

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.¹

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.² 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.³ To measure the effect of connections with the RUC, we develop a measure

¹See 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).

²Medicare 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).

³The 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

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.⁴ We model two types of information helpful for

⁴See 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).⁵

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

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

⁵The 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 Online 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.⁶

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.⁷ 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.⁸ 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

⁶Medicare 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).

⁷The 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 overbilling.

⁸The 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.⁹ 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.¹⁰ 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

⁹Although 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.

¹⁰The 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.¹¹
 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 Online 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.

¹¹If 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.

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 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 Online 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).¹²

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 specialities 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, and outpatient care settings.

To build even more detailed control variables to characterize each service, we merge in a database of service descriptions.¹³ 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

¹²In 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.

¹³In Online Appendix Table A.2, we provide examples of these descriptions.

description.¹⁴

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.¹⁵ 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 $\sigma_{is}^R \equiv \frac{p_i q_{is}}{\sum_i p_i q_{is}}$. The respective $C \times 1$ vectors σ_s^q and σ_s^R define specialty s ’s direct interests over the $C = 11,252$ CPT codes that

¹⁴In 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.

¹⁵The 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.

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 indirect 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.¹⁶ 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.¹⁷ Finally, at a minimum, changes in quantities or prices will affect the Medicare reimbursement for all other services via the conversion factor.¹⁸

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 comovement in price or revenue across our set of C services, as described in Online Appendix II. In brief, we use the empirical $C \times C$ matrix of comovements, $\hat{\Omega}$, to form a vector of related interests, $\tilde{\sigma}_s = \hat{\Omega}\sigma_s$. The i^{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.

¹⁶For 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).

¹⁷Survey instruments ask physicians to use a list of 10 to 20 services preselected 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 a 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.

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

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.¹⁹ 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 same pricing preferences regardless of the 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.²⁰ In Online Appendix II, we show how we can rationalize this affiliation definition as a measure of the alignment of revenue objectives between two specialties.²¹

Figure II shows affiliation measures between specialties, among the 20 specialties with the high-

¹⁹This 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.”

²⁰We show in Online 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.

²¹In Online 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 Online Appendix Table A.3 that the affiliation effect on prices we report in Section 4 is robust across other formulations. In Online Appendix II, we also consider affiliation measures that exploit service comovements.

est 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.²² In contrast, physicians 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 outcome 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.²³ 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 $A(\mathcal{R}_t, \mathcal{S}_i)$.²⁴

²²Many important linkages between seemingly disparate specialties exist: Bronchoscopy is shared by otolaryngology, pulmonary 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.

²³Proposing 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.

²⁴In some cases, described below, we will compute the counterfactual set affiliation for proposal i in a different meeting than

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 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 Online 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 distinguish-

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.

ing two possible sources: random assignment of \mathcal{R}_t or random assignment of \mathcal{S}_i to i . We show in Online Appendix IV that variation in affiliation due to \mathcal{R}_t is a small component of the total identifying variation.²⁵ 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 the source of variation in affiliation influences our interpretation of its effect.²⁶

Why should we expect random variation in proposing specialties, conditional on the specialty utilization shares \mathbf{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 for 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.²⁷ 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 Online 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.²⁸

To assess quasi-experimental variation in \mathcal{S}_i empirically, we conduct four tests, detailed in Online 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.²⁹ Second, we show that the probability of a specialty participating in a proposal is also uncorrelated with differences in affiliation

²⁵In 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 .

²⁶While 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).

²⁷In 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.

²⁸The 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.

²⁹Specifically, 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 \mathbf{w}_i , we find no significant relationship between specialty proposals and the predicted price.

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.

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 α is the effect of increasing set affiliation by a standard deviation.³⁰ 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

³⁰We 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).

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.³¹ In this specification, we find that a standard deviation increase in affiliation increases relative price by 10.1%.³² 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 Online Appendix IV, instead of linear 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 Online Appendix Table A.3, we show robustness of our results to 49 other formulations of affiliation.³³ 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

³¹In practice, because of the high number of procedure code characteristics relative to the number of proposals, we employ 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 jackknifed RVU predictions using the set of post-LASSO OLS controls and using only observations from meetings other than meeting t . Finally, we form jackknifed RVU predictions based on the procedure’s characteristics.

³²Consistent 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.

³³We provide support for our preferred affiliation measure and discuss alternatives in Online Appendix II.

the second, we consider a counterfactual RUC, in which the 25 specialty seats are apportioned based on specialty physician populations, as given in Online 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 through the effect of counterfactual affiliation on service prices, which we have estimated in reduced form from Equation (6).³⁴ 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 Online Appendix V and present changes in BETOS revenue in Online 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.³⁵ 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

³⁴Although 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 logrolling. The first counterfactual scenario involves shutting off any such mechanism. For the second counterfactual scenario, we present some evidence in Online 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.

³⁵We 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 nonprocedural specialties (Bodenheimer et al., 2007).

reimbursement. Overall, this reallocation in dollar terms generally represents only one-fifth of the magnitude of (and is often opposite in direction to) 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 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 Online Appendix V, 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.³⁶

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-

³⁶For 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.

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).³⁷

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 Online Appendix VI, we examine the robustness of our affiliation effect to controlling for moments of utilization or revenue shares by RUC specialties for the service in question (i.e., σ_{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.³⁸ 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 Online 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 Online 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

³⁷While 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 Online 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.

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

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 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 θ but may also have bias. The government may delegate price-setting to the RUC, which then evaluates information from the specialty about θ .³⁹ 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

³⁹We 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).

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 .
2. The specialty may produce hard information verifying that θ 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 $c(L)$.⁴⁰ $c(1) = 0$, $c'(L) < 0$, and $c''(L) > 0$.
3. The specialty observes θ , and then transmits a cheap-talk message m about θ .
4. The RUC sets price p . Nontransferrable 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.⁴¹

⁴⁰In 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 Online Appendix VIII, we consider $\bar{\theta} - \underline{\theta}$ as random, i.e., $L = E[\bar{\theta} - \underline{\theta}]$, which allows θ to remain uniformly distributed in the posterior interval. Neither the uniform distribution of θ nor fixed $\bar{\theta} - \underline{\theta}$ is required for the intuition of this model.

⁴¹This 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).

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 Online 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 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.⁴² As the technology to produce hard information improves (i.e., $c(L)$ becomes smaller), the optimal b_R^* moves closer to 0.⁴³

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

⁴²A 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 .

⁴³In Online Appendix VIII, we show that it is never optimal to have $b_R < 0$. In Online 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.

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., 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.⁴⁴ 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:⁴⁵

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

We use the same controls as in Equation (6). The coefficient of interest, α , 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 Online Appendix Table A.8. We see strong negative effects: In our preferred specification, controlling for proposer utilization of the 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

⁴⁴While 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).

⁴⁵While 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.

of specialty proposers, shown in column (4) of Online 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 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.⁴⁶

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 ($i, y \in$

⁴⁶In 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.

$\{y, y - 1, y - 2\}$.⁴⁷ 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 ξ_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 across categories of Medicare prices:

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

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.⁴⁸

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. Furthermore, RUC-based Medicare prices originating from high-affiliation proposals are followed more closely by private insurance prices than those from low-affiliation propos-

⁴⁷In 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:

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

$\Delta \ln \text{Price}_{i,y}^P \equiv \ln \text{Price}_{i,y}^P - \ln \text{Price}_{i,y-1}^P$ 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.

⁴⁸Most Medicare prices fall in the last category, but, as shown in Online 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. nonfacility 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.

als.⁴⁹

Figure VII shows pooled results, both without and with service fixed effects, corresponding to columns (4) and (5) of Table IV.⁵⁰ 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.⁵¹

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

⁴⁹We 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 Online Appendix Figure A.14, high-affiliation RUC price changes result in steeper private price changes than low-affiliation RUC price changes.

⁵⁰Similar 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 Online 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.

⁵¹In Online Appendix IX, we consider alternatives to our interpretation that affiliation facilitates better information through communication. 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.

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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Supplementary Material

An Online Appendix for this article can be found at The Quarterly Journal of Economics online. Code replicating tables and figures in this article can be found in Chan and Dickstein (2019), in the Harvard Dataverse, doi: 10.7910/DVN/NIBLSO.

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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 number of 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 Online 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	<i>p</i> -value
Male	0.471 (0.107)	0.470 (0.101)	.371
Urban	0.794 (0.052)	0.792 (0.054)	.784
Age > 75	0.405 (0.109)	0.416 (0.106)	.366
Age > 85	0.131 (0.067)	0.135 (0.067)	.745
Medicare aged	0.767 (0.126)	0.782 (0.108)	.463
Medicare disabled	0.155 (0.062)	0.147 (0.058)	.426
Medicare ESRD	0.063 (0.114)	0.054 (0.079)	.903
White race	0.828 (0.077)	0.837 (0.074)	.148
Black race	0.111 (0.059)	0.105 (0.052)	.989
Hispanic race	0.025 (0.012)	0.024 (0.013)	.109
Other race	0.038 (0.015)	0.036 (0.015)	.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 nonmissing 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

	Log RVU					
	(1)	(2)	(3)	(4)	(5)	(6)
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

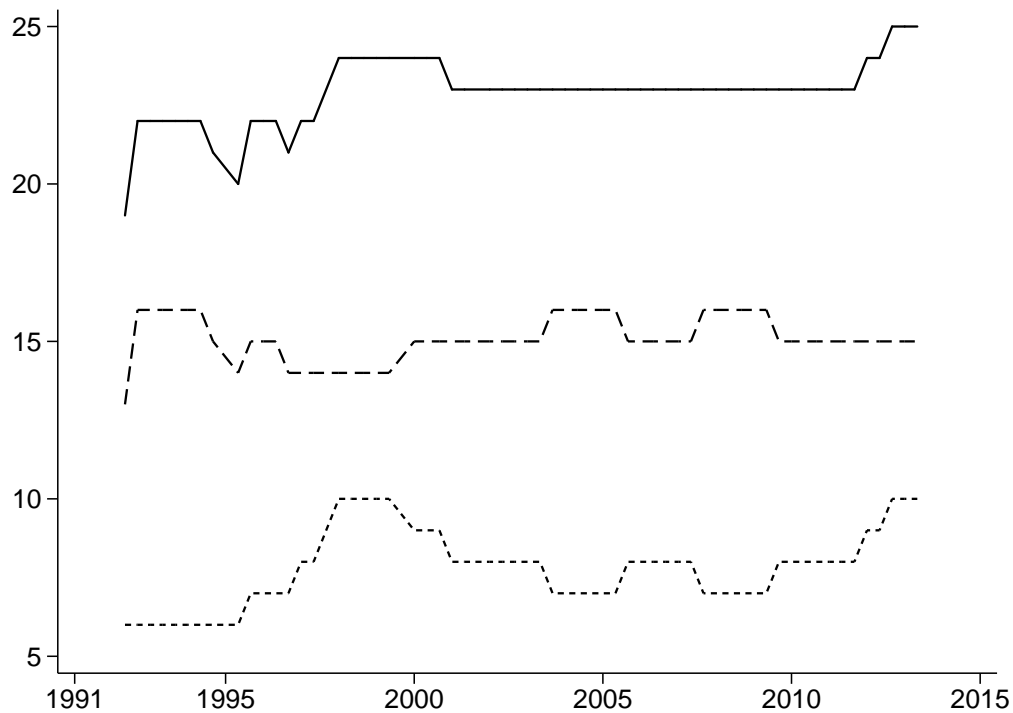
Notes: This table shows results of regressions of log RVU on standardized set affiliation, as stated in Equation (6). Place of service refers to nine categories of the location that the service is performed (e.g., clinic, inpatient hospital, outpatient hospital, laboratory, emergency department, ambulatory 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 (Online Appendix Figure A.9), and described in detail in Online Appendix IV. Regressions are performed on the sample defined in Online 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

	Log private price				
	(1)	(2)	(3)	(4)	(5)
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

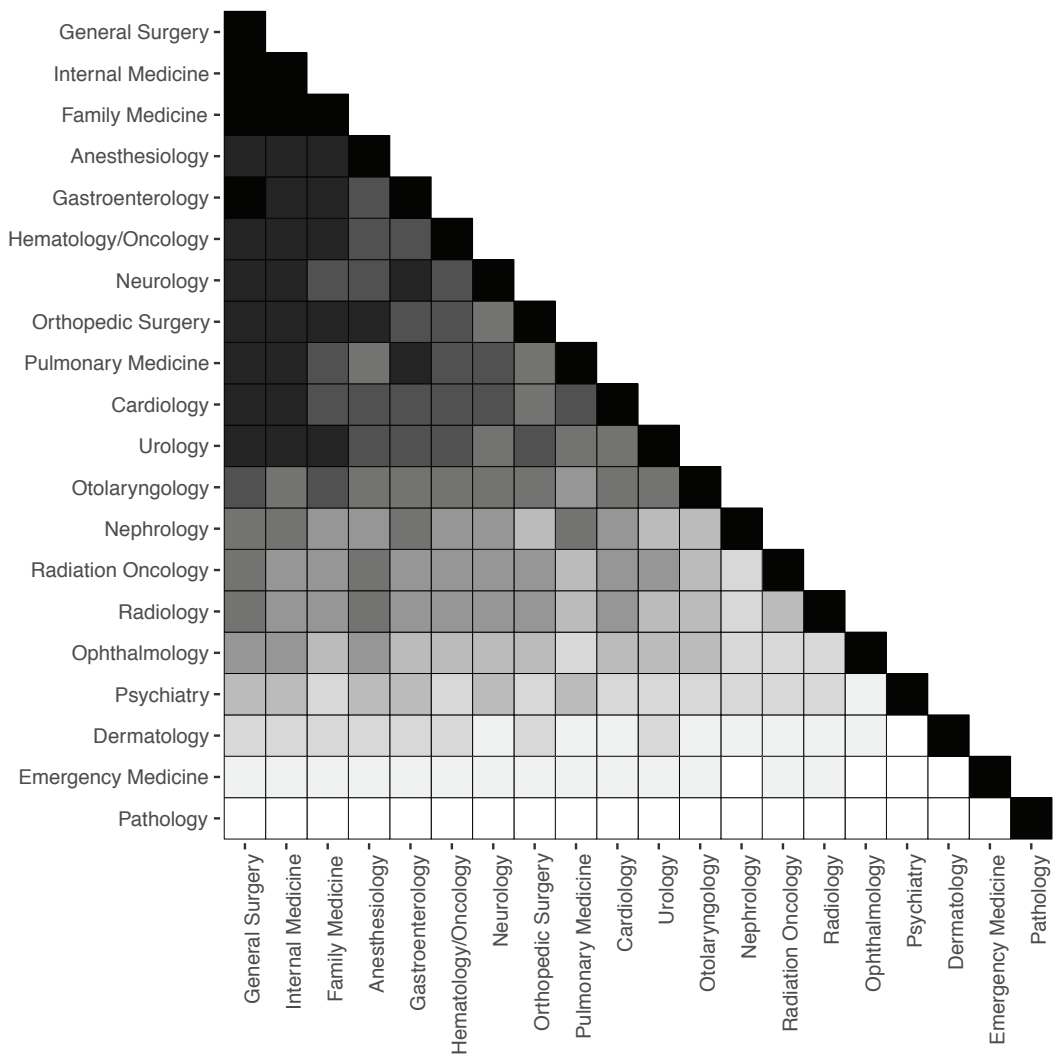
Notes: This table shows results of regressions of log private price on log Medicare price. We define private and Medicare prices as total payments divided by the total volume of claims, for a given service (CPT code) and year, in MarketScan and Medicare, respectively. The regressions use normalized log 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



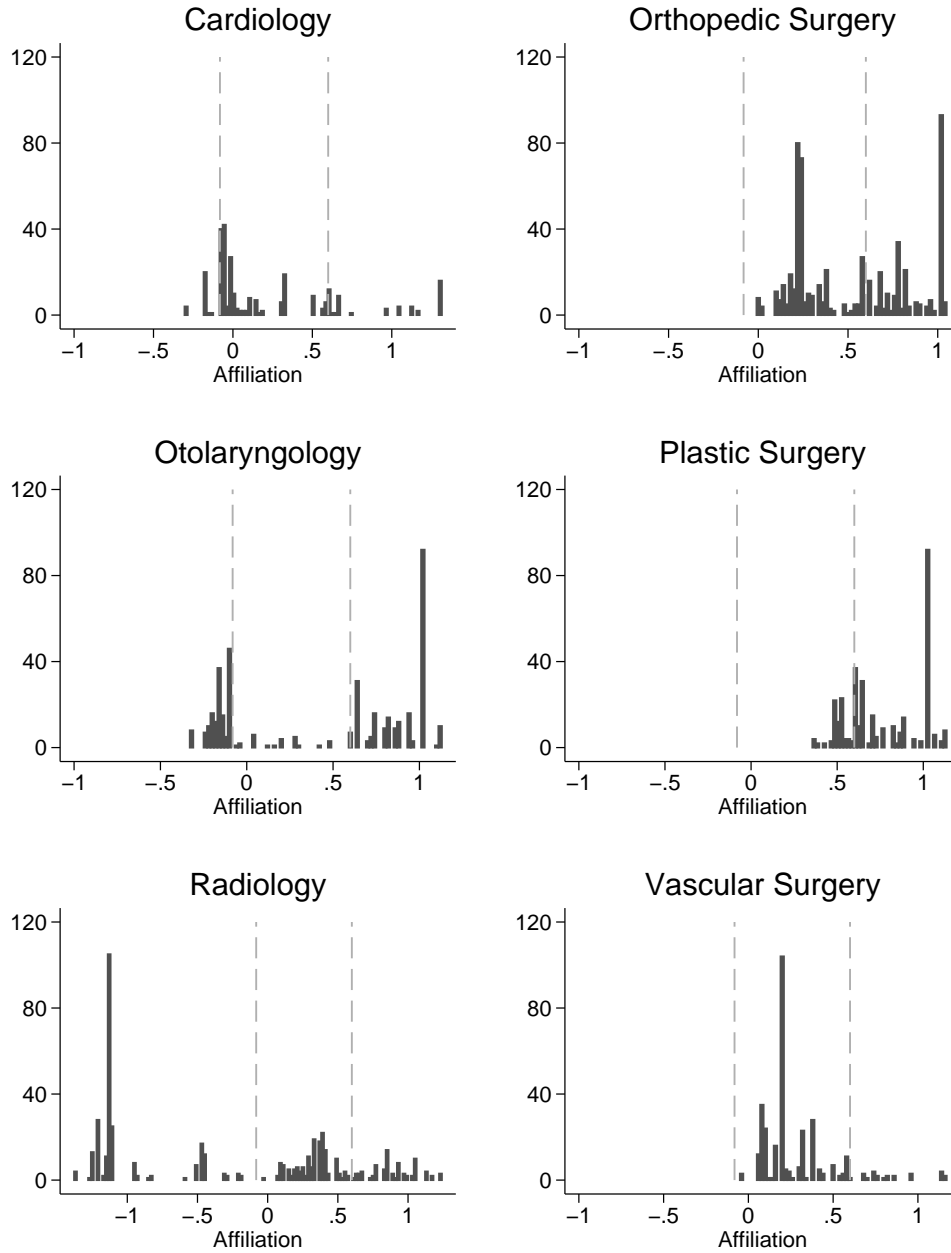
Notes: This figures shows the numbers of voting seats on the RUC over time, in total (solid line) and apportioned between “procedural” (dashed line) and “cognitive” (dotted line) specialties. Based on conversations with the RUC, we assign the “procedural” label to anesthesiology, cardiology, colorectal 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



