Effects of Medicare Advantage Enrollment
on Beneficiary Risk Scores

Alice Burns
Congressional Budget Office
alice.burns@cbo.gov

Tamara Hayford
Congressional Budget Office
tamara.hayford@cbo.gov

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Abstract

Medicare beneficiaries may receive services through a traditional fee-for-service (FFS) program or they may enroll in Medicare Advantage (MA), under which they select a private health insurance plan. Medicare pays the MA plan to provide beneficiaries' health care services. Medicare adjusts payments to MA plans based on beneficiaries' demographic characteristics and documented health conditions: those traits are summarized in a risk score that estimates the relationship between beneficiary characteristics and FFS Medicare spending. Recent literature finds that health conditions are documented more thoroughly for MA enrollees than for FFS beneficiaries. As a result, beneficiaries enrolled in MA plans are assigned higher risk scores than identical beneficiaries in the FFS program, prompting concerns that Medicare is overpaying MA plans. This paper explores the mechanisms contributing to differences in MA and FFS risk scores.

Using Medicare administrative data from 2008–2013, we employ a difference-in-differences model to compare the growth in risk scores of Medicare beneficiaries who switch from FFS to MA (switchers) to the risk-score growth of beneficiaries who remain in FFS (stayers). We find that the risk scores of switchers grew faster than those of stayers, and the effect of MA enrollment on risk scores rose from a 5.0 percent increase in 2009 to an 8.3 percent increase in 2012. Risk scores for MA enrollees who stayed with the same insurer increased an additional 1.5 percent for each continuous year of enrollment. This model suggests that over time, the effects of MA enrollment on risk scores increased for all beneficiaries regardless of the duration of enrollment with a particular insurer. However, risk scores also increased more for beneficiaries who remained with the same insurer. For example, among beneficiaries who switched MA plans in 2009 but remained with the same insurer, continuous enrollment with that insurer accounted for 18.3 percent of risk score growth in 2010 and 34.7 percent of risk score growth in 2012. That finding may suggest a competitive advantage for established MA plans if those plans receive higher payments than new entrants for serving similar beneficiaries.

Keywords: Medicare, Medicare Advantage, selection, risk adjustment

JEL Classification: I13, I18, H51

Contents

Introduction

Medicare beneficiaries may elect to receive their health care services through the traditional fee-for-service (FFS) system or through a managed care plan in the Medicare Advantage (MA) program. Under the FFS system, the government generally pays providers based on the services beneficiaries use and bears the risk of higher-than-expected health care costs. By contrast, in the MA program, the government pays insurance plans a flat fee (or capitation), and the plan in turn pays providers. Under the MA system, plans bear the risk if health care costs exceed Medicare's payments. In 2015, 31 percent of Medicare beneficiaries were enrolled in MA (Kaiser Family Foundation 2015).

Insurers in the MA program have an incentive to enroll beneficiaries who the insurer expects will cost less than the Medicare capitation for that beneficiary. The Medicare program attempts to address that by using a relatively sophisticated risk adjustment mechanism that makes it more difficult for insurers to prospectively determine which individuals will have costs below what Medicare pays. That risk adjustment system assigns all beneficiaries a risk score that adjusts payments to MA plans based on beneficiaries' demographic characteristics and health conditions. As a result, insurers have an incentive to find ways to provide health care that costs less than what Medicare FFS would have paid, and to increase Medicare payments by documenting conditions more thoroughly than those conditions would have been documented in the FFS system. This paper aims to identify the extent to which insurers are engaging in the latter activity.

More specifically, this study uses risk-score data for individual beneficiaries in MA and FFS to explore how MA enrollment affects enrollees' risk scores. Consistent with prior research, we find substantive coding differences between FFS and MA and that those differences are growing over time. We add to prior research by decomposing the mechanisms behind that growth. We explore whether the fact that coding differences continued to grow over time is a function of the fact that MA insurers gather additional data on enrollees over time or whether it reflects more general increases in coding intensity across all MA enrollees regardless of time with the same insurer. We find the majority of risk score differences are attributable to increases that affected all beneficiaries but also find a nontrivial increase in risk scores for enrollees who remain with the same insurer.

Policy Background

MA plans are paid using a methodology that reflects local health care spending, bids by plans, plan quality, and enrollees' characteristics. Each year, plans submit bids to the Centers for Medicare & Medicaid Services (CMS) with the price they propose to charge to provide benefits under Medicare Part A and Part B to an average Medicare beneficiary.[1] CMS compares those bids to benchmarks that reflect Medicare's FFS spending at the county or regional level. If the bid is less than the benchmark, which is true for most plans, the plan's base payment includes a rebate that reflects the difference between the bid and benchmark. (Although CMS pays the rebate to MA plans, the plans must pass the rebate on to enrollees in the form of additional benefits or lower premiums.) If the bid equals the benchmark, the plan's base payment equals the benchmark. If the bid is greater than the benchmark, the plan's base payment equals the benchmark plus a premium paid by enrollees. That premium equals the difference

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[1] MA plans also submit bids to provide prescription drug benefits under Part D—which has its own risk-adjustment system—but this paper analyzes risk scores derived from Part A and B benefits only.

between the bid and the benchmark. Beginning in 2012, CMS has adjusted benchmarks and rebates based on each plan's quality ratings (Medicare Payment Advisory Commission 2016a).

CMS also adjusts the base payments for enrollees' characteristics. Initially, payments were only adjusted for enrollees' age, gender, Medicaid eligibility, residence in a nursing home (or similar institution that provides long-term care), and whether the beneficiary gained eligibility for Medicare on the basis of age or disability (i.e., demographic characteristics). The Balanced Budget Act of 1997 required CMS to incorporate information about health status into those adjustments. Between 2004 and 2007, CMS phased in the current risk-adjustment system, which uses diagnosis information to classify beneficiaries' health conditions into Hierarchical Condition Categories (HCCs).

Risk Scores in FFS and MA

CMS uses an algorithm to derive a single risk score for each enrollee based on HCCs and other beneficiary characteristics. That algorithm reflects the relationship between beneficiary characteristics and spending in the FFS population (CMS 2013, CMS Medicare Plan Payment Group 2011). An enrollee's risk score represents the expected difference in spending for each Medicare beneficiary relative to spending for a FFS beneficiary with average risk. CMS centers FFS risk scores around 1.0. Higher numbers reflect higher expected spending and lower numbers reflect lower expected spending.

