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DISCUSSION PAPER SERIES

IZA DP No. 15392

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ABSTRACT

How Do Insurers Price Medical Malpractice Insurance?*

We study the factors that predict medical malpractice ("med mal") insurance premia, using national data from Medical Liability Monitor over 1990 to 2017. A number of core findings are not easily explained by standard economic theory. First, we estimate long run elasticities of premia to insurers' direct cost (payouts plus defense costs), allowing for lags of up to four years, of only around +0.40, when one might expect elasticities near one. Second, state caps on malpractice damages predict a roughly 50% higher ratio of premia to direct costs even though, in competitive markets, a damages cap should affect premia primarily through effect on cost. A difference-in-differences analysis of the "new cap" states that adopted caps during the early 2000's provides evidence supporting a causal link between cap adoption and the ratio of premium to direct cost. Third, the premium-to-cost ratio, which one might expect to be fairly constant over time, instead varies widely both across states at a given time and within states across time. Our results suggest that insurance companies do not fully adjust revenues to changes in direct costs even over long time periods. Insurers in new-cap states have been able to charge apparently supra-competitive prices for a sustained period.

JEL Classification: D22, G22, K13

Keywords: insurance premium, medical malpractice, physicians

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* We thank Tom Baker, Patricia Born, and seminar participants at University of Haifa law faculty and Tel Aviv University law faculty for comments. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. The research in this paper does not use any confidential Census Bureau information.

1. Introduction

This paper raises puzzles with regard to the operation of the market for medical malpractice ("med mal") insurance, but does not find convincing answers for them. We study how insurers price med mal insurance sold to physicians, using almost 3 decades of data on med mal premia, collected by Medical Liability Monitor (MLM). We assess the extent to which per-physician costs, caps on non-economic or total damages ("damage caps"), and competition from other insurers predict affect premia for the three specialties for which MLM collects data: general surgery, internal medicine, and obstetrics and gynecology (ob-gyn). We find a number of puzzling results, not easily explained by standard economic theory. First, premia are only loosely connected to insurer costs, even over long periods. We estimate long run elasticities of premia to insurers' direct costs (the sum of payouts plus defense costs), allowing for lags of up to four years, of only around +0.40, when one might expect elasticities near one. Yet current costs are highly predictable based on past costs.

Second, premia are much higher in states with damage caps, controlling for costs. Yet, in a competitive market, damage caps should affect premia principally through their effect on costs, and should have little or no additional direct predictive effect. A difference-in-differences analysis of the "new cap" states that adopted caps during the early 2000's provides evidence supporting a causal link between cap adoption and a higher ratio of premia to direct cost ("Premium/Cost Ratio").

Third, one might expect the Premium/Cost Ratio to be fairly constant over time. Insurers need to charge enough to cover their direct costs, plus administrative and marketing costs (which should be predictable and slowly varying), and earn a return on capital. But competition, including new entry and the threat of entry, should constrain the return on capital to a normal level over time, even if not in each year. Instead, we find that the Premium/Cost Ratio varies widely both across states at a given time and within states across time.

Our results suggest that insurance companies do not fully adjust premia to changes in direct costs even over long time periods. Insurers in new-cap states have been able to charge apparently supra-competitive prices for a sustained period, even in markets with a reasonable number of competitors. Our proxy for competition, crude but best available, is the number of insurers form whom MLM reports premia. The combined market shares of the insurers whose premia are reported in MLM average around 70%.

As background, there have been three periods since 1970 in which med mal premia have risen sharply – the mid-1970s, the mid-1980s, and the early 2000s (see the overviews in Baker, 2005a; Black et al., 2021). Physicians and insurers have blamed each spike on rising payouts (not always accurately), and have been able, especially during these waves to persuade many state legislatures to limit med mal lawsuits in various ways. Damage caps are the most important but not the only reform.

Much research has focused on how malpractice liability and damage caps affect healthcare markets, including physicians' clinical decisions (defensive medicine), practice location decisions, and patient health outcomes. A separate strand of literature, to which we contribute, has examined the factors that predict med mal premia, with mixed findings.

Our priors were that insurer direct costs – which we measure as the sum of payouts on claims reported to the National Practitioner Data Bank (NPDB), plus defense costs reported to the National Association of Insurance Commissioners (NAIC) -- would strongly drive premia, perhaps with a lag. We expected damage caps to affect premia primarily through their effect on direct costs, and to otherwise have limited long-term effect on the Premium/Cost Ratio. We expected insurers to respond to each other: changes in one insurer's pricing should predict changes by other insurers in the same market, and markets with more major competitors should exhibit lower prices and a lower Premium/Cost Ratio. We also hypothesized that if multistate insurers use centralized purchase or reinsurance, or common actuarial prediction of future payouts, rate changes by a multistate insurer in one state might predict changes in the rates this insurer charged in other states.

We found instead a market that seems, in important ways, to defy economic logic. The Premium/Cost Ratio captures the two principal time-varying components of insurer cost. We cannot measure the third major cost category -- insurer administrative costs – but these costs should be only slowly time-varying and reasonably consistent across insurers. Thus, the Premium/Cost Ratio should provide a respectable measure of the relative profitability of the med mal insurance business. This ratio, which one might expect to be reasonably stable across states and across time, is instead highly variable: within states over time, nationally over time, and across states at similar times. For example, the univariate correlation between the state-level premium per physician (averaged over the three MLM specialties) and state-level direct cost per physician, over the 28 years from 1990 through 2017, is only 0.38. We find evidence that lags of direct costs up to four years predict current premia. However, even allowing for these lags, long-run elasticities for the response of premia to costs are around 0.40, when naïve theory would predict that they should be close to 1. We find no evidence that premia lead future costs – that insurers are able to use internal data, on claims they have received but not yet paid, to predict future payouts and change premia accordingly.

In a competitive market, one would also expect the effect of damage caps on premia to be largely captured through the effect of caps on insurers' direct costs. We found instead that these caps strongly predict the Premium/Cost Ratio. In a panel data analysis with firm*county*specialty fixed effects (FE), existence of a damages cap strongly predicts a higher Premium/Cost Ratio. This analysis identifies the effect of damage cap adoption solely from states which adopt or remove a cap during our sample period. It is similar to a difference-in-differences (DiD) design if cap adoption is exogenous. An explicit DiD analysis of the "New-Cap States" that adopted damage caps during the early 2000s wave of cap adoptions provides evidence that this association is causal and persists for at least a decade after cap adoption. Based on the Premium/Cost Ratio, med mal insurer profitability, on average across all states, has soared since 2000, but has done so with special strength in the New-Cap States.

One might also expect that competitive pressure, including new entry, would predict lower prices (lower Premium/Cost Ratio). We found no evidence for this. The number of insurers with premia reported by MLM is insignificant as a predictor of premia or the Premium/Cost Ratio, but in regressions, consistently takes the wrong (positive) sign. We find some evidence that med mal insurers change their pricing to respond to other insurers' prices. Cross-elasticities are near 0.4 for premia charged by one firm versus those charged by other firms in the same county, and are similar with or without controls for the other predictors described above. However, these cross-elasticities may reflect common responses of all insurers in a county to unobserved common shocks. For multistate insurers, we find some evidence of cross-subsidization – once we allow for lagged effects, higher prices in the other states in which a multistate insurer operates predict lower prices in a given state.

Our paper makes several contributions to our understanding of med mal insurance market dynamics. First, we use nearly three decades of data for a standardized policy type with constant limits (albeit in nominal dollars), which provides a firm-specific measure of prices charged to physicians over this period for the same coverage. Other studies have studied much shorter periods, and have used the dollar level of direct premia written in each state as a proxy for premia. This measure potentially confounds changes in per-physician prices for the same policy with changes in the number of policyholders and the policy limits they purchase. Neale, Eastman, and Drake (2009) report substantial variation over time in the number of firms writing policies in each state and in firms' market shares (based on direct premia written). Silver et al. (2015), in a case study of Texas, find large variation over time in the typical policy limits that physicians purchase.

Second, we measure insurer costs using actual payouts, as reported to NPDB, plus defense costs. In contrast, Danzon, Epstein, and Johnson (2004) use insurers' expected losses (expected payout plus expected defense costs), as reported to NAIC, to estimate costs.[1] The expected-loss measure confounds changes in actual payouts with changes in insurers' estimates of future payouts on claims already made (Baker, 2005a). Those adjustments could reflect various factors in addition to changes to expected payouts. Historically, when premiums rise in so-called "hard insurance markets," loss estimates often rise as well. Conversely, when premiums fall or remain flat in "soft markets," loss estimates often fall. Changes in these estimates can be far larger than changes in actual paid losses, as Danzon et al. show for their sample period. Other studies (e.g., Kilgore, Morrissey, and Nelson, 2006) have assessed whether damage caps predict premia but have not directly linked premia to payouts or direct costs or asked whether caps predict premia, after controlling for insurer costs.

Third, our long sample period lets us examine determinants of premia both during years when premia are changing rapidly, including the national spike in med mal premia from 2000-2005, and when they are in steady decline (2005-2017), and to examine both the period from 1990-2000, with roughly stable payout/physician, and the period from 2001-2017, with steadily declining payout/physician.

Fourth, we conduct a DiD analysis, which provides evidence both that damage caps causally predict a higher future Premium/Cost Ratio and that the Premium/Cost Ratio rises in New-Cap States beginning two years *before* cap adoption. The pre-adoption rise in premia, beyond the amount that can be explained by rising payouts, is a plausible causal driver of cap adoptions. In

[1] The standard insurance term is ALAE (allocated loss adjustment expense). This category includes expected payout plus defense costs cost for defense counsel, expert witness costs, costs of medical records, and the portion of the insurer's own administrative cost that it allocates to particular claims.

contrast, prior work has found only weak evidence that changes in payouts predict cap adoptions (Paik et al., 2013b).

Fifth, many med mal insurers operate in multiple states; no prior study examines how these insurers behave across different states. We assess whether premia charged by the same parent insurer in one state predict the premia that this insurer charges in another state. Cross-state spillovers could reflect parent's actuaries applying common views of the med mal liability environment across states or the effect of potentially national factors such as reinsurance rates (both factors predict a positive association, or potential cross-subsidization across states within the same parent company. We find some evidence of cross-subsidization, with higher premia in other states predicting lower in-state premia.

The studies most similar in spirit to ours are Danzon, Epstein, and Johnson (2004) and Kilgore, Morrisey, and Nelson (2006). Both use MLM data on premia (as we do); neither takes our extra step of combining these with NPDB data on payouts. Danzon, Epstein, and Johnson (2004) use state-level data over 1994-2002 on premia from MLM, and on insurer "losses" from NAIC. They find that state tort reforms or year-specific influences on all firms have greater predictive power for changes in premia than most firm-specific covariates, including insurers' expected losses as reported to the NAIC.[2] Kilgore, Morrisey, and Nelson (2006) use panel data over 1991-2004, with state and year fixed effects, to estimate the impacts of damage caps, other tort reforms, and investment returns on malpractice premia; they do not study the extent to which actual costs predict premia. They find that damage cap adoption predicts 17-25% lower premia, depending on physician specialty; in contrast we find below that cap adoption by the New-Cap States (over 2002-2005, thus mostly a later time period than they study) predicts *higher* premia.

This paper proceeds as follows. Part 2 presents a conceptual model. Part 3 describes our data and provides summary statistics. Part 4 provides initial graphical evidence. Part 5 details our empirical modeling approach. Part 6 reports regression results, Part 7 performs sensitivity analyses, and Part 8 discusses our findings and concludes.

[2] Danzon et al. (2004) use what would today be seen as a weak empirical specification; they rely on OLS regressions with year but not state fixed effects, and do not cluster standard errors on state.

2. Conceptual Model

We provide here a simple conceptual model of how we expect insurers to price insurance in a competitive market. We treat insurance companies as profit-maximizing firms whose profits depend primarily on the price of the insurance contract offered (the premium) and the cost of providing the contract (insurance payouts, defense costs, and administrative costs). Other sources of revenue for insurance companies include investment income from premia. Medical malpractice insurance has a relatively long "tail" – the time gap between when premia are received and payouts are made; prices should reflect expected income from investing "float" (premia received, but not yet paid out on claims). We regard payouts as a key driver of malpractice insurer costs. This should be especially so for *changes* in payouts, which should be the principal driver of changes in premia. Defense costs are a second important driver, and show a gradually rising trend as a fraction of payouts over our sample period (see Figure 1, Panel D), which has been observed in prior work (Black et al., 2008; Carroll et al., 2012). However, defense costs are reasonably predictable and are unlikely to explain large swings in premia or the Premium/Cost Ratio. Defense costs and payouts are also correlated at the claim level, since defense costs reflect insurers' efforts to limit payouts (Black et al., 2008). Administrative costs and float (and thus expected income on float) should also vary slowly over time, and thus should also not be strong drivers of changes in premia in a panel-data setup.

Firms may set premia either in response to past payouts (a principal source used by insurance actuaries to predict future payouts) or based on private knowledge of expected future payouts. Insurance companies have knowledge of claims filed but not yet paid out, so it is possible for premia to increase before costs if the insurers respond to anticipated higher future payouts or other costs by increasing premia today. Insurance companies may also be surprised by the magnitude of payouts for themselves or competitors and change premia to respond to the implications of those unexpected past payouts for expected future payouts.

Premia can also increase either before or after costs if insurers respond to competitors' premia, both for competitive reasons and because Insurer A's prices may reflect changes in Insurer A's estimate of its expected costs, from which other insurers might infer similar changes in their expected costs. However this channel for med mal insurers to adjust their prices should be limited in time, because the NPDB provides annual data on state-level payouts by all insurers (data for year t becomes available in the first half of year t+1).

In our empirical specifications, we seek to capture insurers' expected revenue and costs other than payouts and defense costs, including administrative costs and income on float, via firm*county*specialty and year fixed effects (FE). The firm*county*specialty FE should capture firm-specific cost structures that may be slow to change over time, as well as time-invariant county, state, or specialty-specific factors affecting premia. The year FE should control for national changes in investment returns, reinsurance rates, or the med mal liability environment. We expect state damage caps to affect both claim rates and payout per claim (Paik et al., 2013b), and therefore costs. However, we expect caps to affect premia principally through their effect on costs.

Insurers operate in markets with various degrees of competition and in less competitive markets may act as monopolistic competitors. Naïve theory would predict that firms in more competitive markets will charge prices close to marginal cost, and will therefore pass on changes in direct costs to physicians at close to dollar-for-dollar, while firms in less competitive markets will charge higher prices (reflected in a higher Premium/Cost Ratio, and may change premia in response to changes in direct cost at higher or lower rates, depending on how their power to charge prices above marginal cost varies with changes in cost. We use the number of firms that provide their premia to MLM in each county as a measure of competition, and estimate the response of firm premia to the mean of competitor premia as a measure of how competition affects prices.

3. Data and Summary Statistics

3.1. **Data and Data Sources**

We obtain annual data on medical malpractice premia from annual surveys conducted by Medical Liability Monitor (MLM) over 1990-2017. We rely on an updated version of an MLM dataset prepared by Black et al. (2017) from the raw MLM data. MLM is the only source of national, longitudinal data on med mal insurance rates and covers three specialties: internists, general surgeons, and obstetricians-gynecologists. The MLM data contain premia for a standard claims-made policy with limits of $1 million per occurrence and $3 million per calendar year in nominal dollars. Insurers often divide a state into a number of pricing regions and charge different premia in different regions – typically higher premia in urban than in rural regions. The Black et al. dataset maps these regions to counties. An observation in the dataset is the premium for a given specialty offered by a company in a given county and year -- a firm*county*specialty*year panel. Insurance is regulated at the state level, and MLM lists insurers by state, but a single parent insurer may operate in different states, often with somewhat different names for subsidiaries in different states. Black et al. use NAIC data to create a parent insurer variable, which captures which parent companies own which state-level insurers. We eliminate the 8 states with patient compensation funds (indicated in Table 1) from our analyses.

We obtain annual data on insurer defense costs from NAIC. NAIC reports insurer direct allocated loss adjustment expenses from 1992-1998 and direct defense and cost containment expenses from 1999-2018, which we aggregate to the state level. This measure includes all fees paid to defense counsel, or expected at that time to be paid, in specific cases but omits expenses that are not allocated to particular cases.[3] This data is available at the state*firm level through 2004, but only at the state level after 2004.

We obtain annual state-level data on paid med mal claims against physicians from the NPDB. The NPDB relies on voluntary reporting by physicians and insurers and may not be complete. However, prior research comparing NPDB claims to other sources for Illinois provides evidence that NPDB captures a large percentage of all paid claims and that the percentage captured is consistent over time (Hyman, Rahmati and Black, 2020, appendix). Prior research also finds that trends in NPDB payouts are consistent with other sources for states where other sources are available (Paik, Hyman, and Black, 2013). We have no reason to believe that any changes over time in NPDB completeness might vary across states in a way that would bias our results. Because the NPDB data on payouts is at the state level, and the NAIC data on defense costs is also at the state level from 2004 on, we can measure direct cost only at the state level. Thus, the premium/direct cost ratio involves a mix of firm*county level data in the numerator and less granular state level in the denominator.

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[3] An insurance industry guide explains, the category of "**Defense and Cost Containment Expenses (D&CC)** includes expenses that are related to the defense, litigation, or cost containment of a claim. Includes surveillance, appraisers, private investigators, and fraud investigators, if working in defense of a claim. Also includes rehabilitation nurses and the cost of engaging experts. Prior to 1/1/98, Defense and Cost Containment Expenses were referred to as Allocated Loss Adjustment Expenses (ALAE)." See https://www.wcf.com/common-terms. See NAIC (1998) for additional details on this measure and how the post-1998 measure differs from the earlier measure.

We obtain counts of active practicing non-federal physicians (below, simply "physicians") by county and specialty from the Area Health Resource File (AHRF).[4] We combine the NPDB, NAIC, and AHRF data to construct state*year data on direct cost per physician

The MLM data lets us assess how competitive interaction between insurers may affect premia. We construct a "Competitor Premium" in a county*specialty*year as the simple average of the premia for that specialty offered by all other firms in that county*year. We also consider whether premia charged by subsidiaries of multistate insurers are influenced by events at the parent company level. To do so, we compute a "Group Premium" for each firm*county*specialty*year as the average premium offered in other states by the out-of-state members of the same parent group, weighted by the number of physicians practicing in each out-of-state county*specialty*year.

3.2. Summary Statistics and Correlations

We divide the 43 states in our sample (after excluding PCF states) into four groups: 6 New-Cap States which adopted damage caps in the early 2000's, which remained in place thereafter (in DiD analyses, we include Georgia and Illinois, which had caps in place from 2005-2009, as additional New-Cap States); 12 states which had a cap on non-economic or total damages adopted before our sample period ("Old-Cap States"), 17 states that had no damage cap in effect during our sample period ("No-Cap States"), and 8 states with another damage cap pattern, usually a cap that was in place for a limited period but was then judicially reversed ("Other States").

