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ABSTRACT

Accurate risk adjustment facilitates healthcare market competition. Risk adjustment typically aims to predict annual costs of individuals enrolled in an insurance plan for a full year. However, partial-year enrollment is common and poses a challenge to risk adjustment, since diagnoses are observed with lower probability when individual is observed for a shorter time. Due to missed diagnoses, risk adjustment systems will underpay for partial-year enrollees, as compared to full-year enrollees with similar underlying health status and usage patterns. We derive a new adjustment for partial-year enrollment in which payments are scaled up for partial-year enrollees' observed diagnoses, which improves upon existing methods. We simulate the role of missed diagnoses using a sample of commercially insured individuals and the 2014 Marketplace risk adjustment algorithm, and find the expected spending of six-month enrollees is underpredicted by 19%. We then examine whether there are systematically different care usage patterns for partial-year enrollees in this data, which can offset or amplify underprediction due to missed diagnoses. Accounting for differential spending patterns of partial-year enrollees does not substantially change the underprediction for six-month enrollees. However, one-month enrollees use systematically less than one-twelfth the care of full-year enrollees, partially offsetting the missed diagnosis effect.

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I. INTRODUCTION

Risk adjustment plays a crucial role in facilitating healthcare market competition. Risk adjustment is used to ensure that when premiums do not vary by health status insurers do not have incentives to avoid sicker enrollees. Moreover, if quality benchmarks are risk adjusted for patient condition severity, providers would want to avoid sicker patients that might make their performance measures look worse. Thus, failures of risk adjustment can lead to serious distortions in insurer and provider behavior, with corresponding welfare loss to consumers (Glazer and McGuire 2000). In this paper, we point out a major failure of existing risk adjustment systems — they do not correctly compensate for enrollees who are observed for less than the full contract year. We quantify the extent of the distortion for commercially insured working age adults and present a model that shows how to correctly adjust for partial year enrollment.

In insurance markets, risk adjustment systems transfer money from plans that enroll a healthier-than-average population to plans that enroll a sicker-than-average population. Most risk adjustment systems are diagnosis-based: the risk adjustment payments an insurance plan receives for its enrollees are a function of the diagnoses those enrollees receive that are coded in insurance claims.[1] For example, in such a system, an insurance plan will receive a larger payment if an individual is diagnosed with diabetes than if they were otherwise healthy.

In insurance markets, risk adjustment helps avoid both pricing distortions due to adverse selection, as well as contract design distortions in which insurers reduce the availability of services valued by sicker enrollees (Geruso and Layton 2015; Glazer and McGuire 2000). As a result, diagnosis based risk adjustment is used in many health insurance markets in the U.S.,

[1] Alternatives to diagnosis-based risk adjustment include payments based simply on age and gender, or based on previous spending amounts.

including Medicare Advantage, Medicare Part D, Medicaid managed care in many states, and most recently, the federal and state health insurance marketplaces ("Marketplaces") created by the 2010 Affordable Care Act (ACA). [2] In European markets with health insurer competition such as Germany and the Netherlands, risk adjustment also plays a major role (Buchner, Goepffarth, and Wasem 2013; van Kleef et al. 2016).[3] A large literature on risk adjustment for health insurance exists (see Van de Ven and Ellis (2000) for a review).

A typical risk adjustment system (e.g. that used in the Marketplaces), predicts an enrollee's spending over a fixed period – generally, one year – based on the diagnoses observed for that patient during that time (Ellis 2007).[4] While health insurance contracts typically last a year, an individual may be enrolled—thus observed by the risk adjustment system—for only a portion of the year if they switch coverage mid-year (e.g., due to a qualifying event).

Diagnosis-based risk adjustment is not limited to insurer competition; it is also used to adjust performance benchmarks in evaluating healthcare quality. For instance, as part of the ACA's Hospital Readmissions Reduction program, hospitals are financially penalized for excess readmissions above a risk-adjusted benchmark (Centers for Medicare & Medicaid Services 2017; McIlvennan, Eapen, and Allen 2015); the risk adjustment for this benchmark uses diagnoses observed in the previous 12 months of claims if available. Moreover, if an individual has a shorter inpatient stay (and thus is less intensely observed by the provider), fewer secondary

[2] For more detail on the role of risk adjustment, see Kautter et al. (2014a) and Hall (2011) on the Marketplaces, Pope et al. (2004) on Medicare Advantage, Hsu (2009) on Medicare Part D, and Center for Health Program Development and Management and Actuarial Research Corporation (2003) and Winkelman and Damler (2008) on Medicaid Managed Care.
[3] See e.g. Buchner, Goepffarth, and Wasem (2013) on Germany and van Kleef et al. (2016) on the Netherlands.
[4] This is called concurrent risk-adjustment, in which data from a period is used to predict that period's costs (e.g., claims data from 2017 are used to predict costs for 2017). Prospective risk adjustment uses data from a previous time period to predict costs in the future, and raises similar issues if individuals vary in the length of time they are observed.

diagnoses may be recorded during this stay; this will result in individuals with shorter hospital stays appearing healthier than they would appear if they were simply observed longer.

For diagnoses to be compensated for, they need to be observed and coded. We examine how variation in the amount of time an individual is enrolled and observed by the system affects risk adjustment. That is, how well does risk adjustment work for individuals who are only enrolled for a portion of the contract year ("partial-year enrollment")? Partial-year enrollment is pervasive in the U.S. In Medicaid, about half of enrollees lose eligibility within a year of joining (Swartz et al. 2015). In the Marketplaces, data suggest that at least a third of enrollees are not enrolled for the full year.[5] Individuals may move between the Marketplaces, Medicaid (Sommers and Rosenbaum 2011), and employer-sponsored insurance (Graves and Swartz 2013) due to income fluctuations that affect Medicaid eligibility or from job transitions entailing a gain or loss of employer sponsored insurance (Buettgens et al. 2012; Short et al. 2012).[6] Partial year enrollment also occurs in Medicare Advantage and Medicare Part D due to aging into the system, death, and specific qualifying events (Centers for Medicare & Medicaid Services 2017b).

Many risk adjustment systems address the issue of partial-year enrollees by ignoring diagnosis data for partial-year enrollees: for instance, in Medicare Advantage and Medicare Part D, payments for enrollees without 12 months of prior claims are paid using separate formulas

[5] Exact data on of partial-year enrollment in the Marketplaces is unavailable. Pre-ACA estimates from individual and small group markets suggest mid-year turnover or enrollment of less than 12 months among approximately 40% of enrollees (Cebul et al. 2008; Ericson and Starc 2012; Hall 2011; Sommers 2014). A 2015 survey indicated 21% of Marketplace enrollees dropped coverage mid-year (McKinsey & Company Center for U.S. Health System Reform 2016), while that same year, 1.6 million people enrolled mid-year via a special enrollment period (about 15% of the number who joined during open enrollment) (Centers for Medicare & Medicaid Services 2016c). Together, these data suggest at least a third of Marketplace enrollees are not enrolled for the full year.