HCCs for beneficiaries in FFS Medicare are obtained from claims that providers submit to receive payment for services. For many types of providers, HCCs in the FFS population are informational only and do not affect payment.[2] In MA, health plans report enrollees' HCCs to CMS each quarter, along with the type of providers that treated the diagnosed conditions and applicable service dates. Demographic characteristics and HCCs determine risk scores, and CMS multiplies the base payment to MA plans by those scores (thus increasing payments for higher-risk individuals and reducing them for lower-risk individuals). Because there are different incentives for MA plans than for FFS providers, health conditions for MA beneficiaries are widely thought to be more comprehensively documented than are health conditions for FFS beneficiaries, resulting in a "coding intensity difference" between FFS and MA risk scores (CMS 2009, pp. 7–11, GAO 2013).

Adjustments for Differences in Coding Intensity

To address differences in coding intensity, the Deficit Reduction Act of 2005 required CMS to adjust risk scores for MA beneficiaries before calculating payment amounts. Between 2010 and 2013, CMS's adjustments reduced risk scores by 3.41 percent. In response to concerns that the adjustments were lower than coding differences, the Affordable Care Act (ACA) established minimum adjustments for 2014 and beyond. The American Taxpayer Relief Act of 2012 increased the statutory minimums to 4.91 percent in 2014, rising gradually to 5.9 percent by 2019. The statutory minimums will end if CMS switches to a risk-adjustment system that relies on MA diagnoses and spending data (Medicare Payment Advisory Commission 2015, p. 329).[3]

Challenges in Estimating Differences in Coding Intensity. Estimating the magnitude of the difference in coding intensity between MA and FFS is a challenge because differences in risk scores can reflect both coding intensity and selection—the different health profiles of individuals who choose MA rather than

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[2] Payments for inpatient hospital care reflect both health status and services provided using diagnosis-related groups. CMS is also testing several demonstration programs that involve using HCCs to adjust provider payments.

[3] CMS began incorporating MA diagnoses and spending data into the risk-adjustment system in 2015 and intends to rely solely on those data by 2020 (GAO 2017).

FFS. Selection may occur if the beneficiaries who choose to enroll in MA have different health characteristics than beneficiaries who remain in FFS. Indeed, research suggests that before the implementation of the current risk adjustment system, beneficiaries in MA tended to be healthier, with less morbidity and lower mortality rates than FFS beneficiaries with similar demographic characteristics (McGuire, Newhouse, and Sinaiko 2011, Morgan et al. 1997, Newhouse 2002, Riley and Zarabozo 2006). By increasing payments for higher-risk individuals and reducing them for lower-risk individuals, incorporating health conditions into risk adjustment mechanisms reduces plans' ability to identify and disproportionately enroll individuals who would be likely to cost plans less than Medicare's capitated payments. Evidence on whether selection still exists in MA is mixed, though most studies find that risk adjustment has reduced its magnitude. (Brown and others 2014, Chao and Wu 2013, Jacobson, Neuman, and Damico 2015, McWilliams, Hsu, and Newhouse 2012, Morrisey and others 2013, Newhouse and McGuire 2014, Newhouse et al. 2012, Newhouse et al. 2013, Newhouse et al. 2014).

Previous Estimates of Coding Intensity Differences. Selection confounds the analysis of coding intensity differences because it would imply that all else being equal, MA enrollees have different risk scores than beneficiaries in Medicare FFS. Existing studies of coding intensity take different approaches to accounting for this challenge. Two studies, by CMS and the Government Accountability Office (GAO), used administrative Medicare data on individual beneficiaries to estimate changes in risk scores over time for FFS and MA beneficiaries by comparing risk score growth among FFS stayers (beneficiaries with at least two years consecutive enrollment in FFS) to MA stayers (beneficiaries with at least two years consecutive enrollment in MA). Using this approach, CMS concluded that risk scores for MA beneficiaries grew 1.75 percent faster than risk scores for FFS beneficiaries for each year of MA enrollment between 2004 and 2007 (CMS 2009, pp. 7–11). GAO estimated that the coding intensity difference was 4.2 percent in 2010 (GAO 2013, p. 3).

Other studies that used alternative methods to account for selection have found somewhat larger differences in coding intensity. Kronick and Welch analyzed risk score growth among FFS and MA beneficiary cohorts, finding that on average, MA risk scores increased from 90 percent of average FFS risk scores in 2004 to 109 percent of FFS risk scores in 2013. They used a decomposition analysis to attribute the growth in risk scores to various causes, including beneficiaries switching into and out of MA, beneficiaries entering the Medicare program, and beneficiaries dying. After accounting for various causes of differential growth, the authors concluded that most of the differential growth was attributable to more intensive coding in the MA population (Kronich and Welch 2014). Similarly, using aggregate data on the way that county-level risk scores vary with changes in MA penetration, Geruso and Layton estimate that the risk scores of MA enrollees are roughly 6 to 16 percent higher than they would have been had those beneficiaries remained in the FFS program (Geruso and Layton 2015).

Finally, the Medicare Payment Advisory Commission (MedPAC) calculated the ratio of the average risk score of beneficiaries who switched from FFS to MA (switchers) relative to the average risk score of beneficiaries who remained in FFS (stayers) for several cohorts of switchers. That analysis found that the ratio of the risk scores of switchers to the risk scores of stayers increased by at least 6 percent during the first year of MA enrollment and an additional 2 percent for each subsequent year of MA enrollment. As a result, the total difference between risk scores was likely 6 percent or more in 2014 (Medicare Payment Advisory Commission 2016b). In an updated analysis in 2017, MedPAC estimated that in 2015, differences in coding intensity resulted in MA enrollees having risk scores that were roughly 10 percent higher than scores for similar FFS beneficiaries (Medicare Payment Advisory Commission 2017, p.347-348).

Although there are few studies on coding differences, the size of the effects is fairly similar across studies, and several studies show that the differences between FFS beneficiaries and MA enrollees are increasing over time. A number of different mechanisms might explain the increasing coding differences

between MA and FFS. For example, MedPAC found that after switching to MA, beneficiaries' risk scores grew more rapidly than stayers' risk scores and that the difference in growth rates was directly related to the time beneficiaries remained enrolled in MA. That could occur as a result of insurers collecting more information about beneficiaries and more accurately documenting their chronic conditions. In that case, the increase in coding differences would occur at an individual level and reflect the length of enrollment in MA—e.g., increasing differences in coding intensity would be a function of individual beneficiaries' enrollment duration.

