The Effect of the Risk Corridors Program on Marketplace Premiums and Participation[*]

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Abstract: We investigate the effect of the Risk Corridors (RC) program on premiums and insurer participation in the Affordable Care Act (ACA)'s Health Insurance Marketplaces. The RC program, which was defunded ahead of coverage year 2016, and ended in 2017, is a risk sharing mechanism: it makes payments to insurers whose costs are high relative to their revenue, and collects payments from insurers whose costs are relatively low. We show theoretically that the RC program creates strong incentives to lower premiums for some insurers. Empirically, we find that insurers who claimed RC payments in 2015, before defunding, had greater premium increases in 2017, after the program ended. Insurance markets in which more insurers made RC claims experienced larger premium increases after the program ended, reflecting equilibrium effects. We do not find robust evidence that insurers with larger RC claims in 2015 were less likely to participate in the ACA Marketplaces in 2016 and 2017. Overall we find that the end of the RC program significantly contributed to premium growth.

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1. Introduction

In 2015, 11.6 million people signed up for insurance coverage in the Health Insurance Marketplaces, and the average Marketplace had 4.9 insurers offering coverage.[1] In 2016, however, premiums rose by 9 percent and insurer participation fell to 4.2 insurers. In 2017, premiums rose a further 25 percent, and participation fell to 2.9 insurers per market. Rapid premium increases and declining insurer participation provoked considerable concern among policymakers. Mark Dayton, governor of Minnesota, publicly noted that the "Affordable Care Act is no longer affordable,"[2] and the Senate majority leader cited both premium increase and insurer exits to justify legislative action.[3]

These premium and participation trends coincided with important regulatory changes in the Health Insurance Marketplaces. The original ACA legislation included a temporary "risk corridors" (RC) program which, along with risk adjustment and reinsurance, was intended to stabilize premiums (*Patient Protection and Affordable Care Act; 45 CFR Parts 153, 155 and 156* 2011). The RC program subsidized insurers whose medical costs exceed a target, equal to 80 percent of revenue, and taxed insurers with costs below the target. The RC program was scheduled to expire at the end of 2016, as was the reinsurance program. However, the ACA did not appropriate funding for the RC program, which in fact was defunded for coverage year 2016 by the Consolidated and Further Continuing Appropriations Act (Cromnibus),[4] effectively ending the RC program a year early. Cromnibus was championed by Senator Marco Rubio, who

[1]On coverage, see https://aspe.hhs.gov/system/files/pdf/83656/ib_2015mar_enrollment.pdf. Statistics on insurer participation and premiums are derived from our data, described below. See http://www.kff.org/health-reform/issue-brief/2017-premium-changes-and-insurer-participation-in-the-affordable-care-acts-health-insurance-marketplaces/
[2] http://minnesota.cbslocal.com/2016/10/12/gov-dayton-affordable-care-act/
[3] "Obamacare Is Hurtling Towards Collapse." https://www.mcconnell.senate.gov/public/index.cfm/pressreleases?ID=2C1887CF-E46C-4F95-B162-2EFBE378D6BF
[4] We provide more details about the timing of Cromnibus in Section 2 below.

boasted that he “Killed Obamacare” by cutting pivotal funding for insurers,[5] a claim which pundits echoed.[6]

In this paper, we assess the importance of the 2016 defunding and 2017 ending of the RC program for rising premiums and falling insurer participation in the Health Insurance Marketplaces. To understand the effects of defunding and ending of the RC program, we begin by developing a model of individual insurers’ premium responses to the program. We show that it can be optimal for some insurers to set premiums low enough to receive a RC payment. For insurers claiming an RC payment, the RC program acts as an implicit subsidy, effectively reducing marginal costs by as much as 40 percent. Intuitively, if a claiming insurer reduces its premium, its revenue and costs both rise, leaving true profit roughly unchanged. Its RC payment rises, however, because costs have increased faster than the RC target amount, which is equal to only 80 percent of revenue. Thus the RC program encourages insurers to reduce premiums, acting as an implicit subsidy. Defunding or ending the RC program removes this subsidy, raising premiums, reducing profitability and potentially discouraging participation. In equilibrium, these effects may be large, as non-claiming insurers respond to the premium increases of claiming insurers by raising their own premiums.

We use two primary data sources to study the RC program. The first source is insurers’ financial filings, which record RC claims (RC owed amounts to insurers) or RC contributions (RC payments from insurers to the program) in 2014 and 2015. The second source is an insurer-plan level dataset recording the prices and characteristics of all plans in the Marketplaces in 2015-2017, from which we infer insurer prices and participation decisions. In 2015, 74 percent

[5] http://www.msnbc.com/rachel-maddow-show/rubios-curious-boast-he-killed-obamacare
[6] See, for example, “How Marco Rubio Is Quietly Killing Obamacare,” https://www.washingtonpost.com/opinions/how-marco-rubio-is-quietly-killing-obamacare/2015/12/14/c706849a-a275-11e5-b53d-972e2751f433_story.html?utm_term=.e3ac21baff81

of insurers had RC claims, and the average claim amount was $53 per member month, or 12 percent of medical claims incurred.

Consistent with our model, we find that that insurers who made risk corridor claims in 2015 had 7 percent higher premium increases over the next two years than did non-claiming insurers, even after adjusting for the higher medical claims costs and lower baseline premiums of claiming insurers. We also find evidence of spillovers from claiming to non-claiming insurers. Conditional on its own claiming status, an insurer with more competitors making RC claims in 2015 itself had larger premium growth from 2015 to 2017. This spillover implies that our simple comparison of claiming and non-claiming insurers potentially understates the true effect of the RC program. To measure the full, equilibrium effect of the program, we look at market-level exposure to the RC program, defined as the fraction of insurers with RC claims in 2015. We find a large and statistically significant association between overall RC exposure in a given market and premium increases from 2015 to 2016 and from 2015 to 2017, even after adjusting for the financial health of the market. Despite the premium effects, we do not find robust evidence that the RC program affected insurer participation in the Marketplaces.

Several pieces of evidence suggest that the end of the RC program itself caused the faster premium growth that we document. We show in placebo test that RC claiming insurers in 2014 had no differential premium growth in 2015, before the program was defunded. Similarly, markets with more claiming insurers in 2014 did not see faster growth in 2015. These facts help rule out mean reversion as an alternative explanation. We rule out several further alternative explanations. The end of reinsurance does not explain our result, as reinsurance is negatively correlated with RC claiming, conditional on our controls. Another explanation is that claiming insurers simply mistakenly priced too low. Although we cannot completely rule out insurer mistakes, we show that insurers with more experience in the individual market prior to 2014—ones less likely to misprice—were more likely to make RC claims, and their premiums responded the most to defunding. Finally we present against evidence the "invest-then-harvest" hypothesis. This hypothesis implies that firms priced low to gain market share while the RC program was in effect, and then raised prices to take advantage of consumer inertia. As Ericson (2014) argues, we can test this hypothesis by looking at whether prices rise faster on older plans, which have more locked in enrollees. We find no evidence for such differential price growth.

Our results help explain rising premiums in 2017. Our estimates imply that each additional insurer making RC claims in a given rating area in 2015 was associated with 4.2 percent higher premium growth in 2016, and 6.6 percent higher growth in 2017. Part of the 2017 premium growth was likely due to the end of the RC program. We can use our estimates to obtain the overall effect of ending the RC program, although doing so requires extrapolating far outside the range of identifying variation in the data. This extrapolation implies that ending the RC program accounts for 86 percent of all premium growth between 2015 and 2017.

Our findings contribute on the recent literature on pricing and participation on the exchanges. This literature has documented that more insurer competition leads to lower prices (Dickstein, Michael J. et al. 2015; Dafny, Gruber, and Ody 2015) and that insurer participation is positively related to market size (Dickstein, Michael J. et al. 2015; Abraham, Jean Marie et al. 2017). These results give few insights about why premiums have risen. Garthwaite and Graves (2017) argue that falling insurer participation reflects a natural shake out as insurers learned whether they could profitably operate on the Exchanges. We show that the defunding and end of the RC program meaningfully raised premiums, although it did not reduce participation. Our results are also related to the literature on reinsurance, i.e. insurance for insurers, of which the

RC program is an example. Geruso and Thomas G. McGuire (2016) and Layton et al. (2016) study the tradeoffs in the design of reinsurance programs. Our focus on the empirical consequences of the RC program for premium and participation complements these papers, which do not consider pricing incentives, nor estimate insurer responses. Finally, our finding that insurers respond to the incentives embedded in the RC program is consistent with a borader literature on the strategic response of insurers to supply-side subsidies (Brown et al., 2014; Geruso and Layton, 2015, Geruso, Layton, and Prinz, 2016, Carey, 2017) (Curto, Vilsa et al. 2015; Decarolis, Ryan, and Polyakova 2016).

2. Background

2.1 Risk Corridors and the Premium Stabilization Programs

The RC program is meant to provide insurance against having higher than expected claims costs, financed with payments from insurers with lower than expected claims costs.[7] It is therefore a profit-sharing program between the government and insurers. Essentially, the RC program allows insurers' markups of premium revenue over medical claims to fall within a narrow range around a target. Insurers with a markup in this range neither make a payment nor receive one, so we call them "neutral." If markups are too high, then insurers must make a payment into the RC program; we call such insurers "contributing." If markups are too low, then insurers receive a payment from the RC program; we call such insurers "claiming."

The target for medical claims costs is equal to 80 percent of premium revenue. If the insurer's claims fall between 97 and 103 percent of the target, the insurer neither makes nor receives a payment (so it is neutral). If the insurer's medical claims fall between 103 and 108 percent of the target, insurer receives a payment equal to 50 percent of the excess over 103

[7] Our description of the RC program, as well as reinsurance and risk adjustment, draws heavily on Cox et al. (2017).

percent. If the insurer's medical claims exceed 108 percent of the target, then insurer receives a payment equal to 2.5 percent of the target (i.e. 50 percent of 108-103), plus 80 percent of the excess over 108 percent. The situation is reversed for insurers with low expenses: they pay in 50 percent on the margin if medical claims are between 92 and 97 percent of the target, and 80 percent on the margin if claims are below 92 percent of the target. Figure 1, panel A illustrates the RC payments as a function of claims, both relative to the target amount. As we emphasize in the model below, the dollar amount for the target is tied to premiums, so an insurer who sets a lower premium (holding fixed its claims) gets a higher RC payment.

