

# INDUSTRY INPUT IN POLICYMAKING: EVIDENCE FROM MEDICARE\*

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## Abstract

In setting prices for physician services, Medicare solicits input from a committee that evaluates proposals from industry. The committee itself comprises members from industry; we investigate whether this arrangement leads to regulatory capture with prices biased toward industry interests. We find that increasing a measure of affiliation between the committee and proposers by one standard deviation increases prices by 10%. We then evaluate whether employing a biased committee as an intermediary may nonetheless be desirable, if greater affiliation allows the committee to extract information needed for regulation. We find industry proposers more affiliated with the committee produce less hard evidence in their proposals. However, on soft information, we find evidence of a trade-off: Private insurers set prices that more closely track Medicare prices generated under higher affiliation.

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# 1 Introduction

In regulation and procurement, governments often face an information deficit. Industry participants know much more about key inputs for policy decisions, such as production costs, but have incentives to provide selected or distorted information to direct policy in their own interests. Thus, obtaining valuable information from industry to make policy decisions may also provide a general pathway for “regulatory capture,” potentially biasing government decisions toward an industry’s preferred policies (Stigler, 1971; Peltzman, 1976). Understanding and measuring this trade-off between better information collected for decision-making and the distortion from regulatory capture seems particularly relevant given the US government’s reliance on advisory committees for many important policy decisions.<sup>1</sup>

Our empirical work focuses on the public procurement of health care services. Medicare, the federal health insurance program for the elderly, sets administered prices for the roughly \$70 billion in annual payments it allocates for physician services.<sup>2</sup> To do so, the government relies on a committee of physicians convened by the American Medical Association (AMA), known as the Relative Value Scale Update Committee (RUC). The committee evaluates proposals from specialty societies to determine the relative resource costs of services. The committee’s recommendations influence not only Medicare’s direct expenditures, but also indirectly shape pricing in the overall market for physician services, valued at \$480 billion per year or 2.7% of the US GDP (Clemens and Gottlieb, 2017). The prices of medical procedures can also drive larger changes in physicians’ procedural choices (Gruber et al., 1999; Clemens and Gottlieb, 2014) and the career decisions of future physicians (Nicholson and Souleles, 2001).

We first ask whether the composition of the RUC leads to prices biased in favor of its members, a concern raised by observers of this committee (Laugesen, 2016). Using novel data from the RUC on the universe of price-setting proposals discussed between 1992 and 2013, we focus on the RUC’s primary role of assessing the work involved for the service in each proposal and recommending a work-based relative value to Medicare.<sup>3</sup> To measure the effect of connections with the RUC, we develop a measure

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<sup>1</sup>See Brown (2009) for an introduction. In 1972, Congress enacted the Federal Advisory Committee Act to track the existence of a large number of federal advisory committees. In 2006, the US government maintained 916 such committees, with 67,346 members, at a cost of \$384 million. While advisory committees may serve to improve the quality of policy decisions, a key challenge for maintaining such committees is to ensure they are “fairly balanced” and free of “inappropriate influence” (p. 23).

<sup>2</sup>Medicare payments to physicians totaled \$70 billion in 2015, and the US Congressional Budget Office projects spending of \$82 billion in 2020, and \$107 billion in 2025 (Congressional Budget Office, 2016).

<sup>3</sup>The work-related component of relative prices have received the most policy and research attention (e.g., Bodenheimer et

of affiliation, to reflect the alignment in preferences between specialties proposing a price for a service and specialties on the RUC who evaluate this proposal. Our measure exploits data on the many interests that each speciality may have, based on the services it performs, and we show that this measure may represent the likelihood that the global revenues of two specialties will covary under any set of price changes. We then examine whether proposals by specialty societies with higher affiliation with the RUC receive higher prices.

To estimate a causal effect of affiliation between proposing specialties and the RUC on the RUC's decisions, we consider two potential sources of identifying variation. First, the composition of RUC voting members changes across meetings, as the RUC has expanded and rotated voting seats over time. Second, the coalitions of specialties proposing to the RUC for a given procedure vary. In particular, the idiosyncratic costs of proposing and barriers to coordination among the many potential proposers generates randomness in participation. We show that a large majority of variation in affiliation derives from this randomness in proposal coalitions. Further, comparing proposals within the same meeting and for services performed by the same specialties, we find evidence of quasi-experimental variation in affiliation that is conditionally unrelated to exogenous measures of a service that predict its price. In several additional analyses, we demonstrate in greater detail that individual specialty participation in proposals, as well as the proposal-level affiliation that results from this participation, appears as good as random.

Exploiting this variation, we find that increasing a proposal's affiliation by one standard deviation increases the price of the relevant service by 10%. Because specialties have multiple, sometimes shared interests, the implications of this effect on specialty revenue requires careful analysis. We conduct a counterfactual calculation in which we equalize affiliation across proposals, holding Medicare's budget fixed. In this counterfactual, roughly 1.9% of revenues would be reallocated across specialties. This percentage shift represents about \$1.3 billion in annual Medicare spending or \$8.9 billion in annual health care spending accounting for both Medicare and private insurance. Unpacking this average level of reallocation, however, we observe distributional consequences by specialty. Emergency medicine would have the largest percentage revenue gain (+17%) from equalizing affiliation, while infectious disease

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al., 2007; Sinsky and Dugdale, 2013; Laugesen, 2016). According to the AMA (2017), this component equals 51% of overall reimbursement. Two other components of relative price are professional liability insurance (4%) and practice expenses (45%) (e.g., ancillary staff labor, supplies, and equipment). The RUC also determines the practice expense component, but via a separate process. We provide more details in Section 2.

would have the largest loss ( $-5.8\%$ ). Interestingly, specialties like internal medicine and family medicine are net beneficiaries of affiliation, because they share many services in common with RUC member specialties, including the standard office visit. Thus, assuming that changing the RUC's composition only acts via affiliation, we find that more than doubling the number of internal medicine seats on the RUC would increase the specialty's revenue by less than 1%.

Our empirical design based on quasi-experimental proposing specialties implies an alternative mechanism behind the effect of affiliation on committee decisions. Previous research on committees typically exploits the rotation of committee members (Zinovyeva and Bagues, 2015; Li, 2017; Camara and Kyle, 2017); with variation in committee composition, researchers can recover committee preferences or measure committee member's information prior to a proposal. Our source of variation, in proposers, allows us to study influence from these special-interest proposers. For random proposers to generate the effects we observe, committees must be imperfectly informed and must gain information from proposers. Our findings thus relate to a theoretical and empirical literature on lobbying (Blanes i Vidal et al., 2012; Bertrand et al., 2014), which emphasizes how lobbyists' influence depends on their credibility, which in turn depends on the alignment between their interests and those of decision-makers they seek to influence (Kessler and Krehbiel, 1996; Hirsch and Montagnes, 2015).

We then turn to a central question of regulatory design: Given the possibility of bias, what value does the government obtain from inviting industry input in policymaking? In settings involving advisory committees, a key feature is the importance of policy-relevant knowledge (e.g., the safety and efficacy of a drug, the benefits and costs of electricity generation) held by industry participants. The government may form advisory committees that either contribute such knowledge directly or extract and synthesize information from outside special interests. We explore whether allowing some bias in these advisory committees may improve regulatory decisions, by facilitating the communication of information needed for regulation. In our setting, we explore whether Medicare can extract more information about physician services and set more appropriate prices by employing the RUC as an intermediary in decision-making.

To address this question, we begin with a conceptual model, borrowing ideas from a large literature on the extraction of information from biased experts.<sup>4</sup> We model two types of information helpful for

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<sup>4</sup>See Grossman and Helpman (2001) for an extensive review. Some prominent papers in this area, spanning political science and economics, include Crawford and Sobel (1982), Calvert (1985), Austen-Smith (1994), Dewatripont and Tirole (1999), and Li et al. (2001).

regulatory decisions. First, we consider “hard” or verifiable information. A committee adversarial to the specialty expert will encourage the expert to generate more of such evidence (Dewatripont and Tirole, 1999; Hirsch and Shotts, 2015). Second, information may be “soft,” or unverifiable. Soft information must be credibly communicated (Crawford and Sobel, 1982); a committee biased in favor of the specialty expert may improve such communication (Dessein, 2002). The net effect of bias on information extraction thus depends on the nature of information relevant for decisions. In the Medicare setting and many others, some information (e.g., the average time for physicians to perform a service) is conceivably verifiable, but much of the relevant information is difficult to verify and therefore soft (e.g., the “difficulty” or “complexity” of a service relative to another).

We test the predictions of this model of information extraction using two objective measures of information quality unique to our setting. First, we test for the effect of greater affiliation on hard information using the quality of survey data presented to the RUC. Consistent with our model, we find that higher affiliation corresponds to less hard information, in that proposals submitted to a RUC with greater affiliation feature fewer physicians surveyed and fewer respondents, conditional on specialty shares and other proposal and procedure characteristics. Also consistent with the theory, greater hard information, conditional on affiliation, is not correlated with higher prices. Thus, we find empirical support for the theoretical notion, as in Aghion and Tirole (1997), Dewatripont and Tirole (1999), and Hirsch and Shotts (2015), that separation in interests can provide motivation for an agent to provide costly but valuable information to a principal.

Second, to examine a policy-relevant metric of the overall level of (hard and soft) information Medicare collects through the RUC, we measure the degree to which Medicare price changes correlate with private insurance price changes (Clemens and Gottlieb, 2017; Clemens et al., 2017). We classify price changes depending upon whether they originate from RUC decisions, and if so, whether they originate from high- vs. low-affiliation proposals. We find that price changes in private insurance track those changes in Medicare more closely when the Medicare price changes arise from RUC decisions. Further, we find stronger price-following for Medicare price changes arising from more highly affiliated proposals to the RUC, relative to price changes from low-affiliation RUC proposals. These findings suggest that affiliation may improve the overall quality of information in Medicare pricing decisions.

We organize the remainder of the paper as follows: Section 2 describes the institutional setting.

Section 3 introduces our data, measure of affiliation, and discusses our identification strategy. Section 4 presents our main results on the effect of affiliation on relative prices and discusses our interpretation of bias. We move to the question of information extraction in Section 5. We introduce a theoretical framework and then present empirical evidence using data on survey quality and on the transmission of Medicare prices to private insurance prices. Section 6 concludes. All appendix materials referenced in the text appear in an online appendix.

## 2 Institutional Setting

We study the price-setting mechanism within Medicare’s Part B, which finances physician and other clinical services as part of the federal health insurance program for the elderly. While in private insurance, providers may negotiate prices directly with payers (Lewis and Pflum, 2015; Ho and Lee, 2017), Medicare sets its prices using an administrative formula. This arrangement is similar to price cap rules in regulated industries, including telephone service in past decades (e.g., Braeutigam and Panzar, 1993), and to fee schedules for medical care in other countries. Similar to these other regulated settings, Medicare’s formula attempts to set payments according to the costs and effort necessary to perform a service.

To tie payments to costs, Medicare measures the level of costs for a service by summing three distinct components: the intensity and effort of the physician’s work ( $W$ ), the practice expense required to perform the service ( $PE$ ), and the professional liability insurance physicians must carry ( $PLI$ ). Each element has its own relative price, known as a “relative value unit,” or RVU. The payment levels adjust for differences in the cost of practicing medicine in different parts of the country. To convert the relative value units into dollars, the sum of the (geographically adjusted) cost components is multiplied by a common conversion factor; in 2014, the conversion factor was approximately \$35.83 per RVU (American Medical Association, 2015).<sup>5</sup>

In notation, for each service  $i$  performed in geographic area  $j$  in year  $t$ ,

$$\text{Reimbursement}_{ijt} = \left[ \sum_{c \in \{W, PE, PLI\}} (\text{RVU}_{it}^c \times \text{GPCI}_j^c) \right] \times \text{CF}_t. \quad (1)$$

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<sup>5</sup>The conversion factor is set administratively so that Medicare’s total payments for procedures in the US falls within a budget determined by factors such as GDP growth and the number of Medicare beneficiaries. We provide more details in Appendix I.

where  $RVU_{it}^c$  is the relative value unit for service  $i$  in year  $t$  for component  $c$ ,  $GPCI_j^c$  is the fixed geographic practice cost index, and  $CF_t$  is the conversion factor.<sup>6</sup>

With the adoption of this formula, Medicare’s administrators also created for themselves a new and complex task: determining the relative values or RVUs. Judging the level of effort required for each medical procedure requires collecting information possessed by actual practitioners. Medicare thus engages with a committee of the American Medical Association (AMA) to collect physicians’ evaluations of the relative effort and advise on proper RVU levels. This committee—the RUC—recommends relative values to Medicare, which Medicare’s administrators adopt over 90% of the time (Laugesen et al., 2012; American Medical Association, 2017).