An alternative explanation for the increasing coding differences between MA and FFS would be that coding differences increased over time for all MA enrollees irrespective of how long they were enrolled in MA. For example, coding differences for all enrollees would increase if insurers became more adept at identifying and documenting beneficiaries' health conditions or if more insurers begin to adopt practices that allow them to thoroughly code beneficiary health conditions. Practices such as administering a health risk assessment to enrollees or working with network providers to comprehensively code medical claims may allow plans to more accurately document beneficiary health conditions but they also create costs for the plans. The technology supporting those practices might have improved, thereby allowing insurers to more precisely document risk, or the technology might have become more accessible or affordable, allowing a wider number of insurers to adopt such practices. Alternatively, insurers that are better at documenting risk might be able to reduce their bids and thus could offer better benefits and attract a larger percentage of MA enrollees. If it is the case that a higher percentage of enrollees select insurers that document HCCs more intensively, then average coding intensity would increase across all MA enrollees.

Although existing research suggests that both enrollment duration and time have contributed to increasing coding differences, research has not explicitly explored the relative contributions of each mechanism. This study builds upon existing research by further analyzing the growth in risk scores over time: It explicitly tests three models of risk-score growth and decomposes the respective contributions of enrollment duration and calendar year to the increased differences in coding intensity.

Data and Methods

Our analysis relied on Medicare administrative data that included information on demographic characteristics, program enrollment, and beneficiary risk scores. We linked each year's risk score data with the prior year's demographic and enrollment data because risk scores for a given year adjust payments to plans for that year, but reflect conditions documented in the prior year. For example, the 2009 risk score data reflect the chronic conditions documented during 2008. That documentation in turn was affected by whether the beneficiary was enrolled in MA or FFS in 2008. For that reason, the demographic and enrollment data come from the 2008–2012 beneficiary summary files and the risk score data come from the 2009–2013 risk adjustment files.

To estimate the effect of MA enrollment on risk scores, we restricted the study population to beneficiaries who were continuously enrolled in Medicare from 2008 through 2013 and were also exclusively enrolled in FFS during 2008. Continuous enrollment allowed us to observe the growth in risk scores over time, and the availability of a FFS-based risk score for all beneficiaries in 2008 ensured that we were able to measure the growth in risk scores from a common FFS baseline. We divided the study population into stayers and switchers: stayers include beneficiaries that remained in FFS for the entire study period and switchers include beneficiaries who switched from FFS to MA in any year from 2009 through 2013. That strategy allowed us to limit the effects of selection because we compared the *growth* in switcher and
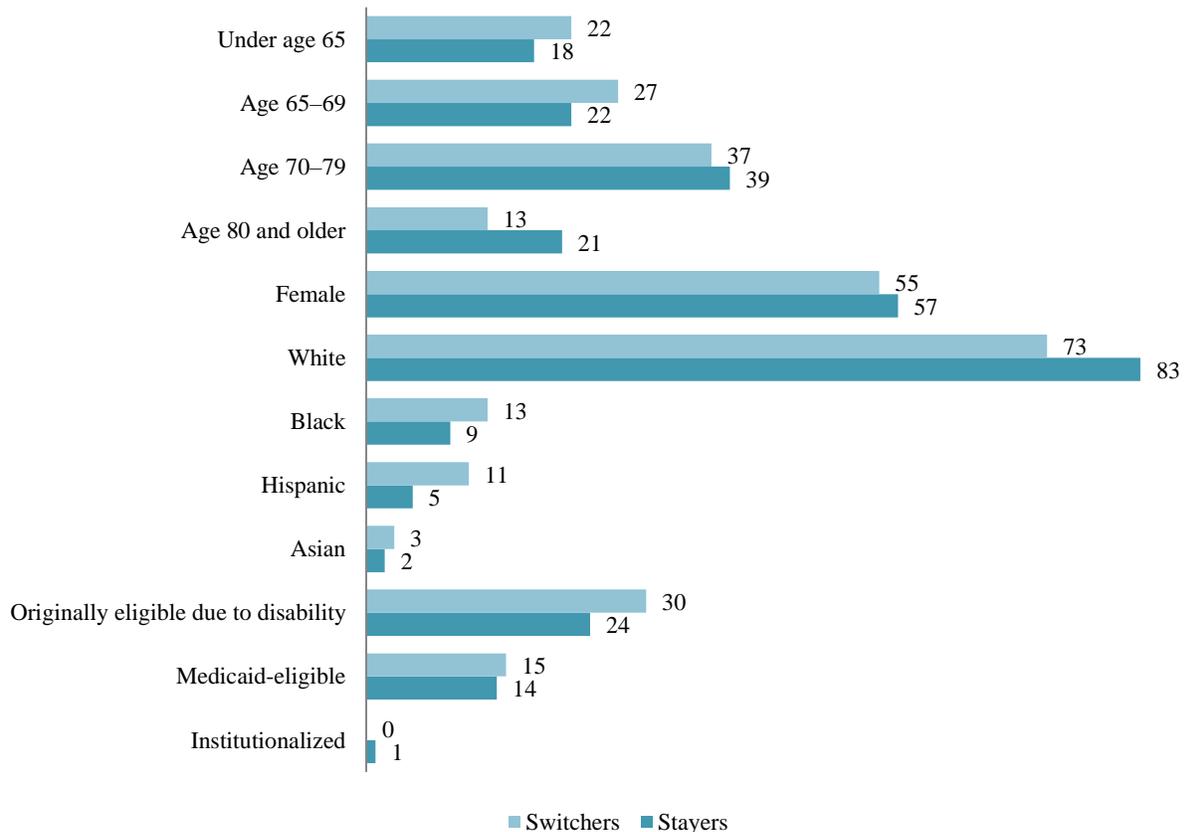
stayer risk scores from a common FFS baseline. Among switchers, we excluded beneficiaries in plans other than health maintenance organizations, preferred provider organizations, private FFS plans, and special needs plans.[4] We also excluded switchers if they switched back to FFS during the study period so that we could focus on the effects of switching from FFS to MA. Those selection criteria resulted in a study population comprising 21.0 million stayers and 2.3 million switchers.