The RC program is one of three "premium stabilized programs" created by the ACA. The others are reinsurance and risk adjustment. Reinsurance and the RC program were both legislated to be in effect for 2014-2016; risk adjustment was permanent. Risk adjustment redistributes revenue among Marketplace insurers, from insurers that enroll few people with expensive diagnoses to insurers that enroll relatively many people with expensive diagnoses. It is not a net subsidy. The reinsurance program, however, is a subsidy for Marketplace insurers: it pays fraction of any individual's medical costs that exceed an attachment point ($45,000 in 2014 and 2015, and $90,000 in 2016).

2.2 Defunding the risk corridors program

As legislated in the Affordable Care Act, the RC program need not be budget neutral; if all insurers experience high medical claims relative to premiums, then the program would call for large net payouts, financed from general revenue. However, the program was made budget neutral by the Consolidated and Further Continuing Appropriations Act (Cromnibus) of December, 2014. Cromnibus required that the Centers for Medicare and Medicaid Services only use payments from contributing insurers to pay claiming insurers. Although HHS was authorized to look for additional sources of funds, Section 227 of the Cromnibus specifically prohibited HHS from borrowing from other accounts. In October 2015, CMS announced that in the first year of the RC program, insurers submitted claims for $2.87 billion in losses, against gains that totaled only $362 million (Department of Health and Human Services 2015; Jost 2015). The shortfall for 2014 meant that health insurers were to be paid only 12.6% on the dollar for their RC claims.[8] Because 2014 claims have seniority over subsequent years, 2015 and 2016 losses were likely to be paid even less. Cromnibus essentially defunded the RC program.

Although Cromnibus passed in 2014, we assume that the earliest it could affect insurers' pricing and participation decisions was for coverage year of 2016. This is because participation, pricing, and enrollment decisions in the Marketplaces are made several months before the start of the coverage year. The process begins in May-June before the coverage year, when participating insurers must submit plan information, including premiums, for certification. After all plans are finalized and certified in late October, data is locked down and insurers cannot change their premiums or plan offerings. Then open enrollment begins, typically running from mid-November through mid-January of the coverage year (Centers for Medicare and Medicaid Services 2014). Thus, by the time Cromnibus was passed, insurers had already committed to their 2015 participation and pricing decisions.

It is possible that insurers anticipated Cromnibus' defunding of the RC program, and priced accordingly, but several considerations make this unlikely. First, insurer anecdotes indicate that they were counting on receiving RC payments. For example, the CEO of Health Republic of Oregon, said in 2015, "We were stable, had a growing membership and could have been successful if we had received those payments. We relied on the payments in pricing our

[8] See https://www.cms.gov/CCIIO/Programs-and-Initiatives/Premium-Stabilization-Programs/Downloads/RiskCorridorsPaymentProrationRatefor2014.pdf

plans."[9] Second, it would have been difficult for insurers to know, even after Cromnibus, exactly how little the RC program would pay out, because the exact payment amount depends on the realized revenues and losses of all insurers. Third, the Department of Health and Human Services (HHS), which oversees the RC program, continued to indicate as late as February 2015 (two months post-Cromnibus) that it expected all RC claims to be paid in 2016. Even if contributions fell short of claims, the regulations indicated that "HHS will use other sources of funding for the risk corridors payments, subject to the availability of appropriations."[10] These appropriations ultimately did not become available, of course. In fact, such assurances may have persuaded some insurers that the RC payments would eventually come through. The shortfall of the RC program became the clear October 1, 2015 through a CMS letter stating that 2014 RC payments would be prorated at 12.6 percent.[11] At that point, it was too late to adjust premiums for 2016. Therefore, while we expect the effect of RC defunding on premiums and participation to occur the earliest for the 2016 coverage year, for some insurers, it may not be until the 2017 coverage year.

2.3 The Minimum Medical Loss Ratio Requirement

The RC program interacts with another ACA regulation: the minimum medical loss ratio (MLR) requirement, which requires that insurers' qualified medical expenses equal at least 80 percent of their premium revenue in the individual market. If expenses fall below this target, then insurers must rebate the difference to their enrollees. The MLR appears to be a reasonable

[9] See "Marco Rubio Quietly undermines Affordable Care Act," https://www.nytimes.com/2015/12/10/us/politics/marco-rubio-obamacare-affordable-care-act.html, Robert Pear, December 9, 2015, last accessed 7/11/2017.

[10] See "Patient Protection and Affordable Care Act; HHS Notice of Benefit and Payment Parameters for 2016," 80 FR 10749, 10749-10877.

[11] https://www.cms.gov/CCIIO/Programs-and-Initiatives/Premium-Stabilization-Programs/Downloads/RiskCorridorsPaymentProrationRatefor2014.pdf

target for regulating insurers' profits (Pinar Karaca-Mandic, Jean Marie Abraham, Kosali Simon, 2015). The MLR's 80 percent target roughly coincides with the 80 percent target for the RC program.[12] For the purposes of MLR calculations, RC contributions count as cost (i.e. RC contributions are paid before MLR rebates). As a result, although the RC program subsidizes insurer losses, it does not penalize insurer gains, because the required RC contribution for a high-margin insurer would go to the MLR program in the absence of the RC program.

3. Model

We develop a model of the RC program to understand its implications for firm-level pricing and participation decisions, as well as market-level premiums.

3.1 Firm-level pricing decisions

We begin by considering the premium response of a single insurer to the incentives created by the RC program. We model insurers as price setters here because the ACA's guaranteed issue provision bars insurers from setting quantity—they must sell insurance to everyone who demands it. We focus on price setting rather than cost reduction because we believe that insurers can much more easily control their prices than their costs. We assume that insurer i sets premiums to maximize profit, equal to revenue less total variable costs and fixed costs, plus a RC transfer:

$$\pi_i = p_i q_i(p_i, p_{-i}) - VC_i(p_i, p_{-i}) - F_i + RC_i,$$

where q_i is demand, VC_i is variable cost, and F_i is the fixed cost. In general, π_i depends on the premiums of all the competitors of i, p_{-i}, but for notational simplicity we omit this dependence

[12] An important distinction to make is that MLR is defined at the state-year level for the entire individual market business of an insurer, including both the exchange and the off-exchange markets. On the other hand, RC is defined for an insurer-year, only for the exchange market. The MLR target and the RC target can diverge if off-exchange business is an important part of an insurer's individual market operations. However for insurers in our analysis sample, exchange premiums represent 89 percent of all premium review in 2015, and exchange costs represent 98 percent of all costs.

in this subsection, and we drop the i subscript. We write variable cost as the product of demand $q(p)$ and an average cost curve $AC(p)$.[13] Average cost may depend on price because of adverse selection, which implies that as the price rises, relatively healthy people are less likely to buy coverage, resulting in higher average costs of the insured.[14] The risk adjustment program may offset adverse selection; the extent or presence of adverse selection does not affect our results.

We model the RC transfer to firm i as a piecewise linear function of variable costs $VC = cq$, with kink points determined by the cost target, which is equal to revenue $R = pq$, scaled by a factor T. In the individual insurance market, $T = 0.8$. There are five line-segments, with four kink points, $k_1, \dots, k_4$, and four non-zero slopes $m_1, \dots, m_4$ These kink points are 0.92, 0.97, 1.03, and 1.08 and the slopes are 0.8, 0.5, 0.5, and 0.8, as shown in Figure 1.

We write the RC payment function as

$$RC(VC, R) = \begin{cases} m_1(VC - k_1TR) + m_2(k_1 - k_2)TR, & VC \leq k_1TR \\ m_2(VC - k_2TR), & k_1TR < VC \leq k_2TR \\ 0, & k_2TR < VC \leq k_3TR \\ m_3(VC - k_3TR), & k_3TR < VC \leq k_4TR \\ m_4(VC - k_4TR) + m_3(k_4 - k_3)TR, & k_4TR < VC \end{cases}$$

At the program parameters, this works out to

$$RC(VC, R) = \begin{cases} 0.8VC - 0.5688R, & VC \leq 0.736R \\ 0.5VC - 0.388R, & 0.736R < VC \leq 0.776R \\ 0, & 0.776R < VC \leq 0.824R \\ 0.5VC - .412R, & 0.824R < VC \leq 0.864R \\ 0.8VC - 0.6712R, & 0.864R < VC, \end{cases}$$

The RC payment is affected by prices in two ways, through both revenue and costs. As long as demand responds to prices, the program creates complex pricing incentives, as Figure 2

[13] We think of marginal costs here as reflecting both actual claims costs and associated variable costs, such as utilization review and disease management. These associated costs also count as costs for the RC program.
[14] Einav, Finkelstein, and Cullen (2010) model adverse selection in this way.

illustrates.[15] With inelastic demand, the RC function is simply piecewise linear in p. With elastic demand, however, the function is highly nonlinear, and can give rise to surprising pricing incentives.

We begin by providing some intuition on how the RC program skews pricing incentives, particularly for claiming insurers. Inspection of the RC equation reveals that claiming insurers would increase their profits if they could raise costs and revenue by one dollar each. Doing so raises RC payments by about $0.13, and otherwise leaves profits unchanged. It may seem surprising that raising both revenue and costs can increase RC payments, since on the margin each $1 of cost above the target only raises payments by $0.8. The reason this strategy is profitable is that the target rises slower than revenue. Increasing revenue and cost by $1 raises the target by only $0.8, and so the RC payment by roughly $0.16 (=0.2*0.8). (The exact increase in RC payment is $0.13 because the RC program only covers 80 percent of costs that exceed 108 percent of the target). These calculations suggest that, on the margin, claiming insurers might prefer small or even negative mark ups. Thus, we expect that the RC program distorts downward the pricing decisions of claiming firms.

