Price-setting by Committee: Evidence from Medicare*

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Abstract

A committee of physicians advises Medicare on setting prices for physician services. 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.

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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 such input provides a pathway for “regulatory capture” (Stigler, 1971; Peltzman, 1976), with government decisions biased toward an industry’s preferred policies. Traditional mechanisms for industry input include hosting lobbyists or empowering politicians with direct business connections to design policy (DellaVigna et al., 2016; Fisman, 2001; Grossman and Helpman, 2001); we explore potential bias stemming from the government’s widespread reliance on advisory committees with industry participants.\(^1\)

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 the composition of the RUC leads to prices 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

\(^1\)See Brown (2009) for an introduction. In 1972, Congress enacted the Federal Advisory Committee Act to track 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 may serve to improve the quality of policy decisions, a key challenge for maintaining such committees is to ensure they are “fairly balanced” and free of “inappropriate influence.”

\(^2\)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).
and assigning a work-based relative price.\textsuperscript{3} To measure how prices are affected by connections with the RUC, we develop a measure of \textit{affiliation}, to reflect the closeness in global preferences between specialties with many interests. Our measure exploits data on the services each specialty 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. We then examine whether proposals by specialty societies with higher affiliation with the RUC receive higher prices.

We find that increasing a proposal's affiliation by one standard deviation increases its price by 10%. To interpret this relationship 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 exploit significant variation in the identities of specialties proposing to the RUC for a given procedure. We control for RUC meeting identities and the shares of a procedure’s Medicare utilization across specialties, to address the concern that procedures with higher intrinsic prices may have greater affiliation through the composition of the RUC and through likely proposers. The remaining variation – in which procedures with the same intrinsic price are assigned different proposal affiliations – plausibly derives from either idiosyncratic specialty costs of proposing or barriers in coordination among many potential proposers. We provide support for this identifying assumption 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 affiliation effect on prices has important distributional consequences. If affiliation were equalized across proposals and if Medicare’s budget remained fixed, roughly $1.9 billion in annual Medicare reimbursement would be reallocated across services. 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 Medicare prices, equalizing affiliation translates to an

\textsuperscript{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.
overall $8.9 billion reallocation in annual health care spending across specialties.

While we have designed our measure of affiliation to reflect congruence in global preferences between specialties (Caillaud and Tirole, 2007), preferences and information held by decision-makers are typically correlated. However, we believe that our result that affiliation leads to higher prices reflects bias, at least in part, for three reasons. First, we show a mechanism that causes decisions in favor of a party, which constitutes prima facie evidence of bias in a growing empirical literature.4 Second, we argue that a mechanism leading to higher prices on average must either reflect biased preferences of a decision-maker or not be Bayesian. Third, and most importantly, affiliation varies in our empirical setting primarily from the identities of the specialty proposers, not the RUC decision-makers. Thus, differential information held by RUC specialties cannot explain our empirical finding. Instead, our empirical design suggests a relationship to a literature on lobbying (Bertrand et al., 2014; Blanes i Vidal et al., 2012), which has shown that a lobbyist’s identity may be valuable because it provides credibility to the message, particularly when her preferences are aligned with those of the decision-maker (Gilligan and Krehbiel, 1989; Kessler and Krehbiel, 1996; Hirsch and Montagnes, 2015).5

The possibility 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 electricity generation) held by industry participants. The government may form the advisory committee with members that hold such knowledge directly. In other cases, committee members may lack direct knowledge, but instead have the task of extracting and synthesizing information from outside special interests. We thus explore whether allowing some bias in advisory committees may improve regulatory decisions, by facilitating the communication of information

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4Camara 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. Zinov’eva and Bagues (2015) examine the role of evaluator bias in academic promotions. Barwick et al. (2017) examine potential conflicts of interest in the real-estate industry.

5This finding also more broadly consistent with a growing literature on the importance of connections in settings of persuasion. 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).
that is neither verifiable nor independently discoverable. In our setting, we explore whether Medicare can extract more information about physician services and set more appropriate prices by employing the RUC as an intermediary in decision-making.

To address this question, we borrow ideas from a large literature on the extraction of information from biased experts.\(^6\) 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) that has preferences closer to the biased expert (the specialty), 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 (potentially most) 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 total information. In our setting, the evidence presented in proposals to the RUC come from surveys of physicians. 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.

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\(^6\)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).
Finally, we examine a policy-relevant metric of the overall level of (hard and soft) information Medicare collects through the RUC by the degree to which Medicare price changes correlate with private insurance price changes (Clemens and Gottlieb, 2017; Clemens et al., 2017). We classify price changes depending upon whether they originate from RUC decisions, and if so, whether they originate from high- vs. low-affiliation proposals. We find that price changes in private insurance track those changes in Medicare more closely when the Medicare price changes arise from RUC decisions. For Medicare price changes arising from more highly affiliated proposals to the RUC, we find stronger price following than for price changes from low-affiliation RUC proposals. These findings suggest that affiliation may improve the overall quality of information in Medicare pricing 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 and discusses our interpretation of bias. We move to the question of information extraction, first with a theoretical framework in Section 5. We then present empirical evidence on hard information in Section 6. Section 7 evaluates the overall information quality of Medicare prices by their transmission to the private sector. Section 8 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 private insurance, providers may 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,” or RVU. The payment levels adjust for differences in the cost of practicing medicine in different parts of the country. 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 $t$,

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

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. Judging the level of effort required for each medical procedure requires collecting information possessed by actual practitioners. Medicare thus engages with a committee of the American Medical Association (AMA) to collect physicians’ evaluations of the relative effort and advise on proper RVU levels. This committee – the RUC – recommends relative values to Medicare, which Medicare’s administrators adopt over 90% of the time (American Medical Association, 2017; Laugesen et al., 2012).

### 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.

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\(^7\)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).
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 25 physician specialty society 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 orthopedic surgery maintain permanent seats, while specialties including pediatric surgery and infectious disease rotate on and off the RUC. In Table 1, we record the number of total meetings 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 committee size has grown over time.

### 2.2 The Price-Setting Process

Each year, in three meetings, approximately 200-300 physician services appear for review before the RUC. The committee will review all newly created services and will re-evaluate some existing services. Evaluations for existing services occur when the description or content of the procedure

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\(^9\) 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 specialty 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.
itself changes, when Medicare requests a revaluation, and, since 2006, when a workgroup from within the RUC identifies a service as potentially misvalued. 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 specialties 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 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 facilitation, the proposed price is often

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12The 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.
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 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.\textsuperscript{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.\textsuperscript{14}

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 Asia.

\textsuperscript{13}In Table A-2, we provide examples of these descriptions.

\textsuperscript{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 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.
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 measure the alignment of preferences between specialties with a diverse set of interests, characterized by the services they each perform. Two specialties may be tightly linked, even if they are discussing a procedure only one performs. For example, suppose the orthopedic surgery specialty proposes a value for a spinal surgery, and this service represents only 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 other procedures 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 detail later in Section 5.\(^{15}\)

To measure alignment in specialty preferences, we must capture the many pathways through which price-setting decisions may affect 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 to change similarly, particularly services that might 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 the similarity of services between two specialties, as a

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\(^{15}\) 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.
nonparametric statistic for alignment in interests when specialties seek to maximize revenue.

Specifically, we denote the quantity utilization of service $i$ by specialty $s$ in year $y$ as $q_{isy}$. We then construct the vector $\sigma_s$ of specialty $s$ utilization shares across all services, where the $i$th element is $\sigma_{is}$, the share of specialty $s$’s utilization of $i$ averaged across years:

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

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:

$$
a(s, s') = -\sqrt{(\sigma_s - \sigma_{s'})^t (\sigma_s - \sigma_{s'})^t}.
$$

In Appendix A-2, we provide further discussion about this measure of affiliation as a preferred 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 nine bins. 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. Perhaps surprisingly, internal medicine is affiliated with many surgical specialties because many surgical specialties also rely on the same evaluation and management procedures 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

$^{16}$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.
measure at the proposal level, since our outcomes measures are specific to a proposal. Thus, we define set affiliation, a measure of affiliation between the set of specialities composing the RUC and the set of specialties party to a proposal.\textsuperscript{17} 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 $t$ is

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

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 $r \in R_t$, we take 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 $A^* \left( R_t, S_i \right)$, based on the intuition in Krishna and Morgan (2001) that communication outcomes are improved when a receiver listens to the most closely aligned sender. We then take the average across RUC members, to reflect that the RUC aggregates opinions across members, not only in voting but also in the committee’s private and public discussions (Li et al., 2001). Finally, for interpretation, we standardize $A^* \left( R_t, S_i \right)$, by subtracting the sample mean and dividing by the sample standard deviation, and denote this standardized measure as $A \left( R_t, S_i \right)$.\textsuperscript{18}

### 3.3 Identification

To estimate the causal effect of affiliation on RUC prices, we need variation in affiliation that is uncorrelated with underlying prices. Variation in affiliation comes from two sources: changes in specialty representation on the RUC over time, and variation in the identities of specialties participating on a proposal. Since RVU decisions are only relative, we condition on RUC meeting identities. Further, because specialties may hold RUC seats and propose for non-random reasons, we condition on 64 specialty utilization shares of a given service:

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

\textsuperscript{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.

