A Denial a Day Keeps the Doctor Away*

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Abstract

Who bears the consequences of administrative problems in healthcare? We use data on repeated interactions between a large sample of U.S. physicians and many different insurers to document the complexity of healthcare billing, and estimate its economic costs for doctors and consequences for patients. Observing the back-and-forth sequences of claim denials and resubmissions for past visits, we can estimate physicians' costs of haggling with insurers to collect payments. Combining these costs with the revenue never collected, we estimate that physicians lose 18% of Medicaid revenue to billing problems, compared with 4.7% for Medicare and 2.4% for commercial insurers. Identifying off of physician movers and practices that span state boundaries, we find that physicians respond to billing problems by refusing to accept Medicaid patients in states with more severe billing hurdles. These hurdles are quantitatively just as important as payment rates for explaining variation in physicians' willingness to treat Medicaid patients. We conclude that administrative frictions have first-order costs for doctors, patients, and equality of access to healthcare. We quantify the potential economic gains—in terms of reduced public spending or increased access to physicians—if these frictions could be reduced, and find them to be sizable.

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1 Introduction

Health insurance features an intricate system of contracts involving many private and public entities. Scholars and policymakers have argued that administering and implementing these contracts, which govern 13 percent of U.S. GDP, increases costs and reduces efficiency of U.S. healthcare (Cutler and Ly, 2011).[1] Measuring administrative costs is inherently difficult and past evidence on their size and impact in healthcare markets has generally been limited to surveys (Cunningham and O'Malley, 2008; Casalino et al., 2009; Morra et al., 2011; Long, 2013) or accounting exercises (Pozen and Cutler, 2010; Tseng et al., 2018).

We use data from an obscure part of the billing system, called "remittance data," to examine whether administrative frictions consume healthcare resources, and consequently distort the availability of care. Doctors and insurers often have trouble determining what care a patient's insurance covers, and at what prices, until after the treatment occurs. This ambiguity leads to a costly billing and bargaining process after care is provided—what we call the *costs of incomplete payments* (CIP). We estimate these costs across insurers and states. We then show that CIP impact Medicaid patients' access to medical care. This impact is quantitatively as relevant as physician payment rates, which are known to influence physicians' acceptance of Medicaid patients (Polsky et al., 2015; Oostrom, Einav and Finkelstein, 2017; Candon et al., 2018; Alexander and Schnell, 2019), and the supply of care more broadly (Gruber, Kim and Mayzlin, 1999; Clemens and Gottlieb, 2014; Dunn and Shapiro, 2018; Gottlieb et al., 2021).

The remittance data capture the billing processes following 90 million visits between 2013–2015. We observe repeated interactions between insurers and physicians, along with information about the patient and the reasons payments are denied. These data provide far more detail about the billing process than the claims data that have become widely used to study healthcare markets. Combined with a model, they enable us to estimate empirically

[1] National health expenditure comprised nearly 18 percent of GDP in 2019, before COVID increased that figure to nearly 20 percent in 2020 (Centers for Medicare and Medicaid Services, 2020). Centers for Medicare and Medicaid Services (2019) reports that 73 percent of this 18 percent was paid by a health insurer.

the costs of haggling between the physician's practice and the insurer.

Payment frictions are particularly large when billing Medicaid—a key part of the U.S. social safety net, which generally provides less access to care than other insurance (Polsky et al., 2015; Candon et al., 2018; Oostrom et al., 2017). We find that 24% of Medicaid claims have payment denied for at least one service upon doctors' initial claim submission. Denials are much less frequent for Medicare (6.7%) and commercial insurance (4.1%). Following a denial, the physician can accept that the claim won't be paid, foregoing the potential revenue, or she can commence a back-and-forth process to quarrel with the insurer over payment.

We show that physicians are more likely to undertake this process when the financial stakes are larger, and when more likely to successfully collect revenues. We leverage this empirical observation and a model of rational dynamic billing decisions to estimate CIP across insurers and states. In the model, doctors (or their billing offices) maximize total expected revenues net of administrative costs, under rational expectations about the probability of future denials and future resubmissions. Using the conditional choice probability method (Hotz and Miller, 1993) we estimate expected continuation values for each feasible resubmission decision, and obtain maximum likelihood estimates of the costs of resubmitting claims.

Our CIP estimates incorporate two concepts: expected foregone revenues and expected additional billing costs that providers incur during the back-and-forth negotiations with insurers. We estimate that CIP average 17.6% of the contractual value of a typical visit in Medicaid, 4.7% in Medicare, and 2.4% in private insurance. These are significant shares—especially for Medicaid, which offers physicians much lower reimbursement rates than other insurers in the first place. In addition to these differences across insurers, we also find significant variation in CIP across states.

The magnitude and variation raise a natural question: does CIP affect physicians' supply of care? We test this using the federalist structure of Medicaid, the federal-state program that insures lower-income adults, pregnant women, and children. While it is largely federally financed, and subject to federal regulations, Medicaid is administered separately by each state—often via contracts to managed care organizations. This structure enables dramatic variation in physician payment rates and processes, driving the empirical variation we find. By adjusting our CIP estimates and fees for patient composition and physician billing skills, we generate state-by-insurer price and CIP indices driven purely by insurance administration.

We combine these indices with administrative data on all physicians' locations and survey data on the near-universe of physicians' Medicaid and Medicare participation decisions from 2009–2015. Our key outcome is whether the physician accepts Medicaid patients when practicing in a given state, in a given year. To avoid confounding due to physicians who are capacity constrained, we focus on physicians who accept Medicare patients; our results are robust to relaxing this restriction.[2]

We use two strategies to identify the impacts of Medicaid prices and CIP. The first studies providers who move across states (Abowd, Kramarz and Margolis, 1999; Finkelstein, Gentzkow and Williams, 2016; Hull, 2018; Molitor, 2018). Second, we compare physicians' Medicaid acceptance across clinic locations that operate in different states but are managed by the same physician group. The first strategy controls for any differences in individual physicians' specialization or preferences, such as the level of altruism towards Medicaid patients. The second strategy addresses the possibility that a group's managerial competence or organizational structure influences Medicaid acceptance decisions.[3]

Examining physicians who move across states, a one-standard-deviation increase in CIP—approximately ten percentage points—reduces physicians' probability of accepting Medicaid patients by 0.8 percentage points. This is larger than the effect of a one-standard-deviation

[2]One issue when constructing CIP indices is that we can only measure CIP for visits that actually took place. If doctors avoid Medicaid patients when expected CIP are high, the observed visits would be non-randomly selected. To address this concern, we construct a version of CIP indices with a Heckman (1979) selection correction, exploiting county-year variation in the share of the population that is covered by Medicaid, which varies the probability that a visit exists in the sample.

[3]Within both strategies, we instrument for the state's CIP index using an index derived only from claim denial information. We do this to isolate variation in CIP that is independent of variation in prices, to ensure that any measurement error in prices does not contaminate our estimates of how physicians respond to CIP.

increase in Medicaid reimbursement rates, which increases the probability of accepting Medicaid patients by 0.6 percentage points. Looking across states within physician group, a one-standard-deviation increase in CIP decreases the probability of accepting Medicaid by 1.5 percentage points, while a one-standard-deviation increase in fees increases Medicaid acceptance by 2.2 percentage points.[4]

These results introduce and quantify a new form of policy leverage that regulators and insurers implicitly use to control access to care, particularly in Medicaid. We use our model of optimal resubmissions, together with the estimated effects of CIP and prices on Medicaid acceptance, to quantify the tradeoffs at stake. We find that decreasing prices by 10 percent, while simultaneously reducing the denial probability by 20 percent, could hold Medicaid acceptance constant while saving an average of $10 per visit.

Although billing processes are costly for physicians, insurers, and patients, they could have offsetting benefits that we do not capture.[5] So our $10 per visit estimate can be interpreted as a minimum value these non-modeled reasons must provide Medicaid in order for denials to be efficient. Although analyzing such benefits is an important direction for further research, the market-shrinking effect of patients losing access to care that we measure here would remain an important tradeoff.

A second limitation is that we only explore one dimension of administrative hassle in healthcare. Beyond the payment process we study, other forms of administrative hassle across (Cutler, 2020) and within (Bloom et al., 2015) healthcare institutions could also contribute to foregone efficiency.

Prior to our study, the relationship between billing hassle and physician behavior has been

[4]These results are robust to alternative specifications, including using OLS rather than instrumenting with denial indices, to including all physicians rather than only those accepting Medicare, to implementing a selection correction when estimating CIP indices, and to controlling for the share of Medicaid enrollees who are covered by a private MCO.

[5]Denials may be part of a process to direct treatment decisions towards more appropriate or cost-effective care (Shi, 2022), or to target programs towards more appropriate providers. Preauthorizations may serve a similar role (Brot-Goldberg, Burn, Layton and Vabson, 2023; Eliason, League, Leder-Luis, McDevitt and Roberts, 2021). Importantly, denials may deter fraud, as Crocker and Morgan (1998); Crocker and Tennyson (2002); Dionne, Giuliano and Picard (2009) consider.

explored in small descriptive surveys (Sloan, Mitchell and Cromwell, 1978; Cunningham and O'Malley, 2008; Long, 2013; Ly and Glied, 2014). In the hospital inpatient context, Gowrisankaran, Joiner and Lin (2019) show that electronic health records and Medicare payment policies interact in subtle ways to drive coding and billing. Zwick (2021) makes a similar point in a very different setting (corporate taxation): accountants' sophistication influences the tax deductions that firms claim.

The fact that insurers' claim denials shrink the market is related to a prediction of Gennaioli et al. (2020). In their model, markets with more claim denials have less insurance sold. Here we identify a distinct, novel channel by which administrative burdens shrink the market: deterring the physicians needed to make health insurance an attractive product. This effect represents a new angle to the public finance literature that considers administrative ordeals facing potential program beneficiaries. These ordeals may (or may not) improve program targeting (Nichols, Smolensky and Tideman, 1971; Nichols and Zeckhauser, 1982; Besley and Coate, 1992; Finkelstein and Notowidigdo, 2019; Deshpande and Li, 2019). In other contexts, program complexity deters beneficiaries' participation in SSI (Bound and Burkhauser, 1999), food stamps (Currie, Grogger, Burtless and Schoeni, 2001), and student aid (Dynarski and Scott-Clayton, 2006).

Finally, our work speaks directly to the empirical literature on sequential bargaining and negotiated price settings (Keniston, 2011; Larsen, 2014; Jindal and Newberry, 2015; Hernandez-Arenaz and Iriberri, 2018; Bagwell, Staiger and Yurukoglu, 2020; Backus, Blake and Tadelis, 2019; Backus et al., 2020), and relates to rationality and transaction costs in presence of incomplete contracts (Tirole, 1999). Backus et al. (2020) provide an extensive review of this empirical literature, which Fudenberg, Levine and Tirole (1985) inspired. As in Backus et al. (2020), we are in the rare position to observe a large dataset that, for a key industry such as healthcare, contains the entire sequences of communications and proposed trades between parties. This enables us to estimate economic costs of resubmitting claims, and document how costly bargaining over payments shrinks the availability of care.

2 Institutional Background and Data

2.1 Billing in the U.S. Healthcare System

We begin with an overview of the U.S. health insurance billing process, which is critical to understanding our data and analysis. Figure 1 provides a schematic overview of this process. When insured patients visit physicians, they rarely make up-front payments. Instead, the medical practice submits a bill to the patient's insurer after the visit. This process is similar for commercial insurers—such as insurance plans sponsored by employers (Einav, Finkelstein and Cullen, 2010; Bundorf, Levin and Mahoney, 2012) or purchased in a health insurance marketplace (Ericson and Starc, 2015; Shepard, 2022; Tebaldi, 2022)—and public insurers, such as Medicare (Curto, Einav, Levin and Bhattacharya, 2021) for the elderly and Medicaid (Dranove, Ody and Starc, 2021) for lower-income beneficiaries.

The first step in billing is to determine exactly which of the 13,000 services defined by the "Healthcare Common Procedure Coding System" (HCPCS) the physician provided.[6] A claim may contain one or more *line items*, each containing one HCPCS code. The physician or biller must classify the patient's diagnosis using International Classification of Diseases (ICD) codes, and collect and report the patient's personal details and insurance coverage.

Once the information is prepared, the biller submits a claim to the patient's insurer. The information required and method of submission are standardized for the initial claim.[7] Using a specific format established by the federal government, the physician provides the insurer with identifying information for the patient and his insurance plan, the treatment provided (using HCPCS codes), the diagnosis (ICD) codes that justify that treatment, and the amount she would like to be paid (the "billed charge").[8]

[6]These codes range from an outpatient visit for a new patient (codes 99201–99205, depending on visit complexity) to an influenza test (code 87804) to a fetal ultrasound (generally code 76801 in the first trimester and 76811 thereafter, but with different codes depending on the thoroughness, method, and for multiple pregnancies).

[7]The standard CMS Form 1500 has been supplanted by its electronic version EDI 837 (established by HIPAA), and insurers respond with Electronic Remittance Advice EDI 835 described in detail below.

[8]These billed amounts are infamously outrageous and, with one minor exception described in Appendix A.2, we do not use them in our analysis. (Though they may sometimes provide a baseline for rate negotiations. In the hospital payment context, Reinhardt (2006) describes these list charges and Cooper et al. (2018) find

The insurer receives the claim from the biller, analyzes it, and adjudicates it. At the initial stage, this processing and decision may be handled by a third-party contractor acting on behalf of the insurer, primarily using an automated system containing payment and audit rules. This system determines whether the patient has eligible insurance, whether the insurance covers the service provided, and whether the medical care was appropriate.[9]

When this evaluation is complete, the insurer makes a payment decision regarding the claim. When the insurer decides to pay, its system must determine the relevant contractual payment for each line item. This amount should follow from an existing regulation or contract: for public insurance, the (state or federal) government establishes the rates by legislation and regulation. For commercial insurance, the insurer and physician will have agreed on a set of payment rules in advance (see Clemens and Gottlieb, 2017, for more details).

The insurer transmits its decision to the physician using a standardized electronic format, called Electronic Data Interchange 835, "Electronic Remittance Advice," to which we refer as simply a "remittance." These remittances tell the physician whether the insurer has approved the claim, how much money to expect from the insurer (the "paid amount"), and how much to collect from the patient. Depending on the physician's billing arrangement, the remittances may be sent straight to the physician's practice or to a clearinghouse—an intermediary contracted to process the practice's claims. If the process goes smoothly, the only remaining step is to collect payment. The insurer should transmit its part of the payment directly to the practice, which bills the patient for any cost-sharing they owe.

But the process is not always smooth. The insurer may deny the claim in full or in part—refusing payments for specific line items—or authorize less payment than the doctor was expecting. This can reflect questions about the validity of the patient's insurance coverage, the medical justification for a specific procedure, whether the physician submitted erroneous

that they still form an important part of many hospitals' payment contracts.)

[9]The insurer can also use this opportunity to look for any fraudulent claims, although there are questions about how thoughtfully they do this (Allen, 2019) and whether they even have incentives to do so (Cicala, Lieber and Marone, 2019).

codes, or whether the patient's contract covers the care provided.[10]

When a claim (or part of it) is denied, the process can continue in a few different ways. The physician can give up on the claim and write off the lost revenue.[11] Alternatively, she can prepare a new claim in an attempt to change the insurer's decision and collect payment. The precise steps required depend on why the claim was denied. If the insurer questioned the medical necessity of the treatment, the physician may have to provide additional documentation about the patient's condition by fax or through an online submission. If there was an administrative error, such as a typo in the patient's name or insurance details, the practice may need to submit corrected information. If the physician thinks that the claim adjudication does not comply with her contract, she may have to submit a formal appeal to the insurer, requiring manual intervention and a decision by someone higher in the insurer's hierarchy. Each time the insurer processes the claim, it generates a new remittance.

