Price-setting by Committee: Evidence from Medicare[*]

David C. Chan and Michael J. Dickstein[†]

PRELIMINARY AND INCOMPLETE: PLEASE DO NOT CITE

September 27, 2017

Abstract

A committee of physicians sets prices for physician services in Medicare. We investigate whether the composition of this committee leads to prices biased in favor of its members. We find evidence of regulatory capture: increasing a measure of affiliation between the committee and proposers by one standard deviation increases prices by 10%. We then evaluate the effect of affiliation on the quality of information used in price-setting. Less affiliated proposals produce more hard information, measured as better survey data. However, affiliation results in prices that are more closely followed by private insurers, suggesting that affiliation may increase the total information used in price-setting.

JEL Codes:

Keywords:

1 Introduction

When governments engage in regulation and procurement, they 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 financial interests. Thus, while government may need information from industry to make policy decisions, inviting industry participation may provide a pathway for "regulatory capture" (Stigler, 1971; Peltzman, 1976). Recent empirical work examines how lobbying and politicians' direct business connections may affect government decisions (e.g., Fisman, 2001; Bertrand et al., 2014; DellaVigna et al., 2016); here, we examine potential bias stemming from the government's widespread reliance on advisory committees with industry membership.[1]

Our empirical work focuses on the US government's 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's price recommendations influence not only Medicare's direct expenditure, 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 (Clemens and Gottlieb, 2014; Gruber et al., 1999) and the specialty career decisions of future physicians (Nicholson and Souleles, 2001).

We first assess whether this committee is captured by special interests. That is, we ask whether the composition of the RUC leads to prices biased in favor of its members, a concern raised by observers of this important 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 assigning a

---

[1]See Brown (2009) for an introduction. In 1972, Congress enacted the Federal Advisory Committee Act to keep track of the existence of a vast number of federal advisory committees. For example, in 2006, the US government maintained 916 such committees, with 67,346 members, at a cost of $384 million. While advisory committees serve the role of improve the quality of policy decisions, a key challenge for maintaining such committees is to ensure that are "fairly balanced" and free of "inappropriate influence."

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

work-based relative price.[3] To measure bias in this price-setting process, we develop a measure of *affiliation*, designed to reflect the closeness in preferences between two specialties. Our measure exploits data on the medical services each speciality performs, to reflect the likelihood that the revenue of two specialties will move together under any set of price changes. We calculate an aggregate measure of affiliation between every proposer and the members of the committee. Thus, to test for bias, we need only test whether proposals from a specialty society that has a high affiliation with the committee receives significantly higher prices.

We indeed find evidence that higher-affiliation proposals receive significantly higher prices: in our baseline specification, the causal effect of increasing affiliation from the 10th to the 90th percentile would result in a 17% higher price. Increasing a proposal's affiliation by one standard deviation would result in a 10% increase in price. To interpret this finding as causal, we rely on two sources of identifying variation. First, the composition of RUC voting members changes across meetings, as the RUC has expanded voting seats over time and as some specialty seats explicitly rotate. Second, we use variation in the identities of the specialties that propose values to the RUC. With this variation, we control for shares of a procedure's Medicare utilization across specialties, to address the concern that specialities who perform difficult services have greater representation on the RUC. We provide support for this identifying variation by showing that, after controlling for meeting identities and specialty shares, the residual affiliation is uncorrelated with exogenous measures of a service that predict its price.

The distributional consequences of this affiliation effect on health spending are large. If affiliation were equalized across proposals, roughly $1.9 billion in annual Medicare reimbursement would be reallocated across services under a fixed Medicare budget. About $1.3 billion (about 66% of the overall reallocation) would be redistributed from specialties with revenue from highly affiliated proposals to those with revenue from less-affiliated proposals. Assuming that private insurance prices adjust in proportion to prices in the Medicare fee schedule, this translates to an overall $8.9 billion reallocation in annual health care spending across specialties.

---

[3]The work-related component of relative prices have received the most policy and research attention (e.g., McCall et al., 2006; Sinsky and Dugdale, 2013; Laugesen, 2016). According to the AMA (2017), this component comprises 51% of overall reimbursement. Two other components of relative price are professional liability insurance (4.3%) and practice expenses (45%) (e.g., ancillary staff labor, supplies, and equipment). The practice expense component is also determined by the RUC but via a separate process in a subcommittee. We provide more details in Section 2.

Our finding of bias in the RUC's decision-making raises an important question of regulatory design: Why would the government rely on a committee comprised of physicians with potential conflicts of interest? In settings involving advisory committees, a key feature is the importance of policy-relevant knowledge (e.g., the safety and efficacy of a drug, or the benefits and costs of an energy source), often held by industry participants. Members of the advisory committee may themselves hold such knowledge.[4] Beyond this, a key task of advisory committees is to extract and synthesize information, not necessarily held by its members, from outside special interests. We thus explore whether bias may *improve* regulatory decisions, by facilitating the communication of information that is neither verifiable nor independently discoverable. That is, in our setting, can Medicare extract more information about physician services and improve its pricing of them by employing the RUC as an intermediary in decision-making?

To address this question, we borrow ideas from a large literature on the extraction of information from biased experts.[5] Following this literature, we model two types of information that the government wishes to extract. If information is soft, or unverifiable, it must be credibly communicated (Crawford and Sobel, 1982). The government may then benefit from delegating decision-making to an intermediary (the RUC) with preferences closer to the biased specialty with information, because aligned preferences improve communication (Dessein, 2002). On the other hand, a committee with adversarial preferences incentivizes the specialty to generate more information that is hard, or verifiable (Dewatripont and Tirole, 1999; Hirsch and Shotts, 2015). The net effect 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 intuitively is soft (e.g., the "difficulty" or "complexity" of a service relative to another).

We exploit our institutional setting to learn about the effect of affiliation on information extraction empirically, both in terms of hard and soft information. In our setting, physician surveys

---

[4]Camara and Kyle (2017) , for example, investigate whether advisors to the Food and Drug Administration with financial ties to the pharmaceutical industry vote differently. Li (2017) examines the role of expertise among peer reviewers evaluating funding proposals before the US National Institutes of Health. Zinovyeva and Bagues (2015) examine the role of evaluator bias in academic promotions.

[5]See Grossman and Helpman (2001) for an extensive review. Some prominent examples of papers in this large literature spanning political science and economics include Crawford and Sobel (1982), Calvert (1985), Austen-Smith (1994), Dewatripont and Tirole (1999), and Li et al. (2001).

about features of a service to be priced form much of the evidence presented in proposals to the RUC. We measure the precision of hard information in the surveys using two summary statistics we observe in the data: the number of physicians surveyed and the number of respondents. 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.

Despite the RUC's formal focus on hard information, pricing physician services is intrinsically complicated, and much of the information about a service cannot be presented as verifiable evidence. We assess the importance of the remaining soft information by testing whether the identities of proposing specialties respond to the composition of the RUC. We use the following logic: If all information for a service were observable and verifiable, then the identities of the proposing specialties should not matter for outcomes, regardless of the preferences of the RUC. On the other hand, if affiliated senders can improve the credibility or interpretability of soft communication, the identities of the proposing specialties do matter and should respond endogenously to the RUC member composition. We find that specialties are in fact more likely to participate in a proposing coalition when they increase the affiliation of a proposal. This finding complements a growing empirical literature on lobbying (Bertrand et al., 2014; Blanes i Vidal et al., 2012) that suggests that the identity of the messenger provides credibility to the message (Gilligan and Krehbiel, 1989; Kessler and Krehbiel, 1996; Hirsch and Montagnes, 2015). The finding that coalitions form to increase affiliation also supports the importance of connections in settings of persuasion.[6]

Finally, we develop a policy-relevant metric of how much overall information is collected by

---

[6]See, for example, Fisman (2001); Khwaja and Mian (2005); Ferguson and Voth (2008); DellaVigna et al. (2016). There are also large literatures concerned with the strategic underpinnings of coalitions (e.g., von Neumann and Morgenstern, 1944; Shapley and Shubik, 1954; Acemoglu et al., 2008) and with the role of network ties in facilitating economic outcomes (e.g., Granovetter, 1973).

Medicare through the RUC, and then translated to prices. Specifically, we examine whether and how the private insurance market follows Medicare (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. For RUC decisions on more highly affilated proposals–i.e. those proposals presented to a more highly affiliated committee—we find even stronger price following. Together, these findings suggest that affiliation may improve the quality of information in Medicare pricing decisions. However, we also find that private insurers *reduce* the level of prices originating from high- vs. low-affiliation RUC proposals. Thus, private insurers may follow high affiliation proposals more closely, but may also adjust for bias from RUC decisions.

The remainder of the paper is organized 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. We move to the question of information extraction, first with a theoretical framework in Section 5. We then present empirical evidence on hard information and on soft information via coalition formation in Section 6 and in 7, respectively. Section 8 evaluates the overall information quality of Medicare prices by their transmission to the private sector. Section 9 concludes.

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 some areas of health care providers negotiate prices directly with payers (Ho, 2009; 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 (Cabral and Riordan, 1989; 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," in a given year. Further, the payment levels adjust for the variation in the cost of practicing medicine in different parts of the country. Three distinct geographic practice cost indices account separately for geographic variation in the costs of physician work, practice expenses, and malpractice insurance. Medicare then sets the payment level equal to the sum of the three geographically adjusted cost components. To convert the relative value units into dollars, the sum of costs is multiplied by a common conversion factor; in 2014, the conversion factor was approximately \$35.83 per RVU (American Medical Association, 2015).[7]

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

$$\text{Reimbursement}_{ijt} = \left[\sum_{c \in \{W, PE, PLI\}} \left(RVU_{it}^c \times GPCI_j^c \right) \right] \times CF_t. \tag{1}$$

where RVU_{it}^c, is the relative value unit for service i in a given year, $GPCI_j^c$ is the fixed geographic practice cost index, and CF_t is the conversion factor.[8]

With the adoption of this formula, Medicare's administrators also created for themselves a new and complex task: determing the relative prices or RVUs. In particular, judging the intensity and level of effort required for a medical procedure requires collecting information possessed by actual practitioners. Medicare thus chose to engage 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 (American Medical Association, 2017; Laugesen et al., 2012).

---

[7]The conversion factor is set administratively so that Medicare's total payments for procedures in the US falls within a budget determined by factors such as GDP growth and the number of Medicare beneficiaries. We provide more details in Appendix A-1.

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

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.[9] We henceforth use the term "RVU" or "relative price" interchangeably with "work RVU," unless otherwise specified.

The main RUC committee, currently comprised of 26 physician representatives, considers all changes to work RVUs. Twenty one of these members occupy permanent seats, while the remaining four rotate.[10] For example, a representative of the specialties of internal medicine, dermatology and orthopeadic surgery mantain permanent seats, while specialities including pediatric surgery and infectious disease rotate on and off the RUC. In Table 1, we record the number of total meeetings at which 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 1, we show the number of voting seats and a breakdown between "cognitive" and "procedural" specialties over time.[11] Using our definition, procedural specialties – i.e those who chiefly carry out surgical services – have a slightly larger share of the RUC's voting members in every year since 1992. Helpful for our analysis later, the composition of the RUC has changed over time both because some of the seats explicitly rotate and because the commitee size has grown over time.

---

[9]The medical and health policy literatures have raised several potential sources of bias in the price-setting process, although largely descriptively and without access to any of the data contained in RUC proposals (e.g., McCall et al., 2006; 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; Rosenthal, 2014; Pear, 2015), and the Affordable Care Act has 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) take stated times to perform certain services as explicit and connect these times with work RVUs in order to detect physician overbilling.

[10]The rotating seats include two from internal medicine subspecialities not on the RUC, one primary care rotating seat, and one seat from a speciality society that is not a permanent member of the RUC and not eligible for one of the other three rotating seats (American Medical Association, 2017).

[11]Although the labels "procedural" and "cognitive" have been frequently used to describe specialties and work 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. Details are given in the note to Figure 1.

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 workgroup from within the RUC identifies a service as potentially misvalued.[12] 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 1118 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 a specialty or set of 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 specialities developing a proposal conduct a survey of their members to collect data about the 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

---

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

arguments for a proposed relative price before the RUC.

2. The RUC members discuss the proposal with each other and with the proposer(s). If the proposal is not approved (by a two-thirds vote), the proposer(s) may discuss their proposal with a smaller Facilitation Committee. In faciliation, the proposed price is often revised downward. Any revisions still must be passed by the RUC. The RUC may also independently recommend a relative price to Medicare if no proposal is successful.

3. The RUC forwards its recommendations to Medicare, which historically accepts the relative prices 90% of the time (American Medical Association, 2017; Laugesen et al., 2012).

3 Empirical Approach

With the conceptual framework described above, we next move to analyze the RUC's price-setting process using data from the committee's internal deliberations from 1992 to 2013. Our substantive goals are twofold. First, we measure the causal effect of the RUC's affiliation with the proposing specialities on the prices set by the committee. Second, we will determine the effect of affiliation on information transmission, either measured as survey precision (hard) or as price following in the private market (hard and soft). 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 casual effect of affiliation on prices and on information transmission.

3.1 Data

Our empirical analyses rely on three sources of data. First, we need information on the RUC's deliberations, including the RUC membership at each decision and the details of the proposal for each service brought up for evaluation before the committee. For this information, we accessed the same database RUC members use to prepare for votes during meetings. In this database, we observe detailed proposal information for each service the RUC evaluated from its inception in 1992 until 2013. In particular, we collect, for each proposal, the identity of the service, the meeting in which the RUC considered the proposal, the specialty society or societies proposing a value, the RVU level proposed, and the RVU eventually recommended by the RUC. We observe

4,423 proposals with known specialty proposers and other selection criteria. We describe our sample creation process in more detail in Table A-1.

The data we use from the RUC's internal accounting also contain detailed characteristics of each proposal. A central component of proposals is a survey; we observe the quality of the survey using the the number of physicians surveyed and the number of respondents. We capture key responses in the survey to questions about the time required for a service, 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. We also observe "reference" services used for comparison in the survey, including the RVUs of these services and the proportion of respondents who judged the service under review to be more intense than the reference service on various qualitative dimensions (e.g., complexity of medical decision-making, urgency, technical skill, physical effort, psychological stress, risk of complications, judgment required).

Second, in addition to the RUC database, we collect objective measures of the 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, including race, age, rural versus urban location, disabled status, and the set of top patient diagnoses; and (iii) the fraction of utilization of the service in different medical settings, including the emergency department, inpatient, outpatient care settings.

To build even more detailed control variables to characterize each service, we merge in a database of service descriptions.[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 description.[14]

---

[13]In Table A-2, we provide examples of these descriptions.

[14]In detail, we identify word stems to account for inflected variations (e.g., "operate" and "operation"), of which there are a total of 9,271 unique stem words from 11,123 original words, excluding stop words such as "the," "and," and "only." The median count of unique word stems across procedure code descriptions is 8, and the 5th and 95th

Finally, third, we collect a time series of private sector prices for each service. We later compare the level of private prices to those set by the RUC, to explore how private firms adjust for possible bias in Medicare's price setting mechanism. We use Truven Health's MarketScan data to measure prices for each service as paid by private insurers. We observe quantities of use, the specialty of the billing physician, and 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 code and for each specialty performing the code.

3.2 Affiliation

We define a notion of affiliation to capture the similarity between two specialties. Our goal is to measure the alignment of preferences between specialties with a diverse set of interests, characterized by the services they perform. For example, an orthopedic surgery specialty is likely to be on a proposal for a spinal surgery service, but this service (or any other service) represents but a small fraction of its specialty revenue. If hand surgery as a specialty holds a committee seat, it may tend to agree with an orthopedic surgery recommendation, even if it performs no spinal procedures, because it shares much in common with orthopedic surgery. The alignment of preferences (or lack thereof) will have implications for both the prices set and the information transmitted in the process, as we will detail further in Section 5.[15]

To measure alignment in specialty preferences, we must capture the many pathways through which price-setting decision may impact a specialty's revenue (or any other function of quantities and prices of services). For example, changing the RVU of a service may affect the quantity of that service and may also affect the quantities of complementary or substitute services. Any change in quantities or RVUs will also affect the conversion factor and therefore the real Medicare reimbursement for any service. Finally, a price change may cause future prices of related services

---

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.