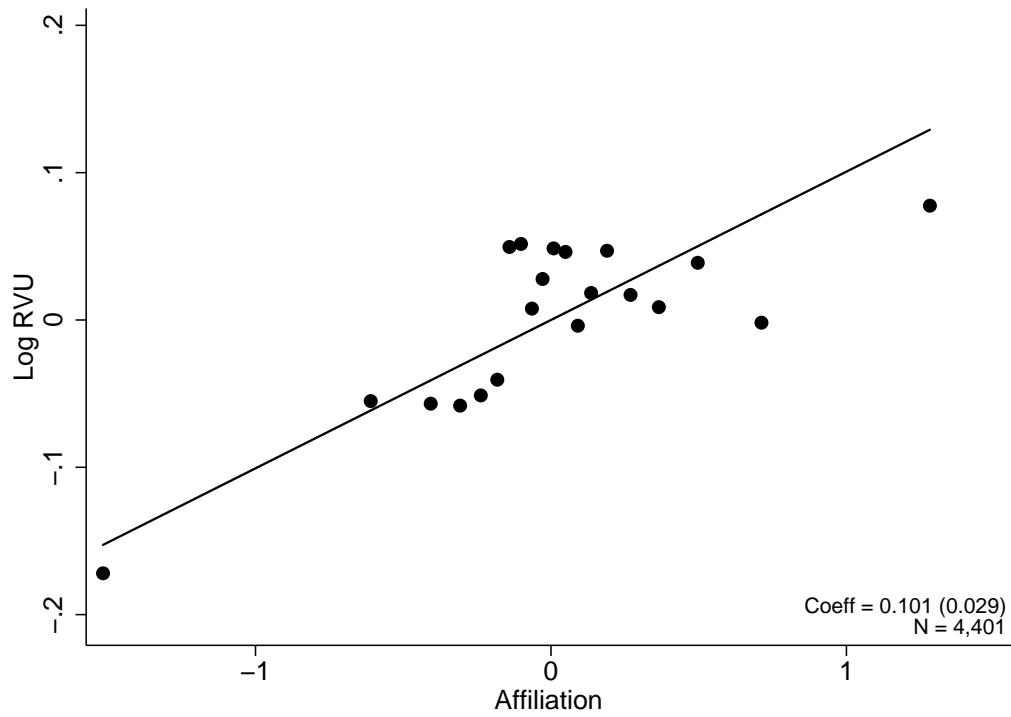
Notes: This figure illustrates affiliation between specialties, where the particular formula used is a negative Euclidean distance, described in Equation (3), for the largest 20 specialties. Affiliation values are divided into nine bins with an equal number of specialty pairs. Darker shades signify stronger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

Figure III: Within-Specialty Variation in Affiliation



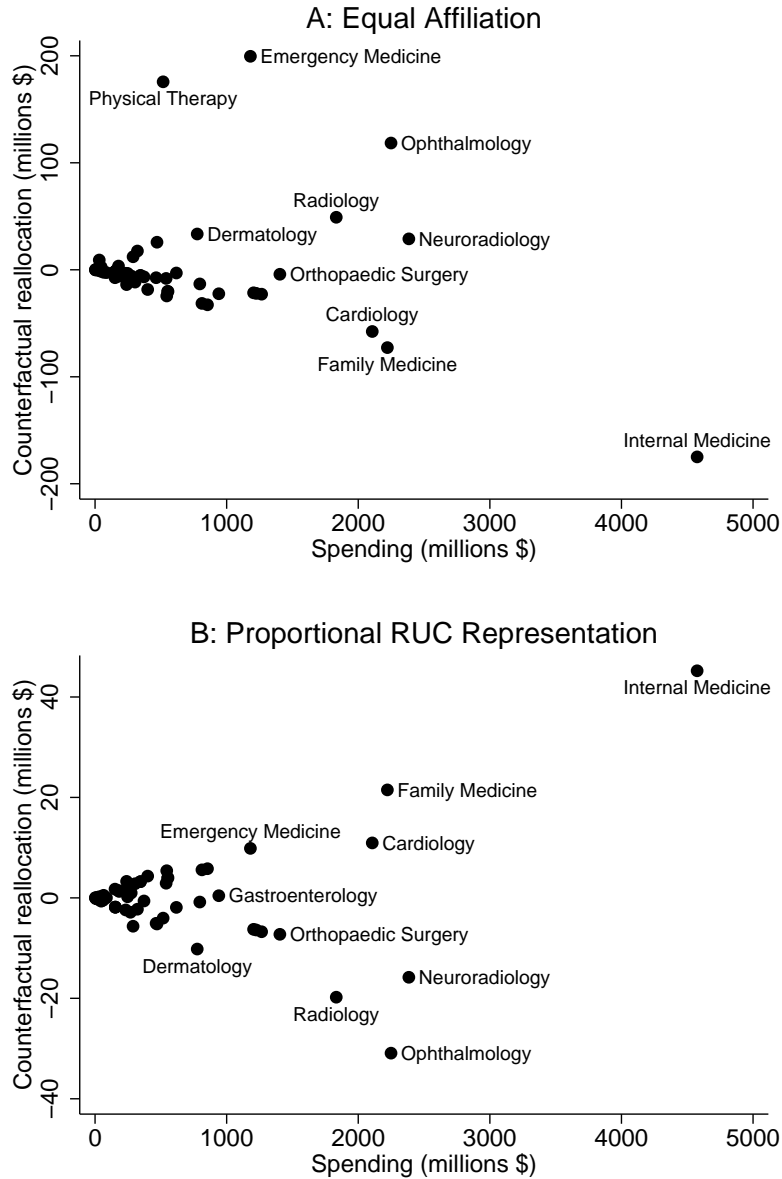
Notes: This figure shows examples of within-specialty variation in standardized set affiliation for proposals that are made by one of the six most commonly proposing specialties. The figure displays in a histogram the distribution of affiliation across proposals within each specialty. Dashed lines denote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

Figure IV: Affiliation Effect on Relative Price



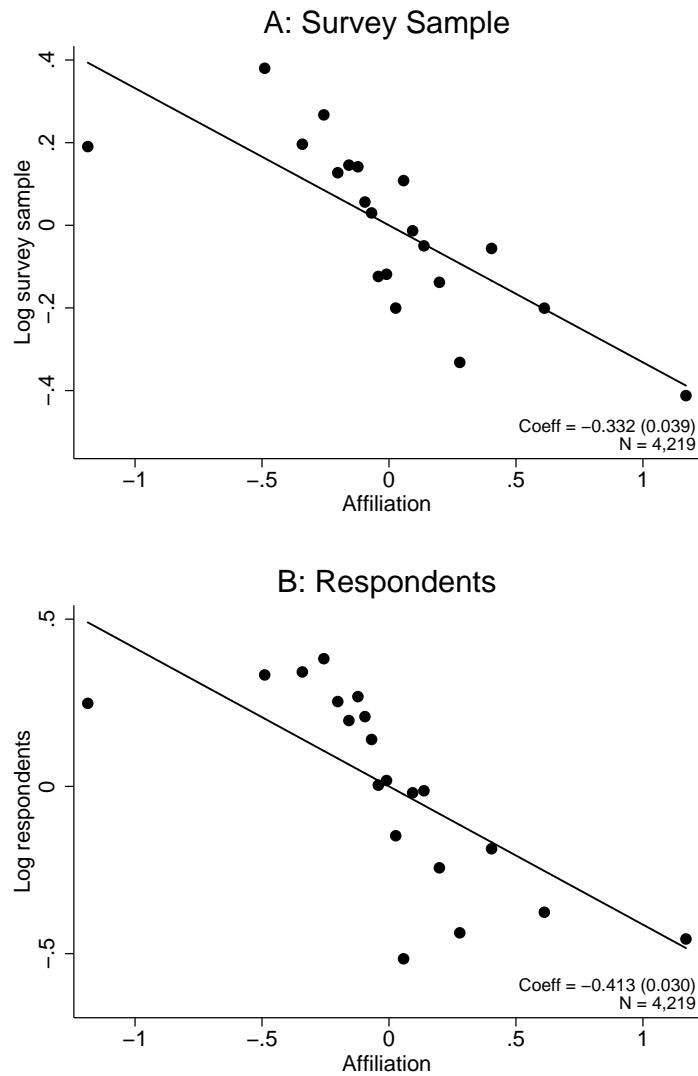
Notes: This figure is a binned scatterplot of residual log RVU on residual affiliation, where each dot represents 5% of the data, ordered by residual affiliations. Residuals are formed by regressing log RVU and affiliation, respectively, on controls specified in column (4) of Table III. The line shows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

Figure V: Revenue Reallocation across Specialties



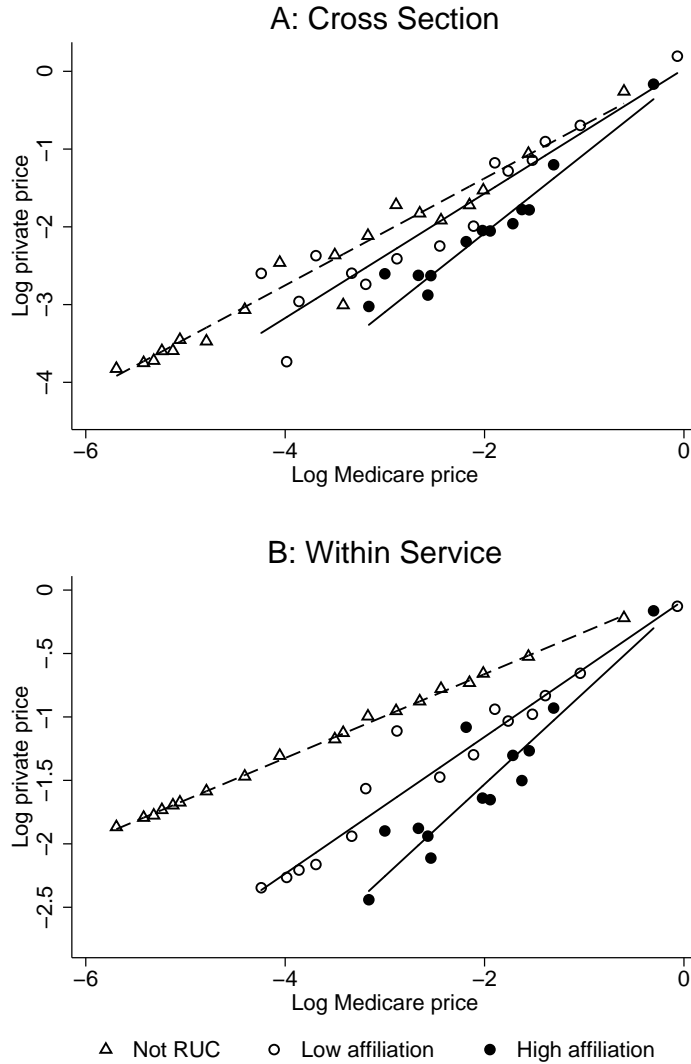
Notes: This figure shows counterfactual yearly revenue reallocation across specialties. In Panel A, we consider equalizing the affiliation of all proposals in each year. In Panel B, we consider changing the RUC membership to be constant and proportional to the population of physician specialties in the US, as given in Online 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) are held fixed, and the annual Medicare budget for physician work is set at $\$70 \text{ billion} \times 51\% = \35.7 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 Online Appendix Table A.8. Lines show the best fit through the residualized data, and the line slopes correspond to the estimated coefficient of interest α 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.

Online Appendix for "Industry Input in Policymaking:
Evidence from Medicare"

David C. Chan and Michael J. Dickstein

January 14, 2019

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I Setting the Medicare Budget

This appendix summarizes the process that sets the overall Medicare budget for physician services, which equivalently determines the conversion factor, or CF_t in Equation (1). We focus on the period between the Balanced Budget Act of 1997 and the Medicare Access and CHIP Reauthorization Act of 2015. A more extensive discussion of this process can be found elsewhere (e.g., American Medical Association, 2015; Centers for Medicare and Medicaid Services, 2014). During this period, CMS set CF_t according to the following formula:

$$CF_t = CF_{t-1} \times (1 + MEI_t) \times (1 + UAF_t) \times BN_t,$$

where MEI_t is the Medicare Economic Index, UAF_t is the Update Adjustment Factor, and BN_t is the Budget Neutrality adjustment.

MEI_t is the weighted-average price change for inputs required to operate a self-employed physician practice in the United States. The measure indexes inflation for medical services. There are two broad categories of inputs: the physician's own time and his or her practice expense. The MEI Technical Advisory Panel continually reviews and updates the index, recommending changes to ensure that MEI_t appropriately meets its statutory purpose.

UAF_t is a mechanism that keeps Medicare spending at an acceptable level given real gross domestic product per capita and year-to-year changes in fees and beneficiaries. The current year's target expenditures are equal to target expenditures in the previous year adjusted by the Sustainable Growth Rate (SGR_t). The update also compares actual expenditures with target expenditures from April 1, 1996 through the preceding year. By federal statute, $UAF_t \in [-7\%, 3\%]$, and the formula for the UAF_t is based on the following identities, relating target and actual spending:

$$\begin{aligned} \sum_{t'=1}^t \text{Target}_{t'} &= \sum_{t'=1}^t \text{Actual}_{t'}; \\ \text{Actual}_t &= \text{Actual}_{t-1} \times (1 + SGR_t) \times (1 + UAF_t); \\ \text{Target}_t &= \text{Target}_{t-1} \times (1 + SGR_t). \end{aligned}$$

These identities yield

$$UAF_t = \frac{\text{Target}_{t-1} - \text{Actual}_{t-1}}{\text{Actual}_{t-1}} \times 0.75 + \frac{\sum_{t'=1}^{t-2} (\text{Target}_{t'} - \text{Actual}_{t'})}{\text{Actual}_{t-1} \times (1 + SGR_t)} \times 0.33,$$

after being modified by “dampening” weights of 0.75 and 0.33, between components from the previous year and all other years before that, respectively.

The Sustainable Growth Rate (SGR_t) used above is calculated according to four factors: (i) the estimated percentage change in fees for physicians' services, (ii) the estimated percentage change in the average number of Medicare fee-for-service beneficiaries, (iii) the estimated 10-year average annual

percentage change in real gross domestic product per capita, and (iv) the estimated percentage change in expenditures due to changes in law or regulations.

The Budget Neutrality adjustment offsets expenditure changes that result from updates to the relative value units of medical services and ensures that RVU inflation does not change the Medicare budget:

$$BN_t = \frac{\sum_i RVU_{i,t-1} \times q_{i,t-1}}{\sum_i RVU_{i,t} \times q_{i,t-1}},$$

which is closely related to the condition in Equation (A.5.1), in Appendix V, that we use in simulating counterfactual revenue in Section 4.2. Historically, BN_t adjustments have been relatively minor considerations in setting CF_t , compared to MEI_t and UAF_t . Changes to the relative value of medical services via BN_t are also limited by statute to \$20 million annually.

Despite scheduled reductions in the CF according to the SGR formula, the most recent year with a CF reduction was 2002. Since then, Congress has annually overridden scheduled reductions (colloquially known as the “doc fix”). Most recently, the Medicare Access and CHIP Reauthorization Act of 2015 removed the SGR formula used to determine the CF. In its place, the act provided a half-percent increase in the physician fee schedule rate until 2020 (Clough and McClellan, 2016).

II Measuring Affiliation

In economics, several threads of literature have developed quantitative measures of relationships between groups. The literature on segregation has developed measures of isolation and dissimilarity to reflect the interaction between groups (White, 1986; Cutler et al., 1999; Gentzkow and Shapiro, 2011; Esteban et al., 2012). A distinct literature on technological spillovers has sought to measure the likelihood that productive entities in multiple fields may affect each other (Jaffe, 1986; Bloom et al., 2013). In our application, we seek to measure the alignment of interests between specialties when interests are multi-dimensional, and the effects of policies on interests are not known with certainty (Caillaud and Tirole, 2007).

Euclidean Distance Metrics

We capture the multidimensional nature of specialty interests with a measure of *affiliation*, or the alignment of interests between two specialties over a distribution of potential revenue changes across services. We argue in Section 3.3 that using the affiliation formulation instead of service-specific interests alone is attractive for both econometric and conceptual reasons.

Our goal in this section is to rationalize our chosen affiliation measures (in Section 3.3) by showing how we can derive these measures starting from the idea that a specialty’s objective will depend on its total revenue. To account for uncertainty in the effects of price changes on total revenue, we consider a specialty’s total revenue as a stochastic object under random price changes and potentially random spillovers across services. Affiliation is our statistic to measure the degree to which the revenues of two

specialties are linked. Two specialties with linked revenues (i.e., high affiliation) should have similar preferences.

Specifically, starting with the formula for specialty revenue $R_s = \sum_i p_i q_{is}$, we can write the first-order effect of a random vector $d\mathbf{p}$ of price changes on R_s as

$$\frac{dR_s}{d\mathbf{p}} = \sum_i \left(q_{is} \frac{dp_i}{d\mathbf{p}} + p_i \frac{dq_{is}}{d\mathbf{p}} \right). \quad (\text{A.2.1})$$

While we observe q_{is} and p_i , $dp_i/d\mathbf{p}$ and $dq_{is}/d\mathbf{p}$ are generally unknown. Thus, to derive a measure of similarity that captures the effects of $d\mathbf{p}$ on the revenue of two different specialties, as in Equation (A.2.1), we need to make simplifying assumptions on the unknown elements. We discuss two such assumptions below, both of which link a statistical comparison of specialty objectives to a specific measure of affiliation.

Quantity Shares

Under the assumption of fixed quantities (i.e., quantities are completely inelastic to price), the derivative in Equation (A.2.1) reduces to

$$\frac{dR_s}{d\mathbf{p}} = \sum_i q_{is} \frac{dp_i}{d\mathbf{p}}.$$

Further, fixed quantities allow us to scale revenue to be per-service; we can then compare specialties of different overall volume:

$$\frac{dr_s}{d\mathbf{p}} = \sum_i \sigma_{is}^q \frac{dp_i}{d\mathbf{p}},$$

where $r_s \equiv R_s / \sum_i q_{is}$ is the per-service revenue, and $\sigma_{is}^q \equiv q_{is} / \sum_i q_{is}$ is the quantity share of i relative to other procedures that s performs.

The difference in the effect on *per-service revenue* between specialties A and B is

$$\frac{dr_A}{d\mathbf{p}} - \frac{dr_B}{d\mathbf{p}} = \sum_i \left(\sigma_{iA}^q - \sigma_{iB}^q \right) \frac{dp_i}{d\mathbf{p}}. \quad (\text{A.2.2})$$

Distances in the vector space of quantity shares, i.e., (σ_A^q, σ_B^q) , thus capture this difference for any arbitrary set of price changes (i.e., any arbitrary \mathbf{p} and the corresponding $dp_i/d\mathbf{p}$ for all i). In addition, the expression in Equation (A.2.2) equivalently represents differences in *per-service profit* due to $d\mathbf{p}$, where “profit” is price minus a concept of service-specific cost, since costs are fixed with fixed quantities.¹ That is, with fixed quantities, a specialty objective that maximizes revenue also maximizes profits.

Given some distribution of price changes $d\mathbf{p}$ with $C \times C$ variance-covariance matrix Ω^q , we can state

¹This cost can be a cost of effort, a financial cost, or an opportunity cost, such as when time used to perform service i detracts from time performing other procedures.

the variance of $dr_A - dr_B$ as

$$\text{Var}(dr_A - dr_B) = (\sigma_A^q - \sigma_B^q)' \Omega^q (\sigma_A^q - \sigma_B^q).$$

Recall that our baseline affiliation metric in Equation (3) is

$$a(s_A, s_B) = -\|\sigma_A^q - \sigma_B^q\|_2 = -\sqrt{(\sigma_A^q - \sigma_B^q)' (\sigma_A^q - \sigma_B^q)}.$$

Here, if two specialties have the same utilization shares (i.e., $\sigma_A^q = \sigma_B^q$), there will be no difference in their per-service revenue (i.e., $dr_A - dr_B = 0$) for any arbitrary distribution of $d\mathbf{p}$. This Euclidean distance is equivalent to the negative standard deviation of $dr_A - dr_B$ under the uninformative prior that $d\mathbf{p}$ follows a distribution with variance-covariance matrix equal to the identity matrix, $\Omega^q = \mathbf{I}_C$. In sum, we can rationalize this affiliation measure if specialties view alignment in interests in terms of per-service revenue, assuming fixed service quantities.