## 2.1 The RUC

The RUC considers evidence and makes recommendations for both the work and practice-expense RVU components of the reimbursement formula, which together account for 96% of total RVUs. We focus on work RVUs, which account for the majority of total RVUs across services and have been the focus of increasing scrutiny.<sup>7</sup> We henceforth use the term “RVU” or “relative price” interchangeably with “work RVU,” unless otherwise specified.

The main RUC committee, currently comprised of 25 physician specialty society representatives, considers all changes to work RVUs. Twenty one of these members occupy permanent seats, while the remaining four rotate.<sup>8</sup> For example, a representative of the specialties of internal medicine, dermatology and orthopedic surgery maintain permanent seats, while specialties including pediatric surgery and infectious disease rotate on and off the RUC. In Table I, we record the number of total meetings at which

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<sup>6</sup>Medicare adopted this formula in 1992 (Hsiao et al., 1988). Prior to the current method, Medicare reimbursements were ill-defined and based on “usual and customary charges” that prevailed in each local (usually state-based) insurance market as administered by the state Blue Cross Blue Shield insurer. These prices resulted from negotiations between providers and insurers; they were thought to unfairly compensate certain specialists and also contribute to rising Medicare spending (Laugesen, 2016).

<sup>7</sup>The medical and health policy literatures have raised several potential sources of bias in the price-setting process, although largely descriptively and without access to the data contained in RUC proposals (e.g., Bodenheimer et al., 2007; Sinsky and Dugdale, 2013; Berenson and Goodson, 2016). The popular press has raised some of the same points (e.g., Whoriskey and Keating, 2013; Pear, 2015), and the Affordable Care Act explicitly funded more systematic evaluations comparing external measures of physician time (work) and Medicare-adopted measures (Wynn et al., 2015; Zuckerman et al., 2016). Recent work by Fang and Gong (2017) takes stated times to perform certain services as a benchmark, and compares these times with work RVUs to detect physician over-billing.

<sup>8</sup>The rotating seats include two from internal medicine subspecialties not on the RUC, one primary care rotating seat, and one seat from a specialty society that is not a permanent member of the RUC and not eligible for one of the other three rotating seats. In addition, there are three voting seats that are not held by physician specialties (American Medical Association, 2017).

a particular specialty society had a voting member on the RUC. Clear from this count, many specialties have had a representative on the RUC since its founding in 1992, and some have had two representatives. In Figure I, we show the number of voting seats and a breakdown between “cognitive” and “procedural” specialties over time.<sup>9</sup> Using our definition, procedural specialties—i.e., those who chiefly carry out surgical services—have a larger share of the RUC’s voting members in every year since 1992. The composition of the RUC has changed over time both because some of the seats explicitly rotate and because the committee size has grown over time.

## 2.2 The Price-Setting Process

Each year, in three meetings, approximately 200-300 physician services appear for review before the RUC. The committee will review all newly created services and will re-evaluate some existing services. Evaluations for existing services occur when the description or content of the procedure itself changes, when Medicare requests a revaluation, and, since 2006, when a working group from within the RUC identifies a service as potentially misvalued.<sup>10</sup> In addition, The Omnibus Budget Reconciliation Act of 1990 requires Medicare’s administrators to review relative values at least every five years, collecting public comments on potentially misvalued codes. The RUC has advised Medicare in these “Five-Year” reviews, evaluating 1,118 services in 1997, 870 codes in 2002, 751 codes in 2007, and 290 additional codes in 2012 (American Medical Association, 2014).

For each code under review, the evaluation process begins by identifying specialties to collect evidence and propose an RVU to the RUC. Any of the 122 specialty societies in the American Medical Association’s House of Delegates may weigh in on the development of an RVU proposal, but typically only those who perform the service will volunteer to collect evidence and contribute to the proposal. We later exploit variation in the exact composition of the proposing group in our empirical analyses.

Briefly, the process from proposal to approval involves the following steps:

1. The specialties developing a proposal conduct a survey of their members to collect data about the

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<sup>9</sup>Although the labels “procedural” and “cognitive” have been used frequently to describe specialties in the policy debate on the RUC (see, e.g., Berenson and Goodson [2016]), there is no set categorization of specialties according to these labels. We assign these labels to specialties based on conversations with the RUC. We provide more detail in the note to Figure I.

<sup>10</sup>The RUC’s Relativity Assessment Workgroup identifies potentially misvalued services by objective screens, such as when physicians bill for a service with low work RVUs in multiple units per patient, or when a service that physicians commonly performed in inpatient settings moves to the outpatient setting (American Medical Association, 2014). Specialties may also appeal to Medicare to request that the RUC review a service; such specialty requests represent a small minority of cases.

work and resource use involved in the given service.

- (a) If surveying, specialties decide on the number of physician members to survey. Physicians are asked to compare the service with “reference services” and to give estimates of the time and other measures of work required (e.g., mental effort, technical skill, psychological stress). The survey contains a standardized vignette for the service, to ensure consistency of the estimates.
  - (b) The one or more specialties who have conducted surveys present their evidence and arguments for a proposed relative price before the RUC.
2. The RUC members discuss the proposal with each other and with the proposer(s). Proposals pass with at least a two-thirds vote of the committee.<sup>11</sup>
  3. The RUC forwards its recommendations to Medicare, which historically accepts the relative prices 90% of the time (Laugesen et al., 2012; American Medical Association, 2017). Medicare, using formulas in Equation (1) and Appendix I, translates these relative prices into payment levels.

### **3 Empirical Approach**

We analyze the RUC’s role in the price-setting process using data from the committee’s deliberations. Our substantive goals are twofold. First, we measure the causal effect of the RUC’s affiliation with the proposing specialties on the prices recommended by the committee. Second, we determine the effect of affiliation on information transmission. To do so, we need to define an empirical measure of affiliation, and then describe the plausibly exogenous variation in this affiliation that allows us to identify the causal effect of affiliation on prices and on information transmission.

#### **3.1 Data**

Our empirical analyses rely on three sources of data. First, we use information on the RUC’s deliberations, including the RUC membership at each decision and the details of the proposal for each service

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<sup>11</sup>If a proposal is not approved, the proposer(s) may discuss their proposal with a smaller “facilitation committee.” In facilitation, the proposed value is often revised downward. The RUC must still pass any revisions. The RUC may also independently recommend a relative price to Medicare if no proposal is successful.

evaluated by the committee. We accessed the same database RUC members use to prepare for votes during meetings, with detailed proposal information for each service the RUC evaluated from its inception in 1992 until 2013. For each proposal, we collect the identity of the service, the meeting in which the RUC considered the proposal, the specialty society or societies involved, the RVU level proposed, and the RVU level recommended by the RUC. We observe 4,423 proposals with known specialty proposers and other selection criteria. We describe details of our sample creation in Appendix Table A.1.

The RUC's database also contains detailed characteristics of each proposal. We observe the characteristics of the survey, a central component of proposals, including the number of physicians surveyed and the number of respondents. We also collect summary statistics of the survey responses regarding the time required for a service, as well as comparisons between the service and a "reference" service along various qualitative dimensions (e.g., complexity of medical decision-making, urgency, technical skill, physical effort).<sup>12</sup>

Second, in addition to the RUC database, we collect characteristics of each service to use as controls in our analyses and to identify the types of physician specialties that use each code. The data come from Medicare, including its annual utilization files and a survey of Medicare beneficiaries. With these data, we define a set of service-specific characteristics, including: (i) yearly Medicare utilization of a given service, broken out by the identity of the specialty providing the service; (ii) average demographics of patients who receive a given service; and (iii) the fraction of utilization of the service in different medical settings, including the emergency department, inpatient, outpatient care settings.

To build even more detailed control variables to characterize each service, we merge in a database of service descriptions.<sup>13</sup> The description field includes a set of words that Medicare, other payers, and clinicians use to categorize physician work for reimbursement and productivity measurement. We identify keywords from this collection of descriptive terms and create variables that reflect a service's description.<sup>14</sup>

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<sup>12</sup>In the survey questions on time, we observe time information broken into preparation time before the procedure (median), the time for the actual service itself (25th, 50th, and 75th percentiles), any post procedure time, and indicators for whether surgical procedures require additional office visits before or after the surgery.

<sup>13</sup>In Appendix Table A.2, we provide examples of these descriptions.

<sup>14</sup>In detail, we identify word stems to account for inflected variations (e.g., "operate" and "operation"), of which there are a total of 9,271 unique stem words from 11,123 original words, excluding stop words such as "the," "and," and "only." The median count of unique word stems across procedure code descriptions is 8, and the 5th and 95th percentiles are 3 and 22, respectively. We use these word stems to create a vector of indicator variables reflecting the content of a service's description field.

Finally, third, we collect a time series of private sector prices for each service. We later compare the changes in private prices to those in Medicare, to explore how private insurers respond to information and possible bias in Medicare’s price setting mechanism. We use the transaction price in Truven Health’s MarketScan data to measure prices for each service as paid by private insurers.<sup>15</sup> We observe quantities of use, the specialty of the billing physician, and a measure of the reimbursement paid to the provider. We scale the MarketScan data by patient demographics in the Medical Expenditure Panel Survey (MEPS) dataset, to find nationally representative estimates of private insurance utilization for each procedure and for each specialty performing it.

### 3.2 Specialty Interests

To characterize how specialties on the RUC may vote in their self-interest, we first define and measure notions of specialty interests. As a natural benchmark, we start by measuring a specialty’s interest in a service using the contribution of the service to the specialty’s revenue. The revenue of specialty  $s$  is  $R_s = \sum_i p_i q_{is}$ , or the sum of revenues from each service  $i$ . Revenue here is the product of the price of  $i$ ,  $p_i$ , and the quantity of  $i$  that specialty  $s$  supplies,  $q_{is}$ .

In this benchmark case, specialties on the RUC, each focused on revenue maximization, will want to increase the price of services that they perform. All else equal, specialties that obtain more of their revenue from a particular service will have a greater interest to increase the price of that service. We define two measures of direct interests from this concept. First, we define the utilization share of service  $i$  in specialty  $s$ ’s total utilization as

$$\sigma_{is}^q \equiv \frac{q_{is}}{\sum_i q_{is}}. \quad (2)$$

Similarly, the revenue share of service  $i$  in the total revenue of specialty  $s$  is  $\sigma_{is}^R \equiv (p_i q_{is}) / (\sum_i p_i q_{is})$ . The respective  $C \times 1$  vectors  $\sigma_s^q$  and  $\sigma_s^R$  define specialty  $s$ ’s direct interests over the  $C = 11,252$  CPT codes that physicians in the specialty may perform for reimbursement in the years of our sample. For our baseline analysis, we consider interests as quantity shares  $\sigma_s = \sigma_s^q$ .

In addition to direct interests, a specialty may consider how setting the price for a particular service influences the price and utilization of other services it performs. We denote these considerations as in-

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<sup>15</sup>The transaction price reported in the MarketScan data reflects the gross payments to a provider for a service, net of discounts, but excluding the patient’s contribution.

direct interests and refer to the combination of direct and indirect interests as related interests. Indirect interests arise in our setting for several reasons. First, a change in a service’s price affects the quantity demanded of both substitute services and complementary services, such as anesthesia for surgical procedures. Second, a single technology may appear in multiple distinct services, used by different physician specialties.<sup>16</sup> Third, as a required element of proposals, specialty societies define “reference services” to justify a price request. Specialties may care about the prices of those services that may later serve as a reference for their own common services.<sup>17</sup> Finally, at a minimum, changes in quantities or prices will affect the Medicare reimbursement for all other services via the conversion factor.<sup>18</sup>

Exactly how related services’ prices and quantities will change is difficult to measure. We would need quasi-experimental supply and demand shifters for each service to recover unbiased estimates of these cross-elasticities. Further, the number of cross-elasticities is large relative to the data points within each service, which leads to severe finite-sample issues (Altonji and Segal, 1996). With these caveats, we empirically measure the co-movement in price or revenue across our set of  $C$  services, as described in Appendix II.C. In brief, we use the empirical  $C \times C$  matrix of co-movements,  $\hat{\Omega}$ , to form a vector of related interests,  $\tilde{\sigma}_s = \hat{\Omega}\sigma_s$ . The  $i^{\text{th}}$  element of  $\tilde{\sigma}_s$  reflects not only specialty  $s$ ’s direct interest in  $i$ , but also the indirect revenue implications of  $i$  on other services that  $s$  performs.

