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The Price Effects of a Large Merger of Health Insurers: A Case Study of UnitedHealth-Sierra

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Abstract

In this paper, we examine the association between market concentration and prices in the health insurance industry. Specifically, we conduct a case study of a large merger between health insurers— UnitedHealth Group and Sierra Health Services—which caused a shock to market concentration in Nevada's health insurance markets. Using a novel data set on health plan attributes, we exploit that natural experiment to obtain estimates of the association between the merger and premiums. The treatment group consists of health plans in markets affected by the merger, and the control group consists of health plans in similar markets that were not affected. Using a difference-in-difference propensity score matching estimator, we compare the change in premiums of health plans in the treatment group to the premium change in the controls. We find that premiums in Nevada markets increased by 13.7 percent after the merger relative to the control group. Our findings suggest that the merging parties exploited the market power gained from the merger.

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EXHIBIT
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1. Introduction

It is well known that the price of health insurance in the U.S. has been going up. Average annual premiums increased by 113 percent over the last decade, reaching $15,073 for commercial family coverage in 2011 (Kaiser and HRET, 2011). Coincident with this trend, concentration in health insurance markets has also increased (American Medical Association 2012; Dafny, Duggan and Ramanarayanan 2012; Robinson 2004). In many markets, this was the result of consolidation among health insurers. There is evidence that health insurance markets are highly concentrated; however, evidence of the impact of such concentration on premiums is largely anecdotal or descriptive (e.g., Robinson 2004). There is a need for more systematic evidence on the premium effects of health insurance market concentration. In this paper, we provide such evidence from a case study of the merger between UnitedHealth Group (United) and Sierra Health Services (Sierra). We find a large increase in health plan premiums in the wake of the merger.

Our findings are relevant to antitrust policy, which seeks to protect consumers by blocking mergers between firms that would allow them to exercise market power. The critical question is whether mergers would harm or benefit consumers. Under the Hart-Scott-Rodino Act, mergers valued at more than $66 million must generally be reviewed by the Department of Justice (DOJ) or Federal Trade Commission (FTC). One of these agencies then evaluates whether a merger would be anti-competitive, and may challenge in the courts mergers that would expand or allow the exercise of market power (increase prices). The antitrust agencies face large numbers of mergers and acquisitions, must *predict* the effects of the merger on market competition in a short period of time, and they have to do this with scarce time and resources. Consequently, some approved mergers may harm consumers, while some blocked mergers may have been beneficial.

In theory, the effect of higher market concentration on insurance premiums is ambiguous. Economic theory predicts that higher concentration can facilitate health insurers' exercise of market power in the output market and thereby lead to higher premiums (Waterson 1984; Wholey, Feldman and Christianson 1995). But higher concentration can also increase insurer bargaining power in input markets (e.g., hospital and physician services), and to the extent their output market is competitive, the merging parties would pass the savings onto consumers as lower premiums. Finally, mergers may create efficiency gains (e.g., economies of scale) that may also lead to lower premiums. Hence, the effect of higher market concentration on premiums is an empirical question.

There is a paucity of research on this question, owing in part to a dearth of publicly-available data on private health insurance plans. In this paper, we use a novel data set built by the benefits consulting firm Mercer Health & Benefits LLC (Mercer) that contains a rich set of information on the characteristics of private health insurance plans, including premiums and plan design.

Another reason for the paucity of research is that it is difficult to overcome the problem of endogeneity between market structure and prices. To our knowledge, there is only one study of the health insurance industry that adequately addressed this issue (Dafny et al. 2012). Using a private data set on health plan information, Dafny et al. (2012) use an instrumental variables (IV) strategy using the 1998 merger between two large insurers, Aetna and Prudential. The merger had differential effects on the HHI across markets, rendering it a valid instrument for the HHI. Dafny et al. (2012) found an average increase in premiums of 7 percent between 1998 and 2006.

Our study differs from Dafny et al. (2012) in several ways. First, we use different data. Second, whereas Dafny et al. (2012) analyze both fully and self-insured arrangements, we study the fully insured market—i.e., the insurers bear the risk. Third, because small employers are more likely than large employers to

fully insure, our analysis mostly focuses on the former. In contrast, Dafny et al. (2012) is based on large employers. Finally, we take a different empirical approach.[1]

We conduct a case study of a large merger between United and Sierra, and use the merger as a natural experiment (Ashenfelter, Hosken and Weinberg 2013; Ashenfelter and Hosken 2010; Simpson and Taylor 2008). This study is in the spirit of a recent series of FTC retrospective studies of hospital mergers.[2] Our empirical analysis assumes the merger is an external shock to market concentration (conditional on the covariates). We estimate the merger's effect on health plan premiums using a local linear difference-in-differences (DID) propensity score matching estimator (Heckman, Ichimura and Todd 1997; Heckman, Ichimura, Smith and Todd 1998). The treatment markets are metropolitan areas[3] that were affected by the merger and the control markets are areas that were not affected. We assess the change in premiums in the treatment markets and compare it to the change in premiums in the control markets.

