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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 claims' 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 17% of Medicaid revenue to billing problems, compared with 5% for Medicare and 3% for commercial payers. 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 just as quantitatively important as payment rates for explaining variation in physicians' willing to treat Medicaid patients. We conclude that administrative frictions have first-order costs for doctors, patients, and equality of access to healthcare.

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1 Introduction

Health insurance features an intricate system of contracts involving many private and public entities. These contracts control 13 percent of U.S. GDP,¹ and impose many different administrative burdens on physicians, payers, and patients. We measure one key administrative burden and ask whether it distorts physicians' behavior and harms patients.

While COVID-19 has highlighted administrative dysfunction in many aspects of the U.S. healthcare system,² administrative problems have been flagged as a reason for high costs and inefficiency since long before the pandemic (Cutler and Ly, 2011). Measuring administrative dysfunction is inherently difficult since measurement requires data, and data require administrative capacity. So past evidence on the size and impact of administrative costs in healthcare markets has generally been limited to surveys (Cunningham and O'Malley, 2008; Casalino et al., 2009; Morra et al., 2011; Long, 2013) and accounting exercises (Pozen and Cutler, 2010; Tseng et al., 2018).

We examine whether administrative frictions stemming from complex, incomplete contracts between healthcare providers and payers 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 physician provides treatment. This ambiguity leads to costly billing and bargaining processes 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 have a major impact on Medicaid patients' access to medical care—quantitatively as potent as physician payment rates.

Our study employs a novel type of healthcare data, called “remittance data”, which

¹Health insurance covers 13 percent of GDP; total healthcare spending is almost 18 percent.

²Cook (2020) describes administrative hurdles impeding COVID-19 patient care. Early problems with the regulatory regime for licensing tests (Sharfstein, Becker and Mello, 2020), confusion over insurance coverage for those tests (Taylor and Slabodkin, 2020), and failure to conduct basic case tracking (Meyer and Madrigal, 2021) are some of many additional administrative failures. Simple measures to protect the most vulnerable residents and staff in nursing homes were disregarded (Chen, Chevalier and Long, 2021). Even when it was clear that vaccines would soon be approved, there was little planning for how to distribute them (Reuters, 2021), widespread confusion about eligibility rules (Hamel et al., 2021), and even the system for tracking distribution failed (Bajak and Heath, 2021).

track the billing processes following 90 million visits between 2013-2015. Gottlieb, Shapiro and Dunn (2018) briefly introduced and summarized these data. The data allow us to observe multiple rounds of interactions between payers and physicians, along with detailed information about the medical provider, the patient, the visit, and the reasons payments are denied. These data provide far more detail about the billing and collection process than the claims data that have become widely used to study healthcare markets.³ As a result, we are able to estimate the costs of haggling between the physician’s practice and the payer.

Raw data show that payment frictions are particularly large in the context of Medicaid—a key part of the U.S. social safety net, but which rarely provides an equal quality of care as other insurance. In particular, Medicaid patients often have trouble finding physicians willing to treat them (Polsky et al., 2015; Candon et al., 2018; Ostrom, Einav and Finkelstein, 2017). We find that 25% of Medicaid claims have payment denied for at least one service upon doctors’ initial claim submission. Denials are less frequent for Medicare (7.3%) and commercial insurers (4.8%). Following a denial, the physician has two choices. She can accept that the claim won’t be paid, foregoing the potential revenue. Or she can commence a costly back-and-forth process to try to convince the insurer to pay.

To estimate CIP we adopt a simple economic model in which providers’ dynamic billing behavior following a visit is optimal. Doctors (or their billing offices) maximize expected revenues considering their own administrative costs, and with rational expectations about payers’ payment processes. When an insurer denies (even partially) the claim after a visit, the provider faces an optimal stopping problem resembling that considered in Hotz and Miller (1993). We identify billing costs from observed differences in expected revenues between visits for which physicians resubmit claims and visits for which they stop attempting to collect payments, after conditioning nonparametrically on the denial reason and many visit

³Recent uses of *claims* data—distinct from our *remittance* data—include the widely used Medicare and Medicaid claims data, MarketScan (Dunn, Liebman, Pack and Shapiro, 2013; Clemens and Gottlieb, 2017), the Health Care Cost Institute (Cooper et al., 2018), individual firm data (Einav, Finkelstein and Cullen, 2010; Brot-Goldberg, Chandra, Handel and Kolstad, 2017) and even many so-called All-Payer Claims Databases (Ericson and Starc, 2016); the latter were kneecapped when the Supreme Court in *Gobeille v. Liberty Mutual* (2016) prevented states from requiring self-insured firms to include their claims.

characteristics. The CIP we estimate thus incorporate two concepts: foregone revenues, directly measured in the remittance data, plus the estimated billing costs that providers accumulate during the back-and-forth negotiations with payers.