Revenue Shares

Rather than assume fixed quantities as in Appendix II, we can alternatively assume that quantities remain allocated across specialties in fixed proportion under a distribution of price changes. Under this assumption, we can rationalize a distance metric based on vectors of revenue shares. We show that this metric corresponds to a measure of the difference between two specialties' percentage change in revenue after a distribution of price changes, $d\mathbf{p}$.

To see this, first consider the accounting relationship $q_{is} = w_{is}q_i$, where w_{is} is defined in Equation (5) and $q_i \equiv \sum_s q_{is}$. If we assume that w_{is} is fixed, then a specialty's percentage revenue change is

$$\begin{aligned} \frac{dR_s/d\mathbf{p}}{R_s} &= \frac{1}{R_s} \sum_i \left(q_{is} \frac{dp_i}{d\mathbf{p}} + p_i \frac{dq_{is}}{d\mathbf{p}} \right) \\ &= \sum_i \frac{q_{is} p_i}{R_s} \cdot \frac{q_{is} \cdot dp_i/d\mathbf{p} + p_i \cdot dq_{is}/d\mathbf{p}}{p_i q_{is}} \\ &= \sum_i \sigma_{is}^R \cdot \frac{q_i \cdot dp_i/d\mathbf{p} + p_i \cdot dq_i/d\mathbf{p}}{p_i q_i}, \\ &= \sum_i \sigma_{is}^R \cdot \frac{d(p_i q_i)/d\mathbf{p}}{p_i q_i}, \end{aligned}$$

where $\sigma_{is}^R \equiv (p_i q_{is})/R_s$ is the revenue share of i relative to other procedures that s performs, and the third line derives from dividing the numerator and the denominator by w_{is} . The term multiplying σ_{is}^R is a constant for each service i ; it does not depend on the identity of s .

The difference in the percentage revenue change between specialties A and B is then

$$\frac{dR_A/d\mathbf{p}}{R_A} - \frac{dR_B/d\mathbf{p}}{R_B} = \sum_i \left(\sigma_{iA}^R - \sigma_{iB}^R \right) \frac{d(p_i q_i)/d\mathbf{p}}{p_i q_i}.$$

Distances in the vector space of revenue shares, i.e., $(\sigma_{iA}^R, \sigma_{iB}^R)$, correspondingly capture this difference in percentage revenue changes. Specifically, given some distribution of proportional revenue changes $(p_i q_i)^{-1} d(p_i q_i) / d\mathbf{p}$ distributed with $C \times C$ variance-covariance matrix Ω^R , we can state the variance of the difference in proportional revenue changes between specialties A and B as

$$\text{Var} \left(\frac{dR_A}{R_A} - \frac{dR_B}{R_B} \right) = (\sigma_A^R - \sigma_B^R)' \Omega^R (\sigma_A^R - \sigma_B^R).$$

Thus, the affiliation metric based on revenue shares,

$$a(s_A, s_B) = -\|\sigma_A^R - \sigma_B^R\|_2 = -\sqrt{(\sigma_A^R - \sigma_B^R)' (\sigma_A^R - \sigma_B^R)}, \quad (\text{A.2.3})$$

can be interpreted as the negative standard deviation of the difference in proportional revenue changes (i.e., $dR_A/R_A - dR_B/R_B$) under the uninformative prior that $(p_i q_i)^{-1} d(p_i q_i) / d\mathbf{p}$ is distributed i.i.d. under $\Omega^R = \mathbf{I}_C$. Specialties with identical utilization shares (i.e., $\sigma_A^q = \sigma_B^q$) will also have identical revenue shares (i.e., $\sigma_A^R = \sigma_B^R$) and no difference in proportional revenue changes (i.e., $dR_A/R_A - dR_B/R_B = 0$) regardless of spillovers in Ω^R . In sum, we can rationalize this affiliation measure if specialties view alignment in interests in terms of proportional changes in revenue, and if changes in service quantities are distributed across specialties in fixed proportion.

Alternative Distance Metrics

In addition to affiliation measures detailed above, we consider several other statistical measures of affiliation, motivated by the large space of CPT codes.² First, we modify our baseline Euclidean distance measures by weighting services with greater variation in σ_{iS} across s :

$$a(s_A, s_B) = -\sqrt{(\sigma_A - \sigma_B)' \mathbf{G} (\sigma_A - \sigma_B)},$$

where \mathbf{G} is a diagonal weighting matrix, such that element (i, i) is the Gini coefficient across σ_{iS} for each service i . This Gini-weighted metric places weight on services with greater variation in σ_{iS} and will naturally result in greater variation in distances.

We also consider Manhattan distance, in L_1 space:

$$a(s_A, s_B) = -\|\sigma_A - \sigma_B\|_1 = -\sum_i |\sigma_{iA} - \sigma_{iB}|,$$

²In addition to quantity shares and revenue shares based on individual services defined by CPT codes, we also consider quantity shares and revenue shares in 107 Berenson-Eggers Type of Service (BETOS) categories. This formulation is more restrictive but uses prior knowledge to group services into categories that likely covary. In this sense, this vector space may improve the characterization of affiliation if BETOS categories capture a sufficiently large amount of information about CPT codes in terms of the price or quantity effects of \mathbf{p} . On the other hand, if there remains substantial heterogeneity in effects within BETOS categories, then affiliation measures based on this vector space will perform less well.

Finally, we consider cosine similarity, given by

$$a(s_A, s_B) = \cos(\sigma_A, \sigma_B) = \frac{\sigma_A \cdot \sigma_B}{\sqrt{\sigma_A \cdot \sigma_A} \sqrt{\sigma_B \cdot \sigma_B}}.$$

Cosine similarity—along with related measures of angular distance and the correlation measures in the technology-spillover literature (Jaffe, 1986; Bloom et al., 2013)—has the feature of normalizing the two vectors under comparison to have the same length.³

In this setting, the magnitudes of elements in any vector σ_s represent specialty interests (i.e., $\sum_i \sigma_{is} = 1$ for any s), while normalizing σ_A and σ_B to length 1 has no meaningful economic interpretation. On the other hand, the cosine similarity between two specialty vectors of within-service shares, or w_{is} as defined in Equation (5), can be interpreted as the correlation in revenue between the specialties. To see this, denote $\tilde{\mathbf{w}}_s$ as the $C \times 1$ vector with i th element equal to w_{is} .⁴ Consider a $C \times C$ variance-covariance matrix $\Omega^{w,R}$ of $p_i q_i$. Then $\tilde{\mathbf{w}}_A \Omega^{w,R} \tilde{\mathbf{w}}_B'$ is the covariance in revenues between specialties A and B , under the assumption that $\tilde{\mathbf{w}}_A$ and $\tilde{\mathbf{w}}_B$ are fixed. The measure

$$a(s_A, s_B) = \cos(\tilde{\mathbf{w}}_A, \tilde{\mathbf{w}}_B) = \frac{\tilde{\mathbf{w}}_A \cdot \tilde{\mathbf{w}}_B}{\sqrt{\tilde{\mathbf{w}}_A \cdot \tilde{\mathbf{w}}_A} \sqrt{\tilde{\mathbf{w}}_B \cdot \tilde{\mathbf{w}}_B}} \quad (\text{A.2.4})$$

reflects correlation in revenue between specialties A and B under the uninformative prior that $\Omega^{w,R} = \mathbf{I}_C$. To differentiate $\cos(\sigma_A, \sigma_B)$ and $\cos(\tilde{\mathbf{w}}_A, \tilde{\mathbf{w}}_B)$, we call the former σ -cosine similarity and call the latter w -cosine similarity. In Appendix Table A.3, as with measures based on σ_{is} , we also present regression results of Equation (6) for affiliation defined by w -cosine similarity measures based on quantity and revenue data.⁵

Cross-Service Spillovers

In Appendices II and II, we describe affiliation measures that assume revenue-relevant variation is i.i.d. across services. Here, we empirically compute and evaluate alternative variance-covariance matrices to represent spillovers. We compute three different matrices relevant for three respective affiliation measures: (i) Ω^q , the variance-covariance matrix of RVU changes dp_i , implicit in Equation (3); (ii) Ω^R , the variance-covariance matrix of percentage revenue changes $d(p_i q_i)/(p_i q_i)$, implicit in Equation (A.2.3); and (iii) $\Omega^{w,R}$, the variance-covariance matrix of revenue $d(p_i q_i)$, implicit in Equation (A.2.4). We com-

³To see the relationship between Euclidean distance and cosine similarity, note that $\|\sigma_A - \sigma_B\|_2^2 = (\sigma_A - \sigma_B)(\sigma_A - \sigma_B)' = \|\sigma_A\|_2^2 + \|\sigma_B\|_2^2 - 2\sigma_A \cdot \sigma_B$. If $\|\sigma_A\|_2^2 = \|\sigma_B\|_2^2 = 1$, then $\|\sigma_A - \sigma_B\|_2^2 = 2(1 - \cos(\sigma_A, \sigma_B))$. Angular distance is defined as $a(s_A, s_B) = \pi^{-1} \cos^{-1}(\cos(\sigma_A, \sigma_B))$, and correlation is defined as $a(s_A, s_B) = \text{corr}(\sigma_A, \sigma_B)$. We find that regressions of Equation (6) yield very similar results when using cosine similarity, angular distance, and correlation. We thus omit results for angular distance and correlation from Appendix Table A.3 for brevity.

⁴This vector is related to \mathbf{w}_i , which is the $S \times 1$ vector with the s th element equal to w_{is} .

⁵Quantity-based w_{is}^q is defined in Equation (5), whereas revenue-based $w_{is}^R = \left(\sum_y p_{iy} q_{isy} \right) / \left(\sum_y \sum_s p_{iy} q_{isy} \right)$. For a single year y , it is obvious that $w_{is}^q = w_{is}^R$. In general, they may not be equivalent when aggregating over years or CPT codes within a BETOS category, but the difference between w_{is}^q and w_{is}^R will be much smaller than the difference between σ_{is}^q and σ_{is}^R , because price differences are much smaller within CPT code as opposed to across CPT codes.

pute these matrices based on observations of p_i in the physician fee schedule and $p_i q_i$ across years in the Medicare data.

The assumptions about cross-service spillovers in each of these matrices will imply different affiliation measures. Specifically, we define

$$\begin{aligned} -\|\sigma_A^q - \sigma_B^q; \Omega^q\|_2 &= -\sqrt{(\sigma_A^q - \sigma_B^q)' \Omega^q (\sigma_A^q - \sigma_B^q)}; \\ -\|\sigma_A^R - \sigma_B^R; \Omega^R\|_2 &= -\sqrt{(\sigma_A^R - \sigma_B^R)' \Omega^R (\sigma_A^R - \sigma_B^R)}; \\ \cos(\tilde{\mathbf{w}}_A, \tilde{\mathbf{w}}_B; \Omega^{w,R}) &= \frac{\tilde{\mathbf{w}}_A \Omega^{w,R} \tilde{\mathbf{w}}_B'}{\sqrt{\tilde{\mathbf{w}}_A \Omega^{w,R} \tilde{\mathbf{w}}_A'} \sqrt{\tilde{\mathbf{w}}_B \Omega^{w,R} \tilde{\mathbf{w}}_B'}}}, \end{aligned}$$

for Euclidean distance in σ^q , Euclidean distance in σ^R , and w -cosine similarity, respectively.

In principle, if spillovers are known without measurement error, these affiliation measures should capture the alignment of specialty revenue interests more closely than a measure that ignores spillovers. However, in practice, there are two empirical difficulties that could degrade the fidelity of these measures relative to our baseline measure. First, we lack sufficient quasi-experimental variation to estimate spillovers across services. Second, the number of observations we have for each service is much smaller than the number of elements in Ω , a well-known problem in the estimation of covariance structures (Altonji and Segal, 1996).

Thus, we introduce two regularization parameters, γ_1 and γ_2 , to enable us to “shrink” the variance-covariance matrix Ω to a matrix $\Omega_{\gamma_1, \gamma_2}$ closer to the identity matrix \mathbf{I}_C :

$$\begin{aligned} \Omega_{\gamma_1, 0} &= (\text{diag}(\Omega))^{-\gamma_1/2} \Omega (\text{diag}(\Omega))^{-\gamma_1/2} \\ \Omega_{\gamma_1, \gamma_2}[i, j] &= (1 - \gamma_2) \Omega_{\gamma_1, 0}[i, j], \text{ for all } i \neq j. \end{aligned}$$

$\gamma_1 \in [0, 1]$ transforms $\Omega_{\gamma_1, 0}$ from a variance-covariance matrix ($\gamma_1 = 0$) to a correlation matrix ($\gamma_1 = 1$), and $\gamma_2 \in [0, 1]$ further transforms Ω_{1, γ_2} from a correlation matrix ($\gamma_2 = 0$) to an identity matrix ($\gamma_2 = 1$).

In Appendix Figure A.1, we evaluate the performance of affiliation metrics that include spillovers, by plotting the coefficient of each affiliation metric in the price regression of Equation (6) with respect to the regularization parameters. We find that accounting for spillovers unambiguously reduces the linkage between RUC price actions and our Euclidean-distance affiliation measures but improves this linkage for w -cosine similarity over some range of (γ_1, γ_2) .

III Mixed Strategies in Endogenous Proposals

In this appendix, we sketch a simple signaling model of proposals to provide intuition for the random variation we observe in the endogenous decisions of specialties to propose. As in our main conceptual framework, in Section 5.1, we assume a specialty society may be biased, but for tractability, we rule out

any downstream communication or any potential bias of the RUC.⁶ The first important feature of the model is that proposals to the RUC are costly. Second, if there is more than one proposing specialty that would have proposed alone, then there cannot be a unique (or symmetric) pure strategy equilibrium that determines specialty proposals. In other words, if specialty societies cannot fully coordinate, then we will have random variation in the identities of proposing specialties. In this sketch, we ignore the possibility that costs may quasi-randomly vary in order to clarify the latter source of random variation.

Specifically, consider specialty society utility

$$u_S = -(\theta + b_S - p)^2 - cD_S,$$

where $\theta \in \{0, 1\}$ is the true price, $b_S > 0$ is the specialty's bias, p is the price recommended by the RUC (and set by the government), c is the cost of proposing, and $D_S \in \{0, 1\}$ is an indicator for the specialty proposing. The RUC's (and the government's) utility is $u_R = -(\theta - p)^2$. We assume that $\Pr(\theta = 1) = \frac{1}{2}$.

In a separating pure strategy equilibrium with a single specialty, the specialty will propose if and only if $\theta = 1$, and the government will set $p = D_S$. The specialty must then have bias $b_S \in \left[\frac{c-1}{2}, \frac{c+1}{2}\right]$. If bias is too low (or cost too high), then the specialty will not want to propose even if $\theta = 1$; if bias is too high (or cost too low), then the specialty will want to propose even if $\theta = 0$.⁷

We then consider two specialties $S \in \{1, 2\}$, and assume that $b_S > \frac{c-1}{2}$ for both specialties. Both specialties would propose if $\theta = 1$ had the other one not existed, yet neither would propose if it knows that the other specialty's strategy is to propose when $\theta = 1$. Thus, there is no unique pure strategy equilibrium of proposals by the two specialties. In the case that $b_1 = b_2$, this implies that there is no symmetric pure strategy equilibrium.⁸ There are at least two types of mixed strategies over the range of this bias-cost space: (i) Neither specialty proposes if $\theta = 0$ and mix (i.e., propose with some probability $\pi_S \in (0, 1)$) if $\theta = 1$, and (ii) both specialties propose if $\theta = 1$ and mix if $\theta = 0$.

Because the number of actual specialty-proposals relative to potential specialty-proposals is empirically low, we focus on the former type of mixed strategies.⁹ When specialties mix when $\theta = 1$, the RUC knows that $\theta = 1$ and sets $p = 1$, if either $D_1 = 1$ or $D_2 = 1$. If $D_1 = D_2 = 0$, the RUC sets

$$p(\pi_1, \pi_2 | D_1 = D_2 = 0) = \frac{(1 - \pi_1)(1 - \pi_2)}{1 + (1 - \pi_1)(1 - \pi_2)},$$

which is the probability that $\theta = 1$ if $D_1 = D_2 = 0$. For a mixed-strategy equilibrium to exist, specialties must be indifferent between proposing and not. Specifically, although proposing will lead to a price

⁶We could introduce these features, but the intuition we wish to formalize would remain the same.

⁷Potters and van Winden (1992) also point out that there exists a mixed strategy equilibrium, in which the specialty certainly proposes if $\theta = 1$ and proposes with some probability $\pi \in (0, 1)$ if $\theta = 0$ for biases $b_S \in \left(\frac{c+1}{2}, c + \frac{1}{4}\right)$ if $c > \frac{1}{2}$.

⁸There may exist, for example, a perfect Bayesian equilibrium with two players in which both would choose to propose if the RUC believed $\theta = 1$ only if it observes both specialties proposing. We could rule out an equilibrium of this form by refining the equilibrium concept such that if the RUC observes only one specialty proposing, it will nonetheless consider that specialty's incentives to propose and update its prior probability that the value of $\theta = 1$ (Grossman and Helpman, 2001).

⁹Parallel results obtain for the latter type, which correspond to the mixed strategy in the single-player case noted by Potters and van Winden (1992), in footnote 7.

increase of $1 - p(\pi_1, \pi_2 | D_1 = D_2 = 0) > 0$, the utility gain by either specialty is equal to the cost of proposing, c . In Appendix Figure A.2, fixing $c = 1$ for the specialties, we show whether a mixed-strategy equilibrium exists in (b_1, b_2) space and, if so, the mixing probabilities for the specialties (when $\theta = 1$) that sustain it.

We first find that if specialty bias is sufficiently low, then there exists no mixed-strategy equilibrium. Failure to coordinate and the temptation to free-ride results in no proposals, reducing signaling equilibria relative to the one-specialty standard. However, if both specialties are sufficiently biased (or equivalently, have low costs), then their equilibrium mixed strategies will involve fairly high π_S , and signaling is possible even for $b_S > \frac{c+1}{2}$, which would have prohibited signaling in the one-specialty case, where the specialty would have proposed even if $\theta = 0$. Finally, and intuitively, when specialties are asymmetric in their bias, signaling occurs mostly through the lower-bias specialty. As the bias of the higher-bias specialty approaches infinity, the equilibrium resembles a single-specialty pure-strategy equilibrium, and signaling is possible at levels of bias (of the lower-bias specialty) close to those in the one-specialty case (i.e., as low as $\frac{c-1}{2}$).

IV Quasi-Experimental Variation in Affiliation

Affiliation $A(\mathcal{R}_t, \mathcal{S}_i)$ is determined as a function of specialties on the RUC at meeting t , \mathcal{R}_t , and specialties on a proposal i , \mathcal{S}_i . In this appendix, we quantify and assess the exogeneity of variation in $A(\mathcal{R}_t, \mathcal{S}_i)$ due to variation in \mathcal{R}_t and variation in \mathcal{S}_i . In particular, we evaluate two potential threats to identification. First, with respect to variation in \mathcal{R}_t , specialties submitting proposals for procedures with intrinsically high prices may choose to submit these proposals at meetings with more affiliated RUC members. Second, specialties may be more likely to propose for procedures with higher potential prices, driving up the affiliation of these proposals with the RUC.

Quasi-Experimental Variation in \mathcal{R}_t

To evaluate variation in affiliation due to \mathcal{R}_t we first compute the affiliation that each proposal i would have over all possible meetings $t' \in T$, generating a set of counterfactual affiliations, $A = \{A(\mathcal{R}_{t'}, \mathcal{S}_i)\}$. We then test whether observed affiliations are statistically distinguishable from these counterfactual affiliations. In Panel A of Appendix Figure A.4, we show that the mean differenced statistic $A(\mathcal{R}_{t'}, \mathcal{S}_i) - A(\mathcal{R}_t, \mathcal{S}_i)$ over all proposals and possible meeting dates (i, t') is not statistically different than 0. However, given relatively stable RUC specialty membership in Table I and Figure I, it is natural that the variation in affiliation due to \mathcal{R}_t is relatively small. If we restrict counterfactual meetings to those within a year of the actual meeting, in Panel B, we find that the distribution of $A(\mathcal{R}_{t'}, \mathcal{S}_i) - A(\mathcal{R}_t, \mathcal{S}_i)$ is even more concentrated around zero.