Table 1 summarizes, by state and for our four state groups defined by their tort-reform status (no-cap, new-cap, old-cap, and other), the "Premium/Cost Ratio", defined as the ratio of the average premium per physician in each state to the average of (payout plus defense cost) per physician in that state, and how that ratio has changed over time.[5] The table shows the average

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[4] **Source**: http://ahrf.hrsa.gov/. The physician count data are missing for 2009 and do not exist at the county level for our specialties of interest prior to 1995. We interpolate missing years using county-specific trends in physician counts for all years where data are available.

[5] To determine the state average premium/physician, we average the firm level premia for each MLM specialty in each county, multiply those averages by the number of physicians in that county*specialty, sum these weighted amounts across all counties in a state, and divide by the number of physicians in the state in the three MLM specialties combined. To determine the state average (payout plus defense cost)/physician, we sum payouts from NPDB and defense costs from NAIC and divide by the number of non-federal physicians. This creates a state-level

Premium/Cost Ratio over four three-year periods – 1992-1994, 1999-2001, 2007-2009, and 2015-2017. We group states by their tort reform status. During the first two periods, the national average is around 2.8. The ratio is somewhat higher in the Old-Cap states than in the other three state groups.

A ratio well above one is expected, for two principal reasons. First, payouts and defense costs represent only part, albeit a large part, of insurer cost. As mentioned above, our cost measure omits insurer administrative costs that the company does not allocate to particular claims. Second, two of the three specialties covered by MLM (general surgery and ob-gyn) are relatively high-risk, and the third (internal medicine) has roughly average risk (Jena et al., 2011; Studdert et al., 2016). Thus, we expect that premia averaged across these three specialties will exceed the average across all specialties. Payout and defense cost, in contrast, are averaged across all specialties. Thus, the observed Premium/Cost Ratio will exceed the average ratio across all specialties.

Several features of the columns in Table 1 for 2005-2007 and 2015-2017 are striking and provide a first look at the puzzles explored by this paper. First, the Premium/Cost Ratio is far higher in 2015-2017 than in 1999-2001 in almost all states. The national average, after remaining roughly stable at around 2.8 during the 1990s, rose to 5.43 in 2005-2007 and 5.75 over 2015-2017. It is difficult to explain both the 1990s levels and the more recent levels as consistent with competitive pricing in both periods. For the cost component we do not measure, insurer administrative cost, we know of no reason to believe that insurers nationwide became dramatically less efficient in processing claims over this period. And other evidence indicates that the period beginning around 2005 has been an extraordinarily profitable one for med mal insurers, with national combined ratios consistently below 100% and sometimes far below, and consistently favorable reserve development (e.g., Wunder and Parker, 2019).

Second, the Premium/Cost Ratio varies widely across states. Small states could have a high or low ratio in a particular year due to the presence or absence of a large paid claim or two, but this cannot explain why, for example, this ratio for 2015-2017 is around 4 in New York and California, 9 in Ohio, 11 in Michigan, and 12 in Texas – all large states. It is hard to explain

ratio. To obtain a national average premium/cost ratio, we weight the state ratios by the number of (ob-gyns + internists + general surgeons) in each state.

these large variations as consistent with plausibly competitive markets; we ourselves have no explanation to offer. Variation across states in administrative costs can provide, at most, a partial explanation.

Third, the change in this ratio from 1999-2001 to 2015-2017 also varies widely across states. For example, there is a 24% increase in California (3.61 to 4.47), a 38% increase in Michigan (8.05 to 11.12), a 74% increase in New York (2.39 to 4.15), a 287% increase in Ohio (2.28 to 8.82), and a 396% increase in Texas (2.48 to 12.29). Even if state-specific factors can somehow explain the large variation across states in the Premium/Cost Ratio, they cannot easily explain the large variation in how this ratio changes across time.

Fourth, both the Premium/Cost Ratio and the percentage change in the ratio from 1999-2001 to 2015-2017 vary substantially across the four groups of states. In 1999-2001, the New-Cap States had an average ratio of 2.73, in-between the 2.30 average for the No-Cap States and the 3.61 average for the Old-Cap States. By 2015-2017, in contrast, the average ratio in the New-Cap States had risen by 211% to 8.49; far more than the 63% rise in the Old-Cap States (to an average of 5.90) or the 98% rise in the No-Cap States (to 4.56). Thus, damage cap status, and damage cap adoption, appear to capture something important about med mal insurance pricing that is not captured by costs. States with damage caps have higher ratios than states without caps. Moreover, cap adoption, in the New-Cap States, predicts a surge in this ratio. Here too, we can think of no plausible explanation that is consistent with reasonably competitive markets.

Table 2 shows an array of summary statistics for our data. Dollar amounts are adjusted for inflation and are reported in 2016 dollars. The panel is somewhat unbalanced for state*year observations because MLM lacks data for all states in its early years of publication; it is also unbalanced for county*firm*year observations because of insurer entries, mergers, and closures during the sample period. Panel A shows means and standard deviations for our dependent and independent variables. The top rows report premia by specialty. Ob-gyns pay the highest average premia, followed by general surgeons and internists. The overall average premium is $33,079 and the average Premium/Cost Ratio is 5.03.

The next set of rows report per-physician values for payout, defense cost, and direct cost (the sum of payout and defense cost), the Premium/Cost Ratio, and whether a damage cap exists. This data comes from NPDB and NAIC and is available at the state*year level. About half of the state*year observations in our sample have a damage cap in place ("Damage Cap Exists").[6] There is enough variation over time in which states have caps to let us study the association among damage caps, premia, and costs in a panel data framework with firm*county*specialty FE.[7] The final rows report data for Group Premium for firms that belong to a multistate group, Competitor Premium, and the number of insurers with prices reported in MLM at the county*year*firm level ("Number of Firms").

Table 2, Panel B reports simple correlations between variables at the firm*state*year level. These correlations illustrate several of the puzzles that we explore in this paper. Payout, defense cost, and direct cost per physician all correlate positively and strongly, with an 0.888 correlation between payout and direct cost per physician. Premia, however, correlate surprisingly weakly with all three cost measures. The correlation between premia and direct cost/physician is only 0.357. Premia also correlate positively with damage caps (r = .084), even though damage caps predict lower payouts (r = -0.176 for damage cap existence vs. direct cost/physician). If we divide direct cost into payout and defense cost, damage caps are strongly associated with lower payout/physician (r = -0.236), but only weakly with defense cost/physician (r = -0.028). The positive correlation between premia and cap existence conflicts with the Kilgore, Morrissey and Nelson finding that damage caps predict lower premia over 1991-2004 and with the evidence in Paik, Black, and Hyman (2013b) that damage caps predict sharply lower payouts, as long as one allows for the cap effect to phase-in over several years as pre-cap cases are resolved.

In contrast to their weak correlations with cost, premia correlate very strongly with Competitor Premia (r = 0.867) and to a lesser degree with the rates charged by other firms in the same group in other states (r = 0.341). It is not surprising for competitor prices to be strongly correlated; basic market theory predicts a strong correlation in competitive markets. But market theory also predicts that prices should correlate strongly with costs for all competitors. That is not observed. Instead, med mal insurers seem to charge premia that correlate much more strongly with what their competitors charge than with their own costs.

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6 We define Damage Cap Exists =1 if a damage cap is in place in a state for part or all of a year (thus including the year of damage cap adoption).

7 State*year premia are calculated by taking the average of county*specialty*year premia, where county*specialty*year premia are weighted by the number of physicians in the given county*specialty*year.

The correlation between local and group premia could arise if a parent group uses similar actuarial assumptions across group firms, or uses similar reinsurance strategies. This correlation could also reflect non-price features or other market segmentation strategies that are similar within group but differ across groups.

In Panel C, we explore further the puzzle of low correlation between premia and cost per physician, by reporting correlations between premia, the cost measures and damage cap existence at the state*year level, including up to six lags and three leads of each of the explanatory variables.[8] This table contains some additional puzzles. Premia should correlate more strongly with recent costs than with distant past costs. Yet the correlation between premia and cost rises as one lags direct cost/physician; rising from 0.377 (contemporaneous) to 0.560 (with 6 lags). The weaker correlation of premia with leads of the cost variables than with contemporaneous cost provide are evidence that the weak contemporaneous correlation does not reflect insurers setting premia based on private information about expected future costs.

In Panel D, we report partial correlations for the same explanatory variables as in Panel C. In each column, we first regress premia on other explanatory variables and determine the residual premium. For direct cost/physician, payout/physician, and defense cost/physician, the other explanatory variables included in the regression are the other four variables from Panel B (Damage Cap Exists, Competitor Premium, Group Premium, and No. of Firms). For Damage Cap Exists, the other explanatory variables in the regression are direct cost/physician plus the other three of these four variables. The table shows the correlation between the residual premium and the predictor variable, again allowing for up to 6 lags. Relative to Panel C, we drop the leads which are small and insignificant in all cases. For all three cost measures , past costs correlate more strongly with residual premia than current costs. Thus, using the residual premium rather than the total premium does not resolve the puzzle of why premia correlate more strongly with past costs than with current costs.

One might expect recent past costs to predict current costs more strongly than more distant past costs. We confirm that expectation in Panel E, by correlating the three cost measures with lags of these measures. The longer the lag, the weaker the correlation between current and past

[8] Note that Panel C reports correlations at the state*year level (averaged across firm*state*year observations), so the contemporaneous correlations differ somewhat from Panel B, which uses firm*state*year observations. We roll up to the state*year level in Panel C because otherwise we would lose observations unless the same firm is observed for 10 consecutive years, which would substantially reduce usable sample size.

cost. This further reinforces the puzzle of why more distant past costs are stronger predictors of premia, even though they are weaker predictors of current cost.

In Panel F, we switch from raw to logged costs, and examine how well logged past costs do at predicting logged current costs. The interpretation of column (1) is that a 1% increase in last year's direct cost per physician predicts an 0.77% increase in current year direct cost per physician. The interpretation of column (2) is that a 1% increase in direct cost per physician, sustained over the last six years, predicts an 0.94% increase in current year direct cost. The interpretation is similar for the other cost measures. Panel F confirms that past cost is a strong predictor of current cost, and that more recent past costs are better predictors than lagged past costs. The puzzle remains: why do distant past costs predict current premia more strongly than more recent costs? And given that recent past costs do well at predicting current costs, why do they not do similarly well at predicting current premia?

4. Graphical Evidence

We turn in this section to graphical evidence, which deepens the puzzles suggested by the summary statistics discussed above. For simplicity, we refer below to direct cost per physician simply as "cost." Figure 1 shows graphs of national average cost, weighted by the number of physicians in each state (multiplied by 3 for the graphical presentation) and average MLM premia across our three specialties, weighted by the number of physicians in each specialty in each county) over our sample period. Panel A shows levels; Panel B shows first differences; Panel C shows the Premium/Cost Ratio; Panel D shows the relationship between defense costs and payouts.

In a competitive market, costs and premia should move in parallel (perhaps with a modest lag between costs and premia). In fact, costs and premia move roughly in parallel both over the "Early Period" of 1992-2000 (a period when cost/physician is gradually rising) and the "Late Period" of 2006-2017 (when cost/physician is falling). But in the "Middle Period" of 2001-2005, the two series depart greatly. By 2005, average premia were close to double the 2000 level ($45,000 in 2005 versus $23,600 in 2000), before beginning to fall in parallel with the continued fall in costs. The sharp rise in premia cannot be explained by the much more modest rise in cost, which rises gradually but moderately over 1998-2003, before beginning to fall.

Can the rise in premia be due to insurers expecting soaring costs, even if that expectation turned out not to be true? This explanation will not work, for several reasons. First, premiums continued to rise strongly in 2004 and 2005, even though insurer costs were falling. Second, the largest component of cost is payout. If claim rates fall, payouts should follow, with a lag between when claims are filed and when they are paid. Paik et al. (2013a) provide evidence that claim rates per physician, began to fall starting in 1999 measured based on when plaintiff injuries occur, and in 2001 based on when lawsuits were filed. These declining claim rates gave insurers reason to expect costs to decline with a lag. And indeed, costs began to fall in 2004. Third, in Table 2, Panel C, there is no evidence that insurers' private information about claims that have been made but not yet resolved is an important factor in setting premia. Future costs predict current premia less well than contemporaneous or lagged costs.

Consistent with prior work (e.g., Black et al., 2005), we find no evidence for a cost trigger that could explain the rapid rise in premia over 2000-2005. Average premia fell slightly in 1997 and 1998, and fell sharply in 1999 (see Panel B). This suggests that at the typical Premium/Cost Ratio of around 3 which prevailed during the 1990s, insurers were not facing strong cost-driven pressure on profitability.

The rapid rise in premia over 2000-2005 produced a dramatic increase in the Premium/Cost Ratio. In Figure 1, Panel C the national Premium/Cost Ratio is fairly stable over 1992-2000 and is 2.71 in 2000. It then soars to 5.04 in 2005 and continues to climb thereafter, setting in a narrow band between 5.76 and 6.07 over 2009-2017. There is no evidence that the Premium/Cost Ratio in the later part of the sample period returned towards the ratios that were typical in the 1990s. This pattern provides evidence that factors other than loss experience and cost containment expenditures can have a first-order effect on premia.

In Figure 1, Panel D, we examine time trends in the ratio of defense costs to payouts, to assess the potential role of rising defense costs in driving total insurer costs. The ratio of defense costs to payouts rises slowly throughout the sample period. During the period when the Premium/Cost Ratio is sharply increasing in the early 2000s, defense costs rise somewhat relative to payouts, but fall back into line with the long term trend by 2007. We thus do not find evidence for a sharp change in defense costs, in a magnitude that could explain the sharp increase in the Premium/Cost Ratio in the early 2000s.[9]

In Figure 2, we further explore the relationship between premia and costs by showing separate graphs for the four sets of states: No-Cap; Old-Cap; New-Cap; and Other States. Our discussion focuses on the first three groups. The panels of Figure 2 show the same premium and 3*cost lines as in Figure 1, Panel A. All four groups show a strong rise in premia over 2000-2005, but with important differences across groups. Consider first the Early Period (1992-1999). In the No-Cap States, the 3*cost/physician line sits somewhat above the Premium line in most years, reflecting an average ratio somewhat below 3. In the late 1990s, premia/physician does not keep pace with gradually rising cost/physician; the Premium/Cost Ratio thus falls. Insurers in these states caught up in the early 2000s, and emerged from this period with an average premiums/cost ratio of around 4 (see Table 1).

The New-Cap States show a time pattern ratio similar to the Old-Cap States over 1996-2000; they experience gradually rising cost/physician and flatter premia, yielding a gradually falling ratio. These states experience a much greater rise in premia than the other groups, leading to a Premium/Cost Ratio of around 9 over 2007-2009 (see Table 1).

In Old-Cap States, there is less evidence for rising costs in the late 1990s (plausibly reflecting the effects of the caps in constraining costs). The premium/physician line lies slightly above the cost/physician line, indicating a Premium/Cost Ratio between 3 and 4; both cost and premia are roughly flat during this period. Premia in these states rise sharply in the early 2000s, leaving to an average Premium/Cost Ratio of 6 or so over 2007-2009.

Comparing No-Cap and Old-Cap states, insurers charge similar premia in both state groups, despite substantially higher cost/physician in the No-Cap States (consistent with damage caps limiting costs).

During the period from 2006-2017, time patterns are again different for the three groups of states. In No-Cap States, premia are flat through 2013 while costs decline, leading to a rising Premium/Cost Ratio. In contrast, in Old-Cap States, premia and costs decline at similar rates;

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[9] Our measure of payouts is actual payouts in closed cases, reported to NPDB. In contrast, our measure of defense costs reflects both actual costs for services already incurred and insurer expectations about future costs. The rise in the ratio of defense costs to payouts in the hard market of the early 2000s, before reverting to trend, could partly reflect the tendency for insurers' predictions about the future to become more pessimistic in hard markets, and more optimistic in soft markets, rather than changes in actual costs (Baker, 2005).

the Premium/Cost Ratio has no particular trend. In New-Cap States, premiums and costs both decline, but cost drop more sharply through 2012.

We would expect competitive markets to generate roughly similar Premium/Cost Ratios across states. This was roughly true in the 1990s, but is manifestly not true thereafter across these three groups of states. Figure 3 presents the average Premium/Cost Ratio over time for the No-Cap, Old-Cap, and New-Cap states. From 1992-2001, the three groups have broadly similar ratios, but these ratios diverge strongly after that. The Premium/Cost Ratio for New Cap States is generally between those for Old-Cap and No Cap states until the cap adoption period of 2002-2005, but then soars and by 2007 is well above the ratios for the other groups. This ratio peaked at 11.5 in 2012, and has been above 8 since 2007. Over 2000-2017, average premia in New-Cap States rose 19%, from $29,000 to $34,000, even though 3*cost fell over this period by 63%, from $35,000 to $13,000. The damage caps adopted by these states sharply reduced insurer costs, without a corresponding fall in premia paid by physicians, even on a lagged basis. As we discuss above, Table 1 shows that there is also large state-level variation in this ratio within each group of states.

5. Empirical Models

We use both panel data and DiD models to evaluate the predictors of med mal premia. Our fixed effects specification is:

$$y_{i,c,s,t} = \alpha + \sum_{m=1}^{4} \left(\gamma_{t-m} * x_{i,c,t-m}\right) + \delta_{i,c,s} + \theta_t + \varepsilon_{i,c,s,t} \quad (1)$$

where $y_{i,c,s,t}$ is the outcome for firm i in county c for physicians in specialty s in year t, $x_{i,t-m}$ are lagged values of covariates with m indicating the number of lags, $\delta_{i,c,s}$ are firm*county*specialty fixed effects,[10] θ_t are year fixed effects, and $\varepsilon_{i,c,s,t}$ is an error term. The firm*county*specialty FE will control for unobserved county*specialty effects that may affect the outcome and allow these effects to differ by firm. The year FE will control for national trends in the outcome. The outcomes we study are premia, the three cost measures, and Premium/Cost Ratio. Our covariates are cost per physician; Competitor Premium as a measure of competitive pressures; Group Premium to assess potential cross-state pricing factors; Damage

[10] Danzon, Epstein, and Johnston (2004) note that there is substantial heterogeneity in the nature of med mal insurers, including large national firms, smaller firms, and in many states, physician-owned mutual insurance companies.

Cap Exists, to measure how caps affect premia and costs; and Number of Firms to assess the effects of competitive pressure. We cluster standard errors at the state level.