The rest of the paper is organized as follows. The next section provides background on the United-Sierra merger. Section 3 presents our research design and methods. The data are described in Section 4, followed by the results in Section 5. We conduct sensitivity analyses in Section 6. Section 7 concludes.

2. The United-Sierra Merger

To identify candidate mergers, we used the 2007 to 2010 editions of the *Health Care Acquisition Reports* corresponding to the years of our Mercer data.[4] We looked for mergers with the potential to facilitate the exercise of market power by the merging insurers. Accordingly, we looked for transactions in which both parties had relatively large commercial enrollments in the same metropolitan areas (we assume metropolitan areas approximate health insurance markets). Second, we identified markets where both merging parties had a meaningful presence to ensure the merger would cause a large change in concentration, as measured by the Herfindahl-Hirschman Index (HHI). Finally, we excluded mergers where there were other reasons for changes in market concentration. These restrictions resulted in the selection of a recent merger between United and Sierra.[5] We discuss the merger and its empirical implications in turn.

United and Sierra merged in 2008. Prior to the merger, there were 5 health insurers with market shares of at least 5 percent in the state of Nevada. Sierra and United had the first and third highest shares, respectively, and WellPoint, Inc. had the second. After the merger, the combined firm became the largest insurer in that state.

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[1] We could not implement an IV strategy because, although there were mergers that occurred during our data period, none met the necessary criteria to be a valid instrument.

[2] See Federal Trade Commission website at http://www.ftc.gov/bc/healthcare/research/behealthcare.htm. In addition to providing a list of several retrospective studies of mergers, the FTC also notes that, "Several FTC staff hospital merger retrospective analyses are published in a special hospital merger retrospective issue of the International Journal of the Economics of Business, 18(1), April 2011."

[3] See Section 4 in the Appendix for a definition of the metropolitan areas. For convenience, metropolitan areas may be referred to as MSAs (metropolitan statistical areas) throughout the paper.

[4] These reports are published by Irving Levin Associates, Inc. and report mergers and acquisitions announced in the health care industry in the previous year.

[5] There were four mergers that at the outset appeared to be suitable for an empirical analysis, but we had to rule them out because they did not meet all the inclusion criteria. We expected that a 2007 merger between Blue Cross Blue Shield of Michigan and M-Care might have affected premiums in Ann Arbor, Michigan, but we did not have the requisite data. The three other mergers involved insurers' whose market shares turned out too small for us to expect to find an effect on premiums. Those mergers were between United and Pacificare (2005), Group Health Incorporated (GHI) and Health Insurance Plan of New York (HIP) (2006) and Cigna and Great West (2008).

3. Research Design and Methods

Key geographic markets affected by the merger were the Las Vegas and Reno metropolitan areas (treatment markets). Table 1 shows that both markets were already concentrated prior to the merger and that they would experience large HHI increases (1140 points and 651 points) after the merger—leaving the market "highly concentrated," as defined by the DOJ/FTC (HHI>2500). These are precisely the ingredients the antitrust agencies look for in presuming mergers to be likely to enhance market power.

Our objective is to obtain estimates of the association between the United-Sierra merger and premiums. We examine the change in premiums in the treatment markets between 2008 and 2009. However, the merger may not be a random event so one cannot infer that the change in premiums was *caused* by the merger. There could have been other shocks to supply and demand for health insurance unrelated to but coincident with the merger. Thus, a simple pre-post comparison of premiums could be biased.

We developed our empirical strategy in an effort to bolster the assumption that, conditional on observed characteristics, the merger is exogenous. We use a local linear difference-in-differences (DID) propensity score matching estimator (Heckman et al. 1997; Heckman et al. 1998). In effect, we compare the increase in insurance premiums in MSAs affected by the merger with increases in a control group of MSAs. Our method involves two steps. We estimate the probability that health plans received treatment—i.e., their market was affected by the merger. This probability, known as the propensity score, is then used to match the control group to the treatment markets. The identifying assumption is that, absent the merger, and conditional on measured characteristics, the premium change post-merger for the treatment and control areas would have been the same.

Prior to matching the markets using the propensity score, we looked at the pool from which they would be selected to ensure they would be suitable controls. First, we excluded markets where other mergers had taken place.[6] Second, given that health care and insurance markets are typically local, we took proximity to the treatment markets into consideration. We first limited the pool of candidate controls to the West region where the treatment group is located, but that did not yield enough observations. We then broadened the pool by adding markets from the South and Midwest. After matching on an exploratory basis, we found that areas in the South (excluding the Midwest) were more similar in characteristics to the treatment markets than were the South and Midwest combined. Therefore, the control group is composed of MSAs from the West and South regions. We also conducted analyses which included all MSAs in the U.S. as an alternative control group.

In sum, first we estimate a model of the probability of a merger occurring in health plans' markets. Second, we construct the matched premium outcomes. The Appendix provides more details about our methods.