We estimate that CIP average 17.4% of the contractual value of a typical visit in Medicaid, 5% in Medicare, and 2.8% in commercial insurance. These are significant losses—especially for Medicaid, which offers physicians much lower reimbursement rates than other insurers in the first place.

These high costs raise a natural question: do they affect physicians' supply of care? Standard economics suggests that doctors' willingness to treat patients should respond not only to the level of prices, but also to the difficulty and administrative burdens necessary to collect revenues. So higher CIP should reduce their incentives to treat patients just as lower prices do.

We test this using the federalist structure of Medicaid. Medicaid is a joint federal-state program that insures lower-income adults, pregnant women, and children. While it is largely federally financed, and subject to certain federal regulations, it is administered separately by each state—often via contracts to managed care organizations. This means physician payment rates and processes vary dramatically across states.

We examine how doctors react to differences in these rates and CIP across states. To ensure we capture state administrative decisions, rather than differences in patient composition or physician billing skill, we adjust our model results for these confounds and estimate state-by-insurer price and CIP indices. We then combine these indices with administrative data on all physicians' locations, and survey data on the near-universe of physicians' Medicaid 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.

We use two identification strategies to isolate exogenous variation in Medicaid prices and CIP. The first strategy exploits providers who move across states across different years. (Abowd, Kramarz and Margolis, 1999; Finkelstein, Gentzkow and Williams, 2016; Hull, 2018;

Molitor, 2018). Second, we compare the Medicaid acceptance probability 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 concern that patient acceptance may depend on a group's managerial competence or organizational structure (Bloom et al., 2017).

These two strategies also obtain economically different objects. The response of an individual physician moving between two states in a particular year ought to be lower than the cross-sectional response of a physician group adjusting its strategy across different clinic locations. Conceptually, the first can be interpreted as a short run elasticity of supply to price and CIP. The second allows for adjustments over a longer time horizon, and aggregates to the organization level across multiple physicians.

If we think of CIP as an implicit tax on doctors' revenues, a ten percentage point increase in CIP—approximately one cross-state standard deviation—is analogous to a tax increase of ten percentage points. Examining physicians who move across states, we estimate that an implicit tax increase of this magnitude reduces physicians' probability of accepting Medicaid patients by 1 percentage point. This is almost equivalent to the effect of a one standard deviation increase in Medicaid reimbursement rates.

Looking across states within physician group, we estimate that the long-run effects are larger. Each standard deviation increase in CIP reduces Medicaid acceptance by 2 percentage points. To understand physicians' decision-making, we rescale the estimates into semi-elasticities of Medicaid acceptance with respect to revenue. Across both strategies, the semi-elasticity of Medicaid acceptance with respect to net-of-CIP revenue is statistically indistinguishable from that with respect to fees. So physicians appear to act consistently across these two domains—they treat a given revenue increase similarly whether it comes from higher reimbursements or lower CIP. Measuring providers' incentives ignoring CIP—as one would do looking at reimbursement rates alone—misses a critical aspect of physicians'

behavior and healthcare policy.

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. Previous work highlighted the effect of prices on physicians' acceptance of Medicaid patients (Polsky et al., 2015; Ostrom et al., 2017; Candon et al., 2018; Alexander and Schnell, 2019), and on the supply of care more broadly (Gruber, Kim and Mayzlin, 1999; Clemens and Gottlieb, 2014; Dunn and Shapiro, 2018; Gottlieb et al., 2021). We show that a reduction in administrative hassle is just as significant.⁴

Physicians base their supply decisions not only on the pre-determined contractual terms agreed upon with a specific payer, but also on the administrative costs necessary to collect revenues after providing care. So if policymakers want to reduce inequality in healthcare access, this paper points to a new tool: without expanding eligibility, or raising reimbursements, improving Medicaid claims administration could help make healthcare for low-income Americans more similar to Medicare or employer-sponsored healthcare.