[6] Partial year enrollment in the Marketplaces can happen in two ways: first, individuals enroll during the annual open enrollment period and drop Marketplace coverage during the year. Second, individuals have a mid-year "qualifying life event" (e.g., loss of ESI) allowing them to enroll through a Special Enrollment Period (SEP) (Centers for Medicare & Medicaid Services 2016d; Hartman et al. 2015), which have been the source of adverse selection concerns. Increased enforcement of eligibility for SEPs started in 2016 to avoid misuse or abuse of SEPs by consumers (Centers for Medicare & Medicaid Services 2016d).

based on demographics such as age, sex, and enrollment type (e.g., whether institutionalized) (Chen et al. 2015; Robst, Levy, and Ingber 2007). This means that plans retain incentives to select for partial-year enrollees who are healthier, conditional on these limited variables. However, when diagnosis-based risk adjustment is used for partial-year enrollees, the common (and intuitive) method is what we term "fractional adjustment". The partial-year enrollee's annual spending is predicted using the same algorithm as for full year enrollees, based on diagnoses observed during the portion of the year they were enrolled. Then, for the partial-year enrollee, the predicted spending is multiplied by the fraction of the year the enrollee is enrolled. This method was originally used in the Marketplaces (which was then later tweaked, as we will discuss). It also underlies many state Medicaid programs (Layton, Ndikumana, and Shepard 2017).[7]

We provide a model showing that the fractional adjustment method will systematically underpredict spending for partial-year enrollees as compared to full-year enrollees with similar true health status and usage patterns. The key intuition is that a diagnosis is more likely to be missed for a partial-year enrollee, as there will be less time to accumulate provider encounters in which a diagnosis might be coded for the health insurance claim. We call this the "missed diagnosis" channel.[8] Thus, whether a specific diagnosis (e.g., diabetes) is observed provides

[7] State Medicaid managed care programs vary in many ways, including in the type of risk adjustment system they use among managed care insurers. This variation is both across states and within states for different Medicaid eligibility groups. For risk adjustment, states use systems such as the Chronic Disability Payment System or Adjusted Clinical Groups to calculate an enrollee's risk score. Many states require only 6 months of enrollment to calculate a risk score for its Medicaid managed care enrollees. Enrollee risk scores are then used to contribute to an aggregate plan-level average risk score or plans may be paid based on each individual's risk score (See Layton, Ndikumana, and Shepard 2017 for a discussion). A system that calculates an average risk score and then pays per enrollee-month will look quite similar to fractional adjustment: the risk score will be underestimated for partial-year enrollees.

[8] Precisely, by "missed diagnoses," we mean that the diagnosis would have been observed if the individual were observed for the full year but is not observed during the partial year in which the individual is enrolled. We do not take a stand on what the "correct" level of diagnostic coding should be, merely that it will be less intense for partial-year enrollees than for full year enrollees.

different information about a partial-year enrollee versus a full-year enrollee; all else equal, partial-year enrollees for whom no diagnosis is observed are sicker on average than full-year enrollees for whom no diagnosis is observed. We frame the model around risk adjustment for health insurance, but it is also applicable to adjustment for quality metrics.

Using the model, we show how to correct the risk adjustment system to account for missed diagnoses in partial-year enrollment. We propose scaling up payments for observed diagnoses in partial-year enrollees to account for the fact that diagnoses are more likely to be missed if an enrollee is observed for a shorter time period. This achieves the dual goals of correctly compensating plans (on average) for both partial-year enrollees and sick enrollees. The alternative policy of simply adding an additional fixed payment based on enrollment duration for partial-year enrollees, as recently implemented in the Marketplaces, can correctly compensate for partial-year enrollees on average, but will then make sick enrollees systematically undercompensated. The intuition is that compensating using an additional fixed payment for all partial-year enrollees leads to overpaying for healthy partial-year enrollees and underpaying for truly sick partial-year enrollees. This can lead insurance companies to develop strategies to avoid enrolling sicker enrollees as a result of the risk adjustment system failure.

Our result is innovative — we are unaware of a risk adjustment method that uses diagnosis information to adjust for partial-year enrollment in this way—and provides a potential solution for programs that have avoided using diagnosis data to risk adjust partial-year enrollees. A commonly cited reason that risk adjustment systems do not use data from actual partial-year enrollees is that sample sizes are too small to accurately calibrate the model for rare conditions (Centers for Medicare & Medicaid Services Center for Consumer Information & Insurance Oversight 2016a). Because the scaling factor in our model is determined based on the probability the diagnosis is observed in the shorter versus longer observation period, simulations from data on full-year enrollees will provide the necessary information for all conditions to correct payments for partial year enrollees.

After presenting our theoretical model, we empirically examine the importance of missed diagnoses in partial-year enrollment. We use the 2014 ACA Marketplace risk adjustment algorithm and data on commercially insured working-age adults. We quantify underprediction of spending due to missed diagnoses by conducting a simulation using data from full year enrollees: if these individuals had been enrolled for only part of the year, how would their predicted spending based on the risk adjustment algorithm compare to their actual spending for the months they were enrolled? We find that six month enrollees' predicted costs are only 81% of their actual costs, while three month enrollees' predicted costs are only 68% of their actual costs on average. Based upon an average annual spending of $4,666 per enrollee, this means that the spending of a six-month enrollees is underpredicted by $443 (calculated as 19% underprediction * 0.5 years enrolled * $4,666 spending/year). Our results are consistent with concerns raised by Marketplace insurers about being undercompensated for partial-year enrollees (Eyles and Gierer 2016; Fisher 2016), as well as with a report from the Centers for Medicare and Medicaid Services[9] and subsequent adjustments to the Marketplace risk adjustment system for enrollment duration (Centers for Medicare & Medicaid Services 2016b; Centers for Medicare & Medicaid Services Center for Consumer Information & Insurance Oversight 2016a).

Our model and empirics also consider a second reason that risk adjustment may fail for partial-year enrollees: partial-year enrollees may have systematically different spending patterns than full year enrollees ("differential spending patterns"), even if no diagnoses are missed by the

[9] This report was concurrent with an earlier draft of this paper.

risk adjustment algorithm. Differential spending patterns may result from factors that increase utilization, including pent up demand, and factors that decrease utilization, such as higher out-of-pocket spending due to annual deductibles not being scaled to partial year enrollment.[10] These differential spending patterns can affect enrollee risk scores and the relationship between risk scores and spending (Centers for Medicare & Medicaid Services Center for Consumer Information & Insurance Oversight 2016a). The differential spending channel can thus lead risk adjustment to over- or under- compensate for partial-year enrollees on average, depending on the utilization patterns of these enrollees.