4. Data

The primary data source we used was the BenefitPoint Health Plan Database (hereafter "Mercer" data). The data were drawn from an online procurement system owned by Mercer's vendor, BenefitPoint, Inc. and used by Mercer and other health benefit advisors. Mercer designed the database to our specifications and worked with BenefitPoint staff to build it. It provides information on the attributes of health plans sold to employers between 2004 and 2009. The employer data were aggregated and provided to us at the state and MSA levels. We use the MSA-level data. For each variable (e.g., premium, coinsurance rate,

[6] The mergers were those listed in footnote 5.

copay), we have different features of the distributions, including the mean, median, minimum, maximum. We use the variable means in the analyses.

The unit of observation is a health plan, where a health plan is defined as a unique combination of a plan type (PPO, HMO), group size (2-199, 200+), geographic market (MSA) and year. An example of a health plan is a PPO plan for small groups in the Las Vegas area in 2008.

The analysis is limited to employee-only plans because we do not know the number of dependents in family plans. We also restrict the sample to plans that are fully insured, since under those plans insurers have more clearly defined roles and measurable influence on pricing. Fully insured plans are dominant in the small-group (and individual) markets; thus, our sample is largely based on small employers. The latter also ameliorates concerns that the employees underlying our MSA-level data may not live in the reported MSA.

We used these data for the dependent variable in the empirical analyses—*premiums*. The *premium* is defined as the average monthly price charged to an employee for single coverage in a health plan as defined above. The other variables we used from this data set describe the plan design and are the *coinsurance rate*, *office visit copay* and *deductible*.[7] In PPO observations, those variables pertain to medical expenses incurred while using in-network providers.[8]

The *coinsurance rate* is the average percentage of medical expenses paid for by the plan.[9] The *office visit copay* is the amount paid by the member for a physician office visit. Finally, the *deductible* is the amount of medical expenses that must be paid for by the insured member before expenses begin to be paid by the insurer.

The second data source is the HealthLeaders-InterStudy (HLIS) Managed Market Surveyors from 2004 to 2009.[10] We used their data on commercial enrollment in PPOs and HMOs to calculate market shares and concentration levels (HHIs).[11] We merged the HLIS data to the Mercer data by MSA and year. The extent of some of the metropolitan areas differed between data sets so we adjusted the HLIS areas to match them to Mercer's.[12]

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[7] Because we use the MSA *averages* of the plan design variables, the interpretation of potentially missing values within MSA-level observations warrant attention. Specifically, the calculation of the averages should take into account the possibility of employer non-response to an attribute. It is not clear whether missing observations are true non-responses—e.g., the respondent did not know—or whether the plan simply did not include the relevant attribute, in which case its value should equal zero. If such zeroes are missing from the calculations, the distributions of coinsurance rates, copays and deductibles *within* MSA-level observations may be left-censored. Consequently, the averages of those variables may be slightly biased upward.

[8] Since HMOs do not cover expenses for medical care when it is received out-of-network, the act of being in- or out-of-network for HMOs is undefined.

[9] There are two possible exceptions to this definition. Some plans require a member copayment for physician office visits, in which case the coinsurance rate applies to lab, x-rays, etc., and usually hospital services. The other exception is that some plans require a member copayment for inpatient hospital stays, in which case coinsurance applies to lab, x-rays, and sometimes office visits.

[10] Managed Market Surveyors, ©2004-2009 HealthLeaders-InterStudy. All rights reserved. Managed Market Surveyor data may not be reproduced, distributed, displayed or modified, in whole or in part, by any means, without the prior written consent of HLIS.

[11] For a description of the construction process used to select a sample from which to calculate the market shares and HHIs, see the American Medical Association's *Competition in Health Insurance: A Comprehensive Study of U.S. Markets.*

[12] For details about the matching, see the Appendix, Section 4.

We then supplemented those data with data from other sources.[13] We merged data on Medicare Parts A and B expenditures from the Centers for Medicare and Medicaid Medicare Advantage Rates and Statistics (FFS Data). Unemployment rate data were obtained from the Bureau of Labor Statistics Local Area Unemployment Statistics. Per-capita income data came from the Bureau of Economic Analysis Local Area Personal Income. Finally, data on demographics (age, racial, and gender make-up of the MSA) came from the U.S. Census Bureau's Population Estimates.

The merged data sample contained 75 MSAs in 2004 and increased to approximately 250 MSAs in 2009. Other restrictions reduce the sample size. First, the propensity score method matched a subset of the available control markets—i.e., those with similar observable characteristics. Second, we restricted the sample to the two-year experimental period for our case study (2008-2009). Third, our dependent variable is the *difference* in premiums between 2008 and 2009 so there is only one observation per plan for the two years. Therefore, we have 187 health plan observations (5 treated and 182 non-treated) in two treatment markets and 92 control markets.

