# Multimarket Contact in Health Insurance: Evidence from Medicare Advantage<sup>\*</sup>

Haizhen Lin Indiana University & NBER

Ian M. McCarthy<sup>†</sup> Emory University & NBER

May 2018

#### Abstract

Many industries, including health insurance, are characterized by a handful of large firms that compete in multiple geographic markets. Such overlap across markets, defined as multimarket contact (MMC), may facilitate tacit collusion and thus reduce the intensity of competition. We examine the effects of MMC on health insurance prices and quality using comprehensive data on the Medicare Advantage (MA) market from 2008 through 2015. Our estimation strategy exploits two plausibly exogenous changes to MMC: 1) a merger-induced change in MMC due to consolidations in other markets; and 2) reimbursement policy changes in which benchmark rates were increased in a subset of markets, encouraging additional entry into those markets and therefore affecting MMC even in markets otherwise unaffected by the policy itself. Across a range of estimates and alternative measures of MMC, our results consistently support the mutual forbearance hypothesis, where we find that prices are significantly higher and hiqh-quality plans less pervasive as MMC increases. These results suggest MMC as one potential channel through which MA policy and cross-market consolidations could alter competitiveness in local markets otherwise unaffected by the policy or merger.

<sup>\*</sup>We are grateful to seminar participants at Stanford University, Indiana University, University of Illinois Urbana-Champagne, University of Tennessee, the Georgia Health Economics Research Day, and the International Health Economics Association Meetings.

<sup>&</sup>lt;sup>†</sup>Correspondence to Ian McCarthy, Emory University, Department of Economics, 1602 Fishburne Dr., Atlanta, GA 30322, U.S.A. E-mail: ian.mccarthy@emory.edu

# 1 Introduction

A large literature in management and economics suggests that competition between firms may be softened as a result of multimarket contact (MMC) (Karnani & Wernerfelt, 1985; Bernheim & Whinston, 1990; Evans & Kessides, 1994; Jans & Rosenbaum, 1997; Ciliberto & Williams, 2014). The possibility that MMC could promote anticompetitive outcomes was first articulated by Edwards (1955): "The multiplicity of firm contacts may blunt the edge of their competition." Bernheim & Whinston (1990) offered one of the first theoretical models of multimarket contact. They show that under the assumption of asymmetry, tacit collusion is sustainable due to the threat of retaliation in multiple markets. The intuition is that MMC serves to pool firms' incentive constraints across markets, and asymmetry allows firms to transfer incentive constraints across markets. Other works have identified additional mechanisms by which MMC could enhance collusion, such as concavity of the profit function (Spagnolo, 1999) and imperfect monitoring (Matsushima, 2001). Collusive outcomes are therefore easier to sustain in markets with higher levels of MMC. This potential softening of competition due to MMC is referred to as the mutual forbearance hypothesis and may ultimately yield higher prices and lower quality than would otherwise be expected.

Given the natural concerns surrounding collusion and its effects on market outcomes, understanding the empirical effects of MMC is critical in designing appropriate antitrust and regulatory policy. Subsequently, there has been interest among strategy researchers and industrial economists in testing the mutual forbearance hypothesis.<sup>1</sup> In this paper, we examine the effect of MMC on prices and quality in health insurance, specifically the Medicare Advantage (MA) market. To the best of our knowledge, we are the first in examining MMC in the U.S. health insurance market.

Our focus on the MA market is highly policy-relevant. First, this market is a large and growing component of the U.S. healthcare system, with 19 million individuals (33% of the Medicare population) currently enrolled in an MA plan for their health insurance benefits.<sup>2</sup> MA is also a prime example of managed competition in which insurers' behaviors are highly influenced by

<sup>&</sup>lt;sup>1</sup>The presence of MMC and mutual forbearance has been examined empirically across several industries, including airlines (Evans & Kessides, 1994; Ciliberto & Williams, 2014), cement (Jans & Rosenbaum, 1997), banking (Molnar *et al.*, 2013), movies (Feinberg, 2015), and radio (Waldfogel & Wulf, 2006), among others. More recently, Schmitt (2017) examines the role of MMC in hospital markets.

<sup>&</sup>lt;sup>2</sup>This reflects nearly a four-fold increase since the Medicare Modernization Act of 2003. Kaiser Family Foundation MA Update, available at https://www.kff.org/medicare/issue-brief/medicare-advantage-2017-spotlight-enrollment-market-update/.

federal Medicare policy. Empirical evidence of MMC in the MA market therefore has the opportunity to directly inform policy in MA and other settings relying heavily on managed competition, including the health insurance exchanges created under the Affordable Care Act (ACA). Perhaps more importantly, recent years have witnessed a significant amount of consolidation and policy changes in the MA market. Such changes offer important sources of variation in estimating the impact of MMC on firms' behaviors, but consolidation and MMC is also interesting to study in its own right. For example, current analyses of changes in competition from mergers and acquisitions typically ignore the impact of MMC, but mergers across distinct markets, having no effect on local market concentration, could still affect market competition due to changes in MMC. Since there has been very little regulatory activity regarding mergers of two firms that do not directly compete against each other in local markets, our study of MMC in the MA market has potential policy implications for mergers and acquisitions in the health insurance market overall.

In addition to policy relevance, the MA market offers a textbook environment for the examination of the mutual forbearance hypothesis for two reasons. First, a critical condition for mutual forbearance is a firm's ability to detect deviations from collusion (Thomas & Willig, 2006). Failing to meet this condition would cause researchers either to underestimate the effect of MMC or (incorrectly) fail to find evidence in support of the mutual forbearance hypothesis. Our study of the MA market has a compelling advantage over existing studies in that price and quality information are publicly available, transparent to competing firms once information is posted during open enrollment, and constant within a calendar year. This transparency intuitively allows for sustained collusion and offers a clearer opportunity to study the effects of MMC. Second, the literature suggests that MMC can facilitate tacit collusion on both price and non-price behavior such as advertising and product quality, but existing empirical work prioritizes price as the outcome of interest mainly due to data constraints.<sup>3</sup> The richness in available data on the MA market allows use to extend the mutual forbearance hypothesis to product quality, which is critical when considering the broader implications for consumer welfare.

Note that MA plan "prices" derive from a competitive bidding process, which we discuss in more detail in Section 3.2. We therefore measure prices using both bids and monthly premiums, where the bid captures the total payment to insure a single individual, and the premium represents the portion of the total payment that is paid directly by the enrollee. We measure quality based

<sup>&</sup>lt;sup>3</sup>Prince & Simon (2009) provide a recent exception in studying quality of service in the US airline industry.

on the plan's overall star rating introduced by CMS in 2009. For both prices and quality, MMC is arguably endogenous. We therefore pursue an instrumental variable strategy where we exploit two plausibly exogenous changes in MMC. The first source exploits out-of-market merger activity among MA insurers. Specifically, we form an instrumental variable that measures the mergerinduced change in pairwise overlaps among non-merging insurers in markets that are otherwise not affected by the merger. The second source of exogenous variation derives from changes in MA reimbursement policy that adjusted CMS payments to MA plans in selected counties. Specifically, increases in MA benchmark rates for urban counties (i.e., "urban floors") were introduced as part of the Benefits Improvement and Protection Act of 2000. As examined in Duggan et al. (2016), the urban floor policy had a significant effect on market entry and is therefore a strong candidate as an instrument for MMC. We also exploit the introduction of "double-bonus" counties in 2012, in which specific counties were selected to receive increases in benchmark rates and bonuses paid to MA plans. Like the urban floor policy, the double-bonus policy acts as an exogenous influence on market entry and exit and will therefore also affect MMC even in markets otherwise unaffected by the policy itself. Indeed, Layton & Ryan (2015) find that the double-bonus program increased the number of plan offerings, again making the double-bonus policy a good candidate as an instrument for MMC.

Our results largely support the mutual forbearance hypothesis in the MA market. We find that a one standard deviation increase in MMC leads to between a \$13 and \$18 increase in Part C bids, representing between 22% and 30% of the bid-benchmark differential of around \$60. There is also some evidence of an increase in monthly premiums of around \$2 to \$3. On a base of approximately 85% of plans with \$0 premiums (i.e., plans with bids below the benchmark rates set by CMS), our estimated premium effects translate to more than a 36% increase in the percent of plans that charge positive Part C premiums. We find very small (if any) effects of MMC on Part D bids or premiums, consistent with lesser transparency in Part D prices relative to Part C.<sup>4</sup> With regard to quality, we find evidence that increasing MMC reduces the prevalence of high-quality contracts, where a one standard deviation increase in MMC leads to as much as a 10% reduction in the percentage of high-rated contracts in a market (where high-rated is defined as receiving a star rating of 4 or more). We also find evidence that MMC has a differential effect on quality across market segments, where quality among highly price-sensitive segments may increase due

<sup>&</sup>lt;sup>4</sup>More details regarding institutional differences between Part C and Part D are discussed in Section 3.2.

to MMC while quality among less price-sensitive segments decreases. Our findings qualitatively persist across a range of specifications, choices of instruments, measures of MMC, and definitions of MA products and markets.

Our paper contributes to the existing literature on MMC in three important ways. First, we offer one of the first studies of MMC in health insurance where overlap across markets appears to be an important characteristic. Our results suggest MMC as one potential channel through which MA policy and cross-market consolidations could alter competitiveness in local markets otherwise unaffected by the policy or merger. Second, with the exception of Prince & Simon (2009), the majority of empirical studies of MMC focus on prices. We extend our understanding of the impact of MMC by examining both pricing and product quality. Our finding of a significant reduction in high-quality contracts from MMC suggests that ignoring non-price attributes is likely to underestimate the total effect of MMC on consumer welfare. Last, while the standard approach of identification relies on market fixed effects, our identification exploits out-of-market consolidations and exogenous MA policies, which has the advantage of controlling for endogeneity caused by time-varying unobservables. The same identification strategy has been used in the hospital setting (Dafny et al., 2017; Lewis & Pflum, 2017; Schmitt, 2017). In this way, our paper is similar to Schmitt (2017) who examines the impact of MMC on estimated hospital prices; however, Schmitt (2017) adopts an event study approach measuring how prices respond to out-of-market mergers, with the assumption that out-of-market mergers capture exogenous changes in hospital MMC. Our identification strategy instead exploits changes in local pairwise overlaps due to out-of-market mergers as an instrument, similar to the simulated change in local market concentration as in Dafny et al. (2012). Our identification therefore allows us to directly quantify the impact of MMC on market outcomes.

# 2 Conceptual Framework

The theory of multimarket contact suggests that the intensity of competition may be dampened through mutual forbearance. We therefore derive our intuition for the likely effect of MMC on price and quality from the literature related to market power and firms' strategic behavior. From this literature, the impact of MMC on prices is intuitively straightforward. Since MMC tends to reduce the intensity of competition, we expect price to increase following increases in MMC. The majority of empirical studies of MMC support this prediction. For example, Evans & Kessides (1994) offer one of the first empirical studies of price and MMC using data from the U.S. airline industry. They find that airlines charge higher prices on routes with a higher level of MMC. Ciliberto & Williams (2014) also examine the airline industry and identify underlying conduct parameters using variation in MMC, therefore directly linking MMC to the degree of coordination. More recently, Schmitt (2017) studies MMC in the hospital setting and finds that hospitals exposed to out-of-market mergers (presumably increasing MMC) charge higher prices.

The effects of MMC on product quality are less clear, especially in a setting where firms choose both price and quality. This indeterminate relationship derives from the ambiguity in theoretical predictions on market power and quality (Dorfman & Steiner, 1954; Spence, 1975; Mussa & Rosen, 1978; Dana Jr & Fong, 2011). Mirroring this theoretical ambiguity, existing empirical studies of the effects of market power on quality offer mixed results (Berry & Waldfogel, 2001; Sweeting, 2010; Fan, 2013; Crawford *et al.*, 2018).<sup>5</sup> Empirical evidence specifically on the relationship between MMC and quality is particularly scarce. The only study of which we are aware is Prince & Simon (2009), who use airline on-time performance as a measure of service quality. They find that MMC increases airline delays (i.e., decreases quality); however, delays are one of many dimensions of quality in this market and may not be fully transparent or predictable in a given purchasing decision.

In the MA market, the effect of MMC on quality is theoretically ambiguous. Drawing from the argument in Dorfman & Steiner (1954), if competition changes the elasticity of demand with respect to quality more (less) than the elasticity with respect to price, we should expect quality to fall (increase) with softened competition; however, consumers might have different underlying preferences for prices and quality. Theoretically, Mussa & Rosen (1978) and Champsaur & Rochet (1989) highlight the potential for differential effects of increased competition when markets consist of heterogeneous price/quality preferences. Following this intuition, we expect different market segments to respond differentially to market power, leading to different predictions of the impact of MMC on product quality. For example, it may be that consumers choosing low-quality insurance

<sup>&</sup>lt;sup>5</sup>Mixed results have also been found in a health care setting, primarily in the hospital market, as in Kessler & McClellan (2000), Gowrisankaran & Town (2003), and Kessler & Geppert (2005). These empirical investigations have largely examined how clinical outcomes vary with market Herfindahl-Hirschman Index. Gaynor (2006) offers an extensive review of this literature. More recent studies, such as Cutler *et al.* (2010), Gaynor *et al.* (2013), and Bloom *et al.* (2015), tend to find that increased hospital competition leads to higher quality.

plans are particularly price sensitive, in which case MMC may facilitate an increase in quality. We examine this issue empirically in Section 5.3.