Differences Between Switchers and Stayers

Switchers and stayers have somewhat similar demographic characteristics (Figure 1) but very different risk score patterns (**Figure 2**). Descriptive data show that switchers and stayers were largely similar in terms of demographic and eligibility characteristics. Switchers were younger than stayers, more likely to be a minority race or ethnicity, more likely to have originally been eligible for Medicare on the basis of disability, and less likely to have spent six or more months in an institution.

Figure 1. Characteristics of Beneficiaries Who Switch to MA (Switchers) and Beneficiaries Who Stay in FFS (Stayers), 2008

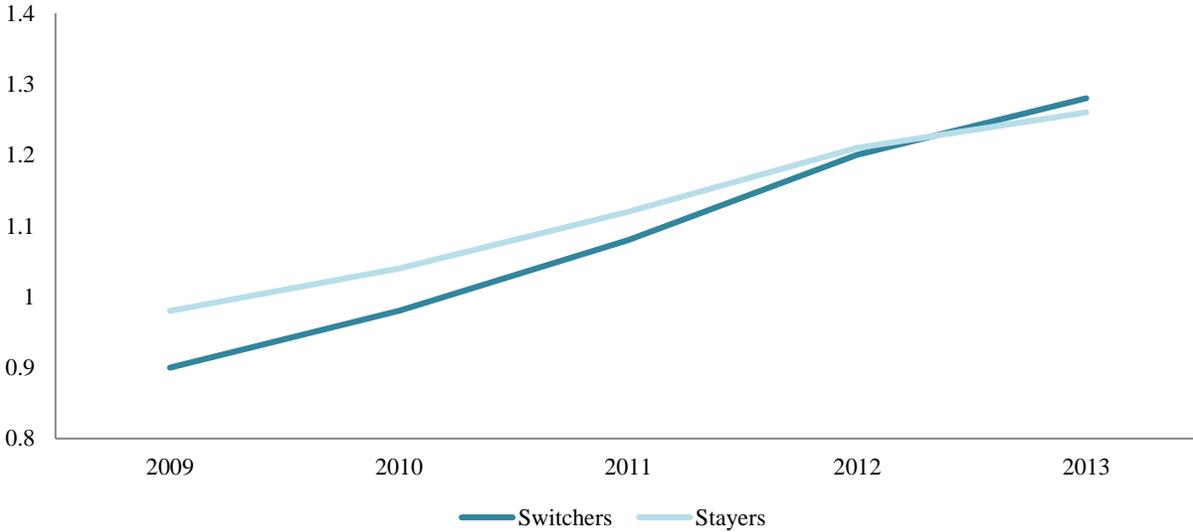**(Percentage of Beneficiaries)**

Source: Authors' analysis of Medicare beneficiary summary file and risk adjustment data, 2008–2013.

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[4] For more information on types of MA plans see CMS, *Medicare Managed Care Manual, Chapter 1 – General Provisions*, (January 7, 2011), Section 20 – Types of MA Plans, https://www.cms.gov/Regulations-and-Guidance/Guidance/Manuals/downloads/mc86c01.pdf.

Medicaid eligibility refers to full Medicaid eligibility; Institutionalized refers to spending at least half of the year in an institution.

Baseline average risk scores are nearly 10 percent lower for switchers than for stayers (0.90 compared to 0.98), yet switchers experienced much faster increases in risk scores over time. Risk scores increased 42 percent for switchers from 2009 to 2013, compared to a 29 percent increase for stayers. We explore the differences between the growth rates for switchers and stayers in the following sections.

Figure 2. Growth in Unadjusted Average Risk Scores for Switchers and Stayers

Source: Authors' analysis of Medicare beneficiary summary file and risk adjustment data, 2008–2013.

Estimation Strategy

To compare the growth in risk scores between switchers and stayers, we employed a differences-in-differences model with individual and year-fixed effects (see **Equation 1**).

$$(1) \quad Risk_{it} = \beta_0 + \beta_1(MA_{it} * I09_{it}) + \beta_2(MA_{it} * I10_{it}) + \beta_3(MA_{it} * I11_{it}) + \beta_4(MA_{it} * I12_{it}) + \beta_5(YearsPostSwitch_{it}) + \beta_6(X_{it}) + \beta_7(I_i) + \beta_8(Y_t) + \varepsilon_{it}$$

The dependent variable, $Risk_{it}$, represents the risk score for beneficiary i for conditions documented in year t. The variables of interest include $MA_{it} * Iyy_{it}$ and $YearsPostSwitch_{it}$. $MA_{it} * Iyy_{it}$ represents a vector of interaction terms between an MA enrollment indicator and year-fixed effects; those enrollment year terms represent the overall effect of being enrolled in MA in a given year. $YearsPostSwitch_{it}$ is an enrollment duration term that represents the subsequent number of years of MA enrollment and captures the effect of additional years of enrollment.

I_i and Y_t represent individual and year-fixed effects. X_{it} represents a vector of individual time-varying control variables. Individual fixed effects allow us to estimate the effect of MA enrollment on risk score growth while controlling for certain observed and unobserved beneficiary characteristics. Those characteristics do not change over time but may differ between switchers and stayers (e.g., gender, race, preferences for health care, and underlying health status). Year-fixed effects allow us to control for unobserved factors that would affect all beneficiary risk scores over time, such as aging, changes in Medicare payment policies, or economic conditions. The vector of individual controls include MA penetration in the beneficiary's county of residence (defined as the percent of Medicare beneficiaries that are enrolled in MA in a given year), indicators for full and partial dual enrollment in Medicaid and an

indicator for spending at least half of the year in an institution.[5] We did not control for gender, race, or other beneficiary characteristics that remain constant over time because the individual fixed effects account for those differences.[6]

Our second model refines the first model by replacing the enrollment duration term with one that reflects the number of years switchers stayed with their current insurer. Among people in the 2009-2011 switch cohorts, 63 percent remained with the same insurer during the analysis period; specifically, 50 percent of the 2009 cohort, 61 percent of the 2010 cohort, and 88 percent of 2011 cohort did not switch insurers during the study period (the 2012 switch cohort are only enrolled in MA for one year). If the effect of MA duration is driven by plans learning more about enrollees, then it is relevant whether enrollees remain with the same insurer or switch between insurers. In **Equation 2**, $YearsPostSwitch\_Ins_{it}$ is constructed similarly to $YearsPostSwitch_{it}$, but represents the number of years since switching to a particular insurer rather than the number of years since switching to MA.[7]

$$(2) \quad Risk_{it} = \varphi_0 + \varphi_1(MA_{it} * I09_{it}) + \varphi_2(MA_{it} * I10_{it}) + \varphi_3(MA_{it} * I11_{it}) + \varphi_4(MA_{it} * I12_{it}) + \varphi_5(YearsPostSwitch\_Ins_{it}) + \varphi_6(X_{it}) + \varphi_7(I_i) + \varphi_8(Y_t) + \varepsilon_{it}$$