[15]We thus depart from previous empirical work on committee bias that is based on financial ties (Camara and Kyle, 2017) or group membership (Zinovyeva and Bagues, 2015; Li, 2017) with respect to a particular proposal. Of note, by measuring connections between senders (proposers) and receivers (committee members), independent of the object of the proposal (the service to be priced), we are able to examine the relationship between preferences and communication, which is central to the information extraction literature.

to change similarly, particularly services that could use the index service as a reference. These mechanisms are complicated. However, by construction, two specialties with identical quantity shares across services will experience the same proportional change in revenue from any arbitrary price change. Thus, we focus on similarity of services between two specialties, and we view this affiliation measure as a nonparametric sufficient statistic of preference alignment between the specialties.

Specifically, we denote the quantity utilization of service i by specialty s in year y as q_{isy}. We then construct the vector σ_s of specialty s utilization shares across all services, where the ith element is σ_{is}, the share of specialty s's utilization of i averaged across years:

$$\sigma_{is} = \frac{\sum_y q_{isy}}{\sum_y \sum_i q_{isy}}, \tag{2}$$

for each service i in the universe of 11,252 Current Procedural Terminology (CPT) codes that physicians perform for reimbursement. We define affiliation between two specialties s and s' as a negative Euclidean distance:

$$a\left(s, s'\right) = -\sqrt{\left(\sigma_s - \sigma_{s'}\right)\left(\sigma_s - \sigma_{s'}\right)'}. \tag{3}$$

In Appendix A-2, we provide further discussion about this measure of affiliation as a preferred sufficient statistic for the alignment of revenue maximization objectives between two specialties.[16]

Figure 2 shows affiliation measures between specialties, among the 20 specialties with the highest revenue, where we divide the measures into quintiles. Many affiliation measures are intuitive: We find high affiliations for related pairs such as between internal medicine and family medicine, between electrodiagnostic medicine and neurology, and between orthopedic surgery and hand surgery. In addition, internal medicine and general surgery are affiliated with a wide range of specialties. Perhaps surprisingly, internal medicine is affiliated with many surgical specialties because many surgical specialties also rely on the same evaluation and management

---

[16]In particular, we discuss the use of quantity shares vs. revenue shares as the vector space upon which to base affiliation, and we discuss alternative distance metrics, such as Manhattan distance, correlation, and angular distance. Although there are theoretical reasons to prefer this affiliation measure, we nevertheless show that the affiliation effect on prices is robust across other formulations in Table A-3.

(E&M) procedure codes that internal medicine uses. In contrast, physicians in allergy, asthma, and immunology use a set of codes rarely used by other specialties, leading to low affiliations. Similarly, emergency medicine physicians provide evaluation and management services using distinct codes specific to emergency patients, and thus have low affiliations.

Our definition of affiliation reflects pairwise comparisons of the similarity in procedure use between two specialties. However, for our eventual empirical specifications, we need an affiliation measure at the proposal level, since our outcomes measures are specific to a proposal. Thus, we define *set affiliation*, a measure of affiliation between the collection of specialities composing the RUC and the collection of specialties party to a proposal.[17] In notation, the set affiliation between the set of proposing specialties S_i for proposal i and the set of RUC member specialties R_t at meeting t as

$$A^* (R_t, S_i) = \frac{1}{\|R_t\|} \sum_{r \in R_t} \max_{s \in S_i} a (r, s),$$ (4)

where $r \in R_t$ denotes a member specialty on the RUC, and $s \in S_i$ denotes a specialty on the proposal. For each $r \in R_t$, this measure takes the maximum affiliation between r and any proposing specialty $s \in S_i$. In this formulation, additional proposing specialties in S_i can only increase $A^* (R_t, S_i)$. These pair-specific affiliation measures are then averaged 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 $A^* (R_t, S_i)$ by subtracting the sample mean and dividing by the sample standard deviation.[18]

3.3 Identification

With our measure of affiliation, we seek to recover the causal effect of affiliation on prices and information quality. To do so, we need plausibly exogenous variation in our measure of affiliation. This variation comes from two sources: changes in specialty representation on the RUC over time,

---

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

[18]In some cases, described below, we will compute the counterfactual set affiliation for proposal i in a different meeting than the actual t. In these cases we continue to normalize with the mean and standard deviation of the actual sample of $A (R_m, S_i)$ in order to maintain comparability.

and variation in the identities of those specialties contributing to a proposal.

Our main concern for identification is that proposals with higher affiliation may have un-measured characteristics that are correlated with the price outcome. Below, we consider three specific reasons why this might occur. First, specialties submitting proposals for more difficult (or otherwise intrinsically high-value) procedures may choose to submit these proposals at meetings with more affiliated RUC members. Second, specialties with systematically more difficult procedures may have greater representation on the RUC for non-random reasons. Finally, third, holding fixed utilization by specialties, procedures that are more difficult may also be more likely to have additional proposing specialties, which tends to increase affiliation.

3.3.1 Endogenous Timing

We look for evidence that specialties choose to propose when they are more affiliated with the RUC. We compute the affiliation that each proposal i would have over all possible alternative meetings $t' \in T \setminus t$, generating a set of counterfactual affiliations, $A = \{A(R_{t'}, S_i)\}$. We then test whether observed affiliations are statistically distinguishable from these counterfactual af-filiations. As shown in Figure 3, the mean differenced statistic $A(R_{t'}, S_i) - A(R_t, S_i)$ over all proposals and possible meeting dates (i, t') is not statistically different than 0. Further, control-ling for average counterfactual affiliation, $\overline{A}(S_i) \equiv \|T\|^{-1} \sum_{t \in T} A(R_t, S_i)$, we find no correlation between price predicted from service characteristics and the realized affiliation. Finally, we show that most of the variation in $A(R_t, S_i)$ across i and t is due to the proposing specialties, S_i and not to the RUC members, R_t.[19]

3.3.2 Systematic Differences across Specialties

To address the possibility that specialties with difficult services may have greater representation on the RUC, we control for specialty utilization shares of a given service:

$$w_{is} = \frac{\sum_y q_{isy}}{\sum_y \sum_s q_{isy}}, \tag{5}$$

---

[19]Specifically, we compare $Var_i\left(A(R_t, S_i) - \overline{A}(S_i)\right)$ and $Var_i\left(\overline{A}(S_i)\right)$ relative to $Var_i\left(A(R_t, S_i)\right)$. The varia-tion due to t is only about 3.7% of the total variation, implying the variation due to proposing specialty identities is about 27 times greater.

for service i, specialty s, and Medicare claim year y. We thus restrict our later comparisons to be between procedures performed by the same specialty mix. Note that if only one specialty performed each procedure (i.e., $w_{is} \in \{0, 1\}$), then controlling for w_{is} would be equivalent to including specialty fixed effects in our later regressions. As shown in Figure 4, there remains substantial variation in affiliation even conditional on a given specialty being part of the proposal.

In Figure 5, we assess balance in plausibly exogenous service characteristics that predict price, linearly controlling for meeting dummies and specialty shares. Characteristics of Medicare beneficiaries receiving services with high residual affiliation are similar to those receive services with low residual affiliation. Despite 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.

3.3.3 Endogenous Proposing Specialties

Among proposals with a given specialty s, there still exists large variation in $A\left(R_t, S_i | s \in S_i\right)$ (Figure 4). In practice, the likelihood of proposing is non-trivial if a specialty's share of a service's utilization is greater 3%; this implies a relatively large set of possible proposers despite that the vast majority of proposals are made by three or fewer proposers. We assess whether the likelihood of a specialty participating on a given proposal, conditional on the vector of specialty utilization shares $\mathbf{w}_i$, can be predicted by observable characteristics of the service.

We first estimate the propensity of each specialty s to propose i, as a flexible function of $\mathbf{w}_i$ and specialty fixed effects. Our relatively simple logit propensity, based solely on $\mathbf{w}_i$, has a pseudo-R^2 of 0.67. We next find that conditional on this propensity, $\pi_{is} = \Pr\left(s \in S_i | s, \mathbf{w}_i\right)$, actual participation in a proposal is uncorrelated with predicted RVU despite an adjusted R^2 of 0.88 for the RVU prediction equation (Figure 6).[20] This supports our identifying assumption that, conditional on $\mathbf{w}_i$, specialty participation in proposals is uncorrelated with service characteristics that predict price.[21] Since affiliation is only a function of S_i (and R_t), this assumption implies

---

[20]We predict RVU using procedure characteristics, including procedure code word descriptions, surveyed time, prior RVU, and Medicare beneficiary characteristics.

[21]For example, we find in regressions that participation is heavily influenced by other proposals a specialty may be on during the same meeting and whether there are other specialties for the index proposal with a high(er) likelihood of participating. The former increases the likelihood of participation while the latter decreases the

that affiliation, holding i and t constant, is quasi-randomly assigned.

4 Affiliation Effect on Prices

4.1 Estimated Effect

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

$$\ln RVU_{it} = \alpha A\left(R_t, S_i\right) + \mathbf{X}_i\beta + \mathbf{T}_t\eta + \mathbf{w}_i\zeta + \varepsilon_{it}, \tag{6}$$

where RVU_{it} is the relative price (RVU) granted to proposal i at meeting t, and α is the effect of increasing set affiliation by a standard deviation. We include fixed effects for the RUC meeting t and control for specialty utilization shares $\mathbf{w}_i$. This compares prices set within the same meeting and for services with the same (linear) composition of specialties who perform the service.

We can potentially control for a large number of procedure code and proposal characteristics $\mathbf{X}_i$ specific to a service i: (i) prior RVU, which exists for the roughly 50% of proposals made for existing codes, (ii) characteristics of Medicare beneficiaries who receive the procedure, (iii) time and work characteristics of the procedure (e.g., total utilization, surveyed time intervals, difficulty of the procedure, or other office visits that are bundled into the code), and (iv) word stems in the code's description. For characteristics that are missing for some observations, we create dummies to indicate a missing characteristic and set the original missing value to 0.[22]

In Table 3, we report results for a variety of control specifications. In Figure 7, we present regression results from the full specification in a binned scatterplot in which we plot residualized price on the y-axis and residualized affiliation on the x-axis. In the full specification, reported in Column 5 of Table 3, we find that a standard deviation increase in affiliation increases relative price by 10.1%.[23] Increasing affiliation from the 10th percentile to the 90th percentile would

---

likelihood. In Section 7, we also find that specialties are more likely to propose when they increase a proposal's affiliation. Note that this finding is nonetheless consistent with our identifying assumption, that the probability to propose, conditional on $\mathbf{w}_i$, is orthogonal to predictors of price.

[22]In 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, then select predictive word stems via LASSO. Finally, we form jack-knifed RVU predictions using post-LASSO OLS on observations other than those in the meeting t. We similarly form jack-knifed RVU predictions based on the procedure's characteristics in (iii).

[23]Consistent with robustness across control specifications, in an Altonji et al. (2005) framework we find that

increase prices by 17%. We interpret this finding, that affiliated specialties on the RUC increases prices, as evidence of bias in favor of proposing specialties.

4.2 Counterfactual Revenue

Given the effect of affiliation on prices, we examine the revenue implications from two counterfactual scenarios that change the affiliation of proposals. In the first scenario, we equalize the affiliation of all proposals, so that no proposal has an advantage (or disadvantage) under affiliation. In the second, we consider a counterfactual RUC, in which the 26 seats are apportioned based on specialty physician populations, as given in Table A-4. 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 thus simulate changes in revenue at the service level solely through the effect of counterfactual affiliation on service prices. We further aggregate counterfactual revenue reallocation to specialties and to types of services, defined by Berenson-Eggers Type of Service (BETOS) codes. We provide details of the simulation algorithm in Appendix A-3.

Equalizing affiliation across proposals would reallocate $1.0 billion (or 2.9% of work-based reimbursement) in yearly Medicare work-based revenue across CPT codes, or $1.9 billion in total Medicare reimbursement, extending 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. We also evaluate which specialties and types of procedures, grouped by BETOS categories, would see the largest revenue reallocations. We illustrate those changes in Figure 8. Although internal medicine has a minority of seats, internal medicine gains from affiliation because many other specialties, including surgical ones, also derive

---

selection on unobservables, controlling for meeting dummies and specialty shares, would need to be 3.9 times greater than selection on observables in order to explain our estimated effect. In Table A-3, we also show that our results are robustness to 49 other formulations of affiliation. We defend our preferred affiliation measure and discuss alternatives in Appendix A-2.

a large share of revenue from office visits.[24] Of specialties, emergency medicine would have the largest percentage revenue gain (+17%), while infectious disease would have the largest loss (−5.8%).

Reapportioning RUC seats based on specialty physician populations would reallocate $230 million (or 0.64% of work-based reimbursement) in yearly Medicare work-based revenue across CPT codes, or $450 million in total Medicare reimbursement. Overall, reallocation figures would generally be only one-fifth in magnitude (and often opposite in direction) of those in the first counterfactual scenario in which we equalize 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 only gain less than 1 percent in revenue. Of specialties, infectious disease would have the largest percentage revenue gain (+1.4%), and ophthalmology would experience the largest percentage revenue loss (−1.4%). We illustrate other individual specialty and BETOS code reallocations in Figure 9.

5   Conceptual Framework of 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 the proposer's preferences? In this section, we introduce a conceptual model that illustrates a trade-off between bias and information. In our framework, the specialty society is a biased expert who has information about the true value of a service to be priced. We denote that value as θ, which we assume varies uniformly on an interval: $\theta \sim U(0,1)$. We classify the specialty's information into two types: "hard" and "soft" information. Hard information is verifiable and publicly interpretable; in this setting it could include the data reported in physician surveys. Soft information, as in a "cheap talk" (Crawford and Sobel, 1982), includes aspects of the service that are not verifiable or interpretable, such as the "difficulty" or "complexity" of a service relative to another. The specialty society can produce and transmit both hard and soft information about θ to the RUC as the intermediary in decision-making.

---

[24]We do not investigate other mechanisms, such as the difficulty in raising prices for common procedures, that may depress prices for office visits and therefore non-procedural specialties like internal medicine (Bodenheimer et al., 2007).

When the government chooses the composition of the RUC, it can choose members that are more or less *affiliated* with the proposer. The degree of bias in price-setting and the quality of information will depend on this affiliation or closeness between the RUC and the speciality society. We use the model to analyze information extraction when affiliation involves bias (i.e., a more affiliated RUC has preferences closer to the specialty society than to those of the government). Although affiliation may also imply shared information, this without bias would not lead to greater prices in favor of the specialty.[25]

5.1 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 uniformly lies on a subinterval of length L (i.e., $\theta \sim U\left(\underline{\theta}, \overline{\theta}\right)$, $L \equiv \overline{\theta} - \underline{\theta} \in [0, 1]$), via a technology that comes at cost $c\left(L\right)$.[26] $c\left(1\right) = 0$, $c'\left(L\right) < 0$, and $c''\left(L\right) > 0$.

3. The specialty observes θ.

4. The specialty transmits a cheap talk message m about θ.

5. The RUC sets price p. Non-transferrable payoffs are as follows for the specialty (u_S), RUC (u_R), and the government (u_G):

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

---

[25] In a simple model with no RUC bias, the average of the *ex post* realization of prices in equilibrium should equal the *ex ante* expectation of θ, regardless of the amount of information the RUC may have. In a more complex world with institutions or policy uncertainty, however, asymmetric expertise may imply *rents*, which instead predict *lower* prices with greater information in an unbiased RUC (Callander, 2008).

[26] In this exposition, we treat $\overline{\theta} - \underline{\theta}$ as known and assert that $\theta \sim U\left(\underline{\theta}, \overline{\theta}\right)$. However, this is not technically correct for all values of L. In Appendix A-4.4, we discuss a complication that considers $\overline{\theta} - \underline{\theta}$ as random, i.e., $L = E\left[\overline{\theta} - \underline{\theta}\right]$, which allows θ to remain uniformly distributed in the posterior interval. Neither the uniform distribution of θ nor fixed $\overline{\theta} - \underline{\theta}$ is required for the intuition of this model.

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, the way that bias b_S and b_R enter into the specialty and RUC utilities, respectively, reflects that even though these agents may prefer higher or lower prices than the government, neither prefers to raise or lower prices without bound.[27]

5.2 Comparative Statics

We consider the comparative statics of changing the RUC's bias, b_R. First, we consider the case where all information is soft and talk is cheap; there is no possible production of hard information (i.e., $L = 1$ regardless). In this world, we find the same results as discussed in Dessein (2002): when the government chooses a more biased RUC, with b_R close to b_S, the expected price will increase with b_R, but the information loss is lower. That is, increasing b_R (i.e. decreasing $b = b_S - b_R$) reduces $E\left[(\theta + b_R - p)^2\right]$. In words, when the intermediary is more biased, with preferences closer aligned to the specialty society, the soft information content of communication between the specialty sender and the RUC receiver improves. Depending on b_S, government utility is maximized at some $b_R^* \in [0, b_S]$. If b_S is sufficiently large, then $b_R^* = 0$; if b_S is sufficiently small, then $b_R^* = b_S$. But it is never optimal to have $b_R^* < 0$ or $b_R^* > b_S$, because this worsens both bias and communication.