# 3 Institutional Background

Our market definition, outcomes of interest, and econometric specifications derive from several institutional features of the MA program. In this section, we discuss the broad background of MA as well as specific features relevant to our measure of price and quality in this market.

## 3.1 The Medicare Advantage Program

The Balanced Budget Act of 1997 (BBA) introduced private health insurance options known as Medicare + Choice plans (M+C, or Medicare Part C). Medicare Part C was then revised as part of the 2003 Medicare Modernization Act and renamed Medicare Advantage (MA), which allowed additional plan types such as Regional PPOs and Special Needs Plans (SNPs) as well as prescription drug coverage. MA plans, like the preceding Medicare Part C plans, are provided by private insurers who contract with CMS annually. Insurers generally operate multiple contracts across (and perhaps within) markets and there is typically more than one individual plan offered under a single contract. Finally, MA insurers can only enroll beneficiaries that live in the plan's geographic service area, which consists of one or more counties selected by the MA insurer when seeking approval from CMS to offer MA services.

For a given calendar year, beneficiaries can enroll in MA plans during an open enrollment period toward the end of the prior year. During this time, eligibles aged 65 years or older without end stage renal disease can choose any plan available in their area. Limited enrollment continues midway through the current year, during which time eligibles may only enroll in an MA plan if the plan is currently accepting new members. Beneficiaries can also switch plans during the limited enrollment period, but only one switch is allowed per year. By choosing an MA plan, beneficiaries no longer receive the traditional benefits of Medicare FFS but must still enroll in Medicare Parts A and B and pay the Part B premium. CMS requires that MA plans offer at least what the beneficiary could receive from Medicare FFS.

As of 2017, MA plans provided coverage to 19 million beneficiaries (33% of the total Medi-

care population), and although numerous plans are available in a given county, these plans are concentrated among relatively few contracts and insurers. A recent Kaiser Family Foundation report found that 65% of nationwide enrollment was concentrated among six firms (Kaiser Family Foundation, 2012). The same report found even higher concentration at the state level. As such, competition in the MA program is weaker than would be expected based on the number of plans available, consistent with previous research documenting a widespread but inaccurate public perception of competition in the U.S. health insurance market (Dafny, 2010; Dafny *et al.*, 2012).

## 3.2 Medicare Advantage Bidding

Premiums for MA plans are determined by a competitive bidding process. Specifically, for Part C services (under most plan types), MA insurers submit bids to CMS intended to reflect the anticipated cost of the plan to cover Medicare Parts A and B benefits. These bids, which we denote by  $b_{c(j)t}$  for plan j under contract c at time t, are then compared to a local benchmark payment rate, denoted  $B_{mt}$  for market m. For  $b_{c(j)t} < B_{mt}$ , CMS pays the insurer the risk-adjusted bid for each enrollee,  $\alpha_i \times b_{c(j)t}$ . CMS also pays these insurers a percentage of the difference between the bid and benchmark in the form of a rebate, denoted  $\gamma_{c(j)t}$ ;<sup>6</sup> however, rebates must be transferred to beneficiaries in the form of added benefits. Therefore, in the case of  $b_{c(j)t} < B_{mt}$ , the insurer's effective price received for enrollee i is simply  $\alpha_i \times b_{c(j)t}$ . Conversely, if insurers submit bids in excess of the benchmark, CMS pays the plan  $\alpha_i \times b_{c(j)t} - (b_{c(j)t} - B_{mt})$ , and enrollees pay the bidbenchmark differential in the form of monthly premiums (in addition to the usual Medicare Part B premiums and any Part D premiums). The additional monthly premium offsets the reduction in per-enrollee payments made by CMS, such that the insurer again receives an effective price of  $\alpha_i \times b_{c(j)t}$  for enrollee *i*. The price ultimately received by the insurer for Part C services is therefore the plan's risk-adjusted bid amount, regardless of whether this bid amount is paid in-part by the enrollee or fully by CMS.

MA plans that also offer prescription drug coverage (MA-PD plans) undergo a similar bidding

<sup>&</sup>lt;sup>6</sup>Since 2012, the benchmark rates were adjusted based on the contract's star rating, with contracts of 4 stars or more receiving a 5% increase in their benchmark rates. New contracts also received a 3.5% increase in benchmark rates. Also, for the years 2012-2014, the percentage received as a rebate,  $\gamma_{c(j)t}$ , is a function of the contract's star rating, with contracts of 4.5 or 5 stars receiving a 70% rebate, contracts of 3.5 or 4 stars receiving a 65% rebate, and contracts of 3 stars or below receiving a 50% rebate. Contracts deemed "too new" for a star rating were assigned a default rating of 3.5-4 stars for rebate calculations (65% of the difference between the bid and benchmark). In all other years, plans receive a set rebate of 75%.

process for Part D benefits but with at least two important differences. First, since traditional Medicare does not cover prescription drugs, CMS relies on the national average bid as a benchmark comparison for a given plan's bid, and this comparison dictates the final monthly premium for a given plan. Second, the Part D program includes a handful of subsidies paid by CMS to the insurer, including subsidies for low-income enrollees and additional payments for high cost enrollees. Insurers can also self-subsidize their Part D premiums using their Part C rebates. For these reasons, Part D bidding and premium information is much less transparent relative to Part C, and deviations from a collusive strategy are therefore less observable. For example, since the Part D benchmarks are determined by the national average bid, low bids may reflect a deviation from collusion or simply an underestimate of the national average bid. Due to the differences in the bidding process between Part C and Part D components of MA, we examine the impact of MMC on Part C and Part D pricing separately.

## 3.3 Medicare Advantage Quality Ratings

Since the passing of the BBA, CMS has undergone a significant effort to better inform Medicare beneficiaries of the quality of health insurance plans available in their area. This quality information was initially limited to specific attributes. For example, an MA plan would be scored based on the percentage of women ages 50 to 69 who received a mammography within the past two years. The percentages for each plan in a beneficiary's area would then be included in the *Medicare and You* booklet.

CMS then launched a star rating program in 2007, by which contracts were rated from one to five stars in each of five different domains.<sup>7</sup> Star ratings in each domain were calculated based on dozens of individual measures from a variety of sources.<sup>8</sup> Beginning in 2009, CMS began assigning an overall star rating to each MA contract, ranging from 1 to 5 stars in half-star increments. These

<sup>&</sup>lt;sup>7</sup>These domains initially were: 1) "helping you stay healthy"; 2) "getting care from your doctors and specialists"; 3) "getting timely information and care from your health plan"; 4) "managing chronic conditions"; and 5) "your rights to appeal." Since 2007, the individual measures and domains have changed nearly every year. For example, CMS expanded the "rights to appeal" domain in 2010 to include measures on complaints and the number of beneficiaries leaving the plan, among others. Also in 2010, the "timely information" domain was replaced by "customer service." In 2009 and 2010, a contract's overall star rating was based solely on Part C measures. Since 2011, the overall star rating now includes measures of Part D performance.

<sup>&</sup>lt;sup>8</sup>The data sources include the Healthcare Effectiveness Data and Information Set (HEDIS), the Consumer Assessment of Healthcare Providers and Systems (CAHPS), the Health Outcomes Survey (HOS), the Independent Review Entity (IRE), the Complaints Tracking Module (CTM), and CMS administrative data.

ratings are provided at the contract-level rather than the plan-level. CMS also introduced Part D measures into the star rating calculation beginning in the 2011 enrollment period.

## 3.4 Timing of Approval and Bidding

The timing of the CMS approval and competitive bidding process is important as it speaks to an insurer's potential information set when making entry/exit decisions and setting bids.<sup>9</sup> Insurers seeking changes to existing products or seeking to expand into new markets must first submit applications to CMS for approval to offer MA contracts in a given market. Insurers are recommended to submit a notice of intent to apply at the end of the prior calendar year but no later than mid-January, with final applications due in February. These applications are reviewed and approvals issued (or denied) over the next 3-4 months. Conditionally approved contracts must then prepare plan bids and cost-sharing details of all plan benefit packages, which are reviewed by CMS and ultimately approved or denied in August of a given calendar year. Final contracts are executed in September, just prior to the beginning of the open enrollment period.

This process means that insurers seeking changes to their contracts (other than premiums) or seeking to enter new markets must make these decisions essentially a year in advance, before any decisions on plan pricing/bids. For example, consider the 2016 open enrollment period beginning in October 2015. The timeline is such that insurers must make decisions on which products to offer in which markets as early as December 2014. At this stage, insurers are therefore operating based on information from the 2015 open enrollment period (October-November of 2014). The bidding process for the 2016 enrollment period, however, does not begin until June 2015, at which point an insurer has more information regarding its competitors since initial applications for CMS approval were due in February. This timeline suggests that, if MMC indeed affects insurer pricing behavior, contemporaneous MMC should be the relevant metric for examining bids and premiums. Meanwhile, the MA star rating program relies on one- or two-year lagged measures, and as such, lagged MMC is used in studying MA quality.

<sup>&</sup>lt;sup>9</sup>See the Medicare Advantage Applications, available at https://www.cms.gov/Medicare/Medicare-Advantage/MedicareAdvantageApps/index.html, for more details.

## 4 Data

We discuss first our primary Medicare Advantage data before turning to the details of our MMC calculations, instrumental variables, product and market definitions, and ultimately our outcomes of interest.

### 4.1 Medicare Advantage Data

We collect data on MA market shares, contract/plan characteristics, and market area characteristics from several publicly available sources from 2008 through 2015. The set of available plans in each county is constructed from the Medicare Service Area files, which list all approved MA contracts within a county/month/year.<sup>10</sup> To these records, we merge enrollment and plan information at the contract/plan level from the MA enrollment files as well as county-level MA penetration information.<sup>11</sup> We exclude plans with missing or fewer than 11 enrollees as all such enrollments are masked in the data. Next, we merge the contract's overall summary star measure, plan premium and rebate information at the contract/plan/county/year level, and county-level census demographic and socioeconomic information from the American Community Survey (ACS). Finally, we incorporate county-level hospital discharge data from the annual Healthcare Cost Reporting Information System (HCRIS) database as well as Part C benchmark rates and average FFS costs by county.

We present summary statistics for our plan/contract-level independent variables as well as our county-level variables in Tables 1 and 2, respectively. Note that we observe from the MA payment files the average Part C payments made by CMS to a given plan. Along with the observed Part C premium, we can estimate each plan's risk-adjusted Part C bid as the sum of the Part C payment and any observed premium. For Part D bids, we observe the CMS "direct subsidy" payment as well as the Part D premium for basic prescription drug coverage (net of any reduction from Part C rebates). Since we do not observe how much of a Part C rebate is used to pay down the Part D basic premium, we cannot directly estimate the Part D bid. We nonetheless consider the net

<sup>&</sup>lt;sup>10</sup>As our base, we use the Service Area files because the CMS enrollment files include those that move and keep their MA coverage despite the fact that a particular MA contract may not be approved in the new market area, and thus, not part of an potential enrollee's choice set. Data are available for download at www.cms.gov.

<sup>&</sup>lt;sup>11</sup>Plan-level enrollments are available monthly, but there is little variation in enrollments across months due to the nature of the open enrollment process. We therefore measure plan enrollments as the average enrollment across months in a given year.

Part D bid (net of any reduction from Part C rebates), estimated as the sum of the CMS direct subsidy payment and the Part D basic premium. Summary statistics of the estimated plan bids are also included in Table 1.

#### Tables 1 and 2

At least four salient features of the MA market emerge from these summary statistics. First, the MA market has become increasingly concentrated in recent years, with a spike in the total number of plan/county observations in 2009 and dropping by more than 33% by 2015, with similar trends in the total number of plans per county. Consistent with these trends, average plan market share increased from 5.7% in 2009 to over 8% in 2011 though 2015. Enrollment per plan similarly increased from 215 enrollees per month in 2009 to nearly 500 beneficiaries per plan per county in 2015. Second, the types of plans available have become more homogeneous in many respects. For example, in 2008, approximately 35% of plans were managed care (HMO or PPO) and around 62%offered prescription drugs. In 2015, 81% of plans offered prescription drug coverage and over 90%of plans were managed care. Third, plan prices have been relatively stable since 2010. Monthly consolidated premiums, for example, increased less than 6% from \$48 per month in 2010 to \$51 per month in 2015. Decomposing these premium changes between Part C and Part D components, the observed increase in premiums has been driven by an increase in Part D premiums while Part C premiums have remained between \$7 and \$10 per month since 2010.<sup>12</sup> Finally, there has also been an increase in average contract quality (as measured by CMS star ratings), with the majority of contracts receiving less than a 3-star rating in 2009 through 2011, over 60% of contracts receiving a 3 to 3.5-star rating in 2012-2014, and 56% of contracts receiving a rating of 4 to 5 stars in 2015(compared to just 31% in 2014 and 18% in 2013).<sup>13</sup>

## 4.2 Multimarket Contact

Included in the MA "landscape" files is the contract parent organization, which identifies the insurer operating each MA contract. We use this insurer-level information in constructing our MMC measures. Specifically, we follow the literature in calculating MMC as the average number

 $<sup>^{12}\</sup>mathrm{These}$  average premiums are based on all plans and therefore include many \$0 premium plans as well.