We show this more formally by considering the first order condition for an insurer that is on the last line segment, meaning that its costs are more than 8% above its target, or put differently that its premium is low relative to its target. The first order condition for such an insurer is

$$p = \frac{(1-m_4)}{1-T(m_4 k_4 - m_3(k_4-k_3))}\left[AC(p) - \frac{AC'(p)}{\eta}\right] + \frac{1}{\eta} = s\left[AC(p) - \frac{AC'(p)}{\eta}\right] + \frac{1}{\eta}, \qquad (1)$$

[15] This differs from Figure 1, which depicts the risk corridor payment as a function of claims expenses (cq, in our notation), given premium revenue (pq). For understanding how the risk corridors program affects pricing incentives, however, we express the risk corridor payment as a function of p alone.

where $\eta \equiv -\frac{\partial q}{\partial p}/q$ is the firm's semi-elasticity of demand, and $s \equiv \frac{(1-m_4)}{1-T(m_4k_4-m_3(k_4-k_3))}$. In the absence of the risk corridor program, the first order condition is

$$p = AC(p) - \frac{AC'(p)}{\eta} + \frac{1}{\eta}.$$

Equation (1) is equivalent to the usual first order condition for a profit-maximizing firm, except for two factors. First, adverse selection means that when the firm raises its price, its average cost may rise as well, making it want a lower price, all else equal; the $AC'(p)$ term captures this effect. Second, the firm acts as if it faces cost curve of $sAC(p)$ rather than $AC(p)$. At the program parameters, $s \approx 0.61$, so the RC program induces insurers with large claims to price as if they faced a 39 percent marginal cost subsidy. For insurers locating on the second-to-last budget segment, the first order condition implies a subsidy of 15 percent of marginal cost.[16]

Figure 2, panel B illustrates the pricing distortion created by the RC program. We show variable profit as a function of premium, for an insurer with constant average costs normalized to 1 and an iso-elastic demand curve with an elasticity of $\epsilon = -4$.[17] With this demand curve, the insurer optimally charges a premium of $(1 + 1/\epsilon)^{-1}$ percent of cost. In the absence of the RC program, the optimal premium is 133 percent of cost. With the RC program, if the insurer did not re-optimize, it would end up making a payment into the RC program equal to roughly half of its profit. With re-optimization, however, the insurer can do better by charging a much lower premium and making a large RC claim. With the RC program, the insurer acts as though it faces a cost of 0.61, and so it charges a markup of 33 percent above that, or a premium of 81 percent of

[16] For such insurers, the first order condition is $p = \frac{1}{\eta} + s'AC - \frac{s'AC'}{\eta}$, where $s' = \frac{1-m_3}{1-m_3k_3T} = 0.85$.

[17] This may seem like a very elastic demand curve, but Abraham et al. (2017) estimate that the average Marketplace plan in 2015 had an elasticity of -4.6 with respect to the unsubsidized premium (i.e. gross of the premium tax credit), which is the relevant elasticity from the insurer's perspective.

its true cost (i.e. 1.33*0.61). The RC's implicit subsidy is so large that it can be optimal for a firm to price below cost.

3.3 Reinsurance, Risk Adjustment, and Cost-Sharing Reductions

Our model easily accommodates reinsurance and risk adjustment, and our results are essentially unchanged once we incorporate them.[18] These programs both essentially involve changing the average cost function. Reinsurance can be modelled as a reduction in average costs equal to the expected reinsurance payment per enrollee, and risk adjustment and cost-sharing reductions affect pricing decisions by changing the average cost function (but not revenue). We can therefore account for these programs by defining an effective average cost, $\widetilde{AC}(p)$ as

$$\widetilde{AC}(p) = AC(p) + Reinsurance(p) + RiskAdjustment(p)$$

where $Reinsurance(p),$ and $RiskAdjustment(p)$ are the expected per-enrollee reinsurance, and Risk Adjustment, payment when the premium is p. Risk Corridor payments are calculated on costs net of reinsurance, risk adjustment, and CSRs, so the first order condition for optimal pricing under the RC program becomes

$$p = s\left[\widetilde{AC}(p) - \frac{\widetilde{AC}'(p)}{\eta}\right] + \frac{1}{\eta}.$$

Allowing for reinsurance or cost sharing reductions does not change the conclusion that the RC program causes insurers to price as though they face an average cost curve scaled by s.

3.4 Insurer participation decisions

Given participation decisions, the RC program distorts premiums downward. The RC program may also affect insurer participation in the Marketplace. To see this, let π_i^* be firm i's

[18] Here we abstract from the influence of risk adjustment on benefit design, which Geruso, Prinz, and Layton (2017) study.

maximal profit, assuming it decided to participate. Insurer i participates if $\pi_i^* > F_i$. The RC program affects participation by changing maximal profit. It is straightforward to see that the RC program must increase profit. At any premium, profit is weakly higher under the RC program (given MLR regulations), so the maximal profit must also be higher under RC program. Thus our model implies at least a small effect of the program on participation.

However this effect need not be large. In particular, even firms making large risk corridor claims may experience small changes in profit and therefore small changes in participation probabilities. Figure 2 gives the intuition. Under the RC program, the firm charges a low premium and receives a large risk corridor payment. Absent the RC program, the firm would charge a much higher premium, undoing most of the loss from the end of the RC program. Thus, even though insurers suffered large losses from the surprise defunding of the RC program, there is no guarantee that insurers will have low profit going forward.

3.5 Equilibrium premium effects

So far, we have considered the premium and participation decisions of a single insurer, taking the premiums and participation of other insurers as given. It is likely, however, that the RC program has aggregate, market-level effects, influencing the premiums even of non-claiming insurers. These aggregate effects arise through two potential channels. First, if the RC program induces entry, then firms may face stiffer competition and steeper residual demand curves, leading to further lower premiums. Second, naturally, when the RC program induces a claiming firm to reduce its premium, a non-claiming firm may want to reduce its premium as well, assuming that premiums are strategic complements. The possibility that the RC program may have spillover effects onto non-claiming insurers is important for our empirical approach. It implies that non-claiming insurers are not a valid control group, and any comparison of claiming and non-claiming insurers may understate the full effects of the RC program. We account for this possibility by directly estimating spillover effects in some specifications, and by looking at market level effects in others.

4. Data

4.1 MLR filing data

The MLR filing data are derived from reports that insurers submit annually to the Center for Medicare and Medicaid Services to document their compliance with the minimum MLR requirements. Since 2014, insurers also report information on their Marketplace business, including any RC claims or contributions. The MLR filing data are publicly available.[19] The unit of observation is an insurer-state, since MLR filings, insurance regulation, and premium rate review occur at the state level. (We will often refer to observations as "insurers" for simplicity, noting that an insurer is actually an insurer-state, such as "Aetna in Indiana.")

We use the 2014 and 2015 MLR filing data to define our independent variables and our analysis sample. Our key independent variables are premiums earned, medical claims incurred (net of risk adjustment payments made or received, and cost sharing reduction (CSR) subsidies received), member-months of enrollment, reinsurance payments (through the premium stabilization program), and, most importantly, RC claims. We define insurers as claiming if they have positive RC claims, contributing if they have negative RC claims, and neutral if they have zero RC claims.

We define the analysis sample as insurers in the MLR data that met several sample selection criteria. First, we only consider insurers who reported positive Marketplace enrollment, Marketplace premiums, and Marketplace medical claims in their 2015 MLR filings. We focus on

[19] See https://www.cms.gov/CCIIO/Resources/Data-Resources/mlr.html

Marketplace participation because only Marketplace plans are eligible for RC payments, and we define the sample based on 2015 variables because future values of RC claims are affected by its defunding. Next, we follow a two-step procedure suggested by Karaca-Mandic et al., (2015) to identify and exclude erroneous observations from the raw data. First, we flag observations with extreme values, defined as insurers with claims cost incurred and premiums revenue both in the top or bottom percentile; or with, either RC net payment per member per month (PMPM)[20] or ratio of claims to premiums fell into the top or bottom percentile. Second, we exclude the six flagged observations in 2015 with fewer than 1,000 member-years of enrollment. We excluded these insurers because the MLR regulations do not apply to insurers with fewer than 1,000 member-years, and we are concerned about small insurers having implausibly large ratios of claims to premiums (and hence large RC payments per member). This leads to a sample of 339 insurer-states participating in 2015. We excluded two insurers whom we could not match to the HIX data (described below), for a final sample of 337 insurers participating in 2015, of whom 282 continued to participate in 2016, and 204 in 2017.

4.2 HIX Compare Data

The HIX dataset, compiled by the Robert Wood Johnson Foundation, contain information on the premiums and characteristics of Marketplace plans offered in 2014-2017.[21] We observe each plan's metal level (measuring plan's generosity, with bronze being the least generous and

[20] For claiming insurers, this amount is the payment per member-month that they expected to receive from the RC program, while for contributing insurers, this is the payment per member-month that they contributed to the RC program.

[21] We obtained the 2014 and 2017 data from http://www.rwjf.org/en/library/research/2017/04/hix-compare-2014-2017-datasets.html. The 2015 and 2016 data were incomplete so we obtained an updated from Vericred, the data vendor. We expect that these data will be publicly available soon. We found that the 2014 and 2015 data sets are incomplete; some insurers with Exchange enrollment in the MLR data do not appear in the latest data release. (There were two such insurers in 2014, and 15 in 2015). By combining these two releases, we ended up with a nearly complete set of all Marketplace offerings in 2015-2017 and silver offerings in 2014. We believe we have all or nearly all offerings because of the very high match rate between the MLR and HIX data: 337 of the 339 Marketplace insurers in the MLR in 2015 are also in the HIX data, and 283 of the 286 in 2014.

platinum being the most), plan type (PPO, HMO, EPO, POS, or other), and premium. The ACA allows insurers to charge different premiums in different geographic rating areas, which are typically aggregations of counties; we observe each plan's premium in each area where it is offered. We exclude 23 plans with monthly premiums over $10,000, which we believe are erroneous. In 2015-2017, we observe all plans in all rating areas. In 2014, however, we only observe silver plans for the states that did not use healthcare.gov (for the healthcare.gov states, we observe all plans). We observe the Health Insurance Oversights System (HIOS) identifier of the insurer offering each plan, except for a handful of 2014 plans in state-based marketplaces, where we impute it based on the reported insurer's name.