We can also quantify the variation component from \mathcal{R}_t relative to overall quasi-experimental variation. For this decomposition, we compute $\bar{A}(\mathcal{S}_i) \equiv \|T\|^{-1} \sum_{t' \in T} A(\mathcal{R}_{t'}, \mathcal{S}_i)$, which is the average variation across all meetings, given \mathcal{S}_i . We then compute the variation in $\bar{A}(\mathcal{S}_i)$, conditional on \mathbf{w}_i ; we denote

$\bar{A}(\mathcal{S}_i)$ residualized by \mathbf{w}_i as $\bar{A}^*(\mathcal{S}_i)$. Variation in $\bar{A}^*(\mathcal{S}_i)$ represents quasi-experimental variation unrelated to \mathbf{w}_i . The component of the variation due to \mathcal{R}_t is $\sigma_{\mathcal{R}}^2 \equiv \text{Var}\left(A(\mathcal{R}_t, \mathcal{S}_i) - \bar{A}(\mathcal{S}_i)\right)$, and the remaining component due to \mathcal{S}_i is $\sigma_{\mathcal{S}}^2 \equiv \text{Var}\left(\bar{A}^*(\mathcal{S}_i)\right)$. We find that $\sigma_{\mathcal{R}}^2 / (\sigma_{\mathcal{R}}^2 + \sigma_{\mathcal{S}}^2) \approx 0.014$ when T is the entire set of meetings, and $\sigma_{\mathcal{R}}^2 / (\sigma_{\mathcal{R}}^2 + \sigma_{\mathcal{S}}^2) \approx 0.007$ when T contains counterfactual meetings at most three meetings (one year) apart from the actual meeting.

Quasi-Experimental Variation in \mathcal{S}_i

To assess quasi-experimental variation in \mathcal{S}_i empirically, we conduct four tests. First, we show that specialty participation in proposals, conditional on specialty dummies, meeting dummies \mathbf{T}_t , and utilization shares \mathbf{w}_i , is uncorrelated with the service's predicted price. Second, we show that specialty proposals are conditionally uncorrelated with time-varying affiliation with the RUC. Third, we show significant variation in the propensity of specialty proposals, even among specialties that actually participate in a given proposal. Fourth, we predict affiliation based on specialty-proposal propensities and show that this prediction is forecast-unbiased (Chetty et al., 2014), while there also remains wide variation in the distribution of actual minus predicted affiliation. We provide more detail on these tests below.

Specialty-Proposal Probability

The first three tests we perform relate to specialty-proposal probabilities. First, in Appendix Figure A.5, we show evidence that the probability a specialty participates in a proposal is conditionally uncorrelated with the predicted price of the relevant service. We predict the RVU of a procedure by its characteristics, including procedure code word descriptions, surveyed time, prior RVU, and Medicare beneficiary characteristics, which yields an adjusted R^2 of 0.88 for the RVU prediction equation. Controlling for specialty dummies, meeting dummies \mathbf{T}_t , and specialty utilization shares $w_{i,s}$, as defined in Equation (5), we find no significant relationship between specialty proposals and predictors of price.

Second, in Appendix Figure A.6, we assess whether specialty proposals are more likely when affiliation with the RUC is higher. We construct a measure of whether affiliation between specialty s is higher at meeting $t(i)$ associated with proposal i than at other meetings

$$A(\mathcal{R}_{t(i)}, s) - \bar{A}(s),$$

where $\bar{A}(s) \equiv \|T\|^{-1} \sum_{t' \in T} A(\mathcal{R}_{t'}, s)$. We standardize $A(\mathcal{R}_{t(i)}, s) - \bar{A}(s)$ to have a distribution with mean 0 and standard deviation 1. We then evaluate whether specialty proposals, or $\mathbf{1}(s \in \mathcal{S}_i)$, is correlated with $A(\mathcal{R}_{t(i)}, s) - \bar{A}(s)$, conditional on dummies for specialty s and for the number of proposing specialties in \mathcal{S}_i , or $\|\mathcal{S}_i\|$. We again find no significant relationship between time-varying affiliation between s and $\mathcal{R}_{t(i)}$ and whether $s \in \mathcal{S}_i$. While this does not rule out strategic proposing with respect to affiliation that is *time-invariant*, given the evidence in Appendix IV, it is intuitive that specialties do not have much scope to respond to time-varying affiliation.

Third, we form a prediction of specialty-proposal propensities, in order to evaluate variation in this propensity and the predictability with which specialties actually propose. We estimate a logit propensity model of specialty-proposal participation, using specialty identities, flexible functions of \mathbf{w}_i , and the procedure’s share of specialty revenue, defined as σ_{is}^R in Appendix II. The logit model is fairly predictive, with a pseudo- R^2 of 0.73 and a log-likelihood of $-8,661.35$ over 248,735 observations, and the standard deviation in specialty-proposal propensities is about 13%. Nonetheless, we find substantial residual variation in specialty proposals. To illustrate this, in Appendix Figure A.7, we show the propensities of 6,929 actual specialty-proposal pairs over 4,199 proposals. While there are many propensities with high values, more than half of the actual specialty proposals have propensities lower than 0.8, and about a quarter have propensities less than 0.5. Similarly, in Appendix Figure A.8, we show the first-, second-, third-, and fourth-ranked specialty propensities for proposals *with at least as many proposers*. Although there are 64 specialties to rank, propensities quickly diminish: The average first-ranked propensity is 0.86, while the average second-, third-, and fourth-ranked propensities are 0.76, 0.69, and 0.54, respectively.

Affiliation Forecast

In our fourth test, we use our estimated specialty-proposal propensities, $\hat{\pi}_{is}$, and the known specialties of RUC members at each meeting, \mathcal{R}_t , to form a prediction of affiliation by simulation. We will use this prediction to evaluate endogeneity at the affiliation level, testing whether affiliation is “forecast-unbiased” (Chetty et al., 2014). We will also evaluate the degree of variation in affiliation that remains conditional on this prediction, which allows for nonlinear relationships in \mathbf{w}_i and σ_{is}^R across specialties.

We proceed as follows:

1. Use estimated specialty-proposal propensities, $\hat{\pi}_{is}$. Drop any specialty-proposal pair with $\hat{\pi}_{is} < 0.01$.
2. For each proposal i , identify number of remaining specialty-proposer candidates, n_i , and the number of actual specialty proposers, k_i . This yields $\|\mathbb{S}_i\| = C(n_i, k_i)$ as the number of potential proposer sets \mathcal{S}_i for i , constraining the number of simulated proposers in each set to be the same as the number of actual proposers. For example, if there remain ten specialty-proposer candidates for a proposal with only one actual specialty proposer, there are $C(10, 1) = 10$ (singleton) sets to draw from. However, if there are fifteen specialty-proposer candidates for a proposal with four actual proposers, there are $C(15, 4) \approx 7.57 \times 10^7$ sets to draw from.
 - (a) For proposals i such that $\|\mathbb{S}_i\| \leq 50$, collect all such potential proposer sets.
 - (b) For the remaining proposals, randomly draw k_i proposers from n_i , oversampling specialty-proposer candidates from those with higher $\hat{\pi}_{is}$. Specifically, generate $r_{is} \sim U(0, 1)$ and subtract this from $\hat{\pi}_{is}$. Within each i , sort specialty-proposer candidates by $\hat{\pi}_{is} - r_{is}$, and choose the top k_i candidates to include in \mathcal{S}_i . Repeat until some stopping rule (e.g., based on the number of unique sets sampled for each i and the lack of new sets sampled for any i in a draw).

(c) Denote as $\mathbb{S}_i^* \subseteq \mathbb{S}_i$ the collection of simulated sets for each proposal i . For each $\mathcal{S}_i \in \mathbb{S}_i^*$, calculate a simulated set affiliation $A(\mathcal{R}_t, \mathcal{S}_i)$ for each \mathcal{S}_i , using known \mathcal{R}_t and the formula in Equation (4).

3. Given $\hat{\pi}_{is}$, and assuming independence of specialty proposals, the probability of drawing \mathcal{S}_i from \mathbb{S}_i is

$$\Pr(\mathcal{S}_i | \mathbb{S}_i^*) \equiv \frac{\prod_{s \in \mathcal{S}_i} \hat{\pi}_{is} \prod_{s \notin \mathcal{S}_i} (1 - \hat{\pi}_{is})}{\sum_{\mathcal{S}_i \in \mathbb{S}_i^*} (\prod_{s \in \mathcal{S}_i} \hat{\pi}_{is} \prod_{s \notin \mathcal{S}_i} (1 - \hat{\pi}_{is}))}.$$

This allows us to weight sets by their probability of occurrence. This also allows us to generate a *predicted* set affiliation,

$$\hat{A}(\mathcal{R}_t, i) = \sum_{\mathcal{S}_i \in \mathbb{S}_i^*} A(\mathcal{R}_t, \mathcal{S}_i) \Pr(\mathcal{S}_i | \mathbb{S}_i^*). \quad (\text{A.4.1})$$

In Appendix Figure A.9, we show the distribution of simulated set affiliations relative to the actual set affiliation for each i , weighted by $\Pr(\mathcal{S}_i | \mathbb{S}_i^*)$, or $\hat{A}(\mathcal{R}_t, i) - A(\mathcal{R}_t, \mathcal{S}_i)$. The weighted standard deviation of the distribution is 0.242, reflecting that there exists meaningful variation in set affiliation based on the specialty-proposal propensities. The variation in this figure is much larger than the variation in Appendix Figure A.6, consistent with the large majority of identifying variation coming from \mathcal{S}_i rather than \mathcal{R}_t . Further, the weighted mean of the distribution of $\hat{A}(\mathcal{R}_t, i) - A(\mathcal{R}_t, \mathcal{S}_i)$ is -0.015 , suggesting very little forecast bias in predicted set affiliation. We use predicted set affiliation as a control, rather than linear specialty shares of CPT utilization, \mathbf{w}_i , in a robustness check of the affiliation effect on prices, in column (5) of Table III; we find a similar estimate of the main effect.

V Counterfactual Revenue Analysis

Simulation Algorithm

We simulate counterfactual revenue in scenarios that entail counterfactual affiliations for proposals. In each scenario, we hold fixed the service and timing of each proposal, the Medicare budget, and the utilization of each service. Counterfactual revenue results solely from the effect of affiliation on relative price. Prices are rationalized so that total spending meets the fixed Medicare budget. The algorithm is as follows:

1. Starting at the first year in which the RUC's pricing decision goes into effect, we replace the relative price RVU_{iy} that followed a RUC recommendation with a counterfactual \widetilde{RVU}_{iy} , by subtracting $\hat{\alpha}(A(\mathcal{R}_t, \mathcal{S}_i) - \tilde{A}_{it})$, where $A(\mathcal{R}_t, \mathcal{S}_i)$ and \tilde{A}_{it} are actual and counterfactual affiliations, respectively, and $\hat{\alpha}$ is the estimated affiliation effect from Equation (6). The counterfactual affiliation in the first scenario is an equalized affiliation across all proposals $i \in I_t$ in the same meeting t : $\tilde{A}_{it} = \|I_t\|^{-1} \sum_{i \in I_t} A(\mathcal{R}_t, \mathcal{S}_i)$. The counterfactual affiliation in the second scenario is $\tilde{A}_{it} = A(\tilde{\mathcal{R}}, \mathcal{S}_i)$, where $\tilde{\mathcal{R}}$ is the counterfactual RUC composed of specialties in Appendix Table A.7. RUC decisions

in meeting t map to prices in the Medicare schedule in year $y(t)$. We repeat for subsequent years, allowing previously set prices to continue forward.

2. We take quantities q_{isy} of service i , by specialty s , in year y , observed in Medicare claims. We set conversion factors CF_y and \widetilde{CF}_y so that the overall spending is \$70 billion in 2014 dollars, which implies that

$$\widetilde{CF}_y \sum_i \sum_s \widetilde{RVU}_{iy} \cdot q_{isy} = CF_y \sum_i \sum_s RVU_{iy} \cdot q_{isy}. \quad (\text{A.5.1})$$

3. The revenue reallocation for service i , specialty s , and year y is

$$\Delta r_{isy} = q_{isy} \left(\widetilde{CF}_y \cdot \widetilde{RVU}_{iy} - CF_y \cdot RVU_{iy} \right).$$

4. We aggregate Δr_{isy} to yearly averages for specialties s or types of service k :

$$\begin{aligned} \Delta R_s &= \|\mathcal{Y}\|^{-1} \sum_{y \in \mathcal{Y}} \sum_i \Delta r_{isy}; \\ \Delta R_k &= \|\mathcal{Y}\|^{-1} \sum_{y \in \mathcal{Y}} \sum_s \sum_{i \in k} \Delta r_{isy}. \end{aligned}$$

Distribution of Counterfactual Affiliations

Our counterfactual analysis is based on a reduced-form estimate of $\hat{\alpha}$ from Equation (6). In the first counterfactual scenario, we assume that affiliation has no effect, or that there is no difference in affiliation across proposals in a given meeting. In the second counterfactual scenario, we consider an alternative RUC membership, and use $\hat{\alpha}$ to impute counterfactual RVUs, as described above. To evaluate the external validity of using $\hat{\alpha}$ in this analysis, we compare the distribution of counterfactual affiliations under this alternative RUC with the observed distribution of actual affiliations.

In Appendix Figure A.11, we plot the distribution of counterfactual affiliations against that of actual affiliations and find very little difference between the two distributions. The Q-Q plot of quantiles of the two distribution essentially lie on the 45-degree line. In the same figure, we also consider the distribution of differences between counterfactual and actual affiliation. This distribution is quite narrow, especially compared to the distribution of the difference between actual and predicted affiliation. Thus, the differences in affiliation induced by a counterfactual RUC appear quite small relative to the quasi-experimental variation in affiliation we observe in the data.

VI Alternative Mechanisms Behind the Price Effect

In this appendix, we consider evidence regarding alternative mechanisms of the affiliation effect on prices, as discussed in Section 4.3. The results are summarized in Appendix Table A.4. All specifications in Appendix Table A.4 include the same controls as in the baseline specification of the price regression,

shown in column (4) of Table III.

First, we consider specifications relating to interests (and information) held by RUC specialties that are specific to the proposed service. Specifically, we consider the service i 's utilization share of all services billed by a RUC specialty s , or σ_{is}^q , as defined in Equation (2). We also consider i 's revenue share of all Medicare revenue to s , or $\sigma_{is}^R \equiv (p_i q_{is})/R_s$, as discussed in Appendix II. These measures capture both specialty s 's interests and information about i : A specialty s with a higher σ_{is}^q or σ_{is}^R should have interests specific to service i to raise its price, and it may also have more knowledge about service i , outside of the proposal process. We perform variants of the regression

$$\ln \text{RVU}_{it} = \alpha A(\mathcal{R}_t, \mathcal{S}_i) + \gamma m(\sigma_i; \mathcal{R}_t) + \mathbf{X}_i \beta + \mathbf{T}_t \eta + \mathbf{w}_i \zeta + \varepsilon_{it}, \quad (\text{A.6.1})$$

where $m(\sigma_i; \mathcal{R}_t)$ is the mean interest σ_{is} across specialties serving on the RUC, $s \in \mathcal{R}_t$, standardized to have mean 0 and standard deviation 1 across i .¹⁰

Columns (1) and (2) of Appendix Table A.4 show results for regressions adding standardized mean σ_{is}^q and σ_{is}^R , respectively. The coefficient on standardized set affiliation remains unchanged in magnitude and significance. The coefficients on the standardized measures of RUC-specialty interest in proposal i are small, though statistically significant. Although we ascribe a causal interpretation to α under Assumption 1 in Section 3.4, the same reasoning does not apply to γ .¹¹ With this caveat, it does not appear that RUC specialty direct interests play a major role in explaining the RUC's price recommendations. In columns (3) and (4), we consider related interests, or elements $\tilde{\sigma}_{is}^q$ and $\tilde{\sigma}_{is}^R$ in vectors $\tilde{\sigma}_s^q = \Omega^q \sigma_s^q$ and $\tilde{\sigma}_s^R = \Omega^R \sigma_s^R$, respectively, where Ω^q and Ω^R are spillover matrices defined in Appendix II. Interestingly, we find that related interests play a larger role in pricing than direct interests.

Next, we consider the possibility that affiliation could reflect signaling “buy-in.” That is, more specialties should be willing to propose for procedures that have a higher intrinsic price. As more specialties propose, set affiliation, as defined in Equation (4), will mechanically increase through max operator in the formula. Higher prices under this scenario are warranted and do not reflect any RUC bias. We modify the baseline price-effect regression in Equation (6) to include proposer-count fixed effects:

$$\ln \text{RVU}_{it} = \alpha A(\mathcal{R}_t, \mathcal{S}_i) + \gamma_n \mathbf{1}(\|\mathcal{S}_i\| = n) + \mathbf{X}_i \beta + \mathbf{T}_t \eta + \mathbf{w}_i \zeta + \varepsilon_{it}. \quad (\text{A.6.2})$$

This specification relies only on within-proposer-count variation to identify the price effect of affiliation. As shown in column (5) of Appendix Table A.4, the coefficient on standardized set affiliation is unchanged, at 0.112, and highly significant.

¹⁰We also perform a regression similar to Equation A.6.1, excluding the term $A(\mathcal{R}_t, \mathcal{S}_i)$, which also yields similar estimates of γ (omitted for brevity). This indicates that $m(\sigma_i; \mathcal{R}_t)$ is for the most part conditionally uncorrelated with $A(\mathcal{R}_t, \mathcal{S}_i)$.

¹¹For nonparametric identification of γ , we would require random variation in RUC specialty composition, \mathcal{R}_t . In order to interpret γ as causal, we would require parametric restrictions on the conditional independence between $\ln \text{RVU}_{it}$ and $m(\sigma_i; \mathcal{R}_t)$ —such as the sufficiency of conditioning on the linear combination $\mathbf{w}_i \zeta$ and $\ln \sum_s q_{is}$. While the causal interpretation of γ is not important for this paper, we conduct balance tests similar to the test that generates Appendix Figure A.3, which generally reject the null of quasi-random assignment, even when we control for $\ln \sum_s q_{is}$.

VII Heterogeneous Effect of Affiliation by Proposal Type

We investigate heterogeneity of the affiliation effect on prices, along four binary dimensions of proposal type: (i) whether the proposal is for a CPT code that existed or was new at the time of the proposal, (ii) whether the proposal is for a CPT code with below- or above-median yearly volume (for the years that it was in existence), (iii) whether the proposal is for a CPT code with below- or above-median price, and (iv) whether the proposal occurred at an earlier or later RUC meeting.¹² For each of these dimensions, we perform the following regression:

$$\ln \text{RVU}_{it} = \sum_{c \in \{0,1\}} (\alpha_{0,c} + \alpha_{1,c} A(\mathcal{R}_t, \mathcal{S}_i)) \cdot \mathbf{1}(c(i,t) = c) + \mathbf{X}_i \beta + \mathbf{T}_t \eta + \mathbf{w}_i \zeta + \varepsilon_{it}, \quad (\text{A.7.1})$$

where $c(i,t) \in \{0,1\}$ depending on CPT code i and meeting t in question.

Appendix Table A.5 shows cross-tabulations of proposals along these types. Approximately 55% of the proposals were for existing CPT codes, while the remaining 45% were for new CPT codes. Existing CPT codes were slightly more likely to have above-median utilization volumes, and much more likely to have above-median prices. High-priced CPT codes were slightly more likely to have higher volumes.