<sup>&</sup>lt;sup>13</sup>Note that these average star ratings in Table 1 are at the contract/county level rather than just the contract level, reflecting an average star rating weighted by prevalence across counties.

of pairwise market overlaps among all insurers in a given market (Evans & Kessides, 1994; Ciliberto & Williams, 2014; Jans & Rosenbaum, 1997; Waldfogel & Wulf, 2006):

$$MMC_{mt} = \frac{1}{N_{mt}(N_{mt}-1)/2} \sum_{i=1}^{N_{mt}-1} \sum_{j=i+1}^{N_{mt}} \mathbb{1}\left[i, j \in N_{mt}\right] \left(mmc_{ijt}-1\right),\tag{1}$$

where  $mmc_{ijt}$  denotes the total number of markets in which firms *i* and *j* overlap in year *t*, and  $N_{mt}$  denotes the set of all insurers operating in market *m* at time *t*. The indicator function,  $\mathbb{1} [i, j \in N_{mt}]$ , is set to 1 if both firm *i* and *j* operate in market *m* at time *t* and 0 otherwise.<sup>14</sup> With a slight abuse of notation,  $N_{mt}$  also denotes the total number of firms in a market. Note that an equivalent expression for  $MMC_{mt}$  is

$$MMC_{mt} = \frac{1}{N_{mt}(N_{mt}-1)} \sum_{i=1}^{N_{mt}} \sum_{j=1, j\neq i}^{N_{mt}} \mathbb{1} [i, j \in N_{mt}] (mmc_{ijt}-1)$$
$$= \frac{1}{N_{mt}} \sum_{i=1}^{N_{mt}} \frac{1}{N_{mt}-1} \sum_{j=1, j\neq i}^{N_{mt}} \mathbb{1} [i, j \in N_{mt}] (mmc_{ijt}-1)$$
$$= \frac{1}{N_{mt}} \sum_{i=1}^{N_{mt}} MMC_{imt},$$
(2)

in which  $MMC_{mt}$  at the market-year level is simply the average of insurer-level MMC measures in a given market and year. This alternative expression in terms of insurer-level MMC is useful since we exploit exogenous variation at the insurer and market level in order to identify the effects of MMC, as discussed in detail in Section 5.1.

To better understand the construction of our  $MMC_{mt}$  variable, Table 3 presents the count of pairwise market overlaps among the top 10 insurers in MA in 2015. We see from the diagonal that Humana is the largest insurer (in terms of markets served), with a presence in over 2,400 markets. UnitedHealth, BlueCross, Aetna, and Wellcare round out the top 5 insurers in MA as of 2015.<sup>15</sup> Table 3 also reflects a substantial amount of market overlap across insurers. For example, out of the 1,222 markets in which BlueCross operated in 2015, the insurer overlapped with Humana in 1,080 of those markets (88%). Similarly, of the 1,370 markets in which UnitedHealth operated,

<sup>&</sup>lt;sup>14</sup>There are 3,102 market/year observations with just one insurer in our data. These markets are relatively small on average, with just 165 enrollees per market compared to an average of over 800 MA enrollees in other markets. We drop these markets in our analysis in Section 5.

<sup>&</sup>lt;sup>15</sup>We refer to all Blue Cross Blue Shield plans and affiliates, including Anthem plans, as Blue Cross.

the insurer overlapped with BlueCross in 531 of those markets (39%).

#### Table 3

In addition to the raw count of market overlaps,  $mmc_{ijt}$ , we consider an alternative measure of  $MMC_{mt}$  that is weighted by the competitiveness of the markets in which the insurer operates, denoted  $MMC_{mt}^{hhi}$  (Jans & Rosenbaum, 1997; Fernandez & Marin, 1998; Prince & Simon, 2009). This amounts to replacing  $mmc_{ijt} - 1$  with  $\sum_m \mathbb{1} [i, j \in m] HHI_{mt}$ .<sup>16</sup> In other words, rather than taking the count of all overlapping markets (i.e.,  $\sum_m \mathbb{1} [i, j \in m]$ ), we take the sum of the HHI across all overlapping markets, where HHI is measured on a scale of 0 to 1. Higher concentrated markets therefore receive the most weight, with the intuition being that any deviation from a collusive strategy will bear a larger cost in more concentrated markets.

Variation in MMC across markets in a given year comes from differences in the set of firms operating in each market, which could derive from changes in the set of firms operating in a given market as well as changes in the set of firms operating in other markets. The source of variation in  $MMC^{hhi}$  is similar, except that changes in local market concentration of each overlap market also contribute to its variation. Note that increasing concentration observed in the MA market does not necessarily imply increasing MMC. Indeed, if each market were served exclusively by just a single insurer, there would be no overlap and therefore no MMC.

Similarly, entry does not always lead to an increase or a decrease in MMC since our measure of MMC is the average number of overlaps across all combinations of firm pairs. When the entrant is a national firm that overlaps significantly with incumbents, MMC is likely to increase. If instead a reginal firm enters, MMC for that market can actually decrease.

To see how our MMC measures vary over time, we present cumulative distribution plots of MMC for 2008, 2012, and 2015. CDFs of  $MMC_{mt}$  are provided in Figure 1, with analogous CDFs for  $MMC_{mt}^{hhi}$  presented in Figure 2. In both figures, CDFs are plotted at the county level, such that each county is reflected once in the CDF. Interestingly, both figures reveal a bifurcation in the level of MMC over time, which is particularly apparent with  $MMC_{mt}^{hhi}$ . On average, both MMC and  $MMC^{hhi}$  have decreased since 2010, but this decrease is characterized by differential changes across markets rather than an overall shift in the MMC distribution.

 $<sup>^{16}</sup>$ In this case, *m* denotes all markets other than the current market under consideration, but we exclude this additional notation for brevity.

#### Figures 1 and 2

## 4.3 Instruments and Endogeneity of MMC

MMC is likely to be correlated with unobservables that affect market structure and prices. For example, a market that is experiencing increased MA penetration may attract more entry, therefore generating increased overlap among competing firms. Such a market might simultaneously experience an increase in premium growth. Ignoring such endogeneity would lead to erroneous conclusions regarding how MMC affects market prices. To address this concern, we pursue an instrumental variables analysis in which we exploit two plausibly exogenous changes thought to influence market structure: 1) the number of "simulated" pairwise overlaps due to out-of-market mergers among other insurers; and 2) exogenous MA policies including the introduction of the urban floor policy in 2001 and double-bonus counties in 2012. We discuss these instruments in more detail below.

#### Simulated Merger Effects

Based on observed changes in the parent organization from year to year, we identify 8 relatively large mergers/acquisitions in the MA market over our study time frame. We refer to all mergers and acquisitions simply as mergers for brevity. These mergers were identified by changes to the parent organization observed in the data, and then confirmed through various sources, including Irving Levin's health care acquisition reports, press releases, and coverage in the news media. A table of all such mergers along with supporting documentation is presented in Table 4.

#### Table 4

Our simulated merger instrument derives from the merger-induced change in pairwise overlaps due to an out-of-market merger. For example, consider the merger between Bravo and Health-Spring finalized in November 2010. This merger event would cause changes in the pairwise overlap for *all* markets where either Bravo or HealthSpring operate. In markets where Bravo currently operates prior to the merger, our IV measure is the count of all markets in which insurer i overlaps with HealthSpring (prior to the merger) but not Bravo. This is because insurer i's overlap with HealthSpring is caused by the merger, while insurer i's overlap with Bravo is not. In this way, our merger-based instrument is intuitively similar to the simulated change in HHI used in Dafny *et al.* (2012). The instrument is calculated based on each insurer's market presence prior to the merger but takes its value in the years after the merger was finalized. In the case of the merger between Bravo and HealthSpring, the instrument is based on market presence in 2010 but takes its value in 2011-2015, which we also interact with year dummy variables.

To better describe our strategy, consider an industry with four insurers (A, B, C, and D) and four markets. Assume that insurer C acquires D. Before the merger, Market 1 (the reference market) consists of insurers {A,B,D}; Market 2 consists also of {A,B,D}; Market 3 consists of {A,B,C}; and Market 4 consists of {A,B,C,D}. For the reference market prior to the merger, insurer A overlaps with insurer B in 3 markets and overlaps with insurer D in 2 markets, for a total pairwise overlap of 5. After the merger, insurer A again overlaps with insurer B in 3 markets but now overlaps with insurer C in 3 markets, for a total pairwise overlap of 6. Our mergerinduced change in pairwise overlaps for insurer A in the reference market therefore takes a value of 1 beginning in the first full year after the merger was finalized, and similarly for insurer B. Note that the instrument for insurer D in the reference market 3, the instrument for insurer C takes the value of the sum of all merger-induced pairwise overlaps for insurer A and B. Effectively, by acquiring insurer D, insurer C introduces additional overlaps with insurers A and B (from Markets 1 and 2).

Although the majority of our identified mergers occur across markets rather than within markets, it is not immediately clear how to treat markets in which both merging insurers operated prior to the merger (Market 4 in our example). Including these markets may call into question the standard exclusion restriction since the merger has a direct effect on prices in such markets; however, since the exclusion restrictions for our other instruments likely still hold, we include these markets in our initial analysis and set the instrument to 0 for all such markets. We consider an alternative analysis in the supplemental appendix where we drop all markets in which both merging firms operated prior to the merger, with little change in our results.

#### **Urban Floor and Bonus Counties**

As discussed in detail in Zarabozo & Harrison (2009) and examined in Duggan *et al.* (2016), the "urban floor" policy was introduced in 2001 as part of the State Children's Health Insurance Program (SCHIP) Benefits Improvement and Protection Act (BIPA). This policy placed a lower bound on the reimbursement paid to MA plans in urban counties, defined as counties in MSAs with at least 250,000 people. Since, at the time, reimbursement was otherwise based on average FFS costs, counties exposed to the urban floor had relatively low FFS costs and were relatively large in terms of population. Beginning in 2004, the MMA again adjusted MA payment rates by instituting a universal payment floor of 100% of Medicare FFS costs in the county. In counties with higher FFS costs, MA benchmarks were set at the prior year's benchmark plus the average national growth rate for FFS costs (or 2% if the growth rate was less than 2%). Therefore, although the effects of the urban floors persisted beyond 2004, a separate payment formula did not apply formally to those counties beyond 2004.

In our analysis, we identify urban floor counties based on FFS costs and population size as of 2004. This was the last year that the policy was officially in place and the largest set of counties directly impacted by the policies. An indicator for these urban floor counties is directly observed from publicly available data on CMS payments to MA plans. We then create an insurer-county measure of urban floor exposure as the count of all other counties in which an insurer operated prior to the urban floor program (in year 2000) that were ultimately treated by the urban floor policy by 2004.<sup>17</sup> We also interact this exposure measure with year dummies to allow effects to dissipate over time.

We similarly exploit the introduction of "double-bonus" counties in 2012 as an additional source of exogenous variation. This policy was intended as a reward system in which the standard bonus paid to high-quality MA contracts (above 3-stars) was doubled for selected counties. Importantly, Layton & Ryan (2015) find that the double-bonus program generated an influx of plans in affected markets but did not directly influence contract quality. Counties were selected for the double bonus program based on: 1) urban floor county as of 2004; 2) at least 25 percent of eligible beneficiaries

<sup>&</sup>lt;sup>17</sup>Our MA data include information on the effective date of each contract. We can therefore identify an insurer's presence in a market in 2000 based on the effective date of all contracts offered in 2008 (the earliest year for which we have complete data on enrollments and approved MA service areas). Since we define exposure at the insurer level (rather than the contract level), our measure of baseline exposure will capture all counties for which the insurer maintained at least one contract in 2000 and 2008, even if some specific contracts or plans were ultimately dropped in those counties.

were enrolled in an MA plan as of 2009; and 3) Medicare FFS costs in that area were lower than the national average. The double bonus counties are therefore a subset of the urban floor counties but with some variation over time due to the consideration of the overall MA market size and average FFS costs. We also observe in the CMS payment data whether a given county qualified for the double bonus payment. Similar to our calculation of exposure to the urban floor policy, we calculate exposure to the double bonus policy as the count of other markets in which a given insurer operated prior to the policy (in year 2011) that were ultimately selected by CMS to receive double-bonus payments. By construction, our measure of exposure to the double-bonus policy is set to 0 prior to 2011 and maintains the same value for the same insurer over time, which we again interact with year dummies.

#### 4.4 Definition of Market and Product

Although the Part C benchmarks are measured at the county level, insurers must submit a single bid for the plan's service area even if the area includes several counties. For this reason, CMS ultimately adjusts its per-enrollee Part C payment based on FFS costs in a given county relative to the plan's overall service area. Premiums are also allowed to vary by segment (collection of one or more counties in a service area) even for the same plan, although few insurers take this approach. These details somewhat obfuscate the definition of market and product from the insurer's perspective.

We define the market as a county mainly because competition differs at the county level. The appropriate definition of a product, however, may vary depending on the outcome of interest. For example, since bids and premiums differ at the plan level (possibly at the plan-market level in the case of premiums with segment IDs), a natural delineation of products is by unique plan ID; however, approval by CMS to provide Medicare benefits applies at the contract level. For this latter reason, authors sometimes adopt the contract as the definition of a unique product (Town & Liu, 2003; Dafny & Dranove, 2008; Curto *et al.*, 2015). Star ratings are also calculated at the contract level, with the caveat that the star rating formula differs for MA plans versus MA-PD plans as of 2011. A case can therefore be made for defining a unique product either at the plan level or at the contract level. For completeness, we present results for both.