We use the HIX dataset to define our insurer-level outcomes. Our first outcome is an insurer-state-year-level premium index, obtained by aggregating premiums across plans and rating areas, and adjusting for plan characteristics. We aggregate premiums to the insurer-state level because RC claiming varies across insurer-states, not plans. To aggregate, we estimate the following hedonic regression for the log premium of plan i offered by insurer-state observation j in rating area a and year :

$$\log p_{ijat} = \mu_{metal} + \tau_{type} + \gamma_{at} + \theta_{jt} + \varepsilon_{ijat}.$$

This regression projects log premiums onto fixed effects for metal level, plan type, rating area-year, and insurer-state-year.[22] We take the insurer-state-year fixed effect $\hat{\theta}_{jt}$ to be the premium index of insurer-state j in year t. It measures how high j's premiums are in a given year, adjusting for the generosity (i.e. metal level) and type of plans j offered, as well as

[22] The dependent variable in these regressions is the premium a 27 year-old would pay. The premium for any other age is equal to this premium times an age factor, so the log price index we estimate is valid for all ages.

characteristics of the market where *j* offered plans in year *t*. We normalize the premium index to zero in 2015 for each insurer-state.

Our second outcome is simply exchange participation, coded as one if an insurer-state offers at least one plan in any rating area in the HIX data in a given state and year.[23] We define participation as an indicator variable equal to one if an insurer-state offers at least one Marketplace plan in a given year. By construction, participation is equal to one in 2015 in our analysis sample.

4.3 Constructing a Rating Area-level dataset

We construct a rating-area level data set to study aggregate, market-level premium effects. The rating area is the natural market, because insurers must set a single premium within that rating area for a given plan. For each of the 504 rating areas in the data, we defined the market premium as the "benchmark" premium in that rating area, following past literature (Dickstein, Michael J. et al. 2015; Dafny, Gruber, and Ody 2015; Krinn, Karaca-Mandic, and Blewett 2015). The benchmark premium is the premium of the second lowest premium silver plan offered.[24] This premium which is important in because it determines the generosity of the advanced premium tax credit. We also record the number of insurers offering plans in each rating area and year. We define aggregate rating area RC exposure as the fraction of insurers operating in a given rating area who had positive RC claims.[25]

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[23] We use the HIX data rather than the MLR filing data to define participation because the MLR data are only available through 2015.

[24] As with the insurer-level premium index, we focus on the premium a 27 year-old faces. Premiums for other ages scale with this premium.

[25] Although a given insurer's RC claims are specific to a state but not a rating area, different areas in a given state can nevertheless have different exposure, because of differences in the insurers operating there. For example, Ohio has 17 rating areas, and there were 16 active insurers across the state. However, they were not all active in every rating area. Blue Cross served all 17 areas, whereas the low-cost insurer Molina served only eight; risk corridor exposure was about 20 percent lower in areas that Molina served.

4.4 Summary statistics

Table 1 presents summary statistics for the insurer-year dataset, separately for claiming, neutral, and RC contributing insurers in 2015. Of the 337 Marketplace insurers in 2015, 74 percent (N=248) were claiming, and 9 percent (N=31) were contributing; the remaining 17 percent (N=58) were neutral. Among claiming insurers, RC claims were large: $53 per member month, or about 12 percent of average medical claims costs. Claiming insurers did not have especially low premium revenue, but they did have high claims costs and high reinsurance payments,[26] Consistent with these high costs, claiming insurers had high reinsurance payments. Claiming insurers were more likely to have participated in the 2012 market: they had more covered lives, and a larger share of them covered at least 1000 lives. Unadjusted rates of participation fell substantially for claiming insurers; only 80 percent participated in 2016, and 54 percent in 2017. For claiming, contributing, and neutral insurers, premium indexes increased on average in 2016 and 2017, but the increase was especially large for claiming insurers.

Table 2 provides summary statistics for the rating area-year dataset. In the average rating area in 2015, participating insurers had RC claims of about $41 per member month, and 78 percent of insurers had RC claims. We report in Table 2 the within-state standard deviation of all variables, including RC exposure. Much of the variation in RC claiming is across states, but some of it is across markets within a given state, which is important because all of our regressions include state fixed effects. The table shows substantial changes in premiums and participation. From 2015 to 2016, benchmark premiums rose on average by 9 percent and the average number of participating insurers fell from 4.9 to 4.2. In 2017, average premiums

[26] This might seem inconsistent with our model, which implies that claiming insurers have low premiums but not necessarily high costs. The claims and premiums in Table 1, however, are not adjusted for differences across insurers in the generosity of plans they offer, and indeed claiming insurers also offer relatively generous plans.

increased a further 25%, and participation fell by 1.4 insurers. We now turn to investigating whether the 2016 defunding and 2017 end of the RC program can explain these trends.

5. The effect of the risk corridor program on participation and premiums

5.1 General approach to identification

The model implies that the RC program reduced premiums for claiming insurers and for their non-claiming competitors. Empirically, we examine whether claiming insurers had larger premium increases after the 2016 RC defunding and 2017 program end. We also consider market-level premium responses, which we expect to be larger in markets in which more insurers made RC claims, and participation decisions. At a broad level, our identification strategy has a difference-in-differences feel: we take advantage of the fact that RC defunding and ending affect 2016 and 2017 decisions, but not earlier ones, and that they differentially affect firms who would make claims under the program, not neutral or contributing firms. We therefore essentially compare the change in outcomes from 2015 to 2016 or from 2015 to 2017, for RC claiming insurers, relative to neutral or contributing RC insurers. This approach relies on the assumption that, in the absence of defunding or ending the RC program, claiming, neutral, and contributing insurers would have similar trends in participation and premiums.

This assumption could fail because claiming is a function of premium revenues and medical claims expenses. If there is mean reversion in these variables, or other sources of differential trends, then our estimates will be biased. We address this bias by controlling linearly for 2015 premiums and medical claims expenses (per member month) in all specifications. We identify off the nonlinearity in RC payment system. These controls help address the possibility that low premium or high claims cost insurers may have differential trends in future premium or participation decisions.

We also conduct placebo tests to validate our identification strategy. These tests are based on the premise that RC claims in 2014 should not be correlated with premium or participation decision in 2015, because insurers made their 2015 pricing and participation decisions without knowledge that the RC program was defunded. It is possible, however, that mean reversion in premiums and claims, or other failures of parallel trends, yield differential trends among claiming insurers. In that case we would expect to see an "effect" of the RC program defunding even in 2015. Thus these placebo tests provide a useful check on the main threat to identification.

Our basic approach assumes substantial persistence in RC claiming, because we relate outcomes in 2016 and 2017 to RC claims in 2015. We think of RC claims in 2015 as a proxy for "RC claims in 2016, had the RC program not been defunded." This interpretation is valid only if there is indeed a high correlation between past and current RC claims. Appendix Table A1 documents this persistence, showing high autocorrelation between 2015 and 2014 in RC claims.

5.2 Insurer-level premium effects

We estimate insurer-level premium effects with the following regression:

$$p_{jt} - p_{jt_0} = \alpha\, 1\{RC\ Claim_j > 0\} + X_j\theta + \mu_s + \epsilon_{jt} \tag{2}$$

Our dependent variable is the difference in the premium index (in logs) of insurer j (recall that insurer *j* represents an insurer-state pair) between year t and a base year t_0 (2015 in our main specifications). We estimate separate models for the 2015-2016 premium changes, the 2015-2017 premium change, and (as a placebo test) the 2014-2015 premium change. The key independent variable is an indicator for whether insurer j has any RC claims in the base year. α measures the differential premium increase for such insurers. *X* includes controls for the base year medical claims expenses (net of risk adjustment and CSR payments), premium revenue, and member months in 2015. We also control for insurer characteristics (nonprofit status and membership in a large insurer group such as Anthem) and state fixed effects, μ_s, which account for statewide trends such as late Medicaid expansion or differential support for the Marketplaces.

We present the estimates in Table 4. In column (1) we look at the 2015-2016 price change. Consistent with the model, we estimate that RC claiming insurers have higher premium growth in 2016 (relative to their 2015 premiums), but the effect is not statistically significant. In column (3), we repeat the same estimation for the premium difference from 2015 to 2017. We estimate a coefficient of 0.07 on RC_j, meaning that insurers who made a RC claim in 2015 increased their prices by 7 percent more than other insurers in the same state in 2017, after adjusting for differences in medical claims, premium revenue, and enrollment.

These specifications assume that there are no differential trends in premiums among claiming insurers, after adjusting for our controls. To test this possibility, we re-estimate the models in columns (1) and (2), but regressing the difference in hedonic premium index (logs) in 2014-2015 on 2014 RC claiming. The coefficient on the interaction, 0.001, is small and statistically insignificant. Differential trends by claiming status do not appear to explain the results.

These specifications identify the effect of the RC program by comparing premium changes among claiming and non-claiming insurers. This comparison understates the program's effect if there are any spillovers from claiming to non-claiming insurers. We test for such spillovers by augmenting Equation (2) to allow insurers to react to their rivals' claiming status. Specifically we estimate

$$p_{jt} - p_{jt_0} = \alpha 1\{RC\ Claim_j > 0\} + \beta Rival\ Claim\ Rate_j + X_j\theta + Z_{m(j)}\gamma + \mu_s + \epsilon_{jt} \qquad (3)$$

where $Rival\ Claim\ Rate_j$ is the fraction of $j's$ competitors making RC claims in the base year t_0. We calculate this fraction by calculating, for each rating area in which j operated in t_0, the fraction of other insurers with RC claims. We then average over the rating areas in which j operated in t_0 to obtain the rival claim rate.[27] Because the rival claim rate depends on the markets in which j operated in t_0, we control for the average characteristics of the markets in which j operated, $Z_{m(j)}$: the average premium revenue, medical claims, and enrollment of insurers who operated in those markets in t_0, and the fraction of markets that have one insurer, two insurer, and so on, through six insurers.