Appendix Table A.6 shows results of the regression in Equation (A.7.1), along each of the four dimensions. Strikingly, nearly all of the effect of affiliation on prices is borne by proposals for new CPT codes. The coefficient on (interacted) set affiliation is twice as high for new CPT codes, at 0.209, while it is small and statistically insignificant for existing CPT codes. The effect of affiliation is also much higher for low-quantity vs. high-quantity CPT codes, and it is much higher for low-priced vs. high-priced CPT codes. Finally, the effect of affiliation is roughly the same in earlier meetings as it is in later meetings. Because proposal types are correlated across dimensions, these heterogeneous treatment effects are only descriptive. However, they are consistent with a story in which affiliation has a greater relative effect for proposals in which there is less evidence (i.e., less hard information) or less at stake for setting a service’s price.

VIII Technical Details of the Conceptual Framework

This appendix provides additional detail behind the conceptual framework we outline in Section 5. We start with more detail about the formula for expected “variance”, $E[(\theta + b_R - p)^2]$, that represents information loss in the standard Crawford and Sobel (1982) model. Next, we provide details of the analysis with hard information and the optimal b_R^* under hard information. Finally, we describe a mechanism of

¹²Although price is endogenous, when considered as an indicator variable for whether the CPT code’s price is below- or above-median, we roughly capture intrinsic characteristics of the procedure. For example, the highest-priced CPT code (CPT code 33935, or heart and lung transplantation) has an RVU of 100, 670 CPT codes have RVUs below 1. The mean RVU was 10.85, and the median RVU was 5.53, shared by CPT 22585 (Anterior or Anterolateral Approach Technique Arthrodesis Procedures on the Spine) and CPT code 33213 (Pacemaker or Pacing Cardioverter-Defibrillator Procedures). We define an “earlier” meeting as occurring before the third meeting of 2005, whereas a “later” meeting occurred at or after the third meeting of 2005.

assigning intervals of *expected* length L such that the posterior distribution of θ remains uniform within each realized interval.

Canonical Crawford and Sobel (1982) Partitions

Consider θ uniformly distributed on the interval $[0, L]$. The sender (the specialty) has bias b , relative to the receiver (the RUC). The formula for the number of partitions supported under $b = b_S - b_R$ over the interval is

$$n^*(b) = \left\lceil \frac{1}{2} \left(1 + \sqrt{1 + \frac{2L}{b}} \right) \right\rceil. \quad (\text{A.8.1})$$

Using Equation (A.8.1), we define the limiting bias such that $n^*(b - \varepsilon) = n$ for any positive but arbitrarily small ε :

$$b^*(n) = \frac{2L}{(2n-1)^2 - 1}.$$

$b^*(n)$ supports n partitions only in the limit. For example, as we show below, $b = \frac{1}{4}$ supports only one partition, since the first partition of technically two partitions will have a length of 0.

The first partition is bounded by $x_0 = 0$ and

$$x_1 = \frac{L}{n} - (n-1)2b, \quad (\text{A.8.2})$$

Subsequent partition lengths increase by $4b$, which implies

$$x_k = 2x_{k-1} - x_{k-2} + 4b, \quad (\text{A.8.3})$$

and Equations (A.8.2) and (A.8.3) imply that $x_n = L$.

We will consider a number of specific examples of n , which exist for $b \in [b^*(n+1), b^*(n)]$. We define the boundaries of the partitions in the space of $[0, L]$, and the variance $E[(\theta + b_R - p)^2]$. For the latter object, we use the fact that the variance of a uniformly distributed random variable along an interval of length L is $L^2/12$. Two partitions exist if $b \in [\frac{L}{12}, \frac{L}{4})$ and are defined by $(0, \frac{L}{2} - 2b, L)$. The variance is given by

$$\begin{aligned} E[(\theta + b_R - p)^2] &= \frac{L^2}{12} \left[\left(\frac{1}{2} - 2b \right)^3 + \left(\frac{1}{2} + 2b \right)^3 \right] \\ &= \frac{1}{12} \left(\frac{L^2}{4} + 12b^2 \right) = \frac{L^2}{48} + b^2. \end{aligned}$$

Three partitions exist if $b \in \left[\frac{L}{24}, \frac{L}{12}\right)$ and are defined by $\left(0, \frac{L}{3} - 4b, \frac{2L}{3} - 4b, L\right)$. The variance is given by

$$\begin{aligned} E[(\theta + b_R - p)^2] &= \frac{L^2}{12} \left[\left(\frac{1}{3} - \frac{4b}{L}\right)^3 + \left(\frac{1}{3}\right)^3 + \left(\frac{1}{3} + \frac{4b}{L}\right)^3 \right] \\ &= \frac{1}{12} \left(\frac{L^2}{9} + 32b^2 \right). \end{aligned}$$

By induction, one can verify that the variance in the equilibrium with n partitions is

$$E[(\theta + b_R - p)^2] = \frac{1}{12} \left(\frac{L^2}{n^2} + A_n b^2 \right), \quad (\text{A.8.4})$$

where $A_1 = 0$, and $A_n = A_{n-1} + 8n - 4$. Note that the variance is continuous across the number of partitions (as b changes). Also, the variance is decreasing in b , holding L fixed.

Hard Information

Given the formula for soft information loss in Equation (A.8.4), we can write the expected utility for the specialty and the government, respectively, as

$$\begin{aligned} E[u_S] &= -E[(\theta + \theta_R - p)^2] - b^2 - c(L) \\ &= -\frac{1}{12} \left(\frac{L^2}{n^2} + A_n b^2 \right) - b^2 - c(L), \end{aligned} \quad (\text{A.8.5})$$

and as

$$\begin{aligned} E[u_G] &= -E[(\theta + \theta_R - p)^2] - b_R^2 \\ &= -\frac{1}{12} \left(\frac{L^2}{n^2} + A_n b^2 \right) - b_R^2. \end{aligned} \quad (\text{A.8.6})$$

In both Equations (A.8.5) and (A.8.6), n is the number of partitions supported by b and L and is given by Equation (A.8.1). Better information, either hard or soft, increases the utility of both the specialty and the government.

Taking the partial derivative of expected specialty utility with respect to L , while holding b and n fixed, yields the following condition for the agent's choice of L :

$$\frac{\partial}{\partial L} E[u_S] = -\frac{L}{6n^2} - c'(L) = 0. \quad (\text{A.8.7})$$

The convexity of $c(L)$ implies that there exists a single optimal candidate that satisfies Equation (A.8.7) for the cheap talk equilibrium with n partitions. Denote the solution to Equation (A.8.7) for a given n , if it exists (i.e., $n^*(b, L_n^*) = n$), as L_n^* .¹³ Intuitively, L_n^* is increasing in n : better soft communication

¹³In Equation (A.8.7), L_n^* is increasing in n , and in Equation (A.8.1), $n^*(b, L)$ is increasing in L . Since (i) $L_n^* \in (0, 1]$ and (ii)

(higher n) reduces the incentive to produce hard information (larger L_n^*). The globally optimal L^* is then given by $L^* = \arg \max_n (E [u_S; L_n^*])$. L^* is decreasing in b : As the specialty and the RUC have divergent preferences, soft communication worsens, and this increases the optimal hard information. Because the set of L_n^* comprises discrete values, $L^*(b)$ is a step function.

Optimal RUC Bias

Because smaller L^* increases government utility in Equation (A.8.6), and because L^* is a decreasing function of $b = b_R - b_S$, the optimal b_R^* from the government's perspective is weakly lower under the possibility of hard information than when we fix $L = 1$.

However, the optimal $b_R^* \geq 0$. That is, an *adversarial* RUC is still never optimal from the government's perspective. In order for $b_R^* < 0$, we need three requirements:

1. The threshold \bar{b}_R where the specialty is indifferent between $n = 1$ and $n = 2$ must be less than 0.
2. The expected government utility when $b_R = \bar{b}_R$ is higher than the maximum expected government utility under $n = 2$:

$$\max E [u_G | n = 2] < E [u_G | b_R = \bar{b}_R].$$

3. The expected government utility when $b_R = \bar{b}_R$ is higher than complete delegation when $b_R = b_S$.

Note also that convexity of $c(L)$ implies that $c'(L_1^*) < c'(L_2^*)$. From the first order conditions that $c'(L_1^*) = -\frac{1}{6}L_1^*$ and $c'(L_2^*) = -\frac{1}{24}L_2^*$, we must have $L_1^* > \frac{1}{4}L_2^*$. Convexity also implies that

$$\frac{c(L_1^*) - c(L_2^*)}{L_2^* - L_1^*} \in \left[\frac{1}{24}L_2^*, \frac{1}{6}L_1^* \right].$$

The threshold \bar{b}_R is defined by the following condition:

$$E [u_G | b_R = \bar{b}_R, n = 1] = E [u_G | b_R = \bar{b}_R, n = 2].$$

In other words

$$\frac{1}{12} (L_1^*)^2 + (\bar{b}_R - b_S)^2 + c(L_1^*) = \frac{1}{48} (L_2^*)^2 + 2(\bar{b}_R - b_S)^2 + c(L_2^*).$$

The threshold is then

$$b_S = \bar{b}_R + \sqrt{\frac{1}{12} (L_1^*)^2 - \frac{1}{48} (L_2^*)^2 + c(L_1^*) - c(L_2^*)}. \quad (\text{A.8.8})$$

Condition 1 and convexity imply that

$$b_S < \sqrt{\frac{1}{12} (L_1^*)^2 - \frac{1}{48} (L_2^*)^2 + \frac{1}{6} L_1^* (L_2^* - L_1^*)}. \quad (\text{A.8.9})$$

$n^*(b, L)$ is bounded by $n^*(b, 1)$, there must be at least one $n \in \{1, \dots, n^*(b, 1)\}$ such that $n^*(b, L_n^*) = n$.

Condition 2 requires that

$$-\frac{1}{12} (L_1^*)^2 - \bar{b}_R^2 > -\frac{1}{48} (L_2^*)^2 - \frac{1}{2} b_S^2, \quad (\text{A.8.10})$$

where the expression on the left is the expected government utility at \bar{b}_R and $n = 1$, and the expression on the right is the expected government utility under the optimal $b_R = \frac{1}{2} b_S$ conditional on $n = 2$. Condition 3 requires that

$$-\frac{1}{12} (L_1^*)^2 - \bar{b}_R^2 > -b_S^2. \quad (\text{A.8.11})$$

The expression on the right is the government utility under full delegation.

We show numerically that there are no values $(L_1^*, L_2^*, b_S, \bar{b}_R)$ that satisfy Equations (A.8.8) to (A.8.11) simultaneously.

Uniform Posterior Intervals

While it is convenient to work with continuous L , there is a technical complication in specifying values of $\underline{\theta}$ and $\bar{\theta}$, such that it remains that $\theta \sim U(\underline{\theta}, \bar{\theta})$ with fixed $L = \bar{\theta} - \underline{\theta}$. For example, consider the case of $L = 0.9$. If $\theta = 0$, then we must have $\underline{\theta} = 0$ with probability 1, but $\bar{\theta} = 0$ with probability less than 1 if $\theta > 0$. Therefore, if any potential interval must have $L = 0.9$, and we have a realized interval $[\underline{\theta}, \bar{\theta}] = [0, 0.9]$, then θ cannot be uniformly distributed within the realized interval.

To preserve uniform posterior distributions within the intervals revealed after hard information, we need sets of potential intervals to be mutually exclusive and collectively exhaustive. Thus, we may have one potential interval of length $L_a = 0.9$ and another potential interval of length $L_b = 0.1$. The ordering of these intervals may be random, but so long as the intervals are not overlapping in a particular ordering, then the posterior distribution of θ within each interval will remain uniform. We operationalize this with the concept that L instead represents the *expected* length of the information interval after hard information, under a mechanism that divides the unit interval into N intervals of length L_a and a remaining weakly shorter interval of length $L_b = 1 - NL_a \leq L_a$.

The probability that θ falls in an interval of length L_a is NL_a , while the probability that θ falls in the remaining interval of length L_b . Thus $L = NL_a^2 + L_b^2 = NL_a^2 + (1 - NL_a)^2$. We can solve for $L_a(L)$, as a function of L , by using the quadratic formula and the fact that $N = \lfloor L^{-1} \rfloor$:

$$L_a(L) = \frac{1 + \sqrt{1 - (1 - L) (\lfloor L^{-1} \rfloor^{-1} + 1)}}{1 + \lfloor L^{-1} \rfloor},$$

which is continuous and monotonically increasing in L .

We modify our equilibrium analysis by stating expected utility $E[u_A]$ (prior to hard information) as

a function of L :

$$\begin{aligned} E[u_A] &= -E[(\theta - p)^2] - b^2 - c(L) \\ &= -\frac{1}{12} \left[\frac{NL_a^3}{n_a^2} + \frac{(1 - NL_a)^3}{n_b^2} + \bar{A}b^2 \right] - b^2 - c(L), \end{aligned} \quad (\text{A.8.12})$$

where $n_a = n^*(b, L_a)$, $n_b = n^*(b, 1 - NL_a) \leq n_a$, and $\bar{A} = NL_a A_{n_a} + (1 - NL_a) A_{n_b}$. The expression for the variance $E[(\theta - p)^2]$ is continuous, monotonically increasing in L (and $L_a(L)$), and piecewise convex in $L_a(L)$. The remainder of the analysis proceeds by identifying solutions $L_{\mathbf{n}}^*$, where $\mathbf{n} = (n_a, n_b)$, and choosing $L^* = \arg \max_{\mathbf{n}} (E[u_S; L_{\mathbf{n}}^*])$.

IX Private Price Transmission Robustness

In Section 5.3, we show that private insurance price changes are more responsive to Medicare price changes when the Medicare price changes originate from RUC decisions and, within RUC decisions, when they originate from a higher-affiliation proposal. We interpret this finding as supporting the hypothesis that RUC decisions, particular those from higher-affiliation proposals, contain valuable information that private insurance follows. In this appendix, we investigate alternative mechanisms that may generate this result.

First, affiliated proposals may result in more informative Medicare prices not because they facilitate communication, as detailed in Section 5, but because RUC members may naturally have more information about the procedures that their specialty societies perform. We investigate this possibility by using proxy measures of the RUC members' own information, based on their utilization of the service in question. In particular, we consider a specialty s 's share of total utilization for service i , w_{is} , as defined in Equation (5), and the service i 's share of the total utilization for specialty s , as defined in (2), averaging across the specialties of RUC members at the relevant meeting:

$$\bar{w}_{iy} = \frac{1}{\|\mathcal{R}_{t(i,y)}\|} \sum_{s \in \mathcal{R}_{t(i,y)}} w_{is}; \quad (\text{A.9.1})$$

$$\bar{\sigma}_{iy} = \frac{1}{\|\mathcal{R}_{t(i,y)}\|} \sum_{s \in \mathcal{R}_{t(i,y)}} \sigma_{is}, \quad (\text{A.9.2})$$

where $\mathcal{R}_{t(i,y)}$ is the set of RUC member specialties at the meeting $t(i, y)$ corresponding to service i and (private) price change year y .

Second, affiliated proposals may disproportionately represent high-volume services for which both private insurers and Medicare have interests in setting accurate prices. Strong correlation between private insurance and Medicare price changes for high-affiliation proposals may then result from careful price-setting in both private insurance and Medicare, and not because affiliation *per se* causes better communication between proposing specialties and the RUC. We consider two measures of volume for

service i : private insurance volume and total (private insurance and Medicare) volume.

Third, we take an omnibus approach, agnostic to the exact forces that may drive greater price following from Medicare to private insurance, by fitting a predictive model of price following. We consider changes in private insurance prices as a function of changes in Medicare prices:

$$\Delta \ln \text{Price}_{i,y}^P = \alpha + \beta_{iy} \Delta \ln \text{Price}_{i,y^M(i,y)}^M + \varepsilon_{iy},$$

where the goal is to predict β_{iy} .¹⁴ To operationalize this approach, as an approximation of β_{iy} , we take the ratio of demeaned $\Delta \ln \text{Price}_{i,y}^P$ and demeaned $\Delta \ln \text{Price}_{i,y^M(i,y)}^M$,

$$\text{Ratio}_{iy} = \frac{\Delta \ln \text{Price}_{i,y}^P - \overline{\Delta \ln \text{Price}^P}}{\Delta \ln \text{Price}_{i,y^M(i,y)}^M - \overline{\Delta \ln \text{Price}^M}},$$

where $\overline{\Delta \ln \text{Price}^P}$ and $\overline{\Delta \ln \text{Price}^M}$ are respective sample means of log private and Medicare price changes, weighted by Medicare volume. We then predict this ratio as a linear function of private insurance volume for i ; total (private insurance and Medicare) volume for i ; time dummies \mathbf{T}_{iy} for $y^M(i,y)$, y , and RUC meeting; and the vector of specialty shares \mathbf{w}_i . We take the predicted ratio, $\widehat{\text{Ratio}}_{iy}$, as an index for predicted price-following based on characteristics of (i,y) .

Given each of these measures that may influence price transmission to private insurance, we assess the robustness of our results to controlling for these measures, both directly and interacted with Medicare prices. Specifically, for each Index_{it} measure (i.e., \overline{w}_{iy} , $\overline{\sigma}_{iy}$, private volume of i , total volume of i , and $\widehat{\text{Ratio}}_{iy}$), we assess price transmission controlling for these proxy measures directly and interacted with Medicare prices, σ_{is} , in regressions similar to Equation (8):

$$\begin{aligned} \ln \text{Price}_{iy}^P &= \sum_c \left(\alpha_c + \beta_c \ln \text{Price}_{i,y^M(i,y)}^M \right) \cdot \mathbf{1}(c(i,y) = c) + \\ &\quad \sum_{\tau=1}^3 \left(\gamma_\tau + \delta_\tau \ln \text{Price}_{i,y^M(i,y)}^M \right) \cdot \mathbf{1} \left(F(\text{Index}_{iy}) \in \left(\frac{\tau-1}{3}, \frac{\tau}{3} \right) \right) + \\ &\quad \mathbf{T}_{iy} \eta + \xi_i + \varepsilon_{iy}, \end{aligned} \tag{A.9.3}$$

where $\tau \in \{1, 2, 3\}$ indicates the tercile, $F(\cdot)$ is the distribution function of the relevant measure Index_{it} , and the rest is the same as in Equation (8). Appendix Table A.9 shows results from these regressions. The key coefficients of interest, β_C , are highly stable regardless of Index_{iy} . Price transmission remains greater for Medicare price changes originating from RUC decisions and, within these decisions, from high-affiliation proposals.

¹⁴This changes-on-changes specification closely matches the fixed-effects specification in Equation (8). As shown in Appendix Figure A.14, separating Medicare price changes into high- and low-affiliation groups gives similar results.

Table A.1: Sample Selection

Sample step	Description	Observations	
		Dropped	Remaining
1. Raw RUC data	Universe of all administrative data used by RUC		17,498
2. Drop observations with no survey information and no RUC recommendation	These observations do not represent RUC decisions, as all decisions require these elements	11,079	6,419
3. Drop observations that appear to be duplicates	Identify observations with the same CPT code, RUC meeting, and survey specialty; if there are differences in other variables between these observations, choose the observation with the most complete data and larger survey sample sizes	132	6,353
4. Combine observations with same CPT code and RUC meeting but different survey specialties	These observations were incorrectly entered as separate lines; use total survey sample and respondent numbers	127	6,226
5. Drop observations with invalid RUC meeting date	83% of these observations have a meeting date of “Editorial,” indicating that the RUC decided that a full decision was not necessary, and no specialty proposals were elicited; 10% of these observations are “HCPAC,” which are not for physician procedures	490	5,736
6. Drop observations with missing survey specialty or specialties	These observations are likely administrative discussions without a full proposal from a specialty or specialties	1,313	4,423
7. Drop observations involving proposing specialties with missing affiliation measures	These involve rare specialty societies that cannot be identified in the Medicare or MarketScan claims	16	4,407

Notes: This table describes key sample selection steps, the observations dropped, and the observations remaining after each step. The sample selection steps were taken after detailed discussions with the RUC to understand their data and aim to retain observations that represent full RUC decisions with a specialty proposal.