## 4.5 Measuring Outcomes of Interest

We are primarily interested in the effects of MMC on prices and quality. In studying prices, we consider both the bid and premium. We focus on premium rather than other cost-sharing provisions such as deductibles, copayments, and co-insurance rates because consumers primarily respond to premiums (Stockley *et al.*, 2014; Curto *et al.*, 2015). We are also interested in the bid for the following reasons. First, a plan's bid captures revenue per enrollee from an insurer's point of view, and it also reflects the total health insurance payment for an individual of baseline risk paid by both CMS and the individual enrollee. Second, most plans (about 85%) charge zero premiums. As we discussed in Section 3.2, monthly Part C premiums are \$0 whenever the Part C bid falls below the benchmark, but increases in bids still reflect an increase in the cost of health insurance from CMS' perspective as well as a reduction in benefit generosity for enrollees. Examining plan bids therefore allows us to explore variation in pricing which is not captured by premiums.

While we do not observe bids directly in the data, we can estimate the bid for Part C services based on the Part C payments and premiums, both of which are observed in the data. Estimating bids for Part D services is less clear because insurers can use their Part C rebates to pay down the "Basic Premium" for prescription drug coverage, but all we see in the data is the net basic premium for each plan. We nonetheless consider a net Part D bid as one of our outcomes of interest.

Collectively, we consider five different measures of price – the Part C bid, the Part D bid, the consolidated monthly premium, the Part C premium, and the Part D premium. Intuitively, deviations from a collusive strategy are most visible with regard to Part C prices versus Part D prices because the necessary data to back-out Part C bids are publicly available. If mutual forbearance occurs, we therefore suspect that it will have the largest effects on Part C bids and premiums.

We also examine the effect of MMC on quality. As discussed in Section 3, CMS adopted an overall star rating system in 2009 in which each contract is given an overall rating of 1 to 5 stars in half-star increments. For 2009 and 2010, all plans operating under the same contract received the same star rating in all markets across the country. As such, there was no cross-sectional variation in contract star ratings (and no plan-level variation in star ratings within the same contract) for those years. This changed with the introduction of Part D measures in 2011, at which point two

plans operating within the same contract (one with and one without prescription drug coverage) could now receive different star ratings, with one plan's rating based on combined Part C and Part D measures and the other plan's rating based solely on Part C measures. To exploit this variation, we calculate the contract-level star rating as the average star rating assigned to all plans in a given contract/county. Our contract-level star rating therefore varies cross-sectionally after 2010 due to variation in the percentage of plans within each contract offering prescription drug coverage across markets. We also consider an indicator for whether the contract received a rating for 4 or more stars. As we discuss in Section 5.3, we consider the latter measure of "high star ratings" due to ambiguity in the likely effect of MMC on low-quality contracts given the potentially higher price elasticity for these products combined with strong CMS initiatives over time to deter enrollment in low star-rated plans.

# 5 Estimation and Results

## 5.1 Empirical Strategy

We estimate effects of MMC on prices and quality with a series of linear regressions of the form

$$y_{c(j)mt} = \beta x_{c(j)mt} + \nu_m + \tau_t + \gamma_c + \alpha M M C_{mt} + \varepsilon_{c(j)mt}, \tag{3}$$

where  $x_{c(j)mt}$  denotes a vector of time-varying product/market characteristics for plan j operating under contract c,  $\nu_m$  denotes county fixed effects,  $\tau_t$  denotes year fixed effects,  $\gamma_c$  denotes contract fixed effects, and  $MMC_{mt}$  denotes our measure of multimarket contact. Recall that we consider two primary measures of MMC, one based on the count of pairwise overlaps and another weighted by the HHI in each overlapping market. We include in  $x_{c(j)mt}$  the following variables: 1) county demographics such as total population, the percent of the population ages 18 to 34, 35 to 64, and 65 or above, the percent of the population classified as Caucasian and percent African American, the percent of the population with household incomes between \$50,000 and \$75,000, between \$75,000 and \$100,000, between \$100,000 and \$150,000, and above \$150,000, the percent of the population with a high school degree and percent with a bachelor's degree, and the percent of the population that is employed full time; 2) hospital variables including the total number of discharges in the county, total number of hospitals, and the hospital HHI; 3) an indicator for prescription drug coverage; and 4) MA variables including average FFS costs and the MA benchmark rate. Many other plan characteristics, such as whether the plan is HMO or PPO, do not vary within a contract over time and are therefore absorbed in the contract fixed effect.

As discussed in Section 4, we suspect that  $MMC_{mt}$  and  $MMC_{mt}^{hhi}$  are correlated with unobservables that affect market structure and prices. We account for this endogeneity with a preliminary prediction of  $MMC_{imt}$  in Equation 2, from which we derive an estimate of  $MMC_{mt}$  as the simple average across insurers in market m and year t. We then employ the estimated MMC,  $\widehat{MMC}_{mt}$ , as an instrument in a standard two-stage least squares (2SLS) estimator.

Specifically, we denote our set of instruments by  $Z_{imt}$ , which consists of all variables created from the urban floor and bonus county policies as well as the merger-related change in MMC.<sup>18</sup> Our generated instrument regression model is then

$$MMC_{imt} = \delta Z_{imt} + \omega_{imt}.$$
(4)

This approach allows us to incorporate insurer- and market-level instruments and therefore exploits all of the available variation in our instrument set. We estimate Equation 4 with ordinary least squares (OLS), from which we obtain predicted values  $\widehat{MMC}_{imt}$  and, subsequently,

$$\widehat{MMC}_{mt} = \frac{1}{N_{mt}} \sum_{i=1}^{N_{mt}} \widehat{MMC}_{imt}.$$

Finally, we use  $\widehat{MMC}_{mt}$  as a generated instrument for  $MMC_{mt}$  in estimating Equation 3. We adopt an analogous approach for  $MMC_{mt}^{hhi}$ . Our generated instrument exploits the available information at the appropriate "level" of the data and acts simply as linear combination of exogenous instruments,  $Z_{imt}$ . A similar approach in which authors estimate a preliminary regression at a different level of the data and employ predicted values as instruments has been used in the trade and labor literatures.<sup>19</sup>

Results for our generated instrument regression in Equation 4 are presented in Table 5, with column 1 focusing on  $MMC_{imt}$  and column 2 focusing on  $MMC_{imt}$ . As indicated in the table, the

<sup>&</sup>lt;sup>18</sup>We consider alternative sets of instruments in the supplemental appendix.

<sup>&</sup>lt;sup>19</sup> See, for example, Wolf (2000), Friedberg (2001), Frankel & Rose (2005), and Chintrakarn & Millimet (2006). As discussed in Wooldridge (2010), "we can ignore the fact that the instruments were estimated in using 2SLS for inference."

proposed instruments are individually and jointly significant predictors of insurer-level MMC for both outcomes.<sup>20</sup>

#### Table 5

The generated instrument regression is a purely statistical construct in which we regress our endogenous variable only on the instruments with no other market or insurer controls. The results in Table 5 should therefore not be interpreted as a causal effect of our instruments on MMC. We nonetheless note the negative estimates for the coefficients on our merger-related variables in 2011, 2013, and 2014. These negative correlations emerge because our outcome in Equation 4 is the count of all pairwise overlaps for a given insurer *i* divided by the number of other insurers in the market, as reflected in Equation 2. By construction, both the numerator and denominator of the outcome variable are positively correlated to the merger-induced change in MMC. This positive correlation is stronger for the denominator in most years, causing the estimated coefficients to be negative. If we instead re-estimate our preliminary regression using only the count of pairwise overlaps ( $\sum mmc_{ijt}$ ) as our outcome and only during the years in which we observe mergers in the data, we estimate positive and significant relationship between the merger IVs and pairwise overlaps; however, since the goal of this generated instrument regression is simply to form a linear combination of our instruments, we adopt  $MMC_{imt}$  as our outcome in order to better align our measure of MMC in Equations 1 and 2.<sup>21</sup>

## 5.2 Multimarket Contact and Prices

We focus first on the plan-level results, in which a product is defined as a unique plan ID. In this analysis, the effect of MMC on price is identified from within-contract variation across plans as well as variation over time for the same plan. Plan-level regression results are summarized in Table 6, with effects for different outcomes presented across the columns and with different measures of MMC across rows. Panel 1 presents results estimated using OLS with fixed effects

<sup>&</sup>lt;sup>20</sup>Recall that the first stage for the 2SLS estimator consists of a regression of  $MMC_{mt}$  on its predicted value from our preliminary regression and the full set of other exogenous variables in Equation 3. Consistent with the discussion of generated instruments in Wooldridge (2010), we therefore do not include any additional covariates in our preliminary regression since all such covariates are ultimately part of the 2SLS estimator.

<sup>&</sup>lt;sup>21</sup>The results are similar in either case but smaller in magnitude when using  $\sum mmc_{ijt}$  as our outcome in the generated instrument regression.

(FE) as indicator in equation 3, and panel 2 presents the FE-IV results. Note that we include only one MMC measure in a given specification, so that each estimate in the table reflects a different regression. All standard errors are clustered at the county level.

#### Table 6

The results are consistent with the mutual forbearance hypothesis, where higher values of MMC lead to higher bids and premiums. Specifically, the estimated coefficient on Part C bids of 3.568 for MMC in Panel 2 implies that an increase of one standard deviation (4.5) in our MMC measure leads to an increase in Part C bids of about \$16 on average. Although the coefficient on  $MMC^{hhi}$  is much larger, the scale of this MMC measure is lower. The overall effect is therefore similar in magnitude when accounting for different levels of competition across market overlaps, where a one standard deviation increase in  $MMC^{hhi}$  (0.93) yields an increase in Part C bids of \$13 on average. We also estimate a positive but small increase of just under \$2 in Part C Premiums from a one standard deviation increase in MMC, although this effect is only significant at the 10% level and only for  $MMC^{hhi}$ . Finally, we estimate very small (and insignificant) effects on Part D premiums, such that the net effect on consolidated premiums is also small and insignificant.

Table 7 presents results at the contract level. Here, premiums and bids are averaged across plans for the same contract. The structure of the table is otherwise analogous to the plan-level results in Table 6, with effects for different outcomes presented across the columns and with different measures of MMC across rows. The results again provide empirical evidence in support of the mutual forbearance hypothesis. Based on the FE-IV estimates in Panel 2 of Table 7, a one standard deviation increase in MMC or  $MMC^{hhi}$  leads to between a \$13 and \$18 increase in Part C bids and around a \$3 increase in Part C premiums. As with the plan-level results, we find very small effects on Part D bids as well as small and insignificant effects on Part D premiums.

#### Table 7

Taken together, we find consistent evidence that MMC tends to increase Part C bids, potentially with some small transfer to Part C premiums. We find no economically meaningful effects on Part D bids or premiums. The differential effect between Part C and Part D pricing is perhaps reflective of the lack of transparency in the Part D program relative to Part C, where the true Part D premium is significantly less observable to competitors (and researchers) than the Part C premium due to the subsidies paid to both insurers and individual enrollees. The differential effect may also be due to the noise in our measure of Part D prices, in which we can only estimate the Part D bid and premium net of any reduction from a Part C rebate.

Our estimated effect of \$13 to \$18 on Part C bids may initially seem relatively low; however, when measured relative to the benchmark (i.e., the amount CMS is willing to pay for an average enrollee in that market), the increase in bids is economically meaningful. For example, the overall average MA benchmark in our data is \$793 compared to an overall average bid of \$735, such that the average bid-benchmark differential is around \$60. The magnitude of our estimates for Part C bids therefore constitutes between 22% and 30% of the bid-benchmark differential.

Relatedly, a \$3 increase in Part C premiums is also consistent with our estimates for Part C bids. For example, approximately 40% of plans with \$0 Part C premiums have bids no more than \$16 below the benchmark rate. The average bid-benchmark differential among all such observations is \$8, such that a \$16 increase in bids for the average plan will generate an \$8 increase in Part C premiums on average. When weighted by the share of plans to the total observations, this reflects an overall average increase of \$3.20 in Part C premiums. Indeed, consider an alternative regression in which our outcome is an indicator for whether the plan charges a positive Part C premium. In this case, we estimate a 5.6 percentage point increase in MMC. On a base of just over 15% of plans with positive premiums, this reflects a 36.5% increase in the percent of plans with positive Part C premiums, which matches closely to our back-of-the-envelope calculations based on bid-benchmark differentials.

## 5.3 Multimarket Contact and Quality

We now extend our analysis of MMC to consider its effect on quality, as measured by contract star ratings.<sup>22</sup> As discussed in Section 2, in the presence of price competition, the effects of MMC on quality are not entirely clear and may depend on the underlying importance of price versus quality to consumers in a given market. In the MA setting, one might expect that low-rated plans attract enrollees who are more price sensitive and less quality sensitive. Competition might then increase

 $<sup>^{22}</sup>$ There is empirical evidence that star ratings do influence MA enrollments, albeit with a relatively small effect (Reid *et al.*, 2013; Darden & McCarthy, 2015; McCarthy, 2018).

price sensitivity, causing price and quality to fall. In the presence of strong interventions by CMS to deter beneficiaries from choosing low-rated plans during our study period, a reduction in price competition may then allow low-quality plans to increase their quality ratings and thereby avoid any penalties levied on low-quality contracts.<sup>23</sup> On the contrary, enrollees of high-rated plans may be less price sensitive and more quality sensitive, in which case competition would tend to depress prices and increase quality (conversely, MMC would tend to increase prices and decrease quality).