\textsuperscript{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 $A \left( R_m, S_i \right)$ in order to maintain comparability.
for service $i$, specialty $s$, and Medicare claim year $y$.

By restricting our comparisons between procedures proposed in the same meeting and performed by the same specialty mix, our goal is to condition on predicted prices and predicted affiliation, as a function of the RUC membership and the likely specialty proposers for a given procedure. 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. Figure 4 shows substantial variation in affiliation even across proposals with the participation of a given specialty. The source of variation in proposing specialties, however, derives from the fact that a given service is usually performed by many specialties. As many as a dozen specialties are eligible to be on the proposal a typical service, while 98% of the proposals involve five or fewer specialties. In practice, the specialty costs and expectations of proposing may vary across meetings, depending for example on the availability of specialty resources to administer surveys and of representatives to present proposals. Further, in Appendix , we show that with costly proposals and two specialties, there often exist no unique pure strategies for proposals, while mixed strategies are introduced. When specialties cannot coordinate, this introduces yet another random source of variation in the identities of proposing specialties for a service.

For identification, we require that proposals with (conditionally) higher affiliation are not for services with (conditionally) higher intrinsic prices. In Figure 5, we assess balance in plausibly exogenous service characteristics that predict price, linearly controlling for meeting dummies and specialty shares. Medicare beneficiaries receiving services with high residual affiliation are similar to those receiving 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. Further, we consider below two types of violations of our identifying assumption. First, specialties submitting proposals for procedures with intrinsically high prices may choose to submit these proposals at meetings with more affiliated RUC members. Second, holding fixed utilization by specialties, procedures with higher intrinsic prices may also be more likely to have more or particular proposing specialties, which may 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 affiliations. 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, controlling for average counterfactual affiliation, $\bar{A}(S_i) \equiv \|T\|^{-1} \sum_{t \in T} A(R_t, S_i)$, we find no correlation between price predicted from service characteristics and the realized affiliation.

3.3.2 Endogenous Proposing Specialties

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, $R_t$. We thus assess whether specialty participation in proposals, conditional on specialty utilization shares $w_i$, is correlated with the service’s predicted price. We first estimate the propensity of each specialty $s$ to propose $i$, as a logit model of $\pi_{is} = \Pr(s \in S_i | s, w_i)$, which has a pseudo-$R^2$ of 0.67. Conditional on this propensity, 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). This supports our assumption that, conditional on $w_i$, the remaining variation in specialty-proposal participation is uncorrelated with underlying price. Further, in Appendix A-3, we show that simulated affiliation, based on a richer model of specialty-proposal propensities, $\pi_{is}$, and $R_t$, exhibits wide variation centered around actual affiliation (Figure A-4), suggesting an unbiased prediction of affiliation with large residual variation.

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19 Specifically, we compare $\text{Var}_i \left( A(R_t, S_i) - A(S_i) \right)$ and $\text{Var}_i \left( A(S_i) \right)$ relative to $\text{Var}_i \left( A(R_t, S_i) \right)$. The variation 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.

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

21 In Appendix A-3, we also provide supporting evidence of wide variation in the propensity of proposing even among actual proposers and among the highest-propensity specialties.
4 Affiliation Effect on Prices

4.1 Estimated Effect

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

$$\ln RVU_{it} = \alpha A(R_t, S_i) + X_i\beta + T_t\eta + w_i\zeta + \varepsilon_{it},$$

(6)

where $RVU_{it}$ is the relative price (RVU) granted to proposal $i$ at meeting $t$, and $\alpha$ 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 $w_i$. 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 $X_i$ 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 the full specification, reported in Column 4, 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 increase prices by 17%. In Figure 7, we present regression results from the full specification in a binned scatterplot of residualized price on the $y$-axis and residualized affiliation on the $x$-axis.

In Column 5 of Table 3, we show a similar effect, controlling for predicted set affiliation, as a function of the RUC membership, $R_t$, and the logit-estimated propensity of each specialty to

\(^{22}\)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 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.
propose, described in Appendix A-3, instead of linear $w_i$. This prediction mechanically controls for any variation in RUC membership over time. In Column 6, we show that our result is robust to controlling for interactions of each specialty share with linear meeting year, which allows for changes in the intrinsic price of each specialty’s procedures over time. Finally, in Table A-3, we show robustness of our results to 49 other formulations of affiliation.\textsuperscript{24}

### 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 25 specialty seats are apportioned based on specialty physician populations, as given in Table A-5. 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-4.

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

\textsuperscript{24}We defend our preferred affiliation measure and discuss alternatives in Appendix A-2.
medicine gains from affiliation because many other specialties, including surgical ones, also derive a large share of revenue from the same evaluation and management services performed in office and inpatient visits. 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 of equalizing affiliation. Even though internal medicine would be given 4 seats, compared to the actual average of 1.5 seats on the RUC, the specialty would gain less than 1 percent in revenue. Infectious disease would have the largest percentage revenue gain (+1.4%), and ophthalmology would experience the largest percentage revenue loss (−1.4%). We illustrate other individual specialty and BETOS code reallocations in Figure 9.

4.3 Interpreting the Effect as Bias

A natural interpretation of the effect of affiliation in raising RUC-recommended prices is that it reflects bias of RUC members to grant higher prices to affiliated specialties. However, preferences and information held by decision-makers are typically correlated. We thus discuss context, intuition, and evidence that the effect is driven by (biased) preferences and not intrinsic information held by the RUC. First, we note that this interpretation is consistent with a growing empirical literature that studies committee and policy decisions in a wide range of settings. This literature usually relies on variation in the identity of decision-makers and an assumption that the decision-maker’s identity should be irrelevant for the “correct” decision.

Second, we observe that if the RUC were unbiased but only varies in its intrinsic level of information across different types of decisions, then its price recommendations should not vary on average in a Bayesian equilibrium. For example, if the RUC were to systematically underestimate prices when uninformed, it would simply benefit from adjusting its recommendations upward

\[^{25}\text{We do not investigate other mechanisms, such as the difficulty in raising prices for common procedures, that may depress prices for office visits and therefore non-procedural specialties like internal medicine (Bodenheimer et al., 2007).}\]
by exactly the average extent to which it underestimates them. This feature holds true in standard models of continuous decision-making under asymmetric information (e.g., Crawford and Sobel, 1982; Grossman and Helpman, 2001). More recent models allow for information rents to be held by an asymmetrically informed sender, e.g., when the sender’s message cannot be fully expropriated to the receiver’s advantage (Callander, 2008). We are unaware of a model in which reducing information asymmetry (i.e., increasing the RUC’s information) leads to average decisions in favor of expert senders.

Third, and most importantly, the large majority of the identifying variation in our empirical setting derives from the identities of the proposing specialties, not the RUC composition. Thus, our effect of affiliation cannot reflect mechanisms due to RUC membership alone, including information held by the RUC. Our finding is instead relevant to an empirical and theoretical literature on lobbying, in which proposers serve as lobbyists and may lead to favorable decisions by their very identity. For the identity of proposers to sway decisions, RUC members (biased or not) cannot directly observe all relevant information to price a service; they also depend on inferences based on the alignment of their interests with those of the proposers. In Appendix A-4, we present results that argue against alternative mechanisms of simple signaling to an unbiased RUC, and of informational mechanisms at the procedure level. These results further support a mechanism driven by global alignment of preferences between specialties.

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? In this section, we introduce a conceptual model that illustrates a trade-off between bias and communication. 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 $\theta$, 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 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 \( \theta \) to the RUC as the intermediary in decision-making.

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 specialty 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.\(^{26}\)

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 \( \theta \) uniformly lies on a subinterval of length \( L \) (i.e., \( \theta \sim U(\bar{\theta}, \bar{\theta}), L \equiv \bar{\theta} - \bar{\theta} \in [0, 1] \)), via a technology that comes at cost \( c(L).^{27} \)

3. The specialty observes \( \theta \).

4. The specialty transmits a cheap talk message \( m \) about \( \theta \).

5. The RUC sets price \( p \). Non-transferrable payoffs are as follows for the specialty \( u_S \), RUC

\(^{26}\)In a simple model with no RUC bias, the average of the \textit{ex post} realization of prices in equilibrium should equal the \textit{ex ante} expectation of \( \theta \), 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).