Table A.2: Example CPT Descriptions

CPT code	Short description	Long description
99214	Office / outpatient visit, established	Office or other outpatient visit for the evaluation and management of an established patient, which requires at least 2 of these 3 key components: A detailed history; A detailed examination; Medical decision making of moderate complexity. Counseling and/or coordination of care with other physicians, other qualified health care professionals, or agencies are provided consistent with the nature of the problem(s) and the patient's and/or family's needs. Usually, the presenting problem(s) are of moderate to high severity. Typically, 25 minutes are spent face-to-face with the patient and/or family.
71010	Chest x-ray 1 view frontal	Radiologic examination, chest; single view, frontal
17003	Destruct premalignant lesion 2-14	Destruction (e.g., laser surgery, electrocautery, cryosurgery, chemosurgery, surgical curettement), premalignant lesions (e.g., actinic keratoses); second through 14 lesions, each (List separately in addition to code for first lesion)
95165	Antigen therapy services	Professional services for the supervision of preparation and provision of antigens for allergen immunotherapy; single or multiple antigens (specify number of doses)
44391	Colonoscopy for bleeding	Colonoscopy through stoma; with control of bleeding (e.g., injection, bipolar cautery, unipolar cautery, laser, heater probe, stapler, plasma coagulator)
96413	Chemo iv infusion 1 hr	Chemotherapy administration, intravenous infusion technique; up to 1 hour, single or initial substance/drug
20610	Drain/inject joint/bursa	Arthrocentesis, aspiration and/or injection; major joint or bursa (e.g., shoulder, hip, knee joint, subacromial bursa)
62311	Inject spine lumbar/sacral	Injection(s), of diagnostic or therapeutic substance(s) (including anesthetic, antispasmodic, opioid, steroid, other solution), not including neurolytic substances, including needle or catheter placement, includes contrast for localization when performed, epidural or subarachnoid; lumbar or sacral (caudal)

Notes: This table shows short and long descriptions of example CPT codes, determined by the AMA CPT Committee prior to a proposal to the RUC. Stem words in the long description are used for predicting RVUs after LASSO selection.

Table A.3: Price Effect of Alternative Affiliation Measures

	(1)	(2)	(3)	(4)	(5)
	<i>Affiliation metric</i>				
<i>Data</i>	Euclidean	Gini-Euclidean	Manhattan	σ -Cosine	w -Cosine
Panel A: Mean affiliation					
Medicare CPT quantity	0.101*** (0.029)	0.103*** (0.030)	0.055** (0.021)	0.061** (0.025)	0.033** (0.015)
Medicare + MarketScan CPT quantity	0.076*** (0.025)	0.079*** (0.026)	0.048** (0.020)	0.057** (0.025)	0.028* (0.015)
Medicare CPT revenue	0.094*** (0.029)	0.094*** (0.029)	0.038* (0.019)	0.037* (0.021)	0.033** (0.015)
Medicare BETOS quantity	0.088*** (0.029)	0.088*** (0.030)	0.056** (0.022)	0.052** (0.025)	0.036** (0.016)
Medicare BETOS revenue	0.072*** (0.027)	0.069** (0.028)	0.045** (0.021)	0.032 (0.020)	0.036** (0.015)
Panel B: 33rd percentile affiliation					
Medicare CPT quantity	0.104*** (0.032)	0.111*** (0.031)	0.061** (0.024)	0.060** (0.026)	0.026* (0.014)
Medicare + MarketScan CPT quantity	0.076*** (0.024)	0.082*** (0.026)	0.062** (0.023)	0.051** (0.024)	0.027* (0.013)
Medicare CPT revenue	0.089*** (0.031)	0.092*** (0.033)	0.039* (0.021)	0.027 (0.022)	0.027* (0.014)
Medicare BETOS quantity	0.086** (0.033)	0.093*** (0.034)	0.066*** (0.025)	0.054** (0.026)	0.038** (0.018)
Medicare BETOS revenue	0.088*** (0.029)	0.085*** (0.029)	0.053** (0.022)	0.043** (0.018)	0.034** (0.016)

Notes: This table shows results of regressions of log RVU on various measures of set affiliation. Each cell represents the coefficient on the affiliation measure in a separate regression, stated as α in Equation (6) and corresponding to the preferred specification of column (4) in Table III. Further details about the regression controls are given in the note for Table III. Rows of the table correspond to underlying data from which affiliation is calculated. Columns correspond to affiliation metrics between two specialties, discussed in Appendix II. Appendix II discusses the baseline metric of Euclidean distance, shown in column (1), in detail, including differences in interpreting using quantity vs. revenue shares. The remaining affiliation metrics are described in Appendix II. Panel A calculates the set affiliation measure as the mean maximized specialty-pair affiliation, which is the default and is given in Equation (4). Panel B calculates the set affiliation measure as the 33rd percentile of the maximized specialty-pair affiliations. Standard errors, clustered by RUC meeting, are in parentheses; *** denotes significance at the 1% level.

Table A.4: Alternative Mechanisms Behind Price Effect

	(1)	(2)	(3)	(4)	(5)
	Log RVU				
Standardized set affiliation	0.098*** (0.029)	0.103*** (0.030)	0.104*** (0.029)	0.098*** (0.029)	0.112*** (0.043)
Standardized measures of RUC-specialty interest					
Mean σ_{is}^q	0.021** (0.009)				
Mean σ_{is}^R		0.031*** (0.007)			
Mean $\tilde{\sigma}_{is}^q$			0.052** (0.012)		
Mean $\tilde{\sigma}_{is}^R$				0.048*** (0.013)	
Baseline controls	Y	Y	Y	Y	Y
Proposer count dummies	N	N	N	N	Y
N	4,401	4,401	4,401	4,401	4,401
Adjusted R -squared	0.891	0.895	0.892	0.892	0.891
Sample mean log RVU	1.567	1.567	1.567	1.567	1.567

Notes: This table shows results of regressions of log RVU on standardized set affiliation, with the addition of controls to test robustness to alternative mechanisms. Columns (1) to (4) relate to alternative mechanisms of service-specific interests or *ex ante* information held by RUC specialties. These specifications, given in Equation (A.6.1), control for mean direct interests (σ_{is}^q and σ_{is}^R in columns (1) and (2), respectively) or related interests ($\tilde{\sigma}_{is}^q$ and $\tilde{\sigma}_{is}^R$ in columns (3) and (4), respectively) across RUC specialties. Measures are standardized to have mean 0 and standard deviation 1. Column (5) tests robustness to the alternative mechanism of signaling “buy-in,” controlling for proposer dummies, as in Equation (A.6.2). Details are given in Appendix VI. All specifications include controls in the baseline price-effect regression, in column (4) of Table III. Standard errors, clustered by RUC meeting, are in parentheses; ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table A.5: Tabulation of Proposal Types

Prior existence	Quantity		Total
	Low	High	
Existing	967	1,394	2,361
New	1,167	740	1,907
Total	2,134	2,134	4,268

Prior existence	Price		Total
	Low	High	
Existing	180	2,201	2,381
New	2,026	0	2,026
Total	2,206	2,201	4,407

Quantity	Price		Total
	Low	High	
Low	1,179	955	2,134
High	908	1,226	2,134
Total	2,087	2,181	4,268

Notes: This table shows counts of proposals along three binary dimensions: (i) CPT code is existing or new at the time of the proposal, (ii) CPT code has an RVU that is below- or above-median, and (iii) CPT code has yearly frequencies in the Medicare data that is below- or above-median, for years that the CPT code was in existence.

Table A.6: Heterogeneous Effect of Affiliation by Proposal Type

	(1)	(2)	(3)	(4)
	Log RVU			
Standardized set affiliation				
× existing CPT	-0.035 (0.031)			
× new CPT	0.209*** (0.030)			
× low-quantity CPT		0.169*** (0.033)		
× high-quantity CPT		0.034 (0.034)		
× low-priced CPT			0.160*** (0.027)	
× high-priced CPT			-0.034 (0.028)	
× early meeting				0.097* (0.049)
× late meeting				0.104*** (0.036)
Baseline controls	Y	Y	Y	Y
<i>N</i>	4,401	4,262	4,401	4,401
Adjusted <i>R</i> -squared	0.896	0.895	0.894	0.891
Sample mean outcome	1.567	1.595	1.567	1.567

Notes: This table shows results of regressions of log RVU on standardized set affiliation interacted with indicators of a proposal type, as stated in Equation (A.7.1). Four types of binary proposal heterogeneity are considered: (i) whether the proposal is for an existing CPT code, in column (1), (ii) whether the proposal is for a CPT code with below- or above-median quantity per year (in years the CPT was in existence), in column (2), (iii) whether the proposal is for a CPT code with below- or above-median price, in column (3), and (iv) whether the proposal occurred in an earlier (before the third meeting in 2005) or later (at or after the third meeting in 2005) RUC meeting, column (4). Tabulations of proposals across the first three characteristics are given in Appendix Table A.5. Baseline controls are the same as in column (5) of Table III. Standard errors, clustered by RUC meeting, are in parentheses; ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table A.7: Specialty Seats on Counterfactual RUC

Specialty	Seats	Specialty	Seats
Anesthesiology	2	Obstetrics and Gynecology	2
Cardiology	1	Oncology	1
Emergency Medicine	2	Ophthalmology	1
Family Medicine	4	Orthopedic Surgery	1
Gastroenterology	1	Pediatrics	2
General Surgery	1	Psychiatry	1
Internal Medicine	4	Radiology	1
Neurology	1		

Notes: This table shows members of a counterfactual RUC, in which seats are assigned in proportion to the population of physicians in each specialty. The number of total seats is 25, as it is in the current RUC. This RUC accommodates the 16 largest specialties; including specialties with fewer physicians would require a larger RUC. Many smaller specialties lack a seat in this RUC; compare this to the broader range of specialties that have some representation on the actual RUC over time in Table I. Physician population numbers are from Table 1.1 of Association of American Medical Colleges (2016), accessible at <https://www.aamc.org/data/workforce/reports/458480/1-1-chart.html>.

Table A.8: Affiliation Effect on Hard Information

	(1)	(2)	(3)
Panel A: Log survey sample			
Standardized set affiliation	-0.228*** (0.071)	-0.332*** (0.076)	-0.146** (0.070)
Baseline controls	Y	Y	Y
Utilization among proposers	N	Y	Y
Proposer count dummies	N	N	Y
<i>N</i>	4,407	4,219	4,219
Adjusted <i>R</i> -squared	0.329	0.332	0.348
Sample mean outcome	4.660	4.619	4.619
Panel B: Log survey respondents			
Standardized set affiliation	-0.219*** (0.076)	-0.413*** (0.049)	-0.082 (0.055)
Baseline controls	Y	Y	Y
Utilization among proposers	N	Y	Y
Proposer count dummies	N	N	Y
<i>N</i>	4,407	4,219	4,219
Adjusted <i>R</i> -squared	0.220	0.253	0.304
Sample mean outcome	3.067	3.071	3.071

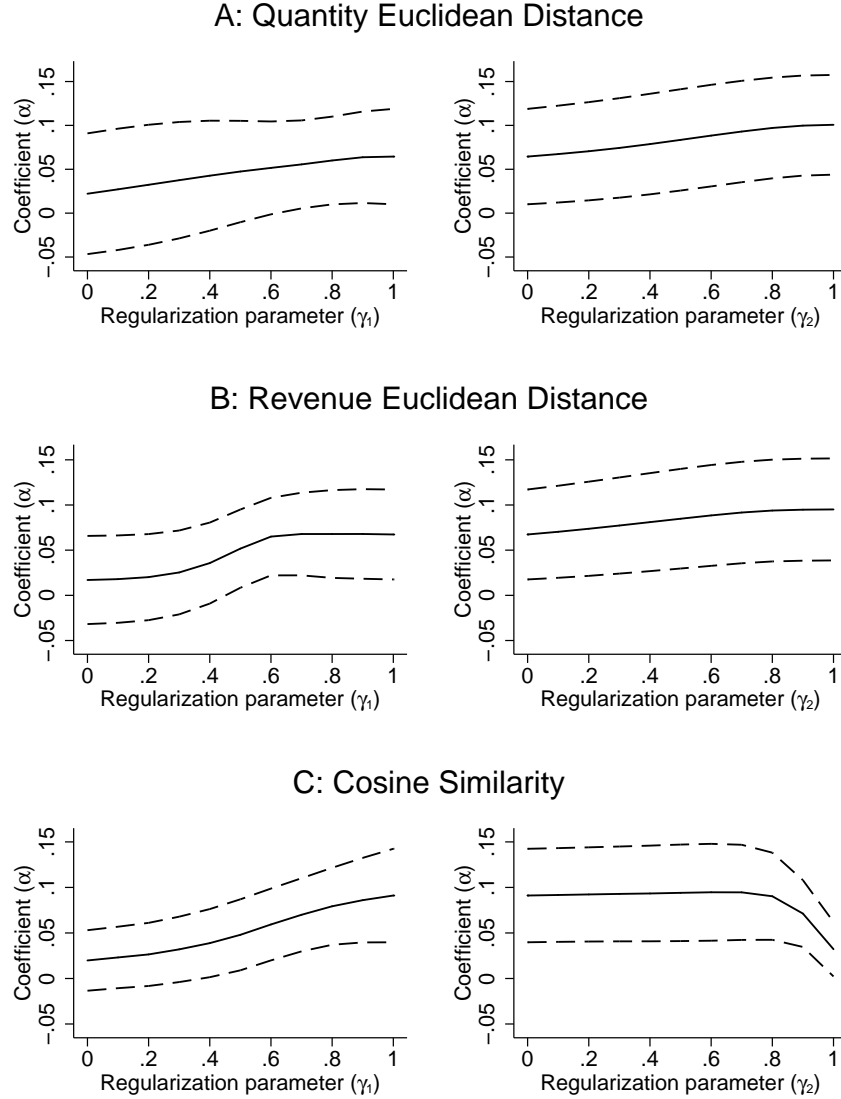
Notes: This table shows results of regressions of survey measures of hard information on standardized set affiliation, based on Equation (7). Survey sample regressions are shown in Panel A, and survey respondent regressions are shown in Panel B. The outcomes are per-specialty measures, constructed by dividing the total survey measures by the number of proposing specialties. Baseline controls are the same as in column (5) of Table III. Columns (2) and (3) control for the log annual utilization of the service among all specialties and the log annual utilization of the service among proposing specialties, dropping observations for which these values are missing. Column (3) also includes dummies for the proposing specialty count. Standard errors, clustered by RUC meeting, are in parentheses; ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table A.9: Price Transmission Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	Log private price					
Log Medicare price						
× not RUC	0.331*** (0.022)	0.291*** (0.022)	0.328*** (0.022)	0.338*** (0.023)	0.329*** (0.022)	0.326*** (0.022)
× RUC, low affiliation	0.520*** (0.023)	0.513*** (0.027)	0.530*** (0.023)	0.536*** (0.024)	0.524*** (0.023)	0.520*** (0.023)
× RUC, high affiliation	0.642*** (0.041)	0.733*** (0.044)	0.653*** (0.041)	0.657*** (0.042)	0.655*** (0.041)	0.629*** (0.04)
RUC, high vs. low affiliation	-0.016 (0.067)	0.168** (0.069)	-0.017 (0.067)	-0.003 (0.067)	0.001 (0.068)	-0.048 (0.066)
Proxy or predictor ($\text{Index}_{i,y}$)	None	$\bar{w}_{i,y}$	$\bar{\sigma}_{i,y}$	Private volume	Total volume	All
N	7,182	7,182	7,182	7,182	7,182	7,182
Adjusted R -squared	0.852	0.859	0.852	0.987	0.987	0.987

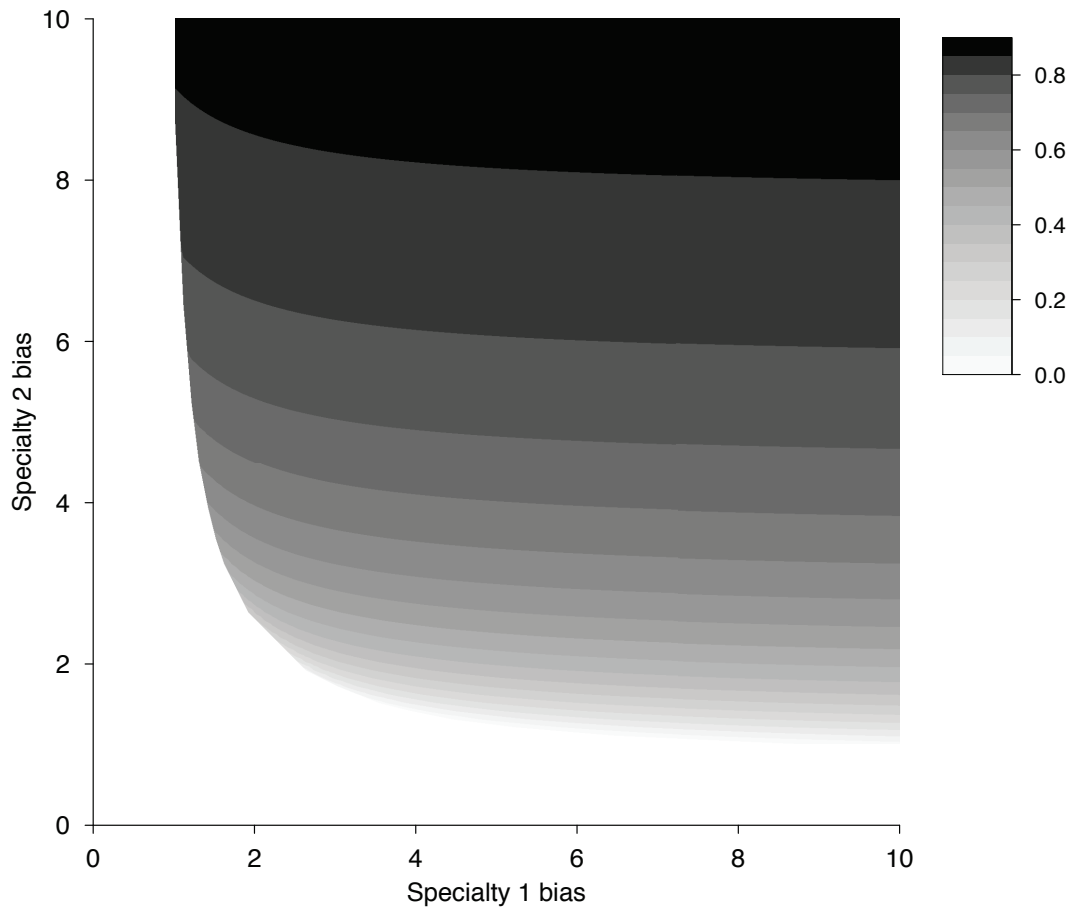
Notes: This table shows results of regressions of log private price on log Medicare price, as in Table IV. Definitions of private and Medicare prices and the merging of the two prices are given in Table IV. Column (1) has no proxy or predictor and is identical to column (5) in Table IV, as written in Equation (9). The remaining columns control for indicators of terciles of a proxy and interactions of these indicators with log Medicare price, as written in Equation (A.9.3). Columns (2) and (3) consider proxies for information that the average RUC member specialty may have about i , specifically $\bar{w}_{i,t}$ and $\bar{\sigma}_{i,t}$, defined as the average specialty share of a service's utilization and the average service share of a specialty's utilization, given in Equations (A.9.1) and (A.9.2), respectively. Columns (4) and (5) consider proxies of the importance of a service i to private insurance, specifically the private insurance volume or the total private insurance and Medicare volume, respectively. Column (6) considers an prediction of price transmission based on private volume, total volume, year dummies, Medicare price change year dummies, RUC meeting dummies, and specialty share w_i . All regressions are run on the same sample of 7,182 observations, weighted by Medicare volume. Standard errors are in parentheses. ** denotes significance at the 5% level; *** denotes significance at the 1% level.