5. Results

We begin the empirical analysis by assessing whether our propensity score matching method performed well in matching control markets to the treatment group. Recall that we sought control markets that are similar to treatment markets in characteristics that determine premiums and premium growth. Table 2 shows the pre-merger differences in characteristics between the treatment and control areas. In general, the table shows that they are similar. The notable exception is baseline (pre-merger) premiums. The average monthly premium level for the control markets is about $67 higher (18 percent) than for the treatment group. This is partly because the plans in control markets were more likely to be PPO. If we limit the comparison to PPOs, the difference shrinks to $45 and becomes statistically insignificant. This does not undermine our empirical analysis because we identify the model using *changes* in premiums. The only other statistically significant difference is by gender. However, it is very small in magnitude; it achieves statistical significance because the standard errors are very small. Finally, there is a statistically *insignificant* difference in the deductible; however, this is in part because the control sample is more likely to be PPO—a plan type which is more likely to include a deductible. In sum, the results in Table 2 suggest that our conditioning variables performed well in matching and yielded a suitable control group for the analysis.

Figure 1 shows premium trends of health plans in the treatment (merger) and control (non-merger) groups. Although premiums went up after the merger for both groups, the premium increase in treatment markets was relatively larger than the premium increase observed for the control markets. Perhaps more important, and consistent with the evidence in Table 2, Figure 1 shows no difference in premium changes prior to the merger between the treatments and controls. These findings are preliminary evidence that the United-Sierra merger resulted in higher premiums in Nevada's health insurance markets.

The main DID regression results are presented in Table 3.[14] The results corroborate the preliminary graphical evidence. The estimates indicate a large, significant, positive association between the United-Sierra merger and premiums. The table shows that premiums increased by 13.7 percent in treatment markets compared to the controls in the wake of this merger.

If our identifying assumption is valid—i.e., that the premium change in the treatment markets would have been the same as the controls' absent the merger—then we can give the estimates a causal interpretation.

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[13] In observations where the MSAs also differed from Mercer's, we took the same approach as with the HLIS data to match the MSAs.

[14] The results from the estimation of the propensity score (Eq. 1) are in the Appendix, Table A1.

In addition to using economic theory to guide our empirical analysis and being careful in selecting a suitable control group, below we bolster our evidence that our estimate of the premium impact of the United-Sierra merger is robust.

6. Sensitivity Analyses

We conducted a series of sensitivity analyses to assess the robustness of the empirical results. One way to assess the validity of our research design is to examine whether treatment and control markets have similar trends in premiums prior to the merger. This would indicate that the control groups perform well in controlling for demand and supply shocks to health insurance services. For this model we were able to increase the sample size by specifying the dependent variable (premiums) in levels rather than differences, and adding the additional pre-merger year (2007) to the sample. Another difference between this and the propensity score matching method above is that we are able to include more conditioning variables in this model. In addition to the conditioning variables used previously, this model also controls for gender-specific age categories and interactions between plan design and plan type.[15] Finally, the present model does not control for baseline premiums. In short, these estimates are from a weighted DID regression model in which treatment (merger) was interacted with the pre-merger year in order to test for pre-existing trends in premiums. The formal model and its description are presented in Section 3 of the Appendix.

Key statistics from estimation of this model are presented in Table 3. The estimates for the independent variables appear in Table A2. Table 3 again shows a large, statistically significant association between the United-Sierra merger and premiums. More important, the interaction of treatment status with the pre-merger year yielded a coefficient estimate equal to zero. This indicates that that there were no differences in premium changes between the treatment and control markets prior to the merger. This bolsters our identifying assumption that, conditional on the observable characteristics, the United-Sierra merger is exogenous.

We also performed other sensitivity analyses.[16] One analysis involved using all available MSAs in the U.S. as candidate markets for the control group, except for those where mergers took place. Again we found that our main results were robust. The estimate of the association between the merger and premiums actually rose to 14.7 percent and remained statistically significant.

In another analysis we limited the sample to PPO plans. Finally, although our main sample consisted mostly of small groups, we conducted a separate analysis where we restricted the sample to only small group plans. In both instances, our empirical results remained robust.

7. Conclusions

In this paper, we examined the association between market concentration and prices in the health insurance industry. Economic theory suggests that these variables are endogenous, so simple OLS estimates of their association could be biased. To overcome this, we conducted a case study using a large merger between United and Sierra and used a difference-in-difference propensity score matching estimator to assess the impact of the merger on premiums.

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[15] Certain attributes of the plan design (e.g., coinsurance, deductible) are more likely to be utilized in one plan type than in another. For example, PPOs are strongly more likely than HMOs to use deductibles, and HMOs are more likely than PPOs to make use of office visit copays.

[16] Results are available upon request.

Our empirical strategy identified markets that were affected by the merger (treatment group) and compared their post-merger premium changes to premium changes in markets with similar observable characteristics but that were not affected by the merger (control group). We provided evidence that the propensity score method performed well in matching the markets. The empirical results showed a large, positive association between the United-Sierra merger and premiums, and the estimate was statistically significant. It indicates that the merger was associated with 13.7 percent higher premiums in Nevada markets relative to a narrowly-defined control group. We performed several sensitivity analyses and found evidence that our results are robust and can be given a causal interpretation. For example, using all MSAs in the U.S. as an alternative control group, we found that the estimate of the premium effect of the merger was 14.7 percent.