Second, closer to our institutional setting, we also allow the specialty to produce *hard information* in the following sense: With verifiable evidence, the specialty may reduce the space $[\underline{\theta}, \overline{\theta}]$ to length $L < 1$, and such evidence eliminates the need for communicating a service's value credibly through soft channels. In Appendix A-4, we analyze the cheap talk game formally and provide the upstream comparative statics of the equilibrium hard information L^* and the optimal bias b_R^*. Intuitively, hard information is most valuable when soft communication is least feasible, such as in settings in which the RUC and specialty proposer have divergent preferences. This implies that greater $b = b_S - b_R$, meaning greater distance in preferences between the RUC and the specialty, induces the specialty to produce more hard information. Since hard information

---

[27]This 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.

increases the government's utility, the optimal RUC has preferences closer to the government's (b_R^* is closer to 0) when hard information is easier to produce. As the technology to produce hard information improves (i.e., $c(L)$ becomes smaller), the optimal b_R^* moves closer to 0.[28] In Figure 10, we illustrate this relationship between welfare (government expected utility) and b_R, letting the cost of hard information, $c(L)$, vary.

In summary, our model predicts that higher affiliation will allow better communication of soft information between the specialty and the RUC. Hard information provision, by contrast, decreases with affiliation. Thus, the overall information content of prices at different levels of affiliation depends on how much each type of information adjusts. When the cost (or feasibility) of producing hard information for the committee falls, the degree of affiliation that maximizes information extraction will decrease. We look for evidence of these comparative statics on information in our empirical setting.

6 Affiliation Effect on Hard Information

We start our empirical assessment of information quality by examining effect of affiliation on the provision of hard information. Our setting is well suited for investigating this general mechanism, as hard information – usually difficult to quantify by the econometrician – can be summarized here using the survey data reported by specialties and observed in our data. As described in Section 2, when specialties propose a new relative value, they argue for higher prices by presenting survey evidence about the work involved in delivering a service, particularly the time involved (Zuckerman et al., 2016; Burgette et al., 2016). 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. However, the act of surveying physicians can also be costly to specialty societies.

Thus, we use log counts of physicians involved in the survey as our measure of hard information. Specifically, we consider the survey sample size and the number of respondents, both total for a proposal (potentially across more than one specialty in a coalition) and per specialty.

---

[28]In Appendix A-4, we show that it is never optimal to have $b_R < 0$. Under hard information, this derives from three necessary conditions: (i) the threshold $\bar{b}_R$ where the specialty is indifferent between $n = 1$ and $n = 2$ must be less than 0; (ii) $E\left[u_G | b_R = \bar{b}_R\right] > \max E\left[u_G | n = 2\right]$; and (iii) $E\left[u_G | b_R = \bar{b}_R\right] > E\left[u_G | b_R = b_S\right]$.

While the total surveyed information is obviously relevant from the perspective of the RUC, there are mechanical rules that require specialties to survey a minimum number of physicians, conditional on surveying (American Medical Association, 2017). Therefore, to assess quantiatively a specialty's decision to scale survey size on the intensive margin, we also consider the effect of affiliation on per-specialty hard information.

We estimate the affiliation effect on hard information measure H_{it} with this regression:

$$\ln H_{it} = \alpha A\left(R_t, S_i\right) + \mathbf{X}_i\beta + \mathbf{T}_t\eta + \mathbf{w}_i\zeta + \varepsilon_{it}, \tag{7}$$

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

$$\ln H_{it} = \alpha A\left(R_t, S_i\right) + \mathbf{X}_i\beta + \gamma_n\mathbf{1}\left(\|S_i\| = n\right) + \mathbf{T}_t\eta + \mathbf{w}_i\zeta + \varepsilon_{it}. \tag{8}$$

Since the per-specialty hard information is $\ln\left(H_{it}/\|S_i\|\right) = \ln H_{it} - \ln\|S_i\|$, estimates of α in Equation (8) do not depend on whether H_{it} is a total or per-specialty measure.

We present results in Table 4. Total measures of both survey sample and respondents show positive but statistically insignificant responses to affiliation. The positive sign we find appears driven by the rule that proposals with more specialties have larger surveys. We thus focus on the remaining columns in the table based on per-specialty survey measures. We see strong negative effects: in our preferred specification, in Column 3, 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 11 shows these results in a binned scatterplot of residual log survey counts against residual set affiliation. The negative effect persists even when controlling for within-proposer-count variation, shown in Column 4 of Table 4, although the effect is no longer statistically significant for the outcome of survey respondents.

7   Soft Information via Coalitions

Measuring the value of soft information poses an empirical challenge, since the nature of soft information is that it is not easily quantifiable. Intuitively, however, soft information plays a key role in committee decision-making (Li et al., 2001). In the extreme, if all information were "hard," in the sense that it could be deciphered and believed by anyone, then committee deliberation would be unnecessary (Dewatripont and Tirole, 2005). In this section, we show empirical support for the role of soft information by studying the likelihood of a specialty to be on a proposal as a function of its effect on set affiliation. If RUC members will vote based on interests and beliefs independent of the identity of the proposers, then the affiliation between proposing specialties and the RUC should not matter, holding the service fixed.

In contrast, in the framework of cheap talk communication, the *identity of the proposer* fundamentally matters for any receiver to interpret a message with soft information. In particular, if a message is sent by an agent with more aligned preferences, then it is more informative, and the payoffs to both the sender and the receiver increase. Kessler and Krehbiel (1996) explore this idea in the setting of legislative co-sponsorship, and a newer literature provides evidence that lobbyists are more valued when they have connections with the politicians they are lobbying (Blanes i Vidal et al., 2012; Bertrand et al., 2014), which suggests the importance of credible messengers in high-stakes communication (Hirsch and Montagnes, 2015).

We test whether specialties are more likely to propose in a coalition if they increase affiliation with the RUC. We condition on a proposal being a coalition (i.e., $\|S_i\| > 1$) and examine whether each specialty s out of 64 possible specialties is more likely to be part of S_i depending on the effect its presence has on the proposal's set affiliation with the RUC. We form a measure of set affiliation *value-added*,

$$
V_s\left(R_t, S_i\right) = \begin{cases} A\left(R_t, S_i\right) - A\left(R_t, S_i \setminus s\right), & s \in S_i \\ A\left(R_t, S_i^- \cup s\right) - A\left(R_t, S_i^-\right), & s \notin S_i \end{cases},
\tag{9}
$$

which compares affiliation under a proposing set that includes s with affiliation under a proposing set that does not include s. If $s \in S_i$, this affiliation comparison is straightforward; if $s \notin S_i$,

we randomly delete a specialty in S_i, calling the new proposing set S_i^-, and compare affiliation under $S_i^- \cup s$ and under S_i^-.

Given measures of affiliation value-added $V_s(R_t S_i)$ for each s and i, we then estimate a logit model of specialty proposal:

$$U_{ist} = \alpha V_s(S_i, R_t) + \beta \mathbf{X}_{ist} + \gamma_s + \nu_i + \varepsilon_{ist}. \tag{10}$$

U_{ist} is the latent utility of specialty s being on proposal i at meeting t, such that $s \in S_i$ if $U_{ist} > 0$. $\mathbf{X}_{ist}$ are characteristics of service i for specialty s at meeting t, such as the revenue share of i for s at t, the volume of share i for s at t, and other characteristics of the service i. We allow for specialty fixed effects γ_s to reflect that certain specialties may have lower costs or other factors that lead to systematic differences in participation. We also include potential random effects for i to account for further heterogeneity. ε_{ist} is a logit type I extreme value error term.

As shown in Table 5, we find a positive relationship between the affiliation value-added and the specialty's likelihood of proposing. The average affiliation value-added across specialties (among the set of proposals with $\|S_i\| > 1$) is 0.44 to 0.46, or about half of the standard deviation of set affiliation across proposals. The effect of affiliation value-added on the decision of a specialty to propose is robust to including specialty fixed effects, service characteristics, and proposal random effects. In summary, increasing affiliation value-added by 1 standard deviation would increase the probability of proposal by 0.95 to 1.28 percentage points from a base of 4.42 to 4.76 percentage points, depending on the sample and model. Reducing affiliation value-added to 0 would reduce the probability of proposal by 0.70 to 0.93 percentage points. We interpret these findings as evidence that specialties respond to the effect their presence will have on affiliation, and as evidence suggestive of the importance of soft information on the RUC's decisions.

8 Price Transmission to Private Insurance

As a final analysis, we examine the extent to which price changes in Medicare prices are transmitted as changes in private insurance prices, as a function of the source of the Medicare price and the affiliation of the proposal that led to a given RUC price. Recent research has documented

strong price following from Medicare to private insurance prices that is nevertheless heteroge-neous across settings (Clemens and Gottlieb, 2017; Clemens et al., 2017). This literature notes two potential mechanisms behind price following: Medicare may serve as an outside option in bargaining between private insurers and physicians, but Medicare also provides a "knowledge standard" with information content.

Given our conceptual framework and our evidence that affiliation is relevant for the transmis-sion of both hard and soft information, we focus on the latter mechanism and view our analysis primarily as a test of the overall informational content of Medicare prices.[29] If Medicare price changes are followed purely because they are a bargaining benchmark, then the degree to which they are followed should not depend on their source and, particularly, the affiliation of a pro-posal to the RUC.[30] Secondarily, we will assess whether Medicare price changes are uniformly discounted as a function of affiliation, which sheds some light on the commitment assumed in our conceptual framework. If the government undoes bias from high-affiliation RUC decisions, then informational advantages from communication will in general be nullified (Ambrus et al., 2013); private insurance is subject to no such commitment.

To carry out our test, we construct private and Medicare prices by dividing total charges by total number of claims observed in MarketScan and Medicare data for a given procedure code in a given year. In order to allow for lagged price transmission to private insurance, we normalize log prices to have a frequency-weighted mean of 0 within payer (private or Medicare) and year, and we then match private prices for each code i and year y to a Medicare price for the same code in the year $y^M(i,y) \in \{y, y-1, y-2\}$ with the closest log price change:

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

where $\Delta \ln \text{Price}_{i,y}^P \equiv \ln \text{Price}_{i,y}^P - \ln \text{Price}_{i,y-1}^P$ is a change in the normalized log private prices

---

[29]We do not require that the origin of the Medicare price changes, particularly affiliation between specialty proposers and the RUC, is fully transparent to private insurance companies. A private insurance company may assess the quality of price-change "rationales" published by the RUC via Medicare. Alternatively, the company may conduct its own investigation into the value of a service after a Medicare price change and independently agree with high-affiliation RUC price changes more often.

[30]Medicare prices with greater informational content may of course provide a stronger bargaining benchmark. This analysis will assign this effect to evidence of information.

for service i in year y, and $\Delta \ln \text{Price}_{i,y}^{M}$ is the analogous Medicare log price change.

We then estimate variants of the following regression to assess average price transmission:

$$\ln \text{Price}_{i,y}^{P} = \beta \ln \text{Price}_{i,y^{M}(i,y)}^{M} + \mathbf{T}_{iy}\eta + \xi_{i} + \varepsilon_{iy}, \tag{11}$$

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 further estimate pooled regressions across categories of Medicare prices:

$$\ln \text{Price}_{iy}^{P} = \sum_{C} \left(\alpha_{C} + \beta_{C} \ln \text{Price}_{i,y^{M}(i,y)}^{M} \right) \cdot \mathbf{1} \left(C(i,y) = C \right) + \mathbf{T}_{iy}\eta + \xi_{i} + \varepsilon_{iy}, \tag{12}$$

where C references one of three categories of Medicare price by source – (i) Medicare prices for a code in a year with an associated RUC decision and an above-median proposal affiliation, (ii) prices with a RUC decision and a below-median proposal affiliation, and (iii) prices not associated with a RUC decision.

The vast majority of Medicare prices fall in the last category, but as shown in Figure A-2, prices associated with RUC decisions represent larger changes from the price in the previous year, as opposed to prices not associated with RUC decisions. Medicare average price changes with no associated RUC recommendation in our dataset may occur for a variety of reasons, including changes in the geographic composition of claims, changes in the facility vs. non-facility composition of claims, conversion factor adjustments, and changes in the practice expense component of RVUs alone. To facilitate closer comparison of the "non-RUC" and "RUC" Medicare prices in the pooled regressions, we restrict attention to non-RUC log price changes of at least 0.3 in absolute value.

In Table 6, our estimates suggest that private prices follow RUC-based Medicare prices to a much larger extent than non-RUC Medicare prices. Estimating Equation (11) separately for RUC and non-RUC Medicare prices and including service fixed effects shows this result most starkly. Within procedure code, log price changes in Medicare originating from the RUC are

transmitted to private insurance with a coefficient of 0.892 (Column 1), while those that have no associated RUC recommendation are transmitted with a coefficient of 0.399 (Column 3) or 0.300 (Column 4), depending on whether the sample includes all non-RUC changes or is restricted to larger changes of 0.3 log points, respectively. Further RUC-based Medicare prices originating from high-affiliation proposals show slightly higher following than those from low-affiliation proposals.[31]

Figure 12 shows pooled results, both without and with service fixed effects, corresponding to Columns 1 and 6 of Table 6. 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.[32] In addition to steeper slopes, the lines are generally lower in levels for RUC Medicare prices (and further for those from high-affiliation proposals). Uniformly lower private insurance price changes corresponding to RUC prices, particularly those from high-affiliation proposals, suggest that private insurance may, to an extent, reverse the bias induced by affiliation.

9 Conclusion

We find evidence of bias or regulatory capture in Medicare's price setting process. Increasing affiliation between the specialties proposing a value and the RUC from the 10th to the 90th percentile would result in a 17% higher price. However, we also find that involving a committee of physicians in price-setting can increase the quality of information used in price-setting. Examining members of proposal coalitions, we find that the identity of proposers matters, suggesting the communication of soft information improves with affiliation. Further, by comparing private prices with public prices, we find patterns suggesting that private insurers follow Medicare prices

---

[31]We also analyze this question in a specification with private log price changes regressed on Medicare log price changes and find similar results. As shown in Figure A-3, high-affiliation RUC price changes result in steeper private price changes than low-affiliation RUC price changes. This result is robust to adding controls.

[32]On their own, these results are only suggestive of better information from high-affiliation proposals *through communication*. It is also possible that the RUC may have more information on high-affiliation decisions, even without communication. We address this possibility in Appendix Table A-5 by using proxy measures of the RUC members' own information, based on their own utilization of the service in question, and find that price transmission remains higher for high-affiliation decisions after controlling for these proxy measures, both directly and interacted with Medicare prices.

more closely when the public prices originate from a RUC vote. The private sector appears to adjust download in levels for bias in the RUC's recommendations, but nonetheless reacts more strongly in terms of slope to price changes from more highly affiliated RUC votes.

Our findings suggest Medicare faces a difficult balancing act in setting prices. Inviting input from the RUC improves the information extracted from specialty proposers, but may introduce bias in prices. We show in counterfactuals how undoing this bias, either by equalizing affiliation or by changing the RUC's membership, reallocates revenue across specialties and creates winners and losers within medicine. These analyses, however, ignore likely quantity effects from price changes, which generate real welfare effects beyond simple transfers in revenue. To the extent physicians are imperfect agents for their patients and deviate toward procedures with greater reinbursement levels (Clemens and Gottlieb, 2014; Gruber et al., 1999), and if physicians-in-training avoid specializing in fields with lower procedural income, the RUC's price setting has consequences for the provision of health care.

References

Acemoglu, D., G. Egorov, and K. Sonin (2008): "Coalition Formation in Non-Democracies," *Review of Economic Studies*, 75, 987–1009.

Aghion, P. and J. Tirole (1997): "Formal and real authority in organizations," *The Journal of Political Economy*, 105, 1–29.

Altonji, J. G., T. E. Elder, and C. R. Taber (2005): "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," *Journal of Political Economy*, 113, 151–184.

Ambrus, A., E. Azevedo, and Y. Kamada (2013): "Hierarchical cheap talk - Ambrus - 2013 - Theoretical Economics - Wiley Online Library," *Theoretical Economics*, 8, 233–261.