Figure A.1: Regularized Affiliation Measures



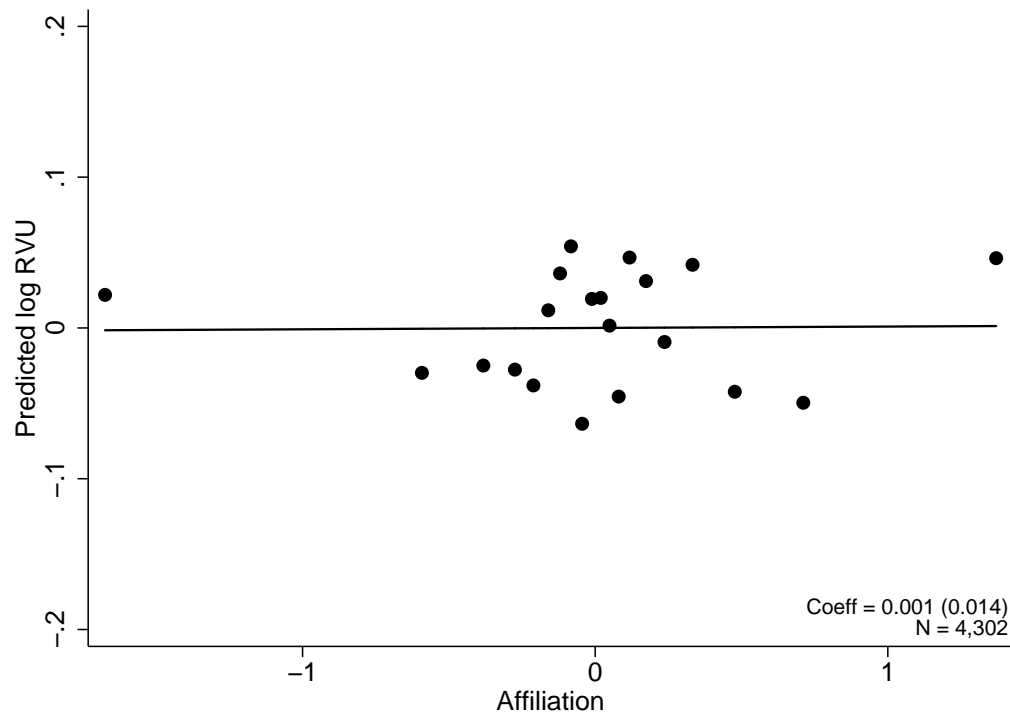
Notes: Each panel in this figure plots the effect of set affiliation based on regularized spillovers matrices: Euclidean distance in σ^Q (Panel A), Euclidean distance in σ^R (Panel B), and w -cosine similarity (Panel C). The y-axis shows coefficient α from Equation (6) (baseline specification of column (4) in Table III) on the y-axis and a regularization parameter on the x-axis. Confidence intervals are shown as dashed lines. The left side of each panel varies a regularization parameter (γ_1) that varies $\Omega_{\gamma_1,0}$ from a variance-covariance matrix ($\gamma_1 = 0$) to a correlation matrix ($\gamma_1 = 1$). The right side of each panel varies a regularization parameter (γ_2) that transforms Ω_{1,γ_2} from a correlation matrix ($\gamma_2 = 0$) to an identity matrix ($\gamma_2 = 1$). Results on the left side of each panel hold fixed $\gamma_2 = 0$, and results on the right side hold fixed $\gamma_1 = 1$. The right-most result ($\gamma_2 = 1$) matches results in Appendix Table A.3, which are implicitly based on $\Omega_{1,1} = \mathbf{I}_C$. Details are discussed in Appendix II.

Figure A.2: Mixed Strategy Proposal Probabilities



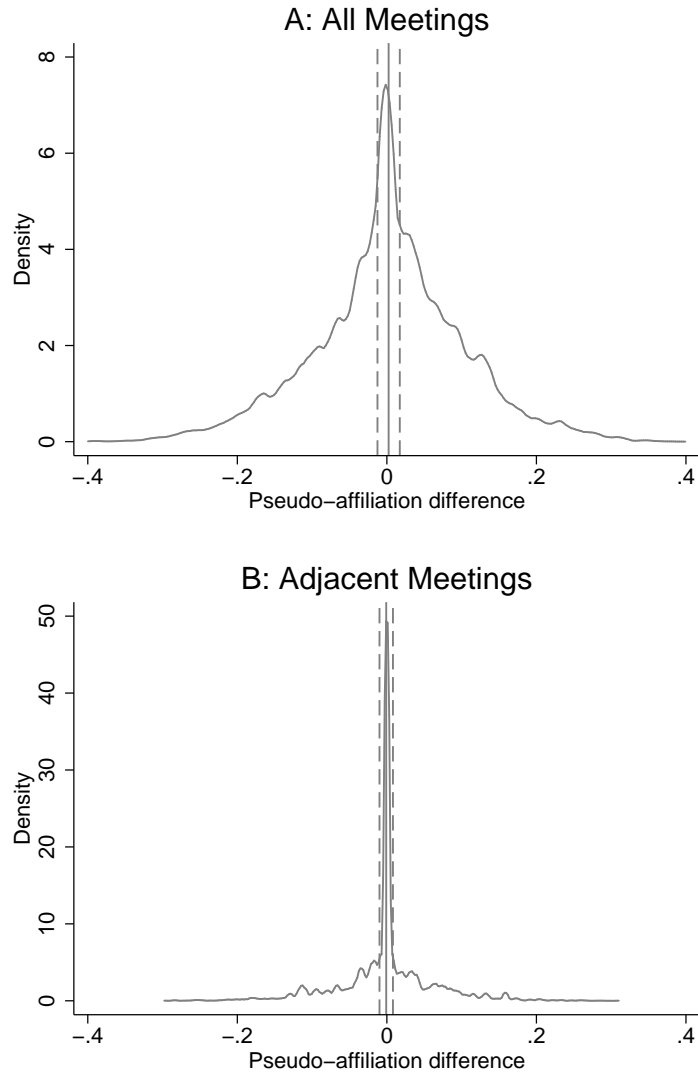
Notes: This figure shows the probability of proposal participation under $\theta = 1$ by specialty 1 in a mixed strategy equilibrium, in which specialties do not propose if $\theta = 0$ and mix if $\theta = 1$, described in Appendix III. Proposal probabilities are depicted in the space of bias by specialties 1 and 2. No mixed strategy equilibria exist in the region shown in pure white.

Figure A.3: Balance of Medicare Beneficiary Characteristics across Affiliation



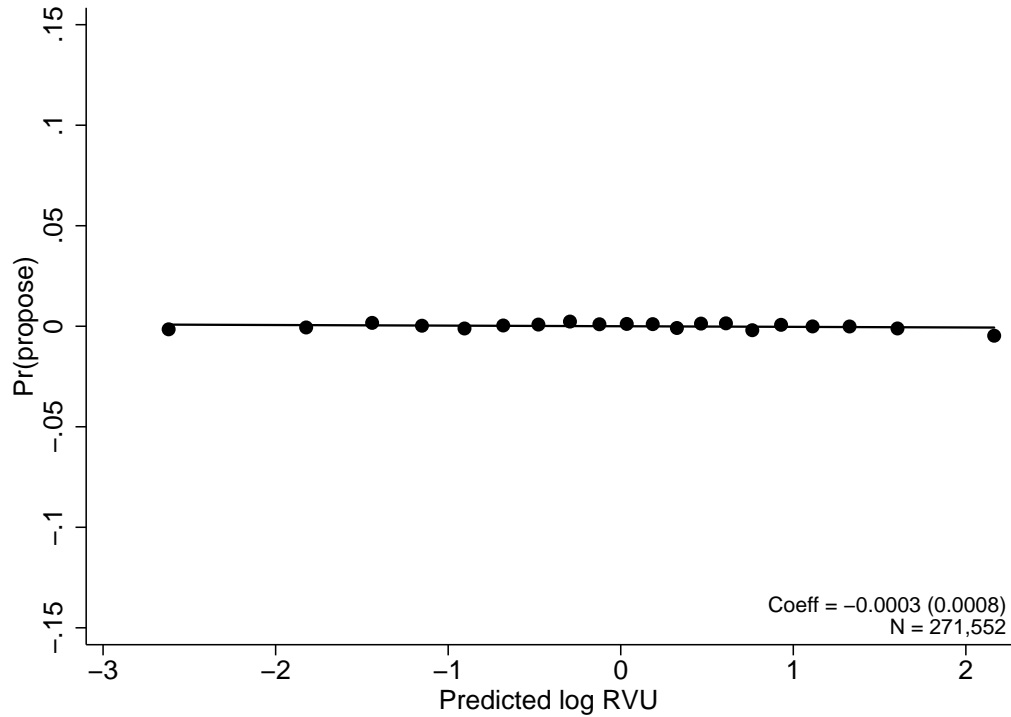
Notes: This figure is a binned scatterplot of residual predicted log RVU, based on Medicare beneficiary characteristics, on residual affiliation, where each dot represents 5% of the data, ordered by residual affiliations. Log RVU is first predicted by Medicare beneficiary characteristics, which are listed in Table II. The R -squared of this prediction equation is 0.249. Residuals are formed by regressing predicted log RVU and affiliation, respectively, on meeting dummies and specialty shares w_j . The line shows the best fit through the residualized data, with corresponding coefficient and standard error clustered by meeting.

Figure A.4: Random Timing of Proposals



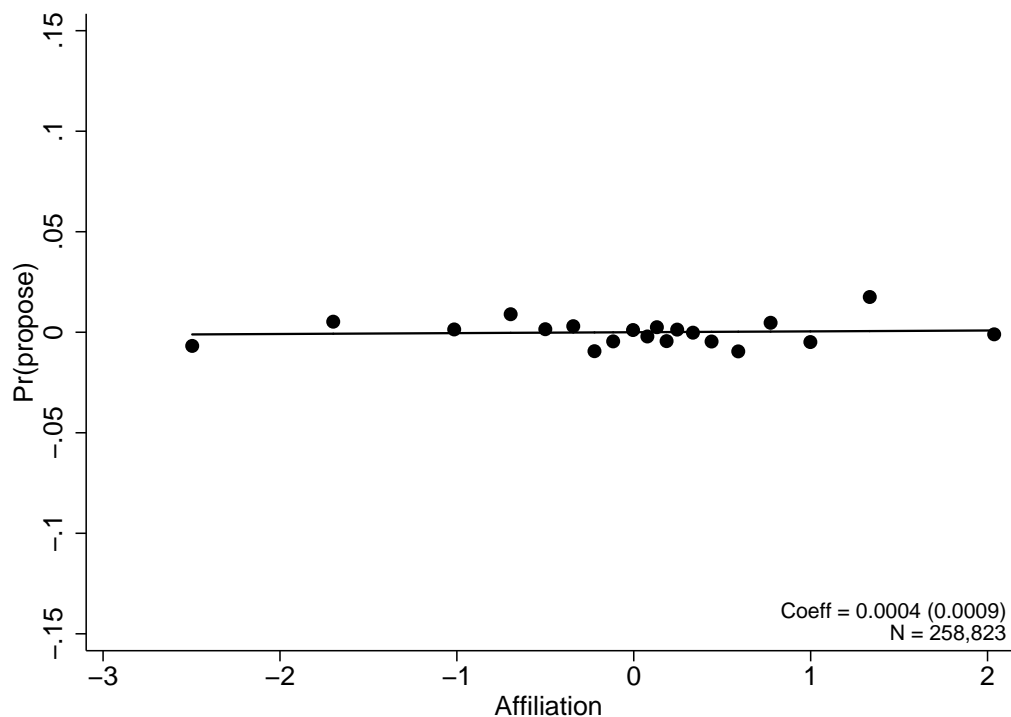
Notes: This figure shows the distribution of the difference between set affiliation in pseudo-meetings and the actual set affiliation of each proposal. All affiliation measures are standardized so that the distribution of actual set affiliation has a standard deviation of 1. In Panel A, we include all 60 meetings for every proposal. In Panel B, we include only meetings that were within three meetings (both earlier or later) of the actual meeting. The mean difference is shown as a solid vertical line. The 95% confidence interval, shown in dashed vertical lines, is calculated by a regression of the difference on a constant, clustering standard errors for meeting identifiers.

Figure A.5: Balance of Proposal Probability on Predicted Price



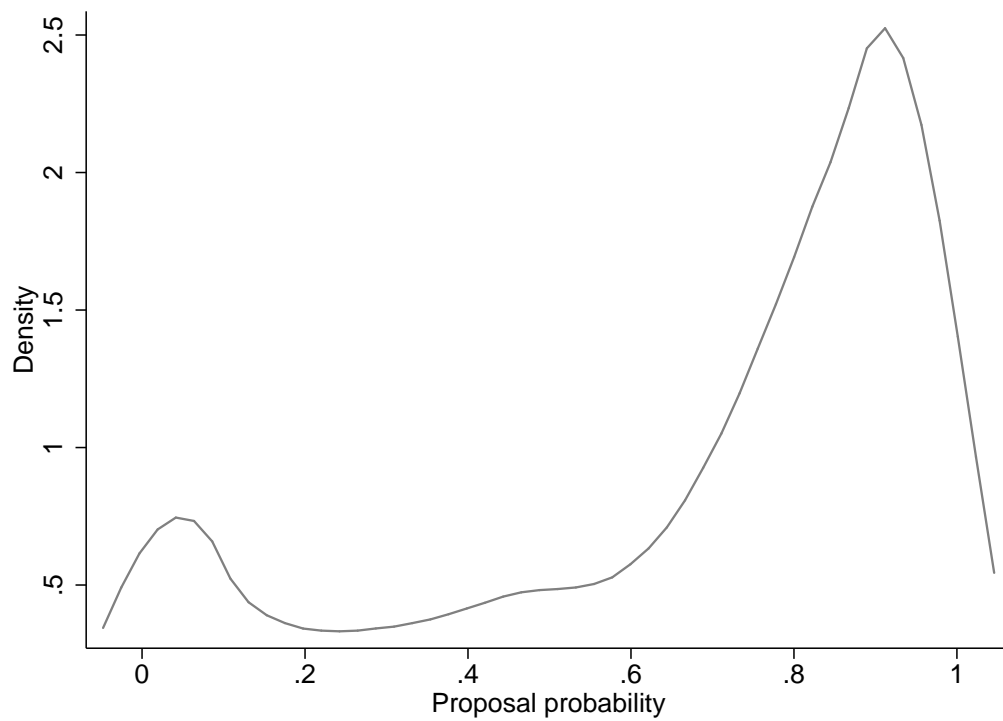
Notes: This figure is a binned scatterplot of residual proposal probability on residual predicted log RVU, where each dot represents 5% of the data, ordered by residual predicted log RVU. Each observation is a proposal-specialty pair, and the outcome variable of interest is an indicator for whether the specialty was part of that proposal. Log RVU is predicted from service (CPT code) characteristics, word descriptions, and prior RVU, which are described in Table III; the prediction equation has an adjusted R -squared of 0.88. The specialty proposal indicator and predicted log RVU are both residualized by the following predictors of proposing: specialty dummies for s , meeting dummies for t , Medicare utilization shares w_{is} for specialty s out of total utilization for service i , and an indicator for whether $w_{is} = 0$. The standard deviation of the proposal propensities, detailed in Appendix IV, is 0.13 across proposal-specialty pairs, so that the span of the y -axis is approximately 1 standard deviation above and below. The line shows the best fit through the residualized data, with corresponding coefficient and standard error clustered by meeting.

Figure A.6: Random Proposals with Respect to Affiliation



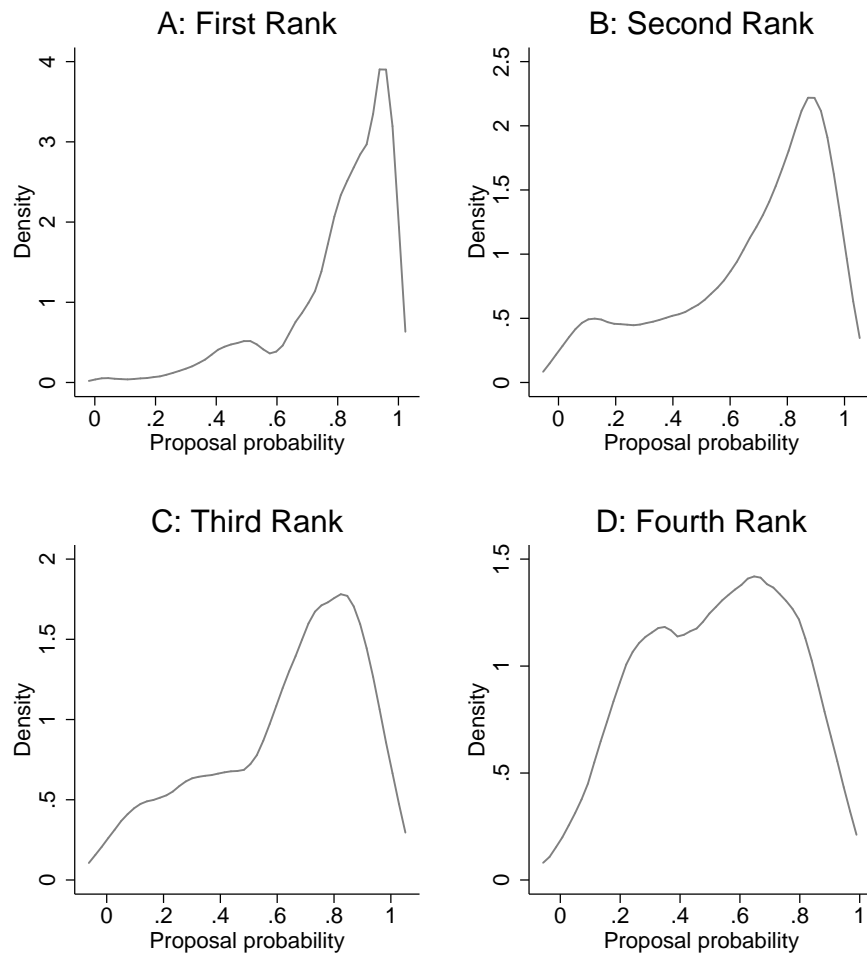
Notes: This figure is a binned scatterplot of residual proposal probability on affiliation between a specialty and the RUC, where each dot represents 5% of the data, ordered by residual affiliation. Each observation is a proposal-specialty pair, and the outcome variable of interest is an indicator for whether the specialty was part of that proposal. Affiliation is calculated between each potential proposing specialty s and the set of RUC specialties \mathcal{R}_t at the relevant meeting t , or $A(\mathcal{R}_t, s)$. The mean affiliation for specialty s across all meetings, or $\bar{A}(s) \equiv \|T\|^{-1} \sum_{t \in T} A(\mathcal{R}_t, s)$, is subtracted from this affiliation, and this difference $A(\mathcal{R}_t, s) - \bar{A}(s)$ is standardized to have mean 0 and standard deviation 1. The proposal-specialty indicator and affiliation are both residualized by indicators for the number of specialties on a given proposal and for the specialty identity. The standard deviation of the proposal propensities, detailed in Appendix IV, is 0.13 across proposal-specialty pairs, so that the span of the y-axis is approximately 1 standard deviation above and below. The line shows the best fit through the residualized data, with corresponding coefficient and standard error clustered by meeting.