\(^{27}\)In this exposition, we treat \( \bar{\theta} - \bar{\theta} \) as known and assert that \( \theta \sim U(\bar{\theta}, \bar{\theta}) \). However, this is not technically correct for all values of \( L \). In Appendix A-6.4, we discuss a complication that considers \( \bar{\theta} - \bar{\theta} \) as random, i.e., \( L = E[\bar{\theta} - \bar{\theta}] \), which allows \( \theta \) to remain uniformly distributed in the posterior interval. Neither the uniform distribution of \( \theta \) nor fixed \( \bar{\theta} - \bar{\theta} \) is required for the intuition of this model.
\( (u_R) \), and the government \((u_G)\):

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

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.\(^{28}\)

### 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; 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 \([\hat{\theta}, \tilde{\theta}]\) to length \(L < 1\), and such evidence eliminates the need for communicating a service’s

\(^{28}\)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.
value credibly through soft channels. In Appendix A-6, 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 low affiliation between the RUC and the specialty, induces the specialty to produce more hard information. Since hard information 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 0.29 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 proposers and the RUC. Hard information provision, by contrast, decreases with affiliation. Thus, the overall information content of prices as a function of affiliation depends on how much each type of information adjusts. When the cost (or feasibility) of producing hard information falls, the degree of affiliation that maximizes information extraction will decrease. We 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 extraction by examining the 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 RVU, they present 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

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29 In Appendix A-6, we show that it is never optimal to have $b_{R} < 0$. Under hard information, this derives from three necessary conditions: (i) the threshold $b_{R}$ where the specialty is indifferent between $n = 1$ and $n = 2$ must be less than 0; (ii) $E[u_{G}|b_{R} = b_{R}] > \max E[u_{G}|n = 2]$; and (iii) $E[u_{G}|b_{R} = b_{R}] > E[u_{G}|b_{R} = b_{S}]$. 

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about physician work, the more concrete is the evidence presented in a proposal to the RUC.\textsuperscript{30} 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 from more than one specialty) and per specialty. 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 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:

$$\ln H_{it} = \alpha A(R_t, S_i) + X_i \beta + T_t \eta + w_i \zeta + \varepsilon_{it},$$  \hspace{1cm} (7)$$

with the same controls as in Equation (6). The coefficient of interest, $\alpha$, reflects the effect of affiliation on the endogenous decision to provide hard information. The number of specialties on a proposal may also affect 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:

$$\ln H_{it} = \alpha A(R_t, S_i) + X_i \beta + \gamma_n 1(\|S_i\| = n) + T_t \eta + w_i \zeta + \varepsilon_{it},$$  \hspace{1cm} (8)$$

Since the per-specialty hard information is $\ln (H_{it}/\|S_i\|) = \ln H_{it} - \ln \|S_i\|$, estimates of $\alpha$ 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

\textsuperscript{30}The RUC often focuses on the distribution of survey outcomes and the number of survey respondents, as a marker of the credibility of a proposal. Although any given survey respondent may exaggerate his or her response, it is more difficult to do so (and generally more costly to lie) in aggregate when there are many respondents, along the lines of (Kartik, 2009).
results based on per-specialty survey measures, in the remaining columns in the table. 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 when controlling for the number of specialty proposers, specified in Equation (8) and shown in Column 4 of Table 4, although the effect is not statistically significant for the outcome of survey respondents.

7 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, depending on 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 heterogeneous 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 transmission 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.\(^{31}\) 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 proposal to the RUC.\(^{32}\) Secondarily, we will assess whether Medicare price changes are uniformly discounted as a function of affiliation, which sheds some light on the private insurance response to possible bias. If the government undoes bias from high-affiliation RUC decisions, then in-

\(^{31}\)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.

\(^{32}\)Medicare prices with greater informational content may of course provide a stronger bargaining benchmark. This analysis will assign this effect to evidence of information.
formational advantages from communication will in general be nullified (Ambrus et al., 2013); private insurance, however, 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. 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:

\[
y^M(i, y) = \arg \min_{y' \in \{y, y-1, y-2\}} |\Delta \ln \text{Price}^P_{i, y} - \Delta \ln \text{Price}^M_{i, y'}|,
\]

where \(\Delta \ln \text{Price}^P_{i, y} = \ln \text{Price}^P_{i, y} - \ln \text{Price}^P_{i, y-1}\) is a change in the normalized log private prices for service \(i\) in year \(y\), and \(\Delta \ln \text{Price}^M_{i, y}\) is the analogous Medicare log price change.

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

\[
\ln \text{Price}^P_{i, y} = \beta \ln \text{Price}^M_{i, y}^M(i, y) + \mathbf{T}_{iy} \eta + \xi_i + \epsilon_{iy}, \tag{9}
\]

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

\[
\ln \text{Price}^P_{iy} = \sum_C \left( \alpha_C + \beta_C \ln \text{Price}^M_{iy}^M(i, y) \right) \cdot \mathbf{1} (C(i, y) = C) + \mathbf{T}_{iy} \eta + \xi_i + \epsilon_{iy}, \tag{10}
\]

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-5,
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 5, our estimates suggest that private prices follow RUC-based Medicare prices to a much larger extent than non-RUC Medicare prices. Estimating Equation (9) 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 2) or 0.300 (Column 3), 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.33

Figure 12 shows pooled results, both without and with service fixed effects, corresponding to Columns 4 and 5 of Table 5. The figure reproduces differences in the slopes of the lines tracing private prices to Medicare prices that depend on the source of the Medicare price. This suggests that Medicare price changes that originate from RUC decisions, and in particular from high-affiliation RUC decisions, appear more informative for private insurance. In addition to steeper slopes, the lines are generally lower in levels for RUC Medicare prices (and further for those from high-affiliation proposals). These uniformly lower private insurance price changes suggest that private insurance may, to an extent, reverse the bias induced by affiliation.

In Appendix A-7, we consider alternatives to our interpretation that affiliation facilitates better information through communication. First, the RUC may have more information on

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33We 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-6, high-affiliation RUC price changes result in steeper private price changes than low-affiliation RUC price changes.
high-affiliation decisions, even without communication, because its members are more likely to perform the services in question. Second, Medicare and private insurance are more likely to get the price “right” for high-volume procedures, which are also more likely to have RUC decisions and high-affiliation proposals. Third, there may be some other unspecified predictor of price transmission that could be correlated with affiliation. We find that our results are robust, accounting for these potential alternative mechanisms.

8 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 setting prices can improve the quality of information used in the process. We find patterns suggesting that private insurers follow Medicare prices more closely when the public prices originate from a RUC vote. The private sector appears to adjust downward 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 balancing act in setting prices. Inviting input from the RUC may introduce bias in prices, but it may also improve the information extracted from specialties. We 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 transfers in revenue. To the extent physicians are imperfect agents for their patients and deviate toward procedures with greater reimbursement levels (Clemens and Gottlieb, 2014; Gruber et al., 1999), and if physicians-in-training avoid specializing in fields with lower procedural income, the actions of the RUC may also have important welfare consequences for health care.
References


### Table 1: Specialty Seats on the RUC

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

**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. Internal medicine had two seats in some of the meetings through the “primary care” rotating seat. 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

<table>
<thead>
<tr>
<th>Medicare Beneficiary Characteristic</th>
<th>Affiliation above mean</th>
<th>Affiliation below mean</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>0.471</td>
<td>0.470</td>
<td>0.371</td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td>(0.101)</td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td>0.794</td>
<td>0.792</td>
<td>0.784</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td>(0.054)</td>
<td></td>
</tr>
<tr>
<td>Age &gt; 75</td>
<td>0.405</td>
<td>0.416</td>
<td>0.366</td>
</tr>
<tr>
<td></td>
<td>(0.109)</td>
<td>(0.106)</td>
<td></td>
</tr>
<tr>
<td>Age &gt; 85</td>
<td>0.131</td>
<td>0.135</td>
<td>0.745</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td>(0.067)</td>
<td></td>
</tr>
<tr>
<td>Medicare aged</td>
<td>0.767</td>
<td>0.782</td>
<td>0.463</td>
</tr>
<tr>
<td></td>
<td>(0.126)</td>
<td>(0.108)</td>
<td></td>
</tr>
<tr>
<td>Medicare disabled</td>
<td>0.155</td>
<td>0.147</td>
<td>0.426</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.058)</td>
<td></td>
</tr>
<tr>
<td>Medicare ESRD</td>
<td>0.063</td>
<td>0.054</td>
<td>0.903</td>
</tr>
<tr>
<td></td>
<td>(0.114)</td>
<td>(0.079)</td>
<td></td>
</tr>
<tr>
<td>White race</td>
<td>0.828</td>
<td>0.837</td>
<td>0.148</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.074)</td>
<td></td>
</tr>
<tr>
<td>Black race</td>
<td>0.111</td>
<td>0.105</td>
<td>0.989</td>
</tr>
<tr>
<td></td>
<td>(0.059)</td>
<td>(0.052)</td>
<td></td>
</tr>
<tr>
<td>Hispanic race</td>
<td>0.025</td>
<td>0.024</td>
<td>0.109</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>Other race</td>
<td>0.038</td>
<td>0.036</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.015)</td>
<td></td>
</tr>
</tbody>
</table>