American Medical Association (2014): *AMA/Specialty Society RVS Update Process*, Chicago: AMA.

——— (2015): *The Physicians' Guide: Medicare RBRVS*, Chicago: AMA.

———— (2017): *AMA/Specialty Society RVS Update Process*, Chicago: AMA.

ASSOCIATION OF AMERICAN MEDICAL COLLEGES (2016): "Physician Specialty Data Report," Tech. rep., Washington, DC.

AUSTEN-SMITH, D. (1994): "Strategic Transmission of Costly Information," *Econometrica*, 62, 955.

BERENSON, R. A. AND J. D. GOODSON (2016): "Finding Value in Unexpected Places: Fixing the Medicare Physician Fee Schedule," *New England Journal of Medicine*, 374, 1306–1309.

BERTRAND, M., M. BOMBARDINI, AND F. TREBBI (2014): "Is It Whom You Know or What You Know? An Empirical Assessment of the Lobbying Process," *American Economic Review*, 104, 3885–3920.

BLANES I VIDAL, J., M. DRACA, AND C. FONS-ROSEN (2012): "Revolving Door Lobbyists," *American Economic Review*, 102, 3731–3748.

BODENHEIMER, T., R. A. BERENSON, AND P. RUDOLF (2007): "The Primary Care-Specialty Income Gap: Why It Matters," *Annals of Internal Medicine*, 146, 301–306.

BRAEUTIGAM, R. R. AND J. C. PANZAR (1993): "Effects of the Change from Rate-of-Return to Price-Cap Regulation," *The American Economic Review*, 83, 191–198.

BROWN, M. B. (2009): "Federal advisory committees in the United States: A survey of the political and administrative landscape," in *Scientific Advice to Policy Making: International Comparison*, Opladen, Germany, and Farmington Hills, MI: Verlag Barbara Budrich., 17–39.

BURGETTE, L. F., A. W. MULCAHY, A. MEHROTRA, T. RUDER, AND B. O. WYNN (2016): "Estimating Surgical Procedure Times Using Anesthesia Billing Data and Operating Room Records," *Health Services Research*.

CABRAL, L. M. AND M. H. RIORDAN (1989): "Incentives for cost reduction under price cap regulation," *Journal of Regulatory Economics*, 1, 93–102.

CALLANDER, S. (2008): "A Theory of Policy Expertise," *Quarterly Journal of Political Science*, 3, 123–140.

CALVERT, R. L. (1985): "The Value of Biased Information: A Rational Choice Model of Political Advice," *The Journal of Politics*, 47, 530–555.

CAMARA, F. AND M. KYLE (2017): "Experts and Financial Ties: Evidence from FDA Advisory Committees," Tech. rep., University of Southern California.

CENTERS FOR MEDICARE AND MEDICAID SERVICES (2014): "Estimated Sustainable Growth Rate and Conversion Factor, for Medicare Payments to Physicians in 2015," Tech. rep.

CLEMENS, J. AND J. D. GOTTLIEB (2017): "In the Shadow of a Giant: Medicare's Influence on Private Physician Payments," *Journal of Political Economy*, 125, 1–39.

CLEMENS, J., J. D. GOTTLIEB, AND T. L. MOLNAR (2017): "Do health insurers innovate? Evidence from the anatomy of physician payments," *Journal of Health Economics*, Forthcoming.

CLEMENS, J. P. AND J. D. GOTTLIEB (2014): "Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health?" *American Economic Review*, 104, 1320–1349.

CLOUGH, J. D. AND M. MCCLELLAN (2016): "Implementing MACRA: Implications for Physicians and for Physician Leadership," *JAMA*, 315, 2397.

CRAWFORD, V. P. AND J. SOBEL (1982): "Strategic information transmission," *Econometrica*, 50, 1431–1451.

DELLAVIGNA, S., R. DURANTE, B. KNIGHT, AND E. LA FERRARA (2016): "Market-Based Lobbying: Evidence from Advertising Spending in Italy," *American Economic Journal: Applied Economics*, 8, 224–256.

DESSEIN, W. (2002): "Authority and Communication in Organizations," *Review of Economic Studies*, 69, 811–838.

DEWATRIPONT, M. AND J. TIROLE (1999): "Advocates," *Journal of Political Economy*, 107, 1–39.

——— (2005): "Modes of Communication," *Journal of Political Economy*, 113, 1217–1238.

FANG, H. AND Q. GONG (2017): "Detecting Potential Overbilling in Medicare Reimbursement via Hours Worked," *American Economic Review*, 107, 562–591.

FERGUSON, T. AND H.-J. VOTH (2008): "Betting on Hitler: The Value of Political Connections in Nazi Germany," *Quarterly Journal of Economics*, 123, 101–137.

FISMAN, R. (2001): "Estimating the Value of Political Connections," *American Economic Review*, 91, 1095–1102.

GILLIGAN, T. W. AND K. KREHBIEL (1989): "Asymmetric Information and Legislative Rules with a Heterogeneous Committee," *American Journal of Political Science*, 33, 459.

GRANOVETTER, M. (1973): "The Strength of Weak Ties," *American Journal of Sociology*, 78, 1360–1380.

GROSSMAN, G. M. AND E. HELPMAN (2001): *Special Interest Politics*, MIT Press, google-Books-ID: B70omthxalQC.

GRUBER, J., J. KIM, AND D. MAYZLIN (1999): "Physician fees and procedure intensity: the case of cesarean delivery," *Journal of Health Economics*, 18, 473–490.

HIRSCH, A. V. AND B. P. MONTAGNES (2015): "The Lobbyist's Dilemma: Gatekeeping and the Profit Motive," Tech. rep., California Institute of Technology.

HIRSCH, A. V. AND K. W. SHOTTS (2015): "Competitive Policy Development," *American Economic Review*, 105, 1646–64.

HO, K. (2009): "Insurer-Provider Networks in the Medical Care Market," *The American Economic Review*, 99, 393–430.

HO, K. AND R. S. LEE (2017): "Insurer Competition in Health Care Markets," *Econometrica*, 85, 379–417.

HSIAO, W. C., P. BRAUN, D. DUNN, AND E. R. BECKER (1988): "Resource-based relative values. An overview," *JAMA*, 260, 2347–2353.

KESSLER, D. AND K. KREHBIEL (1996): "Dynamics of Cosponsorship," *The American Political Science Review*, 90, 555.

KHWAJA, A. I. AND A. MIAN (2005): "Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market," *The Quarterly Journal of Economics*, 120, 1371–1411.

LAUGESEN, M. J. (2016): *Fixing Medical Prices*, Harvard University Press.

LAUGESEN, M. J., R. WADA, AND E. M. CHEN (2012): "In Setting Doctors' Medicare Fees, CMS Almost Always Accepts The Relative Value Update Panel's Advice On Work Values," *Health Affairs*, 31, 965–972.

LEWIS, M. S. AND K. E. PFLUM (2015): "Diagnosing Hospital System Bargaining Power in Managed Care Networks," *American Economic Journal: Economic Policy*, 7, 243–274.

LI, D. (2017): "Expertise versus Bias in Evaluation: Evidence from the NIH," *American Economic Journal: Applied Economics*, 9, 60–92.

LI, H., S. ROSEN, AND W. SUEN (2001): "Conflicts and Common Interests in Committees," *American Economic Review*, 91, 1478–1497.

MCCALL, N., J. CROMWELL, AND P. BRAUN (2006): "Validation of physician survey estimates of surgical time using operating room logs," *Medical Care Research and Review*, 63, 764–777.

NICHOLSON, S. AND N. SOULELES (2001): "Physician Income Expectations and Specialty Choice," Tech. Rep. w8536, National Bureau of Economic Research, Cambridge, MA.

PEAR, R. (2015): "Federal Investigators Fault Medicare's Reliance on Doctors for Pay Standards," *The New York Times*.

PELTZMAN, S. (1976): "Toward a More General Theory of Regulation," *The Journal of Law and Economics*, 19, 211–240.

ROSENTHAL, E. (2014): "Patients' Costs Skyrocket; Specialists' Incomes Soar," *The New York Times*.

SHAPLEY, L. S. AND M. SHUBIK (1954): "A Method for Evaluating the Distribution of Power in a Committee System." *American Political Science Review*, 48, 787–792.

SINSKY, C. A. AND D. C. DUGDALE (2013): "Medicare Payment for Cognitive vs Procedural Care: Minding the Gap," *JAMA Internal Medicine*.

STIGLER, G. J. (1971): "The Theory of Economic Regulation," *The Bell Journal of Economics and Management Science*, 2, 3.

VON NEUMANN, J. AND O. MORGENSTERN (1944): *Theory of Games and Economic Behavior*, Princeton University Press.

WHORISKEY, P. AND D. KEATING (2013): "How a secretive panel uses data that distorts doctors' pay," *Washington Post*.

WYNN, B. O., L. F. BURGETTE, A. W. MULCAHY, E. N. OKEKE, I. BRANTLEY, N. IYER, T. RUDER, AND A. MEHROTRA (2015): "Development of a Model for the Validation of Work Relative Value Units for the Medicare Physician Fee Schedule," Research Report, RAND Corporation.

ZINOVYEVA, N. AND M. BAGUES (2015): "The Role of Connections in Academic Promotions," *American Economic Journal: Applied Economics*, 7, 264–292.

ZUCKERMAN, S., K. MERRELL, R. A. BERENSON, S. MITCHELL, D. UPADHYAY, AND R. LEWIS (2016): "Collecting Empirical Physician Time Data: Piloting an Approach for Validating Work Relative Value Units," Tech. rep., Urban Institute.

Table 1: Specialty Seats on the RUC

Specialty	Meetings	Specialty	Meetings
Anesthesiology	67	Ophthalmology	67
Cardiology	67	Orthopedic Surgery	67
Colorectal Surgery	6	Osteopathic Medicine	66
Dermatology	67	Otolaryngology	67
Emergency Medicine	67	Pathology	67
Family Medicine	67	Pediatric Surgery	24
Gastroenterology	20	Pediatrics	67
General Surgery	67	Plastic Surgery	67
Geriatrics	34	Psychiatry*	67
Hand Surgery	6	Pulmonary Medicine	18
Infectious Disease	12	Radiation Oncology	5
Internal Medicine*	67	Radiology*	67
Nephrology	7	Rheumatology	17
Neurology	54	Thoracic Surgery	67
Neurosurgery	66	Urology	67
Obstetrics and Gynecology	66	Vascular Surgery	18
Oncology	16		

Note: This table shows the numbers meetings during which a specialty had a member on the RUC. There is a total of 67 meetings in our data. * denotes specialties that had two seats at some meetings. Internal medicine, psychiatry, and radiology had two seats at 33, 6, and 6 meetings, respectively. Psychiatry had two seats when both psychiatry and child psychiatry specialty societies had seats at the same meeting. Radiology had two seats when both radiology and nuclear medicine had seats at the same meeting.

Table 2: Balance in Medicare Beneficiary Characteristics

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

Note: 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 $\mathbf{w}_i$. In each cell, we present averages of this residual, conditional on either above- or below-mean affiliation, adding back unconditional mean to aid in interpretation. Standard deviations of each residualized characteristic are given in parentheses. The last column lists the p-value for null hypothesis that the average residual characteristic is not significantly different between samples corresponding to above- and below-mean affiliation.

Table 3: Affiliation Effect on Prices

	(1)	(2)	(3)	(4)	(5)
	Log RVU				
Normalized set affiliation	0.158***	0.118***	0.108***	0.101***	0.102***
	(0.027)	(0.023)	(0.033)	(0.029)	(0.035)
Prior log RVU	Y	Y	Y	Y	Y
Medicare beneficiary	N	Y	Y	Y	Y
Surveyed characteristics	N	N	Y	Y	Y
CPT code description	N	N	N	Y	Y
Specialty shares	Y	Y	Y	Y	N
Predicted set affiliation	N	N	N	N	Y
Meeting fixed effects	Y	Y	Y	Y	Y
N	4,401	4,401	4,401	4,401	4,387
Adjusted R-squared	0.754	0.792	0.889	0.891	0.873
Sample mean log RVU	1.567	1.567	1.567	1.567	1.571

Note: This table shows results of regressions of log RVU on normalized set affiliation, as stated in Equation (6). Medicare beneficiary indicates average characteristics of Medicare beneficiaries who receive the service (CPT code); surveyed characteristics includes total utilization, surveyed time intervals, difficulty of the procedure, and office visits or other E&M CPT codes bundled into the code; and CPT code description indicates word stems predictive of RVUs, as selected by LASSO. Specialty shares $\mathbf{w}_i$ are defined in Equation (5) and are controlled for linearly in Columns 1 to 4. Standard errors, clustered by RUC meeting, are in parentheses; *** denotes significance at the 1% level.

Table 4: Affiliation Effect on Hard Information

	(1)	(2)	(3)	(4)
	Panel A: Log Survey Sample			
Count type	Total	Proposer	Proposer	Proposer
Normalized set affiliation	0.122	-0.228***	-0.332***	-0.146**
	(0.081)	(0.071)	(0.076)	(0.070)
Baseline controls	Y	Y	Y	Y
Utilization among proposers	Y	N	Y	Y
Proposer count dummies	N	N	N	Y
N	4,219	4,407	4,219	4,219
Adjusted R-squared	0.363	0.329	0.332	0.348
Sample mean outcome	4.966	4.660	4.619	4.619
	Panel B: Log Respondents			
Count type	Total	Proposer	Proposer	Proposer
Normalized set affiliation	0.040	-0.219***	-0.413***	-0.082
	(0.047)	(0.076)	(0.049)	(0.055)
Baseline controls	Y	Y	Y	Y
Utilization among proposers	Y	N	Y	Y
Proposer count dummies	N	N	N	Y
N	4,219	4,407	4,219	4,219
Adjusted R-squared	0.272	0.220	0.253	0.304
Sample mean outcome	3.419	3.067	3.071	3.071

Note: This table shows results of regressions of survey measures of hard information on normalized set affiliation. Survey sample regressions are shown in Panel A, and survey respondent regressions are shown in Panel B. Based on Equation (7), Column 1 reports results for total survey measures summed over potentially more than one proposing specialty, while Columns 2 and 3 consider the corresponding per-specialty measures, constructed by dividing the total survey measures by the number of proposing specialties. Column 4 includes dummies for the proposing specialty count, i.e., $\gamma_n \mathbf{1}(\|S_i\| = n)$, as stated in Equation (8). Baseline controls, in Column 2, are the same as in Column 5 of Table 3. In addition, other columns 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. Standard errors, clustered by RUC meeting, are in parentheses; ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 5: Affiliation Effect on Proposals

|	(1)	(2)	(3)	(4)
	Probability of Specialty in Proposal ($s \in S_i$)			
Baseline model probability (in p.p.)	4.42	4.76	4.76	4.63
	(4.37, 4.46)	(4.72, 4.81)	(4.72, 4.81)	(4.60, 4.65)
Panel A: Higher value-added by 1 s.d.				
Counterfactual probability	5.59	5.71	5.77	5.90
(in p.p.)	(5.45, 5.74)	(5.58, 5.85)	(5.63, 5.91)	(5.65, 6.06)
Absolute change (in p.p.)	1.18	0.95	1.00	1.28
	(1.08, 1.27)	(0.86, 1.04)	(0.91, 1.10)	(1.15, 1.41)
Panel B: No value-added				
Counterfactual probability	3.49	4.06	4.05	3.81
(in p.p.)				
Absolute change (in p.p.)	−0.93	−0.70	−0.71	−0.81
	(−0.97, −0.88)	(−0.75, −0.66)	(−0.75, −0.67)	(−0.86, −0.77)
Specialty utilization, revenue shares	Y	Y	Y	Y
Specialty dummies	N	Y	Y	Y
Service controls	N	N	Y	Y
Proposal random effects	N	N	N	Y
N	96,129	89,110	89,110	89,110
Proposals	1,524	1,524	1,524	1,524
Log likelihood	−7765.77	−5821.33	−5761.47	−5626.74
Sample proposal p.p. probability	4.42	4.76	4.76	4.76
Sample mean value-added	0.44	0.46	0.46	0.46

Note: This table reports changes in specialty proposals under logit models and counterfactual affiliation value-added. The affiliation value-added $V_s(R_t, S_i)$ for specialty s at RUC meeting t and in proposal i is defined by Equation (9) and represents the difference in set affiliation that would result by the specialty being on the proposal vs. not. Each column represents a logit model, generically written as Equation (10), of specialty proposal on affiliation value added. All models control for specialty utilization share w_{is}, defined by (5), and the share of specialty s's revenue that the service in i represents. Service (CPT code) controls represent the full set of controls in Column 5 of Table 3. When controlling for specialty dummies in Columns 2 to 4, we lose observations for specialties that never propose a value to the RUC. Two counterfactual scenarios are considered: In Panel A, we increase affiliation value-added by 1 standard deviation; in Panel B, we set value-added to 0 (equivalent to eliminating the affiliation mechanism of proposals). Probabilities are given as percentage points (p.p.). Model estimates and changes corresponding to the 95% confidence interval of the value-added coefficient are shown in parentheses. Because we set value-added to 0 in Panel B, no confidence intervals are shown.