Our third model is a robustness check in which we replicated the approach used by MedPAC. That analysis also compared risk score growth between switchers and stayers, but differed from ours in a key regard. The MedPAC analysis allowed the effect of *switching* from FFS to MA to change over time but it did not allow the effect of *enrollment* in MA to change over time (as ours does). For that reason, **Equation 3** replaces the enrollment year terms from **Equation 1** with indicators for the year in which beneficiaries switched into MA.

$$(3) \quad Risk_{it} = \gamma_0 + \gamma_1(MA_{it} * Switch09_i) + \gamma_2(MA_{it} * Switch10_i) + \gamma_3(MA_{it} * Switch11_i) + \gamma_4(MA_{it} * Switch12_i) + \gamma_5(YearsPostSwitch_{it}) + \gamma_6(X_{it}) + \gamma_7(I_i) + \gamma_8(Y_t) + \varepsilon_{it}$$

In **Equation 3**, $MA_{it} * Switchyy_i$ represents a vector of interaction terms between indicators for each switch-year cohort (2009, 2010, 2011, and 2012) and MA enrollment. Those switch cohort terms represent the effect on beneficiaries' risk scores of switching to MA in a given year. This approach assumes that the effect of *switching* to MA varies over time, whereas the enrollment year terms in equations 1 and 2 allow the effect of *being enrolled* in MA to vary over time. If the program-wide effect of enrollment in MA does vary by year, then the estimated effect of enrollment duration in Equation 3 would be biased upwards because it would also capture any increases in coding intensity that occur for all MA enrollees as a function of time.

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[5] CMS uses separate models for community and institutional beneficiaries to account for significant cost differences between the two populations. For more information see CMS, *Medicare Managed Care Manual,* "Chapter 7 – Risk Adjustment," (January 7, 2011), pp. 11–13, https://go.usa.gov/xRJs6. However, we use the community risk score throughout to ensure that we are making an apples-to-apples comparison of the documentation of conditions across people and years.

[6] Although people's ages change over time, they change at the same rate for each person. The meaningful difference across individuals is their age at the beginning of the analysis period, which does not change over time and is therefore also absorbed by the individual fixed effects.

[7] We use contract identification as a proxy for the insurer. The contract identification represents a contract between an organization and CMS to operate one or more plans in a region. While the same insurer may operate multiple contracts in a region, each contract represents a single insurer.

We also conducted three specification checks for selection bias. Although the analysis controls for beneficiaries' risk prior to switching, selection bias could be present if switchers enrolled in MA because they anticipated a future change in health status or if switchers' risk scores were growing differently than stayers even before the switch. The first specification check tests for pre-switch differences between stayers and switchers by adding two pre-switch indicators to equation (2) to check for differences in pre-existing trends between stayers and switchers. Pre-switch indicators equal 1 for switchers 1 or 2 years before the switch and equal zero otherwise; pre-switch indicators always equal zero for stayers. We also tested the pre-switch trends assumption using the same model but excluding 2009 and 2010 switchers (because they did not have a full set of pre-switch trends) and using three similar models that only include the years of data prior to the switch (one model for 2010 switchers, one for 2011 switchers, and one for 2012 switchers).

Our second specification check limited the analysis to stayers who moved from one state to another state during the study period and switchers who moved at least one year prior to their switch. Moving from one state to another prompts a plausibly exogenous reason to switch for two reasons: first, there will most likely be a different selection of health plans available in a different state, and second, beneficiaries will already need to identify new health care providers so they may be less concerned with whether their long-term provider is part of MA plans' networks. This is an imperfect test for selection because health shocks could be the reason for moving, particularly among the Medicare population. However, if that analysis yields similar results to our primary specifications, it would provide suggestive evidence that our results do not reflect switchers moving to MA in anticipation of health shocks—unless of course, movers who switch are more likely to have done so because of an anticipated health shock than movers who remained in FFS.

In the third specification test, we replaced our dependent variable with an alternative risk adjuster that is less likely to be subject to coding practices, following the methodology described by Colla et al. (2012). That methodology used the combined annual rates of four low-variation conditions (acute myocardial infarction (AMI), colorectal cancer, hip fracture, and stroke) as a substitute risk adjuster because those conditions all require an acute care hospitalization and are less likely to be susceptible to coding differences. If changes in MA enrollees' health were driving the results, the coefficients on the MA variables in that model should be similar to the coefficients in our main model.

One limitation of this specification is that unlike Colla, we did not have access to beneficiaries' inpatient hospital claims and diagnoses to determine which MA enrollees had each of the conditions. Instead, we used HCCs as a proxy for the conditions. Unfortunately, in several cases the HCCs did not overlap perfectly with the four conditions, and thus might have been sensitive to some coding intensity differences. The HCCs we used included: acute myocardial infarction (for AMI); breast, prostate, colorectal and other cancers and tumors (for colorectal cancer); hip fracture/dislocation (for hip fracture); and ischemic or unspecified stroke (for stroke). We also included a specification with AMI likelihood as the dependent variable because that condition overlapped perfectly with the Colla methodology.

Results

Table 1 reports the results from our three primary models. Consistent with existing research, the results for Equation 1 suggest that MA enrollment is associated with an increase in risk scores relative to FFS that has grown over time, from 5.3 percentage points in 2008 to 8.0 percentage points in 2012.