We allow for spillovers in columns (2), (4), and (6) of Table 4. We find that the rival claiming rate has a large association with 2016 and especially 2017 price increases, although only the 2017 association is statistically significant. These coefficients mean that a one standard deviation increase in the rival claiming rate is associated with a roughly 3 percent increase in premiums in 2016, and an 8 percent increase in 2017. By contrast we find an insignificant and economically small effect of spillovers in 2015. We conclude from Table 4 that the RC program had a meaningful effect on premiums, including both a direct effect on claiming insurers and an indirect, spillover effect on non-claiming insurers.

5.3 Market-level premium effects

Given the spillovers on non-claiming firms, it is possible that the equilibrium effects greatly exceed the firm level effects of the RC program. We measure the overall, equilibrium effects of defunding and end of RC program by looking at the relationship between market-level premiums and market-level exposure to the RC program. Figure 4 shows a scatter plot of the

[27] We weight each rating area by the number of plans that j offers in it, to account for the possibility that some rating areas are more important for j than others.

change in log benchmark premium from 2015 to 2016 and 2017, against rating area average RC claims. Because the data are noisy, we bin the data. There is a clear, positive relationship: markets with more RC exposure 2015 experienced larger premium increases in 2016 and 2017.

This figure does not adjust for possible confounders, the most important of which is that markets with a large aggregate RC claims may have many insurers in financial distress, with high medical claims or low premium revenue, who would have raised their premiums even had the risk corridor program continued. We control for such confounders using an aggregate version of Equation (2):

$$p_{at} - p_{at_0} = \alpha(Fraction\ Claiming)_a + X_a\theta + \ \mu_{s(a)} + \varepsilon_a. \tag{4}$$

The dependent variable here is the change in benchmark premium in rating area a from a base year t_0 to a reference year t. We consider 2015 as a base year and 2016 and 2017 as the reference years in our main specifications, and 2014 as the base year and 2015 as the reference year in placebo tests. Our interest is in α, the coefficient on area-level RC exposure, measured as the percentage of insurers in area a with positive RC claims in the base year. α indicates the association between rating area premium growth and RC exposure. We interpret this association as the overall equilibrium effect of the RC program. This effect reflects both the direct effect on claiming insurers, and any spillover effects on non-claiming insurers. To account for the financial position of insurers in area a, we include several controls: average claims expenses (adjusted for risk adjustment and CSR payments) and premium revenue in 2015, as well as total enrollment, among insurers in the rating area in the base year. We also include state fixed effects to account for state wide trends in claiming.

Table 5 shows the results for our market-level models. Our sample includes all 504 rating areas. In column (1) we look at the 2015-2016 premium changes and in column (2) we look at

2015-2017 changes. In both cases we find a statistically significant association between rating area RC exposure in 2015 and subsequent premium increases. The coefficients indicate that each one percentage point increase in the percent of RC claiming insurers in the market is associated with 0.22 percent higher premium growth from 2015 to 2016, and a 0.34 percent higher growth from 2015 to 2017. By contrast we find no association between RC claiming and price growth between 2014 and 2015. We expect to find no effect in 2015, because the RC program was still in effect then. Thus generally rising premiums in areas with more RC claiming do not appear to explain the observed association between aggregate RC claims in 2015 and premium increases in 2016 and 2017.

A back-of-the-envelope calculation helps put these estimate in perspective. In 2015 the average rating area had 4.9 insurers, and 78 percent of insurers in a rating area had made RC claims, implying that roughly 4 out of 5 insurers making RC claims. If an additional insurer made an RC claim – roughly a 20 percentage point increase in the claiming rate – then premiums would have increased by 4.2 percent more in 2016 and 6.6 percent more in 2017. This is a meaningful fraction of the actual benchmark premium increase of 37 percent between 2015 and 2017 (from $230 to $314).

We can also use the estimates to measure the effect of ending the RC program on benchmark premiums. We obtain this effect by asking how premium growth would have changed if no insurers had any RC claims, meaning that $Fraction\ Claiming$ equals zero (instead of its average of 0.78). We caution that this requires extrapolating well outside the range of identifying variation in the data. Conditional on the state fixed effects, there is relatively little variation in $Fraction\ Claiming$; in the most extreme case, it varies by about 0.50 (meaning that in one state, there are rating areas 25 percentage points above and below the state average

$Fraction\ Claiming$). Our estimates imply that if the RC program had not ended, premium growth from 2015 to 2017 would have been about 5 log points, instead of 30. This is a large difference and given the reliance on functional form required to justify our extrapolation, we conclude only that the end of the RC program likely had a meaningful effect on aggregate premium growth in 2017.

5.4 Participation Effects

We estimate the effect of the RC program on Marketplace participation with regressions of the following form:

$$\Pr(Participate_j\ ) = L\big(\alpha 1\big\{RC\ Claim_j > 0\big\} + X_j\theta + \ \mu_{s(j)}\big), \tag{5}$$

where L is the logit function and our outcome is exchange participation in 2016 or 2017. We control for the same variables used in the premium analysis: premiums per member month, claims per member month, member months of enrollment for insurer j, all in 2015, as well as not-for-profit status, membership in a large insurer alliance, and state fixed effects.[28] Although it appears that we estimate equation (2) in levels, we are in fact identifying off of changes in participation, because our sample consists of insurers that participated in 2015. The only way participation is not equal to one, therefore, is if it changes. We ask whether participation is more likely to change in 2016 (and in 2017) among insurers with larger RC claims in 2015, relative to other insurers in the same state and adjusting for financial position.

Table 6 shows the estimates of α. We show the results without state fixed effects in column (1). We find no statistically significant relationship between RC claims and 2016 participation or 2017 participation. We also find a small and insignificant participation effect in a

[28] In some states the 2016 and 2017 participation rate was 100 percent, so their fixed effects are not identified, and we must omit them. In robustness tests below, we estimate linear probability models with state fixed effects, in which case we can include all states.

placebo specification looking at the effect of 2014 RC claiming on 2015 participation. These specifications therefore show little participation effects of the RC program. We conclude that rather than exit the marketplace entirely, insurers reacted to the end of the RC program by raising premiums.

5.5 Robustness checks

In Appendix A, we conduct an extensive series of robustness tests, which we summarize here. For the insurer-level results, we primarily consider robustness to a richer set of controls: nonlinear functions of claims and premiums, richer insurer characteristics (Blue status, and indicators for membership in each of the largest cross-state insurer alliances), and reinsurance payments per member month. We also consider excluding contributing firms—who ended up with MLRs below the statutory minimum—from the analysis. Our estimates are fairly similar across specifications. For the market-level results, we consider nonlinear functions of market-level premium revenue, member months, and claims costs, as well as demographics of the population. We also consider weighting each market by its population. Across all these specifications, we find only small differences in our estimates, except that the RC program has a substantially larger effect when we weight our estimates with market population.

6. Alternative explanations

6.1 "Invest-then-harvest" pricing strategies

We have found robust evidence that insurers making RC claims in 2015 had larger premium growth in 2016 and 2017 than non-claiming insurers, which we attribute to the program defunding and the end. An alternative explanation is that these premium increases represent an "invest-then-harvest" or "penetration pricing" strategy whereby insurers initially price low, to achieve high market share, and then raise premiums, exploiting substantial inertia in health insurance enrollment (e.g., Handel 2013). Ericson (2014) shows that insurers pursued such a strategy during the rollout of Medicare Part D. As low-premium insurers receive RC payments, this strategy generates a correlation between RC claims and future premium growth.

The invest-then-harvest explanation cannot account for all the results we have documented, because it predicts that insurers making RC claims should not exit the market. We further show that invest-then-harvest is unlikely to explain much of the observed differential premium increase among claiming insurers. Our approach uses the test of Ericson (2014), who notes that under invest-then-harvest strategies is that in a given year, older plans should have higher premiums than newer plans, all else equal, because a greater share of their demand consists of inert enrollees who have already made their enrollment decisions. To test this prediction, we estimate the following regression:

$$\ln p_{ijast} = \beta_1(age_{ijast} = 2) + \beta_2(age_{ijast} = 3) + Fixed\ Effects + \epsilon_{it}, \qquad (6)$$

where $\ln p_{ijast}$ is the premium of plan i offered by insurer j in area a, state s, and year t, and age_{ijast} measures the age of the plan in a given rating area, i.e. the number of years it has been continuously offered in that rating area, as of t. We include fixed effects year-by-area, year-by-metal level, and year-by-insurer fixed effects.[29] (Note that, although we have four years of data, we cannot identify an age fixed effect because it is collinear with a 2017 dummy.) The invest-then-harvest strategy implies that $0 < \beta_1 < \beta_2$. We estimate equation (6) treating each plan in a given rating area as a different insurance plan, since insurers can charge different premiums for the same plan in different rating areas.[30] We report these estimates in Table 6. Across all specifications, the plan age fixed effects are economically small—never larger than 0.01—and

[29] These regression contains a large vector of fixed effects, so we estimate them using the *reghdfe* command, described in Correia (2016).
[30] Note that, although we have four years of data, we cannot identify an age fixed effect because it is collinear with a 2017 dummy

statistically insignificant. We conclude that penetration pricing is not an important explanation for the patterns we have documented.[31]

6.2 The end of reinsurance program

The reinsurance program ended at the beginning of 2017, at the same time the RC program ended. RC claiming insurers had high reinsurance payments in 2015, as Table 1 shows, so perhaps they raised their premiums in 2017 because of the end of reinsurance. To investigate the importance of reinsurance, we add 2015 reinsurance payments per member per month as an additional control in our pricing regression, Equation (2). The estimates are in Table 7.