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 $w_i$. 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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log RVU</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized set affiliation</td>
<td>0.158***</td>
<td>0.118***</td>
<td>0.108***</td>
<td>0.101***</td>
<td>0.119*</td>
<td>0.111***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.023)</td>
<td>(0.033)</td>
<td>(0.029)</td>
<td>(0.066)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Prior log RVU</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Medicare beneficiary</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
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<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
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<tr>
<td>CPT code description</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Specialty shares</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Meeting fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Predicted set affiliation</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Specialty shares × linear year</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>N</td>
<td>4,401</td>
<td>4,401</td>
<td>4,401</td>
<td>4,401</td>
<td>4,401</td>
<td>4,401</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.754</td>
<td>0.792</td>
<td>0.889</td>
<td>0.891</td>
<td>0.866</td>
<td>0.897</td>
</tr>
<tr>
<td>Sample mean log RVU</td>
<td>1.567</td>
<td>1.567</td>
<td>1.567</td>
<td>1.567</td>
<td>1.567</td>
<td>1.567</td>
</tr>
</tbody>
</table>

**Note:** This table shows results of regressions of log RVU on standardized set affiliation, as stated in Equation (6). Medicare beneficiary indicates average characteristics of Medicare beneficiaries who receive the service (CPT code); surveyed characteristics includes objective characteristics (e.g., total utilization, surveyed time intervals, and office visits or other E&M CPT codes bundled into the code) and subjective characteristics reflecting the difficulty, riskiness, or physician stress involved in the procedure; and CPT code description indicates word stems predictive of RVUs, as selected by LASSO. Specialty shares $w_i$ are defined in Equation (5) and are controlled for linearly, except in Column 5. Column 5 controls for predicted set affiliation, formed from the simulated distribution of set affiliation based on each specialty’s probability to participate in the proposal (Figure A-4), and described in detail in Appendix A-3. Standard errors, clustered by RUC meeting, are in parentheses; * denotes significance at the 10% level, and *** denotes significance at the 1% level.
Table 4: Affiliation Effect on Hard Information

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Log Survey Sample</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count type</td>
<td>Total</td>
<td>Proposer</td>
<td>Proposer</td>
<td>Proposer</td>
</tr>
<tr>
<td>Standardized set affiliation</td>
<td>0.122</td>
<td>-0.228***</td>
<td>-0.332***</td>
<td>-0.146**</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.071)</td>
<td>(0.076)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>Baseline controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Utilization among proposers</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Proposer count dummies</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>N</td>
<td>4,219</td>
<td>4,407</td>
<td>4,219</td>
<td>4,219</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.363</td>
<td>0.329</td>
<td>0.332</td>
<td>0.348</td>
</tr>
<tr>
<td>Sample mean outcome</td>
<td>4.966</td>
<td>4.660</td>
<td>4.619</td>
<td>4.619</td>
</tr>
</tbody>
</table>

|                  | (1)  | (2)  | (3)  | (4)  |
| **Panel B: Log Respondents** |      |      |      |      |
| Count type       | Total| Proposer | Proposer | Proposer |
| Standardized 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 standardized 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., \( \gamma_n I (\|S_i\| = n) \), 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: Price Transmission to Private Insurance

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log private price</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Medicare price</td>
<td>0.892***</td>
<td>0.399***</td>
<td>0.300***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.003)</td>
<td>(0.012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \times ) not RUC</td>
<td>0.688***</td>
<td>0.331***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.022)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \times ) RUC, low affiliation</td>
<td>0.838***</td>
<td>0.520***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.023)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \times ) RUC, high affiliation</td>
<td>0.917***</td>
<td>0.642***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.041)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RUC, high vs. low affiliation</td>
<td>-0.420***</td>
<td>-0.016</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.067)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Service fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Sample</td>
<td>RUC</td>
<td>Not RUC</td>
<td>Not RUC</td>
<td>Both</td>
<td>Both</td>
</tr>
<tr>
<td>Restrict non-RUC prices changes?</td>
<td>N/A</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>( N )</td>
<td>3,179</td>
<td>184,910</td>
<td>4,003</td>
<td>7,182</td>
<td>7,182</td>
</tr>
<tr>
<td>Adjusted ( R )-squared</td>
<td>0.986</td>
<td>0.987</td>
<td>0.992</td>
<td>0.852</td>
<td>0.987</td>
</tr>
<tr>
<td>Sample mean log private price</td>
<td>4.241</td>
<td>3.980</td>
<td>3.391</td>
<td>4.097</td>
<td>4.097</td>
</tr>
<tr>
<td>Sample mean log Medicare price</td>
<td>3.466</td>
<td>3.412</td>
<td>2.426</td>
<td>3.290</td>
<td>3.290</td>
</tr>
</tbody>
</table>

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 figure 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, 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 shows 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.
Note: This figure shows examples of within-specialty variation in standardized 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 $w_i$. 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 pair, and the outcome variable of interest is an indicator for whether the specialty was part of that proposal. Log RVU is predicted from service (CPT code) characteristics, word descriptions, and prior RVU, which are described in Table 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 $w_i$ and specialty dummies 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 $\alpha$ 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 counterfactual reallocation setting affiliation to the mean for all proposals is on the y-axis. Utilization quantities for each service (CPT code) is held fixed, and the annual Medicare budget for physician work is set at $70 billion \( \times 51\% = $35.7 \) billion. Details are given in Section 4.2.
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-5. 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 counterfactual reallocation setting affiliation to the mean for all proposals is on the y-axis. Utilization quantities for each service (CPT code) is held fixed, and the annual Medicare budget for physician work is set at $70 billion × 51% = $35.7 billion. Details are given in Section 4.2.
Figure 10: Principal Utility and Intermediary Bias

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 \( \theta \sim U(\hat{\theta}, \bar{\theta}) \), where \( L = \bar{\theta} - \hat{\theta} \) 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 \( (\kappa = 0.1) \).
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 $\alpha$ in Equation (7), with standard errors clustered by RUC meeting.
Figure 12: Price Transmission to Private Insurance

\[ \text{A: Cross Section} \]

\[ \text{B: Within Service} \]

**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 5. Panel A shows the relationship without controlling for service (CPT code) and corresponds to Column 4 of Table 5, while Panel B shows this relationship controlling for CPT code and corresponds to Column 5 of Table 5. 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 5.
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:

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

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

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

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

\[
\begin{align*}
\sum_{t'=1}^{t} Target_{t'} &= \sum_{t'=1}^{t} Actual_{t'}; \\
Actual_t &= Actual_{t-1} \times (1 + SGR_t) \times (1 + UAF_t); \\
Target_t &= Target_{t-1} \times (1 + SGR_t).
\end{align*}
\]

These identities yield

\[ UAF_t = \frac{Target_{t-1} - Actual_{t-1}}{Actual_{t-1}} \times 0.75 + \frac{\sum_{t'=1}^{t-2} (Target_{t'} - Actual_{t'})}{Actual_{t-1} \times (1 + SGR_t)} \times 0.33, \]

after being modified by “dampening” weights of 0.75 and 0.33, between components from the previous year and all other years before that, respectively.
The Sustainable Growth Rate (SGR$_t$) used above is calculated according to four factors: (i) the estimated percentage change in fees for physicians’ services, (ii) the estimated percentage change in the average number of Medicare fee-for-service beneficiaries, (iii) the estimated 10-year average annual percentage change in real gross domestic product per capita, and (iv) the estimated percentage change in expenditures due to changes in law or regulations.

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

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

which is closely related to the condition in Equation (A-4.4) 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 $p$ of price changes on $R_s$ as

$$\frac{dR_s}{dp} = \sum_i q_{is} \left( \frac{dp_i}{dp} + p_i \frac{dq_{is}}{dp} \right).$$  \hspace{1cm} (A-2.1)$$

While $q_{iA}$ and $p_i$ are observed, $dp_i/dp$ and $dq_{is}/dp$ are generally unknown.