In a second empirical analysis, we estimate the combined effect of missed diagnoses and differential spending by examining the risk adjustment model's performance on individuals who were enrolled for only part of the year in the Marketscan data. In this partial year sample, the differential spending channel has relatively small effects for six-month and three-month enrollees, indicating that in this sample, utilization patterns are likely similar between full year and partial year enrollees. For example, three month enrollees are predicted by the missed diagnosis analysis to be 68% as costly as their actual spending. When both differential spending and missed diagnoses are accounted for, results are similar: three month enrollees are predicted to be 73% as costly as their actual spending. However, the effects of differential spending patterns for one-month enrollees are larger: while the missed diagnoses predicts that they are 56% as costly as their actual spending, that number rises to 86% once differential spending is accounted for. This result is sensible: one month enrollees don't have much time to consume care

[10] Partial year enrollees will typically spend a higher proportion of their enrollment duration exposed to deductibles (Centers for Medicare & Medicaid Services Center for Consumer Information & Insurance Oversight 2016a; Taubman et al. 2014). Plan parameters for deductibles and maximum out-of-pocket spending caps are based on annual enrollment and are not prorated based on enrollment duration. Previous research has shown that individuals are responsive to this difference in cost-sharing in their utilization patterns and have lower spending than would otherwise be expected (Aron-Dine et al. 2015).

(e.g., it takes time to find an in-network doctor and make an appointment), as indicated by the 79% of one month enrollees who have no spending during the enrollment period.

The effect sizes we find for underprediction of spending for partial year enrollees are substantial. By way of benchmarking, consider another noted failure of risk adjustment, "upcoding". Geruso and Layton (2015) show "upcoding" among Medicare Advantage insurers, in which private plans code diagnoses more intensively than fee-for-service Medicare and thus are overpaid. Individuals of similar underlying health status enrolled in private Medicare Advantage plans have risk scores that are 6-16% higher than individuals in fee-for-service Medicare (Geruso and Layton 2015). Geruso and Layton note that their 6% number is "equivalent to 6% of all consumers in a market becoming paraplegic, 11% of all consumers developing Parkinson's disease, or 39% becoming diabetic". Although this is based on Medicare Advantage enrollees, a different population than the commercially insured working age adults we examine empirically, this comparison is still informative as to the magnitude of the underprediction due to failures of risk adjustment to account for partial year enrollment.

Undercompensating insurers for partial-year enrollees will lead them try to avoid such enrollees. For example, one way to select against partial-year enrollees is through the use of high deductibles.[11] For instance, consider two plans with the same actuarial value, one with a high deductible but low coinsurance rate, the other with a low deductible but high coinsurance rate. Compared to similar full-year enrollees, partial-year enrollees will show a greater preference for the low deductible plan, as they are less likely to be enrolled long enough to benefit from the high deductible plan's lower coinsurance rates. These incentives to discourage partial year

[11] More generally, plans can try to select healthier enrollees using the design of cost-sharing provisions, drug formularies, provider network composition, marketing and customer service, and/or avoiding certain regions or states (Geruso, Layton, and Prinz 2016; Jacobs and Sommers 2015; McGuire et al. 2014; Montz et al. 2016; van de Ven et al. 2015).

enrollees may have contributed to high deductibles seen in many Marketplace plans (Centers for Medicare & Medicaid Services 2016a).

The framework we develop is novel[12] and general enough to be used to improve risk adjustment in the Marketplaces as well as other health insurance markets. It also highlights that risk-adjusted quality measures will likely penalize providers who attract partial-year enrollees unless appropriate adjustments are made. The distinction between the missed diagnosis channel and the differential spending channel is important. Given that selection into partial-year enrollment and resulting usage patterns of these enrollees will likely vary substantially between different markets, differential spending results from one population are difficult to generalize to other populations. However, the missed diagnosis effect is predictable and systematic. Moreover, as our theory and empirical example shows, corrections for the missed diagnosis effect can be made without actually having data on the partial year enrollees.

The paper proceeds as follows: In Section 2 we introduce theory that contains a model of partial-year enrollment and missed diagnoses. It also formally defines the differential spending channel. Section 3 describes our empirical methods, Section 4 shows the results, and Section 5 offers discussion and conclusion.

II. THEORY

[12] For instance, a report that estimated underpayment for partial-year enrollees based on Medicare fee-for-service claims (Mehmud and Yi 2012) only examined the missed diagnoses channel; actual partial-year enrollees in that population may also have differential spending patterns. Older research using 1994 data from three states described the issues of short term enrollees being underpaid by diagnosis based risk adjustment and having more unpredictable spending in select states for Medicaid managed care (Adams, Bronstein, and Raskind-Hood 2002). CMS CCIIO described issues surrounding partial year enrollment and has introduced adjustment factors starting in calendar year 2017 to correct for enrollment duration (Centers for Medicare & Medicaid Services 2016b; Centers for Medicare & Medicaid Services 2016d; Centers for Medicare & Medicaid Services Center for Consumer Information & Insurance Oversight 2016a). Their analyses with MarketScan data found substantial underpayment for partial year enrollees; however, they did not distinguish between the missed diagnoses effect and the differential spending pattern effect.

In this section, we develop a stylized model of diagnosis based risk adjustment and use it to illustrate the effect of partial-year enrollment. The stylized model can represent many diagnosis-based risk adjustment systems that pay for partial-year enrollees, including those used in the Marketplaces and in many states' Medicaid managed care programs. We discuss the model in terms of risk adjustment payments in health insurance, but it could also be applied to risk adjustment for quality measures by interpreting the model as predicting the risk of complications.

Consider a simple diagnosis-based risk adjustment system in which an enrollee *i*'s predicted annual spending $\hat{y}_i$ is a linear combination of a fixed[13] amount α plus observed diagnoses times a set of diagnosis-specific weights β.[14] The diagnosis specific weights are the expected additional spending due to each diagnosis, which are calibrated by the risk adjustment system. That is, $\hat{y}_i = \alpha + \sum_{j=1}^{J} x_{ij}\beta_j$, where $x_{ij} = 1$ if the diagnosis *j* is observed for enrollee *i* and 0 otherwise. Observing a diagnosis increases expected spending, so all $\beta_j > 0$. A diagnosis may be observed anytime during the year in which the enrollee is enrolled, whenever an enrollee interacts with a healthcare provider and has a health insurance claim. We assume that the risk adjustment system is accurately calibrated for full-year enrollees: that is, the average predicted spending $\hat{y}$ conditional on any diagnosis *x* is equal to the average actual spending y conditional on having that diagnosis. That is for any set of diagnoses, $E[\hat{y}|\{x_j\}_{\in J}] = E[y|\{x_j\}_{\in J}]$.

Now, consider a partial-year enrollee *i* who has the same underlying unobserved health status and usage patterns as the full year enrollee. Let $\varphi_i \in (0,1]$ be the fraction of the year that a

[13] Risk adjustment systems in practice may also make use of other data, such as enrollees' age, sex, or actuarial value of plan selected. That is, both α and the β_j could vary by those characteristics. We abstract from those issues in this model, which do not affect our results. However, in our empirical section, we deal with them appropriately.

[14] In our model, the outcome is predicted spending of individuals. In practice, a risk adjustment system often predicts a risk score that is translated to insurer payments/transfers that also includes adjustments for factors such premiums, plan cost-sharing features/actuarial values, and geographic corrections. We abstract away from those concerns in the model.

given enrollee i is enrolled in the health plan and thus observed by the risk adjustment system. We assume that the probability a diagnosis is observed is strictly increasing in the fraction of the year enrolled.[15] We formally define two terms relevant for partial-year enrollees: *fractional adjustment* and *spending scales linearly in time enrolled*.