We use lagged values of covariates to study the time structure of insurer responses to potential determinants of malpractice premia.[11] We use the natural logarithm of all variables so that our coefficient estimates represent elasticities, except for Number of Firms and Damage Cap Exists. Given the fixed effects included in the model, the effect of Damage Cap Exists on outcomes is identified by state adoption or repeal of caps, and the effect of Number of Firms on outcomes is identified by firm entry and exit, which in practice occurs principally at the state level.

For purposes of studying cap adoption, equation (1), with its extensive FE, is similar to an explicit DiD design if cap adoption is exogenous to the state med mal environment. We also estimate DiD models that let us examine, for the New Cap States, how the effects of damage cap adoption change over time since adoption. Our DiD model is specified in event time relative to each state's cap adoption year, which we denote as year 0:

$$y_{i,c,s,t} = \alpha + \sum_{k=-m_0}^{m_1}\left(\beta^k * D_{c,t}^k\right) + \gamma * x_{i,c,t} + \delta_{i,c,s} + \theta_t + \varepsilon_{i,c,s,t} \qquad (2)$$

where $D_{c,t}^k$ is a dummy variable equal to 1 if a county c is located in a state that adopted a damage cap k years ago in year t. The first dummy $k = -m_0$ also captures the treatment effect of years before m_0 and the last dummy $k = +m_1$ captures the effect in years after m_1; we set $m_0 = m_1 = 5$. Model (2) is sometimes called a "leads and lags" specification; it lets us examine graphically whether pre-treatment trends are parallel as well as how the treatment effect evolves over time following cap adoption. All other variables are as defined above.

Similarly, our distributed lag specification is:

$$y_{i,c,s,t} = \alpha + \sum_{j=1}^{n}\left(\beta^j * D_{c,t}^{j-lag}\right) + \gamma * x_{i,c,t} + \delta_{i,c,s} + \theta_t + \varepsilon_{i,c,s,t} \qquad (3)$$

where $D_{c,t}^{j-lag}$ is a dummy variable equal to 1 if county c is located in a state that adopted a damage cap at least j years ago in year t and we include n lags in the model.[12] For example, $D_{c,t}^{1-lag}$ is a dummy variable equal to 1 starting in the year after the year of cap adoption, $D_{c,t}^{2-lag}$

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[11] We tested including up to 7 lags of both the dependent variable (as additional predictors) and the independent variables in both fixed effect and first difference specifications, but find that explanatory variables more than 4 years old have little effect on current premia. We found no evidence of predictive power for leads of the independent variables.

[12] We include individual dummy variables for years 1 through 5 after cap adoption, plus a single dummy variable for years 6 through 10 that reflects the average yearly marginal effect over this period.

is equal to 1 starting 2 years after the year of cap adoption, *et cetera*. In equation (3), the β^j coefficients are estimates of the marginal effect of cap adoption on the outcome of interest in each additional post-adoption year, while in equation (2), the β^k coefficients are estimates of the total effect of cap adoption on the outcome of interest in each post-adoption year. One sums the coefficients on the lags to estimate an overall treatment effect.

Recent research shows that standard DiD models with period and unit fixed effects (i.e., two-way fixed effects) can generate unreliable estimates when there are multiple treated units, treated at different times. For example, De Chaisemartin and d'Haultfoeuille (2021) and Goodman-Bacon (2021) show that, with multiple treated units and treatment effects that vary with time since treatment, estimates using the two-way fixed effects model are weighted averages of the average treatment effect for each treated unit. We expect the potential bias from the two-way fixed effects model to be small in our setting, because we study cap adoptions in 2002-2005, a relatively short period relative to our overall study period, which includes a long time period both pre- and post-adoption. To the extent that the effect of a damage cap emerges gradually over time, as we find in the distributed lag results, the expected bias would be against finding an effect of damage caps on premia or cost. Nonetheless, in robustness checks, we implement one of the new methods that address this potential bias, the FECT (fixed effects counterfactual) approach of Liu, Wang, and Xu (2022), and find results consistent with our main specification.

6. Regression Results

6.1 Premium Estimates

Table 3, Panel A reports results from the FE model in equation (1). We lag cost per physician by one year, so that this variable represents the most recent information that insurers will have in setting rates for a given year, which they do prospectively, usually in the summer or fall of the prior year.[13] We choose not to lag competitor premia; this assumes that insurers set their own premia for a given year knowing their competitors' premia for that year, at least approximately. Panel A shows the predictive effects for premia of lagged cost/physician, competitor premium, group premium, and Damage Cap Exists. In column (1), the coefficient on lagged cost/physician

[13] The annual Medical Liability Monitor issue, reporting next year's rates, is published each year in October.

is surprisingly modest, at 0.170, implying that a $1 change in last year's cost predicts only a $0.17 change in this year's premium. Our prior was that, with our fixed effects, the insurer's own prior-year costs should predict premia with an elasticity near one. In column (2), competitor premia are more strongly predictive of a firm's own premia, with an elasticity of 0.446. A positive elasticity is expected and could arise from two sources: insurers observe each others' prices and compete on price, and all insurers observe payouts and defense costs and adjust their prices to reflect these costs. However, the 0.446 elasticity on competitor premia, which is much larger than the 0.170 elasticity on prior-year cost, implies that insurers pay significant attention to each other's prices in setting their own premia, independent of their own costs. In column (3), the coefficient on group premium is small and insignificant, suggesting that parent insurers set premia in each state largely independently of the contemporaneous premia they charge in other states.

In column (4), the coefficient on cap adoption is positive (opposite from predicted), although insignificant. This is a major surprise. Damage caps predict are known to predict lower payout per claim and lower claim rates (Paik et al, 2013b). We confirm this finding below. Thus, damage caps should predict lower payouts, lower defense costs (since the insurer must defend against fewer, lower-valued claims), and thus lower cost/physician.

We saw in Table 2 that the predictor variables have lagged effects on premia. Also, prior research provides evidence that newly adopted damage caps will affect future costs with a lag, because cases filed before the cap was adopted are typically exempt from the cap and it can take some years for most pre-cap cases to be closed (Paik et al., 2013b). We therefore run separate models in which we include the first four lags of each variable. We report the sum of the direct and lagged coefficients in a separate row in Table 3 and full regression results in the Appendix. When we add lags, the responsiveness of premia to changes in cost/physician increases but remains well below 1: a 1% change in cost/physician predicts an 0.397% change in premia. A 1% change in competitor premia predicts an 0.386% change in an insurer's own premium, close to the contemporaneous correlation. Long-term increases in the premia charged by out-of-state members of the same parent insurance group predict lower long-term in-state premia, consistent with cross-subsidization of firms within groups over time, in contrast to the near-zero same-year correlation we found in regression (3). The long-run elasticity of premia with cap adoption is 0.05 (insignificant), but remains positive, when we would expect it to be strongly negative.

Columns (5) and (6) of Table 3 combine predictor variables in a single regression, to allow for possible collinearity in these variables. Column (5) includes cost/physician, competitor premia, and group premia. Competitor premia remains a strong predictor of a firm's malpractice premium with a point estimate close to its value when used alone in column (1). However, the elasticity of premia with respect to cost/physician weakens substantially and loses statistical significance in the multivariate regression. This is consistent with insurers reacting more strongly to what their competitors charge than to their own actual costs. There is little change in the coefficient on group premia.

In column (6), we study cost/physician and Damage Cap Exists together. On theoretical grounds, we expect damage caps to reduce cost/physician and to affect premia primarily indirectly through their effect on cost/physician. Thus, including them together in the same regression should lead to the Damage Cap Exists variable capturing some of the effect of cost/physician, and thus to a lower coefficient on cost/physician relative to studying cost/physician alone as in column (1). Contrary to this expectation, the predictive power of lagged cost strengthens somewhat when Damage Cap Exists is included. Meanwhile, the coefficient on Damage Cap Exists remains positive (opposite from predicted) and strengthens to marginal significance, when controlling for cost/physician.

The regression model for Panel A includes both year and firm*county*specialty fixed effects, which absorb much of the variation in premia. We therefore also report, in the bottom rows, adjusted R^2 using only these fixed effects, and adjusted R2 after adding the predictor variable(s). Column (1) indicates that including cost per physician increases adjusted R^2 only slightly, from 0.948 to 0.950. In contrast, in column (2), competitor premia explain approximately 17% of the variance in premia left over after including fixed effects, increasing the adjusted R^2 from 0.948 to 0.957. Including group premia or cap adoption does not change adjusted R^2 at all (to three decimal places) in columns (3)-(4). A similar pattern appears in the multivariate regressions in columns (5)-(6). These results provide additional evidence on the importance of competitor premium as a predictor of premia variable compared to the others that we include, especially cost/physician.

In Table 3, Panel B, we explore further the unexpected positive coefficient on Damage Cap Exists in Panel A by using Damage Cap Exists to predict cost/physician and its components, payout and defense cost. We estimate three regressions for each cost measure of cost. In columns (1), (4), and (7), we use only a contemporaneous measure of cap adoption. Damage Cap Exists predicts sharply lower cost across all three measures, with a somewhat larger drop in payout than in defense cost. The -0.531 coefficient in column (1) implies 41% lower cost/physician. In columns (2), (5), and (8), we include the first four lags of Damage Cap Exists, and report the sum of the lagged effects as a separate row in the table. The coefficients on the lags of Damage Cap Exists are uniformly positive, and provide evidence that the effect of a damage cap on cost increases over time after adoption. In column (2), the -0.758 sum of coefficients indicates that including lags, cap adoption predicts a 53% drop in cost/physician. These estimates of a large effect of caps on payouts are consistent with prior work (Paik et al., 2013b) and deepen the puzzle from Panel A of the positive coefficient on Damage Cap Exists in predicting premia. In columns (3), (6), and (9), we include lags of the dependent cost variable along with contemporaneous cap adoption as predictors. Cap adoption continues to predict lower costs, even after controlling for past cost, which ought to capture much of the impact of damage caps on cost. The negative coefficient on cap adoption can be seen as akin to a one-time level shift in the time series of costs, even after controlling for past costs.

6.2 Premium/Cost Ratio Estimates

In Table 4, we use the same predictor variables as in Table 3, Panel A, but switch to the Premium/Cost Ratio (measured in logs) as the dependent variable. This ratio should be a proxy for profitability. As in Table 3, we show the sum of the first four lags in a separate table row. In column (1), higher cost per physician predicts a lower Premium/Cost Ratio. This result strengthens in column (5) where we also control for competitor and group premia. This is not expected in a fully competitive market, in which all insurers should be price takers. The negative coefficient on ln(cost/physician) implies that insurers' ability to charge high prices (a high Premium/Cost Ratio) is reduced in markets where costs are high. This could reflect greater customer resistance to higher prices.

In column (2), competitor premium is a strong predictor of the Premium/Cost Ratio, which one also would not expect in a fully competitive market. This suggests imperfect competition, in which insurers can charge higher premia relative to costs (thus earning higher profits), as long as their competitors do likewise.

Similar to Table 3, the contemporaneous coefficient on group premium is small and insignificant, but becomes strongly negative if we include lags, suggesting cross-subsidization.

The most interesting result from Table 4 is that Damage Cap Exists strongly predicts higher Premium/Cost Ratio, with similar strength whether we do not (column (4)), or do (column (6)) control for cost/physician. In column (4), cap adoption predicts a 46% higher Premium/Cost Ratio, which rises to 58% if we allow for lagged effects. Insurer profitability appears to be much higher in states that adopt damage caps. Yet in a fully competitive market, cap adoption should affect premia only through its effect on cost and should not significantly affect the Premium/Cost Ratio. We thus find strong evidence that insurers, through their collective pricing decisions, are able to earn large excess profits in states that adopt damage caps. These profits are not competed away even over the substantial post-cap adoption time period available in this study.

Recall that with the Damage Cap Exists variable, we effectively study states that adopt or rescind damage caps during our sample period because our FE absorb the effects of caps that were in effect throughout the sample period. The result for cap adoption from our specification can be given a causal interpretation if cap adoption is exogenous. We explore whether that assumption is reasonable in the next section, using an explicit DiD specification.

6.3. DiD Results

We next turn to an DiD approach in which we assess the effect of cap adoption on the Premium/Cost Ratio in New-Cap States. For this approach, we consider the treated states to be the New-Cap states listed in Table 1, plus Georgia and Illinois for the period through 2009. Georgia and Illinois adopted caps in 2005 but their caps were judicially invalidated in 2010. Above, we placed Georgia and Illinois in the "Other States" group. For the DiD analysis, we judged that it made more sense to consider them as treated in 2005, but remove them from the sample starting in 2010.[14] We report results in text using a "broad" control group, consisting of all Old-Cap and No-Cap states, but in the Appendix find similar results with a "narrow" control group, consisting of only No-Cap states. We conduct our analysis in event time, relative to each state's cap adoption year, and use a sample period from year -10 to +10.

6.3.1. Leads-and lags graphs

We begin with a graphical approach. We present leads-and-lags graphs in Figure 4. We normalize the treatment effect to zero in year -3, three years before adoption, and collapse years

[14] In Appendix Table A4, we report similar results when we remove Georgia and Illinois from the group of treated states.

prior to year -5 and after year +5 into the year -5 and year +5 dummy variables, respectively. A vertical line separates the pre-treatment and treatment periods. We provide annual point estimates, and small vertical lines indicate 95% confidence intervals (CIs). In Panel A, we examine ln(direct cost/physician) as the outcome. Pre-treatment trends are reasonably parallel. This provides evidence that caps do not appear to be adopted in response to rising insurer costs. After cap adoption, direct cost/physician is reasonably stable through year +2, a period dominated by older cases not subject to the cap (Paik et al., 2013b). After that, it trends strongly downward as the cap begins to affect decided cases, consistent with prior work (*id.*).

In Panel B, we study premia and find a different pattern. Pre-treatment trends for *ln*(premium) are reasonably flat through year -3. There is an uptick for future treated states in year -2, and then a much sharper relative rise in year -1, which continues through years 0 and _1, before starting to fall. This provides evidence that while cap adoptions do not appear to be caused by differential trends in insurer *costs*, they are associated with rises in *premia*. This association could well be causal. The public choice story is straightforward: med mal premia rise, physicians are unhappy and run to the legislature for relief. Physicians and insurers treat rising premia (the "smoke") as evidence of an underlying "fire" (rising med mal costs) and sometimes succeed in obtaining a damage cap despite the lack of an actual fire. Black et al. (2005) provide evidence supporting this smoke-without-fire story for Texas; we provide evidence that it holds across the New-Cap States. Relative premia do fall as one moves further into the treatment period, but only to the level of years -5 and earlier despite the sharp drop in direct cost/physician seen in Panel A.

In Panel C, we study the Premium/Cost Ratio. The flat pattern for direct cost/physician in Panel A, combined with the pre-cap-adoption rise in premia in Panel B, drive a rise in the Premium/Cost Ratio. Pre-treatment trends are reasonably flat through year -3. After that, there is an uptick in the relative ratio in year -2 and a much stronger uptick in year -1 and year 0. This is consistent with Figure 3, where the Premium/Cost Ratio rises more sharply for New Cap States over 2001-2005 than for Old-Cap and No-Cap states (the control group for the DiD regressions).

After the rise in year -1, the Premium/Cost Ratio remains reasonably stable through year +3, and then begins to rise again. The long-term relative ratio, reflected in the point estimate for year +5 (which is an average for years +5 and after) is well above the pre-cap ratio that prevailed through year -3. These results are consistent with a causal impact of cap adoption on Premium/Cost Ratio. The Premium/Cost Ratio rises for New-Cap states relative to the control states at two different times and for different reasons. The ratio rises in years -2 to 0 because relative premia rise in New-Cap States even though relative costs are flat, and then rises again starting in year +3 as relative costs fall much more sharply than relative premia.

6.3.2. Regression Evidence

We present regression evidence in Table 5. To move from this graphical evidence to regression results, we must address the apparent reverse causation in years -2 and -1, which is consistent with higher premia driving legal reform. In effect, we find evidence that the cap adoption shock is exogenous with regard to direct cost (which is what *should* be driving premia), but not exogenous to premia. We address this concern by dropping years -2, -1, and 0 from the sample. This amounts to assuming that standing in year -3, cap adoption is year 0 is exogenous, even if it is influenced by changes in premia during years -2 and -1. We also drop year 0 because companies set premia in the year before the premia are charged, so year 0 premia cannot be affected by year 0 cap adoptions.

In column (1), the estimated effect of cap adoption on ln(premium/cost) is 0.360 (43% increase), very similar to the 0.377 estimate from the panel data regression in Table 4, column (4). Column (2) presents distributed lag regression results using equation (3), with the sum of the distributed lag effects shown in the last row. The sum of the first four lags of 0.469 is similar to the sum of four lags in Table 4. The full distributed lag sum of coefficients, including additional post-cap years, is somewhat higher at 0.549 (73% increase). The distributed lag results confirm the pattern from Figure 3 of a second significant rise in the Premium/Cost Ratio beginning a few years after cap adoption, as old cases are settled but premia do not fall by enough to reflect the drop in insurer costs.

7. Additional Analyses

7.1. Competition

As discussed above, premia may have different elasticities with respect to our predictors for insurers facing different levels of competition. To address this possibility, we add an additional covariate – the number of firms offering insurance in each county*specialty*year as reported by MLM -- and present results for *ln*(premia) and *ln*(premium/cost) in Table 6. Our regression equation includes firm*county*specialty FE, so the effect of the number of competitors is identified by firm entry or exit. With both outcome variables (columns (1)-(2) and (5)-(6)), we find a positive but small coefficient on number of companies (marginally significant in col. (1)). This result could reflect firms entering/leaving markets where premia are high/low. However, when we include four lags of the number of companies, this coefficient strengthens to .08 and becomes statistically significant. In most markets, new entry should lead to lower prices at least in the medium term, but for med mal insurance, our data does not support this expectation.

In columns (3)-(4), we find that the elasticity of premia with respect to cost/physician is higher when there are more competitors, indicating greater pass-through of costs into premia when competitive pressures are greater. However, the coefficients are small: entry of one additional competitor predicts only a 0.003 increase in elasticity. The coefficients increase if we allow for four lags, but remain economically small. In columns (4) and (8), the coefficients on the interaction between cap adoption and number of firms are small but positive. Thus, new entry does not mitigate the effect of cap adoption in increasing premia and the Premium/Cost Ratio, described above.

7.2. Time Periods

Figure 1, Panels A and B shows that medical malpractice premia were stable in the 1990s, with a sharp increase in rates from 2001 to 2005 and falling rates after 2005. Given this time pattern, we examined whether the determinants of premia and the Premium/Cost Ratio might be different in different time periods. We divided the sample into an early period from 1991-2000 and a later period from 2001-2017. We present results in Table 7 using selected specifications from Table 3, Panel A for premia and Table 4 for the Premium/Cost Ratio. Alternating columns show results for the early versus later periods. Rows at the bottom of each panel show p-values for whether coefficients differ across the two periods.