Figure A.7: Distribution of Specialty-Proposal Propensities among Proposers



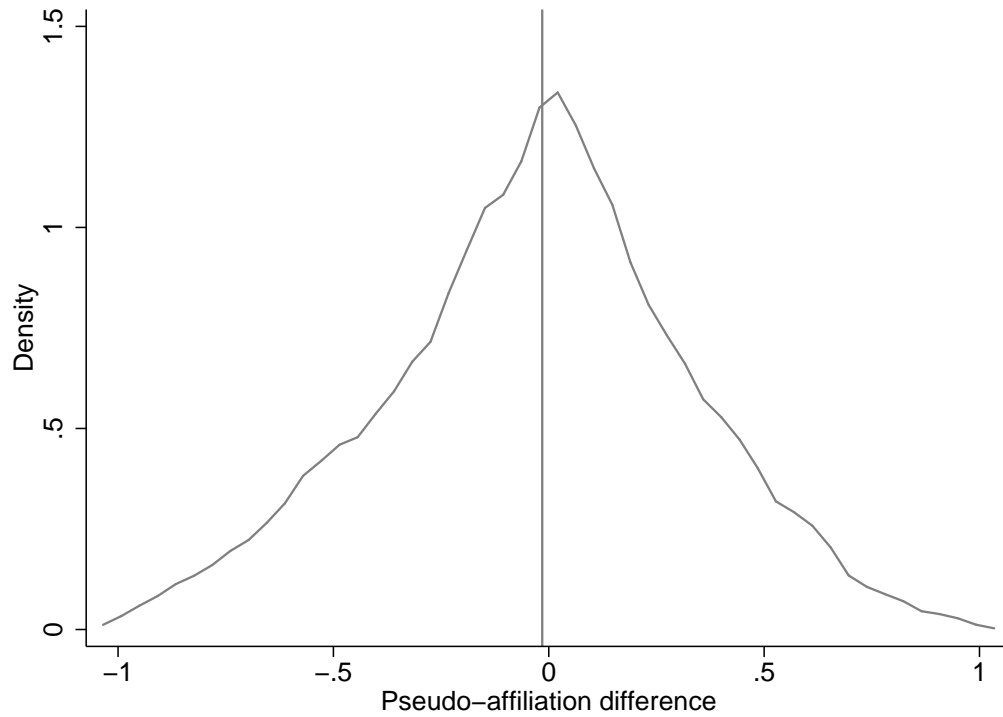
Notes: This figure shows the density of specialty-proposal propensities, estimated by a logit model of 248,735 specialty-proposal pairs as described in Appendix IV. Proposal propensities are shown for 6,929 actual specialty-proposal pairs over 4,199 proposals.

Figure A.8: Distribution of Highly Ranked Specialty-Proposal Propensities



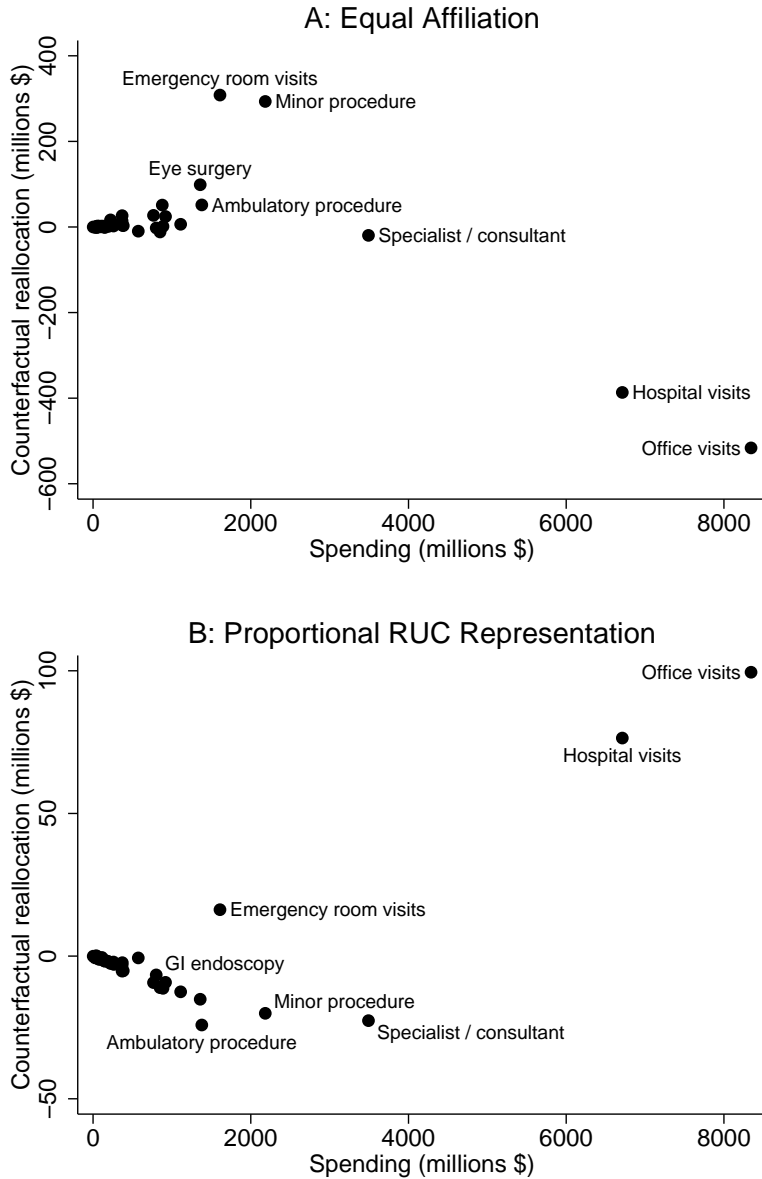
Notes: This figure shows the density of specialty-proposal propensities, estimated by a logit model of 248,735 specialty-proposal pairs as described in Appendix IV. In each panel, proposal propensities are shown only for correspondingly ranked specialty for proposals that have at least as many actual proposers. Specifically, in Panel A, the highest specialty propensity is shown for 4,199 proposals. In Panel B, the second-highest specialty propensity is shown for 1,524 proposals with at least two proposers. In Panel C, the third-highest specialty propensity is shown for 558 proposals with at least three proposers. In Panel D, the fourth-highest specialty propensity is shown for 300 proposals with at least four proposers.

Figure A.9: Distribution of Simulated Set Affiliation Relative to Actual Set Affiliation



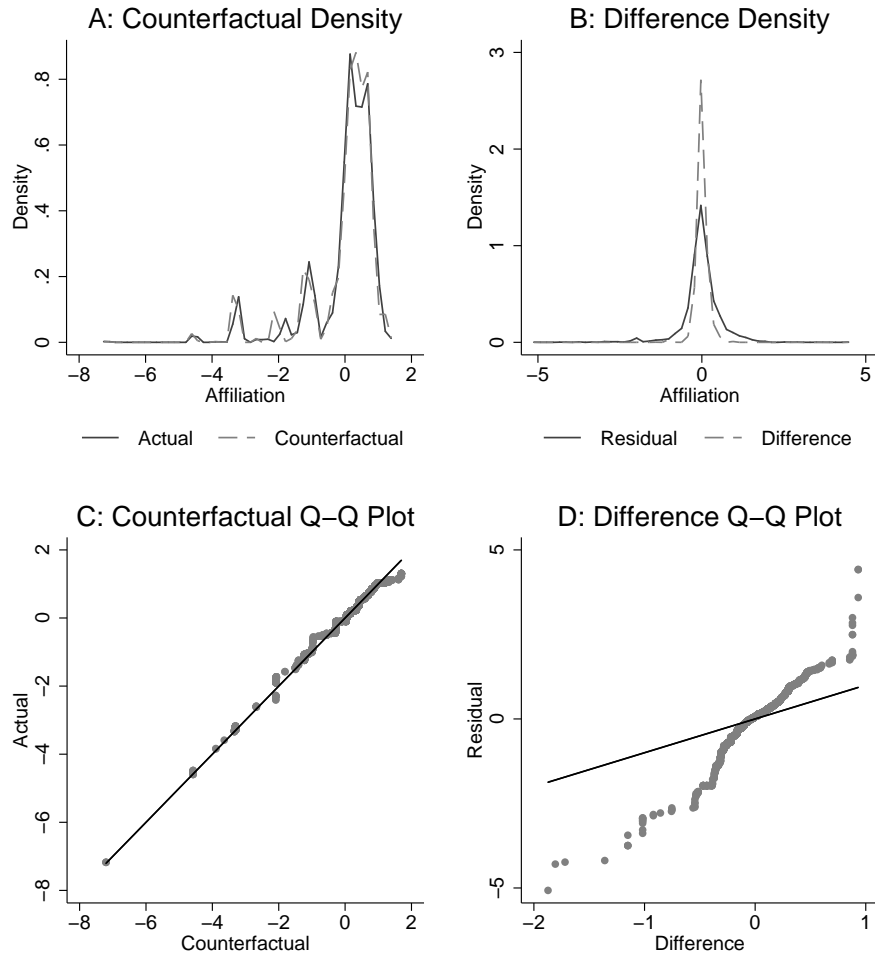
Notes: This figure shows the density of 51,763 simulated set affiliations, using actual \mathcal{R}_i and simulated proposing specialty sets \mathcal{S}_i for each proposal i , differenced by actual set affiliation. Simulated specialty-proposals are derived from a logit model of specialty-proposal propensities, as illustrated in Appendix Figures A.7 and A.8. Simulated observations are weighted by their likelihood of being drawn. The weighted standard deviation of the simulated set affiliations is 0.242, and the weighted mean of the differenced statistic is -0.015 . Details of the simulation algorithm are described in Appendix IV.

Figure A.10: Revenue Reallocation across Service Categories



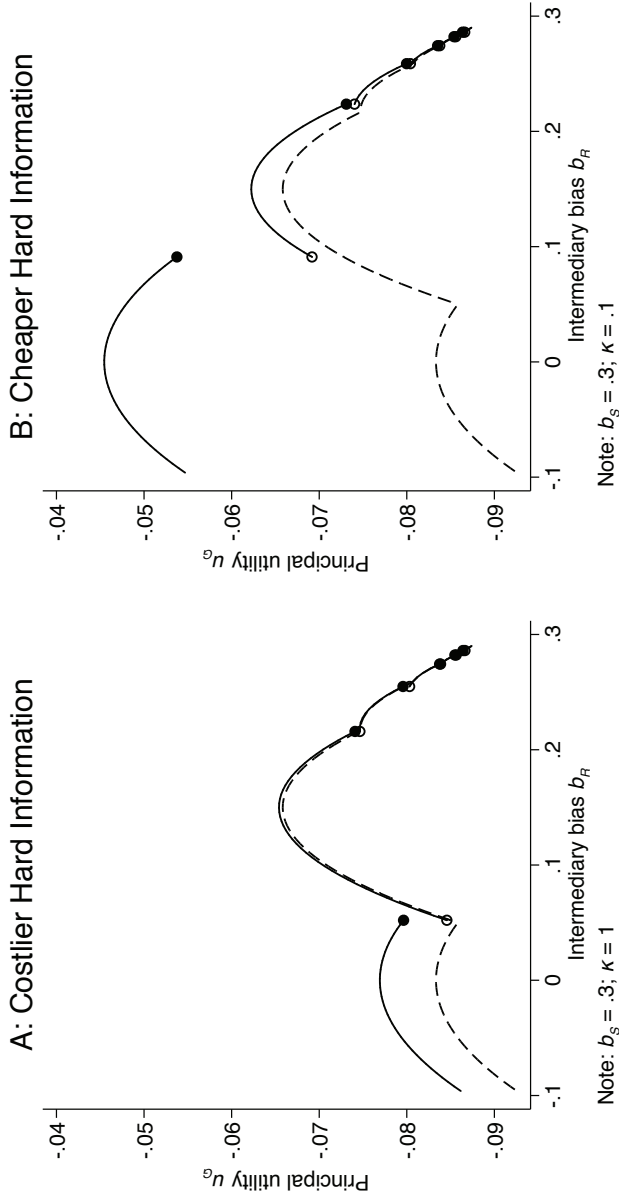
Notes: This figure shows counterfactual yearly revenue reallocation across Berenson–Eggers Type of Service (BETOS) service categories in two counterfactual scenarios. In Panel A, we consider equalizing the affiliation of all proposals in each year. In Panel B, we consider changing the RUC membership 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 billion . Details are given in Section 4.2.

Figure A.11: Counterfactual and Actual Distributions of Affiliation



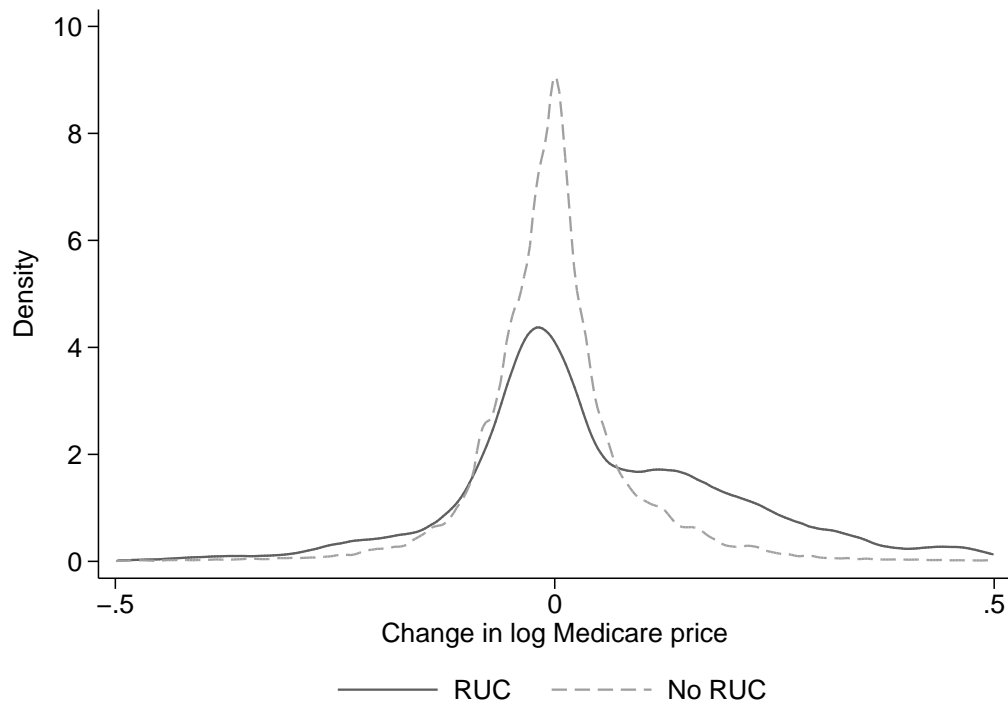
Notes: This figure compares counterfactual and actual distributions of affiliation. Affiliation is detailed in Section 3.3 and is a function of the set of proposing specialties \mathcal{S}_i for a proposal i and the set of RUC specialties \mathcal{R}_t during meeting t , or $A(\mathcal{R}_t, \mathcal{S}_i)$. The counterfactual affiliation for proposal i is given by $A(\tilde{\mathcal{R}}, \mathcal{S}_i)$, where $\tilde{\mathcal{R}}$ is the set of counterfactual RUC specialties given in Appendix Table A.7. Panel A plots the densities of counterfactual and actual distributions of affiliation. Panel B plots the densities of (i) the difference between counterfactual and actual affiliations for each proposal i , and (ii) the difference between actual and predicted affiliations for each proposal i , where predicted affiliation is a linear function of meeting dummies \mathbf{T}_t and specialty shares \mathbf{w}_i , as used in the baseline price regression in Equation (6). Panels C and D show the Q-Q plots that correspond to Panels A and B, respectively. These Q-Q plots display quantiles in the two distributions being compared; quantiles along 45-degree line indicate similarity between the two distributions.

Figure A.12: Principal Utility and Intermediary Bias



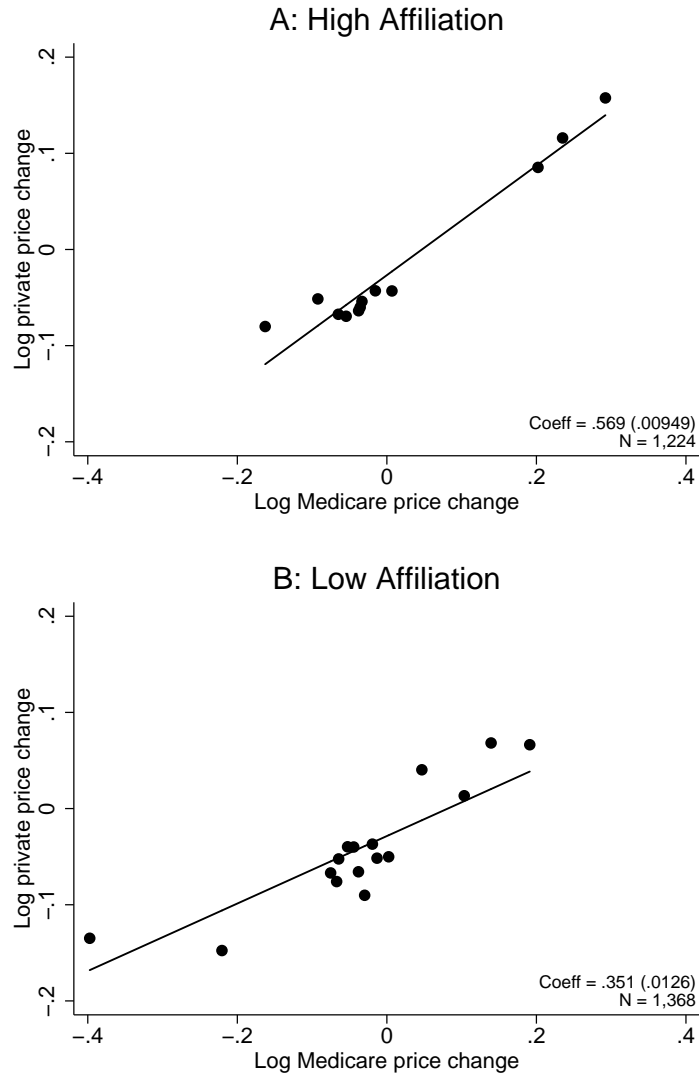
Notes: This figure shows the government utility (u_G) in our conceptual model of cheap talk, outlined in Section 5, in which the government delegates authority to the RUC as an intermediary to decide on proposals by a specialty society. The key parameter is bias of the RUC intermediary, b_R , where $b_R = 0$ indicates that the RUC has the same preferences as the government, and $b_R > 0$ indicates that the RUC is biased in favor of the specialty society, which prefers a higher price with bias $b_S = 0.3$ and $b_R \in [-0.1, 0.3]$, where $b_R = 0.3$ would imply RUC preferences identical to the specialty society. While greater b_R results in more distorted decisions (greater bias), greater b_R also improves communication. $b_R = 0$ only supports a babbling equilibrium with only one communication partition. The specialty society is able to invest in hard information, to reduce the size of the interval from $\theta \sim U(0, 1)$ to $\theta \sim U(\underline{\theta}, \bar{\theta})$, where $L \equiv \bar{\theta} - \underline{\theta}$, at cost $c(L) = \kappa(1 - L)^2$. In both panels, u_G is shown in the case where $\kappa = \infty$ in dashed lines, and shows that the optimal b_R^* is between 0 and 1 (Dessein, 2002). Compared against this benchmark, Panel A shows costlier hard information ($\kappa = 1$), and Panel B shows cheaper hard information ($\kappa = 0.1$).

Figure A.13: Distribution of Normalized Log Medicare Price Changes



Notes: This figure shows the density of Medicare price changes associated with a RUC decision (solid line) or not (dashed line). Medicare prices are defined as the total payments divided by the total volume of claims for each CPT code and year pair observed in the 100% sample of Medicare claims. The figure excludes any pair with fewer than 10 claims. Log prices are then normalized by subtracting the average log Medicare price across CPT codes in a given year, weighted by frequency of claims. The figure plots the difference between the normalized log price for a CPT code in a year and the price for the same CPT code in the previous year.

Figure A.14: Private Price Changes on Medicare Price Changes



Notes: This figure is a binned scatterplot of log private price changes on log Medicare price changes arising from high-affiliation RUC proposals (Panel A) and low-affiliation RUC proposals (Panel B), where each dot represents 5% of the data, ordered by Medicare price change. Lines show the best fit through the data, and the line slopes correspond to coefficients on log Medicare price change in a univariate regression of log private price change. Coefficients are robust to regression controls similar to those in Table IV. For consistency with Table IV, observations are weighted by frequency of Medicare claims for a given service (CPT code). Unweighted observations yield higher coefficients of approximately 1.5 for high-affiliation RUC proposals and 1 for low-affiliation RUC proposals.