2.2 Remittance Data

Our primary data source is IQVIA Real World Data—Remittance Claims, introduced and summarized by Gottlieb, Shapiro and Dunn (2018). IQVIA obtains these data from clearinghouses that receive the remittances on physicians' behalf. Since the physician practice chooses which clearinghouse to work with, our sample is effectively drawn at the physician level.[12] For more than 100,000 unique physicians covered in the sample, we observe their interactions with the full range of insurers, including Medicaid, Medicare, and commercial.

We see the remittances generated each time the insurer responds to a physician's submis-

[10] The organization that manages the Electronic Data Interchange standards maintains a list of around 350 codes for different reasons claims may be adjusted or denied (see http://www.x12.org/codes/claim%2Dadjustment%2Dreason%2Dcodes/, accessed on 8/13/2022).

[11] If she has not signed a payment contract with the insurer (i.e., she is "out-of-network") she may be able to bill the patient directly for any missing revenue. But in the more common situation where the physician has a contract with the insurer ("in-network"), that contract likely forbids her from collecting amounts the insurer has not authorized. So in most cases the physician's only option is to deal with the insurer directly.

[12] Since the data provider includes remittance data from whichever clearinghouses it contracts with, rather than a systematic random sample, one may naturally worry about the sample's representativeness. Upon introducing our data, Gottlieb et al. (2018, online appendix) showed that physicians appear very representative of the covered specialties nationwide; this supports the nationwide representativeness of our results.

sion or resubmission—including those remittances indicating claim denial or nonpayment. For each remittance, the data tell us the providing physician, the practice submitting the bill, its zip code, and the insurer providing the remittance. We see the detailed procedure (HCPCS) codes indicating what care was provided, ICD diagnosis codes, and key dates: when the service was provided, when the claim was submitted, and when the insurer made its decision. We then see how the insurer handled the claim, including the summary of its decision for each procedure (paid, denied, etc.), justification for any adjustments to individual service lines, and how much it is paying. At the patient level, a de-identified code allows us to link the same patient across remittances, and we observe the patient's age.[13]

Note on Terminology. In what follows, *line item value* refers to the contractual amount for a specific procedure for which the physician bills; i.e. it is the amount that the provider would receive if there were no denials. This is simply the observed allowed amount for all claims that are processed smoothly, and otherwise we must impute it. Appendix A.2 describes our imputation process. We use the term *claim value* when referring to the total of line item values for a claim. The *initial claim value* is the claim value for the first claim submitted for a visit.[14] This is the revenue that the provider would collect absent denials.

Summary Statistics. Table 1 offers a first look at our remittance data. Across the 81.4 million visits we observe from 2013–2015, the average initial claim value is $155, the 10th percentile is $30, and the 90th percentile is $240. Visits differ along several dimensions, including the number of line items included. The average visit contains 1.8 line items; ten percent of visits contain three or more.

A key variable for our analysis is whether the insurer denied payment for at least one line item in a claim for a given visit. Table 1 shows that, across all insurers and all years in

[13]Appendix A provides additional details on the construction of our estimation dataset, including the preprocessing leading to our main sample, and the steps to determine the terms of insurer-physician contracts.

[14]It may differ from the value of subsequent claims for the same visit because the payer may only pay a subset of line items and the provider may choose not to resubmit all line denied items.

our sample, 7% of visits contain at least one line item for which payment is denied. Since providers can resubmit claims for the same visit after denials, the average number of claims submitted for each visit is 1.04. 8% of visits in our sample are billed to Medicaid, 46% to Medicare, and 47% to commercial insurers.

The three types of insurers differ in three key dimensions: the amounts that would be paid if there were no denials, the frequency of denials, and providers' ability to collect payments after denials. Table 2 summarizes these differences. The initial Medicaid claim value averages \$102, but one quarter of visits have at least one line item denied upon initial submission. After the sequence of resubmissions and denials that follows, providers receive \$87 on average. Medicare and commercial insurers have higher mean initial claim values (\$135 and \$183, respectively) and lower denial rates (6.7% and 4.1%). Accounting for resubmissions, the total revenue collected for Medicare patients averages \$130 per visit, and \$178 for patients covered by commercial plans.

Table 2 also highlights the multi-period aspect of the billing process following initial denials. After the first denial takes place, 34–62 percent of visits (depending on insurer) see only one claim resubmission. 4.8–6.6 percent of visits go to a second round of resubmission, and 2–3.4 percent of visits go to a third or higher round. So we must consider physicians' beliefs about future denials and the future billing costs they will incur to recover revenues, beyond the initial resubmission.

Table 3 illustrates in richer detail the differences in billing processes across insurers, and how denial reasons relate to payment outcomes.[15] Summarizing data at the line item level,

[15] When a line item is denied payment, we observe a code capturing the denial reason. Since there are hundreds of reason codes, our analysis aggregates them into five mutually exclusive categories: administrative, contractual, coverage, duplicate, and information. Administrative problems include exceeding the time limit for filing a claim; the negotiated rate is not on file or has expired; or prior claim adjudication. The contractual category indicates denials specified in the insurer contract, such as "procedure has a relative value of zero in the jurisdiction fee schedule, therefore no payment is due," or "this procedure is not paid separately." Coverage problems indicate claim denial because the patient isn't insured ("Expenses incurred prior to coverage" or "Expenses incurred after coverage terminated"), the plan doesn't cover the service in question, or the provider is ineligible. Duplicate claims are straightforward: "Exact duplicate claim/service." We use the "information" category to describe denials when the insurer reports insufficient information to pay—such as a lack of medical justification, preauthorization, or referral. Appendix Figure S.1 uses word clouds to summarize the explanations for all the denial reasons within each category.

rather than the visit, this table shows remarkable differences across insurers in denial reasons. Administrative reasons comprise one quarter of denials in Medicaid, 16% in Medicare, and 14% in commercial insurance. Contractual reasons drive 31% of denials in Medicaid, 39% in Medicare, and 60% in commercial insurance. The other major category of denials, coverage problems, may relate to Medicaid patients' high insurance coverage churn (Sommers et al., 2016; MACPAC, 2021).

Differences in denial reasons are associated with different resubmission decisions and ability to recover revenues. When a line item is denied for administrative reasons, we observe a second claim for the same visit 39% of the time in Medicaid, 57% in Medicare, and 26% in commercial insurance. After these billing processes end, providers ultimately recover 58% of revenues in Medicaid, 94% in Medicare, and 72% in commercial insurance. Other reasons for denials lead to different outcomes. For example, coverage issues imply a 32% recovery rate in Medicaid, 34% in Medicare, and 67% in commercial insurance. When the insurer requires additional information before authorizing a payment for a line item, only 29% of Medicaid revenue is recovered, compared to more than 40% for both Medicare and commercial insurance.

The key empirical patterns for our analysis are the relationships between the value of line items, the probability of denials, and the decision to incur billing costs to resubmit claims. Figure 2 summarizes these relationships. For each insurer, we show the histogram of average value for each procedure code in the initial claims. The differences in these distributions confirm that Medicaid tends to pay less than Medicare, which in turn tends to pay less than commercial insurance.

The dots in Panels (b), (d), and (f) all show that the probability of resubmission is increasing with line item value. This provides initial evidence that physician resubmission decision are consistent with rational, profit-maximizing behavior, when facing positive resubmission costs: incurring those costs is more likely to be worthwhile when more revenue is at stake.[16] In contrast, Panels (a), (c), and (e) do not show a pattern of insurers denying payment for higher-value services; if anything, the public insurers are less likely to deny more valuable services. This might suggest that physicians pay more attention when billing procedures with higher value.

2.3 Additional Data Sources

We complement our data with two additional sources, summarized in Table 4. The Centers for Medicare and Medicaid Services provides a dataset that it regularly updates with information on physicians' specialty, location, and practices. We use this file, called Medicare Data on Provider Practice and Specialty (MD-PPAS), to identify where physicians are located and when they move. We also use the tax identifiers it provides to identify those who work in the same practice.

We augment the administrative physician characteristics from MD-PPAS with SK&A survey data also purchased from IQVIA. These data, primarily collected by the firm for marketing purposes, come from administrative records and a manual phone survey of most practicing U.S. physicians. Among the key questions for our purposes, SK&A asks whether each physician accepts Medicare patients and Medicaid patients.[17] To measure the behavior of physicians who are plausibly marginal to the variation we observe, we limit our study of Medicaid acceptance to those physicians who report accepting Medicare patients, though our results are similar when relaxing this restriction. As we show later, Medicaid generally pays less and has higher CIP than Medicare, so physicians who refuse Medicare patients would have even less economic reason to treat Medicaid patients and are unlikely to be responsive to Medicaid variation.

The resulting dataset contains 3.7 million provider-year observations over the 2009–2015

[16] However, these empirical relationships on their own are not sufficient to prove this point, or to estimate the resubmission costs, because they don't account for (1) the probability that a resubmission will succeed, (2) the probability that, when it doesn't, the physician will incur future resubmission costs, or (3) heterogeneity across claims. Our model in Section 3 addresses these issues.

[17] In Appendix A.3 we compare the patterns in Medicaid acceptance from this survey to the patterns observed in the IQVIA sample.

period. Physicians report accepting Medicaid patients 72% of the time, and accepting Medicare patients 84.1% of the time. We view this 84.1 percent as the relevant universe; of these, 80.3% accept Medicaid. In the same period, 1.1% of doctors move across different states and 27.3% of them work in a group that has locations in more than one state.[18]

3 Billing Hurdles and Costs of Incomplete Payments

The patterns in the remittance data highlight two sources of financial losses that a physician can experience after providing medical services. First, she might be partly or fully unable to collect expected revenues. Second, when trying to collect revenues after a claim is denied, she incurs additional administrative costs to address the denial and submit a new claim.

We define the costs of incomplete payments (CIP) as the expected financial losses due to revenues that are never collected plus administrative costs for resubmissions. Formally, for a given visit, let L be the set of line items in the initial claim, and $\pi(L)$ denote the total initial claim value. The CIP for the visit is then

$$CIP \equiv \underbrace{\pi(L) - \mathbb{E}\left[\text{collected revenues}\right]}_{\mathbb{E}[\text{foregone revenues}]} + \mathbb{E}\left[\text{resubmission costs}\right]. \tag{1}$$

Rather than $\pi(L)$, the expected revenue for the visit is $\pi(L)\,(1-\tau)$, where

$$\tau \equiv \frac{CIP}{\pi(L)} \tag{2}$$

is CIP as a share of the visit's value. While collected revenues are observed in the remittance data, to compute τ we must estimate resubmission costs.

To do this, we model resubmissions as the solution of a single agent dynamic decision problem. When resubmitting a claim, a physician knows that future denials are possible, so further resubmissions might be necessary to recover revenues. These dynamic considerations

[18] Appendix A.3 illustrates the Medicaid acceptance patterns within physician groups, and examines the frequency with which physicians change their Medicaid acceptance decision around a move.

reflect the patterns observed in the remittance data.[19] We assume that physicians have rational expectations about billing processes, and that they behave optimally when choosing whether and which line items to resubmit.

We treat the set L of services provided in a given visit as exogenous. In Appendix A.4, we provide evidence to support this assumption by exploring the relationship between the probability that a procedure is administered and its likelihood of having payment denied.[20]

3.1 The Resubmission Problem

Consider a visit j with characteristics X_j (e.g. insurer, diagnosis, procedure, and initial claim value), in which the physician provided a set of procedures L_j. Our model begins when the insurer denies a set of line items $D_j \subset L_j$ with reason code indexed by ρ. The physician i, with characteristics Z_i (including practice size and state), has to decide whether to resubmit a claim for the visit. Doing so would incur administrative costs that depend on the reason for denial, on the physician, visit, and insurer characteristics, and on the number of line items in the new claim. Specifically, when resubmitting the set of line items $R_j \subset D_j$, the physician incurs administrative costs of

$$C_{ij}(R_j) = \mu(|R_j|, X_j, Z_i, \rho) + \varepsilon_{ij}, \tag{3}$$

where $|R_j|$ is the number of resubmitted line items and ε_{ij} is an idiosyncratic error term drawn from a Type 1 extreme value distribution. Our goal is to estimate the parameters of the function μ, assuming that physicians have rational expectations and maximize expected

[19] Table 2 shows that, after the initial denial, the back and forth between physician and insurer can continue to third, fourth, or even later rounds of resubmissions.

[20] A more subtle form of endogeneity would be if physicians adjust intensity of care within procedure (for instance, by providing the service more often or spending more time with the patient) to the presence of billing hurdles. Since we see no response on the extensive margin of procedure choice, we do not delve further into potential intensive margin responses. In subsequent work, Shi (2022) and Brot-Goldberg et al. (2023) study the impacts of hospital audits and drug pre-authorization, respectively—also focusing on extensive margins of healthcare use, such as whether to admit the patient as an inpatient, or whether to consume the drug. (Though the hospital spending outcome in Shi (2022) and the substitution across drugs in Brot-Goldberg et al. (2023) could be viewed as intensive margin responses.)

future payoffs after the visit. As detailed in Appendix B, we let μ vary flexibly by payer, state, reason code, and (in the richest specifications) size of physician practice. The number of line items in the claim enters μ linearly.

For a given function μ, the probability that physician i resubmits the set of line items R_j after the line items in D_j are denied is

$$\Pr\left[R_j | D_j, X_j, Z_i, \rho\right] = \frac{\exp\left[-\mu(\left|R_j\right|, X_j, Z_i, \rho) + \delta\mathcal{V}(R_j, X_j, Z_i, \rho)\right]}{\sum_{R' \subset D_j} \exp\left[-\mu(\left|R'\right|, X_j, Z_i, \rho) + \delta\mathcal{V}(R', X_j, Z_i, \rho)\right]}, \tag{4}$$

where δ is the intertemporal discount factor, which we set to 0.99,[21] and $\mathcal{V}(R_j, X_j, Z_i, \rho)$ denotes the expected continuation value after resubmitting R_j, conditional on X_j, Z_i, ρ.

In Appendix B we derive equation (4) following Hotz and Miller (1993). Their conditional choice probability method allows us to estimate the value function $\mathcal{V}$ directly from the remittance data, and we estimate the parameters of the function μ via maximum likelihood.

3.2 Identification of Resubmission Costs

To identify the parameters of the function μ governing resubmission costs, we exploit the joint variation in resubmission decisions, denied amounts, and expected repayment probabilities, conditional on X_j, Z_i, ρ. Figure 2 illustrates this variation in the raw data.

Ignoring resubmissions in later periods, the payoff from resubmitting a claim is increasing in expected revenue from this resubmission. Expected revenue is the product of the claim value and the expected recovery rate (i.e., the fraction of the resubmitted claim value that the insurer will pay). Different values of μ imply different resubmission probabilities as a function of claim value and probability of collection. If resubmission costs are higher, the probability of collection must increase in order to obtain the same resubmission probability

[21] Although the calendar time between one denial and the next is variable, we disregard these differences and simply treat each submission as one time period. Typical periods observed in the sequences of remittances following a visit are shorter than three months; we set $\delta = 0.99$ following Ahmed, Haider and Iqbal (2012). Gottlieb et al. (2018) show that the actual response time varies across insurers, so a richer analysis could incorporate differences in discounting due to the variation in delays.

for a given claim value.

For a simplified example, consider two pediatric visits with new patients: an infant whose visit costs \$100 and a 10-year-old whose visit costs \$80 according to usual payment rates. Suppose both claims are denied, and we see that resubmissions for both visit types have a 20 percent success rate. We assume that patient age does not affect resubmission costs. So if the doctor chooses to resubmit the claim for the infant's visit but not the 10-year-old's, we infer that the doctor's resubmission cost would have been between \$16 and \$20.