Ln(cost/physician) has low power to predict premia in both periods, and indeed takes a negative but insignificant coefficient in the early period. Existence of a damage cap predicts higher Premium/Cost Ratio in both periods (Panel B) and predicts significantly higher *premia* in the 1990s (Panel A). The coefficients on damage cap exists are similar without (cols. (5)-(6)) versus with (cols. (7)-(8) controlling for *ln*(cost/physician). Overall, our puzzling results for the weak effects of cost/physician on premia and for the unexpected positive effects of damage caps on Premium/Cost Ratio are not driven by the early or the later part of our sample period. At the same time, the variation between the early and late periods supports the importance of studying the med mal insurance market of an extended time period.

7.3. Specialty-Specific Results

MLM includes separate premium data for internists, general surgeons, and obstetricians-gynecologists. Above, we pool this data across specialties. In Table 8, we report selected results by specialty for *ln*(premium) and *ln*(premium/cost). The estimated coefficients are similar to the pooled results, shown in Tables 3 and 4. Thus, no single specialty drives our main results.

7.4. Counterfactual-Based DiD Estimation

As noted above, a potential concern with our DiD analysis is that the panel DiD framework used above will: (i) assign different weights to the treatment effects for different states, because these states adopt damage caps in different years; and (ii) will use the earlier cap-adopters as, in effect, control states for the later adopters. The first concern is not a large one for us because the cap adoptions take place during a limited period, 2003-2005, near the middle of a much longer sample period. The second concern will tend to bias our results toward zero if, as we find, cap adoption effects phase in over time.

As a robustness check, reported in the Appendix, we address these concerns by using the fect.ado package developed by Liu, Wang, and Xu (2022, which uses data from firm*county*specialties in the always-control states to estimate year-by-year counterfactuals for firm*county*specialties in each treated state. This approach is not compatible with county weights and so gives more weight to rural counties, which are numerically dominant within our sample (for example, Georgia has 159 counties; Texas has 254 counties). This approach reproduces the main features of our DiD analysis, including the pre-adoption rise in premia starting in year -2, and a sustained rise in the Premium/Cost Ratio starting in year 0 that continues through year +5.

8. Discussion and Conclusion

We present here a puzzle. Using almost thirty years of data on the medical malpractice insurance market, we report evidence inconsistent with a smoothly functioning, plausibly competitive market. These include: (i) insurer direct costs are a surprisingly weak predictor of premia; (ii) caps on non-economic damages predict a substantially higher Premium/Cost Ratio even when controlling for insurer costs; (iii) competitor premia predict premia much more strongly than measures of insurer cost; (iv) insurers earn consistently high profits, proxied by the Premium/Cost Ratio, from 2005 on, relative to earlier years; (v) there are large variations in the mean Premium/Cost Ratio across states at any point in time, and within states across time; (vi) states with more competing insurers have modestly higher premia in both the near and medium term, suggesting that new entry does not drive down rates; and (vii) premia respond to predictors, including insurer direct cost, with multiyear lags (we study lags up to four years). Using a DiD framework, we find evidence that the association between cap adoption and higher Premium/Cost Ratio is causal: as caps drive down insurer costs, premia do not fall in parallel with costs, leading to rising premia/cost ratios. These persist through the end of our sample period, well over a decade after the early 2000s wave of cap adoptions. We also find evidence for reverse causality, with a rising Premium/Cost Ratio predicting cap adoption.

While we raise a puzzle, we do not solve it. It is not clear why premia and the Premium/Cost Ratio do not fully respond to changes in costs, nor why cap adoption leads to sustained supranormal profits. Future research into the determinants of medical malpractice premia is needed to better understand insurance market dynamics and why the med mal insurance market behaves so strangely.

We close with a speculation as to why competitive pressures appear to be so weak, and operate so slowly. Perhaps, when premia are flat and even more so if they are declining as was the case for 2005 on, physicians are reasonably content and do not often price shop. This lets insurers charge premia, and change their premia, based largely on what their competitors charge, without losing many customers. Their prices are public, which facilitates this approach. We cannot test this speculation with our data.

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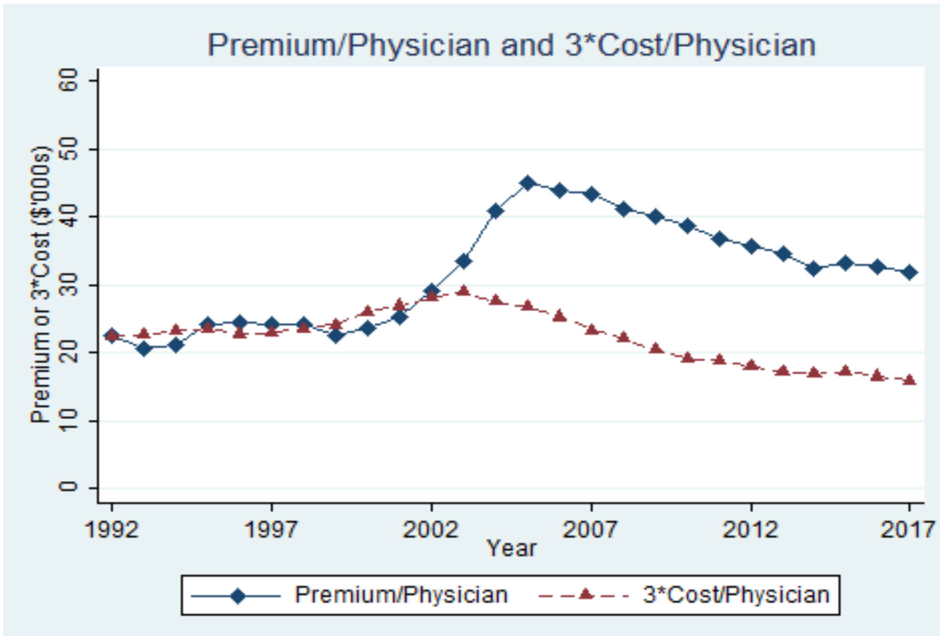
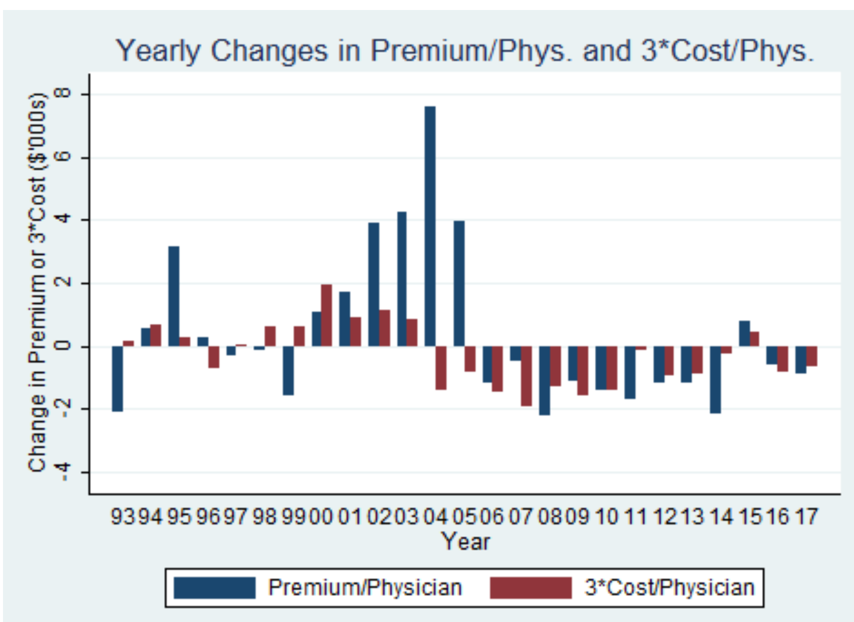
Figure 1: National Trends in Med Mal Premia and Cost/Physician

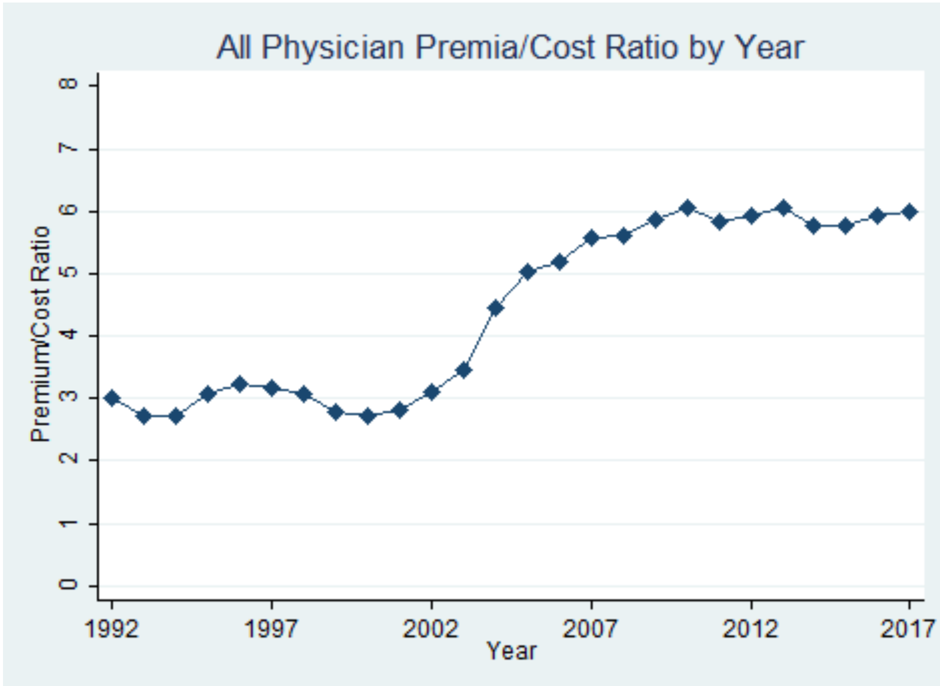
Panel A: National Premium/Physician and Cost/Physician. Figure shows national average premium/physician (solid blue line) and 3* national average cost/physician (dashed red line) over 1992-2017. Premium/physician is average premium for the three MLM specialties in each county, weighted by the number of non-federal physicians in each specialty in that county. Cost per physician is total payments in NPDB plus total defense costs for insurers in NAIC divided by the number of non-federal physicians in the state. Amounts in 2016 $ thousands. Cost per physician is multiplied by 3.



Panel B: Changes in National Premium/Physician and Cost/Physician. Panel shows yearly changes (in $'000's) in premium/physician (solid blue bars) and 3*cost/physician (hatched red bars).



Panel C: National Premium/Cost Ratio. Figure shows annual national average premium/physician, divided by national average cost/physician.



Panel D: Ratio of Defense Cost to Payout. Figure shows national average defense cost/physician divided by national average payout/physician and linear trend line from regressing this ratio on year. Payout and defense cost are at the state level and are weighted by the number of non-federal physicians in the three MLM specialties in each state.

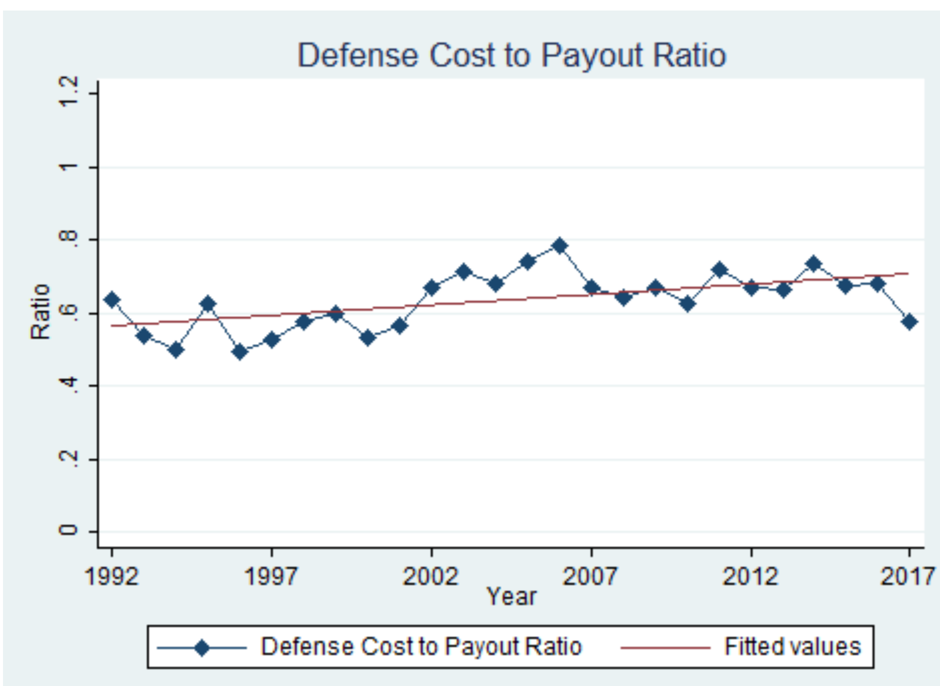
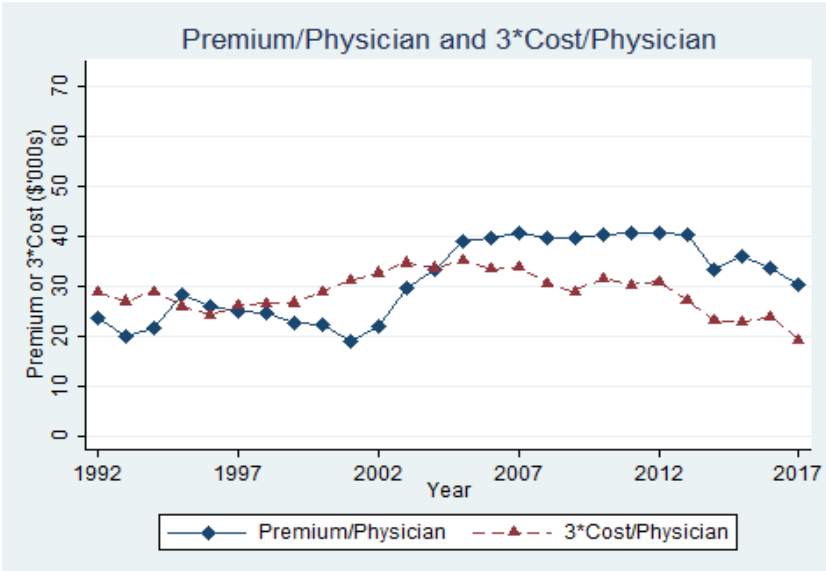


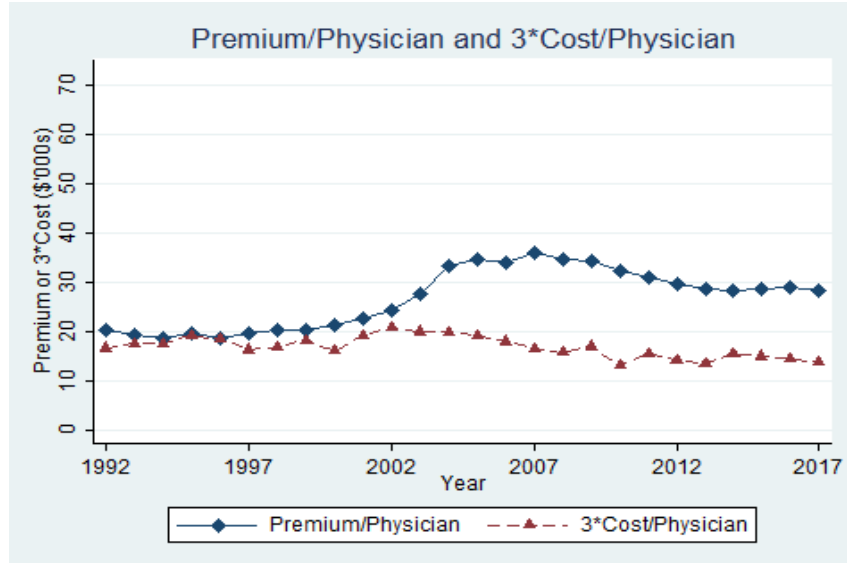
Figure 2: Trends in Med Mal Premia and Cost/Physician by State Damage Cap Status

Same as Figure 1, except separate graphs for No-Cap, Old-Cap, New-Cap, and Other-Cap states.

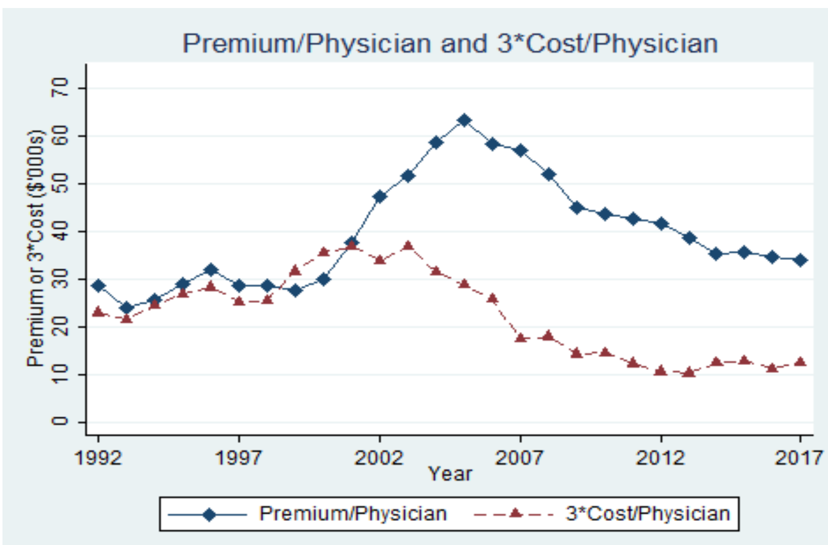
Panel A: No Cap States



Panel B: Old Cap States



Panel C: New Cap States



Panel D: Other Cap States

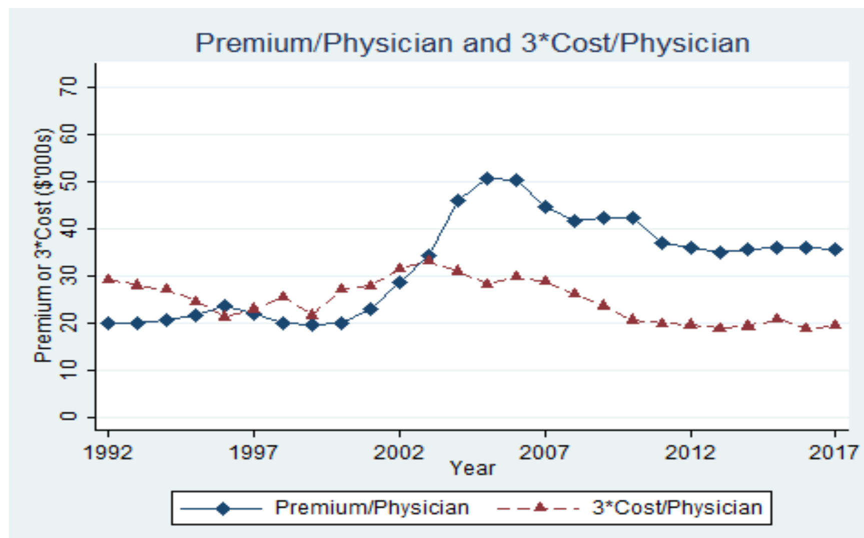


Figure 3: Trends in Premium/Cost Ratio by State Damage Cap Status

Graph is based on Figure 2, and reports the ratio of premium per physician to cost per physician, separately for No-Cap, Old-Cap, and New-Cap states. Ratios are weighted by number of physicians in the three MLM specialties. Vertical lines indicate the start and end of the cap adoption period for the New-Cap States.