Table 1. Regression Results for Equations 1-3

Model	Equation 1. Enrollment Year + Enrollment Duration	Equation 2. Enrollment Year + Insurer Duration	Equation 3. Switch Year + Enrollment Duration
Enrolled in MA in:			
2009	0.053 ***	0.050 ***	
	(0.001)	(0.001)	
2010	0.067 ***	0.066 ***	
	(0.001)	(0.001)	
2011	0.070 ***	0.072 ***	
	(0.001)	(0.001)	
2012	0.080 ***	0.083 ***	
	(0.001)	(0.001)	
Years in MA since switch	0.012 ***		0.020 ***
	(0.000)		(0.000)
Years since switching to current insurer		0.015 ***	
		(0.000)	
Switched to MA in:			
2009			0.051 ***
			(0.001)
2010			0.065 ***
			(0.001)
2011			0.083 ***
			(0.001)
2012			0.072 ***
			(0.001)
MA Penetration Rate	0.061 ***	0.061 ***	0.061 ***
	(0.002)	(0.002)	(0.002)
Eligible for Full Medicaid Benefits	0.507 ***	0.507 ***	0.507 ***
	(0.001)	(0.001)	(0.001)
Eligible for Partial Medicaid Benefits	0.295 ***	0.295 ***	0.295 ***
	(0.001)	(0.001)	(0.001)
Institutionalized for Six Months or Longer	0.087 ***	0.087 ***	0.087 ***
	(0.001)	(0.001)	(0.001)
Number of Observations	116,091,770	116,091,770	116,091,770
R-Squared	0.668	0.668	0.668
Individual and Year Fixed Effects	Yes	Yes	Yes

Source: Authors' analysis of Medicare beneficiary summary file and risk adjustment data, 2008–2013.

Standard errors in parentheses.

*** p < 0.01; ** p < 0.05; * p < 0.10

Each additional year in MA is associated with a 1.2 percentage point increase in risk scores.[8] The controls for dual eligibility and residing in an institution have a substantial and positive effect on risk scores that is consistent across each of the three models (**Table 1**). The results from Equation 2 show that length of enrollment with a particular insurer has a larger effect on risk scores than length of enrollment in MA (though both effects are significant): the estimated effect of remaining enrolled with the same insurer is 25 percent larger than the effect of the enrollment duration term in Equation 1.[9] The coefficients on the enrollment year terms, however, are virtually identical in this model. The coefficients range from 5.0 to 8.3 percentage points.

Both of our enrollment duration estimates are smaller than the duration effect found by MedPAC. However, as noted above, the enrollment duration term in **Equation 3** (our replication of the MedPAC analysis) could be biased upwards. Bias might occur if the effects of increased differences in coding between MA and FFS over time apply to people in all years of MA enrollment rather than only in the year that they switched to MA. The results from **Equation 3** suggest that such is the case. As MedPAC observed in its study, we find that each additional year of MA enrollment is associated with a 2 percentage point increase in risk scores; that coefficient is 67 percent larger than the corresponding coefficient in **Equation 1**.

Mechanisms Contributing to Coding Differences
Our results suggest that increased coding differences over time reflect both increases in average risk scores occurring across all individuals in MA and increases in individual risk scores that occur with continuous enrollment with the same insurer. In **Figure 3**, we show the specific coding intensity increase for four cohorts of switchers who remain with the same MA insurer from the time they switch through 2012.

In the year 2012, we find that the coding intensity increase—relative to stayers—was 12.7 percent for the 2009 cohort but only 8.3 percent for the 2012 cohort. This suggests that for beneficiaries that remained with the same insurer, continuous enrollment with that insurer contributed to 34.7 percent of the risk score increase observed among the 2009 cohort, while overall coding increases contributed 65.3 percent for the year 2012. Alternatively, for the 2011 cohort, continuous enrollment with the same insurer contributed to only 15.0 percent of the total risk score increase, demonstrating that the effects of time versus enrollment duration are quite sensitive to the number of years beneficiaries remain enrolled with the same insurer.
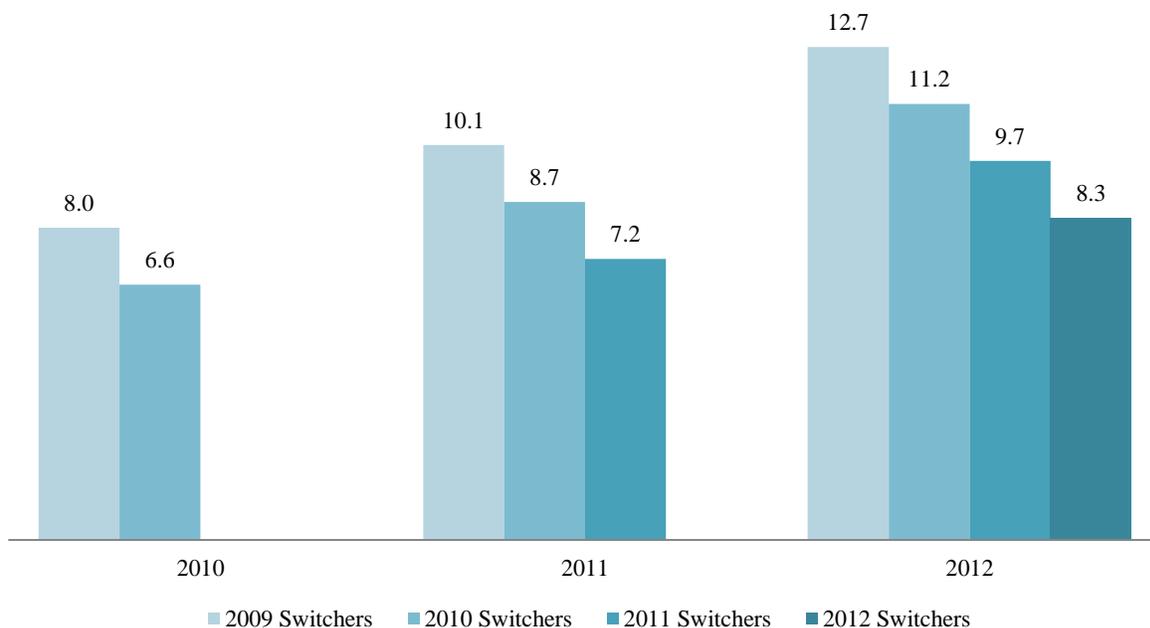
Looking at actual enrollment patterns for the 2009 switcher cohort, we find that as of 2012, 50.0 percent of switchers stayed with the same insurer for four years (2009–2012), 11.7 percent stayed with the same insurer for three years (2010–2012), 26.5 percent for two years (2011–2012), and 11.8 percent were new

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[8] Although our model includes fixed effects, we don't cluster the standard errors in the main specification because the large sample size limited the processing capabilities of SAS, the analytic software we used. Using non-clustered standard errors might lead us to falsely conclude significance if we have underestimated actual standard errors. For that reason, we conducted a robustness check with a 5 percent random sample of the study population using clustered standard errors. That analysis yielded statistically significant results. (Results are available from the authors.)