### 3.3 Affiliation

We further aggregate specialty interests across multiple services into measures of overall alignment in interests between specialties, a concept that we denote as affiliation.<sup>19</sup> This approach allows us to be agnostic in specifying spillovers across services: Two specialties with the same service-specific interests—or specialties that are perfectly affiliated—should have the pricing preferences regardless of the

<sup>16</sup>For example, flexible endoscopy is used in distinct services performed by obstetricians (e.g., CPT 58572), general surgeons (e.g., CPT 44970), gastroenterologists (e.g., CPT 43260), and orthopedic surgeons (e.g. CPT 29883). Ultrasound technology also appears in distinct services billed by radiologists (e.g., CPT 76700), vascular surgeons (e.g., CPT 37250), cardiologists (e.g., CPT 93306), and ophthalmologists (e.g., CPT 76510).

<sup>17</sup>Survey instruments ask physicians to use a list of 10 to 20 services pre-selected by the proposing specialties (American Medical Association, 2017). In an analysis of 1,127 reference services we observe in detailed survey data from 2,011 proposals, we find that each reference service is “used” on average by  $\sum_s \mathbf{1}(w_{is} > 0.01) = 7.5$  specialties, where  $w_{is}$  is defined in Equation (5), while each reference service is referred to on average by set of services  $\mathcal{I}(i)$  that are used by  $\sum_s \max_{i' \in \mathcal{I}(i)} \mathbf{1}(w_{i',s} > 0.01) = 22$  specialties.

<sup>18</sup>In particular, the zero-sum nature of the conversion-factor formula, described in Appendix I, can act to depress prices for common primary care procedures (Bodenheimer et al., 2007).

<sup>19</sup>This concept is similar to *congruence* in Caillaud and Tirole (2007), which they define as the “prior probability that a given member benefits from the sponsor’s project.”

nature of spillovers across services.

Focusing on affiliation not only allows us to bypass the econometric issues of measuring cross-service spillovers, but also allows us to capture two conceptual features of RUC decision-making that one ignores when accounting only for RUC specialty interests in a service. First, RUC specialty representatives may naturally have less information about the services being priced than the proposing specialties, an idea we formally model and test in Section 5. RUC specialties may thus be unable to evaluate fully the implications of a pricing decision on their revenue and instead may need to evaluate proposals by a more easily observed metric, the similarity of their interests with proposing specialties. Second, as long-term actors, specialties may care about their relationships with other specialties. Similar interests would enable specialties to form stronger coalitions over many future price-setting decisions. Thus, differences in affiliation may lead to distinct pricing decisions, holding fixed interests in the service being priced.

We define a baseline affiliation measure between two specialties  $s$  and  $s'$  as a negative Euclidean distance:

$$a(s, s') = -\sqrt{(\sigma_s - \sigma_{s'})'(\sigma_s - \sigma_{s'})}, \quad (3)$$

As we note above, this measure of affiliation between specialties requires no knowledge of the complicated relationships between services.<sup>20</sup> In Appendix II, we show how we can rationalize this affiliation definition as a measure of the alignment of revenue objectives between two specialties.<sup>21</sup>

Figure II shows affiliation measures between specialties, among the 20 specialties with the highest revenue, where we divide the measures into nine bins. Many affiliation measures are intuitive: We find high affiliations for related pairs such as between internal medicine and family medicine, between electro-diagnostic medicine and neurology, and between orthopedic surgery and hand surgery. Perhaps surprisingly, internal medicine is affiliated with many surgical specialties. Although more closely tied to other cognitive specialties, internal medicine's connection to many surgical specialties arises due to a reliance on the same evaluation and management codes billed during office visits.<sup>22</sup> In contrast, physicians

<sup>20</sup>We show in Appendix II that Equation (3) can be thought of as an expected measure of differences in revenue changes between specialties  $s$  and  $s'$  under an uninformative prior of spillovers. If, instead of affiliation, we focused our measurement on service-specific interests, we would ignore potential spillovers by assumption.

<sup>21</sup>In Appendix II, we also discuss alternative distance metrics, such as Manhattan distance and angular distance. Although there are theoretical reasons to prefer our chosen affiliation measure, we nevertheless show in Appendix Table A.3 that the affiliation effect on prices we report in Section 4 is robust across other formulations. In Appendix II.C, we also consider affiliation measures that exploit service co-movements.

<sup>22</sup>Many important linkages between seemingly disparate specialties exist: Bronchoscopy is shared by otolaryngology, pul-

in pathology use a set of codes rarely used by other specialties, leading to low affiliations. Similarly, emergency medicine physicians provide evaluation and management services using distinct codes specific to emergency patients, and thus have low affiliations.

Our definition of affiliation reflects pairwise comparisons of the similarity in procedure use between two specialties. However, for our eventual empirical specifications, we need an affiliation measure at the proposal level, since our outcomes measures are specific to a proposal. Thus, we define set affiliation, a measure of affiliation between the set of specialties composing the RUC and the set of specialties party to a proposal.<sup>23</sup> The set affiliation between the set of proposing specialties  $\mathcal{S}_i$  for proposal  $i$  and the set of RUC member specialties  $\mathcal{R}_t$  at meeting  $t$  is

$$A^*(\mathcal{R}_t, \mathcal{S}_i) = \frac{1}{\|\mathcal{R}_t\|} \sum_{r \in \mathcal{R}_t} \max_{s \in \mathcal{S}_i} a(r, s), \quad (4)$$

where  $r \in \mathcal{R}_t$  denotes a member specialty on the RUC, and  $s \in \mathcal{S}_i$  denotes a specialty on the proposal. For each  $r \in \mathcal{R}_t$ , we take the maximum affiliation between  $r$  and any proposing specialty  $s \in \mathcal{S}_i$ . In this formulation, additional proposing specialties in  $\mathcal{S}_i$  can only increase  $A^*(\mathcal{R}_t, \mathcal{S}_i)$ , based on the intuition in Krishna and Morgan (2001) that communication outcomes improve when a receiver listens to the most closely aligned sender. We then take the average across RUC members, to reflect that the RUC aggregates opinions across members, not only in voting but also in the committee’s private and public discussions (Li et al., 2001). Finally, for interpretation, we standardize  $A^*(\mathcal{R}_t, \mathcal{S}_i)$  by subtracting the sample mean and dividing by the sample standard deviation, and denote this standardized measure as  $A(\mathcal{R}_t, \mathcal{S}_i)$ .<sup>24</sup>

### 3.4 Identification

An ideal experiment to assess the effect of affiliation on price would randomly assign affiliation to proposals, so that affiliation would be independent of potential prices. Lacking random assignment, we exploit quasi-experimental variation in affiliation between proposals within two dimensions. First, since

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monary medicine, and thoracic surgery. Plain x-rays are shared between internal medicine, radiology, and surgery. CT scanning of the head is shared by radiology, neurosurgery, and neurology.

<sup>23</sup>Proposing coalitions exist in our sample. Of the 4,423 proposals in our baseline sample with known proposing specialties, 63% are made by a single specialty, 23% are made by two specialties, and 14% are made by three or more specialties.

<sup>24</sup>In some cases, described below, we will compute the counterfactual set affiliation for proposal  $i$  in a different meeting than the actual  $t$ . In these cases we continue to normalize with the mean and standard deviation of the actual sample of  $A(\mathcal{R}_t, \mathcal{S}_i)$  in order to maintain comparability.

prices are relative within a time period, we condition on a vector of indicators for the RUC meeting  $t$  at which a procedure was valued, or  $\mathbf{T}_t$ . Second, because specialties vary in the types of procedures that they perform and in their affiliation with the RUC, we condition on the specialties that perform the service in question. Specifically, we condition on  $S = 64$  specialty utilization shares:

$$w_{is} = \frac{\sum_y q_{isy}}{\sum_y \sum_s q_{isy}}, \quad (5)$$

for service  $i$ , specialty  $s$ , and Medicare claim year  $y$ . In the extreme, if a single specialty performed the service, conditioning on the  $S \times 1$  vector  $\mathbf{w}_i$  would be equivalent to including specialty fixed effects.

Conditioning on the time period of the meeting and comparing services with similar patterns of specialty usage, we make the following assumption to identify the causal effect of affiliation:

**Assumption 1 (Quasi-Experimental Affiliation).** *Potential outcomes (e.g., price recommendations) conditional on any set of RUC specialties  $\mathcal{R}_t$  and any set of proposing specialties  $\mathcal{S}_i$  for service  $i$  are independent of assigned set affiliation  $A(\mathcal{R}_t, \mathcal{S}_i)$ , conditional on  $\mathbf{w}_i$  and  $\mathbf{T}_t$ .*

To assess Assumption 1, we first check whether proposals with higher vs. lower affiliation have the same intrinsic prices based on exogenous characteristics, conditional on  $\mathbf{w}_i$  and  $\mathbf{T}_t$ . In Table II, we show balance in characteristics for Medicare beneficiaries who receive services with high residual affiliation and those who receive services with low residual affiliation. In Appendix Figure A.3, we similarly show balance in predicted price, as a function of these plausibly exogenous service characteristics, controlling for  $\mathbf{T}_t$  and  $\mathbf{w}_i$ . Despite having no relationship with residual affiliation, these characteristics are nonetheless important: They alone explain about 25% of the variation in prices and are highly correlated with affiliation unconditionally.

We further unpack the quasi-experimental variation in  $A(\mathcal{R}_t, \mathcal{S}_i)$  under Assumption 1 by distinguishing two possible sources: random assignment of  $\mathcal{R}_t$  or random assignment of  $\mathcal{S}_i$  to  $i$ . We show in Appendix IV that variation in affiliation due to  $\mathcal{R}_t$  is a small component of the total identifying variation.<sup>25</sup> This is not surprising given the relatively stable RUC specialty membership reported in Table I and Figure I. Instead, the wide variation in affiliation, even across proposals with the participation of a given specialty (Figure III), appears due to the proposing specialties,  $\mathcal{S}_i$ . In Section 4.3, we discuss how

<sup>25</sup>In particular, we find that only 1.4% of the total identifying variation in  $A(\mathcal{R}_t, \mathcal{S}_i)$  is due to  $\mathcal{R}_t$ .

the source of variation in affiliation influences our interpretation of its effect.<sup>26</sup>

Why should we expect random variation in proposing specialties, conditional on the specialty utilization shares  $w_i$  of  $i$ ? Based on institutional requirements set by the RUC, as many as a dozen specialties are eligible to be on the proposal a typical service, while 98% of the proposals involve five or fewer specialties, which suggests that specialty proposals are not predetermined by eligibility. One source of random variation could derive from a specialty's costs of proposing from meeting to meeting.<sup>27</sup> When proposing involves private costs but all physicians who perform the service capture the rewards of proposing (i.e., higher prices), specialties may choose to free-ride on others' proposals. In Appendix III, we show in a simple model that free-riding implies we are unlikely to find predictable proposing strategies by specialties (i.e., pure strategies are unstable). Instead, we find stable mixed strategies, which, by design, imply uncertainty in proposing and provide a theoretical justification for random variation in the identities of proposing specialties.<sup>28</sup>

To assess quasi-experimental variation in  $S_i$  empirically, we conduct four tests, detailed in Appendix IV. First, we show evidence that the probability a specialty participates in a proposal is conditionally uncorrelated with the predicted price of the relevant service.<sup>29</sup> Second, we show that the probability of a specialty participating in a proposal is also uncorrelated with differences in affiliation with the RUC over time. Third, we form a flexible prediction of specialty-proposal propensities and demonstrate substantial residual variation in specialty proposals. Finally, using our estimated specialty-proposal propensities and the known specialties of RUC members at each meeting, we form a prediction of affiliation by simulation. We use this prediction to evaluate endogeneity in set affiliation by testing whether it is forecast-unbiased (Chetty et al., 2014). We find no evidence of forecast bias in predicted set affiliation, in line with our claim of quasi-experimental variation in specialties' participation in proposals.

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<sup>26</sup>While the former variation has been used previously in empirical assessments of committee decisions (Zinovyeva and Bagues, 2015; Li, 2017), the latter may also be justified by a broad theoretical literature in political science and political economy (e.g., Baron and Ferejohn, 1989).

<sup>27</sup>In interviews, RUC members report that these costs are substantial and could depend on idiosyncratic capacity to administer surveys and send representatives to present a proposal. In data on the history of proposals, we find that a specialty is less likely to propose if there is another procedure in the same RUC meeting that has a higher predicted propensity of the specialty proposing.

