not reported in the table.

Table 9: Determinants of Plan Auto-Assignment

	full sample		
	Wellcare Assigned	*Coventry Assigned*	*Spirit Assigned*
mark up			
beta	-0.029	-0.608	-0.466
s.e	0.054	0.070	0.140
p-value	0.594	0.000	0.001
sample size	*160,263*	*160,263*	*160,263*

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.
Notes: Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "mark up" refers to the percentage an enrollee's auto-assigned plan capitation rate is above the lowest capitation rate among the three plans in that enrollee's capitation category-region. Standard errors are corrected for non-nested, two-way clustering by demographic category and region.

Table 10: Cost Saving sub-sample

	Wellcare Assigned, Wellcare Enrolled	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*	*Wellcare Assigned, Wellcare Enrolled*	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*
assigned						
beta	N/A	0.738	0.627		0.753	0.651
s.e		0.035	0.058		0.036	0.056
assigned * top 90 percentile spending						
beta				N/A	-0.099	-0.149
s.e					0.023	0.024
assigned * 75th percentile spending						
beta					-0.059	-0.107
s.e					0.008	0.021
sample size	*69,099*	*69,099*	*69,099*	*69,099*	*69,099*	*69,099*

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.
Notes: The "Cost Savings sub-sample" are those whose auto-assigned plan had the lowest capitation rate of all three plans in their capitation category x region. Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "enrolled plan" refers to the plan the enrollee ended up being covered under. Each of these regression coefficients is statistically significant at the 1 percent level, so p-values are not reported in the table. Standard errors are corrected for non-nested, two-way clustering by demographic category and region.

Table 11 – New Enrollee (No Cost History) sample

	all regions			West only			Central only			East only		
	Wellcare Assigned, Wellcare Enrolled	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*	*Wellcare Assigned, Wellcare Enrolled*	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*	*Wellcare Assigned, Wellcare Enrolled*	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*	*Wellcare Assigned, Wellcare Enrolled*	*Coventry Assigned, Coventry Enrolled*	*Spirit Assigned, Spirit Enrolled*
assigned												
beta	0.868	0.808	0.701	0.799	0.783	0.667	0.920	0.860	0.808	0.806	0.721	0.515
s.e	0.006	0.005	0.005	0.015	0.015	0.013	0.006	0.006	0.007	0.012	0.011	0.012
sample size	*13,169*	*13,169*	*13,169*	*2,634*	*2,634*	*2,634*	*6,921*	*6,921*	*6,921*	*3,614*	*3,614*	*3,614*

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Services.

Notes: This New Enrollee (No Cost History) sample consists of those who where not enrolled in Medicaid between January 2010 and June 2011, so had no pre-managed care cost history to inform their auto-assignment. Here "assigned plan" refers to the plan that an enrollee was auto-assigned to by the state and "enrolled plan" refers to the plan the enrollee ended up being covered under. Each of these regression coefficients is statistically significant at the 1 percent level, so p-values are not reported in the table.

Table 12: Impact of Adverse Selection on MCO Profitability Simulations

	Initial Assignment		After Open Enrollment	
	Dollars	*Profit Margin*	*Dollars*	*Profit Margin*
Total Capitation Payments	**$55,981,225**		**$56,872,035**	
Wellcare Capitation Payments	$12,784,105		$17,854,347	
Coventry Capitation Payments	$21,197,077		$27,125,786	
Spirit Capitation Payments	$22,000,042		$11,891,902	
Avg. 18-month Pre-Period Cost	**$41,680,520**		**$41,680,520**	
Wellcare Costs	$8,636,483	*48%*	$12,680,575	*41%*
Coventry Costs	$16,786,162	*26%*	$20,751,391	*31%*
Spirit Costs	$16,257,876	*35%*	$8,248,554	*44%*
Cost Factor Adjustment	**1.34**		**1.34**	
Wellcare Adjusted Costs	$11,599,684	*10%*	$17,031,316	*5%*
Coventry Adjusted Costs	$22,545,542	*-6%*	$27,871,252	*-3%*
Spirit Adjusted Costs	$21,836,000	*1%*	$11,078,657	*7%*

Source: Confidential linked Medicaid enrollment and claims data provided by the Kentucky Cabinet for Health and Family Service