[9] In results not reported in this paper but available from the authors, we also estimated a model that included both years after switching to MA and years after switching to the current plan sponsor, to confirm which of the two effects was the driving factor. In that model, the estimated effect of remaining with the same plan sponsor was 1.2 percentage points per year, while the estimated effect of remaining in MA regardless of plan sponsor was 0.4 percentage points. Both estimates were statistically significant at the 1 percent level.

to an insurer in 2012. Accounting for those enrollment patterns, the average 2012 increase in risk score for the 2009 cohort as a whole was 11.3 percentage points. More than one-fourth of that increase, 26.5 percent, stemmed from the insurer duration effect. For our entire study population, the average increase in 2012 risk scores was 10.0 percentage points. Of that increase, 16.8 percent stemmed from the insurer duration effect.

Figure 3. Percentage Increase in Risk Scores for Beneficiaries Who Stay With a Particular MA Plan, by Year of Switch and Calendar Year

Source: Authors' analysis of Medicare beneficiary summary file and risk adjustment data, 2008–2013.

Specification Tests

In the first specification test, we assessed whether there were differences in the pre-switch trends for stayer and switcher risk scores by adding dummy variables to differentiate future switchers from stayers in the years prior to their switch. The coefficients on both indicators were negative and statistically significant, suggesting that switchers' risk scores were growing more slowly than stayers' risk scores before they switched to MA. Two years before the switch, switcher risk scores grew 0.7 percent less than stayers. One year before the switch, switcher risk scores grew 1.0 percent less than stayers (see **Table 2**). The difference between the two years—0.3 percent—is quite small but potentially indicates slower growth in risk scores among future switchers compared to stayers. That finding is consistent with the possibility of favorable selection, which would tend to bias our results towards zero. We obtained similar results from the models that exclude 2009 and 2010 switchers and from the models that only include the years of data prior to the switch.[10]

In the second specification test, we limited the analysis to people who moved from one state to another. Consistent with main results, that analysis also found larger increases in risk scores among switchers

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[10] Results are available from the authors.

compared to stayers (see **Table 2**). One limitation of this test is that people may have moved as the result of an adverse health event—to receive specialized treatment or to be close to a family caregiver, for example. Note, however, that the limitation would only affect our results if switchers moved as the result of adverse health more frequently than did stayers. Repeating that analysis with pre-switch interaction terms suggests that in the years prior to the switch, switchers who relocated had lower risk scores and slower growth in risk scores than did stayers who relocated (see **Table 2**).

Table 2. Regression Results for Specification Tests

Model	Pre-Switch Indicators	Movers Only Main Results	Movers Only, Pre-Switch Indicators	Count of Low-Variable Conditions	Acute Myocardial Infarction
2 years before switch	-0.007 ***		-0.017 ***		
	(0.001)		(0.003)		
1 year before switch	-0.011 ***		-0.022		
	(0.001)		(0.003)		
Years since switching to current insurer	0.013 ***	0.015 ***	0.011 ***	0.001 ***	0.000 ***
	(0.000)	(0.003)	(0.003)	(0.000)	(0.000)
Enrolled in MA in:					
2009	0.041 ***	0.071 ***	0.051 ***	0.003 ***	0.000 ***
	(0.001)	(0.007)	(0.008)	(0.000)	(0.000)
2010	0.057 ***	0.074 ***	0.055 ***	0.002 ***	0.000 ***
	(0.001)	(0.005)	(0.005)	(0.000)	(0.000)
2011	0.065 ***	0.068 ***	0.053 ***	-0.001 ***	0.000 ***
	(0.001)	(0.004)	(0.004)	(0.000)	(0.000)
2012	0.077 ***	0.082 ***	0.071 ***	0.001 *	0.000
	(0.001)	(0.003)	(0.004)	(0.000)	(0.000)
MA Penetration Rate	0.062 ***	0.105 ***	0.106 ***	0.002 **	0.001 **
	(0.002)	(0.004)	(0.003)	(0.001)	(0.000)
Eligible for Full Medicaid Benefits	0.507 ***	0.451 ***	0.451 ***	0.055 ***	0.008 ***
	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)
Eligible for Partial Medicaid Benefits	0.295 ***	0.304 ***	0.304 ***	0.023 ***	0.004 ***
	(0.001)	(0.003)	(0.003)	(0.000)	(0.000)
Institutionalized for Six Months or Longer	0.087 ***	0.056 ***	0.056 ***	-0.032 ***	-0.010 ***
	(0.001)	(0.004)	(0.004)	(0.000)	(0.000)
Number of Observations	116,091,770	4,706,255	4,706,255	116,091,770	116,091,770
R-Squared	0.668	0.647	0.647	0.566	0.247
Individual and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Source: Authors' analysis of Medicare beneficiary summary file and risk adjustment data, 2008–2013.

Standard errors in parentheses.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

In the third specification test, we replaced the dependent variable with two alternatives that are less likely to be affected by coding differences: a count of low-variation conditions and the likelihood of being diagnosed with AMI. That analysis found that the MA variables were all substantively insignificant for both models. In fact, the coefficients for all five of the MA variables were 0.0 (see **Table 2**).[11] Those results suggest that the underlying health status of MA enrollees did not change relative to that of FFS beneficiaries, which in turn implies that the results in our main specifications stem from coding differences rather than selection.

Discussion

In this paper, we build on previous research by exploring the mechanisms by which MA enrollment affects the growth in beneficiary risk scores, using individual-level data to control for baseline differences in risk scores. The magnitudes of the increases we find are similar to other estimates in the literature. Our results suggest that the widening gap in risk scores between FFS and MA enrollees is the result of two factors: an overall increase in risk scores among MA enrollees over time and an additional effect driven by insurers learning about their enrollees over time.

One limitation of this analysis is that we only follow MA enrollees for a maximum of four years. Therefore, it is unclear whether our estimates would be applicable as beneficiaries remain with the same insurer beyond four years. Moreover, although beneficiary risk scores continued to increase with each subsequent year of enrollment with the same insurer during our study period, it is unlikely that those increases would continue indefinitely. Without a longer study period, it is impossible to determine how long those increases might continue.