Our estimate of the premium impact of the merger is larger than the estimate found by Dafny et al. (2012). Several factors may help explain the size of our estimate relative to theirs. One is that there may be differences in specific market conditions. Another is that the employer size in our sample is different. Whereas the data used by Dafny et al. (2012) was based on large employers, our sample was composed primarily of small employers. This is because we focused on fully insured plans, the vast majority of which are in the small group insurance market. All else equal, small employers may have less leverage than large employers when bargaining with insurers. We also focused on the fully insured because under those plans, insurers have more clearly-defined roles and measurable influence on pricing.

Our study has a few limitations. Because our main results are based on a case study, it is unclear whether they have external validity. Nevertheless, they add to the extremely limited evidence on the effect of market concentration on health insurance premiums. Also, although we control for observable factors coincident with the merger that might have affected premiums, our estimates would be biased if there were unobservable factors such as quality that increased after the merger.

In sum, the empirical evidence is consistent with the hypothesis that the merging insurers exercised their market power in the wake of the merger. If there were any benefits to consumers realized from the merger, we could not observe them, and we can infer that they did not come in the form of lower premiums. On the contrary, the evidence suggests that large health insurer mergers are anti-competitive and cause injury to consumers through an increase in the price of health insurance services.

Table 1. Shares and Concentration Levels in Treatment Markets – United-Sierra Merger

Treatment (Merger) Markets	Pre-merger Market Shares (%)		Pre-merger HHI	Change in HHI
	(1)	(2)	(3)	(4)
Las Vegas	United	16	2054	1140
	Sierra	35		
Reno	United	12	1929	651
	Sierra	27		

Notes: Treatment markets are *metropolitan statistical areas* (MSA) as defined by the U.S. Office of Management and Budget (OMB). Pre-merger data are from January 1, 2008.

Table 2. Pre-Merger Differences in Characteristics between Treatment Markets and Control Markets

Variable	Treatment Markets	Control Markets	Difference
	(1)	(2)	(3)
Premium ($)	299.50	366.90	-67.41*
	(53.07)	(66.48)	
Coinsurance	0.116	0.122	-0.006
	(0.081)	(0.071)	
Copay ($)	20.73	21.18	-0.45
	(3.14)	(4.57)	
Deductible ($)	411.27	640.74	-229.47
	(336.12)	(413.17)	
HHI	2915	2942	-27
	(394)	(1070)	
Unemployment rate	0.047	0.047	-0.000
	(0.001)	(0.015)	
Medicare Part A costs per capita ($)	345.43	328.30	17.13
	(45.12)	(46.39)	
Medicare Part B costs per capita ($)	334.27	324.71	9.56
	(42.00)	(68.11)	
Share of MSA Population who are:			
White (non-Hispanic)	0.541	0.592	-0.051
	(0.073)	(0.151)	
Black (non-Hispanic)	0.081	0.128	-0.047
	(0.033)	(0.107)	
Hispanic	0.272	0.200	0.072
	(0.033)	(0.159)	
Female	0.491	0.505	-0.014**
	(0.001)	(0.011)	
Age > 64	0.108	0.126	-0.018
	(0.006)	(0.040)	
Per-capita income ($)	40,387	41,290	-903
	(2545)	(8971)	
Observations	5	182	

Notes: Treatment markets are MSAs that were affected by the United-Sierra merger—i.e., Las Vegas, NV and Reno, NV. Control markets are MSAs that were not affected by the merger *and* that have similar observable characteristics to the merger markets based on a propensity score matching method. Data for most variables are from Jan. 1, 2008, except for the HHI, unemployment rate and Medicare costs per capita, which are from Jan. 1, 2007.
** Significant at the 1 percent level.* Significant at the 5 percent level.

Figure 1. United-Sierra 2008 Merger: Premium Trends in Treatment (Merger) and Control Markets