Since there may be a differential effect of MMC between low versus high price elasticity market segments, we consider two assessments of quality. First, we examine whether the contract received a rating for 4 or more stars in a given year. This measure of "high star ratings" does not only offer an assessment of overall quality, but also allows us to focus our outcome on the higher quality market segment. Second, we examine the average star rating for all contracts, and separately by low- versus high-quality market segments. In splitting the sample, we define the "low-quality" (high price elasticity) market segment as consisting of contracts that received a rating below 3 stars in 2009 or 2010, and we similarly define the "high-quality" market segment as consisting of contracts that received a rating of 4 stars or above in 2009 or 2010.

Recall that, in 2009 and 2010, there was no within-contract variation since prescription drug metrics were not introduced into the rating system until 2011. We therefore exclude 2009 and 2010 from our analysis and focus on the years from 2011-2015. In this way, our designation of low-quality and high-quality based on years 2009 and 2010 is not affected during the timeframe of our analysis. Also note that the MA star rating program relies on one- or two-year lagged measures when calculating a contract's star rating, such that insurers are limited in their ability to manipulate quality ratings in the short-run. Based on the timing of CMS approval and bid review discussed in Section 3, these points suggest that insurers cannot adjust quality based on contemporaneous MMC. Instead, any observed quality changes (either through changes in the mix of plans offered or direct changes to quality metrics) must be in response to MMC from at least the prior year. We therefore include lagged MMC in all specifications.<sup>24</sup> Our empirical analysis is

<sup>&</sup>lt;sup>23</sup>CMS has intervened in the market for low-quality plans in several ways. For example, contracts that are consistently below 3-stars are highlighted on the MA plan finder website with a clear warning sign asking beneficiaries to reconsider choosing that plan. CMS has more recently issued letters and introduced other barriers (e.g., requiring beneficiaries to contact the insurer directly to purchase) aimed at deterring enrollees from purchasing plans that consistently achieve fewer than 3 stars.

<sup>&</sup>lt;sup>24</sup>Alternative specifications where we include lagged values of all other covariates, including benchmark rates and county demographics, are qualitatively unchanged from the results presented here.

otherwise identical to that of contract-level prices. As before, we present the standard FE results as well as our preferred FE-IV results using predicted MMC as our instrument.<sup>25</sup> These results are presented in Table 8.

#### Table 8

Panel 1 presents results based on the FE within-estimator and panel 2 presents the FE-IV results, and each row reflects a different MMC measure  $(MMC_{m,t-1} \text{ and } MMC_{m,t-1}^{hhi})$ . The estimated effects on the probability of receiving a high rating are presented in column 1, where we estimate an economically meaningful decrease in the prevalence of high-rated contracts as MMC increases. For example, the estimated coefficient of -0.059 for  $MMC_{t-1}^{hhi}$  in column 1 suggests that contracts are 5.5 percentage points less likely to receive a high star rating with a one standard deviation increase in MMC. With 56% of contracts receiving a high star rating in 2015, this reflects a 10% reduction in the percentage of high-rated contracts.

Columns 2-4 of Table 8 present the results for the average star rating (column 2) for all contracts, and the average star rating specifically among low- (column 3) and high-quality (column 4) market segments. From column 2, the FE-IV estimates suggest a positive but very small effect of MMC on average star ratings. Recall that the average star ratings range from 1 to 5 and are reported to beneficiaries in half-star increments. An estimated effect of 0.05 is therefore less than 1/10th of a half-star. From columns 3 and 4, the estimated increase in ratings remains relatively small in the low-quality segment, but is much larger in magnitude (and negative) for the highquality market. Specifically, in the high-quality market, we estimate a reduction in star ratings of about 1/5th of a star from a one standard deviation increase in MMC.

Overall, we find MMC reduces incentives to offer high-quality plans (a rating of 4 or more stars). There is a slight increase in average star rating across all plans, and this overall effect is the combination of an increase in ratings in the low-quality segment (highly price-sensitive enrollees) and a decrease in ratings among the high-quality segment (less price-sensitive enrollees). These empirical findings suggest that different market segments respond differentially to competition and allowing for differential effects may be important in examining quality or other non-price attributes.

<sup>&</sup>lt;sup>25</sup>We also estimated results at the county/year level, using average star ratings and percentage of high-rated contracts in the county as our outcomes (Layton & Ryan, 2015). Results are similar to the contract-level analysis in Table 8.

In addition to above analyses, we also estimated effects with a standard logit model to account for the binary nature of our "high rating" outcome; however, it is not computationally feasible to adopt the same specification for those models given the number of fixed effects (contract, county, and year). We instead estimated binary logit models with two-stage residual inclusion (2SRI), including only year and state fixed effects. With 500 bootstrap replications, we estimate a statistically significant (p-value < 0.01) negative effect of MMC on the probability of a high rating. Specifically, we estimate that contracts are around 15 percentage points less likely to receive a high star rating following a one standard deviation increase in MMC. This effect is in the same direction as the linear models but much larger in magnitude, likely due to the exclusion of contract and county fixed effects.<sup>26</sup>

# 6 Robustness

In this section, we gauge the sensitivity of our results to various concerns regarding our identification strategy and measurement of MMC. We also discuss a series of additional sensitivity analyses, the results of which are presented in the supplemental appendix.

## 6.1 Identification from Out-of-market Mergers

We first propose an alternative identification strategy where we directly exploit out-of-market mergers in which a given insurer is exposed to additional market overlaps due a competitor merging with another insurer outside of the reference market. Revisiting our example from Section 4, consider an industry with four insurers (A, B, C, and D) and four markets, and assume that insurer C acquires D. Before the merger, Market 1 (the reference market) consists of insurers {A,B,D}; Market 2 consists also of {A,B,D}; Market 3 consists of {A,B,C}; and Market 4 consists of {A,B,C,D}. When C acquires D, insurers A and B in the reference market are each exposed to one additional overlap due to pre-existing overlap with insurer C in market 3. Since only one of the merging parties operates in the reference market, this is an out-of-market merger in which the average pairwise overlaps changed due to the merger.

 $<sup>^{26}</sup>$ A fixed effects logit model allowing for contract fixed effects also yields statistically significant negative estimates for MMC; however, since this estimator drops contracts that always or never receive a high rating (about 50% of the sample), it is unclear how to interpret these results or how to compare the estimates to the original analysis.

Similar to Schmitt (2017), we adopt the following specification

$$y_{c(j)mt} = \beta x_{c(j)mt} + \nu_m + \tau_t + \gamma_c + \alpha \times \mathbb{1} (t > \tau_{im}) + \varepsilon_{c(j)mt},$$
(5)

where  $\mathbb{1}(t > \tau_{im})$  is a post-treatment indicator variable set to one in the years after an insurer *i* was exposed to a change in MMC in market *m* due to an out-of-market merger.<sup>27</sup> The rest of the variables in equation 5 are as defined previously. We also consider a simplified specification in which we exclude  $x_{c(i)mt}$  from the regression.

Since we are identifying effects based on within-contract changes over time, we exclude all observations associated with insurers that were ultimately part of a merger (e.g., in the context of our example above, insurers C and D would be dropped from our analysis in all years), and we exclude all markets in which both merging insurers existed prior to the merger. We also exclude observations in which an insurer first enters market m in the year a merger was finalized, since we do not have pre-merger prices for such observations. The estimates therefore reflect the change in prices or quality from a plausibly exogenous increase in MMC driven by an out-of-market merger. As in our initial analysis, regressions of contract quality are limited to years 2011 through 2015. Results are summarized in Table 9.

#### Table 9

Across all specifications, the results for bids and premiums are consistent with the findings in Section 5.<sup>28</sup> We estimate significant increases in Part C and Part D bids, which translates into smaller but statistically significant (and economically meaningful) increases in premiums. We also estimate significant reductions in the percentage of high-rated contracts. In contrast with our initial results in Table 8, we now estimate a small but significant reduction in average star ratings both among low- and high-quality market segments; however, we note that around 85% of contracts

<sup>&</sup>lt;sup>27</sup>Since we define  $\tau_{im}$  as an out-of-market merger that changes an insurer's count of pairwise overlaps, we set the indicator to 0 if there was no change in MMC due to the merger. For example, if a fifth insurer (insurer E) operated only in the reference market in our example above, the indicator would be 0 since insurer E's overlap with other insurers is unchanged, even though they compete in the reference market with an insurer that was part of the acquisition. Results are unchanged if we instead exclude these insurers from the analysis.

<sup>&</sup>lt;sup>28</sup>In our main specification, we do not differentiate between insurers exposed to one or many out-of-market mergers over time. We nonetheless re-estimated equation 5 after excluding all insurers/markets exposed to multiple out-of-market mergers. The results are almost identical to those in Table 9, with slightly larger effects on Part C pricing and slightly smaller effects for Part D pricing. For brevity, these estimates are excluded from the paper but available upon request.

in the low-quality market (based on star ratings in 2009 and 2010) are operated by Humana, UnitedHealth, or Wellcare, all of which are part of a merger during our time period. Limiting the sample to insurers that were not directly part of a merger therefore significantly changes the set of plans in this analysis. When we include county and contract-level control variables, this effect on star ratings for the low-quality market segment reduces substantially in magnitude and is no longer statistically significant. The effect among the high-quality market segment, meanwhile, is persistently negative across either specification.

#### 6.2 Additional Robustness Checks

In the supplemental appendix, we first present results based on two alternative sets of instruments. One, we exclude the urban floor instrument as this is not observed for contracts that were not effective as of 2004. The instrument also takes its value prior to the start of our data, and so any effect on MMC may have already occurred by 2008. In excluding the urban floor instrument, we limit the analysis to the years 2011 through 2015 since none of the remaining instruments take values prior to 2011. Two, we exclude both the urban floor and bonus county instruments, focusing only on the merger-induced change in pairwise overlaps in our generated instrument regressions. For this latter set of instruments, our analysis again focuses only on 2011-2015 (the years in which our merger-related instruments take non-zero values).

We also examine the sensitivity of our estimates to variation in samples across outcomes and specifications. Such variation derives from three sources: 1) missing premium and payment information in the raw data; 2) missing MMC measures (by construction) for markets with just one insurer; and 3) differences in the set of plans for which traditional bidding rules apply versus plans for which we observe premium data. In the supplemental appendix, we address these concerns by restricting the sample only to contract/county observations (or plans operating under such contracts) for which all relevant variables are non-missing in all available years and re-estimating our preferred specification for all outcomes.

Finally, we consider the sensitivity of our main results to the presence of markets in which both merging insurers operated prior to a merger. We do this by excluding all observations for counties in which both merging insurers existed together in any year prior to the merge. This restriction reduces the plan-level sample size by just under 10,000 plan/county/year observations, or about

7%.

Across all sensitivity analyses, our results are generally consistent with those presented in Section 5. When considering different instrument sets, our estimated effects of MMC on bids and premiums are larger, suggesting that our main results are perhaps conservative. Conversely, results on the presence of high rated contracts are somewhat mixed, with small negative estimates (and insignificant) when excluding the urban floor instruments and even a small positive effect (significant at the 10% level) when excluding the urban floor and double-bonus county instruments. Our differential estimates between low- versus high-quality contracts nonetheless persists across these different instrument specifications. Finally, the results with a balanced panel and when excluding markets with both merging firms are largely unchanged from those in Section 5.

We conclude from these sensitivity analyses that the positive effect of MMC on Part C bids and premiums is significant and persistent. Some estimates for star ratings appear sensitive to the instrument set; however, the qualitative finding of a differential effect on quality persists, with MMC creating downward pressure on ratings for the high-quality market and upward pressure for the low-quality market. Collectively, our results therefore offer strong evidence in support of the mutual forbearance hypothesis in the MA market.

# 7 Discussion

Tacit collusion driven by contact with the same competitors across markets has been examined across several industries, often with a focus on prices. In this paper, we extend the literature on MMC to the study of health insurance markets. We also consider another important dimension by which MMC may influence firm behavior – namely, product quality. Our results consistently support the mutual forbearance hypothesis, where we find that existing insurers tend to place higher bids and are less likely to offer high-quality contracts when competing against the same insurers across multiple markets. Our results suggest that the effect of MMC on product quality might lead researchers to underestimate the loss in consumer welfare driven by increases in MMC.

Note that we do not interpret increases in MMC as an increase in collusion for the same market. Rather, we interpret increases in MMC as an increase in the probability of collusion. For example, if markets have some latent and heterogeneous threshold beyond which MMC may facilitate collusive behavior, an increase in the continuous MMC measure reflects an increase in the number of markets for which tacit collusion may now occur.

We estimate the largest effects of MMC on Part C bids. By construction, such increases should spill over to plan premiums but at a lesser magnitude. Our estimates are consistent with this relationship. Our results for Part D bids and premiums are smaller in magnitude and insignificant in many cases. These findings offer three central takeaways. First, a firm's ability to detect deviations from collusion is critical in assessing the mutual forbearance hypothesis. The differential effects on Part C and Part D bids/premiums may speak to the difference in transparency of prices and benefits in those two markets. Insurers could maintain some implicit collusion with regard to their Part C pricing due to observability of bids but such collusive behavior is less likely in the Part D component of the market. This also suggests potential spillovers of MMC in a multi-dimensional product market, where firms may compete more intensely over the space in which deviations from collusive behavior are least observable by their competitors. Second, the effect of MMC in Medicare Advantage appears to also reduce plan benefits (and quality) in addition to directly affecting prices. This interpretation follows from the institutional details of the bidding process, wherein the rebated percentage of the bid-benchmark differential (for bids below the benchmark) must go to enrollees in the form of expanded benefits. Since this differential is decreasing due to MMC, this suggests a reduction in plan benefits, although we do not observe the precise dimensions by which benefits are changed. Finally, mirroring the literature on quality and market power, our estimates reveal a more nuanced relationship between MMC and quality. If we assume that low-quality/low-price contracts are designed to appeal to more price sensitive consumers, then MMC may increase quality in this market segment while decreasing quality in segments for which products compete more on quality and less on price. Our empirical results support this relationship, where we estimate an increase in star ratings (albeit small in magnitude) among the low-quality market segment and a decrease in star ratings among the high-quality market segment.