Table 6: Price Transmission to Private Insurance

|	(1)	(2)	(3)	(4)	(5)
			Log private price		
Log Medicare price	0.892***	0.399***	0.300***		
	(0.091)	(0.003)	(0.012)		
× not RUC				0.688***	0.331***
				(0.016)	(0.022)
× RUC, low affiliation				0.838***	0.520***
				(0.006)	(0.023)
× RUC, high affiliation				0.917***	0.642***
				(0.015)	(0.041)
RUC, high vs. low affiliation				-0.420***	-0.016
				(0.040)	(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
N	3,179	184,910	4,003	7,182	7,182
Adjusted R-squared	0.986	0.987	0.992	0.852	0.987
Sample mean log private price	4.241	3.980	3.391	4.097	4.097
Sample mean log Medicare price	3.466	3.412	2.426	3.290	3.290

Note: This table shows results of regressions of log private price on log Medicare price. Private and Medicare prices are defined as the total charges 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, which is demeaned by the average log private price across CPT codes in a given year that is weighted by 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 CPT code, possibly lagged up to 2 years. 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 1: Committee Seats Over Time
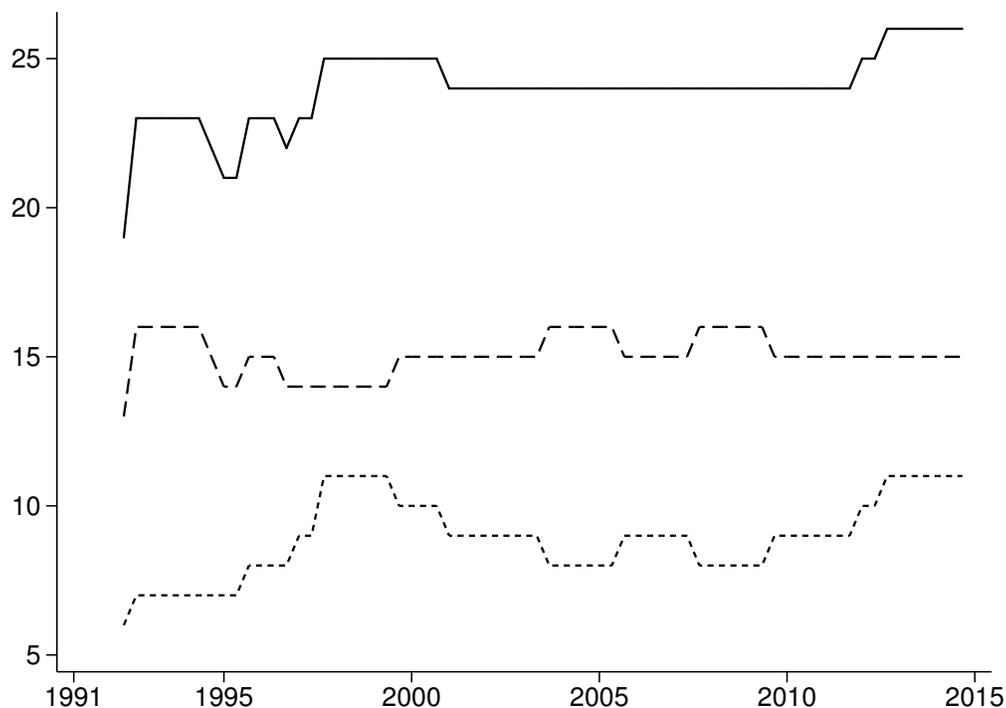
Note: This figures shows the numbers of voting seats on the RUC over time, in total (solid line) and apportioned between "procedural" (dashed line) and "cognitive" (dotted line) specialties. Although the labels "procedural" and "cognitive" have been frequently used to describe specialties and work in the policy debate on the RUC (see, e.g., Berenson and Goodson, 2016), there is no set categorization of specialties according to these labels. Based on conversations with the RUC, we assign the "procedural" label to general surgery, orthopedic surgery, plastic surgery, ophthalmology, pathology, otolaryngology, dermatology, thoracic surgery, radiology, anesthesiology, gastroenterology, urology, cardiology, obstetrics and gynecology, neurosurgery, pediatric surgery, vascular surgery, radiation oncology, hand surgery, and colorectal surgery. We assign the "cognitive" label to emergency medicine, internal medicine, psychiatry, pediatrics, family medicine, osteopathic medicine, geriatrics, neurology, rheumatology, pulmonary medicine, oncology, infectious disease, and nephrology.

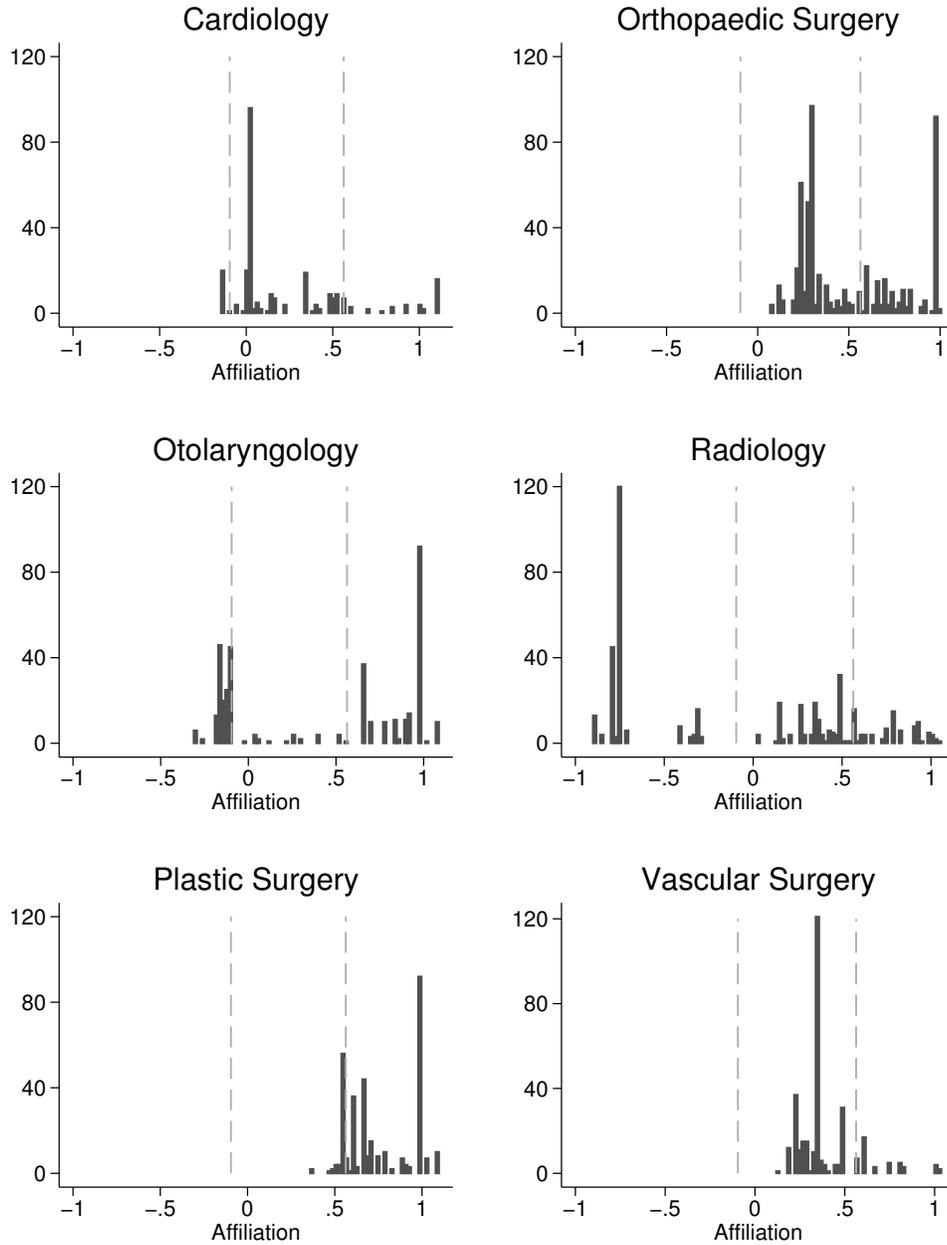Figure 2: Affiliation Between Specialties
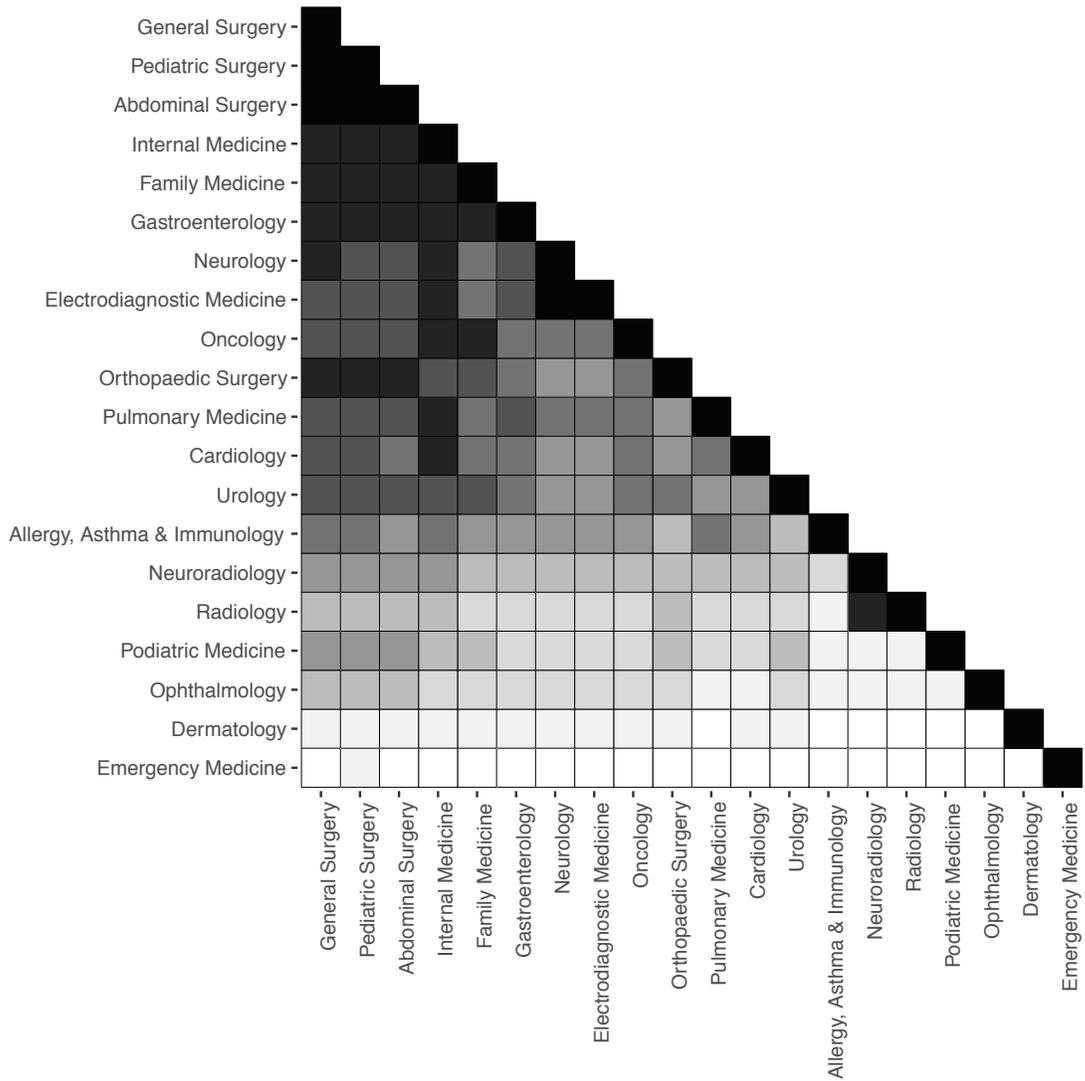
Note: This figure illustrates affiliation between specialties, where the particular formula used is a negative Euclidean distance, described in Equation (3), for the largest 20 specialties. Affiliation values are divided into nine bins with an equal number of specialty pairs. Darker shades signify stronger affiliations.

Figure 3: Random Timing of Proposals
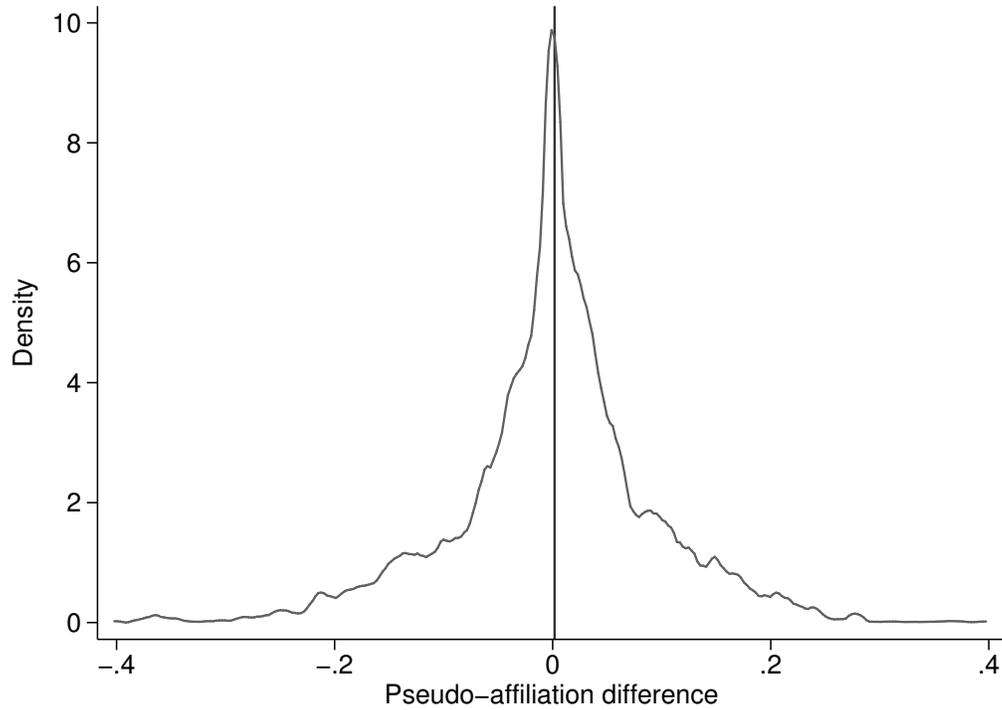
Note: This figure show the distribution of the difference between set affiliation in pseudo-meetings and the actual set affiliation of each proposal. The distribution therefore includes 59 pseudo-affiliation measures corresponding to pseudo-meetings for each of 4,432 proposals. The mean of these observations, 0.0017, is shown with the vertical line. The standard deviation of the distribution is 0.0898, which implies that the standard error of the mean at the proposal level is 0.0013.