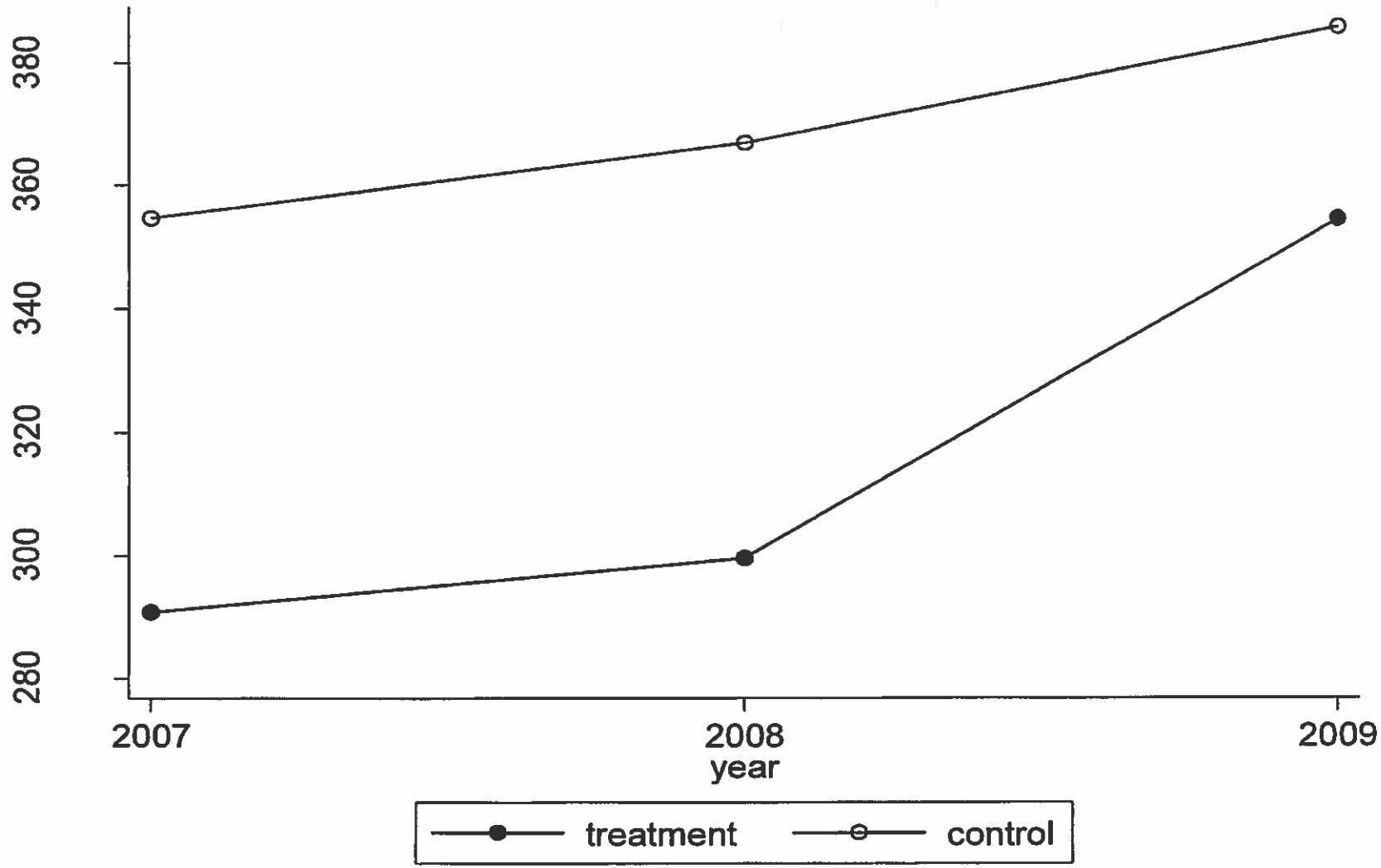

Table 3. Matching Estimates of the Effect of the United-Sierra Merger on Health Plan Premiums

Variable	Local Linear Regression Matching (Study Period: 2008-2009)	Validity of Research Design (Study Period: 2007-2009)
	(1)	(2)
TREAT*POST	0.137*	0.232**
	(0.054)	(0.073)
TREAT*PRE	–	0.014
		(0.036)
Bootstrap Replications	50	-
Observations	187	516

Notes:

1. The dependent variable is the natural logarithm of the average monthly premium for single coverage. The unit of observation is a health plan (HP), where HP is defined as a unique combination of a plan type (PPO, HMO), group size (2-199, 200+), market (MSA), and year.
2. The TREAT*POST estimates in column 1 are from a local linear difference-in-difference (DID) matching estimator. The first stage estimates appear in Appendix Table A1. POST is an indicator of whether the observation is from the post-merger year, 2009.
3. The propensity score from the model underlying column 1 was used as a weight for the regression estimates in column 2. The latter estimates are from a weighted DID regression model in which treatment was interacted with the pre-merger year. PRE is an indicator of whether the observation is from the pre-merger year, 2007. The model underlying column 2 tests for pre-existing trends in premiums. Appendix Table A2 and its *Notes* report the control variables for this model. Standard errors were calculated under the assumption that observations were not independent within MSA.
4. ** Significant at the 1 percent level.* Significant at the 5 percent level.