We conclude with two policy implications. First, as the MA market becomes increasingly characterized by relatively few national insurers, our results suggest that the incentives to collude due to MMC may play an increasing role in the MA market. This further informs future MA policy in that expanded "choice" in the MA market may have less effect on competitiveness when such expansion derives from large, national insurers. MA policy may instead attempt to counter these forces by encouraging entry from smaller or regional insurers for which MMC is less prevalent. Such a strategy would not only maintain choice in the MA market but also minimize the incentives to collude due to MMC.

Second, the existing antitrust enforcement procedures tend to overlook anti-competitive effects of increased MMC (or pro-competitive effects of reduced MMC). However, mergers that have no impact on local market concentration (e.g., cross-market mergers) could potentially lead to large changes in MMC and, through this mechanism, affect the overall intensity of competition. Our results support this hypothesis and suggest that MMC should be considered when assessing changes in competition from MA policies and mergers/acquisitions, especially in settings where national players tend to operate in multiple markets.

# References

- Bernheim, B Douglas, & Whinston, Michael D. 1990. Multimarket contact and collusive behavior. The RAND Journal of Economics, 21, 1–26.
- Berry, Steven T, & Waldfogel, Joel. 2001. Do mergers increase product variety? Evidence from radio broadcasting. *The Quarterly Journal of Economics*, **116**(3), 1009–1025.
- Bloom, Nicholas, Propper, Carol, Seiler, Stephan, & Van Reenen, John. 2015. The impact of competition on management quality: evidence from public hospitals. *The Review of Economic Studies*, 82(2), 457–489.
- Champsaur, Paul, & Rochet, Jean-Charles. 1989. Multiproduct duopolists. *Econometrica: Journal* of the Econometric Society, 533–557.
- Chintrakarn, Pandej, & Millimet, Daniel L. 2006. The environmental consequences of trade: Evidence from subnational trade flows. Journal of Environmental Economics and Management, 52(1), 430–453.
- Ciliberto, Federico, & Williams, Jonathan W. 2014. Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry. The RAND Journal of Economics, 45(4), 764–791.
- Crawford, Gregory S, Shcherbakov, Oleksandr, & Shum, Matthew. 2018. Quality Overprovision in Cable Television Markets. Working Paper. SSRN.
- Curto, Vilso, Einav, Liran, Levin, Jonathan, & Bhattacharya, Jay. 2015. Can Health Insurance Competition Work? Evidence from Medicare Advantage. Working Paper. Department of Economics, Stanford University.
- Cutler, David M, Huckman, Robert S, & Kolstad, Jonathan T. 2010. Input constraints and the efficiency of entry: Lessons from cardiac surgery. *American Economic Journal: Economic Policy*, 2(1), 51–76.
- Dafny, L., & Dranove, D. 2008. Do report cards tell consumers anything they don't already know? The case of Medicare HMOs. *The Rand journal of economics*, **39**(3), 790–821.

- Dafny, Leemore. 2010. Are Health Insurance Markets Competitive? American Economic Review, 100(4), 1399–1431.
- Dafny, Leemore, Duggan, Mark, & Ramanarayanan, Subramaniam. 2012. Paying a Premium on Your Premium? Consolidation in the US Health Insurance Industry. *American Economic Review*, **102**(2), 1161–1185.
- Dafny, Leemore, Ho, Kate, & Lee, Robin S. 2017. The Price Effects of Cross-Market Mergers: Theory and Evidence from the Hospital Industry. Working Paper w22106. Nationa Bureau of Economic Research.
- Dana Jr, James D, & Fong, Yuk-Fai. 2011. Product quality, reputation, and market structure. International Economic Review, 52(4), 1059–1076.
- Darden, M., & McCarthy, I. 2015. The Star Treatment: Estimating the Impact of Star Ratings on Medicare Advantage Enrollments. *Journal of Human Resources*, 50(4), 980–1008.
- Dorfman, Robert, & Steiner, Peter O. 1954. Optimal advertising and optimal quality. American Economic Review, 826–836.
- Duggan, Mark, Starc, Amanda, & Vabson, Boris. 2016. Who benefits when the government pays more? Pass-through in the Medicare Advantage program. *Journal of Public Economics*, 141, 50–67.
- Edwards, Corwin D. 1955. Conglomerate bigness as a source of power. *Pages 331–359 of: Business concentration and price policy*. Princeton University Press.
- Evans, William N, & Kessides, Ioannis N. 1994. Living by the golden rule: Multimarket contact in the US airline industry. *Quarterly Journal of Economics*, **109**(2), 341–366.
- Fan, Ying. 2013. Ownership consolidation and product characteristics: A study of the US daily newspaper market. American Economic Review, 103(5), 1598–1628.
- Feinberg, Robert M. 2015. Pricing of First-Run Movies in Small US Metropolitan Areas: Multimarket Contact and Chain Effects. The BE Journal of Economic Analysis & Policy, 15(1), 285–297.

- Fernandez, Nerea, & Marin, Pedro L. 1998. Market power and multimarket contact: Some evidence from the Spanish hotel industry. *The Journal of Industrial Economics*, **46**(3), 301–315.
- Frankel, Jeffrey A, & Rose, Andrew K. 2005. Is trade good or bad for the environment? Sorting out the causality. The Review of economics and statistics, 87(1), 85–91.
- Friedberg, Rachel M. 2001. The impact of mass migration on the Israeli labor market. Quarterly Journal of Economics, 116(4), 1373–1408.
- Gaynor, Martin. 2006. Is vertical integration anticompetitive?: Definitely maybe (but that's not final). Journal of Health Economics, 25(1), 175–180.
- Gaynor, Martin, Moreno-Serra, Rodrigo, & Propper, Carol. 2013. Death by market power: reform, competition, and patient outcomes in the National Health Service. American Economic Journal: Economic Policy, 5(4), 134–66.
- Gowrisankaran, Gautam, & Town, Robert J. 2003. Competition, payers, and hospital quality1. Health services research, 38(6p1), 1403–1422.
- Jans, Ivette, & Rosenbaum, David I. 1997. Multimarket contact and pricing: Evidence from the US cement industry. International Journal of Industrial Organization, 15(3), 391–412.
- Kaiser Family Foundation. 2012. Medicare Advantage 2012 Data Spotlight: Enrollment Market Update. Tech. rept.
- Karnani, Aneel, & Wernerfelt, Birger. 1985. Multiple point competition. Strategic Management Journal, 6(1), 87–96.
- Kessler, Daniel, & McClellan, Mark. 2000. Is hospital competition socially wasteful? Quarterly Journal of Economics, 2(115), 577–615.
- Kessler, Daniel P, & Geppert, Jeffrey J. 2005. The effects of competition on variation in the quality and cost of medical care. *Journal of Economics & Management Strategy*, **14**(3), 575–589.
- Layton, Timothy J, & Ryan, Andrew M. 2015. Higher incentive payments in Medicare Advantage's pay-for-performance program did not improve quality but did increase plan offerings. *Health* services research, 50(6), 1810–1828.

- Lewis, Matthew S, & Pflum, Kevin E. 2017. Hospital systems and bargaining power: evidence from out-of-market acquisitions. *The RAND Journal of Economics*, **48**(3), 579–610.
- Matsushima, Hitoshi. 2001. Multimarket contact, imperfect monitoring, and implicit collusion. Journal of Economic Theory, 98(1), 158–178.
- McCarthy, Ian. 2018. Quality Disclosure and the Timing of Insurers' Adjustments: Evidence from Medicare Advantage. Working Paper. Emory University.
- Molnar, Jozsef, Violi, Roberto, & Zhou, Xiaolan. 2013. Multimarket contact in Italian retail banking: Competition and welfare. International Journal of Industrial Organization, 31(5), 368–381.
- Mussa, Michael, & Rosen, Sherwin. 1978. Monopoly and product quality. Journal of Economic theory, 18(2), 301–317.
- Prince, Jeffrey T, & Simon, Daniel H. 2009. Multimarket contact and service quality: Evidence from on-time performance in the US airline industry. Academy of Management Journal, 52(2), 336–354.
- Reid, Rachel O, Deb, Partha, Howell, Benjamin L, & Shrank, William H. 2013. Association Between Medicare Advantage Plan Star Ratings and EnrollmentStar Ratings for Medicare Advantage Plan. JAMA, 309(3), 267–274.
- Schmitt, Matt. 2017. Multimarket Contact in the Hospital Industry. Working Paper. UCLA Anderson School of Management.
- Spagnolo, Giancarlo. 1999. On Interdependent Supergames: Multimarket Contact, Concavity, and Collusion. Journal of Economic Theory, 89(1), 127–139.
- Spence, A. 1975. Monopoly, Quality, and Regulation. Bell Journal of Economics, 6(2), 417–429.
- Stockley, Karen, McGuire, Thomas, Afendulis, Christopher, & Chernew, Michael E. 2014. Premium Transparency in the Medicare Advantage Market: Implications for Premiums, Benefits, and Efficiency. Working Paper. National Bureau of Economic Research.

- Sweeting, Andrew. 2010. The effects of mergers on product positioning: evidence from the music radio industry. *The RAND Journal of Economics*, **41**(2), 372–397.
- Thomas, Charles J, & Willig, Robert D. 2006. The risk of contagion from multimarket contact. International Journal of Industrial Organization, 24(6), 1157–1184.
- Town, Robert, & Liu, Su. 2003. The welfare impact of Medicare HMOs. RAND Journal of Economics, 719–736.
- Waldfogel, Joel, & Wulf, Julie. 2006. Measuring the effect of multimarket contact on competition: Evidence from mergers following radio broadcast ownership deregulation. The BE Journal of Economic Analysis & Policy, 5(1).
- Wolf, Holger C. 2000. Intranational home bias in trade. The Review of Economics and Statistics, 82(4), 555–563.
- Wooldridge, Jeffrey M. 2010. Econometric analysis of cross section and panel data. MIT press.
- Zarabozo, Carlos, & Harrison, Scott. 2009. Payment policy and the growth of Medicare Advantage. Health Affairs, 28(1), w55–w67.

## Tables and Figures

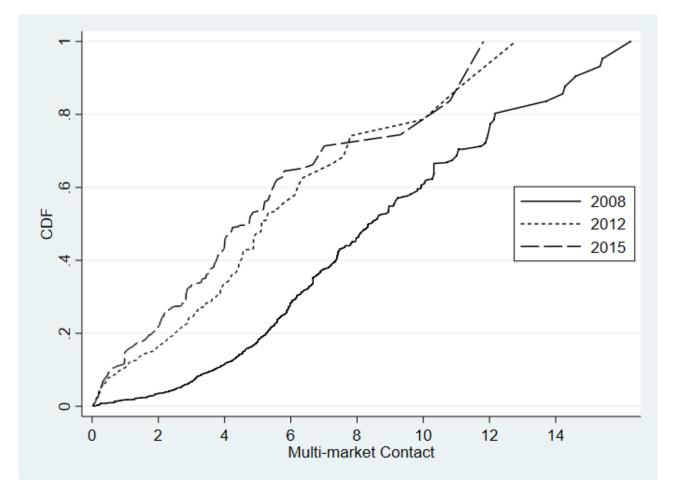
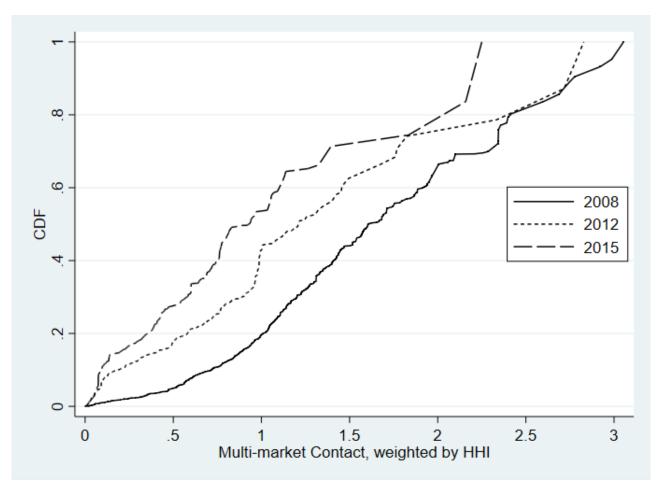