Fractional adjustment is an intuitive method that attempts to account for partial year enrollment:

> **Definition 1: Fractional Adjustment**. A risk adjustment system uses fractional adjustment if the predicted spending for an individual enrolled for fraction φ_i of the year is $\varphi_i(\alpha + \sum_{j=1}^{J} x_{ij}\beta_j)$. That is, a risk adjustment system uses fractional adjustment if it predicts annual spending and then multiplies by the fraction of year enrolled φ_i.

The assumption that *spending scales linearly in time enrolled* captures the claim that partial-year enrollees are the "same as" full-year enrollees, just enrolled for a shorter time:

> **Definition 2: Spending Scales Linearly In Time Enrolled.** For any individual i, if their annual spending is y_i when enrolled for the full-year, their expected spending is $\varphi_i y_i$ if they are enrolled for fraction φ_i of the year.

We view the assumption that spending scales linearly in time enrolled as a reasonable starting point if the underlying health status of partial year enrollees is the same as full year enrollees and spending patterns are similar. However, it may fail. We term the failure of this assumption "differential spending" of partial-year enrollees. It is quick to see that when this assumption fails, fractional adjustment would not generally compensate plans correctly for partial-year enrollees,

[15] The assumption that *each* diagnosis is observed with lower probability for partial-year enrollees rules out cases in which "diabetes with complications" is observed with lower probability but "diabetes without complications" is observed with higher probability. These types of situations can be accommodated in the model by the weaker assumption that on average, partial-year enrollees of identical health status and usage patterns as full year enrollees are observed to be healthier on average, in the sense that E[$\sum_{j=1}^{J} x_j\beta_j$] is lower for partial-year enrollees. We present the simpler model for conciseness.

even if all their diagnoses are properly observed during the shorter time period. There are a number of reasons that this assumption might fail, including pent-up demand (if partial-year enrollees were previously uninsured) and differential exposure to cost-sharing (partial-year enrollees likely spending a longer fraction of the year exposed to the deductible).

What is perhaps more surprising is that even if spending is linear in time enrolled, fractional adjustment is still not the correct strategy for addressing partial-year enrollment. The following proposition shows that fractional adjustment will in fact underpredict the spending of partial-year enrollees. The proof develops a simple single diagnosis example that explains the logic.

> **Proposition 1: Missed Diagnoses Leads to Underpayment.** Suppose the risk adjustment system is accurately calibrated for full-year enrollees and that spending scales linearly in time enrolled. Then, fractional adjustment will underpredict spending for partial-year enrollees on average: for $\varphi_i < 1, E[\varphi\hat{y}] < E[\varphi y]$.
>
> **Proof:** Consider a system that is only based on a single diagnosis, so that predicted annual spending is α without the diagnosis and $\alpha + \beta$ with the diagnosis. Call an individual who gets the diagnosis when enrolled for the full-year "sick" and who does not get the diagnosis when enrolled for the full-year "healthy." A healthy individual does not get the diagnosis when enrolled for either the full or partial-year, as the probability of observing a diagnosis increases in time enrolled. Fractional adjustment is accurate for healthy individuals: predicted and expected actual spending are $\varphi\alpha$.

However, sick enrollees with predicted annual spending of $\alpha + \beta$ only have the diagnosis observed with probability $p<1$ when enrolled for part of the year. If the diagnosis is observed, fractional adjustment again performs accurately: predicted and expected actual spending are $\varphi(\alpha + \beta)$. However, if the diagnosis for the sick individual is missed, predicted spending is only $\varphi\alpha$, which is less than the expected actual spending of $\varphi(\alpha + \beta)$. As a result, the risk-adjustment system with a single diagnosis underpredicts on average for partial-year enrollees. The logic generalizes for a system that is the sum of many diagnoses, under the assumptions that all $\beta_j > 0$ and that the probability a diagnosis is observed is strictly increasing in the fraction of the year enrolled ■

Figure 1 illustrates the intuition behind the proof. Consider two individuals with the same condition who both receive a diagnosis in a February doctor's visit, and assume that this is the only time the diagnosis could be observed that year. Take one individual who is enrolled in the plan for a spell between January and June. In this case, the diagnosis is observed, and the fractional adjustment method will be correct with predicted spending of $\varphi(\alpha + \beta)$. However, consider the second individual enrolled for a spell from July to December. Although this individual has the same underlying condition, the plan does not observe the diagnosis from the February visit. The individual's predicted spending is only $\varphi\alpha$, which is below their true spending of $\varphi(\alpha + \beta)$. This "sick" enrollee has a missed diagnosis and their spending is under-predicted.

Note that on average, the risk adjustment system correctly compensates for "healthy" partial-year enrollees who would not have had a diagnosis observed, even if they were enrolled for the full year. For these "healthy" enrollees, there is no diagnosis to miss. Their spending is $\varphi\alpha$, equal to what is predicted by fractional adjustment.

[FIGURE 1 HERE]

How then should risk adjustment be altered to account for partial-year enrollees? Table 1 examines the case of a single diagnosis and compares three systems: fractional adjustment alone and two modifications to fractional adjustment – an "additive payment" and a "scale up diagnosis payment". The first proposed modification for partial year enrollees is a system in which an additional payment *c* for partial-year enrollees is added over and above the amount implied by fractional adjustment. The payment *c* is based on the number of months enrolled and does not vary based on patient characteristics or observed diagnoses. This proposal to adjust risk scores using an additive factor was adopted in recent revisions to the risk adjustment program for the Marketplaces starting in the 2017 calendar year for risk adjustment (Centers for Medicare & Medicaid Services 2016b).[16] In contrast, the second (preferred) method is novel: we propose scaling-up the diagnosis specific payments (β) for partial year enrollees, based on the inverse of *p*, which is the probability a diagnosis that would be observed for the full-year enrollee is actually observed for the partial-year enrollee.

[TABLE 1 HERE]

The first column of Table 1 shows that the overall payment for sick enrollees under fractional adjustment is $\varphi[\alpha + p\beta]$, which is below their true costs. The second column shows that if *c* is chosen so that partial-year enrollees are correctly compensated on average, then

[16] The additive payment model is very similar to proposals that would estimate an entirely separate risk adjustment model for partial-year enrollees. Having an additive payment c is equivalent estimating a different α in the model. Note for the model presented here, an entirely separate partial-year risk adjustment model would produce the same estimated payments per diagnosis β (recall that here, conditional on observing a diagnosis, the risk adjustment system is accurate for partial-year enrollees).

healthy partial-year enrollees will be over-compensated for and sick partial-year enrollees will be under-compensated for. Thus, the additive payment c cannot be chosen to correctly compensate insurers for both healthy and sick partial-year enrollees. The third column shows our proposed method for correction. Instead of making a payment β for the diagnosis, the system makes a higher payment of $\frac{1}{p}\beta$, where $p < 1$. That is, the third method scales up the payment for partial year enrollees' observed diagnoses to account for the lower probability of observing those diagnoses, relative to a full year enrollee. This then correctly compensates for both healthy and sick partial-year enrollees.