**A-2.1.1 Quantity Shares**

In order to capture similarity in the effects of $p$ 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

$$\frac{dR_s}{dp} = \sum_i q_{is} \frac{dp_i}{dp}.$$  

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

$$\frac{dr_s}{dp} = \sum_i \sigma^q_{is} \frac{dp_i}{dp},$$

where $r_s = R_s/\sum_i q_{is}$ is the per-service revenue, and $\sigma^q_{is} = q_{is}/\sum_i q_{is}$ 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

$$\frac{dr_A}{dp} - \frac{dr_B}{dp} = \sum_i \left( \sigma^q_{iA} - \sigma^q_{iB} \right) \frac{dp_i}{dp}.$$  \hspace{1cm} (A-2.2)$$

Distances in the vector space of quantity shares, i.e., $(\sigma^q_A, \sigma^q_B)$, thus capture this difference for any arbitrary set of price changes (i.e., any arbitrary $p$ and the corresponding $dp_i/dp$ 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 $q_i = w_i q_i$, where $w_i$ is fixed regardless of $q_i \equiv \sum_s q_{is}$. Then note that percentage revenue change is

$$\frac{dR_s / dp}{R_s} = \frac{1}{R_s} \sum_i \left( q_{is} \frac{dp_i}{dp} + p_i \frac{dq_{is}}{dp} \right)$$

$$= \sum_i q_{is} p_i \cdot \frac{q_{is} \cdot dp_i / dp + p_i \cdot dq_{is} / dp}{p_i q_{is}}$$

$$= \sum_i \sigma_{is}^R \cdot \frac{q_i \cdot dp_i / dp + p_i \cdot dq_i / dp}{p_i q_i}$$

$$= \sum_i \sigma_{is}^R \cdot \frac{d(p_i q_i) / dp}{p_i q_i},$$

where $\sigma_{is}^R \equiv (p_i q_{is}) / R_s$ is the quantity share of $i$ relative to other procedures that $s$ performs, and the third line derives from dividing $w_i q_i$ from the numerator and the denominator. The expression multiplying $\sigma_{is}^R$ 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

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

Distances in the vector space of revenue shares, i.e., $(\sigma_{iA}^R, \sigma_{iB}^R)$, 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 $p$. 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:

\[ a(s_A, s_B) = -\sqrt{(\sigma_A - \sigma_B)'(\sigma_A - \sigma_B)}, \]

where \(\sigma_s\) 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 \(A\) and \(B\) corresponds to the difference in total effects on the revenue of the two specialties, particularly if the component effect from each service \(i - dp_i/dp\) or \(d(pq_i)/dp\) 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:

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

where \(G\) is a diagonal weighting matrix, such that \(G(i, i) = G_i\) is the Gini coefficient across \(\sigma_{is}\) 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

\[ a(s_A, s_B) = -\sum_i |\sigma_{iA} - \sigma_{iB}|, \]

and angular distance is in arc space, with affiliation

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

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 \(\sigma_s\) away from shares.\(^{34}\)

\(^{34}\)The argument inside of the angular distance formula is called the cosine similarity, or \(\cos(\sigma_A, \sigma_B)\). Denoting Euclidean distance between \(\sigma_A\) and \(\sigma_B\) as \(\|\sigma_A - \sigma_B\|_2\), \(\|\sigma_A - \sigma_B\|^2 = (\sigma_A - \sigma_B)'(\sigma_A - \sigma_B) = \|\sigma_A\|^2 + \|\sigma_B\|^2 - 2\sigma_A \cdot \sigma_B\).
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 Specialty-Proposal Propensity and Simulated Affiliation

Our measure of affiliation is determined mechanically by specialties on the RUC, $R_t$, and specialties on a proposal, $S_i$. To assess of our identifying assumption – that affiliation is uncorrelated with underlying price, conditional on observable characteristics of a proposal – we pay particular attention on the probability of specialty participation in proposals, as this is an endogenous object. As discussed in Section 3.3, the key intuition for this assumption is that a variety of factors determine the specialty cost of proposing and that, with many potential proposers and costly proposing, there exist multiple pure- and mixed-strategy equilibria. In Figure 6, we show evidence that actual specialty proposals are uncorrelated with predicted price, conditional on specialty-proposal propensities estimated by a logit model of specialty identities and functions of specialty shares of the procedure’s utilization $w_i$. Here, we enrich our specialty-proposal propensity model to (i) show substantial residual variation in proposals and (ii) form a basis to simulate affiliation. We will further use simulated measures of affiliation to (iii) demonstrate unbiasedness in our prediction of affiliation based on proposal propensities and (iv) use predicted (mean simulated) affiliation as a control for robustness.

We first estimate a logit propensity model of specialty-proposal participation, using specialty identities, flexible functions of $w_i$, and the procedure’s share of specialty revenue, defined as $\sigma_{is}^R$ in Appendix A-2.1.2. While the logit model is fairly predictive, with a pseudo-$R^2$ of 0.73 and a log-likelihood of $-8661.35$ over 248,735 observations, we find substantial residual variation in specialty proposals. To illustrate this, in Figure A-2, we show the propensities of 6,929 actual specialty-proposal pairs over 4,199 proposals. While there are many propensities with high values, more than half of the actual specialty proposals have propensities lower than 0.8, and about a quarter have propensities less than 0.5. Similarly, in Figure A-3, we show the first-, second-, third-, and fourth-ranked specialty propensities for proposals with at least as many proposers. Although there are 64 specialties to rank, propensities quickly diminish: The average first-ranked propensity is 0.86, while the average second-, third-, and fourth-ranked propensities are 0.76, 0.69, and 0.54, respectively.

Based on estimated specialty-proposal propensities, $\hat{\pi}_{is}$, and the known specialties of RUC members at each meeting, $R_t$, we can simulate affiliation. We proceed as follows:

$$2\sigma_A \cdot \sigma_B. \text{ If } \|\sigma_A\|_2^2 = \|\sigma_B\|_2^2 = 1, \text{ then } \|\sigma_A - \sigma_B\|_2^2 = 2(1 - \cos(\sigma_A, \sigma_B)).$$
1. Use estimated specialty-proposal propensities, $\hat{\pi}_{is}$. Drop any specialty-proposal pair with $\hat{\pi}_{is} < 0.01$.

2. For each proposal $i$, identify number of remaining specialty-proposer candidates, $n_i$, and the number of actual specialty proposers, $k_i$. This yields $C(n_i, k_i)$ as the number of potential proposer sets $S_i \in S_i$ for $i$, constraining the number of simulated proposers in each set to be the same as the number of actual proposers. For example, if there remain ten specialty-proposer candidates for a proposal with only one actual specialty proposer, there are $C(10, 1) = 10$ (singleton) sets to draw from. However, if there are fifteen specialty-proposer candidates for a proposal with four actual proposers, there are $C(15, 4) \approx 7.57 \times 10^7$ sets to draw from.

(a) Select proposals $i$ such that the number of sets is less than 50, or $\|S_i\| \leq 50$. Calculate a simulated set affiliation $A(R_t, S_i)$ for each $S_i \in S_i$, using known $R_t$ and the formula in Equation (4).

(b) For the remaining proposals, randomly draw $k_i$ proposers from $n_i$, oversampling specialty-proposer candidates from those with higher $\hat{\pi}_{is}$. Specifically, generate $r_{is} \sim U(0, 1)$ and subtract this from $\hat{\pi}_{is}$. Within each $i$, sort specialty-proposer candidates by $\hat{\pi}_{is} - r_{is}$, and choose the top $k_i$ candidates to include in $S_i$. Repeat until some stopping rule (e.g., based on the number of unique sets sampled for each $i$ and the lack of new sets sampled for any $i$ in a draw).

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

$$
\Pr(S_i | S_i) = \frac{\prod_{s \in S_i} \hat{\pi}_{is} \prod_{s \notin S_i} (1 - \hat{\pi}_{is})}{\sum_{S_i \in S_i} \left(\prod_{s \in S_i} \hat{\pi}_{is} \prod_{s \notin S_i} (1 - \hat{\pi}_{is})\right)}.
$$

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

$$
\hat{A}(R_t, i) = \sum_{S_i \in S_i} A(R_t, S_i) \Pr(S_i | S_i).
$$

(A-3.3)

In Figure A-4, we show the distribution of simulated set affiliations relative to the actual set affiliation for each $i$, weighted by $\Pr(S_i | S_i)$. The weighted standard deviation of the distribution is 0.242, reflecting that there exists meaningful variation in set affiliation based on the specialty-proposal propensities. Further, the weighted mean of the distribution is $-0.015$, suggesting very little forecast bias in predicted set affiliation. We use predicted set affiliation as a control, rather than linear specialty shares of CPT utilization, $w_i$, in a robustness check of the affiliation effect on prices, in Column 5 of Table 3, and find a similar estimate of the effect.
A-4 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 $\tilde{RVU}_{iy}$, by subtracting $\hat{\alpha} \left( A(R_t, S_i) - \tilde{A}(R_t, S_i) \right)$, where $A(R_t, S_i)$ and $\tilde{A}(R_t, S_i)$ 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 $\tilde{CF}_y$ so that the overall spending is $\$70$ billion in 2014 dollars, which implies that

$$\tilde{CF}_y \sum_i \sum_s \tilde{RVU}_{iy} \cdot q_{isy} = CF_y \sum_i \sum_s RVU_{iy} \cdot q_{isy}. \quad (A-4.4)$$

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

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

4. We aggregate $\Delta r_{isy}$ to yearly averages for specialties $s$ or types of service $k$:

$$\Delta R_s = \|Y\|^{-1} \sum_{y \in Y} \sum_i \Delta r_{isy};$$

$$\Delta R_k = \|Y\|^{-1} \sum_{y \in Y} \sum_s \sum_{i \in k} \Delta r_{isy}.$$

A-5 Alternative Mechanisms Behind the Price Effect

In this appendix, we consider evidence regarding alternative mechanisms of the affiliation effect on prices, summarized in Table A-4. All specifications in Table A-4 include the same controls in the baseline specification of the price regression, shown in Column 4 of Table 3.