<sup>28</sup>The likelihood of free-riding and relevance of mixed strategies is higher when specialty societies cannot easily coordinate. In our data, we observe 268 named specialty societies representing 64 Medicare specialties. Both the large number of specialty societies and the short amount of time available to complete a proposal may hinder coordinated participation in proposals.

<sup>29</sup>Specifically, we predict the RVU of a procedure by its characteristics, including procedure code word descriptions, surveyed time, prior RVU, and the characteristics of the procedure's patient population; this RVU prediction equation has an adjusted  $R^2$  of 0.88. Controlling for specialty indicators and  $w_i$ , we find no significant relationship between specialty proposals and the predicted price.

## 4 Affiliation Effect on Prices

We use our quasi-experimental design to measure regulatory capture in Medicare’s price setting. We do so first by testing how the degree of affiliation between proposers and RUC members affects the RUC’s price recommendations. We then use this estimated relationship to quantify how much of Medicare’s budget would be reallocated among specialties were the US government to alter the role of affiliation.

### 4.1 Estimated Effect

We estimate the effect of affiliation on RUC-recommended relative price with the following equation:

$$\ln RVU_{it} = \alpha A(\mathcal{R}_t, \mathcal{S}_i) + \mathbf{X}_i \beta + \mathbf{T}_t \eta + \mathbf{w}_i \zeta + \varepsilon_{it}, \quad (6)$$

where  $RVU_{it}$  is the relative price granted to proposal  $i$  at meeting  $t$ , and  $\alpha$  is the effect of increasing set affiliation by a standard deviation.<sup>30</sup> We include fixed effects for the RUC meeting  $t$  and control for specialty utilization shares  $\mathbf{w}_i$  in all specifications. Thus we compare prices within the same meeting and for services with the same (linear) composition of specialties performing the service.

We can control for a large number of additional service and proposal characteristics  $\mathbf{X}_i$ . In Table III, we report results for key control specifications. In all specifications, we control for prior RVU, which exists for proposals made for an existing service (about 50% of the proposals). Even the most basic specification, in column (1), predicts a high degree of variation in RVUs. In column (2), we add controls for average characteristics of Medicare beneficiaries who receive the service (listed in Table II), and for a vector of shares across eight “place-of-service” categories (e.g., clinic, inpatient hospital, emergency department). The latter place-of-service shares further differentiate services performed by the same specialties but delivered in different settings by potentially distinct subspecialties.

Our results remain stable when we add even more detailed controls. In column (3), we add surveyed characteristics, such as total utilization, surveyed time intervals needed to perform the service, and surveyed measures of service difficulty. Column (4) represents the full specification and adds word stems from the procedure’s description.<sup>31</sup> In this specification, we find that a standard deviation increase in af-

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<sup>30</sup>We study the effect of affiliation on log RVU, because relationships between components of price (e.g., time and intensity of a service) are viewed as multiplicative (Hsiao et al., 1988).

<sup>31</sup>In practice, because of the high number of procedure code characteristics relative to the number of proposals, we employ

affiliation increases relative price by 10.1%.<sup>32</sup> In Figure IV, we illustrate this result in a binned scatterplot of residualized price on the  $y$ -axis and residualized affiliation on the  $x$ -axis. Increasing affiliation from the 10th percentile to the 90th percentile would increase prices by 17%.

In column (5), we show a similar effect when we control for predicted set affiliation, as a function of the RUC membership,  $\mathcal{R}_t$ , and the predicted propensity of each specialty to propose, described in Appendix IV, instead of linear  $\mathbf{w}_i$ . This prediction mechanically controls for any variation in RUC membership over time. In column (6), we show that our result is robust to controlling for interactions of each specialty share with linear meeting year, which allows for changes in the average intrinsic value of each specialty's procedures over time. In Appendix Table A.3, we show robustness of our results to 49 other formulations of affiliation.<sup>33</sup> To the extent that we measure affiliation with error, in that we may fail to capture important linkages between specialties (e.g., between anesthesiology and surgery), our results can be interpreted as a lower bound of the effect of affiliation on prices.

## 4.2 Counterfactual Revenue

Given the effect of affiliation on recommended prices, we examine the revenue implications from two counterfactual scenarios that change the affiliation of proposals. In the first scenario, we equalize the affiliation of all proposals, so that no proposal has an advantage (or disadvantage) under affiliation. In the second, we consider a counterfactual RUC, in which the 25 specialty seats are apportioned based on specialty physician populations, as given in Appendix Table A.7. This scenario, which generally reallocates RUC seats away from "procedural" specialties, has been a common policy intervention advocated by critics of the RUC who wish to close the "primary care-specialty income gap" (Bodenheimer et al., 2007; Laugesen, 2016).

In both counterfactual scenarios, we hold fixed the timing of each proposal, the Medicare budget, and the utilization of each service over time. We simulate changes in revenue at the service level solely

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methods to avoid overfitting. For example, for a code description's word stems, we remove collinear word stems and then select predictive word stems via LASSO. We also form jack-knifed RVU predictions using the set of post-LASSO OLS controls and using only observations from meetings other than meeting  $t$ . Finally, we form jack-knifed RVU predictions based on the procedure's characteristics.

<sup>32</sup>Consistent with robustness across control specifications, we show via an Altonji et al. (2005) framework that selection on unobservables, controlling for meeting dummies and specialty shares, would need to be 3.9 times greater than selection on observables to explain our estimated effect.

<sup>33</sup>We provide support for our preferred affiliation measure and discuss alternatives in Appendix II.

through the effect of counterfactual affiliation on service prices, which we have estimated in reduced form from Equation (6).<sup>34</sup> We further aggregate counterfactual revenue reallocation to specialties and to types of services, defined by Berenson-Eggers Type of Service (BETOS) codes. Figure V shows changes in specialty revenue under both counterfactual scenarios. We provide details of the simulation algorithm in Appendix V and present changes in BETOS revenue in Appendix Figure A.10.

Equalizing affiliation across proposals would reallocate \$1.0 billion (or 2.9% of work-based reimbursement) in yearly Medicare work-based revenue across procedures, or \$1.9 billion in total Medicare reimbursement, if we extend the affiliation effect to practice-expense reimbursement (also priced by the RUC). Assuming a proportional price change in private insurance, the cross-service reallocation would be \$13.4 billion yearly. Notably, although internal medicine has a minority of seats, it gains from affiliation because many other specialties, including surgical ones, also derive a large share of revenue from the same evaluation and management services performed in office and inpatient visits.<sup>35</sup> Of specialties, emergency medicine would have the largest percentage revenue gain (+17%), while infectious disease would have the largest loss (−5.8%). At the specialty level, we find overall that 1.9% of revenues would be reallocated across specialties, or about \$1.3 billion in Medicare spending or \$8.9 billion in annual health care spending from both Medicare and private insurance.

Reapportioning RUC seats based on specialties' relative physician populations would reallocate \$230 million in yearly Medicare work-based revenue across procedures, or \$450 million in total Medicare reimbursement. Overall, this reallocation in dollar terms generally represents only one-fifth of the magnitude (and often opposite in direction) of the reallocation when equalizing affiliation. Even though internal medicine would be given 4 seats, compared to the actual average of 1.5 seats on the RUC, the specialty would gain less than 1 percent in revenue. Infectious disease would have the largest percentage revenue gain (+1.4%), and ophthalmology would experience the largest percentage revenue loss (−1.4%).

Our counterfactual analysis is based on a reduced-form estimate of  $\hat{\alpha}$  from Equation (6). Conducting this analysis based on a reduced form estimate would be invalid if counterfactual affiliations differ greatly

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<sup>34</sup>Although we formally model the relationship between affiliation and pricing decisions as a static game in Section 5.1, this relationship may empirically capture both static effects and dynamic mechanisms, such as log-rolling. The first counterfactual scenario involves shutting off any such mechanism. For the second counterfactual scenario, we present some evidence in Appendix V that counterfactual changes in affiliation are “in-sample” in terms of magnitudes and thus unlikely to involve changes in equilibrium outside the sample of our reduced-form analysis.

<sup>35</sup>We do not investigate other mechanisms, such as the difficulty in raising prices for common procedures, that may depress prices for office visits and therefore affect the revenues of non-procedural specialties (Bodenheimer et al., 2007).

from actual affiliations; our analysis in such a scenario would require “out-of-sample” extrapolation, and would suggest moving instead to a structural approach. In Appendix V.B, we evaluate the external validity of using  $\hat{\alpha}$  in this analysis, by comparing the distribution of counterfactual affiliations under this alternative RUC with the observed distribution of actual affiliations. We find the differences in affiliation induced by a counterfactual RUC are small relative to the variation in affiliation we observe in the data.

### 4.3 Mechanisms Behind the Price Effect

We interpret the finding that greater affiliation results in higher prices as evidence of a bias among RUC members to recommend higher prices for affiliated specialties. This interpretation is consistent with a recent empirical literature on political rents.<sup>36</sup>

As we note in Section 3.4, affiliation varies predominantly via the identity of specialty proposers. Thus, unlike settings in which rotating decision-makers have different preferences or ex ante information for a given decision (Zinovyeva and Bagues, 2015; Li, 2017; Camara and Kyle, 2017), our setting is closer to a lobbying environment: Variation in decisions is potentially induced by relationships between specialties. Recent empirical work has suggested that affiliation between lobbyists and decision-makers may determine the effectiveness of lobbying (Blanes i Vidal et al., 2012; Bertrand et al., 2014). In the lobbying environment, a theoretical literature suggests lobbyists may have an effect because decision-makers are imperfectly informed and are willing to vote in favor of a proposal when the proposal is backed by a lobbyist with aligned interests (Kessler and Krehbiel, 1996; Hirsch and Montagnes, 2015).<sup>37</sup>

Given our source of variation, we view alternative mechanisms that depend only on the identities of committee members to be unlikely explanations for the effect of affiliation on price. These alternatives include voting behavior that depends only on RUC members’ pure service-specific interests or ex ante information. Nonetheless, In Appendix VI, we examine the robustness of our affiliation effect to

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<sup>36</sup>For notable examples in the economics literature, see Fisman (2001); Khwaja and Mian (2005); Faccio (2006); Ferguson and Voth (2008). This literature generally views relationships between firm valuations and political actors as *prima facie* evidence of rents and corruption. In medical price-setting, Bertoli and Grembi (2017) study regional-government inpatient prices for obstetric admissions in Italy, as a function of the number of physicians in government positions. Recent papers of committee decision-making, by Li (2017) and Camara and Kyle (2017), explicitly consider information alongside bias. Their frameworks would also interpret decisions systematically skewed toward or against randomly assigned applicants (i.e., equal expected quality) as bias.

<sup>37</sup>While this presents an incentive for affiliated specialties to participate in proposals, if the RUC membership is stable, this incentive should be constant and should not contribute to variation in proposers. In Appendix III, we formally discuss a model of random proposers when there are costs and benefits of proposing. Recall that we show evidence of random proposals in Section 3.4.

controlling for moments of utilization or revenue shares by RUC specialties for the service in question (i.e.,  $\sigma_{is}$ ), as defined in Section 3.2. These shares proxy for both interests and ex ante information that RUC specialties may have about a given service, prior to any proposal. We find that the effect of set affiliation is unchanged when we control for these shares. Further, the relationship between prices and service-specific interests is small and represents only a fraction of this effect.<sup>38</sup> Interestingly, however, we find that related interests, which account for spillover effects on the revenue of other services, may be more relevant for RUC decisions than direct interests.

In Appendix VI, we also consider a simple signaling mechanism that does not depend on RUC bias. In this alternative mechanism, the RUC interprets larger coalitions of proposing specialties (and thus higher affiliation) as evidence of higher quality proposals; the decision to increase price in this framework is thus not based on RUC members' preferences to increase the revenue of some specialties over others. However, in our data, we find a slightly larger effect of affiliation on prices when controlling for the number of proposing specialties, contradicting this hypothesis.

Finally, in Appendix VII, we investigate heterogeneous treatment effects of affiliation on prices, depending on both the type of CPT code being discussed and on the meeting date. The evidence suggests large differences in treatment effects across proposals. The effect of affiliation is almost entirely borne by proposals for new CPT codes, and it is substantially larger for CPT codes with lower revenues (i.e., lower volumes or price). This heterogeneity is consistent with larger effects of affiliation when there is more uncertainty about a procedure's value and when a smaller share of Medicare's total spending is at stake. That is, affiliation between specialties appears to play a greater role in committee decisions precisely when information extraction is likely to be more important relative to entrenched interests. We turn to information extraction next.