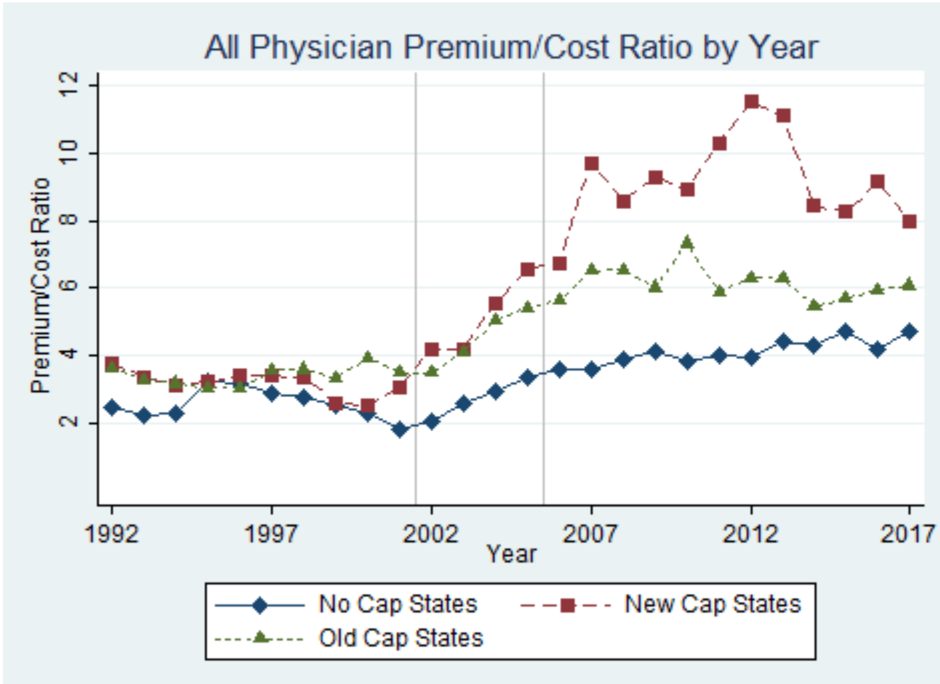
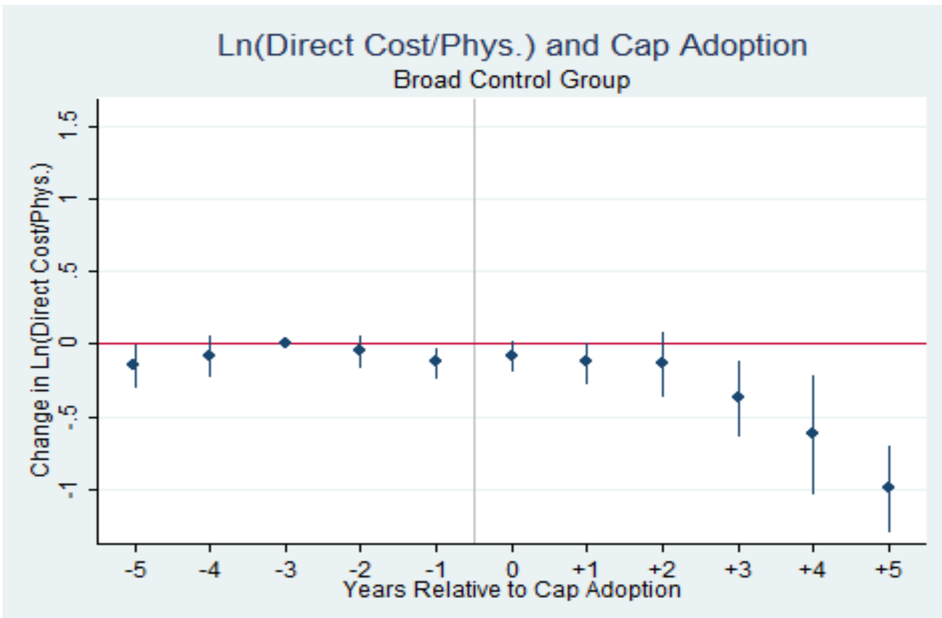


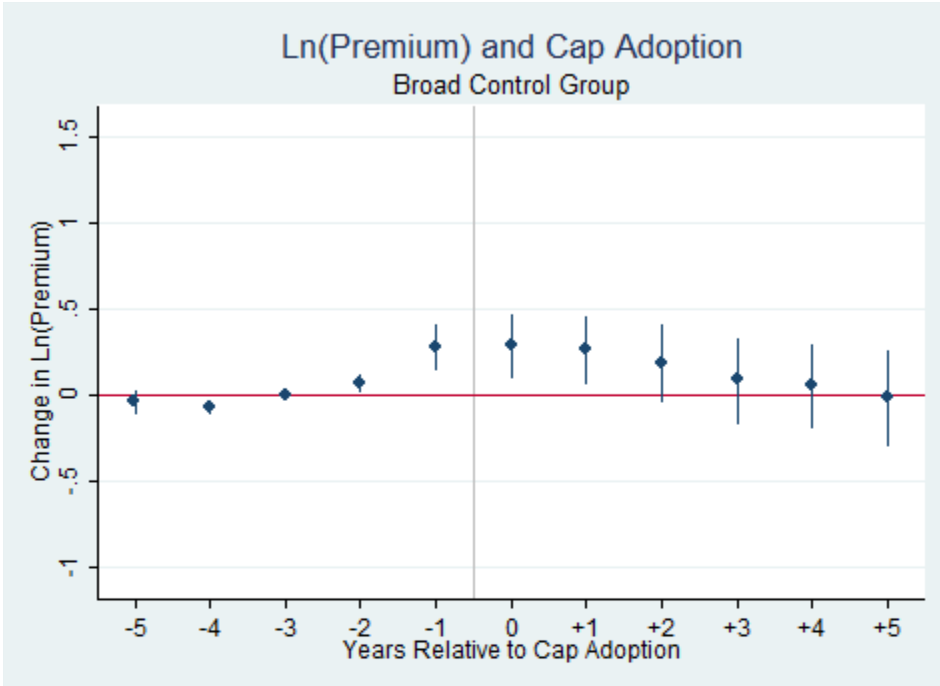
Figure 4: DiD Leads-and-Lags Analysis: Premia, Costs, and Cap Adoption

Dots indicate coefficients from a regression including dummies for leads and lags of cap adoption in New-Cap states (plus Georgia and Illinois during 2005-2009, when these states had caps in effect) relative to broad control group (No-Cap and Old-Cap states). Vertical lines indicate the start of the cap adoption period. **Panel A:** Dependent variable is direct cost per physician. Regression includes state FE. **Panel B:** Dependent variable is premium. Regression includes firm*county*specialty FE. **Panel C:** Dependent variable is premium/cost ratio. Regression includes firm*county*specialty FE. **All panels:** Regressions include year FE. Standard errors (s.e.'s) are clustered on state. Coefficient and s.e. shown for year -5 are averages over years (-10, -5), and for year +5 are averages for years (+5, +10). Vertical lines indicate 95% confidence intervals.

Panel A: Direct Cost per Physician



Panel B: Med Mal Premia



Panel C: Premium/Cost Ratio

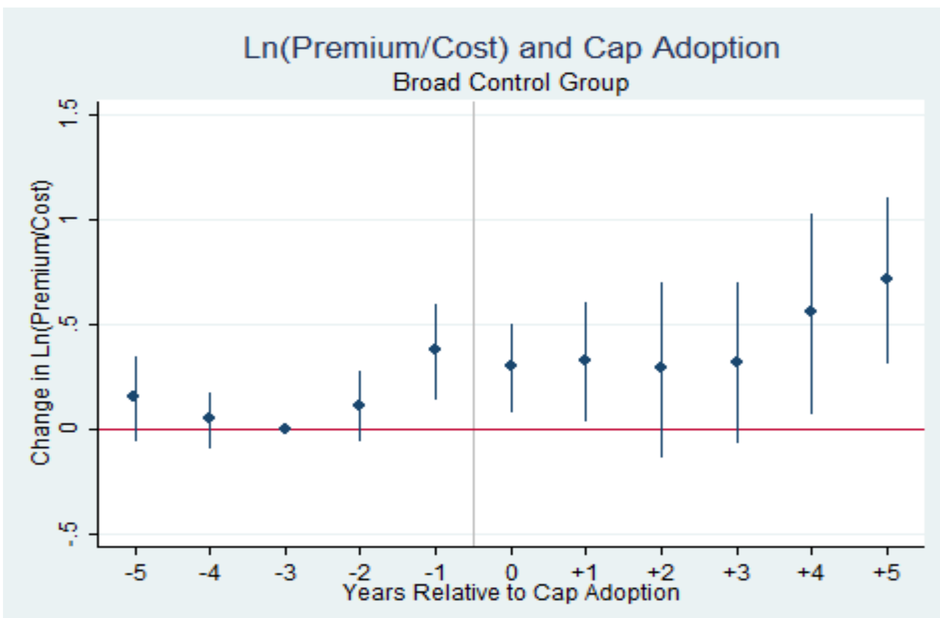


Table 1. Reform Status and Premium/Payout Ratios by State

Table shows damage cap status of each state, and ratio of average premium/physician to average cost/physician (terms are defined in Figure 1) in 1999-2001, 2007-2009, and 2015-2017. Average for each group of states is weighted by number of active non-federal physicians in the three MLM specialties in each state. Amounts in 2016 $ millions. * indicates 8 states with patient compensation funds (PCFs): Indiana; Kansas; Louisiana; Nebraska; New Mexico; Pennsylvania; South Carolina, Wisconsin. We exclude the PCF states in our analyses. In DiD analyses, we include Georgia and Illinois in the group of New-Cap States, for the period during which they had damage caps in place (2005-2009).

	Damage Caps			**Average Premium/Average Cost**				
State	**Non-econ**	**Total**	**Avg. Cost (2015-17)**	**1992-1994**	**1999-2001**	**2007-2009**	**2015-2017**	**Change (1999-2001 to 2015-17)**
A. No-cap states (excl. PA) (17)			**7857**	**2.30**	**2.30**	**3.76**	**4.56**	**98%**
Alabama	1987-91		4302	3.37	2.30	5.61	4.60	100%
Arizona			6262	2.57	2.31	5.37	5.10	121%
Arkansas			5985	1.39	1.55	2.91	3.50	126%
Connecticut			8373	3.42	2.13	6.21	6.52	206%
Delaware			5643	2.62	2.62	4.22	6.63	153%
Dist. Of Columbia			1639	3.34	2.43	10.21	37.09	1426%
Iowa			4720	3.50	1.85	2.88	3.41	84%
Kentucky			5976	2.46	3.07	3.93	5.04	64%
Maine			5145	2.81	2.03	3.37	4.36	115%
Minnesota	1986-89		2269	2.66	3.18	3.44	4.99	57%
New Hampshire	1977-80; 1986-90		10594	---	2.28	4.72	3.24	42%
New Jersey			10385	1.56	1.94	3.94	3.94	103%
New York			14092	2.31	2.39	2.76	4.15	74%
Pennsylvania*			12203	1.24	0.99	3.57	2.98	201%
Rhode Island			7451	---	2.30	5.47	6.33	175%
Vermont			1878	---	2.85	3.56	12.49	338%
Washington	1986-88		4456	3.06	3.00	5.82	6.10	103%
Wyoming			10175	1.92	2.45	5.73	4.05	65%
B. New-cap states (excl. SC) (6)			**3152**	**3.41**	**2.73**	**9.30**	**8.49**	**211%**
Florida	1986-87; 2003-		6843	4.59	3.06	9.21	7.77	154%
Mississippi	2003-		4063	2.09	1.46	5.42	5.03	245%
Nevada	2002-		7859	2.46	2.45	4.06	4.19	71%
Ohio	1975-91; 1997; 2003-		3492	3.02	2.28	10.50	8.82	287%
Oklahoma	2003-		7507	---	0.99	2.61	3.76	280%
South Carolina*	2005-		4986	1.25	0.71	5.87	5.75	710%
Texas	2003-	1977-87	2221	2.75	2.48	13.65	12.29	396%
C. Old-cap states (excl. 5 PCF states) (12)			**4839**	**3.39**	**3.61**	**6.37**	**5.90**	**63%**
Alaska	1986-		6425	3.11	2.59	7.47	3.76	45%
California	1975-		4285	2.96	3.61	6.06	4.47	24%
Colorado	1986-	1988-	4427	3.28	3.01	4.76	5.95	98%
Hawaii	1986-		4612	3.93	2.34	6.54	4.35	86%
Idaho	1987-	1975-80	6085	2.28	2.95	3.89	3.09	5%
Indiana*		1975-	5861	2.09	1.08	2.96	2.35	118%
Kansas**	1986-	1986-87	5625	1.64	1.54	3.13	2.49	62%
Louisiana*		1975-	6615	2.59	2.54	2.27	3.15	24%
Maryland	1986-		6577	3.31	3.83	7.22	7.23	89%
Massachusetts	1986-		6757	3.62	2.80	3.40	4.84	73%

	Damage Caps			Average Premium/Average Cost				
State	**Non-econ**	**Total**	**Avg. Cost (2015-17)**	**1992-1994**	**1999-2001**	**2007-2009**	**2015-2017**	**Change (1999-2001 to 2015-17)**
Michigan	1986-		3457	7.86	8.05	10.56	11.12	38%
Missouri	1986-		5233	3.15	3.07	6.19	5.97	94%
Nebraska*		1976-	4955	---	1.41	1.92	1.48	5%
New Mexico*		1976-	10264	1.50	1.82	3.67	3.29	81%
Utah	1987-		5486	2.69	2.73	4.14	6.24	129%
Virginia		1977-	4248	2.44	2.12	6.89	7.36	247%
West Virginia	1986-		12287	2.12	1.72	4.95	3.44	100%
Other States (8) (excl. WI)			**6590**	**2.16**	**2.56**	**4.93**	**5.87**	**129%**
Georgia	2005-09		7375	3.76	1.74	4.14	4.95	184%
Illinois	1995-97; 2005-09		9676	1.98	3.07	5.46	6.12	99%
Montana	1995-		9779	1.55	1.82	3.65	4.36	140%
North Carolina	2011-		2520	2.52	2.70	6.70	10.62	293%
North Dakota	1995-		1625	1.71	1.77	4.15	8.24	366%
Oregon	1987-99		5063	3.12	2.70	4.10	4.34	61%
South Dakota	1976-85; 1996-	1986-95	3630	1.94	1.28	2.78	3.59	180%
Tennessee	2011-		5124	1.92	1.83	2.83	4.05	121%
Wisconsin*	1986-90; 1995-		1192	2.21	3.25	2.99	9.66	197%
National Total (43 States)			**6057**	**2.82**	**2.81**	**5.43**	**5.75**	**105%**

Table 2: Summary Statistics and Correlations

Panel A: Summary Statistics

Observations at the firm*county*year level for all variables except those indicated by *, which are at the state*year level. For specialty premiums, means and standard deviations are weighted by the number of physicians in the given county*specialty*year. Average across specialties is computed for firm*county*years with observations for all three specialties. For variables measured at the state*year level, mean and standard deviation is weighted by the number of non-federal physicians in the three MLM specialties in each state*year. Group Premium is average premium charged by the same parent insurer for the same county*specialty*year in other states, averaged across specialties. Competitor Premium is average premium charged by competing insurers in the same county*specialty*year, averaged across specialties. Number of Firms is the number of insurers reporting premia to MLM in the same county*specialty*year, averaged across specialties. Amounts in 2016 $.

		Weighted		Unweighted	
Variable	**Obs.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Premiums:					
General Surgeons	223,355	46,599	29,713	37,114	20,271
Internal Medicine	223,650	15,005	9,743	10,939	6,251
Ob/Gyn	223,772	70,286	39,500	53,864	26,043
Average across specialties	223,914	33,079	32,921	33,992	26,246
*Payout/Physician	1,127	4,641	2,555	4,374	2,243
*Defense Cost/Physician	1,127	2,909	1,549	2,806	1,685
*Direct cost/Physician	1,127	7,549	3,703	7,180	3,264
*Premium/Cost Ratio	1,127	5.033	3.212	5.638	4.814
*Damage Cap Exists	1,160	0.513	0.500	0.456	0.498
Group Premium	141,755	34,042	27,954	46,562	29,892
Competitor Premium	216,215	33,354	32,048	34,369	25,276
Number of Firms	224,352	4.09	1.61	3.79	1.39

Panel B. Contemporaneous Correlations

Full sample is 3,517 state* firm*year observations. Panel reports the Pearson correlation coefficients for the indicated variables. Observations at the county*specialty*firm*year are averaged across counties and the three specialties, weighted by number of physicians each specialty in each county*year. No. of Firms is total number of insurers who report premia to MLM for the same state*firm*county* specialty*year. Sample for each pairwise correlation is observations with nonmissing data for the indicated correlations, and varies from 2,273 to 3,465. Significant results (at 1% level or better) in **boldface;** significant results at 5% level are in *italics*.