We first consider the possibility that affiliation could reflect signaling “buy-in.” More specialties should be willing to propose for procedures that need to be priced more highly, which mechanically raises set affiliation, as defined in Equation (4), through max operator in the formula. Higher prices under this mechanism are warranted and do not reflect any RUC bias. We
modify the baseline price-effect regression in Equation (6) to include proposer-count fixed effects:

$$\ln RVU_{it} = \alpha A(R_t, S_i) + \gamma \|S_i\| = n + X_i\beta + T_t\eta + w_i\zeta + \varepsilon_{it}. \quad (A-5.5)$$

This specification relies only on within-proposer-count variation to identify the price effect of affiliation. As shown in Column 1 of Table A-4, the coefficient on standardized set affiliation is unchanged, at 0.112, and highly significant.

Next, we consider a range of specifications relating to interests (and information) held by RUC specialties that are specific to the proposed service. Specifically, we consider the service $i$’s utilization share of all services billed by a RUC specialty $s$, or $\sigma_{is}^q$, as defined Equation (2) and discussed in Appendix A-2.1.1. We also consider the $i$’s revenue share of all Medicare revenue to $s$, or $\sigma_{is}^R$, as defined and discussed in Appendix A-2.1.2. These measures capture both proposal-specific interests and information about $i$, but to the extent that specialty interests are multifaceted across many services, they may weigh more heavily on information. We perform variants of the regression

$$\ln RVU_{it} = \alpha A(R_t, S_i) + \gamma m_{s \in R_t}(\sigma_i) + X_i\beta + T_t\eta + w_i\zeta + \varepsilon_{it}, \quad (A-5.6)$$

where $m_{s \in R_t}(\sigma_i)$ is a moment function of the vector service-specific utilization or revenue share across specialties on the RUC, $s \in R_t$.

Columns 2 and 3 of Table A-4 show results for regressions adding standardized mean $\sigma_{is}^q$ and $\sigma_{is}^R$, respectively. Columns 4 and 5 show results for regressions adding standardized 33rd percentile $\sigma_{is}^q$ and $\sigma_{is}^R$, respectively. In all specifications, the coefficient on standardized set affiliation remains unchanged in magnitude and significance. The coefficients on the standardized measures of RUC-specialty interest in $i$ (or $\gamma$) are small, though statistically significant. Although we ascribe a causal interpretation to the effect of affiliation, given our discussion in Section 3.3, the same reasoning does not hold for $\gamma$.\textsuperscript{35}

A-6 Technical Details of the Conceptual Framework

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

\textsuperscript{35}For $\gamma$ to have a causal interpretation, we would require random variation in RUC specialty composition, $R_t$. As we discuss in Section 3.3, the RUC has had a relatively fixed composition over time, compared to variation in specialty proposals. In contrast, note that $m_{s \in R_t}(\sigma_i)$ is invariant to the specialty identities in the proposal, $S_i$. 

A-9
A-6.1 Canonical Crawford and Sobel (1982) Partitions

Consider \( \theta \) 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

\[
n^* (b) = \left\lfloor \frac{1}{2} \left( 1 + \sqrt{1 + \frac{2L}{b}} \right) \right\rfloor.
\] (A-6.7)

Using Equation (A-6.7), we define the limiting bias such that \( n^* (b - \varepsilon) = n \) for any positive but arbitrarily small \( \varepsilon \):

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

\( b^* (n) \) 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

\[
x_1 = \frac{L}{n} - (n - 1) 2b,
\] (A-6.8)

Subsequent partition lengths increase by \( 4b \), which implies

\[
x_k = 2x_{k-1} - x_{k-2} + 4b,
\] (A-6.9)

and Equations (A-6.8) and (A-6.9) imply that \( x_n = L \).

We will consider a number of specific examples of \( n \), which exist for \( b \in \left[ b^* (n + 1), b^* (n) \right) \). 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 \( b \in \left[ b^* (n + 1), b^* (n) \right) \) and are defined by \((0, \frac{L}{n - 2}, \frac{L}{n} - 4b, L)\). 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 \( b \in \left[ \frac{b^* (n + 1)}{2}, \frac{b^* (n)}{2} \right) \) and are defined by \((0, \frac{L}{3} - 4b, \frac{2L}{3} - 4b, L)\). 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
\[
E \left[ (\theta + b_R - p)^2 \right] = \frac{1}{12} \left( \frac{L^2}{n^2} + A_n b^2 \right),
\]
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-6.2 Hard Information

Given the formula for soft information loss in Equation (A-6.10), we can write the expected utility for the specialty and the government, respectively, as
\[
E \left[ u_S \right] = -E \left[ (\theta + \theta_R - p)^2 \right] - b^2 - c(L) \\
= -\frac{1}{12} \left( \frac{L^2}{n^2} + A_n b^2 \right) - b^2 - c(L),
\]
and as
\[
E \left[ u_G \right] = -E \left[ (\theta + \theta_R - p)^2 \right] - b_R^2 \\
= -\frac{1}{12} \left( \frac{L^2}{n^2} + A_n b^2 \right) - b_R^2.
\]

In both Equations (A-6.11) and (A-6.12), \(n\) is the number of partitions supported by \(b\) and \(L\) and is given by Equation (A-6.7). Better information, either hard or soft, increases the utility of both the specialty and the government.

Taking the partial derivative of expected specialty utility with respect to \(L\), while holding \(b\) and \(n\) fixed, yields the following condition for the agent’s choice of \(L\):
\[
\frac{\partial}{\partial L} E [u_S] = -\frac{L}{6n^2} - c'(L) = 0.
\]

The convexity of \(c(L)\) implies that there exists a single optimal candidate that satisfies Equation (A-6.13) for the cheap talk equilibrium with \(n\) partitions. Denote the solution to Equation (A-6.13) for a given \(n\), if it exists (i.e., \(n^* (b,L) = n\)), as \(L_n^*\). Intuitively, \(L_n^*\) is increasing in \(n\):

\[\text{(A-6.13)}\]

In Equation (A-6.13), \(L_n^*\) is increasing in \(n\), and in Equation (A-6.7), \(n^* (b,L)\) is increasing in \(L\). Since (i)
better soft communication (higher \(n\)) reduces the incentive to produce hard information (larger \(L_n^*\)). The globally optimal \(L^*\) is then given by \(L^* = \arg \max_n (E[u_S; L_n^*])\). \(L^*\) is decreasing in \(b\): As the specialty and the RUC have divergent preferences, soft communication worsens, and this increases hard information. Because the set of \(L_n^*\) is comprised of discrete values, \(L^* (b)\) is a step function.

**A-6.3 Optimal RUC Bias**

Because smaller \(L^*\) increases government utility in Equation (A-6.12), and because \(L^*\) is a decreasing function of \(b = b_R - b_S\). The optimal \(b^*_R\) from the government’s perspective is weakly lower under the possibility of hard information than when we fix \(L = 1\).

However, the optimal \(b^*_R \geq 0\). That is, an adversarial RUC is still never optimal from the government’s perspective. In order for \(b^*_R < 0\), we need three requirements:

1. The threshold \(\bar{b}_R\) where the specialty is indifferent between \(n = 1\) and \(n = 2\) must be less than 0.

2. The expected government utility when \(b_R = \bar{b}_R\) is higher than the maximum expected government utility under \(n = 2\):

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

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

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

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

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

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

In other words

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

\(L_n^* \in (0, 1]\) and (ii) \(n^* (b, L)\) is bounded by \(n^* (b, 1)\), there must be at least one \(n \in \{1, \ldots, n^* (b, 1)\}\) such that \(n^* (b, L_n^*) = n\).

---

A-12
The threshold is then

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

(A-6.14)

Condition 1 and convexity imply that

\[ b_S < \sqrt{\frac{1}{12} (L_1^*)^2 - \frac{1}{48} (L_2^*)^2 + \frac{1}{6} L_1^* (L_2^* - L_1^*)}. \]  

(A-6.15)

Condition 2 requires that

\[ -\frac{1}{12} (L_1^*)^2 - \bar{b}_R^2 > -\frac{1}{48} (L_2^*)^2 - \frac{1}{2} b_S^2, \]  

(A-6.16)

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

\[ -\frac{1}{12} (L_1^*)^2 - \bar{b}_R^2 > - b_S^2. \]  

(A-6.17)

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

We show numerically that there are no values \((L_1^*, L_2^*, b_S, \bar{b}_R)\) that satisfy Equations (A-6.14) to (A-6.17) simultaneously.