We find that the estimated effect of the RC program on premium growth becomes larger when we control for reinsurance, as the comparison of columns (1) and (2) show. This is surprising because we also find that reinsurance payments in 2015 are positively associated with price growth in 2017. In columns (3)-(5) of the table, we show that conditional on our controls, reinsurance payments are negatively correlated with RC payments. This explains why our results are robust to controlling for reinsurance, despite the clear unconditional correlation between reinsurance and RC claiming, and the conditional association between reinsurance payments in 2015 and subsequent price growth.

6.3 Mispricing and insurer learning

A potential alternative explanation for our results is insurer learning. In 2014 insurers faced considerable uncertainty about the costliness of Marketplace enrollees, and some insurers may

[31] Note that this finding in no way invalidates the results in Ericson (2014). The Health Insurance Marketplaces differ in important ways from Medicare Part D. In particular, there is considerable churn in the Marketplaces, as people may lack employer-sponsored insurance in one year and then obtain it the next, whereas there is essentially no churn in eligibility for Medicare.

have set premiums too low. Such insurers would have made RC claims early on, and then raised their premiums, even independent of any true effect of the RC program.

Although insurer learning likely contributes to the overall price dynamics during this period, several factors suggest that insurer learning do not explain all the results here. First, we observe no response in 2015 to 2014 RC claiming, although learning would imply faster premium growth in 2015 for 2014 claiming insurers. Second, we control for premiums and claims, so we control for premium changes that are linearly related to premiums and claims. Third, if learning or mispricing is a problem, then it is likely a problem for neutral as well as claiming insurers, as neutral insurers have thin margins as well. Yet we see in Figure 3 that neutral insurers have premium changes like contributing insurers, not like claiming insurers. Fourth, experienced insurers—ones with at least 1,000 covered lives in the 2012 individual market—were more likely to make RC claims, as Table 1 shows. They also responded somewhat more to defunding and the end of the RC program, as Table 8 shows. Under the hypothesis that these insurers understood the market best, this is suggestive evidence that learning does not explain the observed association between RC claiming and premium growth. We view this evidence as suggestive, because experience in 2012 may be an unreliable guide to 2014, after community rating and guaranteed issue came into effect, and because the estimates in Table 8 are somewhat noisy. Nonetheless the available evidence suggests that, although learning is important in influencing premium and participation dynamics during this period, it likely does not explain our key findings.

7. Conclusions

In 2016 and 2017, premiums in the Health Insurance Marketplaces rose rapidly, while insurer participation fell. At the same time, the RC program was defunded and then ended.

Collectively, insurers in 2015 expected to receive billions of dollars from this program. We have shown theoretically that the RC program encourages claiming insurers to reduce their premiums, with likely spillover effects to non-claiming insurers, so the end of the program could have caused premiums to rise. Empirically, we find that insurers making RC claims in 2015 had larger premium increases by 2017, and markets in which more insurers made RC claims had much larger premium increases. We found no evidence, however, that insurers making RC claims were particularly likely to exit the market. It is possible nonetheless that the RC program encouraged participation. One motivation for the program was to protect insurers from aggregate uncertainty in 2014 about the likely composition of enrollees. Our design, which looks at behavior after this uncertainty is resolved, cannot detect this effect.

The end of the RC program may explain much of the dramatic increases in premiums in 2017. We simulate this effect by asking how premiums would have changed had no insurers made RC claims in 2015. This simulation is outside the range of the variation we use for identification, so we view it as suggestive rather than definitive. However, we find that in the absence of the RC program ending, premiums would have risen by only 10 percent between 2015 and 2017, instead of the actual 37 percent we observe. This finding suggests that rising premiums in the Marketplaces in 2017 do not necessarily reflect market instability or an adverse selection death spiral, but rather the end of a large, effective subsidy.

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TABLES

Table 1: Insurer-state level summary statistics

Insurer type:	Claiming		Contributing		Neutral	
	Mean	SD	Mean	SD	Mean	SD
2015 variables:						
Risk corridor claims PMPM	52.5	54.8	-9.8	9.6	0	-
Premium revenue PMPM	362.65	83.43	372.66	59.93	368.79	65.69
Medical claims costs PMPM	433.03	140.98	280.31	67.15	317.5	83.13
Member months (1000s)	495.4	1,060.60	247.4	422.5	479.0	1,051.10
Reinsurance claims PMPM	58.0	39.8	28.9	18.7	35.9	20.3
2012 Individual market						
Covered lives (1000s)	13.9	43.2	3.9	18.9	4.6	8.6
% Covering > 1000 lives	42	50	19	40	40	40
Participation, by year						
2015	1.00	-	1.00	-	1.00	-
2016	0.80	0.40	0.94	0.25	0.93	0.26
2017	0.54	0.50	0.74	0.44	0.79	0.41
Premium index, by year						
2015	0	-	0	-	0	-
2016	0.10	0.11	0.04	0.08	0.04	0.14
2017	0.32	0.19	0.15	0.14	0.16	0.15
Number insurers	248		31		58	

Notes: Sample consist of insurer-states participating in the exchanges in 2015 and meeting the sample restrictions described in the text. Claiming insurers have positive RC claims, contributing insurers have negative RC claims, and neutral insurers have zero RC claims. Premium revenue, medical claims costs, member months, and RC are derived from insurer's annual MLR filings. "PMPM" means "per member per month." Participation is a dummy variable indicating whether the insurer offers any Marketplace plans, and price index is an index of the log price of plans offered by the insurer, adjusting for plan and market characteristics in a given year, with 2015 normalized to zero. Price index is missing for insurers who exit the exchanges.

Table 2: Rating area-level summary statistics

Variable	Mean	Standard deviation	Within-state standard deviation
2015 Financial variables			
Average RC Claim	40.87	27.04	9.90
Fraction with RC claims > 0	0.78	0.23	0.08
Average premium PMPM	372.29	57.9	16.69
Average medical claim PMPM	424.48	76.18	33.76
Benchmark premium in			
2014	227.69	42.75	24.41
2015	229.98	40.09	23.14
2016	251.15	49.03	26.39
2017	314.15	82.81	46.24
Number of insurers in			
2014	3.63	2.13	1.29
2015	4.87	2.37	1.39
2016	4.24	2.25	1.41
2017	2.86	1.82	0.99

Notes: Sample consists of 504 rating areas. Financial variables are average characteristics of insurers operating in a given rating area. Medical claims costs are net of risk adjustment payments and cost sharing reduction subsidies. Benchmark premium is the premium a 27 year-old would pay for the second lowest cost silver plan in that rating area and year.

Table 3: Direct and spillover effects of RC claiming on changes in premiums

Outcome	$p_{2016} - p_{2015}$		$p_{2017} - p_{2015}$		$p_{2015} - p_{2014}$ (placebo)	
	(1)	(2)	(3)	(4)	(5)	(6)
1{RC claims >0}	0.027	0.041	0.072	0.118	-0.012	-0.031
	(0.021)	(0.028)	(0.032)	(0.039)	(0.041)	(0.046)
Fraction rivals with RC claims		0.123		0.335		0.005
		(0.087)		(0.140)		(0.074)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Insurer level controls	Yes	Yes	Yes	Yes	Yes	Yes
Market level controls	No	Yes	No	Yes	No	Yes
Fraction with RC claims >0	0.706	0.706	0.662	0.662	0.580	0.580
Mean, % rivals with RC claims	0.755	0.755	0.750	0.750	0.471	0.471
SD, % rivals with RC claims	0.236	0.236	0.241	0.241	0.352	0.352
# Insurer-states	282	282	204	204	255	255

Notes: Table shows coefficients on the indicated variables, from a regression of the change in insurers' log premium index between the indicated years. Insurer controls, not shown, include medical claims PMPM, premium revenue PMPM, member months PMPM, a nonprofit indicator, and an indicator for membership in a large insurer alliance. Market level controls, also not shown, include within-market averages of premium revenue PMPM, medical claims PMPM (net of risk adjustment and cost sharing reduction subsidies), and member months (averaged over the markets in which the insurer operates), as well as a set of controls for the fraction of markets in which the insurer operates that have exactly one, two, three, four, five, six insurers. (Seven or more insurers is the omitted category.) Variables are measured at the time of the base year (2015 in columns 1-4, 2014 in columns 5-6). The sample consists of insures on the exchange in both the base and the final year, and meeting the sample inclusion criteria in the base year. Robust standard errors in parentheses.

Table 4: Markets with more RC exposure in 2015 had higher premium growth in 2016 and 2017

Outcome	$p_{2016} - p_{2015}$	$p_{2017} - p_{2015}$	$p_{2015} - p_{2014}$ (Placebo)
	(1)	(2)	(3)
Fraction of insurers with RC claims > 0	0.205	0.323	-0.029
	(0.062)	(0.117)	(0.052)
Average premium revenue PMPM ($100s)	-0.002	0.037	-0.031
	(0.052)	(0.078)	(0.039)
Average medical claims PMPM ($100s)	0.007	0.000	0.007
	(0.022)	(0.034)	(0.014)
Average Member months (millions)	-0.021	-0.016	0.035
	(0.015)	(0.023)	(0.010)
Number issuer fixed effects?	Yes	Yes	Yes
State fixed effects?	Yes	Yes	Yes
Mean average owed PMPM	0.782	0.782	0.477
# Insurer-states	504	504	504

Notes: Table shows coefficients on the indicated variables, from a rating area-level regression of the change in benchmark price between the indicated years. Variables are measured at the time of the base year (2015 in columns 1 and 2, 2014 in column 3) and averaged over insurers participating in the rating area. Medical claims costs are net of risk adjustment payments and cost sharing reduction subsidies. The sample consists of all rating areas.