Our approach to identify the parameters in μ refines this intuition. In particular, we calculate the continuation values of every available resubmission decision, assuming that providers behave rationally when solving the dynamic resubmission problem. Figure 3 shows the empirical relationship between the probability that a set of denied line items is resubmitted, and the expected continuation value estimated with the remittance data.

The extent to which providers make decisions that seem consistent with forward-looking, revenue-maximizing behavior is striking. The sharp monotonic relationship between continuation values and probability of resubmission provides information about resubmission costs. Appendix Table B.1 further illustrates the difference between continuation values across observed and counterfactual resubmission choices. The continuation values for the set of line items that physicians resubmit are significantly higher than for the non-chosen alternatives. Resubmission costs are identified by treating observed resubmissions as optimal up to idiosyncratic errors, and treating the continuation values as known. We exploit residual variation as exogenous after conditioning on payer, state, reason code, initial claim amount, and size of physician groups (and, in our richest specifications considered in the Appendix, individual diagnosis and procedure codes).

3.3 Estimates of Resubmission Costs and Costs of Incomplete Payments

3.3.1 Resubmission Costs

Figure 4 summarizes the estimated resubmission costs for claims with one line item, varying across payers, states, reason codes, and size of physician practice. Appendix Table B.2 shows the details of all parameter estimates. We estimate that resubmitting a claim to Medicaid costs the physician office \$14 on average. This value ranges across type of claims and states, from near zero to over \$40 per resubmission. These estimates are sizable, representing 14% of the mean initial claim value and 16% of collected revenues. They line up with prior estimates based on time accounting (Tseng et al., 2018; CAQH, 2020).[22]

Resubmission costs for Medicare claims are generally lower, averaging \$10, and less dispersed. This is consistent with Medicare administration being coordinated at a more aggregate level, rather than state-by-state, as well as a larger volume of patients leading to more experience in solving billing issues.

Resubmitting claims to commercial insurers (which occurs rarely compared to Medicaid and Medicare) is more expensive on average, and dispersed. Our estimates for commercial payers show an average resubmission cost of \$17, with significantly more mass above \$30.

3.3.2 Costs of Incomplete Payments

We use our estimated resubmission costs to compute the expected CIP and τ for each visit in our data. Table 5 reports the averages of these measures. The table contains three panels, one for each category of insurance, each with five model specifications (shown in separate columns). Within each panel, the top row reports the average τ and the second row the average CIP implied by that model across all visits in our estimation sample.[23]

[22]While the settings and specific numbers reported are slightly different, both sources are in the same ballpark. For instance, CAQH (2020) reports that a claim status inquiry costs a provider \$9.37 when completed manually, and merely processing a remittance advice \$3.96. Tseng et al. (2018) report that billing costs \$20.49 for a primary care visit and \$215.10 for an inpatient surgery.

[23]Appendix Table B.2 presents a more detailed version of this table that reports the average parameter estimates for the function μ defined in Section 3.1, as well as standard errors (which we omit from Table 5 to economize on space). Appendix Tables S.1 and S.2 report estimates from further versions of the model in which we relax some of the main model's assumptions (detailed in Appendix B).

The first model for each insurer disregards resubmission costs, i.e. it imposes μ constant and equal to 0. The CIP in this case come only from the revenue ultimately not collected. We estimate CIP of \$9.75, \$2.66 and \$1.79, corresponding to τ of 0.141, 0.033, and 0.019 for Medicaid, Medicare, and commercial insurance, respectively.[24]

These numbers increase significantly once we incorporate the resubmission costs. The second model for each insurer implements this in a simple way, estimating parameters of μ that do not depend on the denial reason. Expected CIP increase to \$12.43, \$3.94, and \$2.36, and τ to 0.174, 0.047, and 0.024 for the three types of insurance, respectively.

The third model for each insurer is richer, estimating μ separately based on the denial reason. The average τ and CIP change little, but Appendix Table B.2 shows that the estimated resubmission costs differ substantially by denial reason.

In the final two columns, we estimate this richest model separately for smaller and larger physician groups. We find that smaller groups incur higher resubmission costs across all insurance categories. Small groups' costs are about 8 percent higher than large groups' when billing Medicaid, and 30–40 percent higher (though on a much smaller base) when billing Medicare or commercial insurance. Qualitative patterns according to denial reason are similar across group size (see Appendix Table B.2). We take this richer model as our baseline for the rest of the paper.[25]

Figure 5 shows that there is meaningful variation in CIP and τ across states, particularly in Medicaid. Expected CIP ranges from less than \$5 to more than \$30, while the CIP share τ is higher than 0.25 in Texas, Illinois, and Pennsylvania, and lower than 0.1 in Colorado and Idaho. In contrast, except for Medicare in Alaska, no state's τ exceeds 0.1 for either

[24]Differences in the estimation sample cause the CIP estimates in Table 5 and Table B.2 to differ from the average final denied amount in Table 2. First, the estimation sample for resubmission costs excludes visits with rare characteristics for which we cannot compute continuation probabilities. Second, as Appendix A.1 details, we eliminate outliers from our estimation sample, which lowers the estimates of CIP and τ. This is another reason to interpret the estimates in Table 5 as conservative.

[25]We have considered finer definitions of group size, but estimated meaningful differences only between the two categories shown here. One could alternatively let size affect resubmission costs (and strategies) parametrically, but we prefer a flexible approach. We use only these two size bins because further granularity causes us to lose visits for which we do not have enough observations within each combination of conditioning variables, without revealing additional economic content.

commercial insurance or Medicare.

4 Do Billing Hurdles Keep Physicians Away from Medicaid?

We now ask whether CIP affect physicians' behavior. Intuitively, rational physicians would care about the net revenue $\pi(L)\,(1-\tau)$, and not simply about the prices $\pi(L)$. While physicians may respond to this net reimbursement along a variety of margins, we focus on one of the simplest and most extreme: the choice of whether to treat Medicaid patients. We focus on Medicaid because, as Figure 5 shows, it has substantial variation in CIP, which enables our estimation. As Table 4 shows, Medicaid also has low physician participation rates—a relevant margin along which physicians could respond to CIP.

This margin—refusal to treat Medicaid patients—is a natural focus because of the uncertainty inherent in the CIP. By its very nature, CIP is the mean over a risky distribution: physicians know that Medicaid will deny many payments, and billing will be costly, but may not know exactly which claims will be denied. Even if they did know, it may be difficult to supply care selectively to Medicaid patients at low risk for claim denial, while refusing those with higher risk. A blanket decision—to accept Medicaid patients or not—may be the easiest margin to adjust. Moreover, the evidence in Appendix A.4 suggests that different treatment choices are not likely to be of first order importance.[26]

4.1 Indices of Fees and CIP Across States

We use variation in fees and CIP across states to study physicians' Medicaid acceptance. We first construct state-insurer-specific measures of π and τ that adjust for the composition of visits and physicians' billing skills.[27] The fee measure is conceptually simple: we would like to know how much more one state's Medicaid program would pay for identical care compared with another state's. Because care is so heterogeneous, we cannot simply compare average prices for all treatments. Other research on Medicaid fees, such as Alexander and

[26]Appendix Tables S.24 and S.25 examine the share of Medicaid patients physicians choose to treat.
[27]We drop the explicit indication $\pi(L)$ in favor of simply π when no confusion might arise.

Schnell (2019), has had to hand-collect data from each state. This has limited most studies to considering a few specific services, such as primary care. In order to account for the broader set of care included in our sample, we estimate the following regression to compute price indices that account for the plethora of treatments included:

$$\ln(\pi_{\ell j}) = \xi_{s,k} \cdot \mathbb{1}_{s(j)} \cdot \mathbb{1}_{k(j)} + \chi_h \cdot \mathbb{1}_{h(\ell)} + \varphi_t \cdot \mathbb{1}_{t(j)} + \gamma_1 \text{age}_j + \gamma_2 \text{comorbidities}_j + \epsilon_{\ell j}. \tag{5}$$

Each observation in this regression is one service line in one visit; $\pi_{j\ell}$ is the allowed amount for service ℓ in visit j. Crucially, the regression estimates insurer-by-state fixed effects $\widehat{\xi}_{s,k}$, where s indicates the state and k the insurer. These fixed effects represent the contribution of the state and insurer to explaining the variation in payment level, and they serve as our state-insurer log fee index. Since the dependent variable is in logs, we can interpret a 0.01 change in $\widehat{\xi}_{s,k}$ as approximately a 1 percent change in the insurer/state's fee. We treat commercial insurance as a single category and omit its indicator, so our index $\widehat{\xi}_{s,k}$ is estimated relative to the national commercial average.

This regression adjusts the raw value, $\pi_{j\ell}$, for the service's and claim's characteristics. Most significantly, we include fixed effects for the specific procedure code, $\mathbb{1}_{h(\ell)}$, and year, $\mathbb{1}_{t(j)}$. We also control for patient characteristics, such as age and other diseases they have, in case these influence the cost.

We estimate a similar index for CIP. We follow the same logic as in equation (5), but replace the dependent variable with τ_j, expected CIP as a share of visit j's value. Unlike with fees, τ_j ranges from zero to one so we do not take its log. First, we compute this following equations (1) and (2), using expected lost revenues and expected resubmission costs conditional on that visit's characteristics. Second, we estimate:

$$\begin{aligned} \tau_j = {} & \psi_{s,k} \cdot \mathbb{1}_{s(j)} \cdot \mathbb{1}_{k(j)} + \eta_i \cdot \mathbb{1}_{i(j)} + \varphi_t \cdot \mathbb{1}_{t(j)} + \sigma_{k,\Sigma} \cdot \mathbb{1}_{k(j)} \cdot \mathbb{1}_{\Sigma(i(j))} \\ & + \theta_{0,k} \mathbb{1}_{k(j)} \cdot \text{RVUs}_j + \theta_1 \text{age}_j + \theta_2 \text{comorbidities}_j + \epsilon_j. \end{aligned} \tag{6}$$

This specification controls for the individual physician $\mathbb{1}_{i(j)}$ and other visit characteristics that could affect payment difficulty, including the intensity of care (RVUs) interacted with payer effects. These controls ensure that our indices reflect differences between comparable medical care rather than differences in physician composition. When controlling for physician, the state-by-insurer indices are identified off of physicians who practice across multiple insurers. $\mathbb{1}_{\Sigma(i(j))}$ is a set of indicators for the size of the physician's group, which we allow to have a different relationship with τ for each insurer.

The estimated $\widehat{\psi}_{s,k}$ coefficients serve as our index of the CIP share for each state-by-insurer. The resulting index $\widehat{\psi}_{s,k}$ can be interpreted as capturing differences in the CIP share, with a 0.01 higher value representing a 1 percentage point higher CIP share for the insurer-state pair.[28]

Since we only observe visits for which the physician chose to treat the patient, a natural concern is that the true (unconditional) values of τ are even larger than what we estimated in Section 3. To address this concern, we apply a Heckman (1979) selection correction for some estimates of equation (6). A natural choice of instrument that does not affect τ_j, while affecting the probability that a Medicaid visit takes place—and therefore the observability of τ_j in our sample—is the share of the population in the county-year covered by Medicaid.[29]

Figure 6 shows a scatterplot relating the τ index $\widehat{\psi}_{s,k}$ and $\log(\pi)$ index $\widehat{\xi}_{s,k}$ across states

[28]Some of the empirical analysis described below also requires an index constructed using only claim denial information, and not relying on the values $\pi_{j\ell}$ (which enter the denominator of τ_j). We therefore estimate denial-only indices $\psi^D_{s,k}$ using a model exactly analogous to (6):

$$d_j = \psi^D_{s,k} \cdot \mathbb{1}_{s(j)} \cdot \mathbb{1}_{k(j)} + \eta_i \cdot \mathbb{1}_{i(j)} + \varphi_t \cdot \mathbb{1}_{t(j)} + \sigma_{k,\Sigma} \cdot \mathbb{1}_{k(j)} \mathbb{1}_{\Sigma(i(j))} + \theta_{0,k} \mathbb{1}_{k(j)} \cdot \text{RVUs}_j + \theta_1 \text{age}_j + \theta_2 \text{comorbidities}_j + \epsilon_j. \tag{7}$$

where d_j is an indicator for whether visit j had a denial.

[29]Formally, letting W_j denote the population share covered by Medicaid, we estimate the visit-level Probit:

$$\Pr\left[\text{Patient covered by Medicaid}_j\right] = F_\Phi\left(\lambda_1 W_j + \lambda_2 \text{age}_j + \lambda_3 \text{comorbidities}_j + \lambda_t \cdot \mathbb{1}_{t(j)}\right), \tag{8}$$

where $F_\Phi(\cdot)$ is the standard Gaussian CDF and $f_\Phi(\cdot)$ the corresponding PDF. The estimated parameters of (8) allow us to construct the inverse Mills ratio

$$\widehat{\text{IMR}}_j = \frac{f_\Phi\left(\widehat{\lambda}_1 W_j + \widehat{\lambda}_2 \text{age}_j + \widehat{\lambda}_3 \text{comorbidities}_j + \widehat{\lambda}_t \cdot \mathbb{1}_{t(j)}\right)}{F_\Phi\left(\widehat{\lambda}_1 W_j + \widehat{\lambda}_2 \text{age}_j + \widehat{\lambda}_3 \text{comorbidities}_j + \widehat{\lambda}_t \cdot \mathbb{1}_{t(j)}\right)}. \tag{9}$$

and across insurers. We show Medicare observations with red circles, and Medicaid observations with state abbreviations. The pattern across insurers is striking: with a few exceptions such as North Dakota, which reimburses Medicaid care quite well, Medicaid generally has lower fees and much higher CIP than Medicare. Medicaid is also notable for the tremendous variance in both dimensions, while Medicare observations are concentrated in the high-fee, low-CIP corner of the graph. This is consistent with Medicare being a centralized program, reducing geographic differences in administration.[30]

4.2 Empirical Strategies

We are interested in the relationship between each physician's reported willingness to treat Medicaid patients and her state's Medicaid billing hassle and reimbursement rates. For numerous reasons, the observational relationship between these variables need not be causal; for example, physicians who want to treat Medicaid patients may differ from others, or they may select into states with different Medicaid policies.

We use two empirical strategies to address these concerns. Our first strategy uses a physician movers design to address concerns about physician-level characteristics, such as unobservable desire to treat Medicaid patients. In our second strategy, we use physicians in groups that span state boundaries. By controlling for group fixed effects, we account for the possibility that the primary decision-maker is the group, rather than the individual physician. The group's Medicaid acceptance decisions could vary due to practice characteristics such as investment in billing technology, other aspects of billing skill, the group's experience with a particular part of the market, organizational structure (such as not-for-profit status,

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We then estimate the following modified version of equation (6):

$$\tau_j = \psi_{s,k} \cdot \mathbb{1}_{s(j)} \cdot \mathbb{1}_{k(j)} + \varphi_t \cdot \mathbb{1}_{t(j)} + \sigma_{k,\Sigma} \cdot \mathbb{1}_{k(j)} \mathbb{1}_{\Sigma(i(j))} + \theta_{0,k} \mathbb{1}_{k(j)} \cdot \text{RVUs}_j + \theta_1 \text{age}_j + \theta_2 \text{comorbidities}_j + \theta_3 \widehat{\text{IMR}}_j + \epsilon_j. \tag{10}$$

This does not include physician fixed effects, since W_j does not vary within physician.

[30] Appendix Table S.3 summarizes variation in these indices, and shows robustness to other choices in data and index construction, such as which controls to include, whether to omit imputed contractual amounts, and weighting. Note that the indices are all normalized to have the mean of the raw data for the respective variable.

academic affiliation, or physician leadership) or social mission. The group fixed effects remove such differences and allow us to estimate the impacts of state policy differences even if the organizations play a major role in Medicaid acceptance decisions.