For multiple diagnoses, one would need to adjust by $1/p_j$ for each diagnosis based on the probability that diagnosis j is observed among partial-year enrollees. Also note that the probabilities p_j also depend on the fraction of the year enrolled φ. That is, the probability a diagnosis is observed will generally differ between a one-month versus six-month enrollee.

The scaling- up method has advantages: of the three methods considered, it is the only one that removes the incentives for insurers to distort contracts and services to avoid the sick enrollees. However, the method also brings with it complications. While it removes the incentives to select for or against sick enrollees, it increases the incentives for insurers attract and code the diagnoses for sick partial-year enrollees. Thus, it will need to be recalibrated as firms change their coding intensity. Moreover, by increasing the variance in payments, it may create more scope for insurers to cherry-pick enrollees who are "cheap" for their risk score (see e.g., Brown et al. (2014)). In general, a risk adjustment system must tradeoff the removal of incentives for service-level selection against other concerns such as statistical fit (e.g. R^2), incentives for cost-containment (i.e. power), and balance in incentives across different services; for a discussion, see Geruso and McGuire (2016).

III. EMPIRICAL EXAMPLE: METHODS

The theory model illuminates the role of missed diagnosis and differential spending in risk adjustment for partial-year enrollees. We now ask the question, how important are each of these factors empirically? Additionally, how much does the explanatory power vary for partial year enrollees? We take as our empirical example the risk adjustment algorithm used for the ACA Marketplaces. Since claims data are unavailable for the Marketplaces, we apply the algorithm to data on a similar population that is used for calibrating this risk adjustment algorithm: commercially insured working age enrollees included in Truven MarketScan data. MarketScan data are used in the Marketplaces to calculate risk adjustment models and partial year adjustment factors.[17]

III.A. Risk Adjustment Algorithm

We applied the HHS risk adjustment algorithm used on the federally facilitated and state-based Marketplaces (version 03) for benefit year 2014 (Department of Health and Human Services 2013). The risk adjustment algorithm predicts an enrollee risk score based on diagnosis categories. We applied the algorithm to calculate risk scores based on claims from different time periods as described below. Based on the algorithm, we limited to inpatient hospital, outpatient facility, and professional claims to calculate risk scores (Kautter et al. 2014).

[17] CMS explains their use of Marketscan, saying that while "many projected characteristics of the individual market enrollees were similar to those of both enrollees in employer-sponsored insurance and Medicaid enrollees, on average they tended to be closer to enrollees in employer-sponsored insurance" (Centers for Medicare & Medicaid Services Center for Consumer Information & Insurance Oversight 2016a). In future years, starting as early as 2019, they plan to use data from the individual and small group market to calibrate the model although they note they do not have evidence that using Marketscan is less accurate (Centers for Medicare & Medicaid Services Center for Consumer Information & Insurance Oversight 2016b).

The algorithm used *International Classification of Diseases – Ninth Edition* (ICD-9) diagnostic codes and Current Procedural Terminology (CPT) procedure codes to create hierarchical condition categories (HCCs). Codes were then ranked by severity, and patients assigned to their highest severity condition within that condition category. Risk scores were assigned based on these 127 binary HCC indicators plus age and sex variables (Kautter et al. 2014).

In the Marketplaces, these risk scores are averaged across plans for an insurer to calculate risk transfers (Kautter et al. 2014). Insurers whose enrollees have lower predicted spending based on risk scores make risk transfer payments, while insurers whose enrollees have higher predicted spending based on risk scores receive payments, for an overall market net transfer amount of zero.[18] Risk transfers account for plan enrollee composition, measured by risk scores based on diagnosis and demographic characteristics; adjustments are also made for geographic cost variations and plan actuarial values (Pope et al. 2014).

The algorithm adjusted risk scores for insurance plan coverage using metal levels – for example, an individual with identical characteristics and condition categories in a "gold" plan with an actuarial value of 80% would be predicted to have a higher risk score and associated costs than the same individual enrolled in a "silver" plan with an actuarial value of 70% (Department of Health and Human Services 2013). We assigned all individuals to the "silver" risk score with no cost sharing reductions. We conducted sensitivity analyses for other metal levels: bronze, gold, and platinum.

III.B. Data

[18] We do not address two other transitional policies were implemented in the Marketplaces: risk corridors and reinsurance. These policies were temporary for 2014-2016, while risk adjustment is permanent.

We used the 2013 Truven Health Analytics MarketScan Commercial Claims and Encounters database, containing information from almost 100 payers, including commercial insurance companies and self-insured employers. Enrollment data were combined with complete claims information. Total spending included inpatient, outpatient, and pharmacy claims.

Analyses were conducted in SAS version 9.0 (SAS Corporation; Cary, NC) and Stata version 14.1 (StataCorp; College Station, TX).

III.C. Analytic Samples

We constructed two analytic samples. The “full year sample” was adults aged 21-64 continuously enrolled for the 2013 calendar year. We limited to individuals with complete demographic information, prescription drug coverage, integrated mental health/substance abuse coverage, who did not have capitated payments, and who had non-negative spending for the full period. We included those in all types of insurance plans. The “partial year sample” included adults aged 21-64 enrolled for at least 1 day and fewer than 365 days in 2013, with the same restrictions as the full year sample.

III.D. Missed Diagnoses Alone Analysis

To determine the effect of missed diagnoses, we conducted simulations of partial year enrollment. Using the full year sample, we simulated three shorter enrollment periods: what if each enrollee had only been enrolled for six months? For three months? For one month? These simulated enrollment periods were created by breaking up the full year into non-overlapping periods. For example, when simulating three-month enrollment periods, each enrollee produced four different simulated periods (i.e., Quarters 1, 2, 3, and 4 of 2013). For each of the shorter enrollment periods, we calculated risk scores from that period’s data and calculated total spending from claims during that period. This method isolates the missed diagnosis effect to quantify how much risk adjustment might underpredict the spending of partial-year enrollees with identical underlying health status and usage patterns. Simulating shorter enrollment periods affects what risk scores will be calculated because all diagnoses may not be included on the specific claims during this period, but is not affected by other factors such as the higher cost-sharing experienced by partial year enrollees or changes in sample composition.

We estimated a regression to convert risk scores to annual spending in order to calculate predictive ratios as described below.[19] Thus, the average annual risk score predicts the average annual spending for the full year sample; we used this to compare to actual spending in the simulated shorter durations as described below.

$$\textit{annual spending} = \beta_0 + \beta_1\ \textit{annual risk score} \qquad \text{(Eqn 1)}$$

For partial-year enrollees, we implement fractional adjustment—the risk adjustment system for the ACA Marketplaces before the addition of adjustment factors for enrollment duration. For a member enrolled *d* days out of the year, we estimated $\textit{risk score}_{d\ days}$ based on claims observed during *d* days of the year. The actual number of days in each observed period is used for the calculations (e.g., second quarter 2013 has 91 days). We then simulated predicted spending using fractional adjustment as follows:

$$\textit{Predicted spending}_{d\ days} = \frac{d}{365}(\beta_0 + \beta_1\ \textit{risk score}_{d\ days}) \qquad \text{(Eqn 2)}$$

where coefficients β_0 and β_1 come from Equation 1.