Table 5: Insurers with more 2015 risk corridor claims did not participate less in 2016-2017

	(1)	(2)	(3)
Outcome:	On exchange, 2016	On exchange, 2017	On exchange, 2015 (placebo)
RC claim > 0	0.90	-0.75	0.26
	(0.95)	(0.52)	(1.08)
Premiums PMPM	2.65	1.44	-0.37
	(0.63)	(0.43)	(0.70)
Medical claims PMPM	-1.78	-0.81	-0.06
	(0.38)	(0.28)	(0.28)
Member Months	1.40	1.29	8.51
	(0.59)	(0.40)	(4.63)
Nonprofit	0.81	1.47	-0.06
	(0.59)	(0.36)	(0.89)
Big group member	0.75	-0.29	-1.95
	(0.57)	(0.36)	(0.99)
State FE?	Yes	Yes	Yes
Participation rate	0.77	0.59	0.81
Fraction with RC claim > 0	0.76	0.73	0.54
Average effect of defunding	0.09	-0.09	0.01
# Observations	242	311	102

Notes: Table shows the coefficients on the indicated variables from a logit regression of participation the indicated year, against a dummy for having RC claims in 2015 (for participation in 2016 and 2017) or 2014 (for participation in 2015), as well as the indicated controls. Because we include state fixed effects, the sample excludes states with 100 percent participation in the indicated year. 2015 participation is a placebo test as the RC program was in effect then. Medical claims PMPM are net of risk adjustment payments and cost sharing reduction subsidies. Average effect is the change in predicted participation rates from setting the RC coefficient to zero. Robust standard errors in parentheses.

Table 6: Older plans do not have higher premiums

$y = \log Premium$	(1)	(2)	(3)	(4)	(5)
$1\{Age = 2\}$	-0.011	-0.010	-0.002	0.000	0.001
	(0.013)	(0.013)	(0.008)	(0.007)	(0.005)
$1\{Age = 3\}$	-0.009	-0.007	0.006	0.007	0.009
	(0.014)	(0.016)	(0.010)	(0.008)	(0.007)
Fixed effects for					
Plan-area	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes			
Metal-year		Yes	Yes	Yes	Yes
State-year			Yes		
Area-year				Yes	Yes
Insurer-year					Yes
# Observations	58,479	58,479	58,479	58,460	58,452
# Insurer-states	311	311	311	311	309

Notes: Table shows coefficients on indicators for plan age = 2 and age = 3, obtained from a regression of log premium on age indicators, as well as the indicated fixed effects. The unit of observation is an insurance plan in a given rating area and year. The sample is limited to observations belonging to non-singleton cells. Robust standard errors, clustered on insurer, in parentheses.

Table 7: The end of reinsurance does not explain the observed association between RC claiming and premium growth

Specification	Baseline	+Reinsurance	No controls	Control for claims, premiums, enrollment	All controls
	$Y = \ln p_{2017} - \ln p_{2015}$		$Y = 2015\ Reinsurance\ payments\ PMPM$		
	(1)	(2)	(3)	(4)	(5)
$1\{RC\ CLaim > 0\}$	0.072	0.086	0.191	-0.069	-0.103
	(0.032)	(0.032)	(0.040)	(0.029)	(0.034)
Reinsurance PMPM		0.129			
		(0.054)			
Observations	204	204	204	204	204

Notes: Table shows that controlling for reinsurance payments raises the coefficient on RC claiming, because reinsurance is conditionally correlated with price increases, but conditionally negatively correlated with claiming. Columns (1) and (2) show the results of regressing the change in log premiums between 2015 and 2017 on RC claiming dummy, reinsurance per member per month (in $100s), and the baseline controls (medical claims PMPM, premium revenue PMPM, member months PMPM, a nonprofit indicator, and an indicator for membership in a large insurer alliance. In columns (3)-(5) the dependent variable is reinsurance payments per member per month. There are no additional controls in column (3), controls only for claims, premiums, and enrollment in column (4), and the full set of controls in column (5). Robust standard errors in parentheses.

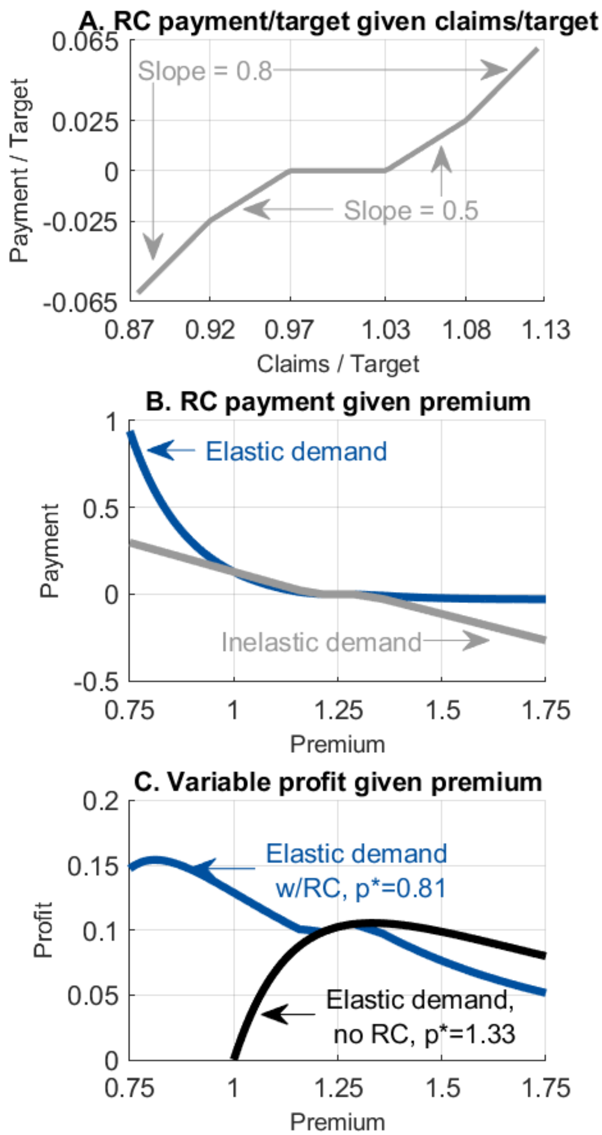
Table 8: Effect of Risk Corridors on premium growth, by prior individual market experience

Outcome	$p_{2016} - p_{2015}$			$p_{2017} - p_{2015}$		
Sample	All	Prior experience	No prior experience	All	Prior experience	No prior experience
	(1)	(2)	(3)	(4)	(5)	(6)
1{RC Claim >0}	0.027	0.075	0.004	0.072	0.092	0.063
	(0.021)	(0.036)	(0.032)	(0.032)	(0.048)	(0.051)
# Observations	282	108	74	204	84	120

Notes: Table show the coefficient on an indicator for 2015 RC claims. Additional controls, not shown, include (medical claims PMPM, premium revenue PMPM, member months PMPM, a nonprofit indicator, an indicator for membership in a large insurer alliance, and state fixed effects. Columns (1) and (4) use the full sample, columns (2) and (5) are limited to experienced insurers, and columns (3) and (6) are limited to inexperienced insurers. Insurers with prior experience are ones with at least 1,000 covered lives in the 2012 individual insurance market. Robust standard errors in parentheses.

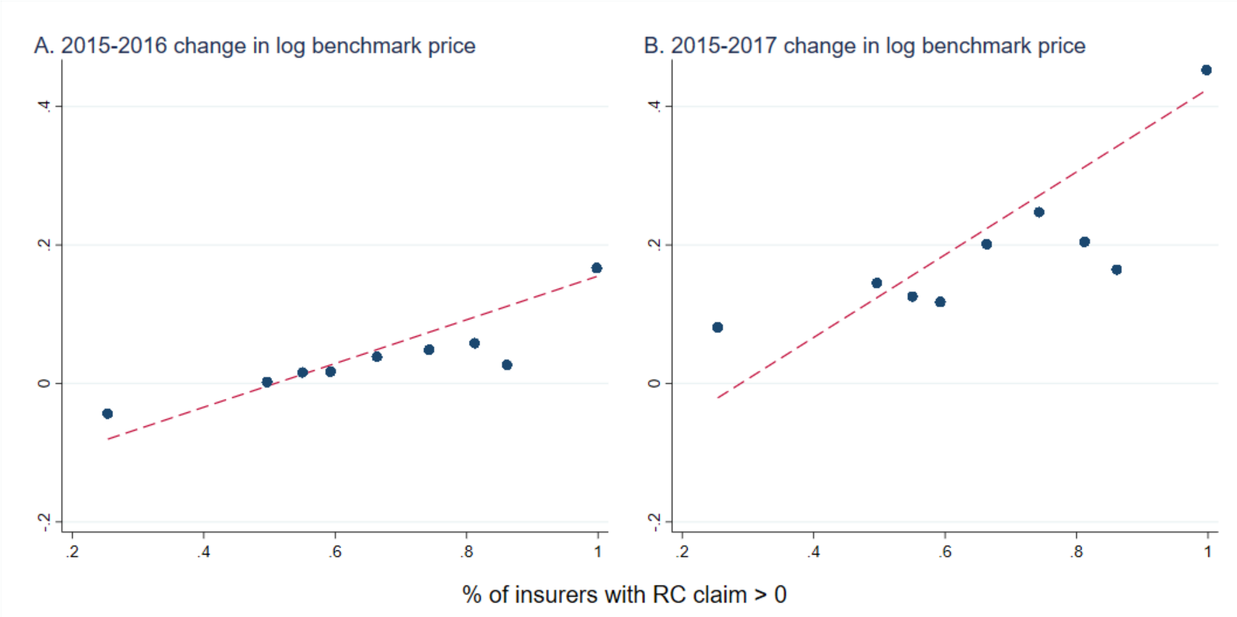
FIGURES

Figure 1: Risk corridor payments and profit



Notes: Panel A shows the risk corridor payment as a function of medical claims, both scaled by the target amount, which is equal to 80 percent of premium revenue. Panel B shows the risk corridor payment as a function of premium, for an insurer facing the demand curve $q = p^{\epsilon}$, with $\epsilon = -4$ ("elastic demand") or $\epsilon = 0$ ("inelastic demand"), assuming marginal cost $c = 1$. Panel C shows variable profit for an insurer with elastic demand, under the risk corridor program ("w/RC") or not ("No RC").