Figure 4: Within Specialty Variation in Affiliation

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

Figure 5: Balance of Medicare Beneficiary Characteristics across Affiliation
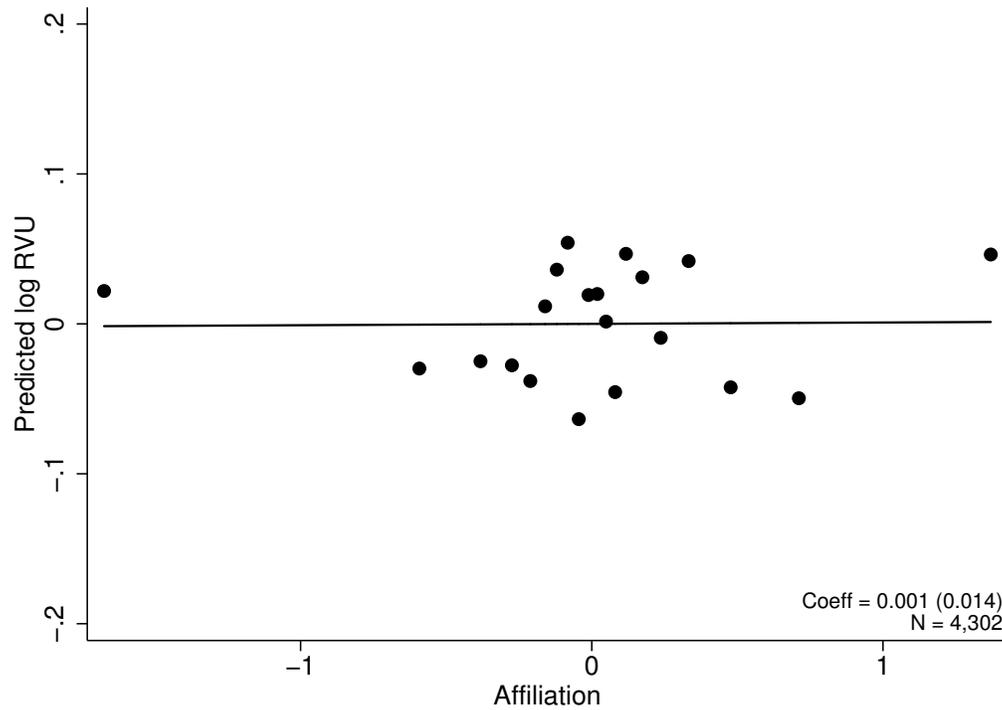
Note: This figure is a binned scatterplot of residual predicted log RVU, based on Medicare beneficiary characteristics, on residual affiliation, where each dot represents 5% of the data, ordered by residual affiliations. Log RVU is first predicted by Medicare beneficiary characteristics, which are listed in 2. 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 $\mathbf{w}_i$. The line shows the best fit through the residualized data, with corresponding coefficient and standard error clustered by meeting.

Figure 6: Balance of Proposal Probability on Predicted Price
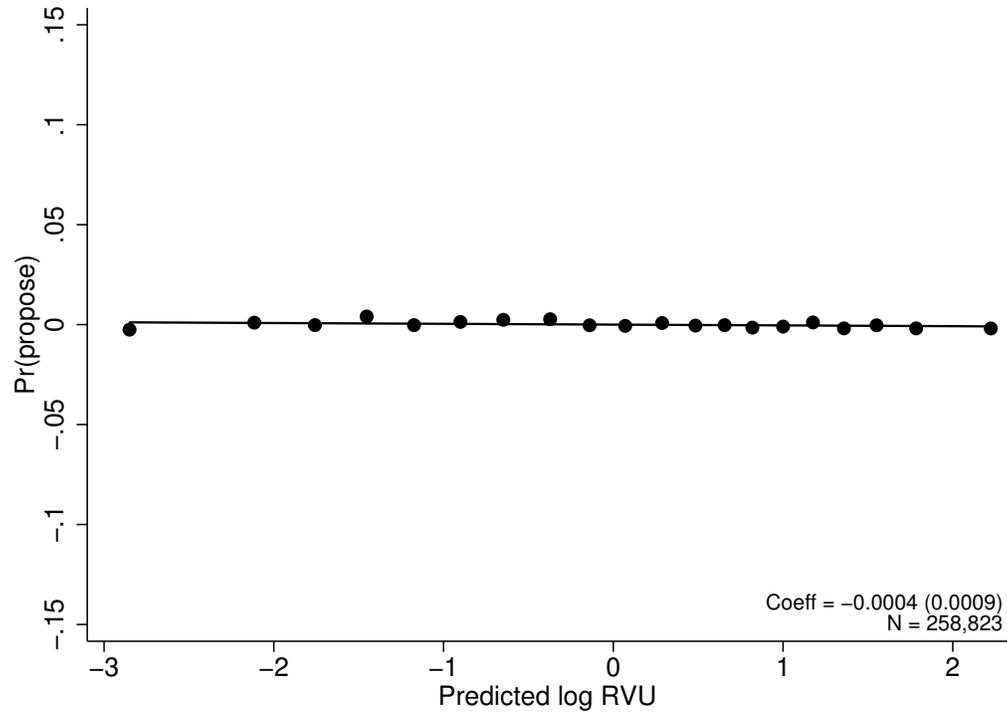
Note: This figure is a binned scatterplot of residual proposal probability on residual predicted log RVU, where each dot represents 5% of the data, ordered by residual predicted log RVU. Each observation is a proposal-specialty combination, and the outcome variable of interest is an indicator for whether 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 3; the prediction equation has an adjusted R-squared of 0.88. The specialty proposal indicator and predicted log RVU are both residualized by the proposal propensity, which is calculated by a logit model of flexible functions of $\mathbf{w}_i$ alone. This propensity model has a pseudo-R-squared of 0.67. The standard deviation of the proposal propensities across proposal-specialty pairs is 0.13, 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 7: Affiliation Effect on Relative Price
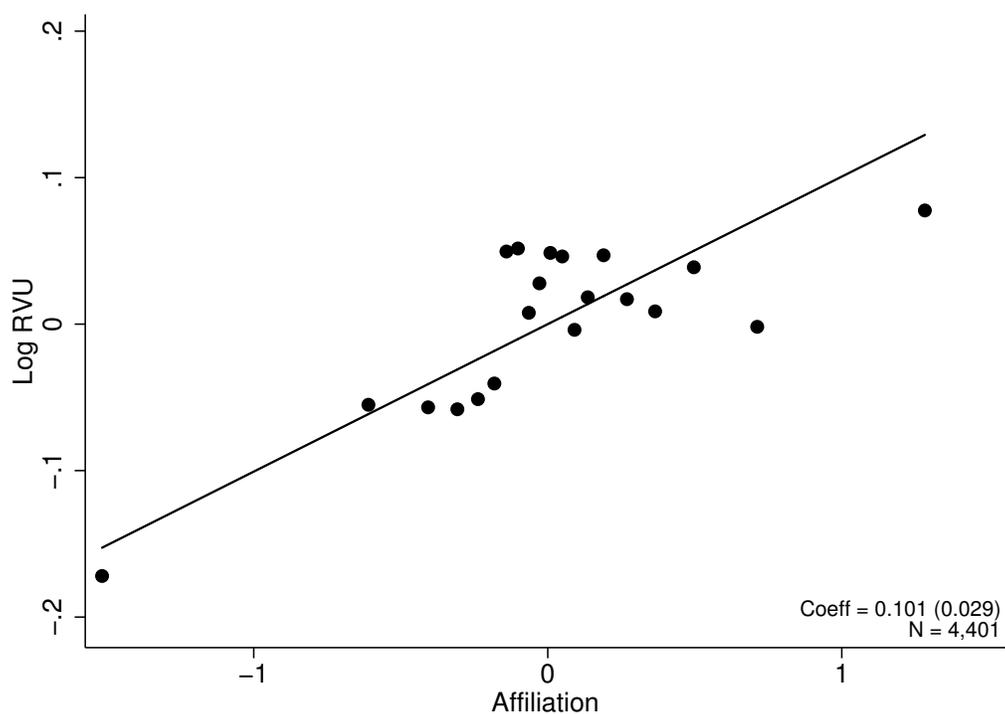
Note: This figure is a binned scatterplot of residual log RVU on residual affiliation, where each dot represents 5% of the data, ordered by residual affiliations. Residuals are formed by regressing log RVU and affiliation, respectively, on controls specified in Column 4 of Table 3. The line shows the 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 8: Revenue Reallocation with Equal Affiliation
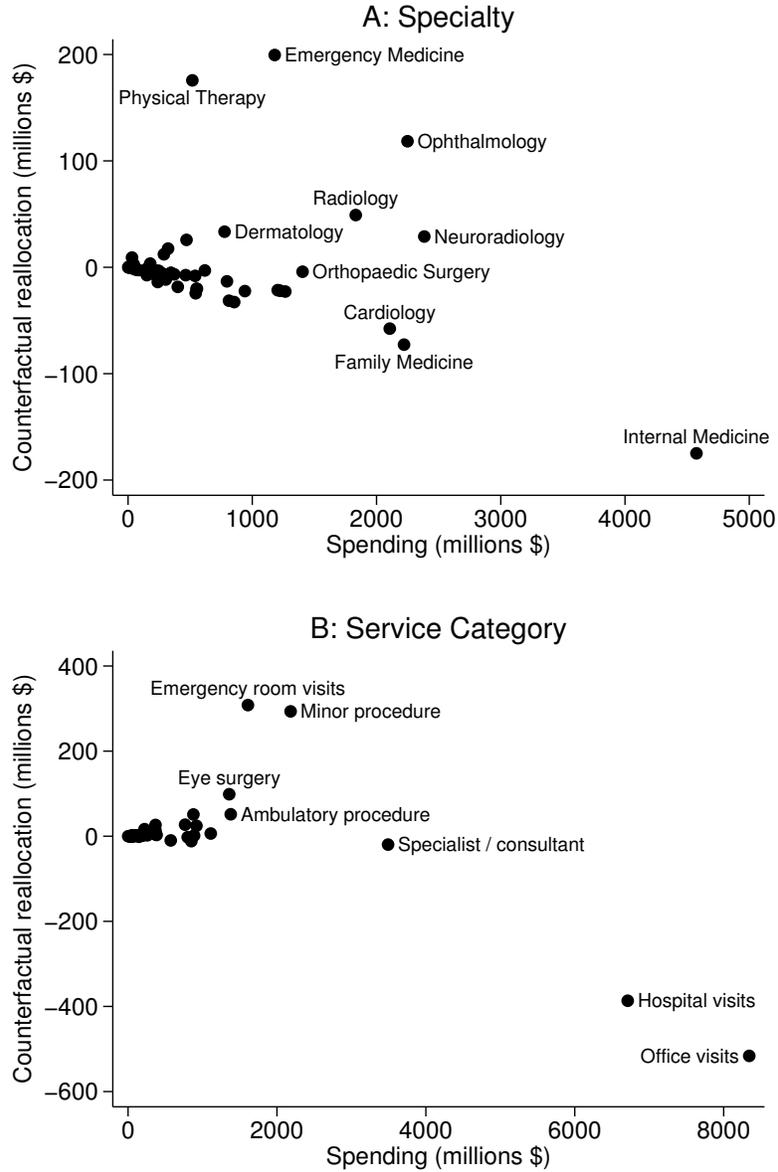
Note: This figure shows counterfactual yearly revenue reallocation by equalizing the affiliation of all proposals in each year. Panel A shows reallocation across specialties; Panel B shows reallocation aggregated across Berenson-Eggers Type of Service (BETOS) categories. Average annual spending for each specialty is on the x-axis, while the ccounterfactual 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 billion $\times 51\% = \$35.7$ billion. Details are given in Section 4.2.

Figure 9: Revenue Reallocation with Proportional RUC Representation

A: Specialty

B: Service Category
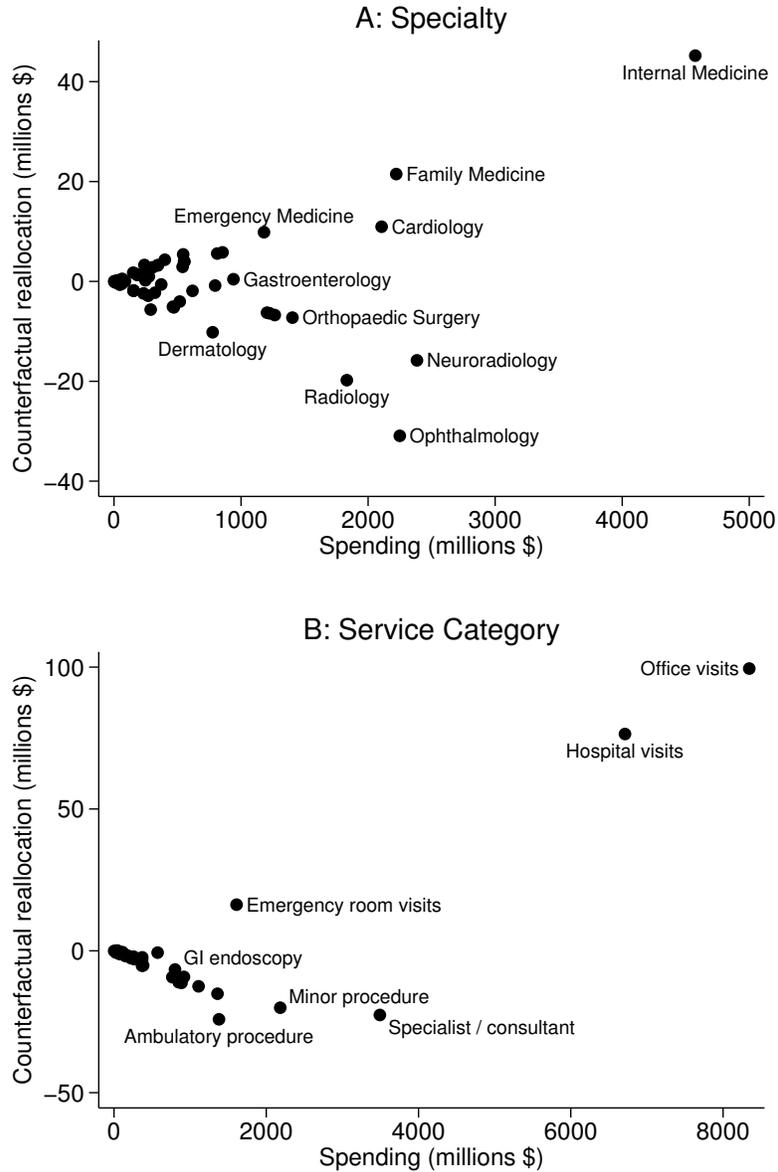
Note: This figure shows counterfactual yearly revenue reallocation by changing the RUC membership to be constant and proportional to the population of physician specialties in the US, as given in Table A-4. Panel A shows reallocation across specialties; Panel B shows reallocation aggregated across Berenson-Eggers Type of Service (BETOS) categories. Average annual spending for each specialty is on the x-axis, while the ccounterfactual 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 billion $\times 51\%$ = $35.7 billion. Details are given in Section 4.2.

Figure 10: Principal Utility and Intermediary Bias

A: Costlier Hard Information

B: Cheaper Hard Information
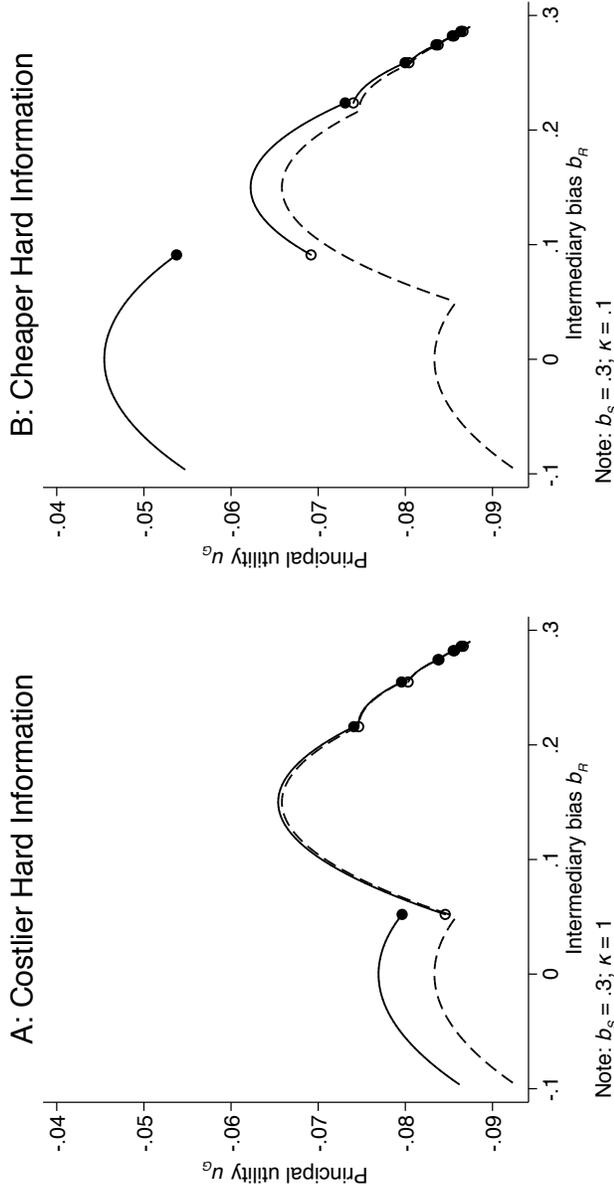
Note: This figure shows the government utility (u_G) in our conceptual model of cheap talk, outlined in Section 5, in which the government delegates authority to the RUC as an intermediary to decide on proposals by a specialty society. The key parameter is bias of the RUC intermediary, b_R, where $b_R = 0$ 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 $b_S > 0$. The figure shows $b_S = 0.3$ 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 $\theta \sim U(\underline{\theta}, \overline{\theta})$, where $L \equiv \overline{\theta} - \underline{\theta}$, 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, in solid lines, Panel A shows costlier hard information ($\kappa = 1$), and Panel B shows cheaper hard information ($\kappa = 0.1$).