## 5 Affiliation Effect on Information Extraction

Given the evidence of bias due to affiliation, we return to a broader question posed by the prevalence of advisory committees: Why would the government involve an intermediary that may be biased toward

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<sup>38</sup>Given that we have little variation in the RUC membership, we do not focus on the causality of these relationships. However, specialty interests ( $\sigma_s$  or  $\bar{\sigma}_s$ ) as described in Section 3.3 are distinct from specialty utilization shares of a service ( $w_i$ ) that we use for controls and require for identification in Assumption 1. This distinction allows us to estimate these regressions.

industry? In this section, we first introduce a conceptual model that illustrates a trade-off between bias and information extraction. In our framework, the specialty society is a biased expert that has information about the true value of a service to be priced. We show that the quality of information extracted and used in price-setting may improve with affiliation between the RUC and the specialty society. We then test the predictions of this model using two objective measures of information quality uniquely available in our setting. First, we test for the effect of greater affiliation on the quality of survey information presented to the RUC. Second, we use data on prices from private insurers to evaluate how price-following from Medicare to the private sector depends on affiliation, as a measure of the information content of the RUC's recommendations.

## 5.1 Conceptual Framework

Consider a government that procures a service at relative price  $p$ , ideally set at  $\theta \sim U(0, 1)$ . A specialty society knows  $\theta$  but may also have bias. The government may delegate price-setting to the RUC, which then evaluates information from the specialty about  $\theta$ .<sup>39</sup> Information can be communicated in two forms: “hard” and “soft.” Hard information is verifiable and interpretable but costly to produce. In this setting, hard information includes the data reported in physician surveys, for example. Soft information, as in “cheap talk” (Crawford and Sobel, 1982), includes aspects of the service that cannot be verified by evidence, such as the “difficulty” or “complexity” of one service relative to another.

The government chooses the specialty composition of the RUC, so that the RUC may be more or less affiliated with the proposer. The degree of bias in price-setting and the quality of information will depend on this affiliation between the RUC and the speciality society.

### 5.1.1 Timing and Payoffs

The timing and payoffs are as follows:

1. The government delegates to a RUC intermediary with bias  $b_R$ .

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<sup>39</sup>We follow a standard setup from Dessein (2002). This modeling assumption may be supported by the fact that Medicare follows the RUC price recommendations 90% of the time. More recent cheap talk models study sequential cheap talk and are more complicated. If the government undoes bias from high-affiliation RUC decisions, then informational advantages from communication will in general be nullified (Ambrus et al., 2013).

2. The specialty may produce hard information verifying that  $\theta$  lies uniformly on a subinterval of length  $L$  (i.e.,  $\theta \sim U(\underline{\theta}, \bar{\theta})$ ,  $L \equiv \bar{\theta} - \underline{\theta} \in [0, 1]$ ), via a technology that comes at cost  $c(L)$ .<sup>40</sup>  $c(1) = 0$ ,  $c'(L) < 0$ , and  $c''(L) > 0$ .
3. The specialty observes  $\theta$ , and then transmits a cheap talk message  $m$  about  $\theta$ .
4. The RUC sets price  $p$ . Non-transferrable payoffs are as follows for the specialty ( $u_S$ ), RUC ( $u_R$ ), and the government ( $u_G$ ):

$$\begin{aligned} u_S &= -(\theta + b_S - p)^2 - c(L); \\ u_R &= -(\theta + b_R - p)^2; \\ u_G &= -(\theta - p)^2, \end{aligned}$$

where  $b_S$  and  $b_R$  are biased preferences for the specialty and RUC, respectively, and  $b_S > 0$  without loss of generality.

As in the standard cheap talk model, bias  $b_S$  and  $b_R$  enter the specialty and RUC utilities, respectively, such that even though these agents may prefer higher or lower prices than the government, neither prefers to raise or lower prices without bound.<sup>41</sup>

### 5.1.2 Comparative Statics

We consider the comparative statics of changing the RUC's bias,  $b_R$ , focusing on the key trade-off between bias and information. We describe the results in more detail in Appendix VIII.

First, we consider the case in which all information is soft—i.e.,  $L = 1$  for all services, regardless of the costs of producing hard information. In this scenario, outcomes follow Dessein (2002): If the government chooses a RUC with preferences biased toward the specialty (i.e.,  $b_R$  close to  $b_S$ ), the expected price will move away from the government's ideal, but more information is communicated. The optimal RUC bias

<sup>40</sup>In this exposition, we treat  $\bar{\theta} - \underline{\theta}$  as known and assert that  $\theta \sim U(\underline{\theta}, \bar{\theta})$ . However, this is not technically correct for all values of  $L$ . In Appendix VIII.D, we consider  $\bar{\theta} - \underline{\theta}$  as random, i.e.,  $L = E[\bar{\theta} - \underline{\theta}]$ , which allows  $\theta$  to remain uniformly distributed in the posterior interval. Neither the uniform distribution of  $\theta$  nor fixed  $\bar{\theta} - \underline{\theta}$  is required for the intuition of this model.

<sup>41</sup>This modeling of utility can be interpreted as a common preference held by all agents for “sensible” prices that are neither too high nor too low; they may directly value this sensibility or they may value credibility to the government to ensure they continue to have a role in setting prices. Further, it is important to note that  $p$  is a relative price, which a literature on comparative cheap talk has noted will further improve the quality of communication (Chakraborty and Harbaugh, 2010; Che et al., 2013).

is  $b_R^* \in [0, b_S]$ . If the specialty’s bias,  $b_S$ , is sufficiently large, then the government’s optimal choice is to choose an unbiased RUC with the government’s preferences,  $b_R^* = 0$ . If  $b_S$  is sufficiently small, then  $b_R^* = b_S$ ; that is, the value of information makes it worthwhile for the government to establish a biased RUC. It is never optimal to have  $b_R^* < 0$  or  $b_R^* > b_S$ , because this worsens both bias and communication.

Second, when we allow the specialty to produce hard information—reducing the space  $[\underline{\theta}, \bar{\theta}]$  to length  $L < 1$  with this verifiable evidence—such evidence lowers the need to communicate a service’s value through soft channels. Hard information is most valuable when the RUC and specialty proposer have divergent preferences and cannot communicate. This implies that greater  $b = b_S - b_R$  (i.e., low affiliation) induces the specialty to produce more hard information. On the other hand, affiliation eliminates the benefit of producing costly hard information, since information can be cheaply communicated when the proposer has the same preferences as the committee. Because hard information improves the quality of prices (i.e., government’s utility), the optimal RUC preference is closer to the government’s ( $b_R^*$  is closer to 0) and farther away from  $b_S$  when hard information is possible.<sup>42</sup> As the technology to produce hard information improves (i.e.,  $c(L)$  becomes smaller), the optimal  $b_R^*$  moves closer to 0.<sup>43</sup>

In summary, our model predicts that higher affiliation will allow better communication of soft information between proposers and the RUC. Hard information provision, by contrast, decreases with affiliation. Thus, the overall information content of prices as a function of affiliation depends on how much each type of information adjusts. When the cost (or feasibility) of producing hard information falls, the degree of affiliation that maximizes information extraction will decrease. We next test these comparative statics using our empirical measures of information quality.

## 5.2 Affiliation Effect on Hard Information

Unlike many other settings, our dataset contains an objective measure of hard information. As we describe in Section 2, when specialties propose a new RVU, they present survey evidence about the work involved in delivering a service, particularly the time needed (Zuckerman et al., 2016; Burgette et al.,

<sup>42</sup>A similar intuition exists in papers studying the strategic revelation of hard information, as in Kamenica and Gentzkow (2011) and Alonso and Camara (2016). The latter paper studies optimal voting rules in the presence of strategic hard-information revelation and finds that supermajority voting rules will be preferable to simple majority rules; a supermajority voting rule is equivalent to increasing  $b$ .

<sup>43</sup>In Appendix VIII, we show that it is never optimal to have  $b_R < 0$ . In Appendix Figure A.12, we illustrate this relationship between welfare (government expected utility) and  $b_R$ , letting the cost of hard information,  $c(L)$ , vary.

2016). We use this survey data as our measure of hard information—the more physicians that a specialty or a coalition of specialties surveys about physician work, the more concrete is the evidence presented in a proposal to the RUC.<sup>44</sup> However, surveying more physicians is costlier for specialty societies.

Using per-specialty survey sample size and the number of respondents as measures of hard information, denoted  $H_{it}$ , we estimate the affiliation effect on hard information measure with the following regression:<sup>45</sup>

$$\ln H_{it} = \alpha A(\mathcal{R}_t, \mathcal{S}_i) + \mathbf{X}_i \beta + \mathbf{T}_t \eta + \mathbf{w}_i \zeta + \varepsilon_{it}, \quad (7)$$

We use the same controls as in Equation (6). The coefficient of interest,  $\alpha$ , reflects the effect of affiliation on the endogenous decision to provide hard information. The number of specialties on a proposal may also affect per-specialty survey samples, e.g., through coordination issues. Therefore, to isolate empirically the mechanism of affiliation on hard information, we can also control for indicators of the number of specialty proposers.

We present results in Appendix Table A.8. We see strong negative effects: In our preferred specification, controlling for proposer utilization of the a procedure, in column (2), a one standard-deviation increase in affiliation decreases per-specialty survey sample size by 33.2% and per-specialty number of respondents by 41.3%. Figure VI shows these results in a binned scatterplot of residual log survey counts against residual set affiliation. The negative effect persists when controlling for the number of specialty proposers, shown in column (4) of Appendix Table A.8, although the effect is not statistically significant for the outcome of survey respondents.

### 5.3 Price Transmission to Private Insurance

As a complementary assessment of information quality, we examine how private prices track changes in Medicare prices, depending on the source of the Medicare price and the affiliation of the proposal that led to a given RUC-recommended price. Recent research shows strong price-following from Medicare to

<sup>44</sup>While survey respondents may in principle engage in strategic reporting, we argue that this behavior is less likely when there are many survey respondents. Thus, a larger survey begins to approximate hard information. Supporting this argument, the RUC often focuses on the *distribution* of survey outcomes and the number of survey respondents, as a marker of the credibility of a proposal. Although any given survey respondent may exaggerate his or her response, it is more difficult to do so (and generally more costly to lie) in aggregate when there are many respondents, along the lines of Kartik (2009).

<sup>45</sup>While the total surveyed information is obviously relevant from the perspective of the RUC, there are mechanical rules that require specialties to survey a minimum number of physicians, conditional on surveying (American Medical Association, 2017). Therefore, for proposals with more than one specialty, we consider the effect of affiliation on per-specialty hard information.

private insurance prices, potentially due to two mechanisms (Clemens and Gottlieb, 2017; Clemens et al., 2017): Medicare may serve as an outside option in bargaining between private insurers and physicians, or Medicare may provide a “knowledge standard” with information content.

By comparing Medicare price changes from different sources, we focus on the latter mechanism of information provision. If Medicare price changes serve solely as a bargaining benchmark, then the degree to which they are followed should not depend on their source and, in particular, on the affiliation of a proposal at the time of the RUC’s vote. In contrast, if Medicare prices serve as a knowledge standard, private insurers may follow more closely those Medicare price changes that contain more information, judged either via beliefs about the quality of information extracted in the Medicare pricing process, or if an insurer’s own due-diligence agrees with the RUC’s assessment.<sup>46</sup>

We first construct private and Medicare average prices by dividing total payments by the total number of claims observed in MarketScan and Medicare data for a given procedure code in a given year. To allow for lagged price transmission to private insurance, we normalize log prices within payer and then match private prices for each code  $i$  and year  $y$  to a Medicare price for the same code in the year  $y^M(i, y) \in \{y, y - 1, y - 2\}$ .<sup>47</sup> We then estimate the following regression to assess price transmission:

$$\ln \text{Price}_{i,y}^P = \beta \ln \text{Price}_{i,y^M(i,y)}^M + \mathbf{T}_{iy} \eta + \xi_i + \varepsilon_{iy}, \quad (8)$$

where  $\mathbf{T}_{iy}$  is a vector of time dummies (year  $y$ , Medicare year  $y^M$ , and the RUC meeting, for Medicare prices associated with a RUC decision) and  $\xi_i$  is a service fixed effect for the procedure code. The service fixed effect implies that we focus on changes in private insurance prices in response to changes in Medicare prices, holding constant any characteristic of the service. We also estimate pooled regressions

<sup>46</sup>In interviews with RUC members, one described an informal process in which private insurance administrators consult with trusted clinical sources (often friends) who perform procedures, asking whether prices seemed reasonable.