These strategies are complementary because of their different limitations. A limitation of the movers strategy is that physicians might require some time to learn how Medicaid works in their new state, and thus might not respond immediately. Some physicians may also work as part of groups that limit their individual decision-making about which patients to treat. In contrast, the second strategy controls for unobservables at the group level but not for the individual physician. Even within a group, physicians with a stronger preference for treating Medicaid patients could sort across states in ways correlated with their Medicaid policies.

4.2.1 Movers

Following Molitor (2018), who uses physician movers, and other mover designs in labor and health economics (Abowd et al., 1999; Finkelstein et al., 2016; Hull, 2018), we examine the impact of a physician's move between states with different payment rates and billing difficulty. Consider physician i who moves from state s to s'.

We define $\Delta \ln \text{Fee}_i \equiv \widehat{\xi}_{s',\text{Medicaid}} - \widehat{\xi}_{s,\text{Medicaid}}$ as the difference between the $\log(\pi)$ indices in the pre-move and post-move states' Medicaid programs. Similarly, $\Delta\tau_i \equiv \widehat{\psi}_{s',\text{Medicaid}} - \widehat{\psi}_{s,\text{Medicaid}}$ is the difference in the τ index for Medicaid before and after the move. Under the usual assumption that the timing and the origin-destination pair of a physician's cross-state move is independent of other shocks affecting her willingness to treat Medicaid patients, we use these changes to estimate the effect of both fees and CIP on the decision to accept Medicaid patients, while controlling for time-invariant physician unobservables.

Using data for years indexed by t around physician i's move, we estimate the following regression at the physician-year level:

$$Y_{i,t} = \beta\Delta \ln \text{Fee}_i \cdot \mathbb{1}_{\text{Post}_{i,t}} + \gamma\Delta\tau_i \cdot \mathbb{1}_{\text{Post}_{i,t}} + \eta_i \cdot \mathbb{1}_i + \phi\text{Controls}_{i,t} + \epsilon_{i,t} \tag{11}$$

The dependent variable $Y_{i,t}$ is an indicator for whether the physician reports accepting Medicaid patients. The key controls here are individual physician fixed effects η_i. This strategy identifies the coefficients β and γ exclusively based on physicians who move. The key moment is the difference in those physicians' post- and pre-move Medicaid acceptance decisions, and how that difference varies with differences in the states' policies.

To visualize the time trends in these results, we begin by estimating a dynamic event study version of equation (11), namely:

$$Y_{i,t} = \sum_{\zeta \neq 0} \beta_\zeta \Delta \ln \text{Fee}_i \cdot \mathbb{1}_\zeta + \sum_{\zeta \neq 0} \gamma_\zeta \cdot \Delta \tau_i \cdot \mathbb{1}_\zeta + \eta_i \cdot \mathbb{1}_i + \epsilon_{i,t}, \tag{12}$$

where ζ denotes the year relative to that in which the physician moved.

4.2.2 Cross-State Groups

The second strategy uses physician groups that span state boundaries. This encompasses longer-term decisions that a practice makes, such as specific location choice, hiring appropriate staff, and marketing to the target population. So these estimates can be thought of as responses implemented over a longer time horizon than those estimated by the movers strategy. Moreover, the decision maker is the group, rather than the individual physician.

Using the cross-state groups, we introduce practice group fixed effects into a physician-level regression of Medicaid acceptance on Medicaid fee and CIP indices:

$$Y_{i,t} = \beta \widehat{\xi}_{s(i),\text{Medicaid}} + \gamma \widehat{\psi}_{s(i),\text{Medicaid}} + \vartheta_g \cdot \mathbb{1}_{g(i)} + \eta \cdot \mathbb{1}_t + \phi \text{Controls}_{i,t} + \epsilon_{i,t}. \tag{13}$$

The dependent variable is the same as in regression (11), an indicator for whether the physician reports accepting Medicaid patients. The key controls are fixed effects $\mathbb{1}_{g(i)}$ for each physician group, defined based on the practice's tax identifier reported in MD-PPAS. Given these fixed effects, we identify β and γ off of differences in Medicaid acceptance among physicians within the same practice.

4.2.3 Instrumenting for τ Indices Using Denial Indices

We measure CIP as a share τ_j of claim value π, according to equation (2), and this τ_j share is our dependent variable when constructing the CIP index, $\widehat{\psi}_{s,k}$. So any measurement error in π could bias estimation based on $\widehat{\psi}_{s,k}$: measurement error in π would enter positively into the fee index $\widehat{\xi}_{s,k}$ and negatively into the CIP index $\widehat{\psi}_{s,k}$, potentially inducing a spurious negative correlation between their coefficients $\hat{\gamma}$ and $\hat{\beta}$. We address this by using the denial-only index $\widehat{\psi}^D_{s,k}$ from equation (7) as an instrument for the overall CIP index $\widehat{\psi}_{s,k}$. As this index is based only on an indicator variable for claim denial, it does not contain the same measurement error that could appear in $\widehat{\xi}_{s,k}$. The denial-only index $\widehat{\psi}^D_{s,k}$ strongly predicts the full CIP index $\widehat{\psi}_{s,k}$, as we show in Appendix Table C.1.

To use this instrument, we define $\Delta\text{Denial}_i = \widehat{\psi}^D_{s',\text{Medicaid}} - \widehat{\psi}^D_{s,\text{Medicaid}}$ analogously to $\Delta\tau_i$, and estimate the first-stage equation

$$\Delta\tau_i \cdot \mathbb{1}_{\text{Post}_{i,t}} = \alpha_1 \Delta \ln \text{Fee}_i \cdot \mathbb{1}_{\text{Post}_{i,t}} + \alpha_2 \Delta\text{Denial}_i \cdot \mathbb{1}_{\text{Post}_{i,t}} + \eta_i \cdot \mathbb{1}_i + \phi\text{Controls}_{i,t} + \nu_{i,t}. \quad (14)$$

We then replace $\Delta\tau_i \cdot \mathbb{1}_{\text{Post}_{i,t}}$ with the fitted values from (14) when estimating equation (11). We use an analogous 2SLS approach with the cross-state groups strategy.

4.3 The Effect of Billing Hurdles on Medicaid Acceptance

Figure 7 shows physicians' responses to fees and CIP around a move. Panel (a) plots $\hat{\beta}_\zeta$, the response to moving to a state with higher fees, while Panel (b) shows $\hat{\gamma}_\zeta$, the response to moving to a state with higher τ. The coefficients and confidence intervals shown come from 2SLS estimates of equation (12), when instrumenting for $\Delta\tau_i$ with ΔDenial_i.

The pre-move trends in both panels are flat and close to zero. Prior to the physician's move, we see no relationship between the upcoming changes in fees or CIP and physicians' Medicaid acceptance decisions. After the move, we see clear positive coefficients for fees and negative for CIP. Higher π increase the probability of Medicaid acceptance, while a higher

τ reduces the probability. We discuss the magnitudes below, but for now simply note that the response is prompt and significant. The point estimates for fees increase over time, but are not precise enough to rule out a constant effect in years 1 through 4 after the move.

Table 6 shows estimates of equation (11), which pools the pre-move and post-move years and estimates a single coefficient on each index. Column 1 shows the OLS estimates using indices from equation (6) (with no selection correction). Column 2 instruments for $\Delta\tau_i$ with ΔDenial_i as described in Section 4.2.3 above. Columns 3 and 4 are analogous, but use the τ index estimated with a Heckman selection correction rather than physician fixed effects.[31]

To interpret our results, the coefficient on log fees shows the effect of a 1 log point change in Medicaid rates on the probability of accepting Medicaid patients. For instance, the fee coefficient in column 1 means that a 0.1 increase in log fees (approximately 10 percent) leads to a 0.3 percentage point increase in physicians' propensity to accept Medicaid. The coefficient on $\Delta\tau$ multiplies a share coefficient, so a 10 percentage point increase in τ reduces the probability of accepting Medicaid patients by 0.8 percentage points. The 95 percent confidence interval around this estimate ranges from 0.3 to 1.3 percentage points.

To put these magnitudes in context, we compare a one-standard-deviation change in each key variable. The $\log(\pi)$ index has a cross-state standard deviation of 0.2, while the τ index has a standard deviation of 0.11 (from Appendix Table S.3). Using the estimates from column 2 of Table 6, moving to a state with one standard deviation higher fees increases the probability of accepting Medicaid patients by 0.6 percentage points, while moving to a state with one standard deviation higher CIP share reduces the probability by 0.8 percentage points. While these estimates—especially the impact of fees—have substantial uncertainty, our main takeaway is that CIP is just as important for understanding the variation in physicians' willingness to treat Medicaid patients as reimbursement rates are.

Correcting the τ index for non-random selection of visits slightly increases our estimated effect of billing hurdles on Medicaid acceptance. The impact of instrumenting for $\Delta\tau$ with

[31] Columns 3 and 4 still have physician fixed effects in the movers regression, just not in estimating the $\psi_{s,k}$ indices used to construct $\Delta\tau$.

the index of denial probability is even larger: the estimated coefficient on the CIP share shown in Column 4 of Table 6 is -0.078, 12 percent larger than the OLS estimates.

Table 7 reports the results from our second strategy, exploiting variation in Medicaid acceptance across groups that cross state boundaries. We obtain slightly higher coefficients, as might be expected from longer-run responses. Indeed, the coefficients around 0.1 on log fees are very similar to the point estimate for year 4 after the move from Figure 7a. This coefficient implies that physicians in a state with one standard deviation higher Medicaid reimbursements are around 2 percentage points more likely to accept Medicaid patients. Physicians in a state with one standard deviation higher CIP are 2 (based on column 3) to 2.8 (based on column 4) percentage points less likely to accept Medicaid patients. CIP is again just as important as reimbursements.

The Appendix contains versions of Tables 6 and 7 incorporating a variety of robustness checks. First, we consider alternative constructions of the $\log(\pi)$ and τ indices, including—among others—PCP- vs. specialist-specific indices, indices that do not include resubmission costs in computing CIP, indices that are weighted by fees for τ, and by RVUs for π. Second, we extend our estimating sample to physicians who do not accept Medicare. Third, we show results when distinguishing between Medicaid MCO and Medicaid FFS in the model, and controlling for the Medicaid MCO share in the regressions. Fourth, we include π and CIP in levels rather than as a share (τ) or log. We also include controls for the average commercial fees in a state, and consider a version of Table 7 which includes group-year fixed effects instead of group and year fixed effects separately. Our results remain robust and quantitatively similar across these specifications.

To summarize, these results demonstrate the profound importance of administrative hassles for Medicaid patients' access to care. Physicians appear to treat higher CIP just like they do lower fees: a loss in expected revenue that makes them reluctant to treat lower-income Americans. This is true both qualitatively and quantitatively—their behavioral responses to a given percentage change in net revenue are similar whether the change comes through fees or CIP. This highlights an important new dimension of health insurance that has been largely overlooked in policy discussions.[32]

5 Welfare: Policy Counterfactuals and Limitations

5.1 Increases in Fees vs. Reductions in Denials

Our results introduce a new channel through which payers—particularly Medicaid—directly affect expected profitability of patients, thus impacting physicians' supply of care. We see that lowering CIP increases physicians' propensity to accept Medicaid patients in the same way that an increase in the reimbursement rate does.

In this section, we study the effect of changes in denial probabilities (d) and changes in fees (π) on CIP (τ), revenue collected per visit, and propensity to accept Medicaid. Policymakers and Medicaid administrators don't directly control τ, as they can't choose which claims physicians resubmit. So instead of treating τ as a policy parameter, we assume payers set the denial frequency. Physicians adjust their resubmission choices optimally in response to the fees and denial probabilities they face. This analysis combines our model of optimal resubmission decisions with the estimated effects of τ and π on Medicaid acceptance.[33]

First, we use the estimated resubmission costs from Section 3 to solve for the optimal resubmission strategy. We begin with the joint distribution of fees and denial probabilities across visits, denoted $F(\pi, d)$. For any value (π, d), we use our model estimates to calculate each visit's CIP.[34] Given any distribution $F(\pi, d)$, we denote the average CIP share as

[32] While other types of administrative controls, such as pre-authorization for drug prescriptions, may improve the value of those prescription programs (Brot-Goldberg et al., 2023), driving physicians to drop out of the Medicaid program entirely clearly cannot specifically target wasteful or unnecessary care.

[33] When holding π constant, reducing the share of claims denied affects τ: the initial denied amounts are lower, and physicians change their resubmission decisions in light of the higher chance of receiving payments. When holding denial probability constant, changes to π also alter τ: the amounts at stake are different, so physicians change their resubmission decisions. The denominator in equation (2) defining τ is also different.

[34] We simplify our calculations by considering the decision to resubmit or not the entire claim, ignoring differences between line items (more than half of the observations in our data include a single line). For a visit with given values of (π, d) the physician resubmits a claim if

$$\beta\left(\pi(1-d) + d\mathcal{V}^{\star}(\pi, d) - C\right) \geq 0,$$

$\bar{\tau}(F(\pi, d))$, since it depends on the distribution $F()$. Appendix Figure S.3 shows this $\bar{\tau}$ function. We then use this $\bar{\tau}(F(\pi, d))$ together with the new values of π and d to compute two objects. First, we compute the change in spending at (π, d), accounting for physicians' changing resubmission decisions as described in footnote 34. Second, we use our Medicaid acceptance estimates from Section 4.2.1 to identify the points (π, d), which induce values of $\bar{\tau}(F(\pi, d))$ that hold physicians' Medicaid acceptance rate constant.

Figure 8 summarizes the results. The horizontal axis shows fee changes ranging from −20% to +20%. The vertical axis shows changes in the denial probability from −30% to +30%. There are two types of level curves: first, the dashed lines show the changes in per-visit Medicaid payments to physicians in response to changes in fees and denial probabilities. For example, a 10% decrease in fees accompanied by a 20% decrease in denial probabilities would reduce per-visit spending by an average of \$10. Aggregating this across all Medicaid physician visits nationally adds up to \$2 billion per year.[35]

The solid line is a level curve that holds constant the probability physicians accept Medicaid. While our Medicaid acceptance regressions from Section 4.2.1 have substantial confidence intervals, we plot a single curve based on the point estimates. Since this curve runs through the same point (−10%, −20%) discussed above, these \$10 savings could be achieved holding constant physicians' Medicaid acceptance. This specific change is only one of the (infinitely) many examples of "deviations" from the status-quo that could generate savings while maintaining the same physician access. Alternatively, the savings could be used to increase reimbursements and thus expand physician access.

Another way to view these results is as a lower bound on the value Medicaid must get

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where $\mathcal{V}^\star(\pi, d)$ solves the corresponding Bellman equation

$$\mathcal{V}^\star(\pi, d) = \max\left\{0, \beta\left(\pi(1-d) + d\mathcal{V}^\star(\pi, d) - C\right)\right\}.$$

[35]As of August 2022 there are 83 million Medicaid enrollees (https://www.medicaid.gov/medicaid/program-information/medicaid-and-chip-enrollment-data/report-highlights/index.html; accessed on December 13, 2022), and the average number of annual doctor visits is 2.4 (authors' calculations using the Medical Expenditure Panel Survey, obtained from https://www.meps.ahrq.gov/mepsweb/).

from denials for its current policy to be justified. If the current denial rate helps Medicaid reduce fraud or wasteful care by at least \$10 per visit, the proposed deviation to (-10%, -20%) would not be efficient. Figure 8 shows the incremental denials must be worth at least \$10 per visit—relative to a denial rate 20% lower—for the current policy to be justified.

This section illustrates our findings' first-order policy implications. Beyond fees, market sponsors affect Medicaid acceptance and spending by determining how physicians interact with insurers. We have estimated the potential savings from changing this process. Given the magnitude of potential gains, the caveats, limitations, and unmodeled reasons for denials would need to also be economically large to justify the observed denial rate.