	Premium	**Direct cost/ Physician**	**Payout/ Physician**	**Def. Cost/ Physician**	**Damage Cap Exists**	**Competitor Premium**	**Group Premium**
Premium							
Direct cost/Physician	**0.357**						
Payout/Physician	**0.300**	**0.888**					
Def. Cost/Physician	**0.303**	**0.780**	**0.406**				
Damage Cap Exists	**0.084**	**-0.176**	**-0.236**	-0.028			
Competitor Premium	**0.867**	**0.372**	**0.308**	**0.324**	**0.094**		
Group Premium	**0.341**	0.006	**-0.071**	**0.111**	0.040	**0.335**	
No. of Firms	**0.163**	**0.156**	**0.155**	**0.100**	0.013	**0.136**	**0.069**

Panel C: Sample Correlations of MLM Premia with Other Factors

Observations are at the state*year level. Panel reports the Pearson correlation coefficient between the average MLM premium for all three specialties. We roll up from county- to state-level by weighting county*specialty*firm*year premia by number of physicians in the given county*specialty*year) and the average value of the variable listed in the first row (computed similarly). This gives equal weight to each firm. Lags and leads are denoted "Lag#" and "Lead#", respectively, where # is the number of years that the variable in the top row lags or leads the average MLM premium. For example, for Lag2, we correlate MLM premium with (other variable)$_{t-2}$. Significant results (at 1% level or better) in **boldface;** significant results at 5% level are in *italics*.

Premia with	Direct cost/ Physician	Payout/ Physician	Defense Cost/ Physician	Damage Cap Exists
Lead3	**0.212**	**0.165**	**0.194**	**0.123**
Lead2	**0.277**	**0.216**	**0.252**	**0.122**
Lead1	**0.332**	**0.267**	**0.289**	**0.117**
Contemporaneous	**0.377**	**0.317**	**0.308**	**0.101**
Lag1	**0.435**	**0.370**	**0.351**	**0.087**
Lag2	**0.497**	**0.434**	**0.384**	*0.063*
Lag3	**0.536**	**0.479**	**0.396**	0.040
Lag4	**0.557**	**0.515**	**0.388**	0.019
Lag5	**0.568**	**0.536**	**0.380**	-0.003
Lag6	**0.560**	**0.547**	**0.351**	-0.016

Panel D: Partial Correlations of MLM Residual Premia with Other Factors

Observations are state*years. Panel reports Pearson correlation coefficient between residual premium (residual from regression of average MLM premium on other variables (listed below)) and the average value of the variable listed in the first row, both computed as in Panel C) For direct cost/physician, payout/physician, and defense cost/physician, other variables are Damage Cap Exists; Competitor Premium, Group Premium, and No. of Firms. For Damage Cap Exists, the other variables are direct cost/physician, Competitor Premium, Group Premium, and No. of Firms. Lags and leads are denoted as in Panel C. Significant results (at 1% level or better) in **boldface;** significant results at 5% level are in *italics*.

Residual Premia with	Direct cost/ Physician	Payout/ Physician	Defense Cost/ Physician	Damage Cap Exists
Contemporaneous	0.046	0.043	0.033	0.002
Lag1	0.052	0.039	0.050	0.001
Lag2	0.057	0.052	0.041	-0.007
Lag3	**0.090**	**0.088**	0.057	-0.011
Lag4	**0.201**	**0.196**	**0.130**	0.028
Lag5	**0.228**	**0.201**	**0.174**	-0.018
Lag6	**0.217**	**0.205**	**0.153**	-0.025

Panel E: Correlations Between Contemporaneous and Past Costs and Payouts

Observations are state*years. Panel reports Pearson correlation coefficient between the contemporaneous value of the cost variable listed in the first row (computed as in Panel C) and indicated lags of that variable. Lags are denoted as in Panel C. All correlations are significant at 1% level or better.

	Direct cost/Physician	Payout/Physician	Defense Cost/Physician
Lag1	0.730	0.685	0.530
Lag2	0.684	0.637	0.513
Lag3	0.638	0.588	0.471
Lag4	0.585	0.556	0.422
Lag5	0.550	0.544	0.376
Lag6	0.500	0.497	0.326

Panel F: Predicting Current Logged Costs with Past Logged Costs

Prediction of current year costs, based on past costs, over 1990-2017. For even-numbered columns, Sum of Lagged Effects reports the sum of coefficients for 6 lags of the dependent variable. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent variable	**Ln(Direct cost/Phys.)**		**Ln(Payout/Phys.)**		**Ln(Def. Cost/Phys.)**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable$_{t-1}$	**0.772*** (0.0209)**	**0.466*** (0.0355)**	**0.699*** (0.0223)**	**0.413*** (0.0347)**	**0.591*** (0.0242)**	**0.390*** (0.0360)**
Dep. Variable$_{t-2}$		**0.220*** (0.0388)**		**0.262*** (0.0390)**		**0.173*** (0.0386)**
Dep. Variable$_{t-3}$		**0.187*** (0.0404)**		0.0367 (0.0414)		**0.197*** (0.0392)**
Dep. Variable$_{t-4}$		0.0641 (0.0406)		**0.0930** (0.0420)**		0.0606 (0.0388)
Dep. Variable$_{t-5}$		-0.00945 (0.0392)		**0.0915** (0.0405)**		-0.0172 (0.0380)
Dep. Variable$_{t-6}$		0.0168 (0.0364)		0.0585 (0.0367)		0.00970 (0.0347)
Sum of Lagged Effects		**0.944*** (0.0265)**		**0.955*** (0.0287)**		**0.813*** (0.0325)**
State and Year FE	N	N	N	N	N	N
No of obs.	1,077	855	1,079	862	1,057	800
Adj. R^2	0.559	0.646	0.476	0.599	0.361	0.480

Table 3: Determinants of Med Mal Premia and Costs

Panel A: Factors Predicting Med Mal Premia

Determinants of premia over 1990-2017, with year and firm*county*specialty FE. Sum of Lagged Effects reports the sum of coefficients for the contemporaneous variable plus lags t-1 through t-4 of this variable, for competitor premia, group premia, and cap adoption; and the sum of coefficients including the first four lags of the predictor variable, estimated in separate regressions. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent variable	**Ln(premium)**					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Cost/Physician)$_{t-1}$	**0.170*** (0.0461)**				0.0481 (0.0378)	**0.197*** (0.0487)**
Ln(Competitor Premium)$_t$		**0.446*** (0.0516)**			**0.426*** (0.0513)**	
Ln(Group Premium)$_t$			0.0236 (0.0910)		0.0269 (0.0477)	
Damage Cap Exists$_t$				0.115 (0.0898)		0.170* (0.0870)
Sum of Lagged Effects	**0.397** (0.159)**	**0.386*** (0.0742)**	**-0.151** (0.0704)**	0.0482 (0.141)		
No of obs.	353,428	408,417	272,682	424,325	246,014	353,202
Adj. R^2	0.950	0.957	0.955	0.945	0.967	0.951
Adj. R^2, using only FE	0.948	0.948	0.955	0.945	0.960	0.948

Panel B: Cap Adoption as Predictor of Cost/Physician

Regressions of indicated measures of cost on cap adoption and lags of cap adoption over 1990-2017, with year and state FE. Cost per physician (Cost/Phys.) is the sum of defense cost per physician (Def. Cost/Phys.) and payout per physician (Payout/Phys.). State*year observations are weighted by the number of non-federal physicians in the state*year. Sum of Lagged Effects reports the sum of coefficients including the first four lags of the indicated predictor variable. Nine observations with negative defense costs and one observation with negative direct cost are dropped. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent variable	**Ln(Cost/Phys.)**			**Ln(Def. Cost/Phys.)**			**Ln(Payout/Phys.)**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cap Adoption$_t$	**-0.531** **(0.195)**	0.0475 (0.0911)	**-0.270***** **(0.0553)**	**-0.505** **(0.246)**	-0.0463 (0.162)	**-0.386***** **(0.0803)**	**-0.570***** **(0.185)**	0.0618 (0.0872)	**-0.272***** **(0.0626)**
Cap Adoption$_{t-1}$		**-0.0876** **(0.0345)**			-0.109 (0.143)			-0.116 (0.0841)	
Cap Adoption$_{t-2}$		**-0.140** **(0.0562)**			-0.109 (0.142)			-0.142 (0.0941)	
Cap Adoption$_{t-3}$		-0.120 (0.0953)			0.0634 (0.111)			**-0.279***** **(0.0988)**	
Cap Adoption$_{t-4}$		**-0.459***** **(0.0946)**			**-0.694***** **(0.110)**			**-0.277** **(0.128)**	
Dep. Variable$_{t-1}$			**0.271***** **(0.0903)**			**0.228***** **(0.0578)**			**0.308***** **(0.0564)**
Dep. Variable$_{t-2}$			**0.127** **(0.0617)**			0.0686 (0.0593)			**0.144** **(0.0615)**
Dep. Variable$_{t-3}$			**0.221***** **(0.0491)**			**0.214***** **(0.0484)**			0.0559 (0.0613)
Dep. Variable$_{t-4}$			**0.0724** **(0.0294)**			0.0893 (0.0542)			**0.119***** **(0.0430)**
Sum of Lagged Effects		**-0.758***** **(0.204)**	**0.692***** **(0.0474)**		**-0.803***** **(0.242)**	**0.600***** **(0.0633)**		**-0.752***** **(0.204)**	**0.627***** **(0.0545)**
State and Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
No of obs.	942	813	783	934	805	749	943	814	788
Adj. R^2	0.777	0.844	0.874	0.581	0.671	0.729	0.805	0.856	0.874

Table 4: Determinants of Premium/Cost Ratio

Determinants of ln(premia/cost) (cost = payout + defense cost) ratio over 1990-2017, with year and firm*county*specialty FE. Sum of Lagged Effects reports the sum of coefficients including the first four lags of the independent variable in that column, including the contemporaneous term for competitor and group premia, as estimated in a separate regression. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent Variable			**Ln(Premium/Cost)**			
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Cost/Physician)$_{t-1}$	**-0.213***** **(0.097)**				**-0.297**** **(0.112)**	-0.158* (0.089)
Ln(Competitor Premium)$_t$		**0.285***** **(0.097)**			**0.320**** **(0.120)**	
Ln(Group Premium)$_t$			-0.0279 (0.132)		-0.00767 (0.083)	
Damage Cap Exists$_t$				**0.377***** **(0.085)**		**0.347***** **(0.093)**
Sum of Lagged Effects	-0.167 (0.151)	**0.312***** **(0.115)**	**-0.335***** **(0.0978)**	**0.455**** **(0.174)**		
No of obs.	353,200	403,476	270,459	416,942	245,900	352,974
Adj. R^2	0.924	0.925	0.922	0.922	0.935	0.927
Adj. R^2, using only FE	0.922	0.921	0.922	0.918	0.928	0.922

Table 5: Effect of Cap Adoption on Premium/Cost Ratio

Table shows simple DiD and distributed lag regressions estimating the effect of cap adoption on premia/(payout + defense cost) ratio over 1990-2017, with year and firm*county*specialty FE. Treated states are New-Cap states (plus Georgia and Illinois during 2005-2009, when these states had caps in effect) relative to broad control group (No-Cap and Old-Cap states). Column (1) reports results for the difference-in-difference specification using equation (1), while column (2) reports results for the distributed lag specification using equation (3). "Sum of Distributed Lags" reports the sum of the distributed lag coefficients. Results omit years -2, -1, and 0 for states that adopt damage caps. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent variable	**Ln(Premium/Cost)**	
	(1)	(2)
Cap Adoption$_t$	**0.360** **(0.165)**	
Year 1		**0.221**** **(0.0977)**
Year 2		-0.00557 (0.0897)
Year 3		0.00914 (0.0415)
Year 4		**0.241**** **(0.0960)**
Year 5		0.0330 (0.161)
Year 6-10		0.0500 (0.0320)
Sum of Distributed Lags		**0.549***** **(0.179)**
No of obs.	301,174	301,637
Adj. R^2	0.921	0.923
Control Group	Broad	Broad

Table 6: Determinants of Premia and Premium/Cost Ratio, Controlling for No. of Companies

Determinants of firm*county*year*specialty premia and premia/(payout + defense cost) ratio over 1990-2017, with year and firm*county*specialty FE. Columns (1)-(4) report results for dependent variable ln(premium), while columns (5)-(8) report results for dependent variable ln(premium/payment + defense cost). Sum of Lagged Effects rows report the sum of coefficients from regressions that include the contemporaneous term plus the first four lags for the indicated variables, with no change in the other variables. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent variable	**Ln(Premium)**				**Ln(Premium/Cost)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Competitor Premium)$_t$		**0.419*** (0.0614)**				**0.313** (0.117)**		
Ln(Cost/Physician)$_{t-1}$		0.0453 (0.0397)	**0.151*** (0.0452)**	**0.178*** (0.0483)**		**-0.300** (0.111)**	**-0.232** (0.0946)**	**-0.179** (0.0862)**
Ln(Group Premium)$_t$		0.0302 (0.0460)				-0.00462 (0.0811)		
Cap Adoption$_t$				0.0304 (0.122)				0.308 (0.190)
No. of Companies$_t$	0.0303* (0.0153)	0.0153 (0.0113)			0.0182 (0.0219)	0.0141 (0.0187)		
Ln(Cost/Phys)$_{t-1}$ * Num. of Companies$_{t-1}$			0.00297* (0.00162)	**0.00303** (0.0013)**			0.00296 (0.00247)	0.00348* (0.00189)
Cap Adoption$_t$ * Num. of Companies$_t$				0.0399* (0.0230)				0.0144 (0.0404)
Sum of lagged effects for num. of companies	**0.0799*** (0.0270)**	0.0173 (0.0147)			**0.0795** (0.0387)**	**0.0399** (0.0186)**		
Sum of lagged effects for num. of companies * cost			**0.00635** (0.00261)**	**0.00654** (0.00260)**			**0.00735** (0.00366)**	**0.00776** (0.00335)**
Sum of lagged effects for num. of companies * cap				0.000295 (0.0553)				-0.0649 (0.0671)
No of obs.	425,044	246,014	353,428	353,202	417,661	245,900	353,200	352,974
Adj. R^2	0.946	0.968	0.950	0.952	0.918	0.935	0.924	0.928
Adj. R^2, using only FE	0.945	0.960	0.948	0.948	0.918	0.928	0.922	0.922

Table 7: Determinants of Premia and Premium/Cost Ratio, with Sample Period Split

Selected regressions, similar to Table 3, except sample period is divided into early (1990-2000) and late (2001-2017). "Diff (p-value)" reports the p-value of a test of equality for the coefficients on the independent variable listed at left across the two time periods. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Panel A: Med Mal Premia

Dependent variable	**Ln(Premium)**							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time Period	**1990-2000**	**2001-2017**	**1990-2000**	**2001-2017**	**1990-2000**	**2001-2017**	**1990-2000**	**2001-2017**
Ln(Cost/Physician)$_{t-1}$	-0.0702 (0.0738)	**0.187**** **(0.0922)**					-0.0490 (0.0655)	**0.198**** **(0.0898)**
Ln(Competitor Premium)$_t$			**0.177*** **(0.0924)**	**0.413***** **(0.0543)**				
Damage Cap Exists$_t$					**0.187***** **(0.0541)**	-0.0286 (0.0895)	**0.165***** **(0.0407)**	0.0861 (0.0880)
No of obs.	91,111	262,317	120,088	288.329	133,206	291,119	91,111	262,091
Diff (p-value):								
Ln(Cost/Physician)$_{t-1}$	0.062						**0.047**	
Ln(Competitor Premium)$_t$			0.249					
Damage Cap Exists$_t$					0.358		0.347	
Adj. R^2	0.970	0.956	0.973	0.960	0.965	0.953	0.970	0.956
Adj. R^2, using only FE	0.969	0.954	0.972	0.953	0.964	0.953	0.969	0.954

Panel B: Premium/Cost Ratio

Dependent variable	**Ln(Premium/Cost)**							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time Period	**1990-2000**	**2001-2017**	**1990-2000**	**2001-2017**	**1990-2000**	**2001-2017**	**1990-2000**	**2001-2017**
Ln(Cost/Physician)$_{t-1}$	-0.145 (0.116)	-0.169 (0.139)					-0.0997 (0.111)	-0.138 (0.136)
Ln(Competitor Premium)$_t$			**0.193**** **(0.0717)**	0.160 (0.138)				
Damage Cap Exists$_t$					**0.394***** **(0.0585)**	**0.240**** **(0.0967)**	**0.348***** **(0.0514)**	**0.229**** **(0.106)**
No of obs.	90,883	262.317	115,147	288,329	125,823	291,119	90,883	262,091
Difference in coeffs. (p-value):								
Ln(Cost/Physician)$_{t-1}$	0.545						0.973	
Ln(Competitor Premium)$_t$			0.903					
Damage Cap Exists$_t$					0.307		0.133	
Adj. R^2	0.929	0.932	0.930	0.931	0.923	0.931	0.932	0.933
Adj. R^2, using only FE	0.928	0.921	0.927	0.922	0.920	0.922	0.928	0.921

Table 8: Determinants of Medical Malpractice Premia, By Specialty

Determinants of Firm*county*year premia within the given specialty over 1990-2017, with year and firm*county FE. Specialties are general surgery (GS), internal medicine (IM) and ob-gyn (OB). *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Panel A: General Surgery

Dependent variable	Ln(Premium)				Ln(Premium/Cost)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ln(Cost/Physician)_{t-1}$	**0.197*** (0.0478)**			**0.222*** (0.0532)**	**-0.174** (0.0850)**			-0.122 (0.0788)
$Ln(Competitor\ Premium)_t$		**0.430*** (0.0532)**				0.196* (0.115)		
$Damage\ Cap\ Exists_t$			0.0999 (0.0869)	0.165* (0.0824)			**0.359*** (0.0837)**	**0.343*** (0.0974)**
No of obs.	117,992	136,397	141,961	117,927	117,908	134,770	139,436	117,843
Adj. R^2	0.891	0.906	0.880	0.893	0.842	0.846	0.840	0.850
Adj. R^2, using only FE	0.886	0.888	0.879	0.886	0.886	0.889	0.882	0.886

Panel B: Internal Medicine

Dependent variable	Ln(Premium)				Ln(Premium/Cost)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ln(Cost/Physician)_{t-1}$	**0.146*** (0.0500)**			**0.174*** (0.0511)**	**-0.235** (0.101)**			-0.179* (0.0936)
$Ln(Competitor\ Premium)_t$		**0.412*** (0.0532)**				**0.287*** (0.0932)**		
$Damage\ Cap\ Exists_t$			0.131 (0.0915)	0.173* (0.0891)			**0.397*** (0.0874)**	**0.352*** (0.0889)**
No of obs.	135,134	156,483	162,362	135,043	135,054	154,560	159,604	134,963
Adj. R^2	0.880	0.897	0.873	0.882	0.829	0.830	0.826	0.837
Adj. R^2, using only FE	0.877	0.879	0.871	0.877	0.877	0.879	0.874	0.877

Panel C: Obstetrics/Gynecology

Dependent variable	Ln(Premium)				Ln(Premium/Cost)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ln(Cost/Physician)_{t-1}$	**0.202*** (0.0451)**			**0.228*** (0.0485)**	-0.194* (0.103)			-0.143 (0.0959)
$Ln(Competitor\ Premium)_t$		**0.516*** (0.0416)**				**0.283** (0.111)**		
$Damage\ Cap\ Exists_t$			0.0912 (0.0967)	0.168* (0.0931)			**0.344*** (0.0903)**	**0.336*** (0.104)**
No of obs.	100,302	115,537	120,002	100,232	100,238	114,146	117,902	100,168
Adj. R^2	0.870	0.893	0.856	0.873	0.795	0.803	0.796	0.806
Adj. R^2, using only FE	0.865	0.863	0.855	0.865	0.865	0.865	0.859	0.865

APPENDIX

A.1. Lagged Independent Variables

For our main results, we assume that when an insurer sets premia for year *t*, it knows competitor premia and its own group premia for year *t*, cost for year *t*-1, and whether the state has a damage cap in year *t*. We also assume that the most recent values available for these predictor variables contain all of the information that a firm uses when setting its own premia for year *t*.[15] However, lagged information may matter if premium determinants exhibit trends or if information about changes in conditions arrives over time, such as the effect of damage caps on costs being revealed to insurers over time (Paik, Black, and Hyman, 2013b). In text Tables 3 and 4, we present results that sum the coefficient for each predictor variable and its first four lags. We present the full regression results underlying Table 3, Panel A, and Table 4 in Appendix Tables A1 and A2.