49

Figure 11: Affiliation Effect on Hard Information
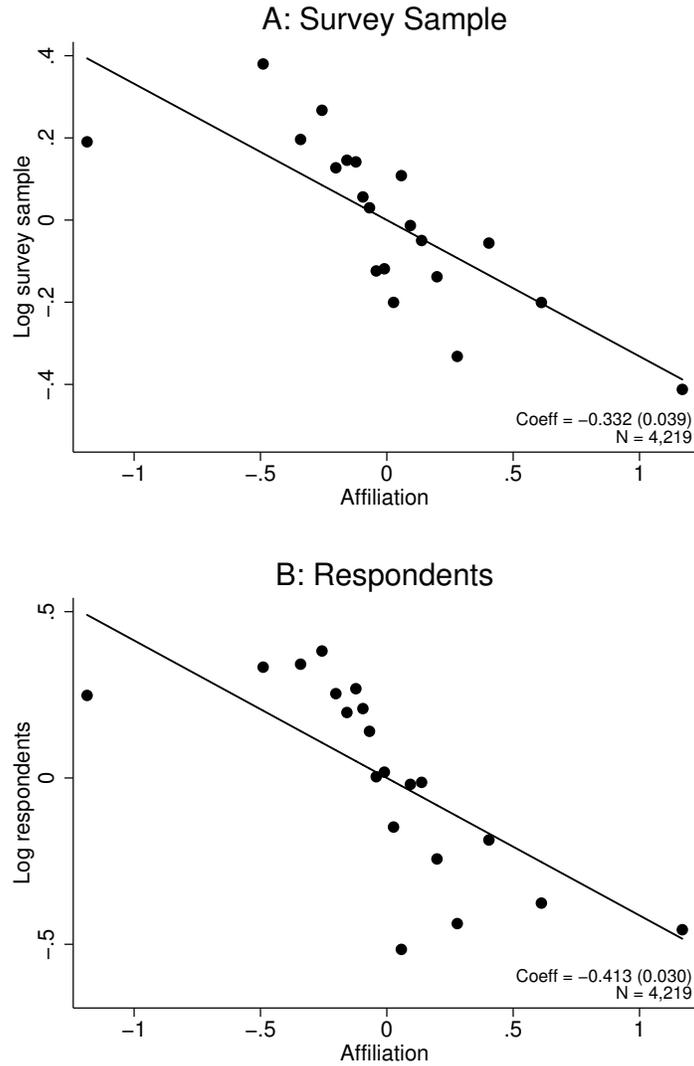
Note: This figure is a binned scatterplot of the residual log per-specialty survey sample (Panel A) and log per-specialty survey respondents (Panel B) on residual affiliation, where each dot represents 5% of the data, ordered by residual affiliations. We form residuals by regressing the survey variables of interest and affiliation on the controls specified in Column 3 of Table 4. 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 12: Price Transmission to Private Insurance
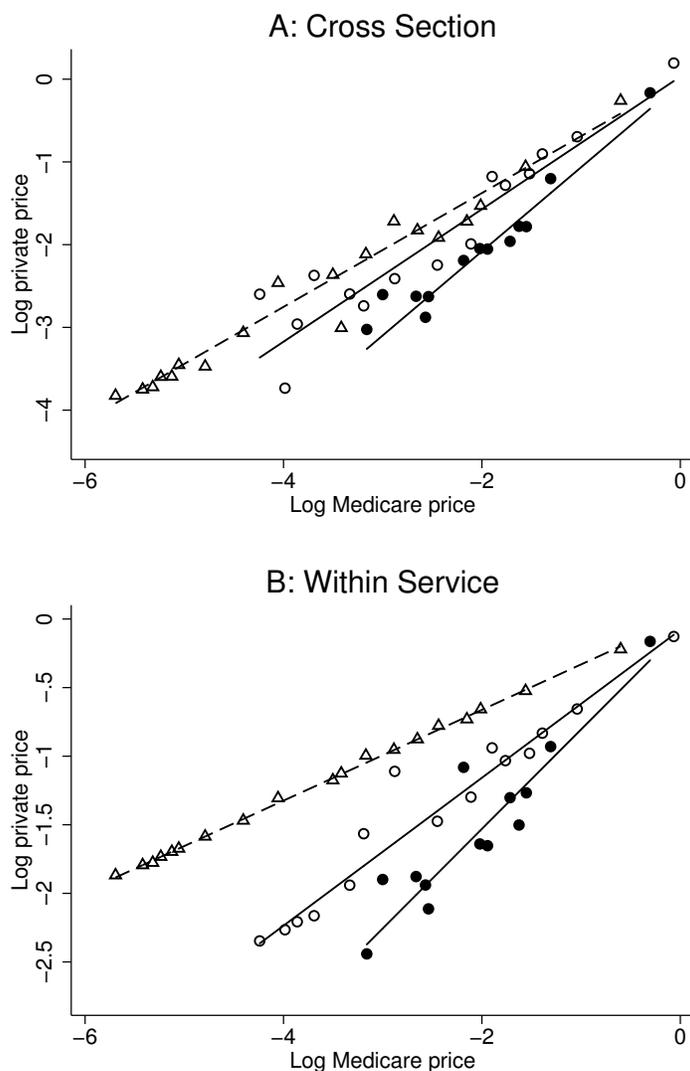
Note: This figure is a binned scatterplot of the relationship between normalized log Medicare price and normalized log private price, as described in the note for Table 6. Panel A shows the relationship without controlling for service (CPT code) and corresponds to Column 1 of Table 6, while Panel B shows this relationship controlling for CPT code and corresponds to Column 6 of Table 6. 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 6.

Appendix

A-1 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 this formula:

$$\text{CF}_t = \text{CF}_{t-1} \times (1 + \text{MEI}_t) \times (1 + \text{UAF}_t) \times \text{BN}_t,$$

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, $\text{UAF}_t \in [-7\%, 3\%]$, and the formula for the UAF_t is based on the following identities, relating target and actual spending:

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

These identities yield

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

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:

$$\text{BN}_t = \frac{\sum_i RVU_{i,t-1} \times q_{i,t-1}}{\sum_i RVU_{i,t} \times q_{i,t-1}},$$

which is closely related to the condition in Equation (A-3.3) 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 ("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).

A-2   Measuring Affiliation

As discussed in Section 3.2, our preferred measure of affiliation is a negative distance between vectors of quantity shares corresponding to two specialties. In this appendix, we discuss why this measure may represent differences in specialty interests, and how this conceptualization depends on the vector space and on the distance metric.

A-2.1   Vector Spaces

A natural benchmark for a specialty's objective is its revenue. Consider the revenue of specialty s as

$$R_s = \sum_i p_i q_{is},$$

or the sum of revenues from each service i, which in turn is the price of i, p_i, multiplied by the quantities of i provided by s, q_{is}.

A change in price for any service may lead to changes in the price of many other services, because by nature, prices are *relative* and can be used to justify prices of comparable services. Further, the fixed budget implies that any given price change mechanically affects all prices. Additionally, pricing changes are not made in isolation, and instead several price change actions

by the RUC and relevant specialties may be made in concert. Finally, if physicians (or patients) are responsive to price in their decisions, a price change or changes can lead to changes in quantities provided (and demanded) of the service undergoing the price change. The quantities of substitute or complementary services may adjust as well.

To capture this combination of mechanisms, we can write the first-order effect of a vector $\mathbf{p}$ of price changes on R_s as

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

While q_{iA} and p_i are observed, $dp_i/d\mathbf{p}$ and $dq_{is}/d\mathbf{p}$ are generally unknown.

A-2.1.1 Quantity Shares

In order to capture similarity in the effects of $\mathbf{p}$ on the revenue of two different specialties, as in Equation (A-2.1), we need to make simplifying assumptions. Under the assumption of fixed quantities (i.e., quantities are completely inelastic to price), this derivative reduces to

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

Further, fixed quantities allows us to scale revenue to a per-service concept that allows us to compare specialties of different sizes:

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

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

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

Distances in the vector space of quantity shares, i.e., $\left(\sigma_A^q, \sigma_B^q \right)$, 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).

As an additional advantage, note that this derivative difference equivalently represents differences in the response of *per-service profit*, where "profit" is any concept of price minus cost, c_{iA}. This cost can be a financial cost or an opportunity cost in the sense that physicians in a specialty require time to perform service i that can detract from time performing other procedures. For any arbitrary set of procedure costs that vary by i and specialty, the derivative of profit with respect to price changes remains the same.

A-2.1.2 Revenue Shares

If we instead assume that quantities are allocated across specialties in fixed proportion, then we may use the vector space of revenue shares to measure similarity in percentage change in revenue. To see this, first assume that $q_{is} = w_{is}q_i$, where w_{is} is fixed regardless of $q_i \equiv \sum_s q_{is}$. Then note that percentage revenue change is

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

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

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

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

Distances in the vector space of revenue shares, i.e., $\left(\sigma_{iA}^R, \sigma_{iB}^R\right)$, correspondingly focus on this difference.

Whether this is a meaningful vector space for distance depends on the plausibility of the assumption that quantities for a given service i are allocated across specialties in fixed proportions, regardless of q_i. In addition, this vector space does not allow us to measure similarity in specialty interests other than revenue, i.e., any concept of specialty profit would not be effectively captured by measures in this vector space.

A-2.1.3 Alternative Groupings

In 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.

A-2.2 Distance Metrics

As our baseline distance metric, we use the standard Euclidean distance:

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

where σ_s is the vector of quantity or revenue shares for specialty s across services or BETOS categories of services. The Euclidean distance between the two vectors σ_A and σ_B corresponds to the difference in total effects on the revenue of the two specialties, particularly if the component effect from each service $i - dp_i/d\mathbf{p}$ or $\frac{d(p_i q_i)/d\mathbf{p}}{p_i q_i}$ on quantity or revenue shares, respectively – is orthogonal (independent) and equal (identical).

We also consider a Euclidean distance metric weighted by the Gini coefficient of each service:

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

where $\mathbf{G}$ is a diagonal weighting matrix, such that $G\left(i, i\right) = G_i$ is the Gini coefficient across σ_{is} for services i, which places more weight on services that differ in shares across specialties. This Gini-weighted metric will naturally result in greater variation in distances.

Finally, we consider a number of other "high-dimensional" distance metrics, including Manhattan distance, angular distance, and correlation. Manhattan distance is in L_1 space, with affiliation

$$a\left(s_A, s_B\right) = -\sum_i \left|\sigma_{iA} - \sigma_{iB}\right|,$$

and angular distance is in arc space, with affiliation

$$a\left(s, s'\right) = -\frac{2}{\pi}\cos^{-1}\left(\frac{\sigma_A \cdot \sigma_B}{\sqrt{\sigma_A \cdot \sigma_A}\sqrt{\sigma_B \cdot \sigma_B}}\right).$$

Correlation is not a true distance metric, as it does not satisfy the triangle inequality property. These high-dimensional distance metrics are not necessarily more founded on economic concepts but are often used in settings when many features (or elements of a vector) sampled with noise can lead to randomly large Euclidean distances. In our setting, we observe Medicare quantity shares and prices perfectly and therefore do not share this concern. Instead, a large difference in the quantity or revenue share of a particular service is a meaningful economic concept. Both correlation and angular distance share the feature that vectors are normed to have a length of 1, which distorts the meaning of elements of σ_s away from shares.[33]

---

[33]The argument inside of the angular distance formula is called the cosine similarity, or $\cos\left(\sigma_A, \sigma_B\right)$. Denoting Euclidean distance between σ_A and σ_B as $\|\sigma_A - \sigma_B\|_2$, $\|\sigma_A - \sigma_B\|_2^2 = \left(\sigma_A - \sigma_B\right)\left(\sigma_A - \sigma_B\right)' = \|\sigma_A\|_2^2 + \|\sigma_B\|_2^2 -$

In Figure (A-1), we find that in our data, Euclidean distance and weighted Euclidean distance are quite similar, while the other metrics tend to shrink larger distances. In numerical simulations comparing the performance of Manhattan distance and Euclidean distance in predicting the correlation of total revenue effects based on random draws of component effects, we find that the relative performance depends on the number of services and the variation of component effects that is shared across services vs. variation that is independent.

A-3   Counterfactual Revenue 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 $\hat{\alpha}\left(A\left(R_t, S_i\right) - \tilde{A}\left(R_t, S_i\right)\right)$, where $A\left(R_t, S_i\right)$ and $\tilde{A}\left(R_t, S_i\right)$ are actual and counterfactual affiliations, respectively, and $\hat{\alpha}$ is the estimated affiliation effect from Equation (6). 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

$$\widetilde{CF}_y \sum_i \sum_s \widetilde{RVU}_{iy} \cdot q_{isy} = CF_y \sum_i \sum_s RVU_{iy} \cdot q_{isy}. \tag{A-3.3}$$

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:

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

$2\sigma_A \cdot \sigma_B$. If $\|\sigma_A\|_2^2 = \|\sigma_B\|_2^2 = 1$, then $\|\sigma_A - \sigma_B\|_2^2 = 2\left(1 - \cos\left(\sigma_A, \sigma_B\right)\right)$.

A-4 Technical Details of 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", $E\left[(\theta + b_R - p)^2\right]$, 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 assigning intervals of *expected* length L such that the posterior distribution of θ remains uniform within each realized interval.

A-4.1 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

$$n^* (b) = \left\lfloor \frac{1}{2}\left(1 + \sqrt{1 + \frac{2L}{b}}\right)\right\rfloor. \tag{A-4.4}$$

Using Equation (A-4.4), 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 length of 0.

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

$$x_1 = \frac{L}{n} - (n - 1)\, 2b, \tag{A-4.5}$$

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

$$x_k = 2x_{k-1} - x_{k-2} + 4b, \tag{A-4.6}$$

and Equations (A-4.5) and (A-4.6) 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 $E\left[(\theta + b_R - p)^2\right]$. 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 $b \in \left[\frac{L}{12}, \frac{L}{4}\right)$ and are defined by

$\left(0, \frac{L}{2} - 2b, L\right)$. The variance is given by

$$E\left[(\theta + b_R - p)^2\right] = \frac{L^2}{12}\left[\left(\frac{1}{2} - 2b\right)^3 + \left(\frac{1}{2} + 2b\right)^3\right]$$

$$= \frac{1}{12}\left(\frac{L^2}{4} + 12b^2\right) = \frac{L^2}{48} + b^2.$$

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

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

$$= \frac{1}{12}\left(\frac{L^2}{9} + 32b^2\right).$$

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

$$E\left[(\theta + b_R - p)^2\right] = \frac{1}{12}\left(\frac{L^2}{n^2} + A_n b^2\right), \tag{A-4.7}$$

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.

A-4.2 Hard Information

Given the formula for soft information loss in Equation (A-4.7), we can write the expected utility for the specialty and the government, respectively, as

$$E[u_S] = -E\left[(\theta + \theta_R - p)^2\right] - b^2 - c(L)$$

$$= -\frac{1}{12}\left(\frac{L^2}{n^2} + A_n b^2\right) - b^2 - c(L), \tag{A-4.8}$$

and as

$$E[u_G] = -E\left[(\theta + \theta_R - p)^2\right] - b_R^2$$

$$= -\frac{1}{12}\left(\frac{L^2}{n^2} + A_n b^2\right) - b_R^2. \tag{A-4.9}$$

In both Equations (A-4.8) and (A-4.9), n is the number of partitions supported by b and L and is given by Equation (A-4.4). 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:

$$\frac{\partial}{\partial L} E\left[u_S\right] = -\frac{L}{6n^2} - c'\left(L\right) = 0. \tag{A-4.10}$$

The convexity of $c\left(L\right)$ implies that there exists a single optimal candidate that satisfies Equation (A-4.10) for the cheap talk equilibrium with n partitions. Denote the solution to Equation (A-4.10) for a given n, if it exists (i.e., $n^*\left(b, L_n^*\right) = n$), as L_n^*.[34] Intuitively, L_n^* is increasing in n: better soft communication (higher n) reduces the incentive to produce hard information (larger L_n^*). The globally optimal L^* is then given by $L^* = \arg\max_n \left(E\left[u_S; L_n^*\right]\right)$. L^* is decreasing in b: As the specialty and the RUC have divergent preferences, soft communication worsens, and this increases hard information. Because the set of L_n^* is comprised of discrete values, $L^*\left(b\right)$ is a step function.