5.2 Caveats and Limitations

The results in this paper highlight an important friction in healthcare markets, but it is important to clarify what they do and don't demonstrate. First, billing hassles could have benefits we don't measure, such as deterring wasteful care or detecting fraud. Future work should investigate these effects in Medicaid, as recent work has done in other contexts in Medicare (Shi, 2022; Brot-Goldberg et al., 2023; Eliason et al., 2021). Even if there are offsetting benefits, the administrative costs are high and deter physicians from participating in Medicaid. Unless these marginal physicians offer particularly inefficient or fraudulent care—another important question for future work—shrinking Medicaid patients' choice set is a concern for those interested in the quality of Medicaid or equity in healthcare access.

Second, we only consider one type of administrative hassle: the billing process after care is provided. We do not incorporate the costs of preparing initial submissions, or the fixed costs of setting up a billing office or contracting with outside billing firms. Physicians' other administrative burdens include licensure and registration with insurers, establishing payment contracts (Clemens, Gottlieb and Molnár, 2017), and obtaining preauthorization for care (Brot-Goldberg et al., 2023). Patients face their own burdens, including signing up for insurance and finding providers whose care their insurer covers (Handel and Kolstad, 2015;

Brot-Goldberg, Layton, Vabson and Wang, 2021). Identifying a broader concept of administrative dysfunction may yield opportunities to make healthcare markets more efficient.[36] We also exclude the insurer's own billing costs. Each interaction we observe from the physician's end has a corresponding cost for the insurer who processes it. Our cost estimates are undoubtedly a lower bound.

Third, our counterfactual analysis in the previous subsection only considers the patient acceptance response margin. States, insurers, and physicians may have other margins of response to use when payment rates change: Physicians can change their efforts to recruit Medicaid and non-Medicaid patients, or try to cream-skim patients who are less costly to treat. Insurers can adjust coverage rules or preauthorization requirements, and states can change Medicaid enrollment numbers. While Appendix A.4 finds no evidence that denial rates impact care patterns conditional on patient characteristics, there could be some types of patients we don't identify whose care is affected.

Finally, we do not consider the incentives of states or insurers. Our estimates of physicians' behavior do not account for strategic behavior on the other side of this negotiation. States, and the Medicaid insurers they contract with, are relevant players whose decisions should also enter into positive and normative analysis of this market.

6 Conclusion

This paper examines the economics of one of the largest sources of administrative problems in healthcare: how physicians and insurers haggle over payments for medical care. We find evidence that these payments are frequently incomplete, and we estimate that physicians incur large costs from this incompleteness—especially when submitting bills to Medicaid.

We show that these costs depress doctors' supply of care to Medicaid patients. Their

[36] Some current missed opportunities include failure to adopt cheap, effective technologies (Skinner and Staiger, 2005, 2015); overuse of low-value care (Schwartz et al., 2014; Alsan et al., 2015); omitting simple procedures that would improve efficiency of care allocation; and failing to maximize insurance coverage among populations that benefit (Hendren and Sprung-Keyser, 2020; Goldin, Lurie and McCubbin, 2021; Miller, Johnson and Wherry, 2021).

willingness to participate in Medicaid responds just as much to billing difficulty as to the reimbursement rate. Our framework identifies deviations in Medicaid fees and claim denials that could save money while maintaining patients' access to physicians.

These findings demonstrate the value of well-functioning business operations in healthcare. Difficulty with payment collection meaningfully impacts firms' willingness to engage in markets. In the case of a major government healthcare program, this hassle compounds the effect of low payment rates to deter physicians from treating publicly insured patients.

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References

Abowd, John M., Francis Kramarz, and David N. Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–333.

Ahmed, Waqas, Adnan Haider, and Javed Iqbal, "Estimation of discount factor (beta) and coefficient of relative risk aversion (gamma) in selected countries," 2012.

Alexander, Diane and Molly Schnell, "The impacts of physician payments on patient access, use, and health," Working Paper 26095, National Bureau of Economic Research July 2019.

Allen, Marshall, "We Asked Prosecutors if Health Insurance Companies Care About Fraud. They Laughed at Us.," *ProPublica*, September 10 2019. Available online at https://www.propublica.org/article/we-asked-prosecutors-if-health-insurance-companies-care-about-fraud-they-laughed-at-u

Alsan, Marcella, Nancy Morden, Joshua D. Gottlieb, Weiping Zhou, and Jonathan Skinner, "Antibiotic Use in Cold and Flu Season and Prescribing Quality: A Retrospective Cohort Study," *Medical Care*, December 2015, *53* (12), 1066–1071.

Backus, Matthew, Thomas Blake, and Steven Tadelis, "On the empirical content of cheap-talk signaling: An application to bargaining," *Journal of Political Economy*, 2019, *127* (4), 1599–1628.

— , — , **Brad Larsen, and Steven Tadelis**, "Sequential bargaining in the field: Evidence from millions of online bargaining interactions," *Quarterly Journal of Economics*, 2020, *135* (3), 1319–1361.

Bagwell, Kyle, Robert W Staiger, and Ali Yurukoglu, "Multilateral trade bargaining: A first look at the GATT bargaining records," *American Economic Journal: Applied Economics*, 2020, *12* (3), 72–105.

Besley, Timothy and Stephen Coate, "Workfare versus Welfare: Incentive Arguments for Work Requirements in Poverty-Alleviation Programs," *American Economic Review*, 1992, *82* (1), 249–261.

Bloom, Nicholas, Carol Propper, Stephan Seiler, and John Van Reenen, "The impact of competition on management quality: evidence from public hospitals," *The Review of Economic Studies*, 2015, *82* (2), 457–489.

Bound, John and Richard V. Burkhauser, "Economic analysis of transfer programs targeted on people with disabilities," in "Handbook of Labor Economics," Vol. 3 of *Handbook of Labor Economics*, Elsevier, 1999, chapter 51, pp. 3417 – 3528.

Brot-Goldberg, Zarek C, Timothy Layton, Boris Vabson, and Adelina Yanyue Wang, "The Behavioral Foundations of Default Effects: Theory and Evidence from Medicare Part D," Working Paper 28331, National Bureau of Economic Research January 2021.

Brot-Goldberg, Zarek, Samantha Burn, Timothy Layton, and Boris Vabson, "Rationing Medicine Through Bureaucracy: Authorization Restrictions in Medicare," Working Paper 30878, National Bureau of Economic Research January 2023.

Bundorf, M Kate, Jonathan Levin, and Neale Mahoney, "Pricing and welfare in health plan choice," *American Economic Review*, 2012, *102* (7), 3214–48.

Candon, Molly, Stephen Zuckerman, Douglas Wissoker, Brendan Saloner, Genevieve M. Kenney, Karin Rhodes, and Daniel Polsky, "Declining Medicaid Fees and Primary Care Appointment Availability for New Medicaid Patients," *JAMA Internal Medicine*, 01 2018, *178* (1), 145–146.

CAQH, "2020 CAQH INDEX: Closing the Gap: The Industry Continues to Improve, But Opportunities for Automation Remain," 2020. Available online at https://www.caqh.org/sites/default/files/explorations/index/2020-caqh-index.pdf.

Casalino, Lawrence P, Sean Nicholson, David N Gans, Terry Hammons, Dante Morra, Theodore Karrison, and Wendy Levinson, "What Does It Cost Physician Practices To Interact With Health Insurance Plans? A new way of looking at administrative costs—one key point of comparison in debating public and private health reform approaches.," *Health Affairs*, 2009, *28* (Suppl1), w533–w543.

Centers for Medicare and Medicaid Services, "The Nation's Health Dollar ($3.8 Trillion), Calendar Year 2019: Where It Came From," 2019. Available online at https://web.archive.org/web/20210216022424/https://www.cms.gov/files/document/nations-health-dollar-where-it-came-where-it-went.pdf (accessed September 16, 2022).

_ , "National Health Expenditures 2020 Highlights," 2020.

Cicala, Steve, Ethan MJ Lieber, and Victoria Marone, "Regulating Markups in US Health Insurance," *American Economic Journal: Applied Economics*, 2019, *11* (4), 71–104.

Clemens, Jeffrey and Joshua D. Gottlieb, "Do Physicians' Financial Incentives Affect Treatment Patterns and Patient Health?," *American Economic Review*, April 2014, *104* (4), 1320–1349.

_ **and** _ , "In the Shadow of a Giant: Medicare's Influence on Private Payment Systems," *Journal of Political Economy*, February 2017, *125* (1), 1–39.

_ **,** _ **, and Tímea Laura Molnár**, "Do Health Insurers Innovate? Evidence From the Anatomy of Physician Payments," *Journal of Health Economics*, September 2017, *55*, 153–167.

Cooper, Zack, Stuart V Craig, Martin Gaynor, and John Van Reenen, "The Price Ain't Right? Hospital Prices and Health Spending on the Privately Insured," *Quarterly Journal of Economics*, 09 2018, *134* (1), 51–107.

Crocker, Keith J and John Morgan, "Is honesty the best policy? Curtailing insurance fraud through optimal incentive contracts," *Journal of Political Economy*, 1998, *106* (2), 355–375.

_ **and Sharon Tennyson**, "Insurance fraud and optimal claims settlement strategies," *The Journal of Law and Economics*, 2002, *45* (2), 469–507.

Cunningham, Peter J. and Ann S. O'Malley, "Do Reimbursement Delays Discourage Medicaid Participation By Physicians?," *Health Affairs*, 2008, *27* (Supplement 1), w17–w28.

Currie, Janet, Jeffrey Grogger, Gary Burtless, and Robert F. Schoeni, "Explaining Recent Declines in Food Stamp Program Participation," *Brookings-Wharton Papers on Urban Affairs*, 2001, pp. 203–244.

Curto, Vilsa, Liran Einav, Jonathan Levin, and Jay Bhattacharya, "Can Health Insurance Competition Work? Evidence from Medicare Advantage," *Journal of Political Economy*, 2021, *129* (2), 570–606.

Cutler, David M., "Reducing Administrative Costs in U.S. Health Care," The Hamilton Project Policy Proposal 2020-09, Brookings Institution March 2020. Available online at https://www.brookings.edu/wp-content/uploads/2020/03/Cutler_PP_LO.pdf.

— **and Dan P. Ly**, "The (Paper)Work of Medicine: Understanding International Medical Costs," *Journal of Economic Perspectives*, 2011, *25* (2), 3–25.

Deshpande, Manasi and Yue Li, "Who is screened out? application costs and the targeting of disability programs," *American Economic Journal: Economic Policy*, 2019, *11* (4), 213–48.

Dionne, Georges, Florence Giuliano, and Pierre Picard, "Optimal auditing with scoring: Theory and application to insurance fraud," *Management Science*, 2009, *55* (1), 58–70.

Dranove, David, Christopher Ody, and Amanda Starc, "A Dose of Managed Care: Controlling Drug Spending in Medicaid," *American Economic Journal: Applied Economics*, 2021, *13* (1), 170–97.

Dunn, Abe and Adam Hale Shapiro, "Physician competition and the provision of care: evidence from heart attacks," *American Journal of Health Economics*, 2018, *4* (2), 226–261.

Dynarski, Susan and Judith E. Scott-Clayton, "The Cost of Complexity in Federal Student Aid: Lessons From Optimal Tax Theory and Behavioral Economics," *National Tax Journal*, 2006, *59* (2), 319–56.

Einav, Liran, Amy Finkelstein, and Mark R Cullen, "Estimating welfare in insurance markets using variation in prices," *Quarterly Journal of Economics*, 2010, *125* (3), 877–921.

Eliason, Paul, Riley League, Jetson Leder-Luis, Ryan C. McDevitt, and James W. Roberts, "Ambulance Taxis: The Impact of Regulation and Litigation on Health Care Fraud," Working Paper No. 29491, National Bureau of Economic Research November 2021.

Ericson, Keith M Marzilli and Amanda Starc, "Pricing regulation and imperfect competition on the massachusetts health insurance exchange," *Review of Economics and Statistics*, 2015, *97* (3), 667–682.

Finkelstein, Amy and Matthew J Notowidigdo, "Take-Up and Targeting: Experimental Evidence from SNAP," *Quarterly Journal of Economics*, 05 2019, *134* (3), 1505–1556.

— **, Matthew Gentzkow, and Heidi Williams**, "Sources of Geographic Variation in Health Care: Evidence From Patient Migration," *Quarterly Journal of Economics*, 07 2016, *131* (4), 1681–1726.

Fudenberg, Drew, David K Levine, and Jean Tirole, "Sequential bargaining with many buyers," Working Paper No. 366 February 1985.

Gennaioli, Nicola, Rafael La Porta, Florencio Lopez de Silanes, and Andrei Shleifer, "Trust and Insurance Contracts," Working Paper 27189, National Bureau of Economic Research May 2020.

Goldin, Jacob, Ithai Z Lurie, and Janet McCubbin, "Health insurance and mortality: Experimental evidence from taxpayer outreach," *Quarterly Journal of Economics*, 2021, *136* (1), 1–49.

Gottlieb, Joshua D., Adam Hale Shapiro, and Abe Dunn, "The Complexity Of Billing And Paying For Physician Care," *Health Affairs*, April 2018, *37* (4), 619–626.

_ , Maria Polyakova, Kevin Rinz, Hugh Shiplett, and Victoria Udalova, "Who Values Human Capitalists' Human Capital? The Earnings and Labor Supply of U.S. Physicians," June 2021. University of Chicago, mimeo.

Gowrisankaran, Gautam, Keith A Joiner, and Jianjing Lin, "How Do Hospitals Respond to Payment Incentives?," Working Paper 26455, National Bureau of Economic Research November 2019.

Gruber, Jon, John Kim, and Dina Mayzlin, "Physician Fees and Procedure Intensity: the Case of Cesarean Delivery," *Journal of Health Economics*, August 1999, *18* (4), 473–490.

Handel, Benjamin R and Jonathan T Kolstad, "Health insurance for" humans": Information frictions, plan choice, and consumer welfare," *American Economic Review*, 2015, *105* (8), 2449–2500.

Heckman, James J, "Sample selection bias as a specification error," *Econometrica: Journal of the econometric society*, 1979, pp. 153–161.

Hendren, Nathaniel and Ben Sprung-Keyser, "A unified welfare analysis of government policies," *Quarterly Journal of Economics*, 2020, *135* (3), 1209–1318.

Hernandez-Arenaz, Iñigo and Nagore Iriberri, "Women ask for less (only from men): Evidence from bargaining in the field," *Journal of Economic Behavior & Organization*, 2018, *152*, 192–214.

Hotz, V Joseph and Robert A Miller, "Conditional choice probabilities and the estimation of dynamic models," *The Review of Economic Studies*, 1993, *60* (3), 497–529.

Hull, Peter, "Estimating Treatment Effects in Mover Designs," Technical Report 1804.06721, arXiv.org April 2018.

Jindal, Pranav and Peter Newberry, "Price negotiations and bargaining costs," Technical Report, Mimeo, Pennsylvania State University. Available online at https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.709.2075&rep=rep1&type=pdf. April 2015.

Keniston, Daniel, "Bargaining and welfare: A dynamic structural analysis of the autorickshaw market," *Unpublished manuscript, Yale University*, 2011.

Larsen, Bradley, "The efficiency of real-world bargaining: Evidence from wholesale used-auto auctions," Working Paper No. 20431, National Bureau of Economic Research 2014.

Long, Sharon K., "Physicians May Need More Than Higher Reimbursements To Expand Medicaid Participation: Findings From Washington State," *Health Affairs*, 2013, *32* (9), 1560–1567. PMID: 24019360.

Ly, Dan P and Sherry A Glied, "The impact of managed care contracting on physicians," *Journal of General Internal Medicine*, 2014, *29* (1), 237–242.