<sup>47</sup>In detail, we normalize log prices to have a frequency-weighted mean of 0 within payer (private or Medicare) and year, and we then match private prices for each code  $i$  and year  $y$  to a Medicare price for the same code in the year  $y^M(i, y) \in \{y, y - 1, y - 2\}$  with the closest log price change:

$$y^M(i, y) = \underset{y' \in \{y, y-1, y-2\}}{\text{arg min}} \left| \Delta \ln \text{Price}_{i,y}^P - \Delta \ln \text{Price}_{i,y'}^M \right|.$$

$\Delta \ln \text{Price}_{i,y}^P \equiv \ln \text{Price}_{i,y}^P - \ln \text{Price}_{i,y-1}^P$  is a change in the normalized log private prices for service  $i$  in year  $y$ , and  $\Delta \ln \text{Price}_{i,y}^M$  is the analogous Medicare log price change.

across categories of Medicare prices:

$$\ln \text{Price}_{iy}^P = \sum_c (\alpha_c + \beta_c \ln \text{Price}_{i,y}^M(c,i,y)) \cdot \mathbf{1}(c(i,y) = c) + \mathbf{T}_{iy} \eta + \xi_i + \varepsilon_{iy}, \quad (9)$$

where  $c$  references one of three sources of Medicare’s price for service  $i$  in year  $y$ : (i) prices not following a recent RUC recommendation, (ii) prices following a RUC recommendation from a low-affiliation proposal, and (iii) prices following a RUC recommendation from a high-affiliation proposal.<sup>48</sup>

In Table IV, our estimates suggest that private prices follow RUC-based Medicare prices to a larger extent than non-RUC Medicare prices. Within procedure code, log price changes in Medicare originating from the RUC are transmitted to private insurance with a coefficient of 0.892, in column (1), while those that have no associated RUC recommendation are transmitted with a coefficient of 0.399 or 0.300, in columns (2) and (3), respectively, depending on whether the sample includes all non-RUC changes or is restricted to larger changes. Further RUC-based Medicare prices originating from high-affiliation proposals show slightly higher following than those from low-affiliation proposals.<sup>49</sup>

Figure VII shows pooled results, both without and with service fixed effects, corresponding to columns (4) and (5) of Table IV.<sup>50</sup> The figure reproduces differences in the slopes of the lines tracing private prices to Medicare prices that depend on the source of the Medicare price. This suggests that Medicare price changes that originate from RUC decisions, and in particular from high-affiliation RUC decisions, appear more informative for private insurance. In addition to steeper slopes, the lines are generally lower in levels for RUC Medicare prices (and further for those from high-affiliation proposals). These uniformly lower private insurance price changes suggest that private insurance may, to an extent, reverse the bias induced by affiliation.<sup>51</sup>

<sup>48</sup>Most Medicare prices fall in the last category, but, as shown in Appendix Figure A.13, prices changes in this category are smaller. Medicare average price changes with no associated RUC recommendation in our dataset may occur for a variety of reasons, including changes in the geographic composition of claims, changes in the facility vs. non-facility composition of claims, conversion factor adjustments, and changes in the practice expense component of RVUs alone. To facilitate closer comparison of the “non-RUC” and “RUC” Medicare prices in the pooled regressions, we restrict attention to non-RUC log price changes of at least 0.3 in absolute value, although our results are not sensitive to this restriction.

<sup>49</sup>We also analyze this question in a specification with private log price changes regressed on Medicare log price changes and find similar results. As shown in Appendix Figure A.14, high-affiliation RUC price changes result in steeper private price changes than low-affiliation RUC price changes.

<sup>50</sup>Similar to the difference between columns (2) and (3), we test alternative definitions for the set of non-RUC changes for column (4) and a within-service specification that generates Appendix Figure A.14. Our alternative samples range from including 100,102 non-RUC price changes to a more-restricted sample of 1,002 non-RUC price changes such that  $|\Delta \ln \text{Price}_{i,y}^M| \geq 0.45$ . Results comparing high-affiliation with low-affiliation RUC price following are qualitatively unaffected.

<sup>51</sup>In Appendix IX, we consider alternatives to our interpretation that affiliation facilitates better information through com-

## 6 Conclusion

We find evidence of bias or regulatory capture in Medicare’s price setting process. Increasing affiliation between special-interest proposers and the advisory committee we study would result in higher prices. However, we also find that this committee’s involvement can improve the quality of information used in the price-setting process. Private insurers seem to follow Medicare prices more closely when the public prices originate from a RUC recommendation, particularly those committee recommendations that rely on highly affiliated proposals.

We show how undoing this bias or changing the RUC’s membership reallocates revenue across specialties and creates winners and losers among medical specialties. These analyses, however, ignore likely utilization effects from price changes, which generate real welfare effects beyond transfers in revenue. To the extent physicians are imperfect agents for their patients and deviate toward procedures and opt to train in specialties with greater reimbursement levels (Gruber et al., 1999; Clemens and Gottlieb, 2014), the actions of the RUC may have broader welfare consequences for health care. Even if pricing decisions were unbiased, pricing based on poor information could generate large random deviations from socially appropriate prices.

Our findings suggest that Medicare faces a balancing act in setting prices. Inviting input from the RUC may introduce bias in prices, but it may also improve the information extracted from specialties. We expect that this trade-off is common to many policy decisions for which regulators lack key information about the optimal decision and may seek advice from outside experts. While regulation and technology (e.g., systematic data from electronic medical records) may help reduce the uncertainty along some dimensions, the most important inputs to policy decisions may always require interpretation and communication by experts.

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munication. First, the RUC may have more information on high-affiliation decisions, even without communication, because its members are more likely to perform the services in question. Second, Medicare and private insurance are more likely to get the price “right” for high-volume procedures, which are also more likely to have RUC decisions and high-affiliation proposals. Third, there may be some other unspecified predictor of price transmission that could be correlated with affiliation. We find that our results are robust, accounting for these potential alternative mechanisms.

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Table I: Specialty Seats on the RUC

Specialty	Meetings	Specialty	Meetings
Anesthesiology	63	Oncology	12
Cardiology	63	Ophthalmology	63
Child Psychiatry	6	Orthopedic Surgery	63
Colorectal Surgery	6	Otolaryngology	63
Dermatology	63	Pathology	63
Emergency Medicine	63	Pediatric Surgery	12
Family Medicine	63	Pediatrics	63
Gastroenterology	20	Plastic Surgery	63
General Surgery	63	Psychiatry	63
Geriatrics	30	Pulmonary Medicine	18
Infectious Disease	9	Radiation Oncology	5
Internal Medicine	63	Radiology	63
Nephrology	6	Rheumatology	17
Neurology	50	Spine Surgery	6
Neurosurgery	63	Thoracic Surgery	63
Nuclear Medicine	7	Urology	63
Obstetrics and Gynecology	53	Vascular Surgery	18

*Notes:* This table shows the numbers meetings during which a specialty had a member on the RUC from May 1992 to April 2013. There were a total of 63 meetings during this time period. Each year generally had three meetings, except for the years 1992, 2001, and 2013, which each had two meetings. There were officially four meetings in 1993, but we considered the April and June meetings as one meeting. Each of the specialties listed had one seat at each of its meetings, except for internal medicine, which had two seats in 25 meetings. In our analysis, we considered child psychiatry as psychiatry, since there is no specialty code for child psychiatry in the Medicare data. Similarly, we considered nuclear medicine as radiology. Three meetings had either no services reviewed or had no observations remaining after the sample selection procedure described in Appendix Table A.1. Finally, the American Medical Association, the American Osteopathic Association, and Health Care Professional Advisory Committee (HCPAC) each had a permanent voting seat throughout this time period; we did not include them in our analysis.

Table II: Balance in Medicare Beneficiary Characteristics

Medicare beneficiary characteristic	Affiliation above mean	Affiliation below mean	$p$ -value
Male	0.471 (0.107)	0.470 (0.101)	0.371
Urban	0.794 (0.052)	0.792 (0.054)	0.784
Age > 75	0.405 (0.109)	0.416 (0.106)	0.366
Age > 85	0.131 (0.067)	0.135 (0.067)	0.745
Medicare aged	0.767 (0.126)	0.782 (0.108)	0.463
Medicare disabled	0.155 (0.062)	0.147 (0.058)	0.426
Medicare ESRD	0.063 (0.114)	0.054 (0.079)	0.903
White race	0.828 (0.077)	0.837 (0.074)	0.148
Black race	0.111 (0.059)	0.105 (0.052)	0.989
Hispanic race	0.025 (0.012)	0.024 (0.013)	0.109
Other race	0.038 (0.015)	0.036 (0.015)	0.018
Observations (proposals)	3,046	1,256	

*Notes:* This table shows average Medicare beneficiary characteristics for procedure codes in proposals with above-versus below-mean affiliation. We residualize each characteristic, controlling for meeting identities and specialty shares  $w_i$ . In each cell, we present averages of this residual, conditional on either above- or below-mean affiliation, adding back the unconditional mean to aid in interpretation. Standard deviations of each residualized characteristic are given in parentheses. The last column lists the  $p$ -value for the null hypothesis that the average residual characteristic is not significantly different between samples corresponding to above- and below-mean affiliation. The last row gives the number of proposals with non-missing Medicare beneficiary characteristics for the relevant CPT code and with above-mean affiliation or below-mean affiliation, in the respective columns.

Table III: Affiliation Effect on Prices

	(1)	(2)	(3)	(4)	(5)	(6)
			Log RVU			
Standardized set affiliation	0.158*** (0.027)	0.118*** (0.023)	0.108*** (0.033)	0.101*** (0.029)	0.121* (0.065)	0.111*** (0.033)
Prior log RVU	Y	Y	Y	Y	Y	Y
Medicare beneficiary, place of service	N	Y	Y	Y	Y	Y
Surveyed characteristics	N	N	Y	Y	Y	Y
CPT code description	N	N	N	Y	Y	Y
Specialty shares	Y	Y	Y	Y	N	Y
Meeting fixed effects	Y	Y	Y	Y	Y	Y
Predicted set affiliation	N	N	N	N	Y	N
Specialty shares $\times$ linear year	N	N	N	N	N	Y
<i>N</i>	4,401	4,401	4,401	4,401	4,401	4,401
Adjusted <i>R</i> -squared	0.754	0.792	0.889	0.891	0.866	0.897
Sample mean log RVU	1.567	1.567	1.567	1.567	1.567	1.567

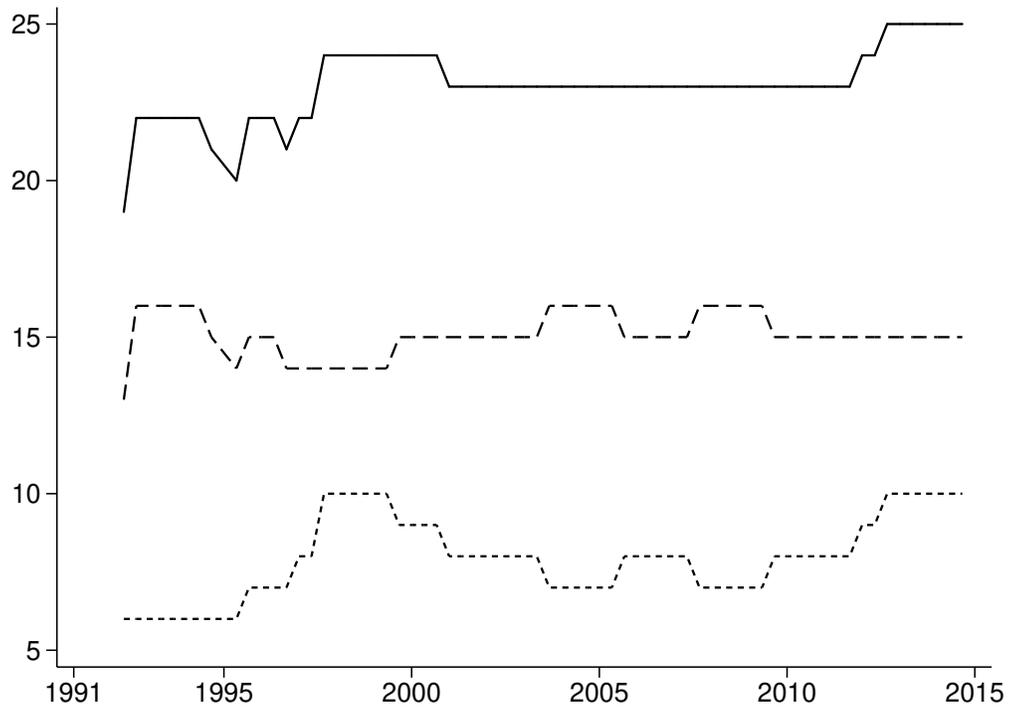
*Notes:* This table shows results of regressions of log RVU on standardized set affiliation, as stated in Equation (6). Place of service refers to nine categories of the location that the service is performed (e.g., clinic, inpatient hospital, outpatient hospital, laboratory, emergency department, ambulatory surgical center, domiciliary location, psychiatric facility, or other); Medicare beneficiary indicates average characteristics of Medicare beneficiaries who receive the service (CPT code), including those listed in Table II; surveyed characteristics includes objective characteristics (e.g., total utilization, surveyed time intervals, and office visit codes bundled into a procedure code) and subjective characteristics reflecting the difficulty, riskiness, or physician stress involved in the procedure; and CPT code description indicates word stems predictive of RVUs, as selected by LASSO. Specialty shares  $w_i$  are defined in Equation (5) and are controlled for linearly, except in column (5). Column (5) controls for predicted set affiliation, formed from the simulated distribution of set affiliation based on each specialty's probability to participate in the proposal (Appendix Figure A.9), and described in detail in Appendix IV. Regressions are performed on the sample defined in Appendix Table A.1, except for six observations for which RUC recommended RVU equals 0. Standard errors, clustered by RUC meeting, are in parentheses; \* denotes significance at the 10% level, and \*\*\* denotes significance at the 1% level.