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Appendix

Research Methodology

The empirical strategy proceeds in two steps.[17] First we estimate a model of the probability of a merger occurring in health plans' markets. Second, we construct the matched premium outcomes. To guide the empirical analysis, we rely on two economic theories. We consider models of competition in the spirit of Waterson (1984), Feldman (1994) and Wholey et al. (1995), and we combine them with models of selection and matching (Roy 1951; Heckman 1974; Heckman et al. 1997; Heckman et al. 1998). Economic theory predicts that firms merge in markets where the merger would increase their profits.[18]

Consider the following notation:

- Let Y_1 denote the premium among health plans that received the treatment—i.e., a merger affected their market.
- Let Y_0 denote the premium without treatment—i.e., a merger did not affect their market.
- Let $D = 1$ if health plans received treatment, $D = 0$ otherwise.
- Let X denote other characteristics used as conditioning variables.
- Let $P(X) = Pr(D = 1 | X)$

1. Step One: Probability of a Merger Occurring in a Health Plan's Market

The last entry above is very important and is our first equation of interest:

(1) $P(X) = Pr(D = 1 | X)$

The first step is to estimate equation (1)—also known as the propensity score—which is the probability of a merger occurring in health plans' markets. This involves selecting a set of conditioning variables X. The MSA fixed effects in the empirical model control for any unmeasured, time-invariant MSA-level factors that affect premiums. However, there may be other unmeasured, *time-varying* shocks to supply and demand of health insurance that were coincident with the merger and that also affected premiums. This is why we seek control markets that face such similar shocks. Accordingly, the first conditioning variable is baseline (pre-merger) premiums.

We assume that firms merge in markets that give them the ability to exercise market power. This ability will be a function of the competitive landscape and the elasticity (firm and market) of demand. Thus, we seek markets with similar competitive landscapes and demand elasticities. To the extent these factors are time-invariant, they would be captured by the market fixed effects. But if they vary over time, we need to control for them. Accordingly, a measure of market structure (i.e., HHI) is included as a conditioning variable. Also included in X is the local unemployment rate, which serves as a control for local economic conditions.

To control for the elasticity of demand, X also includes consumers' characteristics, including the MSA's per-capita income, the proportions of the population that are: age 65 and over, black, Hispanic, other race and female.

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[17] We borrow freely from the guidance in Todd (1999) for implementing the matching estimator.

[18] In the spirit of the program evaluation literature, this is akin to a person choosing to enroll in a job training program only when the expected increase in earnings outweighs its expected costs (foregone earnings).

Key inputs into the production of health insurance are hospital and physician services. Thus, to control for those supply costs, we also condition on the markets' health care expenditures (Medicare costs per capita, Parts A and B).

Finally, considering that plans may differ in characteristics that would affect their price, we control for the plan design. Specifically, we condition on the average of the MSAs' coinsurance rate, office copay and deductible.

2. Step Two: Constructing the Matched Premium Outcomes

The next step is to construct the counterfactual change in premiums, Y_0. This is calculated as a weighted average of outcomes in the control markets, where the weights are positive functions of the propensity scores. The key parameter that we are interested in estimating is the *average treatment on the treated* (ATT) effect. More formally, we estimate the following equation:

(2) $\Delta_{D=1}(X) = E(Y_1 - Y_0 | X, D = 1)$

The conditions to justify the application of the DID matching estimator are given by Eq. 3 and 4:

(3) $E(Y_{0t} - Y_{0t'} | P(X), D = 1) = E(Y_{0t} - Y_{0t'} | P(X), D = 0)$

(4) $0 < \Pr(D = 1 | X) < 1$

Under these conditions, Eq. 2 can be estimated by the following equation:

(5)
$$\Delta^{hat\,DID}_{D=1} = n_{1t}^{-1} \sum_{\substack{i=1 \\ \{D=1\}}}^{n_{1t}} \{Y_{1ti}(X_i) - E^{hat}(Y_{0ti} | P(X_i), D_i = 0)\} - n_{1t'}^{-1} \sum_{\substack{j=1 \\ \{D_j=1\}}}^{n_{1t'}} \{Y_{0t'}(X_j) - E^{hat}(Y_{0t'j} | P(X_j), D_j = 0)\}$$

where n_{1t} and n_{1t} are the number of observations in the two time periods.

Constructing matched outcomes requires estimating $E(Y_{0ti} | P(X_i), D_i = 0)$ and $E(Y_{0t'j} | P(X_j), D_j = 0)$. We use a local linear regression (LLR) estimator to estimate those conditional means. The LLR of the conditional means is a weighted average of the comparison group outcomes, where the weights are a function of the log-odds ratio $log \frac{P^{hat}(X_i)}{1-P^{hat}(X_i)}$, where P^{hat} is the propensity score we estimated in Step One.

3. Validity of the Research Design

One way to assess the identification assumption underlying Eq. (2) is to examine whether treatment and control markets have similar year effects prior to the merger. To assess this possibility, we estimate the following equation:

$$\ln prem_{mtpg} = \mu_m + \tau_t + \beta_0(TREAT_m * PRE_t) + \beta_1(TREAT_m * MERG_t) + \beta_2(TREAT_m * POST_t) + \varphi X_{mt-1} + \chi C_{mt} + \gamma design_{mtpg} + \pi_p + \varepsilon_{mtpg}$$

(6) m = 1,…,M (markets)
t = 2007,…,2009 (years)
p = PPO,HMO (plan types)
g = 2-199, 200+ (group sizes)

In Eq. (6), *TREAT* is an indicator (equal to one and zero otherwise) of whether a merger occurred in market *m*. *PRE* is an indicator of whether the observation is from the pre-merger year, 2007, *MERG* is an indicator of whether it is from the merger year, 2008, and *POST* is an indicator of whether it is from the post-merger year, 2009. Note that the main effect of the merger, *TREAT*, and the post-merger period, *POST*, cannot be identified in this model because of the inclusion of market (μ) and year (τ) fixed effects. The key independent variable in Eq. (6) is the interaction between *TREAT* and *PRE*. This is a test of the validity of our research design. If the design is valid, the coefficient on that pre-merger interaction should be equal to zero.