MACPAC, "An Updated Look at Rates of Churn and Continuous Coverage in Medicaid and CHIP," October 2021. Issue Brief. Available online at https://www.macpac.gov/wp-content/uploads/2021/10/An-Updated-Look-at-Rates-of-Churn-and-Continuous-Coverage-in-Medicaid-and-CHIP.pdf.

Miller, Sarah, Norman Johnson, and Laura R Wherry, "Medicaid and mortality: new evidence from linked survey and administrative data," Working Paper 26081, National Bureau of Economic Research January 2021.

Molitor, David, "The Evolution of Physician Practice Styles: Evidence from Cardiologist Migration," *American Economic Journal: Economic Policy*, February 2018, *10* (1), 326–56.

Morra, Dante, Sean Nicholson, Wendy Levinson, David N Gans, Terry Hammons, and Lawrence P Casalino, "US physician practices versus Canadians: spending nearly four times as much money interacting with payers," *Health Affairs*, 2011, *30* (8), 1443–1450.

Nichols, Albert L. and Richard J. Zeckhauser, "Targeting Transfers through Restrictions on Recipients," *American Economic Review*, 1982, *72* (2), 372–377.

Nichols, Donald A., Eugene Smolensky, and Thorwald N. Tideman, "Discrimination by Waiting Time in Merit Goods," *American Economic Review*, 1971, *61* (3), 312–323.

Oostrom, Tamar, Liran Einav, and Amy Finkelstein, "Outpatient office wait times and quality of care for Medicaid patients," *Health Affairs*, 2017, *36* (5), 826–832.

Polsky, Daniel, Michael Richards, Simon Basseyn, Douglas Wissoker, Genevieve M. Kenney, Stephen Zuckerman, and Karin V. Rhodes, "Appointment Availability after Increases in Medicaid Payments for Primary Care," *New England Journal of Medicine*, 2015, *372* (6), 537–545.

Pozen, Alexis and David M Cutler, "Medical spending differences in the United States and Canada: the role of prices, procedures, and administrative expenses," *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, 2010, *47* (2), 124–134.

Reinhardt, Uwe E., "The Pricing Of U.S. Hospital Services: Chaos Behind A Veil Of Secrecy," *Health Affairs*, 2006, *25* (1), 57–69. PMID: 16403745.

Schwartz, Aaron L, Bruce E Landon, Adam G Elshaug, Michael E Chernew, and J Michael McWilliams, "Measuring low-value care in Medicare," *JAMA internal medicine*, 2014, *174* (7), 1067–1076.

Shepard, Mark, "Hospital network competition and adverse selection: evidence from the Massachusetts health insurance exchange," *American Economic Review*, 2022, *112* (2), 578–615.

Shi, Maggie, "Monitoring for Waste: Evidence from Medicare Audits," September 2022. University of Chicago, mimeo. Available online at https://mshi311.github.io/website2/Shi_MedicareAudits_2022_09_15.pdf (accessed September 15, 2022).

Skinner, Jonathan and Douglas Staiger, "Technology adoption from hybrid corn to beta blockers," Technical Report, National Bureau of Economic Research 2005.

_ **and** _ , "Technology diffusion and productivity growth in health care," *Review of Economics and Statistics*, 2015, *97* (5), 951–964.

Sloan, Frank, Janet Mitchell, and Jerry Cromwell, "Physician participation in state Medicaid programs," *Journal of Human Resources*, 1978, pp. 211–245.

Sommers, Benjamin D., Rebecca Gourevitch, Bethany Maylone, Robert J. Blendon, and Arnold M. Epstein, "Insurance churning rates for low-income adults under health reform: lower than expected but still harmful for many," *Health Affairs*, 2016, *35* (10), 1816–1824.

Tebaldi, Pietro, "Estimating equilibrium in health insurance exchanges: Price competition and subsidy design under the aca," Technical Report, National Bureau of Economic Research 2022.

Tirole, Jean, "Incomplete contracts: Where do we stand?," *Econometrica*, 1999, *67* (4), 741–781.

Tseng, Phillip, Robert S. Kaplan, Barak D. Richman, Mahek A. Shah, and Kevin A. Schulman, "Administrative Costs Associated With Physician Billing and Insurance-Related Activities at an Academic Health Care System," *JAMA*, 02 2018, *319* (7), 691–697.

Zwick, Eric, "The costs of corporate tax complexity," *American Economic Journal: Economic Policy*, 2021, *13* (2), 467–500.

Table 1: Remittance Data Summary, Visit Level

	Mean	SD	10th Percentile	90th Percentile	Observations
Initial claim value ($)	155.12	401.58	29.21	240.00	81,392,495
Number of line items	1.81	1.51	1.00	3.00	81,392,495
Number of submitted claims	1.04	0.24	1.00	1.00	81,392,495
Some items denied (0,1)	0.07	0.25	0.00	0.00	81,392,495
Initial denied amount ($)	9.39	115.60	0.00	0.00	81,392,495
Final denied amount ($)	5.96	87.64	0.00	0.00	81,392,495
Medicare patient (0,1)	0.46	0.50	0.00	1.00	81,392,495
Medicaid patient (0,1)	0.08	0.26	0.00	0.00	81,392,495
Private patient (0,1)	0.47	0.50	0.00	1.00	81,392,495

NOTE: This table summarizes the remittance data at the visit level. See Section 2.2 and Appendix A.2 for details. All visits are included in all rows, so all moments are unconditional. This means denial amounts include zeros for all non-denied line items.

Table 2: Claim Values and Denials by Insurer, Visit Level

	Medicaid	Medicare	Commercial
Initial claim value ($)	101.78	135.47	182.84
Some items denied (0,1)	0.242	0.067	0.041
Initial denied amount ($)	20.03	9.18	7.88
Final denied amount ($)	15.02	5.63	4.82
Collected visit revenue ($)	86.75	129.84	178.01
Share of denied claims resubmitted:			
Once	0.342	0.617	0.603
Twice	0.066	0.065	0.048
Three times	0.021	0.018	0.013
Four times	0.009	0.005	0.005
Five or more times	0.004	0.002	0.002

NOTE: This table reports averages across visits for each payer category. All visits are included in each average in the first five rows, so all averages are conditional only on the payer category. This means denial amounts include zeros for all non-denied line items. "Some items denied" takes value one if one or more line items within the claim are denied initial payment. The rows under "Share of denied claims resubmitted" are conditional on an initial denial. They summarize the number of iterations following this initial denial. For example, the value of 0.342 for Medicaid claims resubmitted once indicates that 34.2 percent of denied claims are resubmitted, while in the remaining 65.8 percent of cases physicians forego denied amounts.

Table 3: Summary of Remittance Data Following Denials, Line Item Level

	Denial Rate	Share of Denials	Mean Line Item Value	Mean Pr. of Resubmission	Mean # of Resubmissions	Mean Recovery Rate
Panel a: Medicaid						
Administrative	0.057	0.247	53.68	0.39	0.51	0.58
Contractual	0.070	0.305	44.91	0.35	0.43	0.92
Coverage	0.055	0.240	57.03	0.25	0.34	0.32
Duplicate	0.010	0.043	60.14	0.19	0.24	0.14
Information	0.038	0.164	64.13	0.42	0.58	0.29
Panel b: Medicare						
Administrative	0.010	0.163	89.66	0.57	0.66	0.94
Contractual	0.025	0.389	84.55	0.82	0.88	0.98
Coverage	0.014	0.226	83.00	0.39	0.49	0.34
Duplicate	0.007	0.116	82.87	0.46	0.57	0.45
Information	0.007	0.105	90.11	0.60	0.77	0.54
Panel c: Commercial						
Administrative	0.005	0.138	103.29	0.26	0.31	0.72
Contractual	0.022	0.596	101.35	0.79	0.85	0.99
Coverage	0.003	0.077	124.55	0.43	0.52	0.67
Duplicate	0.004	0.104	103.86	0.22	0.27	0.20
Information	0.003	0.085	146.48	0.47	0.62	0.43

NOTE: This table reports averages across line items (procedures) for each payer category, distinguishing between reasons (categories) of denials. The first column summarizes the probability of a payment for a line item being denied, for each reason category and payer. The second column adds up to 100 within payer, showing the frequency of different reason categories across line items that are denied initial payment. The third column shows average values of line items denied across payers and reasons. The fourth column shows the probability that a line item is resubmitted after the initial denial. The fifth column shows the average number of resubmissions following the initial denial, while the last column shows the probability that the line item is ultimately reimbursed.

Table 4: Physician Survey Summary

	Mean	Observations
Physician accepts:		
Medicaid (0,1)	0.720	3,688,970
Medicare (0,1)	0.841	3,688,970
Medicaid | Doctor accepts Medicare	0.803	3,102,638
Medicaid | Doctor does not accept Medicare	0.288	586,332
Cross-state mover (0,1)	0.011	3,688,970
Cross-state group (Tax ID; 0,1)	0.273	3,688,970

NOTE: This table summarizes the SK&A survey augmented with the MD-PPAS dataset at the physician-year level. The top panel includes a summary of the two indicators for whether a physician accepts Medicaid or Medicare, respectively. Rows 3 and 4, respectively, focus only on physicians accepting Medicare, and only on physicians not accepting Medicare. The bottom panel includes an indicator for physicians who move across states (relative to the prior year), and an indicator taking for whether the physician works in a group active across multiple states.

Table 5: Estimates of Per-Visit CIP and τ

	All Phys.	All Phys.	All Phys.	Small Group	Large Group
Panel a: Medicaid					
Average τ	0.141	0.174	0.176	0.183	0.174
Average CIP	9.75	12.43	12.50	13.06	12.30
Panel b: Medicare					
Average τ	0.033	0.047	0.047	0.059	0.044
Average CIP	2.66	3.94	3.93	4.97	3.60
Panel c: Commercial					
Average τ	0.019	0.024	0.024	0.031	0.023
Average CIP	1.79	2.36	2.37	2.95	2.19
Resubmission cost	No	Yes	Yes	Yes	Yes
Denial reason heterogeneity	No	No	Yes	Yes	Yes
Practice size heterogeneity	No	No	No	Yes	Yes

NOTE: This table summarizes our estimates of CIP and τ across payers and across alternative model specifications. Column 1 corresponds to a model that ignores resubmission costs, Column 2 considers resubmission costs that do not vary across denial reasons, Column 3 allows resubmission costs to vary by reason, and Column 4 and 5 allows resubmission costs to vary by size of physician practice, distinguishing between 1–2 physicians, or larger. See Table B.2 for details on the estimates of the parameters in the resubmission cost function μ.

Table 6: Effect of CIP and Fees on Medicaid Acceptance: Movers Strategy

	Accept Medicaid Patients?			
	(1)	(2)	(3)	(4)
Post-move $\times \Delta\tau$ index	-0.0670***	-0.0773***	-0.0695***	-0.0779***
	(0.0218)	(0.0249)	(0.0189)	(0.0245)
Post-move $\times \Delta \log \pi$ index	0.0321**	0.0311**	0.0296**	0.0285**
	(0.0127)	(0.0130)	(0.0126)	(0.0130)
Estimator	OLS	2SLS	OLS	2SLS
Subsample Accepting Medicare	Yes	Yes	Yes	Yes
N. Physicians	8,182	8,182	8,182	8,182
N. Physicians-Years	47,806	47,806	47,806	47,806
Physician FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
τ index:				
Physician FE	Yes	Yes	No	No
Selection Correction	No	No	Yes	Yes

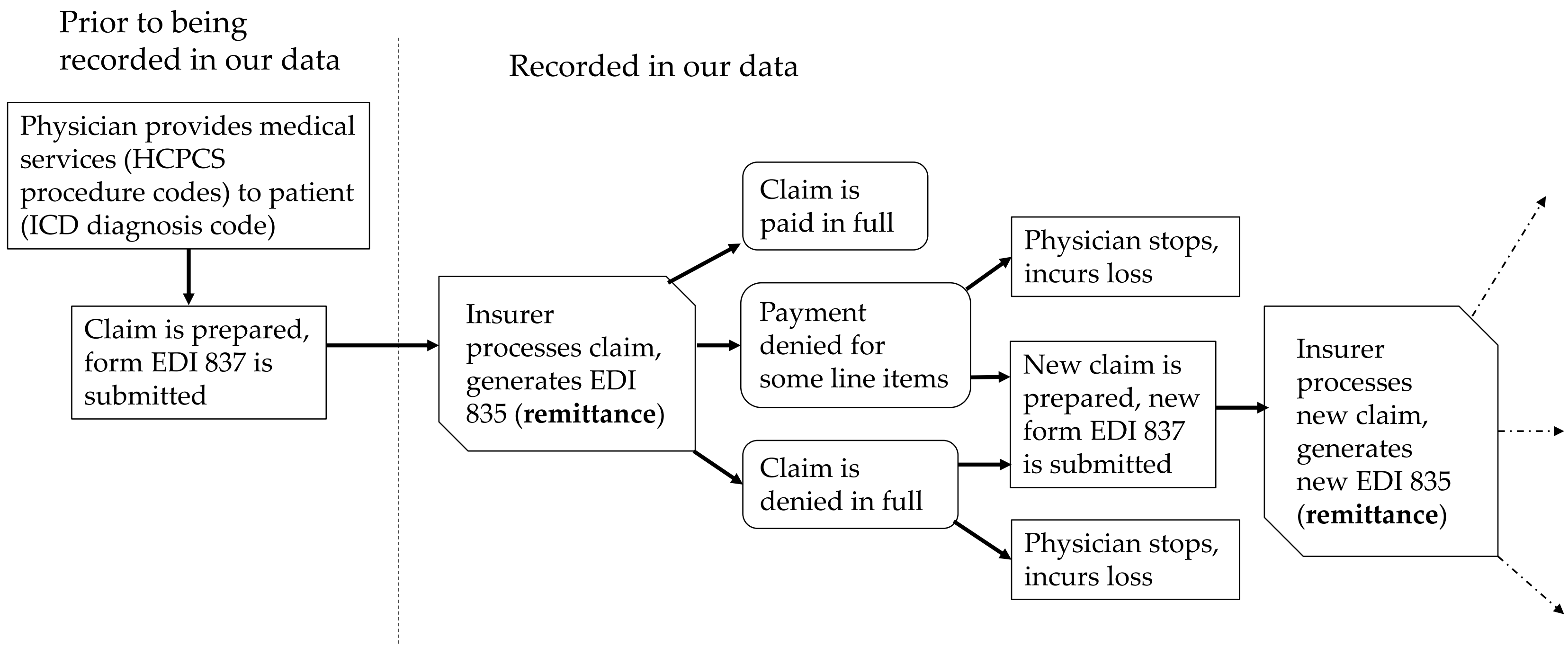
NOTE: This table shows the estimates of β and γ of equation (11). Standard errors are clustered at the state level. Each observation is a physician-year, including only physicians moving across states, from 3 years before the move through 4 years after. The sample is limited to physicians accepting Medicare (this is relaxed in the Appendix). All specifications include physician fixed effects and control for the share of individuals in the county covered by Medicaid, the share of uninsured individual, the average Medicare HCC risk score, the number of physicians, the number of physicians per capita, unemployment, share white, population, share veterans, share below poverty, and median household income. Columns 1 and 3 are OLS estimates, while Columns 2 and 4 are 2SLS estimates instrumenting for $\Delta\tau_i$ with ΔDenial_i as described in Section 4.2.3. Columns 1 and 2 use τ indices estimated with physician fixed effects, without selection correction. Columns 3 and 4 use τ indices estimated without physician fixed effects, with a selection correction.