Figure 2: Rating areas with more claiming insurers in 2015 had larger unadjusted premium increases in 2016 and 2017



Notes: Figure shows the average change in the log benchmark premium in a given rating area, 2015-2016, against the % insurers with RC claim in that area in 2015, as well as the OLS fit, for each bin of RC owed amount in 2015. The bins are ventiles of fraction claiming amount, but 45% of rating areas have 100% claiming rates.

Appendix A: Robustness tests

We consider a series of tests to show that our results are robust to the key threats to identification, and to alternative specifications. Our robustness tests differ slightly from outcome to outcome, because of differences in the underlying data, but in general we show robustness to how we control for 2015 premiums and claims, to the presence of other controls, and to functional form. We find that our estimates are typically similar across alternative specifications, but in some specifications, they are substantially larger.

A.1 Robustness of insurer-level premium estimates

Appendix Table A2 shows the robustness of the insurer-level premium estimates. Column (1) shows the baseline estimates. Our key identification assumption is that, had the program not been defunded or ended, insures with RC claims would have had similar trends in premiums as non-claiming insurers. The main threat to identification is that, by construction, insurers with large RC claims in 2015 had high costs relative to premiums, so our main specifications control for 2015 medical claims and premium revenue, as well as total enrollment. However, there need not be a linear relationship between participation probabilities (or participation indices) and premium revenue, medical claims, or enrollment. In column (2) of the table, we add controls for all second-order terms: quadratics for medical claims, premium revenue, and enrollment, plus all two-way interactions. The estimated coefficients are a bit smaller and the 2017 coefficient is now marginally significant (p=0.07). In column (3), we add additional controls for the insurer, in particular we add a set of dummy variables indicating Blue status, and indicating membership in each of the five largest insurer alliances (Aetna, Cigna, Humana, UnitedHealthCare, and Wellpoint). These additional controls change the estimated coefficients only slightly. In column (4), we control for 2015 reinsurance claims PMPM, and in column (5) we control for all variables considered. The coefficients are quite similar to the baseline estimates. In column (6), we exclude from the sample RC contributors, insurers who paid into the RC program in 2015. Thus in this column we are identified by comparing claiming insurers to neutral insurers, whose claims are between 77 and 83 percent of premium revenue, and who therefore more closely resemble claiming insurers. We continue to find similar effects of the defunding and end of the RC program, although the 2017 standard error rises and the point estimate is only marginally significant (p=0.07), reflecting our lower power. Overall we conclude that our insurer-level premium estimates are not highly sensitive to the exact set of controls used or the comparison group.

A.2 Robustness of market-level price effects

Appendix Table A3 shows the robustness of the market-level results. Column (1) reports the baseline estimates, where we relate the change in premiums in a given rating area to the fraction of insurers making RC claims in 2015. We show in column (2) that further controlling for the average RC claim amount does not much change the estimated coefficient, and indeed the amount claimed is less important than the fraction claiming. In column (3) we add a richer set of controls: the average of the nonlinear terms for premium revenue, medical claims, and member months, controlling for quadratics and interactions among these variables, each interacted with 2016 and 2016 dummies. The 2016 and 2017 coefficients on average owed amount are quite similar. In column (4), we show that the results are also robust to controlling for a large set of interactions between rating area characteristic. In particular, we use ACS data to obtain for each rating area the log population, and the fraction age 0-17, 18-64, male, college educated, white, black, income below 124% of FPL, and income 125-400% of FPL. These variables are available at the county level, not the rating area level, so we omit the 28 rating areas that are not exact aggregations of counties. The estimates are slightly larger with these controls. Finally in column (6) we re-estimate, weighting each rating area by its population (as estimated in the ACS). Weighting by population produces substantially larger estimates, with a coefficient of 0.35 in 2016 and 0.53 in 2017. We focus on the smaller, unweighted result to be conservative.

A.3 Robustness of participation estimates

Appendix Table A4 shows the robustness of the participation estimates. Column (1) reports the baseline estimates, for 2016 in Panel A and 2017 in Panel B. In columns (2)-(6) we go through the same robustness tests as in the premium specifications, controlling nonlinearly for the financial variables, adding richer insurer controls, controlling for reinsurance, or excluding contributors. In none of the specifications do we find a significant association between RC claiming and insurer participation. In the final column, we estimate a linear probability model, and we continue not to find a significantly negative association (for 2016 we find a marginally positive association). Thus the non-association between participation and RC claiming is robust to alternative controls and specifications.

Appendix tables

Appendix Table A1: Autocorrelation in risk corridor exposure, 2014 to 2015

Outcome	1{RC Claims >0}	RC Claims PMPM	% of insurers claiming
	(1)	(2)	(3)
Coefficient on lag of outcome	0.248	0.58	0.27
	(0.058)	(0.12)	(0.04)
Constant	0.571	20.12	0.65
	(0.048)	(3.31)	(0.02)
Observations	249	246	504
Unit of observation	Insurer-State	Insurer-State	Rating area

Notes: Table shows the estimated autocorrelation coefficient obtained from a regression of the indicated variable in 2015 on its 2014 lag. Aggregate RC claims is the average risk corridor claim per member month, among insurers offering coverage in the rating area. The sample in columns (1) and (2) consists of the 248 insurers participating in both 2014 and 2015. The sample in column (3) consists of all rating areas.

Appendix Table A2: Robustness of insurer pricing effects

Specification:	Baseline	Nonlinear controls	Richer insurer controls	Control for reinsurance	All controls	Exclude contributors
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Outcome = Change in log premium index, 2015 to 2016					
$1\{Claim > 0\}$	0.027	0.016	0.033	0.025	0.022	0.025
	(0.021)	(0.022)	(0.023)	(0.021)	(0.024)	(0.026)
# Insurer-states	282	282	282	282	282	253
	B. Outcome = Change in log premium index, 2015 to 2017					
$1\{Claim > 0\}$	0.072	0.057	0.072	0.086	0.064	0.068
	(0.032)	(0.032)	(0.031)	(0.032)	(0.030)	(0.038)
# Insurer-states	204	204	204	204	204	181

Notes: Table shows the coefficient from a regression of insurer price index on the indicated variables. Additional controls always include medical claims per member month, premium revenue per member month, member months, nonprofit status, and membership in an insurer alliance and state fixed effects. In column (2) we add controls for all quadratic terms and interactions among claims per member month, premium per member month, member months, each interacted with year dummies. In column (3) we add controls a set of dummies indicating Blue status, and membership in each of the five largest insurer alliances, all interacted with year dummies. In column (4) we add controls for 2015 reinsurance claims PMPM. In column (5), we add all the controls tried in columns (2), (4), and (4). In column (5), we repeat the base specification but exclude insurers who made positive RC contributions. Robust standard errors in parentheses.

Appendix Table A3: Robustness of market-level results pricing effects

Specification:	Baseline	Amount owed	Nonlinear controls	Demographics	Demographics, weight by population
	(1)	(2)	(3)	(4)	(5)
	A: Outcome = Change in log benchmark premium, 2015 to 2016				
$\% \ Claiming$	0.22	0.22	0.24	0.23	0.35
	(0.06)	(0.06)	(0.08)	(0.07)	(0.10)
Average claim		0.09			
		(0.09)			
# Rating areas	504	504	504	476	476
	B: Outcome = Change in log benchmark premium, 2015 to 2017				
$\% \ Claiming$	0.34	0.34	0.30	0.33	0.53
	(0.11)	(0.12)	(0.12)	(0.12)	(0.16)
Average claim		-0.03			
		(0.14)			
# Rating areas	504	504	504	476	476

Notes: Table shows coefficients on the indicated variables, from a rating area-level regression of the change in benchmark price between the indicated years. Variables are measured at the time of the base year (2015). Additional controls always include average medical claims costs are net of risk adjustment payments and cost sharing reduction subsidies, average premium revenue, and average member months of enrollment (averaged over insurers operating the rating area in 2015). The sample consists of all rating areas. In column (2) we also control for the average amount claimed among insurers in the rating area. In column (3) we add controls for all quadratic terms and interactions among claims per member month, premium per member month, member months, each interacted with year dummies. In column (4) we add controls for rating area average demographics: log population; fraction aged 0-17 and 18-64; fraction male, college educated, white, and black; and fraction with income below 125% of the poverty line, and between 125 and 400% of poverty line. These variables are not available for 28 rating areas which are not coterminous with county boundaries. In column (5) we weight the regression by each rating area population. Robust standard errors in parentheses.

Appendix Table A4: Robustness of insurer participation effects

Specification:	Baseline	Nonlinear controls	Richer Insurer controls	Reinsurance Controls	All Controls	Exclude Contributors	Linear probability model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A: Outcome = 2016 exchange participation						
$1\{RC\ claim > 0\}$	0.90	0.20	1.54	1.03	1.71	1.67	0.10
	(0.95)	(1.19)	(0.94)	(1.00)	(1.24)	(0.99)	(0.05)
Sample size	242	242	180	242	180	206	337
	Panel B: Outcome = 2017 participation						
$1\{RC\ claim > 0\}$	-0.75	-0.31	-0.36	-0.62	0.00	-0.89	-0.11
	(0.52)	(0.56)	(0.67)	(0.53)	(0.73)	(0.68)	(0.07)
Sample size	311	311	298	311	298	247	337

Notes: Table shows the estimated coefficient from a regression of Marketplace participation in the indicated year on an indicator for positive RC claims. Additional controls always include premium revenue per member month, claims expenses per member month, and member months in 2015, as well as dummy variables for nonprofit status and membership in an insurer alliance, and state fixed effects. In column (2), we also control for all quadratic terms and interactions among premium revenue per member month, claims expenses per member month, and member months. In column (3) we add controls a set of dummies indicating Blue status, and membership in each of the five largest insurer alliances. (United and Wellpoint had no exits in 2016, so these insurer groups are dropped.) In column (4) we add controls for reinsurance claims per member per month. In columns (5) we add the nonlinear controls, richer insurance controls, and reinsurance controls. In column (6) we use the base controls but exclude contributing insurers. Columns (1)-(6) are estimated with logistic regression and the reported coefficient is an adjusted log odds ratio. In column (7) we estimate a linear probability model. Robust standard errors in parentheses.