4. Matching Plans to MSAs

In general, the Mercer data only include metropolitan statistical areas [i.e., MSAs—as defined by the Office of Management and Budget (OMB)]. When MSAs extend across multiple states, there is a unique observation for each state-specific portion of the MSA. The HLIS metropolitan areas includes mostly MSAs, but also a few metropolitan divisions and New England Cities and Town Areas (NECTAs). For convenience, we refer to all areas as MSAs. When there was not an exact match between MSAs, we made our best efforts to match them appropriately. First, when the HLIS data came at the metropolitan-division level, and the corresponding Mercer MSA was located in a single state, we aggregated the HLIS areas to correspond to the Mercer MSA. Second, when the HLIS data came at the metropolitan division level, and the Mercer MSA extended across multiple states, we matched the HLIS area to the state-specific portion of the Mercer MSA that most closely corresponded to it geographically. Third, we matched the HLIS NECTAs to the Mercer MSAs with the same name. Finally, there were twelve Mercer MSAs that extend across multiple states, but for which there is only one observation in the HLIS. We merged the single HLIS MSA to the multiple observations for the Mercer MSA.

Supplemental Results

Table A1. Predicted Probability of a Health Plan being affected by the Merger (Treatment)

Pre-Merger Characteristics	Coefficient	Standard Error
	(1)	(2)
Premium	-0.037*	0.017
HHI	0.0021	0.0015
Coinsurance Rate	16.49	11.69
Copay	0.074	0.214
Deductible	-0.005	0.003
Unemployment rate	-1.379	1.422
(ln)Med. Part A cost per cap	6.272	8.889
(ln)Med. Part B cost per cap	5.769	10.68
% Population - Age > 64	0.337	49.42
% Population - Black (non-Hispanic)	-19.44	22.27
% Population – Hispanic	-2.539	12.14
% Population – Other Race	20.47	19.46
% Population – Female	-164.6^{+}	86.24
Per-capita income ($)	0.000	0.000
Pseudo-*R*-square	0.52	
Observations	187	

Notes: The dependent variable is a dummy variable equal to unity if the United-Sierra merger affected a health plan—i.e., if the market was Las Vegas, NV or Reno, NV. A health plan in this model is defined as a unique combination of a plan type (PPO, HMO), group size (2-199, 200+) and market (MSA). Data for most of the variables are from Jan. 1, 2008, except for the HHI, unemployment rate and Medicare costs per capita, which are from Jan. 1, 2007. * Significant at the 5 percent level.$^{+}$ Significant at the 10 percent level.

Table A2. Estimates of the Effect of the United-Sierra Merger on Health Plan Premiums
Testing the Validity of the Research Design

Variable	Weighted DID Regression (Study Period: 2007-2009)
TREAT*POST	0.232**
	(0.073)
TREAT*PRE	0.014
	(0.036)
Coinsurance	0.675*
	(0.263)
Coinsurance*PPO	-0.783*
	(0.374)
Copay	-0.003
	(0.004)
Copay*HMO	0.001
	(0.006)
Deductible/100	-0.004
	(0.005)
Deductible*PPO/100	-0.005
	(0.007)
PPO	0.269**
	(0.088)
Unemployment rate	-0.004
	(0.014)
Ln(Med. Part A cost per capita)	-0.031
	(0.203)
Ln(Med. Part B cost per capita)	0.128
	(0.455)
Observations	516

Notes: This is a test of the validity of the research design, in which treatment (i.e., the merger affected the health plan's market) is interacted with the pre-merger year in the data. The dependent variable is the ln(average premium). These results are based on a weighted difference-in-difference (DID) regression model, where the weight is the propensity score estimated in the model underlying Table 3. The coefficient for TREAT*POST is the DID estimate. TREAT*PRE is the interaction between treatment and the pre-merger year, 2007. The regression model also controls for MSA and year fixed effects, the proportion of the MSA's population in gender-specific age categories, the proportion of the MSA's population who are white/non-Hispanic, black non-Hispanic, Hispanic, and other; the proportion of the MSA's population who are female or age > 64; and per-capita income. The unemployment rate and Medicare Parts A and B costs per capita are lagged by one year. Standard errors were calculated under the assumption that observations were not independent within MSA.
** Significant at the 1 percent level.* Significant at the 5 percent level.$^{+}$ Significant at the 10 percent level.