Extending our current analysis to include new years of data also poses some methodological concerns because CMS has made several changes to the risk adjustment system. First, in 2014, CMS changed the existing system to weight some HCCs more heavily and others less heavily. Second, in 2016, CMS began to incorporate data on the services MA plans provided to enrollees (e.g., encounter data) into the risk adjustment formula (Medicare Payment Advisory Commission 2017). As a result, incorporating newer data would require either shifting to the new risk adjustment model or continuing to use the old model even though coding incentives have changed, neither of which would be an apples-to-apples comparison to previous years.

Because increases in coding intensity translate directly into increased payments to MA plans, there have been many calls for reforms that would reduce overpayments to MA plans. In theory, reform could address either the increased documentation of MA enrollees' conditions or the lack of diagnostic information among FFS beneficiaries. Kronick notes that "diagnostic reporting in FFS Medicare is woefully incomplete" and provides an example: Only 60 percent of FFS beneficiaries with quadriplegia in one year have a claim with quadriplegia in the subsequent year (2017, p. 325). Increased information on MA enrollees' diagnoses is not in itself problematic; indeed, detailed information on conditions may help MA plans to better manage health care for their enrollees. However, because MA payments are based on the relationship between conditions and use of resources in the FFS system, differences in coding intensity may result in overpayments to MA plans.
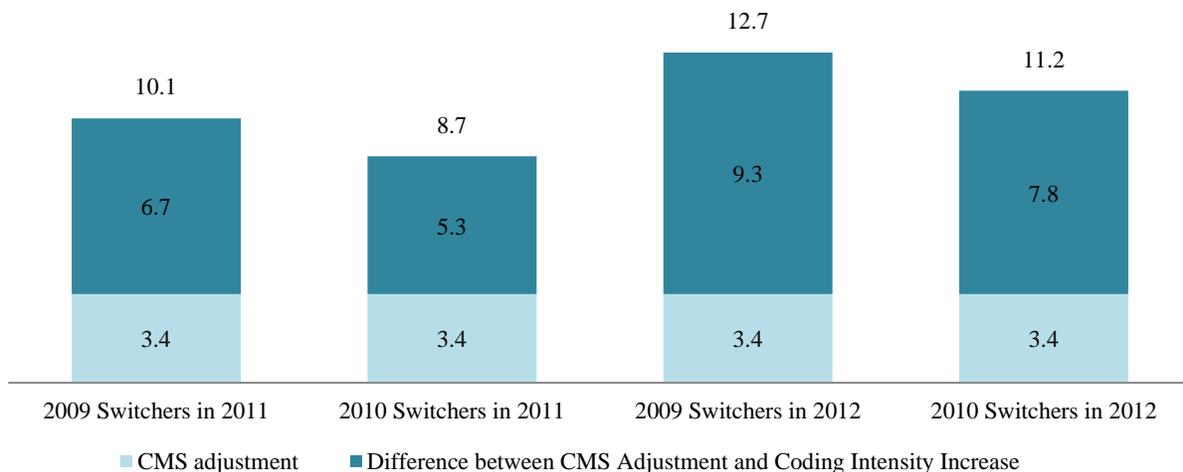
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[11] We also tested models with each of the other four conditions as the dependent variables and a model where the dependent variable was the probability of having any of the four conditions. In all cases, the MA results were substantively insignificant. The results are available from the authors.

The current policy for reducing coding-related overpayments to MA plans is to apply a coding intensity adjustment to reduce risk scores for all MA enrollees. As noted above, the ACA and subsequent legislation increased the minimum amount of the coding intensity adjustment but our results suggest that coding intensity is higher than that minimum and that it changes over time (while the minimum will remain constant starting in 2018). Moreover, flat annual adjustments for all MA plans treat all plans and beneficiaries equally, despite the fact that our paper and other research suggest that coding intensity differences vary across beneficiaries and MA insurers. Across-the-board adjustments may therefore give a competitive advantage to certain insurers. For example, our paper finds that length of enrollment with the same insurer increases the risk score. As a result, incumbents have a competitive advantage under the current risk adjustment system: the same beneficiary garners the insurer a higher Medicare payment by remaining enrolled with that insurer. Those findings suggest that differences in coding intensity across beneficiary populations and insurers would be a valuable topic for future research.

To depict how coding intensity differences vary over time and over years of enrollment with a single insurer, **Figure 4** illustrates those factors for hypothetical cohorts of beneficiaries who switched from FFS to MA in 2009 and 2010 and remained with the same MA insurer through 2012. In 2012, coding differences led to an 11.2 percentage-point increase in risk scores among beneficiaries who switched to MA in 2010 and a 12.7 percentage-point increase for those who switched in 2009. Those differences were larger than the differences for 2011 (8.7 and 10.1 percentage points respectively). They highlight the notion that accounting for both time trends and enrollment patterns is important in estimating coding differences between MA and FFS.

Figure 4. Differences Between Risk Score Increase and CMS Adjustment for Switchers That Remain Enrolled With a Particular Insurer

(Percentage Increase in Risk Score)

Source: Authors' analysis of Medicare beneficiary summary file and risk adjustment data, 2008–2013.

The challenges associated with risk adjustment in MA may be instructive for other Medicare reforms and for additional public programs. In January 2015, CMS announced a goal of moving 30 percent of Medicare FFS payments into alternative payment models by 2016 and 50 percent of FFS payments into such systems by 2018 (CMS 2015). These models will require risk adjustment to function effectively, and will face the same challenges that arise in the MA risk-adjustment system. Further, almost 80 percent of Medicaid beneficiaries were enrolled in a managed care plan in 2014 (CMS 2016, p. 17), and risk adjustment is used in the health insurance marketplaces established by the Affordable Care Act.

As capitated payment models using risk adjustment become more prevalent in the health care market, the MA experience offers several useful lessons for implementing alternative payment mechanisms. First, risk adjustment creates incentives to thoroughly document health risks; that documentation may help health plans and providers manage enrollees' health. Second, because the accumulation of data on enrollees allows for higher payments in some cases, risk adjustment may favor incumbents and disadvantage new entrants into insurance markets. That occurs because established insurers have panels of enrollees on whom they have accumulated data, and therefore may be paid more than new entrants for beneficiaries with similar health care costs. Finally, the MA experience shows that risk adjustment requires information both on beneficiary characteristics and on the relationship between beneficiary characteristics and resource use. Insufficient information on either beneficiary characteristics or how beneficiary characteristics affect resource use is likely to introduce inequity and inefficiency into the risk-adjustment system.

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