Table IV: Price Transmission to Private Insurance

	(1)	(2)	(3)	(4)	(5)
			Log private price		
Log Medicare price	0.892*** (0.091)	0.399*** (0.003)	0.300*** (0.012)		
× not RUC				0.688*** (0.016)	0.331*** (0.022)
× RUC, low affiliation				0.838*** (0.006)	0.520*** (0.023)
× RUC, high affiliation				0.917*** (0.015)	0.642*** (0.041)
RUC, high vs. low affiliation				-0.420*** (0.040)	-0.016 (0.067)
Service fixed effects	Y	Y	Y	N	Y
Sample	RUC	Not RUC	Not RUC	Both	Both
Restrict non-RUC prices changes?	N/A	N	Y	Y	Y
<i>N</i>	3,179	184,910	4,003	7,182	7,182
RUC Medicare price changes	1,756	0	0	1,756	1,756
Non-RUC Medicare price changes	0	100,342	2,381	2,381	2,381
Adjusted <i>R</i> -squared	0.986	0.987	0.992	0.852	0.987

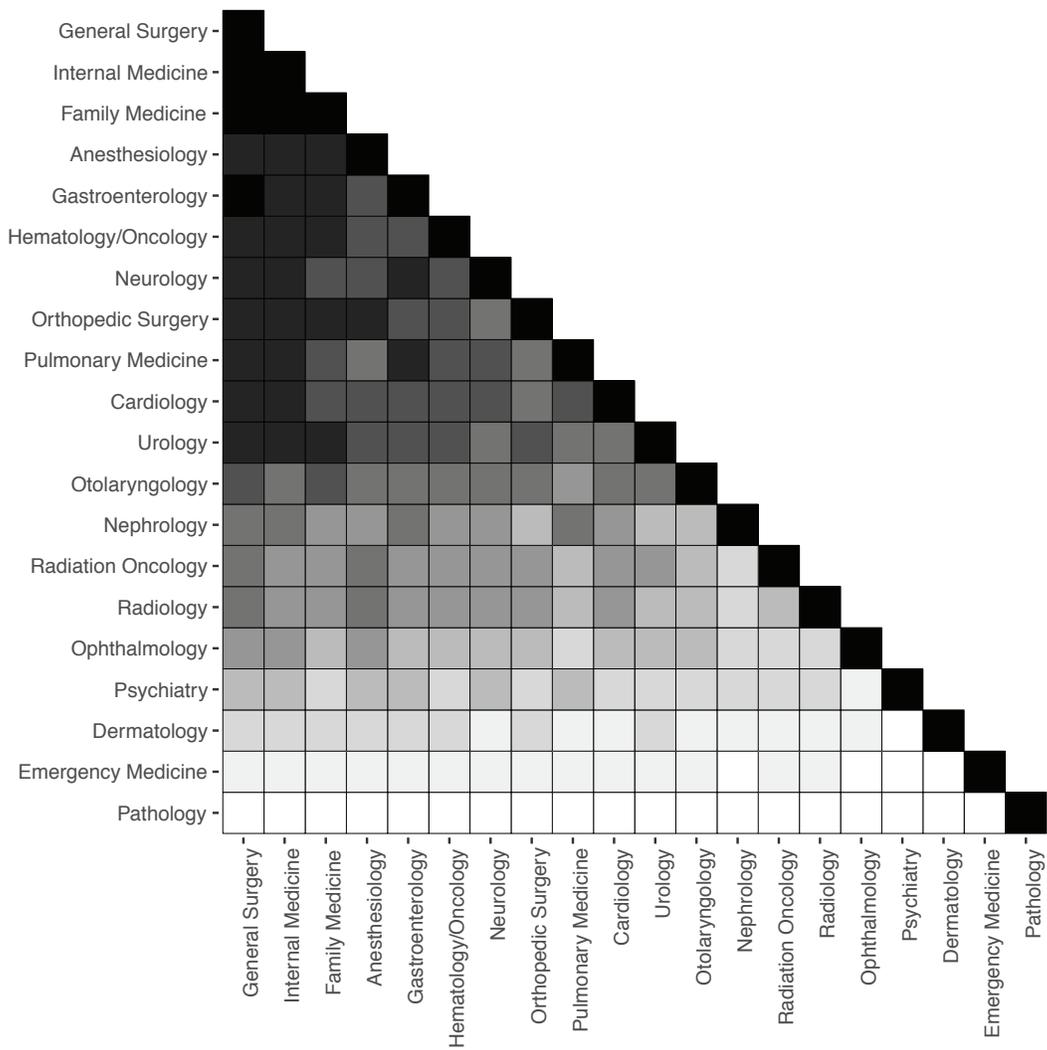
*Notes:* This table shows results of regressions of log private price on log Medicare price. We define private and Medicare prices as total payments divided by the total volume of claims, for a given service (CPT code) and year, in MarketScan and Medicare, respectively. The regressions use normalized log private price. We normalize private price by the average private price across services in a given year, weighted by the frequency of claims in the MarketScan data. We repeat the same procedure using Medicare data to calculate the normalized log Medicare price. Regression observations are weighted by frequency of Medicare claims. Normalized private prices are merged onto the closest normalized Medicare prices for the same service, possibly lagged up to 2 years. The maximum number of RUC price changes after this merge is 1,807. Column (4) does not include service (CPT code) fixed effects, while other columns do. Relevant samples, noted in the table, depend on whether the Medicare price change is associated with a RUC decision. Column (1) includes only Medicare prices set by the RUC, columns (2) and (3) include only non-RUC price changes, and columns (4) and (5) include both RUC and non-RUC observations. In columns (3) to (5), to improve comparability with the RUC-only sample, we include only those non-RUC CPT-code-year observations in which the absolute change in the normalized log Medicare price from the previous year is greater than 0.3. Standard errors are in parentheses. \* denotes significance at the 10% level, and \*\*\* denotes significance at the 1% level.

Figure I: Committee Seats Over Time



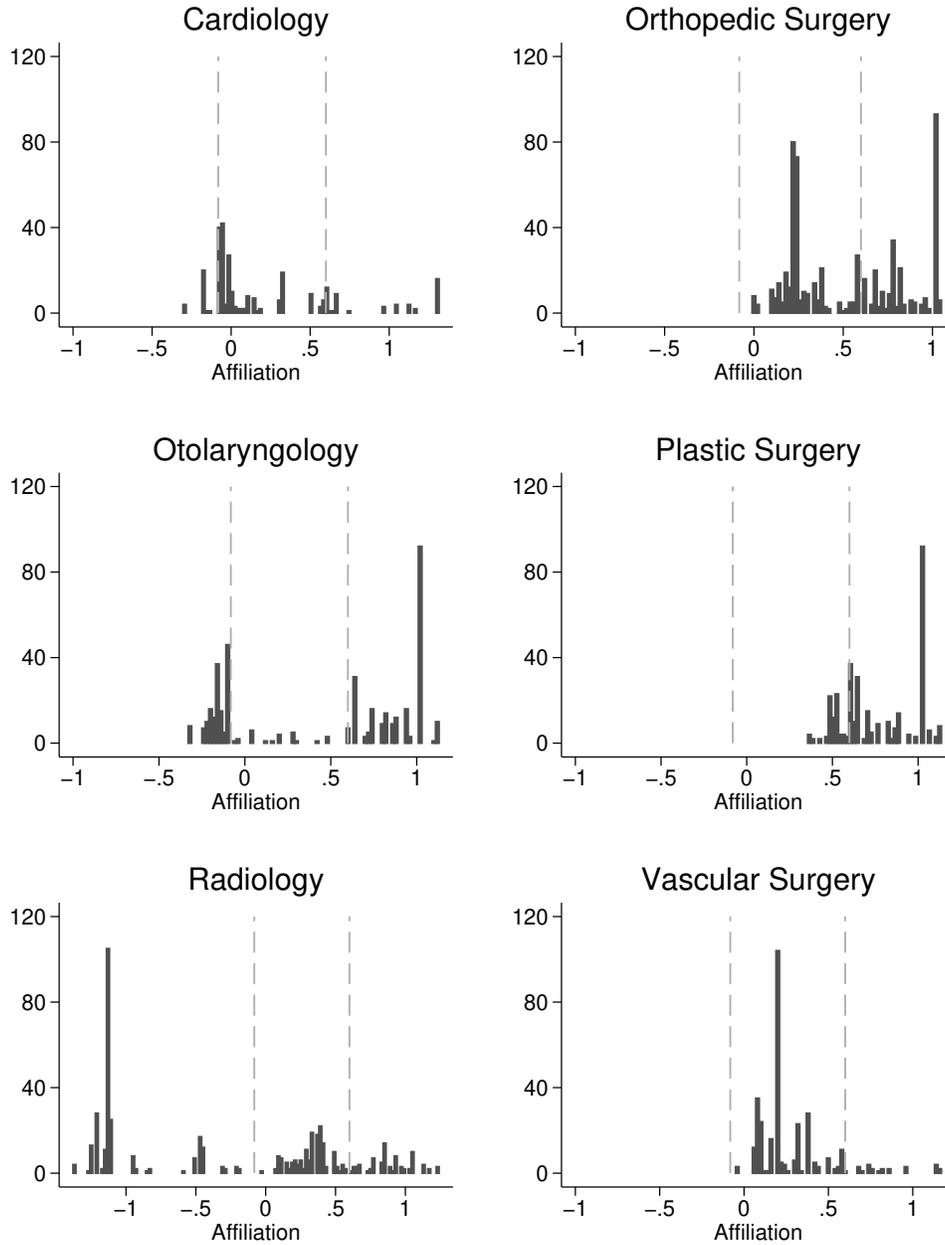
*Notes:* This figures shows the numbers of voting seats on the RUC over time, in total (solid line) and apportioned between “procedural” (dashed line) and “cognitive” (dotted line) specialties. Based on conversations with the RUC, we assign the “procedural” label to anesthesiology, cardiology, colorectal surgery, dermatology, gastroenterology, general surgery, hand surgery, neurosurgery, obstetrics and gynecology, ophthalmology, orthopedic surgery, otolaryngology, pathology, pediatric surgery, plastic surgery, radiation oncology, radiology, thoracic surgery, urology, and vascular surgery. We assign the “cognitive” label to emergency medicine, family medicine, geriatrics, infectious disease, internal medicine, nephrology, neurology, oncology, pediatrics, psychiatry, pulmonary medicine, and rheumatology.