Figure 1: CDF for MMC





	2008	2009	2010	2011	2012	2013	2014	2015	Overall
Plan/County Data									
$Enrollment^{a}$	219.1	214.6	258.1	354.5	392.9	415.3	462.4	498.2	336.3
	(1151.8)	(1152.1)	(1210.7)	(1482.6)	(1562.7)	(1632.4)	(1748.1)	(1852.9)	(1462.7)
MA Share <sup><math>b</math></sup>	0.0618	0.0568	0.0697	0.0865	0.0866	0.0824	0.0808	0.0815	0.0741
	(0.101)	(0.0913)	(0.106)	(0.124)	(0.126)	(0.123)	(0.121)	(0.119)	(0.113)
Part C Bid	697.5	733.6	756.5	741.8	738.4	742.6	763.0	716.8	735.0
	(57.99)	(68.96)	(79.64)	(79.28)	(73.16)	(83.87)	(83.42)	(78.70)	(77.56)
Part D Bid	64.58	69.53	71.31	69.96	69.01	64.46	61.87	60.95	66.75
	(12.90)	(15.00)	(14.55)	(15.04)	(16.08)	(16.76)	(18.68)	(19.39)	(16.48)
$\operatorname{Premium}^{c}$	36.24	38.00	48.44	44.21	44.02	45.41	47.97	51.07	43.94
	(41.93)	(44.79)	(48.61)	(49.50)	(48.74)	(50.97)	(53.84)	(54.21)	(49.00)
Part C Premium <sup><math>d</math></sup>	1.727	5.103	10.53	8.931	7.223	9.415	9.329	9.991	7.517
	(12.78)	(22.37)	(30.32)	(27.87)	(23.64)	(28.21)	(28.08)	(29.90)	(25.77)
Part D Premium <sup><math>e</math></sup>	19.56	20.98	19.25	20.07	20.70	21.93	26.02	28.19	21.90
	(17.24)	(18.13)	(17.37)	(18.34)	(19.26)	(19.98)	(22.64)	(23.35)	(19.73)
Drug Coverage <sup>f</sup>	0.615	0.669	0.738	0.772	0.786	0.798	0.800	0.811	0.739
$\mathrm{HMO}^{g}$	0.206	0.212	0.249	0.328	0.342	0.361	0.373	0.389	0.297
$PPO^{h}$	0.152	0.180	0.274	0.412	0.450	0.471	0.505	0.515	0.349
Observations	28,988	33,224	29,212	22,447	22,337	23,029	22,000	$21,\!430$	$202,\!667$
Contract/County Dat	ta								
Star Rating 3 to 3.5		0.161	0.206	0.462	0.621	0.652	0.612	0.325	0.354
Star Rating 4 to 5		0.028	0.057	0.100	0.115	0.182	0.312	0.557	0.154
Plans Offered <sup><math>i</math></sup>	1.791	1.766	1.801	1.745	1.742	1.723	1.710	1.673	1.748
	(1.064)	(1.051)	(1.063)	(1.003)	(0.991)	(1.000)	(0.994)	(0.955)	(1.021)
Observations	16,185	18,815	16,224	12,865	12,822	13,363	12,869	12,812	115,955

 Table 1: Plan- and Contract-level Summary Statistics

<sup>a</sup>Defined as the average monthly enrollment for a plan.

 $^{b}$ Defined as a plan's share of the MA market.

<sup>c</sup>Denotes the consolidated Part C and Part D premium, including an \$0 premium plans.

<sup>d</sup>Reflects the premium only for Part C benefits, including \$0 premium plans.

<sup>e</sup>Defined as the total Part D premium (sum of the basic and supplemental premiums), net of any rebates from Part C.

 ${}^{f}$ An indicator for whether the plan offers Part D benefits.

 ${}^{g}\mathrm{An}$  indicator for whether the contract is a Health Maintenance Organization.

<sup>h</sup>An indicator for whether the contract is a Preferred Provider Organization.

<sup>*i*</sup>Defined as the number of plans offered under a given contract.

	2008	2009	2010	2011	2012	2013	2014	2015	Overall
MA Penetration <sup><math>a</math></sup>	0.146	0.159	0.160	0.170	0.183	0.201	0.221	0.233	0.184
	(0.105)	(0.109)	(0.113)	(0.119)	(0.123)	(0.126)	(0.128)	(0.131)	(0.123)
Number of $Plans^b$	10.03	11.39	9.919	7.630	7.577	7.906	7.727	7.559	8.721
	(9.241)	(9.976)	(8.528)	(6.546)	(6.532)	(6.594)	(6.493)	(6.270)	(7.781)
$Insurers^{c}$	4.382	4.638	3.952	3.112	2.944	2.965	2.942	2.890	3.480
	(2.470)	(2.497)	(2.128)	(1.726)	(1.640)	(1.672)	(1.796)	(1.795)	(2.106)
Benchmark $\operatorname{Rate}^d$	766.3	792.8	789.5	789.9	794.7	805.6	831.5	774.8	793.1
	(70.01)	(71.50)	(71.83)	(72.15)	(69.97)	(67.01)	(60.11)	(53.20)	(69.77)
Mean FFS Costs	7992.7	7950.0	8185.6	8363.6	8340.9	8272.0	8334.9	8580.0	8251.5
	(1294.8)	(1281.2)	(1354.4)	(1252.0)	(1224.1)	(1280.9)	(1148.7)	(1134.6)	(1263.6)
Population (1000s)	158.6	102.9	102.7	103.7	104.3	106.2	109.2	110.3	109.9
	(395.5)	(319.9)	(317.8)	(320.4)	(323.0)	(327.6)	(334.7)	(338.6)	(332.5)
$\%~{\rm Age} \geq 65$	0.139	0.152	0.154	0.157	0.160	0.163	0.166	0.170	0.158
	(0.0339)	(0.0407)	(0.0403)	(0.0405)	(0.0408)	(0.0411)	(0.0413)	(0.0419)	(0.0412)
% Employed	0.387	0.376	0.375	0.375	0.376	0.370	0.369	0.371	0.375
	(0.0537)	(0.0579)	(0.0585)	(0.0593)	(0.0607)	(0.0610)	(0.0611)	(0.0620)	(0.0598)
% White	0.828	0.840	0.841	0.839	0.839	0.838	0.834	0.833	0.837
	(0.143)	(0.160)	(0.161)	(0.161)	(0.162)	(0.161)	(0.162)	(0.162)	(0.160)
% Black	0.0930	0.0920	0.0925	0.0938	0.0947	0.0957	0.0979	0.0981	0.0948
	(0.125)	(0.145)	(0.147)	(0.147)	(0.148)	(0.148)	(0.149)	(0.149)	(0.146)
College Graduate	0.134	0.123	0.125	0.126	0.127	0.128	0.130	0.132	0.128
	(0.0561)	(0.0526)	(0.0536)	(0.0526)	(0.0527)	(0.0532)	(0.0538)	(0.0544)	(0.0536)
Observations	2,890	2,918	2,945	2,942	2,948	2,913	2,847	2,835	23,238

 Table 2: County-level Summary Statistics

 $^a\mathrm{Defined}$  as the overall share of MA relative to the total Medicare market

 $^b\mathrm{Denotes}$  the total number of plans in a county

 $^c\mathrm{Denotes}$  the number of unique insurers in a county

 $^d\mathrm{Reflects}$  the average Part C benchmark payment for each county

	Aetna	BlueCross	Cigna	HealthNet	Humana	Kaiser	UCare MN	UnitedHealth	Universal	WellCare
Aetna	614									
BlueCross	283	1,222								
Cigna	80	197	298							
HealthNet	31	64	9	67						
Humana	544	1,080	287	54	2,490					
Kaiser	25	37	9	25	58	76				
UCare MN	0	0	0	0	99	0	108			
UnitedHealth	378	531	190	51	1,182	58	0	1,370		
Universal	35	57	15	5	65	5	0	85	95	
WellCare	95	187	86	15	284	23	0	207	24	304

Table 3: Pairwise Overlaps Among Top 10 Insurers in 2015<sup>a</sup>

<sup>a</sup>Numbers reflect the total count of market overlaps between each insurer in 2015. The values are denoted by  $mmc_{ijt}$  in Equation 1. "BlueCross" reflects all Blue Cross and Blue Shield plans and affiliates.

Acquired	Acquiring	Date Finalized	Year in $Data^a$	Source
Bravo	HealthSpring	November 2010	2011	Modern Healthcare
Sisters of Mercy	Coventry	2010	2011	St. Louis Business Journal
HealthSpring	Cigna	January 2012	2012	Cigna Press Release
XLHealth	United Healthcare	February 2012	2012	UHC Press Release
Arcadian	Humana	April 2012	2012	Humana Press Release
Munich American	Windsor	2011	2012	Munich Press Release
Coventry	Aetna	May 2013	2013	Aetna Press Release
Windsor Health	WellCare	January 2014	2014	Yahoo Finance Article

## Table 4: Identified Mergers/Acquisitions

<sup>a</sup>Based on first observed change in "parent organization" or "organization marketing name" in the MA data, which appears to occur before some acquisitions are completely finalized.