For each duration of one month, three months, six months, and 12 months, we calculate the "predictive ratio" as $\textit{mean predicted spending}_{d\ days} / \textit{mean actual spending}_{d\ days}$. We averaged the predicted period spending based on the period risk score and compared to the averaged actual

[19] In individual and small group markets (including the Marketplaces), the risk transfer formula scales plan risk scores to spending levels using information about statewide premiums, which reflect statewide cost levels (Pope et al.). Here, we use actual costs in our population. Premiums may diverge from costs: see Mahoney and Weyl (Forthcoming) and Ericson and Starc (2015) for more on imperfect competition in selection markets.

period spending. If the risk score predicts spending perfectly on average, the predictive ratio would be 1 (Kautter et al. 2012; Kautter et al. 2014).

We also calculated the explanatory power for each time period by estimating a regression of spending during the time period (e.g., one month) on the risk score calculated for that period. The explanatory power, measured by the R-squared, is the amount of variation in spending explained by the risk score. All else equal, higher explanatory power is better, since risk adjustment systems with more residual variation in spending create more scope for insurers to cherry-pick enrollees who are "cheap" for their risk score (see e.g., Brown et al. (2014)).

We calculated the proportion of enrollees who had no inpatient, outpatient, or pharmaceutical spending during each period. We also measured out-of-pocket spending by totaling all forms of cost-sharing (e.g., copay, deductible) and calculating this as a proportion of total spending.

II.E. Partial-Year Enrollment Analysis: Differential Spending + Missed Diagnosis

While the simulations described in the previous section, "Missed Diagnoses Alone," will show the effects of missed diagnoses due to only being observed part of the year, we also examine the combined effect of differential spending patterns and missed diagnoses for partial year enrollees. We use the partial year sample, comprised of individuals enrolled for less than a full year, to examine spending patterns and risk scores.

We analyzed differences in demographics, spending patterns, and risk scores between partial year and full year samples. We compared per member per month spending, out of pocket spending as a percent of total spending, and the percent of enrollees with no spending during the period. We also compared spending patterns and risk scores to those calculated in the missed diagnoses alone analysis.

We then calculated the predictive ratio by number of months enrolled by using a similar process as described previously. We used Equation 1, with coefficients estimated on the full year sample, to calculate predicted annual spending for each enrollee. We then calculated each enrollee's predicted spending based on days enrolled using Equation 2. For each number of months enrolled, we calculated the predictive ratio by averaging predicted period spending compared to the averaged actual period spending for those enrolled for that duration.[20]

IV. EMPIRICAL RESULTS

IV.A. Missed Diagnoses Alone Analysis

1. Descriptive Statistics. The full year sample had 13,069,722 enrollees continuously enrolled in the same plan for 2013. Descriptive statistics showed an average age of 43.8 with slightly more females (52.4%) (Table 2). The average silver risk score for the full year sample was 1.28; these individuals were predicted to be 28% more costly than the average plan liability expenditure for the calibration sample (Kautter et al. 2014; Kautter, Pope, and Keenan 2014).[21] The average annual medical spending for 2013 was $4,666.

[TABLE 2 HERE]

2. Simulation Analysis. Simulations with the full year sample showed the predictive ratio varied substantially with enrollment duration, with lower ratios for shorter periods (Table 3); the predictive ratio for one month was 0.56, and for six months was 0.81. A predictive ratio of 0.56 indicates that the predicted spending based on risk scores for simulated one month enrollees was 56% of actual medical spending for these enrollees.

[20] We categorized into number of months enrolled by calculating number of days enrolled, dividing by 30.4, and rounding to the nearest number of months.
[21] The calibration sample uses MarketScan data and contains both full and partial year enrollees. It was designed to be representative of individuals enrolling in the small group and individual market.

[TABLE 3 HERE]

Risk scores had low to moderate explanatory power that varied substantially over time periods (Table 3), with a one year period having almost twice the explanatory power as a one month period (0.34 vs. 0.19). That is, for the simulated one month period, 19% of the variation in spending was explained by variation in risk scores.

III.B. Partial Year Enrollment Analysis: Differential Spending + Missed Diagnosis

1. Descriptive Statistics. There were 7,601,091 partial year enrollees, slightly more than half the number of full year enrollees. These enrollees had an average enrollment duration of 5.2 months (Table 2). The average silver risk score ranged from 0.59 for those enrolled zero to three months to 1.07 for those enrolled nine to fewer than 12 months. Shorter enrollment durations had more males enrolled than females, with shorter enrollment durations also having younger enrollees.

2. Partial Year Comparisons to Full Year Sample. To understand differential spending patterns, we compared spending for partial year enrollees versus full year enrollees and the simulated shorter periods. Partial year spending during the enrollment period was lower for all periods for actual partial year enrollees versus simulated full year enrollees, as was per month spending (Table 4). For one-month actual partial year enrollees, per month spending was $215, compared to $389 for simulated one month enrollees. For each enrollment duration, the percentage of enrollees with no spending during the enrollment period was higher for actual partial year enrollees than simulated enrollees for the same period; for one month, 79% of one month actual partial year enrollees did not have spending during the month versus 66% of simulated enrollees. Out of pocket spending was generally lower for the full year simulated enrollees versus partial year enrollees, although for the three month enrollees, simulated enrollees had higher out of pocket spending.

[Table 4 HERE]

3. Partial Year Predictive Ratio Analysis. We calculated predictive ratios for partial year enrollees using regression estimates from the full year sample, and compared these to the predictive ratios calculated in the full year simulations. For one and three month durations, the predictive ratios were higher for partial year enrollees than simulated enrollees. For six month and one-year durations, the predictive ratios were higher for simulated enrollees than partial year enrollees.

[TABLE 5 HERE]

We repeated all analyses for the other three metal levels and found similar results.

V. DISCUSSION

We provide a framework for why risk adjustment will not work properly for partial-year enrollees: missed diagnoses and differential spending patterns. Distinguishing between these two effects is important for improving risk adjustment models. Our model shows that the standard method of fractional adjustment will lead risk adjustment to underpredict spending for partial-year enrollees, relative to similar full-year enrollees. This results from the missed diagnoses channel, and is a general point that applies to many markets—it is not merely a failure to calibrate the risk adjustment model correctly, but a fundamental consequence of the fractional adjustment approach to risk adjustment.

The magnitude of the underprediction of spending is substantial using data for enrollees who are similar to those enrolled in the Marketplaces. The missed diagnosis channel alone will lead to underprediction for shorter enrollment durations, even if partial-year enrollees are not any sicker than full-year enrollees, there is no pent-up demand effect, and partial year enrollees have similar overall cost-sharing as full year enrollees. The intuition for this finding is that insurers are not compensated by risk transfers for the additional costs of enrollees whose diagnoses are missed due to partial year enrollment. These enrollees, however, continue to have spending commensurate with their underlying (unobserved) health status and usage patterns. We also show that risk scores have lower explanatory power for partial-year enrollees; they do not explain as much of the variation in costs for these enrollees, leaving scope for additional risk selection (see Brown et al. (2014)).