Table 7: Effect of CIP and Fees on Medicaid Acceptance: Group Strategy

	Accept Medicaid Patients?			
	(1)	(2)	(3)	(4)
τ index	-0.1291***	-0.1437***	-0.1014*	-0.1482***
	(0.0458)	(0.0423)	(0.0526)	(0.0431)
$\log \pi$ index	0.1157***	0.1142***	0.1170***	0.1116***
	(0.0201)	(0.0203)	(0.0212)	(0.0212)
Estimator	OLS	2SLS	OLS	2SLS
Subsample Accepting Medicare	Yes	Yes	Yes	Yes
N. Physicians	232,590	232,590	232,590	232,590
N. Physicians-Years	807,599	807,599	807,599	807,599
Group FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
τ index:				
Physician FE	Yes	Yes	No	No
Selection Correction	No	No	Yes	Yes

NOTE: This table shows the estimates of β and γ of equation (13). Standard errors are clustered at the state level. Each observation is a physician-year combination, the sample is restricted requiring that the physician accepts Medicare (this is relaxed in the Appendix). All specifications include group fixed effects and control for the share of individuals in the county covered by Medicaid, the share of uninsured individual, the average Medicare HCC risk score, the number of physicians, the number of physicians per capita, unemployment, share white, population, share veterans, share below poverty, and median household income. Columns 1 and 3 are OLS estimates, while Columns 2 and 4 are 2SLS estimates instrumenting for $\Delta\tau_i$ with ΔDenial_i as described in Section 4.2.3. Columns 1 and 2 use τ indices estimated with physician fixed effects, without selection correction. Columns 3 and 4 use τ indices estimated without physician fixed effects, with a selection correction.

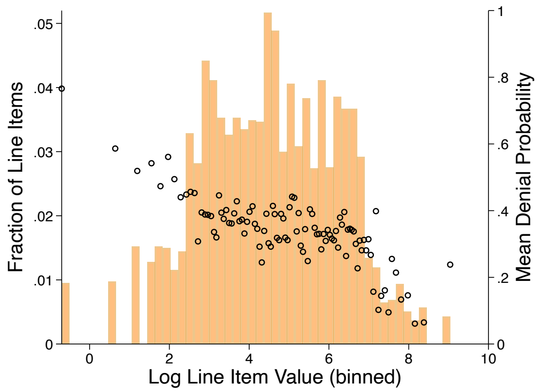
Figure 1: Overview of The Billing Process Underlying the Remittance Data



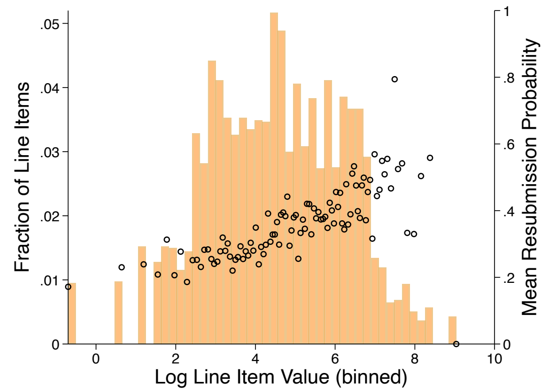
NOTE: This figure represents a schematic overview of the billing processes following a visit. The vertical dashed line separates the part of the process that is not observed (on the left) from the part observed in the remittance data (on the right).

Figure 2: Variation in Visit Amounts, Denials, and Resubmissions

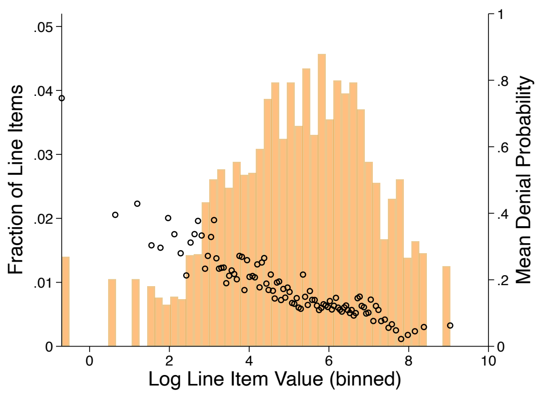
(a) Medicaid, Amounts and Denials



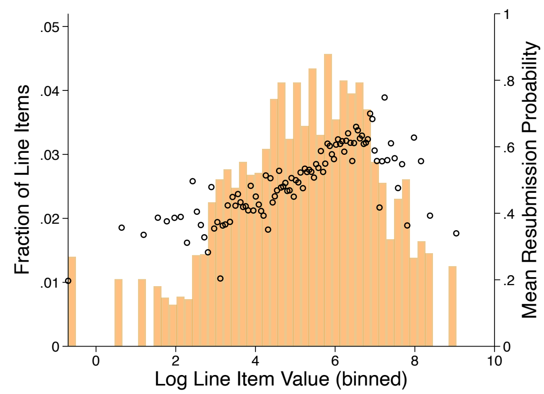
(b) Medicaid, Amounts and Resubmissions



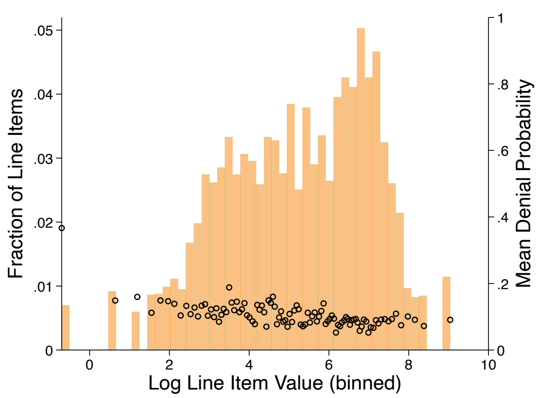
(c) Medicare, Amounts and Denials



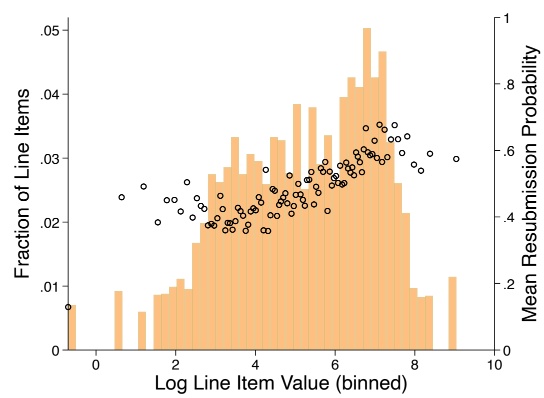
(d) Medicare, Amounts and Resubmissions



(e) Comm., Amounts and Denials



(f) Comm., Amounts and Resubmissions

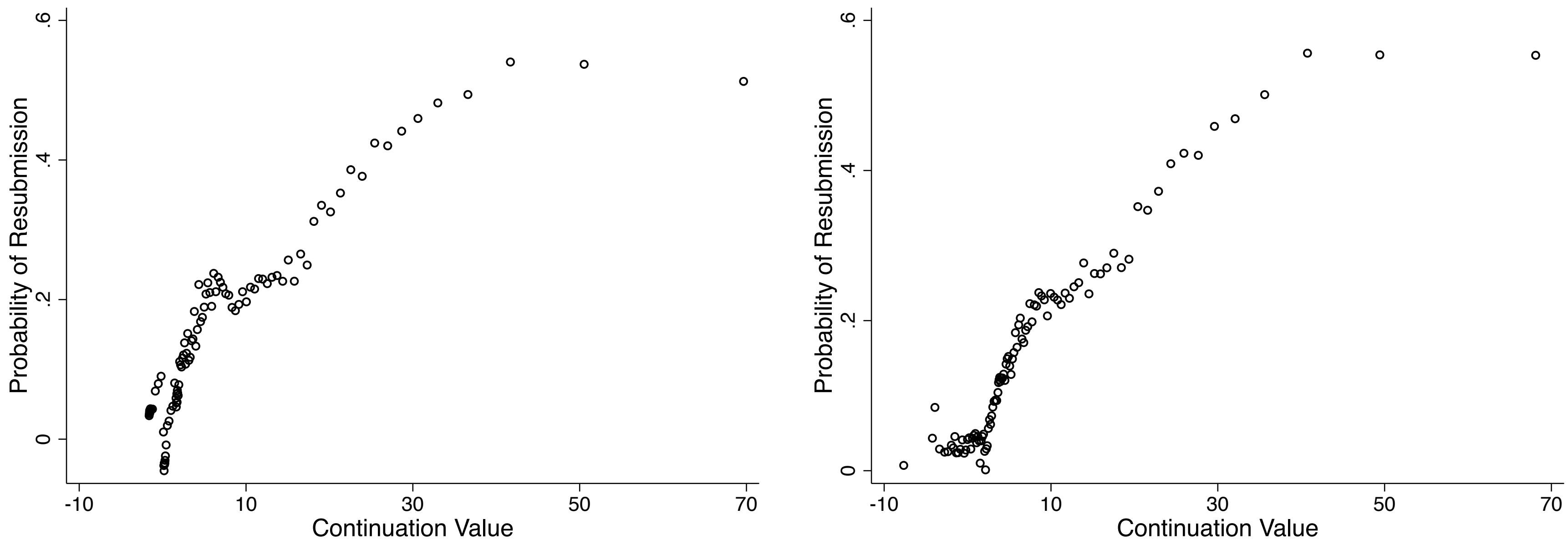


NOTE: For each payer, this figure overlays a histogram of the initial claim values at the visit level (values can be read on the left vertical axis) with a binscatter plot of the probability of denial (Panels (a), (c) and (e)) and a binscatter plot of the probability that a denied item is resubmitted (Panels (b), (d) and (f)).

Figure 3: Probability of Resubmission and Continuation Value

(a) Conditional on Payer

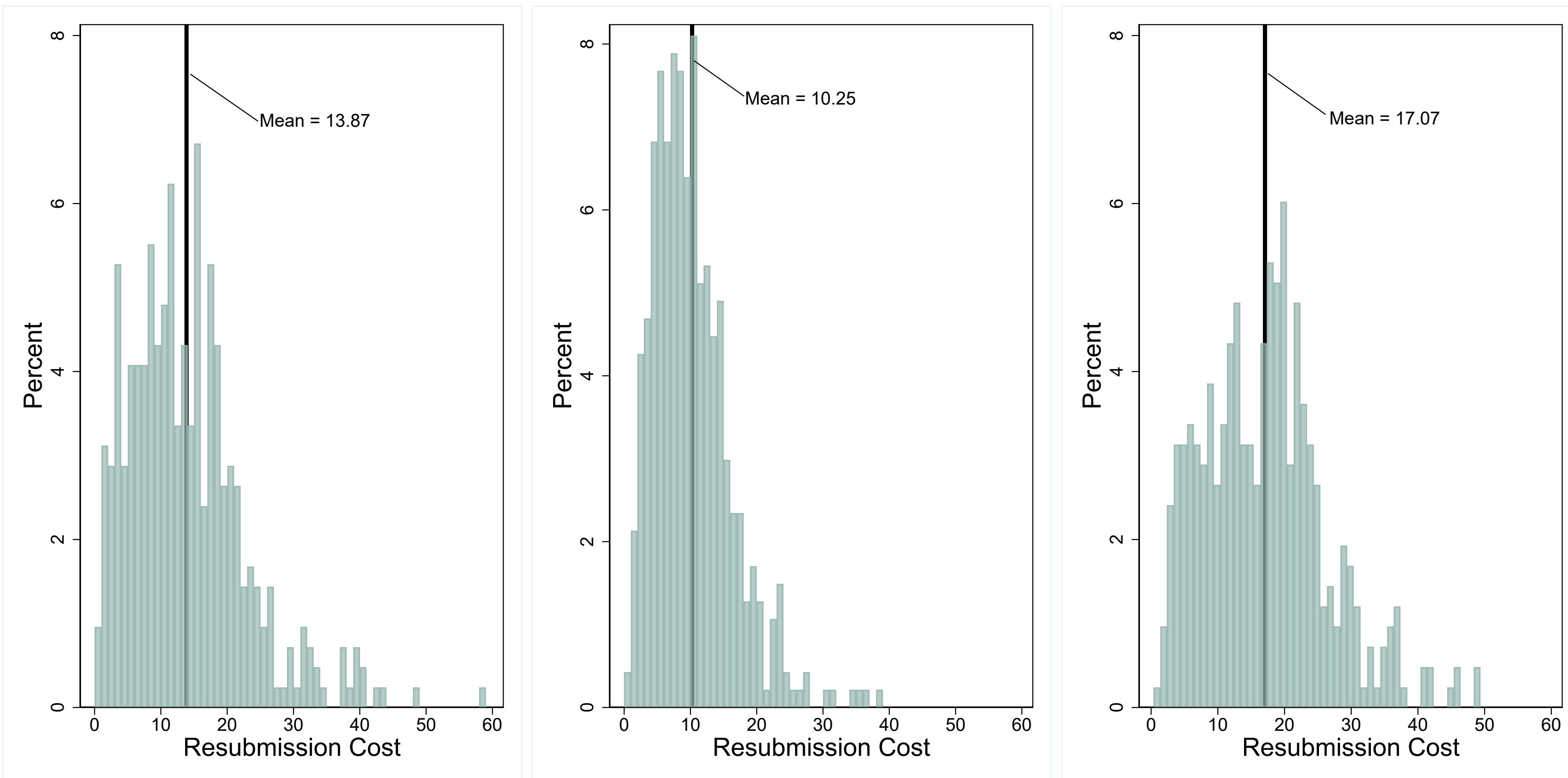
(b) Conditional on Payer and Diagnosis



NOTE: This figure shows a binscatter of the probability that a set of line items is resubmitted (vertical axis) plotted against the continuation value estimated with the remittance data, accounting for future payments, denials, and the probability of submitting further claims. Panel (a) is plotted conditional on payer, and Panel (b) conditional on payer and diagnosis (ICD) code.

Figure 4: Estimates of Resubmission Costs

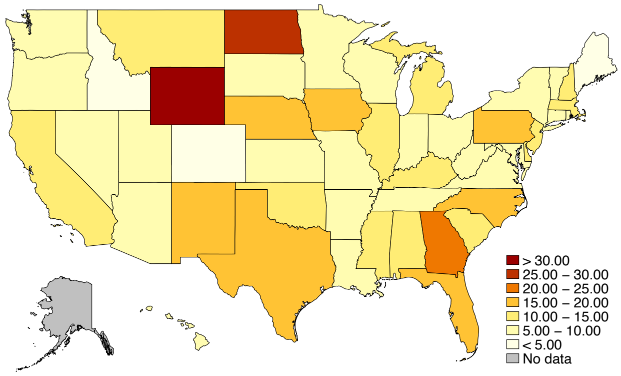
(a) Medicaid (b) Medicare (c) Commercial



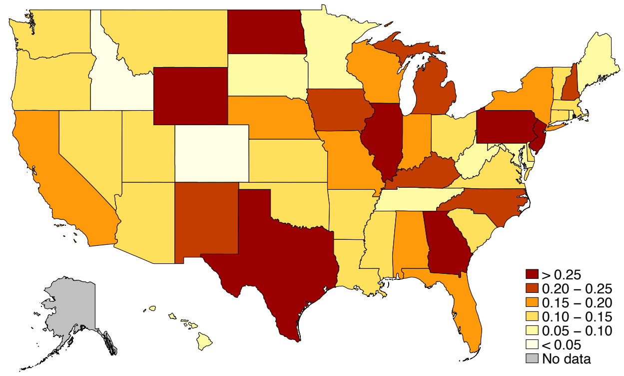
Note: This figure contains histograms of the estimated resubmission costs (for visit with one line item) varying across state, reason code, and size of physician practice. Each panel corresponds to a payer, and the vertical black line denotes the mean resubmission cost.