**A-6.4 Uniform Posterior Intervals**

While it is convenient to work with continuous \( L \), there is a technical complication in specifying values of \( \theta \) and \( \theta \), such that it remains that \( \theta \sim U(\bar{\theta}, \theta) \) with fixed \( L = \bar{\theta} - \theta \). For example, consider the case of \( L = 0.9 \). If \( \theta = 0 \), then we must have \( \bar{\theta} = 0 \) with probability 1, but \( \theta = 0 \) with probability less than 1 if \( \theta > 0 \). Therefore, if any potential interval must have \( L = 0.9 \), and we have a realized interval \([\underline{\theta}, \bar{\theta}] = [0, 0.9]\), then \( \theta \) 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 \( \theta \) 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 \( \theta \) falls in an interval of length \( L_a \) is \( NL_a \), while the probability that \( \theta \)
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 $N = \lfloor L^{-1} \rfloor$:

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

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 $L$:

$$E[u_A] = -E[(\theta - p)^2] - b^2 - c(L)$$

$$= -\frac{1}{12} \left[ \frac{NL_a^2}{n_b^2} + \frac{(1 - NL_a)^3}{n_b^2} + A b^2 \right] - b^2 - c(L), \quad (A-6.18)$$

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

### A-7 Private Price Transmission Robustness

In Section 7, we show that private insurance price changes are more responsive to Medicare price changes when the Medicare price changes originate from RUC decisions and, within RUC decisions, when they originate from a higher-affiliation proposal. We interpret this finding as supporting the hypothesis that RUC decisions, particular those from higher-affiliation proposals, contain valuable information that private insurance follows. In this appendix, we investigate alternative mechanisms that may generate this result.

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

\[
\begin{align*}
\overline{w}_{iy} &= \frac{1}{\|R_t(i,y)\|} \sum_{s \in R_t(i,y)} w_{is}; \\
\sigma_{iy} &= \frac{1}{\|R_t(i,y)\|} \sum_{s \in R_t(i,y)} \sigma_{is},
\end{align*}
\]

(A-7.19) \hspace{1cm} (A-7.20)

where \( R_t(i,y) \) is the set of RUC member specialties at the meeting \( t \) \((i, y)\) corresponding to service \( i \) and (private) price change year \( y \).

Second, affiliated proposals may be for high-volume services that both private insurance and Medicare have interests in setting accurate prices. Strong correlation between private insurance and Medicare price changes for high-affiliation proposals may then result from careful price-setting in both private insurance and Medicare, and not because affiliation \emph{per se} causes better communication between proposing specialties and the RUC. We consider two measures of volume for service \( i \): private insurance volume and total (private insurance and Medicare) volume.

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

\[
\Delta \ln \text{Price}^P_{i,y} = \alpha + \beta_{iy} \Delta \ln \text{Price}^M_{i,y} + \varepsilon_{iy},
\]

where the goal is to predict \( \beta_{iy} \). To operationalize this, as an approximation of \( \beta_{iy} \), we take the ratio of demeaned \( \Delta \ln \text{Price}^P_{i,y} \) and demeaned \( \Delta \ln \text{Price}^M_{i,y} \):

\[
\text{Ratio}_{iy} = \frac{\Delta \ln \text{Price}^P_{i,y} - \overline{\Delta \ln \text{Price}^P}}{\Delta \ln \text{Price}^M_{i,y} - \overline{\Delta \ln \text{Price}^M}},
\]

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

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

\[A-15\]

\[37\] This changes-on-changes specification closely matches the fixed-effects specification in Equation (9). As shown in Figure A-6, separating Medicare price changes into high- and low-affiliation groups gives similar results.
\[
\ln \text{Price}_{iy}^P = \sum_C \left( \alpha_C + \beta_C \ln \text{Price}_{i,y}^M M(i,y) \right) \cdot 1 \left( C(i,y) = C \right) + \\
\sum_{\tau=1}^{3} \left( \gamma_{\tau} + \delta_{\tau} \ln \text{Price}_{i,y}^M M(i,y) \right) \cdot 1 \left( F(\text{Index}_{iy}) \in \left( \frac{\tau - 1}{3}, \frac{\tau}{3} \right) \right) + \\
T_{iy} + \xi_i + \varepsilon_{iy},
\]

where \( \tau \in \{1, 2, 3\} \) indicates the tertile, \( F(\cdot) \) is the distribution function of the relevant measure \( \text{Index}_{it} \), and the rest is the same as in Equation (9). Table A-6 shows results from these regressions. The key coefficients of interest, \( \beta_C \), are highly stable regardless of \( \text{Index}_{iy} \). Price transmission remains greater for Medicare price changes originating from RUC decisions and, within these decisions, from high-affiliation proposals.
Table A-1: Sample Selection

<table>
<thead>
<tr>
<th>Sample step</th>
<th>Description</th>
<th>Observations</th>
<th>Dropped</th>
<th>Remaining</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Raw RUC data</td>
<td>Universe of all administrative data used by RUC</td>
<td></td>
<td>17,498</td>
<td></td>
</tr>
<tr>
<td>2. Drop observations with no survey information and no RUC recommendation</td>
<td>These observations do not represent RUC decisions, as all decisions require these elements</td>
<td></td>
<td>11,079</td>
<td>6,419</td>
</tr>
<tr>
<td>3. Drop observations that appear to be duplicates</td>
<td>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</td>
<td></td>
<td>132</td>
<td>6,353</td>
</tr>
<tr>
<td>4. Combine observations with same CPT code and RUC meeting but different survey specialties</td>
<td>These observations were incorrectly entered as separate lines; use total survey sample and respondent numbers</td>
<td></td>
<td>127</td>
<td>6,226</td>
</tr>
<tr>
<td>5. Drop observations with invalid RUC meeting date</td>
<td>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</td>
<td></td>
<td>490</td>
<td>5,736</td>
</tr>
<tr>
<td>6. Drop observations with missing survey specialty or specialties</td>
<td>These observations are likely administrative discussions without a full proposal from a specialty or specialties</td>
<td></td>
<td>1,313</td>
<td>4,423</td>
</tr>
</tbody>
</table>

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

**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

<table>
<thead>
<tr>
<th>Affiliation vector space</th>
<th>Euclidean</th>
<th>Gini-Euclidean</th>
<th>Manhattan</th>
<th>Correlation</th>
<th>Angular</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Mean affiliation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medicare CPT quantity</td>
<td>0.101***</td>
<td>0.104***</td>
<td>0.055**</td>
<td>0.061**</td>
<td>0.059**</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.030)</td>
<td>(0.021)</td>
<td>(0.025)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Medicare + Marketscan</td>
<td>0.076***</td>
<td>0.079***</td>
<td>0.048**</td>
<td>0.057**</td>
<td>0.055**</td>
</tr>
<tr>
<td>CPT quantity</td>
<td>(0.025)</td>
<td>(0.026)</td>
<td>(0.020)</td>
<td>(0.025)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Medicare CPT revenue</td>
<td>0.094***</td>
<td>0.094***</td>
<td>0.038*</td>
<td>0.036*</td>
<td>0.036*</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.029)</td>
<td>(0.019)</td>
<td>(0.021)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Medicare BETOS quantity</td>
<td>0.088***</td>
<td>0.089***</td>
<td>0.056**</td>
<td>0.049**</td>
<td>0.050**</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.030)</td>
<td>(0.022)</td>
<td>(0.024)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Medicare BETOS revenue</td>
<td>0.073***</td>
<td>0.068**</td>
<td>0.045**</td>
<td>0.030</td>
<td>0.033*</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.028)</td>
<td>(0.021)</td>
<td>(0.020)</td>
<td>(0.019)</td>
</tr>
<tr>
<td><strong>Panel B: 33rd percentile affiliation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medicare CPT quantity</td>
<td>0.104***</td>
<td>0.111***</td>
<td>0.061**</td>
<td>0.060**</td>
<td>0.060**</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.031)</td>
<td>(0.024)</td>
<td>(0.026)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Medicare + Marketscan</td>
<td>0.076***</td>
<td>0.081***</td>
<td>0.062**</td>
<td>0.052**</td>
<td>0.050**</td>
</tr>
<tr>
<td>CPT quantity</td>
<td>(0.024)</td>
<td>(0.026)</td>
<td>(0.023)</td>
<td>(0.024)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Medicare CPT revenue</td>
<td>0.089***</td>
<td>0.091***</td>
<td>0.039*</td>
<td>0.027</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.033)</td>
<td>(0.021)</td>
<td>(0.022)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Medicare BETOS quantity</td>
<td>0.086**</td>
<td>0.093***</td>
<td>0.066***</td>
<td>0.051**</td>
<td>0.053**</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.034)</td>
<td>(0.025)</td>
<td>(0.025)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Medicare BETOS revenue</td>
<td>0.088***</td>
<td>0.083***</td>
<td>0.053**</td>
<td>0.034**</td>
<td>0.043**</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.029)</td>
<td>(0.022)</td>
<td>(0.016)</td>
<td>(0.018)</td>
</tr>
</tbody>
</table>