We then considered another channel for why risk adjustment might fail—systematically different spending patterns for partial year versus full year enrollees. The "differential spending patterns + missed diagnoses" analysis of 6-month and shorter partial-year enrollees showed they had lower per month spending than full-year enrollees simulated over the same time periods, meaning the spending of partial-year enrollees was systematically different than full-year enrollees. In calculating predictive ratios with the partial year risk scores, we find differential spending partially offsets the missed diagnosis effect, but still leaves a substantial underprediction for partial-year enrollees.

Due to the fact that we do not have claims of actual Marketplace enrollees, partial year enrollees in the Marketplaces may differ from those in Marketscan. For example, they may be more likely to be previously uninsured and may also face different levels of cost-sharing. As a result, the differential spending channel may be different empirically in the Marketplaces. Differential spending of partial year enrollees in Medicare Advantage and Medicaid managed care is likely to be quite different than those in commercial insurance, showing the importance of our theoretical model in noting a way to fix risk adjustment for partial year enrollees without relying on data for these enrollees, which may be problematic due to small samples.

Our theoretical results also show how to fix the risk adjustment formula such that it accounts for the missed diagnosis effect: scale up the payments for a diagnosis in partial-year enrollees to account for the fact that the diagnosis will be missed. This adjustment is quite different than the additive partial-year adjustment factors implemented in revisions to the Marketplace risk adjustment model, which are right on average but create additional incentives for insurers to avoid sicker partial year enrollees. The scaling method is more complex than the additive factor in that it requires the estimating how observing an enrollee for a shorter duration affects the probability the diagnosis would be observed. However, this probability should be simulated from data on full-year enrollees, reducing concerns about having small sample sizes for partial year enrollees with relatively rare (and often expensive) conditions.

An alternative to scaling up diagnosis payments in diagnosis-based risk adjustment might be a more radical revision of the risk adjustment model itself. Many commentators have proposed using prescription drug claims in a risk adjustment model, as including prescription claims adds substantial predictive power (e.g. Layton, Geruso, and Prinz (2016) on the Marketplaces, and Hsu et al. (2009) on Medicare Part D). Drugs taken regularly for a chronic illness might be observed more frequently than office-visits for that illness, and thus reduce the missed diagnosis problem for partial year enrollees. Although using prescription drug utilization in the risk adjustment model for the Marketplaces has been criticized as being open to gaming and perverse incentives for insurers (Centers for Medicare & Medicaid Services Center for Consumer Information & Insurance Oversight 2016a), CMS is planning to incorporate such information to the risk adjustment for the Marketplace to improve the predictive ability starting in 2018

(Centers for Medicare & Medicaid Services 2016b). Future research should explore whether the addition of information from prescription drug utilization to risk adjustment systems improves predictions for partial year enrollees as well as for full year enrollees.

We have focused on predicting the spending of enrollees, but insurers' costs will diverge from enrollees' spending due to cost sharing. In some markets (e.g. Medicaid Managed Care), cost-sharing is small in magnitude. But in others (e.g. bronze Marketplace plans), cost-sharing can be substantial. In these cases, adjustment for the differential cost-sharing borne by partial-year enrollees should be incorporated into a risk transfer system. However, such an adjustment should depend on the design of the insurance plan, rather than simply be based on actuarial value. Consider two plans with the same actuarial value (for the entire population): a plan with a high deductible and a plan with no deductible but high copays per-visit and per-admission. In the high-deductible plan, cost-sharing is front-loaded in the year, and partial-year enrollees will pay a higher fraction of their spending out-of-pocket than full-year enrollees will, thereby lowering their costs to the insurer. But in the no-deductible, high-copay plan, cost-sharing is spread throughout the year, so full-year and partial-year enrollees will pay similar fractions of spending out of pocket. Thus, any partial-year enrollment correction for cost-sharing must consider not just actuarial value but the structure of plan design.

Failures of risk adjustment can have substantial impacts on both firm profits and consumer welfare. This is true, even if partial-year enrollees were equally allocated across insurers, and even though risk adjustment payments are revenue neutral. This is due to the fact that errors in risk adjustment will lead to contract distortion as insurers seek to avoid less profitable enrollees.[22] In this context, higher deductibles (holding fixed a plan's actuarial value) are useful to deter partial-year enrollees from enrolling. This distorts the contract away from what might be optimal for both consumer welfare and firm profitability (i.e., both full-year enrollees and firms might be better off with plan with lower deductibles in the absence of wanting to avoid partial-year enrollees).

Moreover, risk adjustment may interact with imperfect competition. Premiums are likely marked up over cost in the Marketplaces and other contexts. In that case, even if partial-year enrollees are underpaid relative to full-year enrollees, they may still be paid above cost.[23] Changes to a revenue-neutral risk adjustment system can affect profits with imperfect competition, even if each firm winds up enrolling an equal share of partial-year enrollees. For instance, Ericson and Starc (2015) show that insurer profits are affected by regulations that change the cost of the marginal enrollee. They examined modified community rating regulations that linked the premiums for the old and the young, but a similar logic applies to risk adjustment regulations, given that firms must charge the same monthly premium to full and partial-year enrollees. Depending on whether partial-year enrollees are more or less sensitive to premiums than full-year enrollees, underpaying for partial-year enrollees could lower or raise firm profits; we do not have the data necessary to run the simulations that would answer this question.

We have focused on the implications for risk adjustment in insurance payments. Risk adjusted quality benchmarks also underlie many important payment formulas in health care. The

[22] See, for instance, Geruso, Layton, and Prinz (2016) for how formulary design responds to other errors in Marketplace risk adjustment system, and Carey (2017) for how formulary design in Medicare Part D responds to errors in risk adjustment induced by technological change.

[23] The ACA requires that the Medical Loss Ratio be at least 80% for the individual and small group market. So for a firm with maximum markups, six-month enrollees (whose spending we find to be underpredicted based on missed diagnoses by 19%) may be on the margin of being profitable or unprofitable. The extent of insurer underpayment due to underprediction of risk scores for partial year enrollees will depend on differential cost-sharing for partial year enrollees and the size of risk transfer payments relative to insurer spending on enrollees.

same missed diagnosis channel that leads to underprediction for partial-year enrollees in health insurance also will lead individuals who are observed for less than a full year to appear healthier than they actually are. Thus, providers that disproportionately attract partial-year enrollees may appear to have more complications than would be justified by their underlying patients' health status. Future work could estimate both the magnitude of the problem and propose solutions for different provider quality benchmarks using the framework in this paper.