A-4.3   Optimal RUC Bias

Because smaller L^* increases government utility in Equation (A-4.9), 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 $n = 2$:

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

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

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

---

[34]In Equation (A-4.10), L_n^* is increasing in n, and in Equation (A-4.4), $n^*\left(b, L\right)$ is increasing in L. Since (i) $L_n^* \in (0, 1]$ and (ii) $n^*\left(b, L\right)$ is bounded by $n^*\left(b, 1\right)$, there must be at least one $n \in \{1, \ldots, n^*\left(b, 1\right)\}$ such that $n^*\left(b, L_n^*\right) = n$.

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

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

In other words

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

The threshold is then

$$b_S = \bar{b}_R + \sqrt{\frac{1}{12}\left(L_1^*\right)^2 - \frac{1}{48}\left(L_2^*\right)^2 + c\left(L_1^*\right) - c\left(L_2^*\right)}. \tag{A-4.11}$$

Condition 1 and convexity imply that

$$b_S < \sqrt{\frac{1}{12}\left(L_1^*\right)^2 - \frac{1}{48}\left(L_2^*\right)^2 + \frac{1}{6}L_1^*\left(L_2^* - L_1^*\right)}. \tag{A-4.12}$$

Condition 2 requires that

$$-\frac{1}{12}\left(L_1^*\right)^2 - \bar{b}_R^2 > -\frac{1}{48}\left(L_2^*\right)^2 - \frac{1}{2}b_S^2, \tag{A-4.13}$$

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

$$-\frac{1}{12}\left(L_1^*\right)^2 - \bar{b}_R^2 > -b_S^2. \tag{A-4.14}$$

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

We show numerically that there are no values $\left(L_1^*, L_2^*, b_S, \bar{b}_R\right)$ that satisfy Equations (A-4.11) to (A-4.14) simultaneously.

A-4.4 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 $\theta \sim U\left(\underline{\theta}, \bar{\theta}\right)$ 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 $\underline{\theta} = 0$ with probability less than 1 if $\theta > 0$. Therefore, if any potential interval must have $L = 0.9$, and we have a realized interval $\left[\underline{\theta}, \bar{\theta}\right] = [0, 0.9]$, 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 $N = \lfloor L^{-1} \rfloor$:

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

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:

$$
\begin{aligned}
E[u_A] &= -E\left[(\theta - p)^2\right] - b^2 - c(L) \\
&= -\frac{1}{12}\left[\frac{NL_a{}^3}{n_a^2} + \frac{(1 - NL_a)^3}{n_b^2} + \overline{A}b^2\right] - b^2 - c(L),
\end{aligned}
\tag{A-4.15}
$$

where $n_a = n^*(b, L_a)$, $n_b = n^*(b, 1 - NL_a) \leq n_a$, and $\overline{A} = NL_a A_{n_a} + (1 - NL_a) A_{n_b}$. The expression for the variance $E\left[(\theta - p)^2\right]$ 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 $L^* = \arg\max_{\mathbf{n}} (E[u_S; L_{\mathbf{n}}^*])$.

Table A-1: Sample Selection

		Observations	
Sample step	Description	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

Note: 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, electrosurgery, 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)

Note: 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)
	Affilition metric				
Affiliation vector space	Euclidean	Gini-Euclidean	Manhattan	Correlation	Angular
Panel A: Mean affiliation					
Medicare CPT quantity	0.101***	0.104***	0.055**	0.061**	0.059**
	(0.029)	(0.030)	(0.021)	(0.025)	(0.022)
Medicare + Marketscan CPT quantity	0.076***	0.079***	0.048**	0.057**	0.055**
	(0.025)	(0.026)	(0.020)	(0.025)	(0.023)
Medicare CPT revenue	0.094***	0.094***	0.038*	0.036*	0.036*
	(0.029)	(0.029)	(0.019)	(0.021)	(0.020)
Medicare BETOS quantity	0.088***	0.089***	0.056**	0.049**	0.050**
	(0.029)	(0.030)	(0.022)	(0.024)	(0.022)
Medicare BETOS revenue	0.072***	0.068**	0.045**	0.030	0.032*
	(0.027)	(0.028)	(0.021)	(0.020)	(0.019)
Panel B: 33rd percentile affiliation					
Medicare CPT quantity	0.104***	0.111***	0.061**	0.060**	0.060**
	(0.032)	(0.031)	(0.024)	(0.026)	(0.025)
Medicare + Marketscan CPT quantity	0.076***	0.081***	0.062**	0.052**	0.050**
	(0.024)	(0.026)	(0.023)	(0.024)	(0.023)
Medicare CPT revenue	0.089***	0.091***	0.039*	0.027	0.026
	(0.031)	(0.033)	(0.021)	(0.022)	(0.022)
Medicare BETOS quantity	0.086**	0.093***	0.066***	0.051**	0.053**
	(0.033)	(0.034)	(0.025)	(0.025)	(0.025)
Medicare BETOS revenue	0.088***	0.083***	0.053**	0.034**	0.043**
	(0.029)	(0.029)	(0.022)	(0.016)	(0.018)

Note: 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 in Equation (6) and corresponding to the preferred specification of Column 4 in Table 3. Further details about the regression controls are given in the note for Table 3. Rows of the table correspond to the vector space upon which affiliation is calculated; all vector spaces are in shares (i.e., elements of the vector for each specialty sum to 1). Columns correspond to affiliation metrics between two specialties, discussed in Appendix A-2. 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: 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	Pathology	1
General Surgery	1	Pediatrics	2
Internal Medicine	4	Psychiatry	1
Neurology	1	Radiology	1

Note: 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 26, 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 1. 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-5: Robustness of Private Price Transmission to RUC Information

|	(1)	(2)	(3)	(4)	(5)	(6)
			Log private price			
Log Medicare price						
× not RUC	0.688***	0.692***	0.688***	0.331***	0.328***	0.330***
	(0.016)	(0.015)	(0.016)	(0.022)	(0.022)	(0.022)
× RUC, low affiliation	0.838***	0.880***	0.838***	0.520***	0.520***	0.522***
	(0.006)	(0.006)	(0.006)	(0.023)	(0.024)	(0.023)
× RUC, high affiliation	0.917***	1.031***	0.921***	0.642***	0.610***	0.647***
	(0.015)	(0.016)	(0.015)	(0.041)	(0.041)	(0.041)
RUC, high vs. low affiliation	-0.420***	-0.255***	-0.412***	-0.016	-0.040	-0.013
	(0.040)	(0.040)	(0.040)	(0.067)	(0.067)	(0.067)
Service fixed effects	N	N	N	Y	Y	Y
RUC information proxy	None	w_{is}	σ_{is}	None	w_{is}	σ_{is}
Adjusted R-squared	0.852	0.859	0.852	0.987	0.987	0.987

Note: This table shows results of regressions of log private price on log Medicare price, as in Table 6. Definitions of private and Medicare prices and the merging of the two prices are given in Table 6. Columns 1 to 3 do not include service (CPT code) fixed effects; while Columns 4 to 6 do. Columns 1 and 4 do not control for RUC member specialty utilization of the service i, as a proxy for information about i, and are identical to Columns 4 and 5, respectively, in Table 6. The remaining columns control for an indicator for whether an information proxy (for services originating from the RUC) is above median and an interaction of this indicator with log Medicare price. In Columns 2 and 5, the proxy is the average RUC member specialty share of total service utilization, w_{is}, as defined in Equation (5). In Columns 3 and 6, the proxy is the average service utilization share of total specialty utilization for each RUC member specialty, σ_{is}, as defined in Equation (2). All regressions are run on the same sample of 7,182 observations. Standard errors are in parentheses. *** denotes significance at the 1% level.

Figure A-1: Relationship between Affiliation Measures
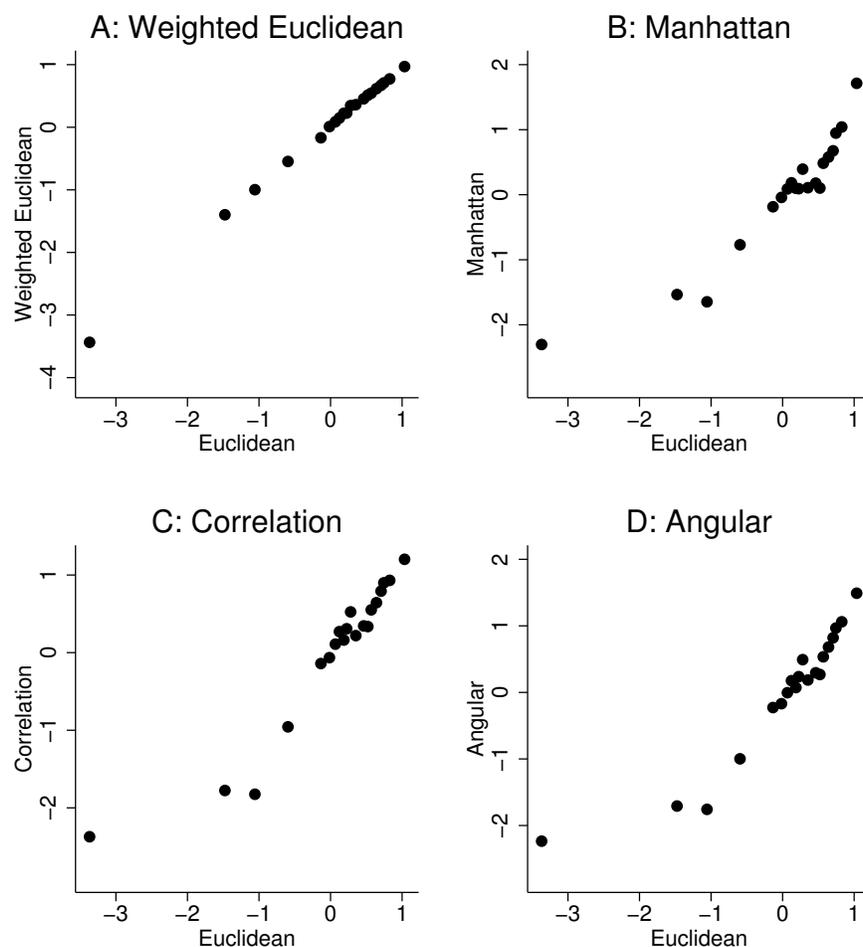
Note: This figure shows the relationship between different affiliation measures and the baseline measure of Euclidean distance. All measures are in the affiliation vector space of Medicare quantity shares. In each panel, the alternative affiliation measure is plotted against the Euclidean distance affiliation measure, for the sample of 4,423 proposals. Each dot represents a 5% sample of the data, ordered by the Euclidean distance affiliation measure, and averages of the respective affiliation measures are plotted. Further details on the definition of affiliation measures are given in Appendix A-2.

Figure A-2: Distribution of Normalized Log Medicare Price Changes
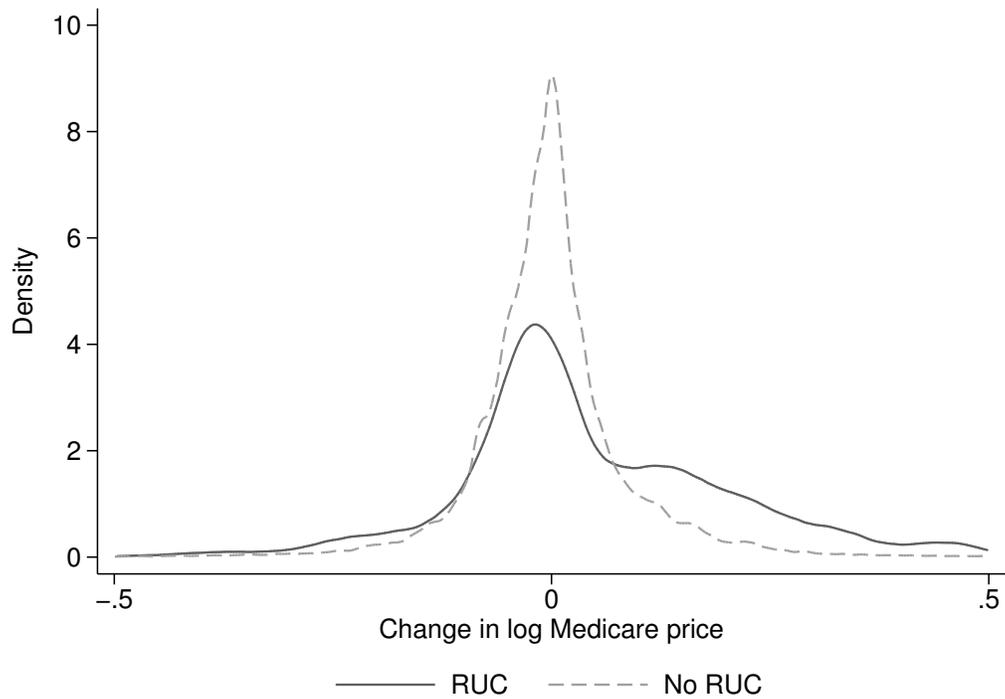
Note: This figure shows the density of Medicare price changes associated with a RUC decision (solid line) or not (dashed line). Medicare prices are defined as the total charges divided by the total volume of claims for each CPT code and year combination observed in the 100% sample of Medicare claims. The figure excludes any combination 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-3: Private Price Changes on Medicare Price Changes

A: High Affiliation

Coeff = .569 (.00949)
N = 1,224

B: Low Affiliation

Coeff = .351 (.0126)
N = 1,368
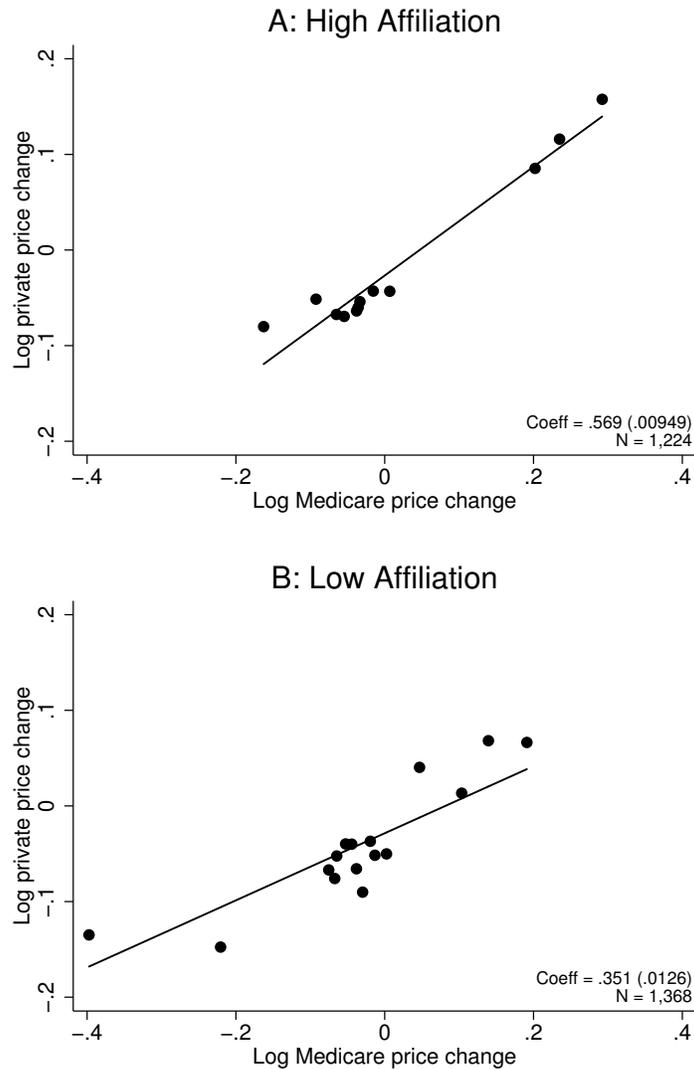
Note: This figure is a binned scatterplot of log private price changes on log Medicare price changes arising from high-affiliation RUC proposals (Panel A) and low-affiliation RUC proposals (Panel B), where each dot represents 5% of the data, ordered by Medicare price change. Lines show the best fit through 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 6. For consistency with Table 6, 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.