Figure II: Affiliation Between Specialties



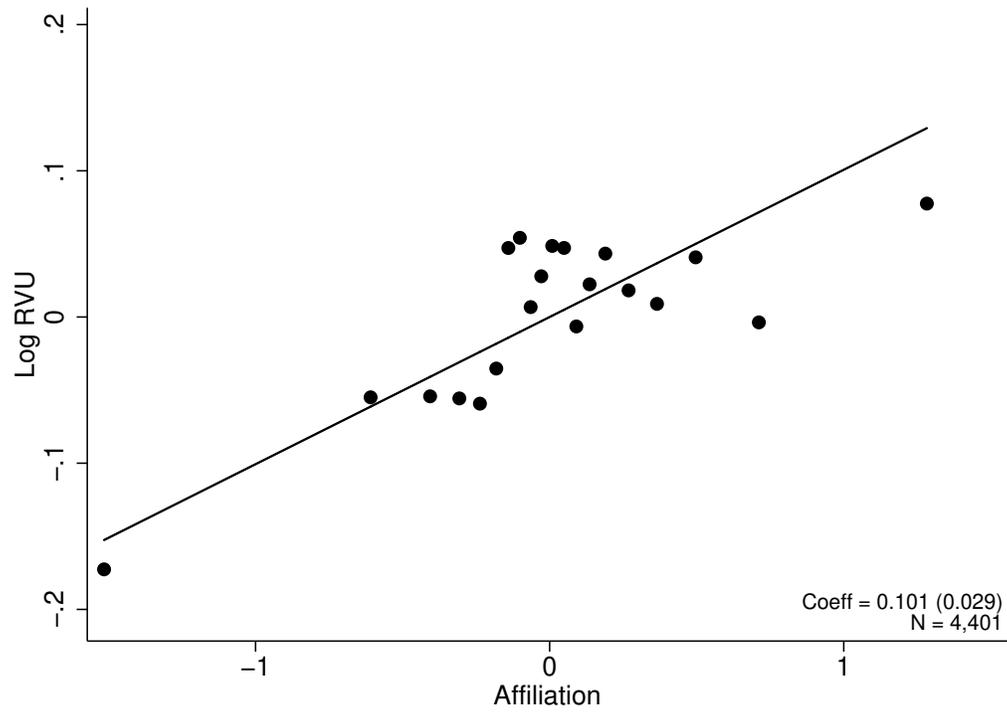
Notes: This figure illustrates affiliation between specialties, where the particular formula used is a negative Euclidean distance, described in Equation (3), for the largest 20 specialties. Affiliation values are divided into nine bins with an equal number of specialty pairs. Darker shades signify stronger affiliations.

Figure III: Within Specialty Variation in Affiliation



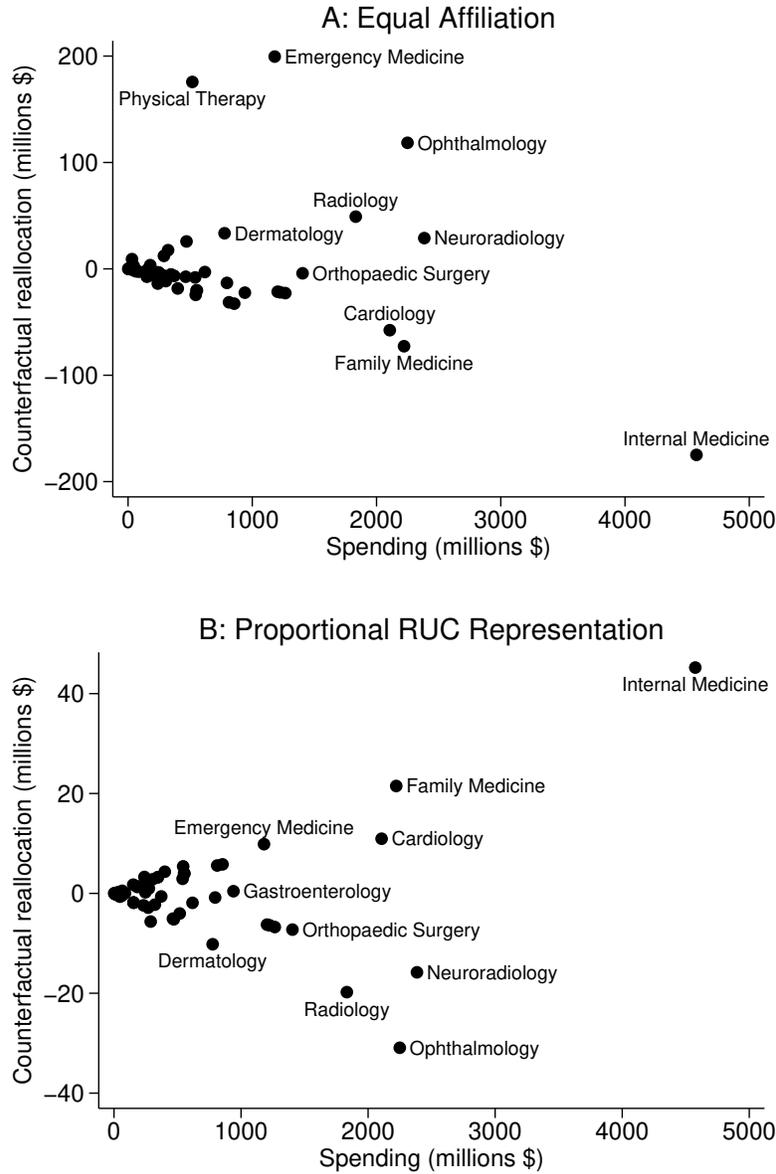
*Notes:* This figure shows examples of within-specialty variation in standardized set affiliation for proposals that are made by one of the six most commonly proposing specialties. The figure displays in a histogram the distribution of affiliation across proposals within each specialty. Dashed lines denote the 25th and 75th percentiles of affiliation overall.

Figure IV: Affiliation Effect on Relative Price



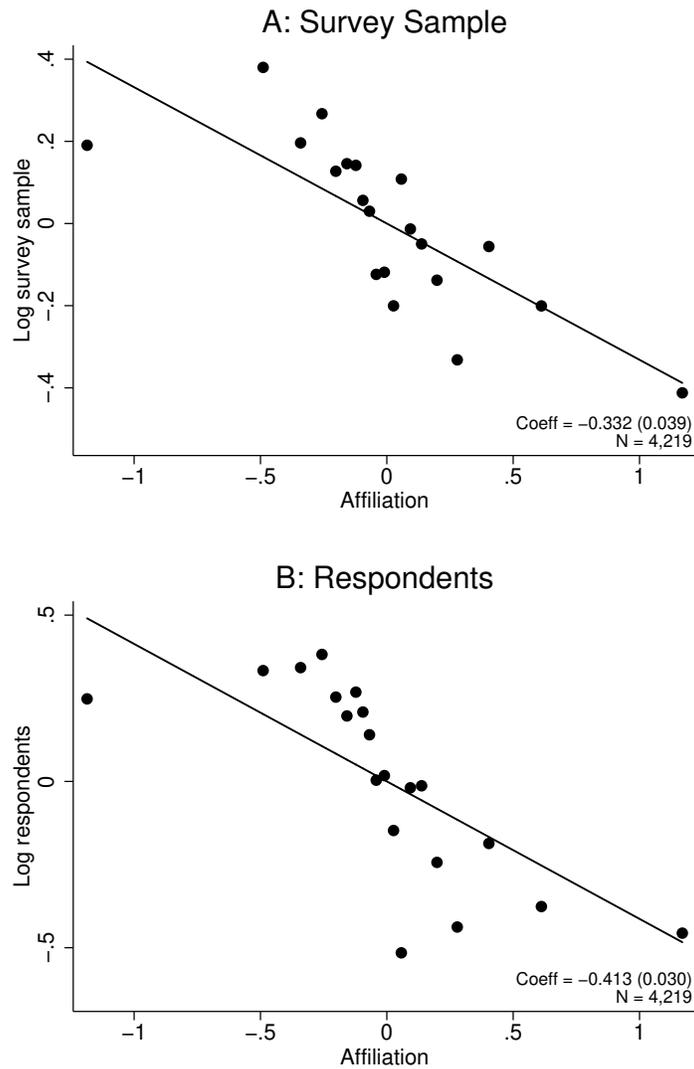
*Notes:* This figure is a binned scatterplot of residual log RVU on residual affiliation, where each dot represents 5% of the data, ordered by residual affiliations. Residuals are formed by regressing log RVU and affiliation, respectively, on controls specified in column (4) of Table III. The line shows the best fit through the residualized data, and the slope corresponds to the estimated coefficient of interest  $\alpha$  in Equation (6), with standard errors clustered by RUC meeting.

Figure V: Revenue Reallocation across Specialties



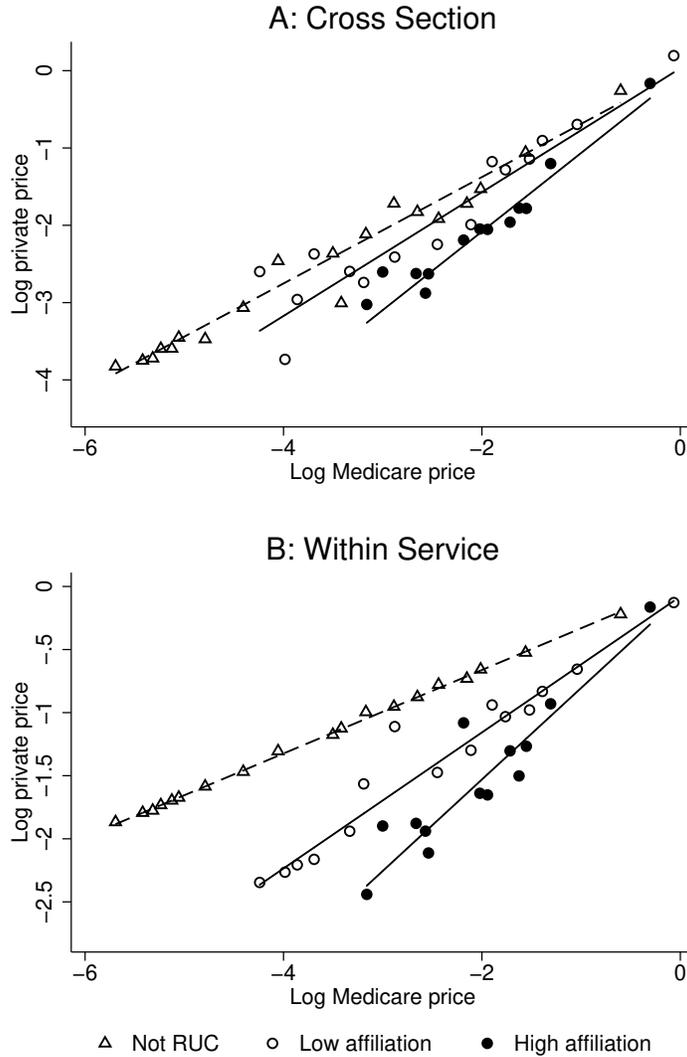
*Notes:* This figure shows counterfactual yearly revenue reallocation across specialties. In Panel A, we consider equalizing the affiliation of all proposals in each year. In Panel B, we consider changing the RUC membership to be constant and proportional to the population of physician specialties in the US, as given in Appendix Table A.7. Average annual spending for each specialty is on the  $x$ -axis, while the counterfactual reallocation setting affiliation to the mean for all proposals is on the  $y$ -axis. Utilization quantities for each service (CPT code) is held fixed, and the annual Medicare budget for physician work is set at  $\$70 \text{ billion} \times 51\% = \$35.7 \text{ billion}$ . Details are given in Section 4.2.

Figure VI: Affiliation Effect on Hard Information



*Notes:* This figure is a binned scatterplot of the residual log per-specialty survey sample (Panel A) and log per-specialty survey respondents (Panel B) on residual affiliation, where each dot represents 5% of the data, ordered by residual affiliations. We form residuals by regressing the survey variables of interest and affiliation on the controls specified in column (2) of Appendix Table A.8. Lines show the best fit through the residualized data, and the line slopes correspond to the estimated coefficient of interest  $\alpha$  in Equation (7), with standard errors clustered by RUC meeting.

Figure VII: Price Transmission to Private Insurance



*Notes:* This figure is a binned scatterplot of the relationship between normalized log Medicare price and normalized log private price, as described in the note for Table IV. Panel A shows the relationship without controlling for service (CPT code) and corresponds to column (4) of Table IV, while Panel B shows this relationship controlling for CPT code and corresponds to column (5) of Table IV. In each panel, residuals of the relevant regression are added to predictions of normalized log private price based on normalized log Medicare price and the following Medicare price categories: not associated with RUC proposal (triangles), associated with RUC proposal with lower affiliation (hollow circles), and associated with RUC proposal with higher affiliation (solid circles). Each marker represents 5% of the data conditional on the relevant Medicare price category. Lines show the best fit through the markers and by construction have slopes equivalent to the relevant interaction terms in Table IV.