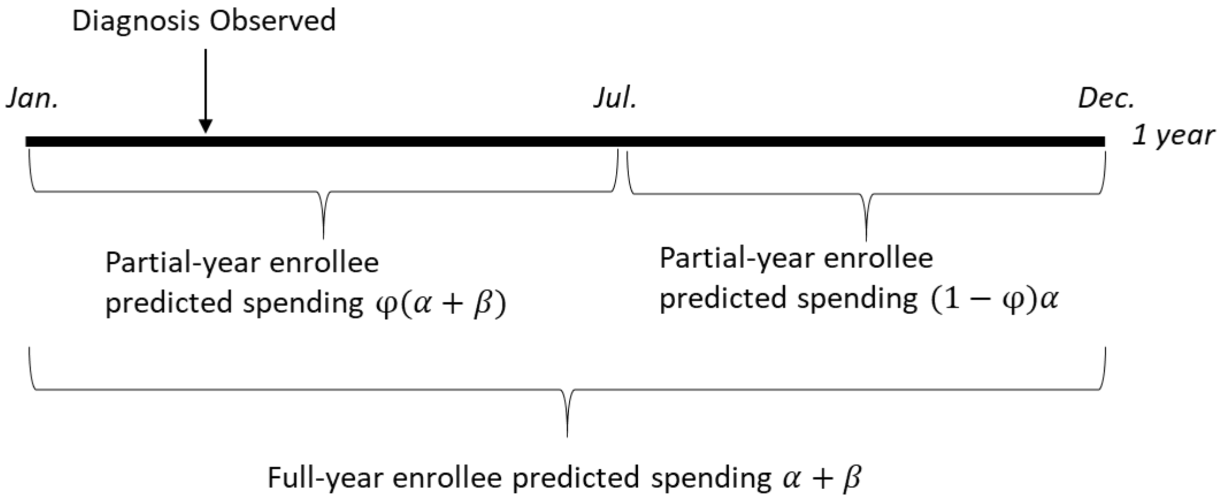

Figure 1: Missed Diagnosis Leads to Underprediction on Average for Partial-Year Enrollees under Fractional Adjustment. Note: Shows the consequences of splitting a sick enrollee's full-year enrollment spell into two partial year enrollment spells (Jan.-Jun., Jul.-Dec.). When the "sick" partial-year enrollee's diagnosis is observed in the coverage window, they are correctly adjusted for (left), but spending is underpredicted when it is missed (right).

	Fractional Adjustment Only	Additive Payment for Partial-Year Enrollees	Scaled Up Diagnosis Payment for Partial Year Enrollees
Healthy enrollee with expected costs $\varphi\alpha$	$\varphi\alpha$	$\varphi\alpha + c$	$\varphi\alpha$
Sick enrollee with expected costs $\varphi(\alpha + \beta)$			
… Diagnosis observed with probability p	$\varphi(\alpha + \beta)$	$\varphi(\alpha + \beta) + c$	$\varphi\left(\alpha + \frac{1}{p}\beta\right)$
… Diagnosis missed with probability 1-p	$\varphi\alpha$	$\varphi\alpha$+c	$\varphi\alpha$
… Sick Overall	$\varphi[\alpha + p\beta]$	$\varphi[\alpha + p\beta] + c$	$\varphi(\alpha + \beta)$

Table 1: Different Methods of Adjusting for Partial-Year Enrollment. Note: Considers the single diagnosis example discussed in text for an individual enrolled for fraction φ of the year. Healthy enrollees are those who would not have had a diagnoses observed if they were enrolled for the full year, while sick enrollees would.

Table 2: Descriptive Statistics

	Full Year Enrollees	Partial Year Enrollees 0-3 months	3-6 months	6-9 months	9-<12 months
Annual Spending (in $)	4666 (18550)				
Per Month Spending (in $)	389 (1545.9)	274 (3165.1)	325 (2098.4)	384 (2109.9)	392 (1855.9)
Percentage of Enrollees with No Spending During Enrollment Period	15	69	47	34	27
Out of Pocket Spending as Percent of Total	31.2	41.6	37.9	36.4	36.0
Enrollee Risk Score					
Platinum (90% actuarial value)	1.61 (3.52)	0.84 (2.00)	1.01 (2.74)	1.23 (3.44)	1.37 (3.75)
Gold (80% actuarial value)	1.45 (3.42)	0.73 (1.95)	0.89 (2.67)	1.10 (3.36)	1.22 (3.66)
Silver (70% actuarial value)	1.28 (3.37)	0.59 (1.93)	0.75 (2.64)	0.95 (3.31)	1.07 (3.61)
Bronze (60% actuarial value)	1.10 (3.36)	0.44 (1.92)	0.60 (2.63)	0.79 (3.31)	0.91 (3.60)
Gender of Patient					
Male	47.6	51.5	50.0	49.7	49.6
Female	52.4	48.5	50.0	50.3	50.4
Age of Patient	43.8 (12.2)	40.9 (13.3)	39.3 (12.9)	39.8 (13.2)	40.7 (13.1)
Plan Type*					
Comprehensive	2.7	1.7	1.8	2.1	2.2
Exclusive Provider Organization	1.0	4.4	2.8	2.4	4.2
Health Maintenance Organization	9.8	8.8	9.2	8.9	8.6
Point of Service	8.8	8.9	7.2	7.3	7.1
Preferred Provider Organization	64.0	63.1	64.9	64.4	61.4
Point of Service with Capitation	0.1	0.6	0.7	0.5	0.4
Consumer Directed Health Plan	7.4	4.7	5.6	6.2	5.7
High Deductible Health Plan	6.3	7.9	7.9	8.2	10.4
Number of Enrollees	13,069,722	2,392,981	2,232,620	1,773,550	1,201,940

Note: Standard deviation in parentheses. *Plan Type has 140,997 missing observations.

Table 3: Predictive Ratio and Predictive Power for Different Enrollment Durations for Silver Metal Level

Time Period	**Predictive Ratio**	**R-squared**
One Month	0.56	0.19
Three Months	0.68	0.23
Six-Months	0.81	0.27
One Year	1.00	0.34

Note: Result of missed diagnoses alone simulations, described in text.

Table 4: Comparison of Spending Patterns and Risk Scores for Full Year and Partial Year Enrollees

	1 month enrollees		3 month enrollees		6 month enrollees	
	Full Year Simulated	Partial Year Enrollees	Full Year Simulated	Partial Year Enrollees	Full Year Simulated	Partial Year Enrollees
Spending During Enrollment Period ($)	389 (3366)	218 (3196)	1167 (6879)	911 (7547)	2333 (11174)	2069 (11731)
Per Month Spending (in $)						
Mean	389 (3366)	215 (3169)	389 (2293)	305 (2536)	389 (1862)	345 (1956)
Median	0	0	33	0	52	22
Percentage of Enrollees with No Spending During Enrollment Period	65.9	79.1	42.4	54.8	27.0	39.7
Out of Pocket Spending as Percent of Total	35.6	42.0	44.1	40.3	32.1	36.8
Adult silver enrollee`s risk score	0.64 (1.49)	0.52 (1.38)	0.82 (2.07)	0.66 (2.27)	1.00 (2.62)	0.83 (2.77)
Number of Enrollees	13,069,722	1,180,020	13,069,722	831,560	13,069,722	798,395

Table 5: Comparison of Predictive Ratios for Different Enrollment Durations

Enrollment Duration	**Missed Diagnosis Alone** (Simulated From Full Year Sample)	**Missed Diagnosis + Differential Spending** (Partial Year Sample)
1 month	0.56	0.86
2 months		0.74
3 months	0.68	0.73
4 months		0.75
5 months		0.73
6 months	0.81	0.78
7 months		0.76
8 months		0.78
9 months		0.82
10 months		0.85
11 months		0.83
12 months*	1.00	0.94

Note: *12 month sample of partial year enrollees has only 9,990 enrollees.

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