Figure 5: Costs of Incomplete Payments Estimated Across States and Payers

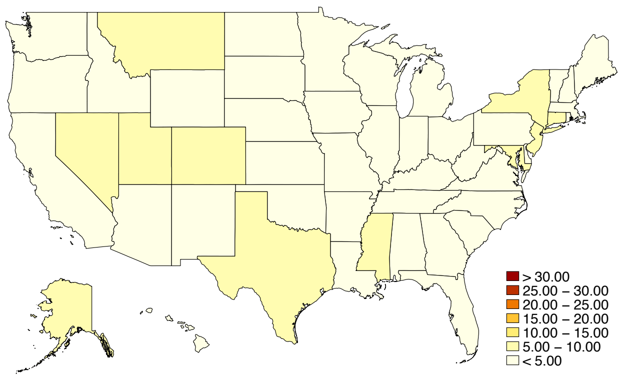
(a) Medicaid, CIP



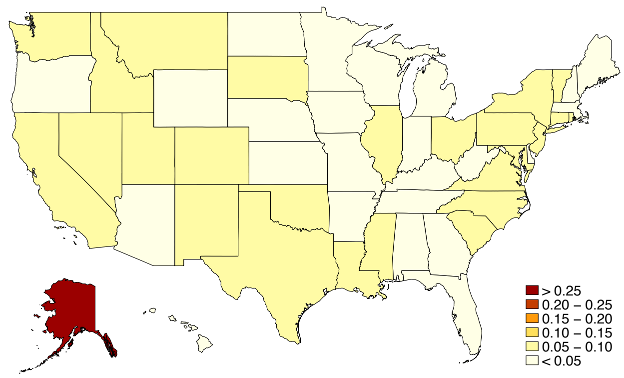
(b) Medicaid, τ



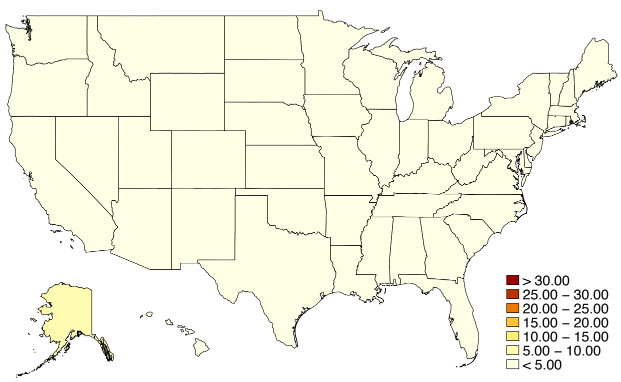
(c) Medicare, CIP



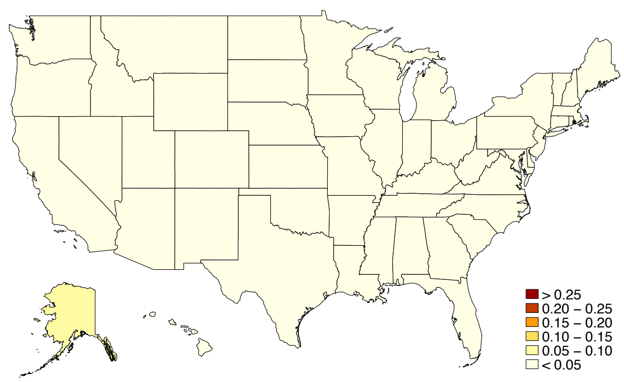
(d) Medicare, τ



(e) Commercial, CIP

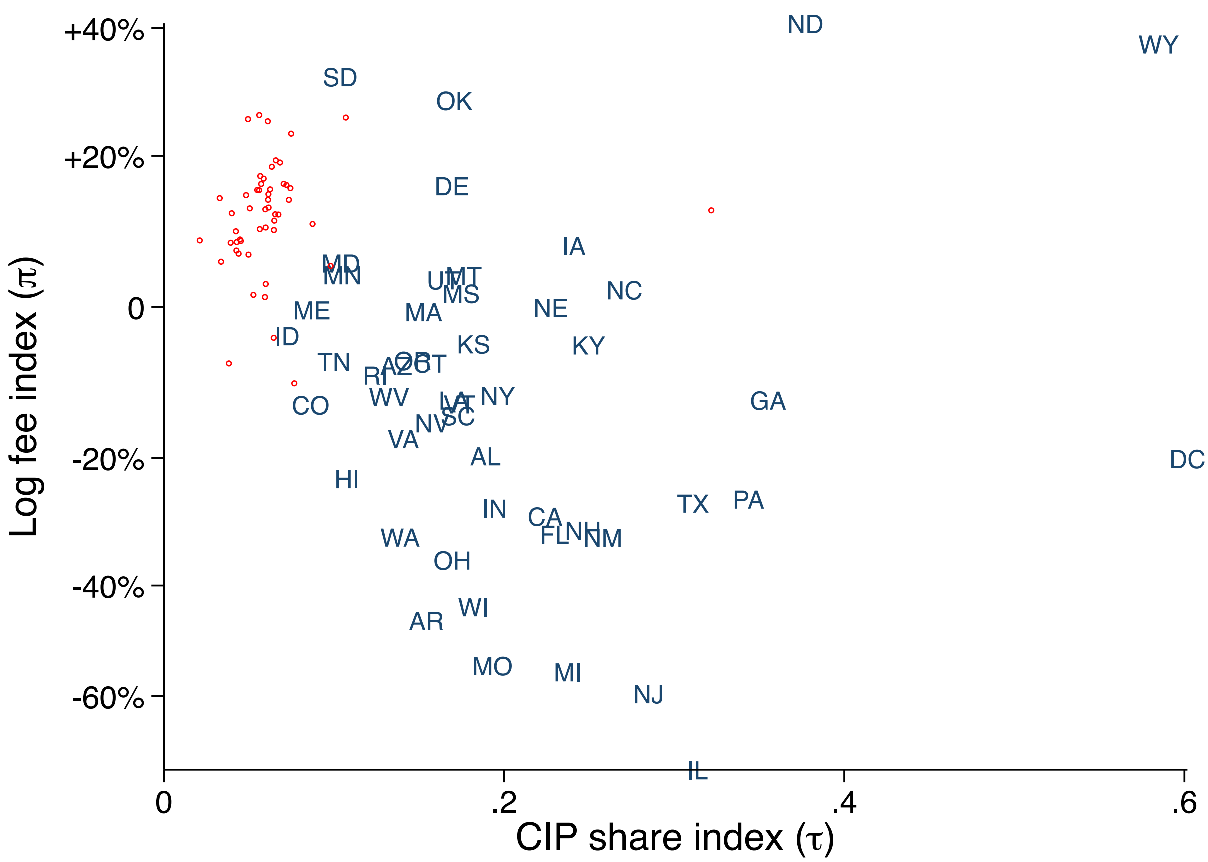


(f) Commercial, τ



NOTE: The left column shows the mean estimated costs of incomplete payments (CIP) by state and payer. The right column shows the mean CIP as a share of visit value by state and payer. For each state and payer, we compute the average across observed visits using the estimates corresponding to columns (4) and (5) in Table 5.

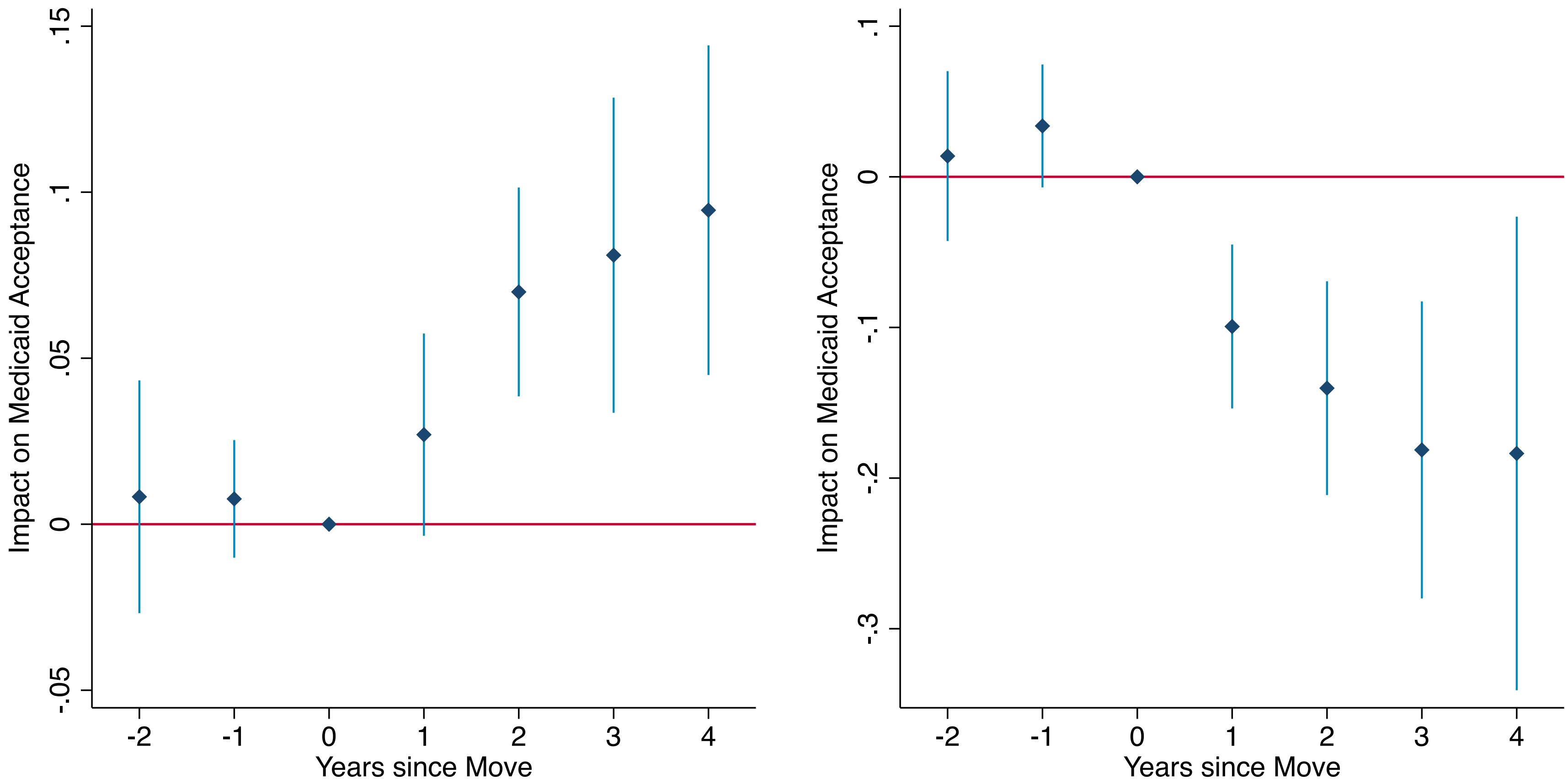
Figure 6: Log(π) and τ Indices Across States



NOTE: This figure plots the indices for log(π) and τ estimated in equations (5) and (6), including the selection correction described in footnote 29. The red dots correspond to Medicare indices, one for every state. Medicaid indices are plotted using each state's postal abbreviation.

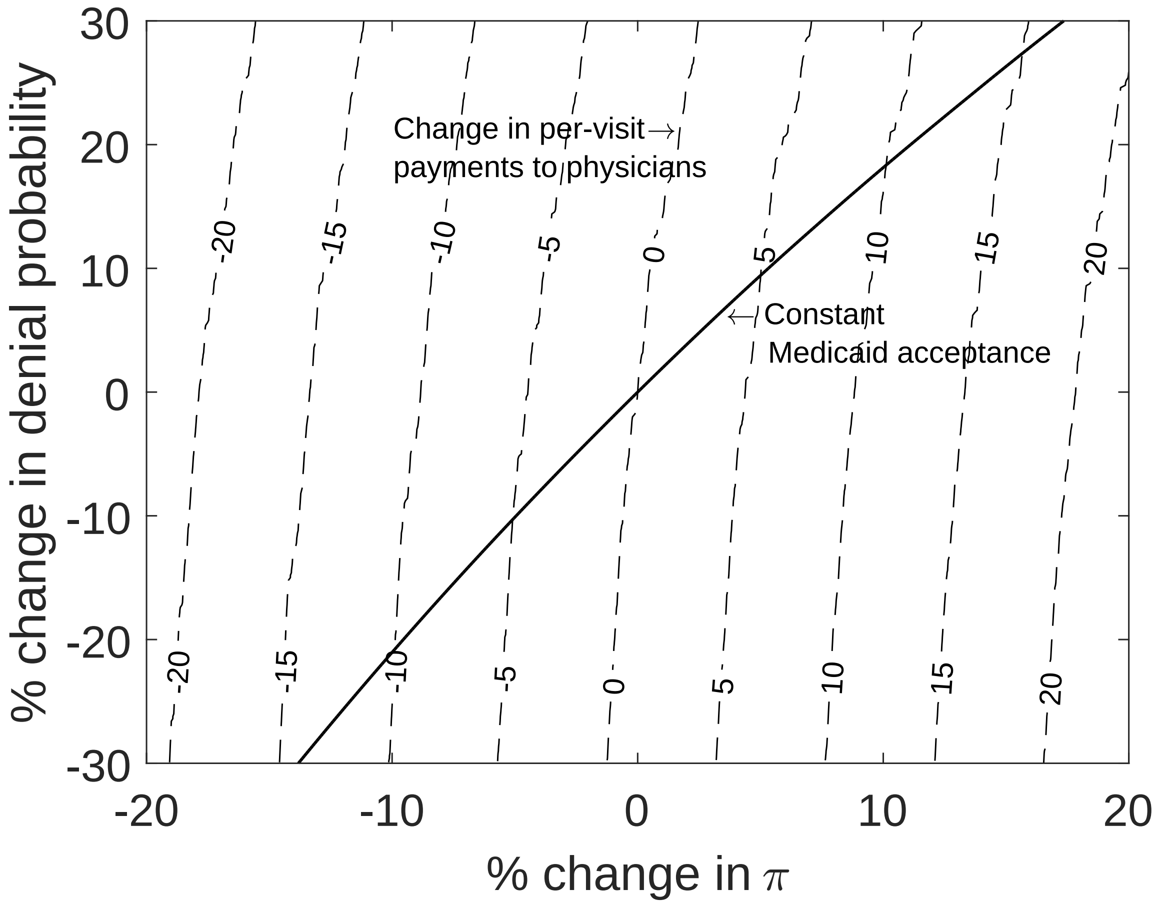
Figure 7: Event Study Graphs: Estimates from Equation (12)

(a) β_ζ: Effect of $\ln \pi$ (b) γ_ζ: Effect of τ



NOTE: This figure plots the coefficients of the movers event study $\hat{\beta}_\zeta$ and $\hat{\gamma}_\zeta$ from estimating equation (12). Each observation in the underlying regression is a physician-year, including only physicians moving across states, from 2 years before the move through 4 years after. Panel (a) shows the coefficients $\hat{\beta}_\zeta$, capturing the effect of the fee index on the probability physicians accept Medicaid patients. Panel (b) shows the coefficients $\hat{\gamma}_\zeta$, capturing the effect of τ on the same probability. In both panels, the horizontal axis ζ indicates the year relative to the physician's move. Standard errors are clustered at the state level.

Figure 8: Policy Counterfactuals Varying Fees and Denials



NOTE: This figure shows how percentage changes in fees and denial probabilities affect Medicaid acceptance and per-visit payments to physicians. The origin for both axes is normalized to the observed level in the data. Values on the horizontal axis correspond to a percentage change in π, and values on the vertical axis a percentage change in d. For example, a value of +10 on the vertical axis means that we change the distribution $F(\pi, d)$ to $F(\pi, 1.1d)$. The solid line indicates changes in fees and denial probabilities that keep Medicaid acceptance constant. The dashed lines indicate varying levels of per-visit payments to physicians.