The long run estimated elasticity for some predictors is meaningfully different than the contemporaneous elasticity. In Appendix Table A1, col. (1), we find that lags of cost per physician strongly predict firm premia. The long-run elasticity of premia with respect to cost is 0.397, more than double the value of elasticity to prior year cost shown in text Table 3, Panel A. Some lag is not surprising, because a single year could be an outlier and insurance actuaries look at longer period in estimating future payouts. However, it is still surprising that the long-run elasticity is so much higher than the short-run elasticity, with current premia responding strongly to costs from 3 and 4 years ago. The responsiveness of premia to costs is still far from 1, indicating that prices do not adjust fully to changes in costs even over a fairly long horizon. In column (2), we show that the long-run estimated elasticity of a firm's own premia with respect to competitor premia is 0.386, which is within the 95% confidence interval for the contemporaneous estimate of 0.446. The similar short- and long-run elasticities are consistent with firms responding more to their competitors' current prices than to older prices. Column (3) of Appendix Table A1 reports that the impact of an increase in premia among other insurance group members leads to a long-run decrease in a firm's premium, with an elasticity of -0.151. This contrasts with the small, positive, but insignificant short-run elasticity shown in text Table 3, Panel A. The negative long-run elasticity is consistent with the existence of small but

[15] One could quibble about whether in the specific year that a cap is adopted, insurers will anticipate cap adoption in setting prices for that year.

meaningful cross-subsidies between insurance firms in different states that are owned by the same parent company. Column (4) shows no statistically significant impact of cap adoption on premia. The long-run elasticity remains positive, although insignificant, despite strong evidence that it ought to be strongly negative, especially in the medium term, because caps do reduce costs.

Column (5) corresponds to text Table 6, column (1), where we found a small, marginally significant, positive elasticity of price to number of competitors. The long-term elasticity is more than twice as large at 0.08, indicating that competitor entry predicts 8% higher long-run premia. This positive elasticity is unexpected. Insurers are likely to enter markets with high premia, but we would expect entry to moderate future premia increases.

Appendix Table A2 should be read together with text Table 4. It shows coefficients on lags of the same predictor variables, but with *ln*(premium/cost ratio) as the outcome. In column (1), the long-run elasticity of -0.167 is statistically insignificant but consistent in magnitude with the near-term elasticity of -0.213. This finding is consistent with the ability of insurers to raise prices, as reflected in the premium/cost ratio, being constrained by higher costs. An economically small coefficient is consistent with competitive markets. In column (2), the long-run elasticity of 0.312 is similar to the near-term elasticity of 0.285, consistent with the evidence from Appendix Table A1 that a firm's own premia respond more to their competitors' current prices than to older prices.

In column (3), we find further evidence for cross-subsidization across different insurers owned by the same parent. The short-run elasticity is small and insignificant, but the long-run elasticity is substantial at -0.335 and is strongly significant. In column (4), the near- and long-term elasticities are similar. However, the lag analysis provides evidence that the puzzling strength of a damage cap in predicting higher premium/cost ratio is a long-run effect, with the largest coefficient on the earliest lag (year -4). This pattern is consistent with the long-run increase in premium/cost ratio found in the DiD analysis, shown in text Figure 4, Panel C and Table 5.

The time pattern for the effect of number of firms in column (5) is similar to that in Table A1, with a stronger long-run than near-term positive coefficient. Lengthening the time period to allow for competitive effects to influence profitability does not resolve the puzzle of the positive correlation between entry and insurer profits.

A.2. Payouts and Defense Costs

In the text, we combine payout to plaintiffs and defense cost into a single measure of insurer cost. By adding these two variables, we are implicitly assuming that a 1% increase in cost/physician has the same effect on the dependent variable regardless of whether that increase came from increased payout or increased defense expenditures. In Appendix Table A3, we present regression specifications similar to those in the text, principally those in text Table 3, Panel A, and Table 4, but replace the single cost/physician independent variable with separate variables for payout and defense cost.

In columns (1) and (2) of Appendix Table A3, the estimated elasticities of premia with respect to payout per physician and defense costs per physician are very similar, at 0.113 and 0.102 respectively. This finding supports combining these variables in our main specification. Columns (3) and (4) provide evidence that using payout per physician or both payout and defense cost per physician does not impact estimates of the elasticities of premia with respect to other variables. The coefficient on damage cap existence in column (3) of Appendix Table A3 is similar to that in column (6) of text Table 3, Panel A. Similarly, in column (4) of Appendix Table A3 and column (2) of text Table 6, the coefficients on other predictor variables are very similar.

This picture changes somewhat when we switch to premium/cost as the dependent variable. In columns (5) and (6), changes in payout per physician appear to have a larger influence in reducing the premium/cost ratio than changes in defense costs per physician. However, both values are within the 95% confidence interval of the point estimate on the joint effect shown in Table 4, column (1). Column (7) of Appendix Table A3 shows a similar impact of damage cap adoption on insurer profitability as in column (6) of text Table 4, while column (8) shows that all other covariates have similar elasticities as estimated in column (6) of text Table 6. Overall, we find that payout per physician and defense costs per physician have similar predictive power for premia and the premium/cost ratio.

A.3. Additional DiD Results

Our DiD leads-and-lags results show the effect of cap adoption in New-Cap states plus Georgia and Illinois relative to the broad control group of No-Cap and Old-Cap states. We present here results using a narrow control group consisting only of No-Cap states. Appendix

Figure A1 shows results analogous to those of Figure 4. In all three panels, we find that the estimated effects of the impact of cap adoption on direct costs per physician, premia, and the premium/cost ratio are very similar to those using the broad control group. As expected, standard errors are slightly larger when using the narrow control group. Appendix Table A4 shows DiD and distributed lag results using the narrow control group that are analogous to those using the broad control group presented in text Table 5. The point estimates are very similar, but standard errors are larger.

Georgia and Illinois adopted damage caps in 2005 but the caps were invalidated by state supreme courts in 2010. We include Georgia and Illinois in the main results in text (dropping them from the sample after 2009), but assess whether our results are robust to excluding them in Appendix Table A5. Odd-numbered columns use the broad control group and even-numbered columns use the narrow control group. In general, we find a larger predicted long-run effect of cap adoption on the premium/cost ratio when excluding these two states. Our main results show a second increase in the premium/cost ratio starting 4 years after cap adoption, as insurer costs fall more than premia. Since both Georgia and Illinois have only 4 years of post-cap data, these states experience fewer years with these larger long-run effects of cap adoption on insurer profitability and should therefore have a smaller overall estimated treatment effect. The simple-DiD estimates in columns (1) and (2) of Appendix Table A5 are indeed larger than the corresponding estimates in column (1) of text Table 5. Similarly, the sum of distributed lag coefficients in columns (3) and (4) of Appendix Table A5 is larger than the corresponding sum in text Table 5. We conclude that including Georgia and Illinois in our main regressions provides conservative estimates of the long-run effect of cap adoption on the premium/cost ratio.

Our main DiD results exclude years -2, -1, and 0 from the sample for states that adopt damage caps to reflect the rising premium/cost ratio that we observe in the years immediately prior to cap adoption. Appendix Table A6 provides a robustness check in which we include year -2 in the pre-treatment period instead of excluding it. Results are similar to those presented in text Table 5 but are somewhat more precisely estimated because of the larger sample size.

A.4. Predicting Current Costs Based on Past Costs

Table 2, Panel E in the main text shows that direct costs per physician, payout per physician, and defense costs per physician are strongly predicted by their past values measured in logs. Appendix Table A7 is similar, but all variables are measured in levels. When costs/physician are denoted in levels, past per-physician costs are still very strong predictors of current costs, for all three cost measures direct costs, payouts, and defense costs. Thus, the predictive power of past costs for current costs is not sensitive to whether one represents the past and current costs in log or linear form.

A.5. Counterfactual-Based DiD Estimation

As a robustness check motivated by the different times of damage cap adoption by different states that provide identification in our DiD design, we use the fixed effect counterfactual estimator (FECT) developed by Liu, Wang, and Xu (2022). We generate an annual counterfactual by specialty for firm*county observations in states that adopt damage caps, using firm*county observations in states that never adopt caps. We create these counterfactuals for years -5 through +5, relative to the cap adoption year, for each firm in the treated state by MLM specialty. We report results in Appendix Figure A2.

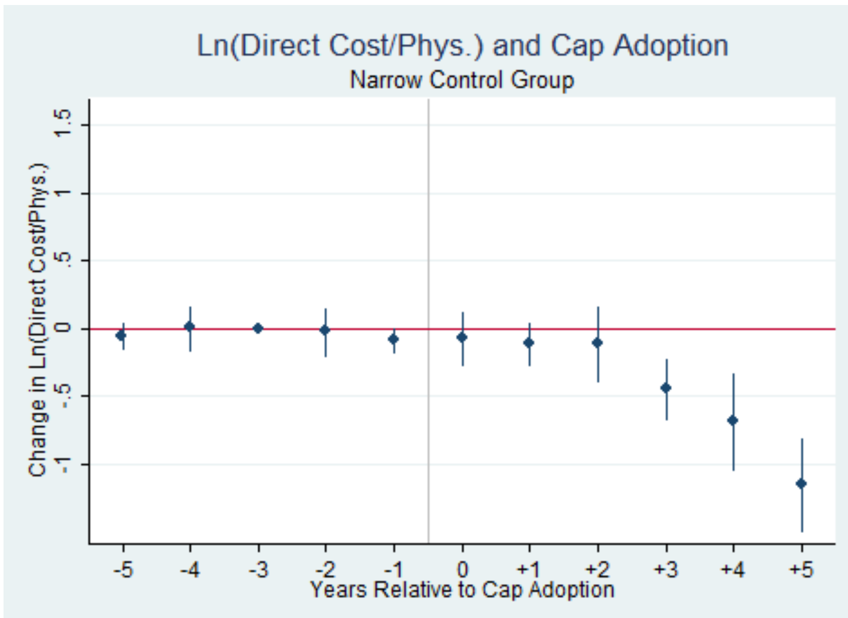
Panel A shows the estimated impact of cap adoption on insurer direct costs, while Panels B and C show the effects on premia and the premium/cost ratio, respectively. The results in all three panels are similar to those in text Figure 4. Panel A of Appendix Figure A2 shows a decrease in direct costs that grows larger after year +2, similar to text Figure 4, Panel A. Panels B1, B2, and B3 indicate that the trends in premia are very similar for all specialties in response to cap adoption. We find a pattern comparable to that of Panel B in text Figure 4, with a pre-adoption rise in premia beginning in year -2 and growing less positive a few years after cap adoption. Panels C1, C2, and C3 show that the premium/cost ratio also follows a similar path across specialties in response to cap adoption. Similar to our findings in Panel C of text Figure 4, we find evidence of an increase in insurer profitability near the time of cap adoption and a second increase after year +4.

The FECT approach has limitations in our setting. FECT does not permit the use of weights, so: (i) counties are equally weighted, and (ii) we cannot readily combine results for the three specialties to present an average across specialties. Equal weighting leads to rural counties (which are most counties by number in most states) having much larger weight using FECT than in the results reported in text, which are weighted by number of physicians. Nonetheless, the FECT results replicate the main features of our DiD analysis.

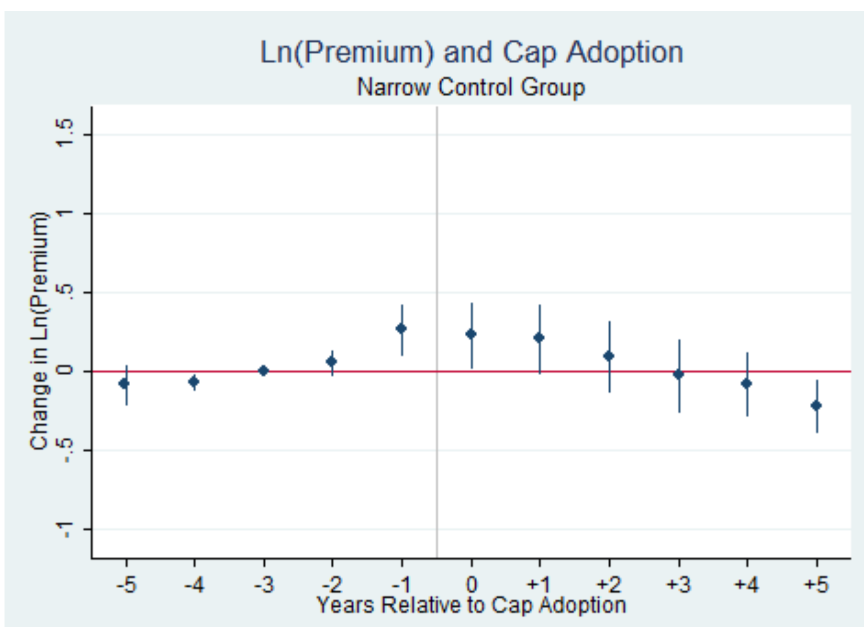
Appendix Figure A1: DiD Leads-and-Lags Analysis: Narrow Control Group

Dots indicate coefficients from a regression including dummies for leads and lags of cap adoption in New-Cap states (plus Georgia and Illinois during 2005-2009, when these states had caps in effect) relative to narrow control group (No-Cap states). Vertical lines indicate the start of the cap adoption period. **Panel A:** Dependent variable is direct cost per physician. Regression includes state FE. **Panel B:** Dependent variable is premium. Regression includes firm*county*specialty FE. **Panel C:** Dependent variable is premium/cost ratio. Regression includes firm*county*specialty FE. **All panels:** Regressions include year FE. Standard errors (s.e.'s) are clustered on state. Coefficient and s.e. shown for year -5 are averages over years (-10, -5), and for year +5 are averages for years (+5, +10). Vertical lines indicate 95% confidence intervals.

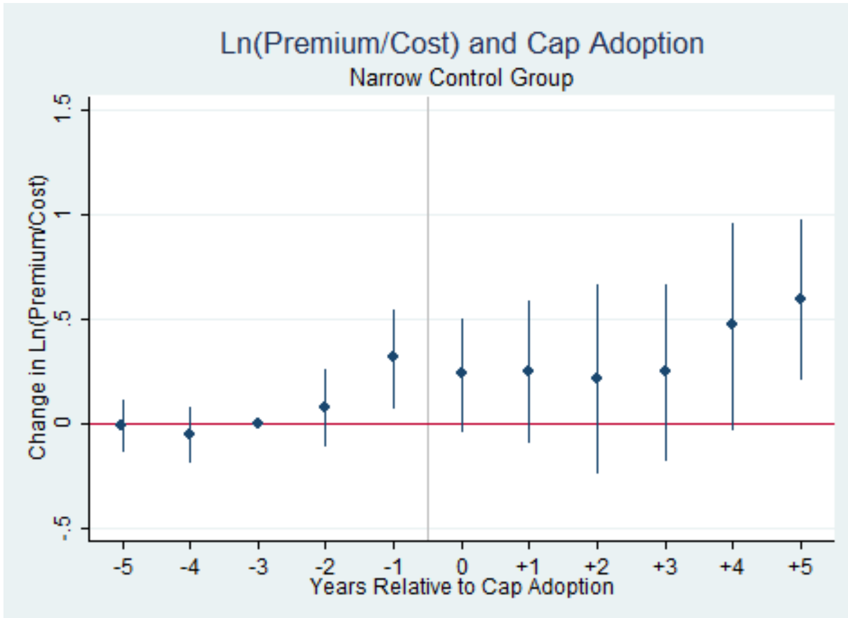
Panel A: Direct Cost per Physician



Panel B: Med Mal Premia



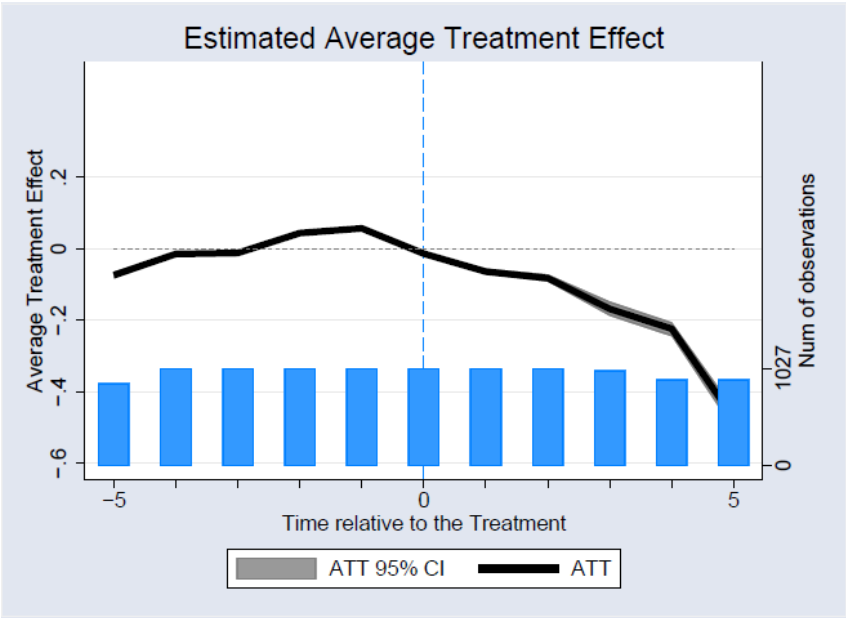
Panel C: Premium/Cost Ratio



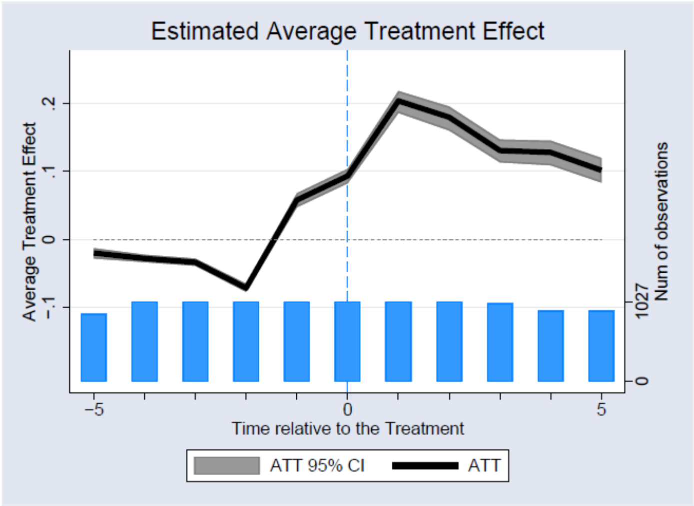
Appendix Figure A2: Counterfactual-Based DiD Analysis

Solid line shows the annual average treatment effect on the treated (ATT) (left-hand axis) estimated using the fect.ado (fixed effects counterfactual) approach developed by Lin, Wang, and Xu (2020) for years (-5, 5). All regressions include year and firm*county FE, do not use county weights (not available in fect) and are estimated separately by specialty, except for direct cost per physician for which we have data at the state level (assigned to each firm*county observation for a given state*year). Vertical dashed line indicates cap adoption year. The fect command estimates confidence intervals using a block bootstrap at the observation level (for us, firm*county). Bars (right-hand axis) indicate number of firm*county observations in treatment states in each year. **Panel A:** Dependent variable is *ln*(direct cost per physician). **Panel B:** Dependent variable is *ln*(premium), by specialty. **Panel C:** Dependent variable is *ln*(premium/cost ratio), by specialty.