**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: Alternative Mechanisms Behind Price Effect

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Log RVU</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized set affiliation</td>
<td>0.112***</td>
<td>0.098***</td>
<td>0.103***</td>
<td>0.098***</td>
<td>0.104***</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.029)</td>
<td>(0.030)</td>
<td>(0.030)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Standardized measures</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>of RUC-specialty interest</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean $\sigma^q_{is}$</td>
<td></td>
<td>0.021**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.009)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean $\sigma^R_{is}$</td>
<td></td>
<td></td>
<td>0.031***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>33rd percentile $\sigma^q_{is}$</td>
<td></td>
<td></td>
<td></td>
<td>0.028***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>33rd percentile $\sigma^R_{is}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.030***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Baseline controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Proposer count dummies</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>$N$</td>
<td>4,401</td>
<td>4,401</td>
<td>4,401</td>
<td>4,401</td>
<td>4,401</td>
</tr>
<tr>
<td>Adjusted $R$-squared</td>
<td>0.891</td>
<td>0.891</td>
<td>0.895</td>
<td>0.891</td>
<td>0.895</td>
</tr>
<tr>
<td>Sample mean log RVU</td>
<td>1.567</td>
<td>1.567</td>
<td>1.567</td>
<td>1.567</td>
<td>1.567</td>
</tr>
</tbody>
</table>

**Note:** This table shows results of regressions of log RVU on standardized set affiliation, with the addition of controls to test robustness to alternative mechanisms. Column 1 tests robustness to the alternative mechanism of signaling “buy-in,” controlling for proposer dummies, as in Equation (A-5.5). Columns 2 to 5 relate to alternative mechanisms of proposal-specific information held by RUC specialties. These specifications, given in Equation (A-5.6), control for proposal-specific measures of utilization or revenue shares by RUC specialties, or $\sigma^q_{is}$ and $\sigma^R_{is}$. Measures are moments (mean or 33rd percentile) in the distribution across RUC specialties and are standardized to have mean 0 and standard deviation 1. Details are given in Appendix A-5. All specifications include controls in the baseline price-effect regression, in Column 4 of Table 3. Standard errors, clustered by RUC meeting, are in parentheses; ** denotes significance at the 5% level, and *** denotes significance at the 1% level.
Table A-5: Specialty Seats on Counterfactual RUC

<table>
<thead>
<tr>
<th>Specialty</th>
<th>Seats</th>
<th>Specialty</th>
<th>Seats</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anesthesiology</td>
<td>2</td>
<td>Obstetrics and Gynecology</td>
<td>2</td>
</tr>
<tr>
<td>Cardiology</td>
<td>1</td>
<td>Oncology</td>
<td>1</td>
</tr>
<tr>
<td>Emergency Medicine</td>
<td>2</td>
<td>Ophthalmology</td>
<td>1</td>
</tr>
<tr>
<td>Family Medicine</td>
<td>4</td>
<td>Orthopedic Surgery</td>
<td>1</td>
</tr>
<tr>
<td>Gastroenterology</td>
<td>1</td>
<td>Pediatrics</td>
<td>2</td>
</tr>
<tr>
<td>General Surgery</td>
<td>1</td>
<td>Psychiatry</td>
<td>1</td>
</tr>
<tr>
<td>Internal Medicine</td>
<td>4</td>
<td>Radiology</td>
<td>1</td>
</tr>
<tr>
<td>Neurology</td>
<td>1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 25, as it is in the current RUC. This RUC accommodates the 16 largest specialties; including specialties with fewer physicians would require a larger RUC. Many smaller specialties lack a seat in this RUC; compare this to the broader range of specialties that have some representation on the actual RUC over time in Table 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-6: Price Transmission Robustness

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Medicare price</td>
<td>Log private price</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>× not RUC</td>
<td>0.331***</td>
<td>0.291***</td>
<td>0.328***</td>
<td>0.338***</td>
<td>0.329***</td>
<td>0.326***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.023)</td>
<td>(0.022)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>× RUC, low affiliation</td>
<td>0.520***</td>
<td>0.513***</td>
<td>0.530***</td>
<td>0.536***</td>
<td>0.524***</td>
<td>0.520***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.027)</td>
<td>(0.023)</td>
<td>(0.024)</td>
<td>(0.023)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>× RUC, high affiliation</td>
<td>0.642***</td>
<td>0.733***</td>
<td>0.653***</td>
<td>0.657***</td>
<td>0.655***</td>
<td>0.629***</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.044)</td>
<td>(0.041)</td>
<td>(0.042)</td>
<td>(0.041)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>RUC, high vs. low affiliation</td>
<td>-0.016</td>
<td>0.168**</td>
<td>-0.017</td>
<td>-0.003</td>
<td>0.001</td>
<td>-0.048</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td>(0.069)</td>
<td>(0.067)</td>
<td>(0.067)</td>
<td>(0.068)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Proxy or predictor (Indexiy)</td>
<td>None</td>
<td>wi_y</td>
<td>i_y</td>
<td>Private volume</td>
<td>Total volume</td>
<td>All</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.852</td>
<td>0.859</td>
<td>0.852</td>
<td>0.987</td>
<td>0.987</td>
<td>0.987</td>
</tr>
</tbody>
</table>

Note: This table shows results of regressions of log private price on log Medicare price, as in Table 5. Definitions of private and Medicare prices and the merging of the two prices are given in Table 5. Column 1 has no proxy or predictor and is identical to Column 5 in Table 5, as written in Equation (10). The remaining columns control for indicators of tertiles of a proxy and interactions of these indicators with log Medicare price, as written in Equation (A-7.21). Columns 2 and 3 consider proxies for information that the average RUC member specialty may have about i, specifically wi_y and i_y, defined as the average specialty share of a service’s utilization and the average service share of a specialty’s utilization, given in Equations (A-7.19) and (A-7.20), respectively. Columns 4 and 5 consider proxies of the importance of a service i to private insurance, specifically the private insurance volume or the total private insurance and Medicare volume, respectively. Column 6 considers a prediction of price transmission based on private volume, total volume, year dummies, Medicare price change year dummies, RUC meeting dummies, and specialty share wi. All regressions are run on the same sample of 7,182 observations, weighted by Medicare volume. Standard errors are in parentheses. ** denotes significance at the 5% level; *** denotes significance at the 1% level.
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 Specialty-Proposal Propensities among Proposers

Note: This figure shows the density of specialty-proposal propensities, estimated by a logit model of 248,735 specialty-proposal pairs as described in Appendix A-3. Proposal propensities are shown only for 6,929 actual specialty-proposal pairs over 4,199 proposals.
Figure A-3: Distribution of Highly Ranked Specialty-Proposal Propensities

Note: This figure shows the density of specialty-proposal propensities, estimated by a logit model of 248,735 specialty-proposal pairs as described in Appendix A-3. In each panel, proposal propensities are shown only for correspondingly ranked specialty for proposals that have at least as many actual proposers. Specifically, in Panel A, the highest specialty propensity is shown for 4,199 proposals. In Panel B, the second-highest specialty propensity is shown for 1,524 proposals with at least two proposers. In Panel C, the third-highest specialty propensity is shown for 558 proposals with at least three proposers. In Panel D, the fourth-highest specialty propensity is shown for 300 proposals with at least four proposers.
Figure A-4: Distribution of Simulated Set Affiliation Relative to Actual Set Affiliation

Note: This figure shows the density of 51,763 simulated set affiliations, using actual $R_t$ and simulated proposing specialty sets $S_i$ for each proposal $i$, differenced by actual set affiliation. Simulated specialty-proposals are derived from a logit model of specialty-proposal propensities, as illustrated in Figures A-2 and A-3. Simulated observations are weighted by their likelihood of being drawn. The weighted standard deviation of the simulated set affiliations is 0.242, and the weighted mean of the differenced statistic is $-0.015$. Details of the simulation algorithm are described in Appendix A-3.
Figure A-5: 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 pair observed in the 100% sample of Medicare claims. The figure excludes any pair with fewer than 10 claims. Log prices are then normalized by subtracting the average log Medicare price across CPT codes in a given year, weighted by frequency of claims. The figure plots the difference between the normalized log price for a CPT code in a year and the price for the same CPT code in the previous year.
Figure A-6: Private Price Changes on Medicare Price Changes

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 5. For consistency with Table 5, 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.