$\begin{array}{c} 1.927^{***} \\ (0.609) \\ 1.744^{***} \\ (0.571) \\ 1.623^{***} \\ (0.522) \\ 1.155^{**} \\ (0.491) \\ \hline \\ Urban Floor \\ 2.023^{*} \\ (1.195) \\ 2.815^{**} \\ (1.353) \\ 1.919 \\ (1.173) \\ 0.653 \\ (0.901) \\ -0.839^{***} \\ \end{array}$	$\begin{array}{c} 0.367\\ (0.225)\\ 0.484^{*}\\ (0.245)\\ 0.525^{*}\\ (0.271)\\ 0.214\\ (0.182)\end{array}$
$\begin{array}{c} 1.927^{***} \\ (0.609) \\ 1.744^{***} \\ (0.571) \\ 1.623^{***} \\ (0.522) \\ 1.155^{**} \\ (0.491) \\ \hline \\ Urban Floor \\ 2.023^{*} \\ (1.195) \\ 2.815^{**} \\ (1.353) \\ 1.919 \\ (1.173) \\ 0.653 \\ (0.901) \\ -0.839^{***} \\ \end{array}$	$\begin{array}{c} 0.506^{***}\\ (0.126)\\ 0.405^{***}\\ (0.119)\\ 0.294^{***}\\ (0.109)\\ 0.220^{**}\\ (0.102)\\ \hline at \ Baseline\\ \hline \\ 0.367\\ (0.225)\\ 0.484^{*}\\ (0.245)\\ 0.525^{*}\\ (0.271)\\ 0.214\\ (0.182)\\ \hline \end{array}$
$\begin{array}{c} (0.609) \\ 1.744^{***} \\ (0.571) \\ 1.623^{***} \\ (0.522) \\ 1.155^{**} \\ (0.491) \\ \hline \\ \hline \\ \hline \\ \\ \hline \\ \\ \hline \\ \\ \\ \\ \\ \\ \\ $	$\begin{array}{c} (0.126)\\ 0.405^{***}\\ (0.119)\\ 0.294^{***}\\ (0.109)\\ 0.220^{**}\\ (0.102)\\ \hline at \ Baseline\\ \hline \\ \hline \\ at \ Baseline\\ \hline \\ 0.367\\ (0.225)\\ 0.484^{*}\\ (0.245)\\ 0.525^{*}\\ (0.271)\\ 0.214\\ (0.182)\\ \hline \end{array}$
$\begin{array}{c} 1.744^{***} \\ (0.571) \\ 1.623^{***} \\ (0.522) \\ 1.155^{**} \\ (0.491) \\ \hline \\ \hline \\ Urban Floor \\ \hline \\ 2.023^{*} \\ (1.195) \\ 2.815^{**} \\ (1.353) \\ 1.919 \\ (1.173) \\ 0.653 \\ (0.901) \\ -0.839^{***} \\ \hline \end{array}$	$\begin{array}{c} 0.405^{***}\\ (0.119)\\ 0.294^{***}\\ (0.109)\\ 0.220^{**}\\ (0.102)\\ \hline at \ Baseline\\ \hline \\ 0.367\\ (0.225)\\ 0.484^{*}\\ (0.245)\\ 0.525^{*}\\ (0.271)\\ 0.214\\ (0.182)\\ \hline \end{array}$
$\begin{array}{c} (0.571)\\ 1.623^{***}\\ (0.522)\\ 1.155^{**}\\ (0.491)\\ \hline \\ \hline \\ Urban \ Floor\\ \hline \\ 2.023^{*}\\ (1.195)\\ 2.815^{**}\\ (1.353)\\ 1.919\\ (1.173)\\ 0.653\\ (0.901)\\ -0.839^{***}\\ \hline \end{array}$	$\begin{array}{c} (0.119)\\ 0.294^{***}\\ (0.109)\\ 0.220^{**}\\ (0.102)\\ \hline at \ Baseline\\ \hline \\ 0.367\\ (0.225)\\ 0.484^{*}\\ (0.245)\\ 0.525^{*}\\ (0.271)\\ 0.214\\ (0.182)\\ \end{array}$
$\begin{array}{c} 1.623^{***} \\ (0.522) \\ 1.155^{**} \\ (0.491) \\ \hline \\ Urban Floor \\ \hline \\ 2.023^{*} \\ (1.195) \\ 2.815^{**} \\ (1.353) \\ 1.919 \\ (1.173) \\ 0.653 \\ (0.901) \\ -0.839^{***} \end{array}$	$\begin{array}{r} 0.294^{***}\\ (0.109)\\ 0.220^{**}\\ (0.102)\\ \hline \text{at Baseline}\\ \hline \\ 0.367\\ (0.225)\\ 0.484^{*}\\ (0.245)\\ 0.525^{*}\\ (0.271)\\ 0.214\\ (0.182)\\ \end{array}$
$\begin{array}{c} (0.522)\\ 1.155^{**}\\ \hline (0.491)\\ \hline \\ \mbox{Urban Floor}\\ \hline 2.023^{*}\\ (1.195)\\ 2.815^{**}\\ (1.353)\\ 1.919\\ (1.173)\\ 0.653\\ (0.901)\\ -0.839^{***}\\ \hline \end{array}$	$\begin{array}{r} (0.109)\\ 0.220^{**}\\ (0.102)\\\hline at \ Baseline\\\hline 0.367\\ (0.225)\\ 0.484^{*}\\ (0.245)\\ 0.525^{*}\\ (0.271)\\ 0.214\\ (0.182)\\\hline \end{array}$
$\begin{array}{c} 1.155^{**}\\ (0.491)\\ \hline \\ \text{Urban Floor}\\ \hline 2.023^{*}\\ (1.195)\\ 2.815^{**}\\ (1.353)\\ 1.919\\ (1.173)\\ 0.653\\ (0.901)\\ -0.839^{***}\\ \end{array}$	$\begin{array}{r} 0.220^{**} \\ (0.102) \\ \hline \text{at Baseline} \\ \hline \\ 0.367 \\ (0.225) \\ 0.484^{*} \\ (0.245) \\ 0.525^{*} \\ (0.271) \\ 0.214 \\ (0.182) \\ \end{array}$
$\begin{array}{r} (0.491)\\ \hline \\ \text{Urban Floor}\\ \hline 2.023^{*}\\ (1.195)\\ 2.815^{**}\\ (1.353)\\ 1.919\\ (1.173)\\ 0.653\\ (0.901)\\ -0.839^{***} \end{array}$	(0.102) at Baseline 0.367 (0.225) 0.484* (0.245) 0.525* (0.271) 0.214 (0.182)
	at Baseline 0.367 (0.225) 0.484* (0.245) 0.525* (0.271) 0.214 (0.182)
$\begin{array}{c} 2.023^{*} \\ (1.195) \\ 2.815^{**} \\ (1.353) \\ 1.919 \\ (1.173) \\ 0.653 \\ (0.901) \\ -0.839^{***} \end{array}$	at Baseline 0.367 (0.225) 0.484* (0.245) 0.525* (0.271) 0.214 (0.182)
$\begin{array}{c} (1.195) \\ 2.815^{**} \\ (1.353) \\ 1.919 \\ (1.173) \\ 0.653 \\ (0.901) \\ -0.839^{***} \end{array}$	$\begin{array}{c} (0.225) \\ 0.484^{*} \\ (0.245) \\ 0.525^{*} \\ (0.271) \\ 0.214 \\ (0.182) \end{array}$
2.815** (1.353) 1.919 (1.173) 0.653 (0.901) -0.839***	$\begin{array}{c} 0.484^{*} \\ (0.245) \\ 0.525^{*} \\ (0.271) \\ 0.214 \\ (0.182) \end{array}$
$\begin{array}{c} (1.353) \\ 1.919 \\ (1.173) \\ 0.653 \\ (0.901) \\ -0.839^{***} \end{array}$	(0.245) $0.525^{*}$ (0.271) 0.214 (0.182)
$\begin{array}{c} 1.919\\ (1.173)\\ 0.653\\ (0.901)\\ -0.839^{***} \end{array}$	$0.525^{*}$ (0.271) 0.214 (0.182)
$\begin{array}{c} 1.919\\ (1.173)\\ 0.653\\ (0.901)\\ -0.839^{***} \end{array}$	$0.525^{*}$ (0.271) 0.214 (0.182)
(1.173) 0.653 (0.901) $-0.839^{***}$	(0.271) 0.214 (0.182)
0.653 (0.901) -0.839***	0.214 (0.182)
(0.901) - $0.839^{***}$	(0.182)
-0.839***	(0.104)
	-0.186***
	(0.054)
(0.247) -0.604**	-0.138*
(0.285)	(0.073)
-0.473	-0.095
· · · ·	(0.079)
	-0.108
	(0.069)
ced Overlaps	
	-2.359**
(1.210)	(1.059)
	-2.718***
	(0.941)
	-1.427***
(0.301)	(0.253)
<pre>/ · · · · · · · · · · · · · · · · · · ·</pre>	-0.900***
· /	(0.262)
	-0.330
· /	(0.212)
	from 2012 Mergers
	0.043
( /	(0.071)
	0.145
(0.124)	(0.097)
	0.230***
(0.074)	(0.041)
$0.311^{***}$	0.226***
(0.062)	(0.034)
ced Overlaps	from 2013 Mergers
-1.027***	-0.752***
(0.337)	(0.256)
-0.902***	-0.631***
	(0.195)
	-0.542***
	(0.154)
	from 2014 Mergers
-0.991***	-0.906***
	(0.213)
-0.991***	-0.885***
(0.212)	(0.182)
0.118	0.120
	$\begin{array}{c} -0.040 \\ (0.100) \\ 0.101 \\ (0.124) \\ 0.245^{***} \\ (0.074) \\ 0.311^{***} \\ (0.062) \\ \hline \\ red \ Overlaps \\ -1.027^{***} \\ (0.337) \\ -0.902^{***} \\ (0.337) \\ -0.902^{***} \\ (0.300) \\ -0.736^{***} \\ (0.218) \\ \hline \\ red \ Overlaps \\ -0.991^{***} \\ (0.235) \end{array}$

 Table 5: Preliminary Regression Results for Generated Instrument<sup>a</sup>

<sup>&</sup>lt;sup>*a*</sup>Estimates from linear regression of insurer-level MMC ( $MMC_{imt}$  from Equation 2) on the instrument set. Standard errors in parenthesis clustered at the insurer level. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01

	Bi	ds	Premiums				
	Part C	Part D	Parts $C + D$	Part C	Part D		
FE Regres	sion Results						
MMC	0.265**	-0.141***	-0.043	-0.049	-0.139***		
	(0.108)	(0.019)	(0.049)	(0.038)	(0.023)		
$MMC^{hhi}$	$0.985^{*}$	-0.720***	-0.295	-0.098	-0.715***		
	(0.513)	(0.089)	(0.232)	(0.180)	(0.106)		
FE-IV Reg	gression Rest	ılts					
MMC	3.568***	0.086	0.321	0.258	-0.058		
	(0.732)	(0.128)	(0.259)	(0.219)	(0.150)		
	[170.61]	[202.57]	[217.39]	[212.90]	[202.61]		
$MMC^{hhi}$	13.531***	-0.085	0.950	$1.729^{*}$	-0.655		
	(2.834)	(0.511)	(1.064)	(0.919)	(0.602)		
	[227.25]	[260.82]	[279.70]	[274.73]	[260.85]		
N	142,780	118,745	161,262	168,541	118,759		

Table 6: Effects of MMC on Pricing at Plan-level<sup>a</sup>

<sup>*a*</sup>Plan-level regression results, with standard errors in parenthesis clustered at the county level. First-stage F-statistics for our our generated instrument are presented in brackets. Additional independent variables not in the table include contract fixed effects, county and year fixed effects, county-level demographic variables, an indicator for prescription drug coverage, average FFS costs in the county, the MA benchmark rate, and measures of the local (county) hospital market including HHI, total discharges, and number of hospitals. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01

	Bi	ds	Premiums				
	Part C	Part D	Parts $C + D$	Part C	Part D		
FE Regres	sion Results						
MMC	0.532***	-0.136***	-0.038	0.030	-0.126***		
	(0.107)	(0.017)	(0.047)	(0.037)	(0.019)		
$MMC^{hhi}$	$1.930^{***}$	-0.679***	-0.344	0.189	-0.641***		
	(0.511)	(0.082)	(0.223)	(0.177)	(0.090)		
FE-IV Regression Results							
MMC	4.100***	0.267**	0.558**	0.739***	0.134		
	(0.719)	(0.110)	(0.254)	(0.212)	(0.122)		
	[163.12]	[202.73]	[206.84]	[202.84]	[202.73]		
$MMC^{hhi}$	14.053***	0.585	1.494	2.991***	0.098		
	(2.799)	(0.442)	(1.036)	(0.871)	(0.486)		
	[219.66]	[262.45]	[269.64]	[265.82]	[262.46]		
N	77,114	82,611	90,938	93,234	82,616		

Table 7: Effects of MMC on Pricing at Contract-level<sup>a</sup>

<sup>a</sup>Contract-level regression results, with standard errors in parenthesis clustered at the county level. First-stage F-statistics for our generated instrument are presented in brackets. Additional independent variables not in the table include contract fixed effects, county and year fixed effects, county-level demographic variables, the percentage of plans offering prescription drug coverage, average FFS costs in the county, the MA benchmark rate, and measures of the local (county) hospital market including HHI, total discharges, and number of hospitals. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01

	High Star Rating $(4+)$		Average Star Ratings				
		Overall	Low Quality <sup><math>b</math></sup>	High Quality <sup><math>c</math></sup>			
FE Regress	sion Results						
$MMC_{t-1}$	-0.003***	-0.000	0.001	-0.019***			
	(0.001)	(0.001)	(0.001)	(0.004)			
$MMC_{t-1}^{hhi}$	-0.021***	-0.004	0.007	-0.083***			
	(0.003)	(0.004)	(0.005)	(0.020)			
FE-IV Reg	ression Results						
$MMC_{t-1}$	-0.008*	0.018***	0.020***	-0.070***			
	(0.004)	(0.005)	(0.007)	(0.018)			
	[170.05]	[170.05]	[129.95]	[48.05]			
$MMC_{t-1}^{hhi}$	-0.059***	$0.056^{***}$	$0.086^{***}$	-0.232***			
	(0.017)	(0.021)	(0.029)	(0.069)			
	[200.95]	[200.95]	[132.04]	[65.57]			
N	44,086	44,086	15,712	4,503			

## Table 8: Effects of MMC on Quality at Contract-level<sup>a</sup>

<sup>a</sup>Contract-level regression results based on years 2011-2015, with standard errors in parenthesis clustered at the county level. First-stage F-statistics for our generated instrument are presented in brackets. Additional independent variables not in the table include contract fixed effects, county and year fixed effects, county-level demographic variables, the percentage of plans offering prescription drug coverage, average FFS costs in the county, the MA benchmark rate, and measures of the local (county) hospital market including HHI, total discharges, and number of hospitals. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01

 $^b {\rm The}$  low-quality market segment consists of any contract receiving below a 3-star rating in 2009 or 2010.

 $^c\mathrm{The}$  high-quality market segment consists of any contract receiving a 4-star rating or above in 2009 or 2010.

	Plan	-level	$Contract-level^b$		
	(1)	(2)	(3)	(4)	
Part C Bids	8.485***	9.804***	7.749***	9.521***	
	(1.589)	(1.633)	(1.658)	(1.793)	
	[41, 440]	[37, 212]	[16, 237]	[14, 337]	
Part D Bids	3.507***	$3.684^{***}$	$3.698^{***}$	$3.858^{***}$	
	(0.372)	(0.386)	(0.430)		
	L / J	[30, 664]	[17, 834]		
Consolidated Premiums	3.092***	$3.630^{***}$	3.986***	$4.296^{***}$	
	(1.118)	(1.192)	(1.203)	· · · · ·	
		$[38,\!083]$	[18,279]	[16,053]	
Part C Premiums	4.425***	4.873***	3.758***	4.097***	
	(0.737)	(0.811)	(0.720)	(0.813)	
		[40, 307]	[18, 593]	L / J	
Part D Premiums	2.885***	$3.495^{***}$	2.527***	$3.198^{***}$	
	· · · · ·	(0.516)	(0.530)	( /	
	[34, 445]	[30, 667]	[17, 835]	[15, 697]	
High $(4+)$ Star Ratings			-0.084***	-0.083***	
			(0.012)	(0.013)	
			[10,608]	[9,371]	
Average Star Ratings			-0.012	-0.008	
			(0.014)		
			[10,608]	[9,371]	
Low Quality <sup><math>c</math></sup>			-0.120***	0.038	
			(0.029)	(0.047)	
			[1,613]	[1,414]	
High Quality <sup><math>d</math></sup>			-0.105***	-0.114***	
			(0.038)	(0.039)	
			[3,540]	[3,117]	
Contract, year, county FE	Yes	Yes	Yes	Yes	
Additional controls <sup><math>e</math></sup>	No	Yes	No	Yes	

Table 9: Effects of Out-of-market Mergers<sup>a</sup>

<sup>b</sup>Results for star ratings are based on years 2011-2015.

<sup>&</sup>lt;sup>a</sup>Estimates presented for coefficient on  $\mathbb{1}(t > \tau_{im})$  in Equation 5, with standard errors in parenthesis clustered at the county level. Columns 1-2 present plan-level results, and columns 3-4 present contract-level results. Markets in which both merging insurers operated prior to a merger, as well as all observations associated with a merging firm, are excluded from the analysis. Sample sizes presented in brackets. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01

<sup>&</sup>lt;sup>c</sup>The low-quality market segment consists of any contract receiving below a 3-star rating in 2009 or 2010.

 $<sup>^{</sup>d}$ The high-quality market segment consists of any contract receiving a 4-star rating or above in 2009 or 2010.

<sup>&</sup>lt;sup>e</sup>Additional controls consist of county-level demographic variables, an indicator for prescription drug coverage, average FFS costs in the county, the MA benchmark rate, and measures of the local (county) hospital market including HHI, total discharges, and number of hospitals.