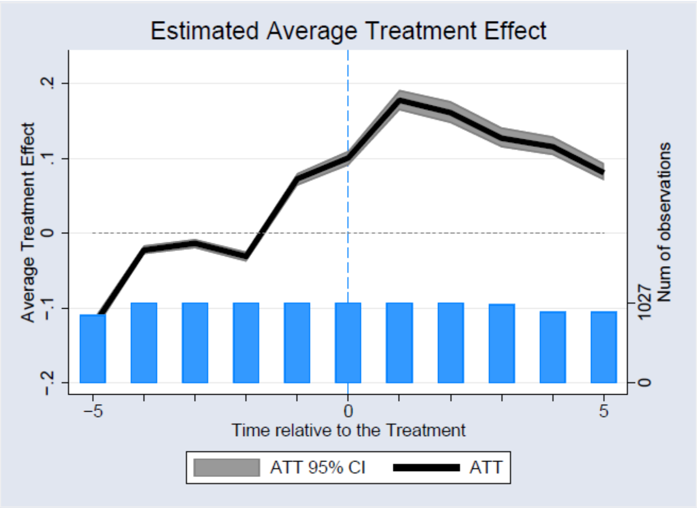
Panel A: Direct Cost per Physician



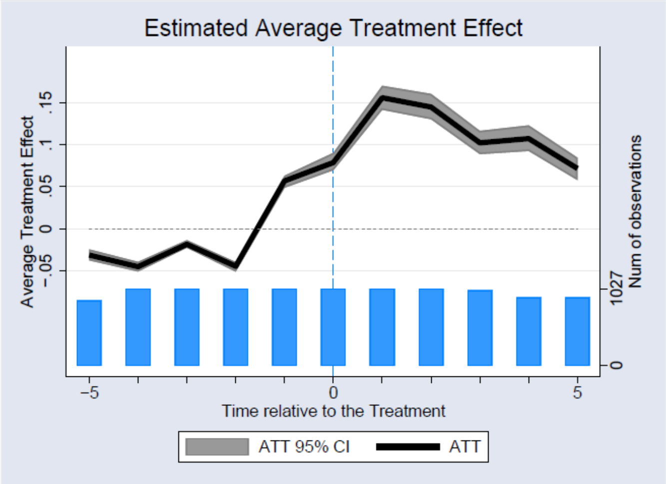
Panel B1: Med Mal Premia (General Surgery)



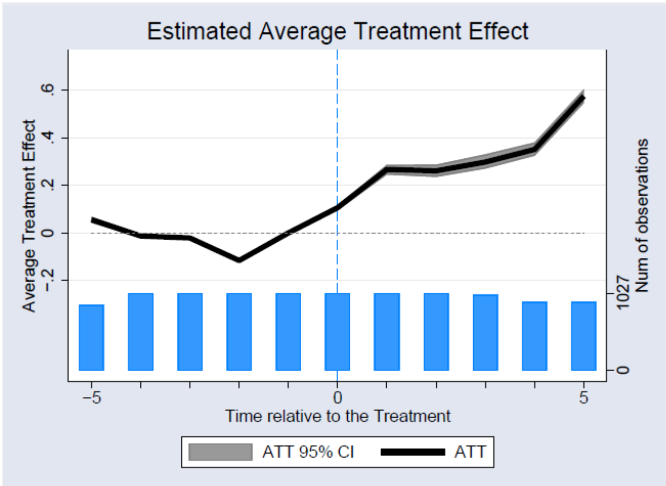
Panel B2: Med Mal Premia (Internal Medicine)



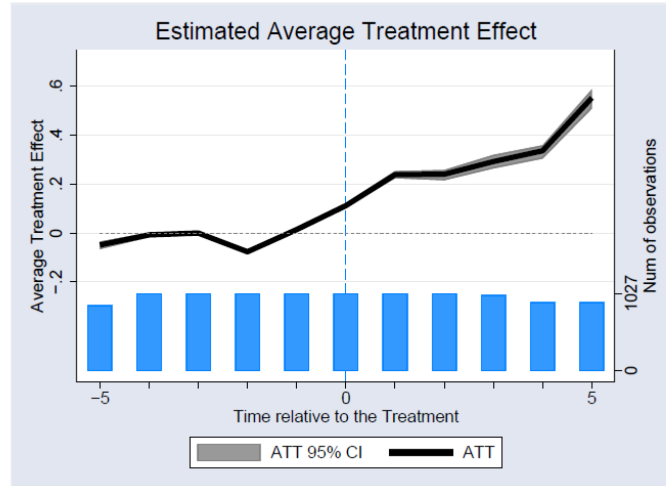
Panel B3: Med Mal Premia (Ob-Gyn)



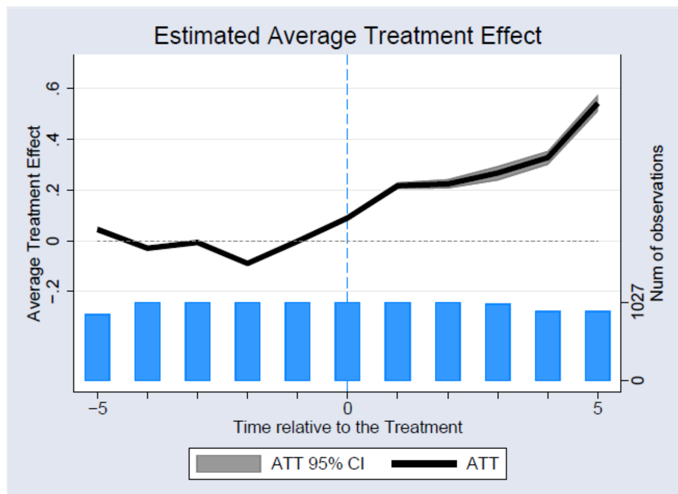
Panel C1: Premium/Cost Ratio (General Surgery)



Panel C2: Premium/Cost Ratio (Internal Medicine)



Panel C3: Premium/Cost Ratio (Ob-Gyn)



Appendix Table A1: Determinants of Med Mal Premia, with Lagged Independent Variables

Similar to text Table 3, Panel A, except we add four lags of the predictor variables. Competitor Premium, Cost/Physician, and Group Premium are measured in logs. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Predictor	**Cost/Physician**	**Competitor Premium**	**Group Premium**	**Cap Adoption**	**No. of Firms**
	(1)	(2)	(3)	(4)	(5)
$Predictor_t$		**0.158*** (0.0364)**	**-0.0873** (0.0339)**	0.0413 (0.0769)	**0.0359*** (0.00950)**
$Predictor_{t-1}$	0.0259 (0.0305)	**0.0734** (0.0282)**	0.0409 (0.0244)	0.0386 (0.0283)	0.00788 (0.00610)
$Predictor_{t-2}$	0.0794 (0.0540)	0.0587 (0.0443)	-0.0228 (0.0262)	-0.00554 (0.0291)	**0.00986** (0.00457)**
.$Predictor_{t-3}$	**0.126** (0.0526)**	**0.0723** (0.0318)**	-0.0229 (0.0240)	-0.0231 (0.0377)	0.00128 (0.00909)
$Predictor_{t-4}$	**0.166*** (0.0561)**	0.0244 (0.0327)	**-0.0589** (0.0271)**	-0.00302 (0.0771)	**0.0250*** (0.00875)**
Sum of Lagged Effects	**0.397** (0.159)**	**0.386*** (0.0742)**	**-0.151** (0.0704)**	0.0482 (0.141)	**0.0799*** (0.0270)**
No of obs.	208,017	195,314	110,317	213,906	214,114
Adj. R^2	0.958	0.965	0.974	0.953	0.956
Adj. R^2, FE only	0.954	0.960	0.973	0.953	0.953

Appendix Table A2: Determinants of Premium/Cost Ratio, with Lagged Independent Variables

Similar to text Table 4, except we add lags of the predictor variables. Competitor Premium, Cost/Physician, and Group Premium are measured in logs. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Predictor	Cost/Physician	Competitor Premium	Group Premium	Cap Adoption	No. of Firms
	(1)	(2)	(3)	(4)	(5)
$Predictor_t$		0.112	**-0.185****	0.145	**0.0294****
		(0.0676)	**(0.0754)**	(0.102)	**(0.0142)**
$Predictor_{t-1}$	-0.198*	-0.115	0.0135	0.103	0.0170
	(0.111)	(0.116)	(0.0390)	(0.0683)	(0.0136)
$Predictor_{t-2}$	-0.0565	0.107	**-0.132****	-0.000936	0.00930
	(0.0703)	(0.0773)	**(0.0595)**	(0.0582)	(0.0119)
$Predictor_{t-3}$	-0.0503	**0.146****	-0.00421	0.0123	-0.00789
	(0.0605)	**(0.0589)**	(0.0422)	(0.0440)	(0.0138)
$Predictor_{t-4}$	**0.138****	0.0636	-0.0355	**0.252****	0.0317*
	(0.0617)	(0.0892)	(0.0443)	**(0.116)**	(0.0158)
Sum of Lagged Effects	-0.167	**0.312*****	**-0.335*****	**0.455****	**0.0795****
	(0.151)	**(0.115)**	**(0.0978)**	**(0.174)**	**(0.0387)**
No of obs.	207,903	195,200	110,260	213,792	214,000
Adj. R^2	0.930	0.937	0.949	0.933	0.931
Adj. R^2, FE only	0.928	0.933	0.947	0.928	0.928

Appendix Table A3: Separate Payout and Cost Variables

Determinants of firm*county*year*specialty premia and premia/(payout + defense cost) ratio over 1990-2017, with year and firm*county*specialty FE. Columns (1)-(4) report results for dependent variable ln(premium), while columns (5)-(8) report results for dependent variable ln(premium/payment + defense cost). *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent variable		**Ln(Premium)**				**Ln(Premium/Cost)**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Competitor Premium)$_t$				**0.417*** (0.0620)**				**0.323*** (0.114)**
Ln(Payout/Physician)$_{t-1}$	**0.113** (0.0492)**		**0.144*** (0.0486)**	0.0159 (0.0293)	**-0.239*** (0.0776)**		**-0.180** (0.0708)**	**-0.277*** (0.0816)**
Ln(Def. Cost/Physician)$_{t-1}$		**0.102*** (0.0248)**		0.0310 (0.0202)		-0.0760 (0.0477)		**-0.0823** (0.0385)**
Ln(Group Premium)$_t$				0.0286 (0.0464)				-0.00587 (0.0774)
Damage Cap Exists$_t$			0.170* (0.0903)				**0.329*** (0.0896)**	
No. of Companies$_t$				0.0155 (0.0113)				0.0148 (0.0178)
Cap Adoption$_t$ * No. of Com panies$_t$								
No of obs.	353,660	351,948	353,434	245,253	353,432	351,720	353,206	245,139
Adj. R^2	0.949	0.949	0.950	0.968	0.925	0.923	0.928	0.936
Adj. R^2, using only FE	0.948	0.948	0.948	0.960	0.922	0.922	0.922	0.929

Appendix Table A4: Effect of Cap Adoption on Premium/Cost Ratio: Narrow Control Group

Table shows simple DiD and distributed lag regressions estimating the effect of cap adoption on premia/(payout + defense cost) ratio over 1990-2017, with year and firm*county*specialty FE. Treatment group is New-Cap states (plus Georgia and Illinois during 2005-2009, when these states had caps in effect) relative to narrow control group (No-Cap states). Column (1) reports results for the difference-in-difference specification using equation (1), while column (2) reports results for the distributed lag specification using equation (3). "Sum of Distributed Lags" reports the sum of the distributed lag coefficients through year 6. Results omit years -2, -1, and 0 for all states that adopt damage caps. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent variable	**Ln(Premium/Cost)**	
	(1)	(2)
Damage Cap Exists$_t$	0.389 (0.228)	
Year 1		0.257 (0.193)
Year 2		0.00620 (0.0959)
Year 3		0.00165 (0.0560)
Year 4		**0.232**** **(0.110)**
Year 5		0.0724 (0.167)
Year 6-10		0.0116 (0.0303)
Sum of Distributed Lags		**0.581**** **(0.228)**
No of obs.	185,238	185,457
Adj. R^2	0.924	0.924
Control Group	Narrow	Narrow

Appendix Table A5: Effect of Damage Caps on Premium/Cost Ratio, Exc. GA and IL

Table shows difference-in-difference, event study, and distributed lag regressions estimating the effect of damage caps on premia/(payout + defense cost) ratio over 1990-2017 excluding Georgia and Illinois from the sample, with year and firm*county*specialty FE. Columns (1) and (2) report results for the difference-in-difference specification using equation (1), while columns (3) and (4) report results for the distributed lag specification using equation (3). "Sum of Distributed Lags" reports the sum of the distributed lag coefficients through year 6. Results omit years -2, -1, and 0 for all states that adopt damage caps. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent variable	**Ln(Premium/Cost)**			
	(1)	(2)	(3)	(4)
Damage Cap Exists$_t$	**0.626*** (0.0997)**	**0.711*** (0.179)**		
Year 1			**0.354*** (0.0926)**	**0.449** (0.181)**
Year 2			0.132 (0.0828)	**0.178** (0.0846)**
Year 3			-0.0332 (0.0407)	-0.0687 (0.0551)
Year 4			**0.334*** (0.0115)**	**0.352** (0.130)**
Year 5			-0.135 (0.153)	-0.161 (0.155)
Year 6-10			0.0565* (0.0311)	0.0233 (0.0282)
Sum of Distributed Lags			**0.709*** (0.169)**	**0.772*** (0.222)**
No of obs.	279,523	163,343	279,523	163,343
Adj. R^2	0.921	0.924	0.924	0.927
Control Group	Broad	Narrow	Broad	Narrow

Appendix Table A6: Effect of Damage Caps on Premium/Cost Ratio, Inc. Year -2

Table shows simple DiD and distributed lag regressions, with year and firm*county*specialty FE, for the effect of damage caps on premia/(payout + defense cost) ratio over 1990-2017. Regressions are similar to text Table 5, but include year -2 in the pre-adoption period, Columns (1) and (2) report results for the simple DiD specification in equation (1), while columns (3) and (4) report results for the distributed lag specification in equation (3). "Sum of Distributed Lags" reports the sum of the distributed lag coefficients through year 6. Results omit years -1 and 0 for all states that adopt damage caps. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent variable	**Ln(Premium/Cost)**			
	(1)	(2)	(3)	(4)
Damage Cap Exists$_t$	**0.360** **(0.164)**	0.372* (0.211)		
Year 1			**0.222** **(0.0957)**	0.239 (0.170)
Year 2			-0.00730 (0.0893)	0.00552 (0.0951)
Year 3			0.00741 (0.0409)	0.000499 (0.0577)
Year 4			**0.241** **(0.0958)**	**0.232** **(0.110)**
Year 5			0.0449 (0.165)	0.0839 (0.175)
Year 6-10			0.0484 (0.0323)	0.0101 (0.0314)
Sum of Distributed Lags			**0.556***** **(0.184)**	**0.572** **(0.220)**
No of obs.	306,994	190,814	306,994	163,343
Adj. R^2	0.920	0.920	0.923	0.924
Control Group	Broad	Narrow	Broad	Narrow

Appendix Table A7: Predicting Costs with Past Costs, In Levels

Determinants of costs over 1990-2017. Fixed effects excluded from regressions. Sum of Lagged Effects reports the sum of coefficients for lags t-1 through t-6 of the dependent variable. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significant results (at 5% level or better) in **boldface**. Standard errors, with state clusters, in parentheses.

Dependent variable	**Direct cost/Phys.**		**Payout/Phys.**		**Def. Cost/Phys.**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable$_{t-1}$	**0.726*** (0.0207)**	**0.471*** (0.0336)**	**0.687*** (0.0223)**	**0.463*** (0.0335)**	**0.516*** (0.0251)**	**0.293*** (0.0332)**
Dep. Variable$_{t-2}$		**0.222*** (0.0388)**		**0.186*** (0.0352)**		**0.211*** (0.0347)**
Dep. Variable$_{t-3}$		**0.135*** (0.0371)**		**0.0830** (0.0356)**		**0.202*** (0.0353)**
Dep. Variable$_{t-4}$		0.0411 (0.0367)		0.0659* (0.0355)		**0.0760** (0.0351)**
Dep. Variable$_{t-5}$		0.0183 (0.0354)		**0.0727** (0.0346)**		0.0246 (0.0339)
Dep. Variable$_{t-6}$		0.0369 (0.0320)		0.0216 (0.0321)		-0.0145 (0.0317)
Sum of Lagged Effects		**0.891*** (0.0251)**		**0.892*** (0.0267)**		**0.793*** (0.0346)**
State and Year FE	N	N	N	N	N	N
No of obs.	1,079	862	1,079	862	1,079	862
Adj. R^2	0.533	0.631	0.468	0.594	0.280	0.411