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.

Our results have two limitations, which raise important issues that should motivate future work. First, we only explore one dimension of administrative hassle in healthcare. Physicians' other administrative burdens include licensure and registration with insurers, establishing payment contracts, and obtaining preauthorization for care (Clemens, Gottlieb and Molnár, 2017). Patients face their own burdens, including signing up for insurance and finding providers whose care their insurer covers (Handel and Kolstad, 2015; Brot-Goldberg,

⁴The relationship between billing hassle and physician behavior has only been 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 how hospitals code and bill for the care they provide. Zwick (2021) makes a similar point in a very different setting (corporate taxation): accountants' sophistication influences the tax deductions that firms claim.

Layton, Vabson and Wang, 2021). Identifying a broader concept of administrative dysfunction may yield opportunities to make healthcare markets more efficient. 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 missed opportunities to make healthcare more efficient.

Second, we don't necessarily capture the full economic incidence of CIP—and, although they impose costs on physicians, they could conceivably be efficient for the aggregate market. Claim denials may be part of a process to direct providers' treatment decisions towards appropriate or cost-effective care. They may help target programs towards more appropriate providers, if (unlike in recent evidence on beneficiary targeting) those physicians more able to bear the administrative burdens are better at caring for Medicaid patients. They may deter or detect fraud, as Crocker and Morgan (1998); Crocker and Tennyson (2002); Dionne, Giuliano and Picard (2009) consider. While all of these effects may exist, they seem unlikely to dominate the costs: if they did, physicians in high-CIP states would have no reason to avoid Medicaid. There could be a compositional effect, in which CIP drive some physicians from the market, and those who remain might recoup their costs through higher prices or higher patient volumes. But even if this leaves the remaining physicians no worse off, the market-shrinking effect of patients losing access to care that we document and measure would remain.

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).

Instead of focusing on the beneficiary-program relationship, we highlight the importance

of ongoing administrative hassles in a business relationship between providers and payers. This has a direct effect on the costs of supplying healthcare, as these costs must account for the billing processes necessary to collect revenues. Administrative hassles then impact beneficiaries and program targeting through a sizable indirect effect, by which higher costs limit the supply of care to Medicaid patients.

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 Iribarri, 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. We therefore are not limited by observing only final trades, as in Crawford and Yurukoglu (2012), and our empirical model relies on fairly weak assumptions of optimality and consistent beliefs. Although we focus only on the physician's side of the bargaining process, we move beyond testing theories (Morton, Silva-Risso and Zettelmeyer, 2011; Backus et al., 2020; Grennan and Swanson, 2020): we estimate economic costs of submitting 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

Institutional details of the U.S. health insurance system are critical to understanding our data and analysis, so we begin with an overview of the insurance billing process.

When patients covered by health insurance 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 et al., 2010; Bundorf, Levin and Mahoney, 2012) or purchased in a health insurance marketplace (Ericson and Starc, 2015; Shepard, 2016; Tebaldi, 2017)—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 what care the physician provided. The physician describes this care in detail using the “Healthcare Common Procedure Coding System” (HCPCS), which defines approximately 13,000 medical services. 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). A claim may contain one or more *line items*, each containing one HCPCS code. The physician or biller must also classify the patient’s diagnosis using International Classification of Diseases (ICD) codes. She also needs to 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.⁵ 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”).⁶

The insurer receives the claim from the biller, analyzes, and processes 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.

⁵The 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.

⁶These billed amounts are infamously outrageous and, with one minor exception described on page 11, we do not use them in our analysis. (Though they may sometimes provide a baseline for the negotiated rates we use. In the hospital payment context, Reinhardt (2006) describes these list charges and Cooper et al. (2018) find that they still form an important part of many hospitals’ payment contracts.)

This system determines whether the patient has eligible insurance, whether the insurance covers the service provided, and whether the medical care was appropriate.⁷

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.⁸

The insurer transmits its decision to the physician using a standardized electronic format, called Electronic Data Interchange 835, “Electronic Remittance Advice,” which we refer to 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 they are authorized to collect from the patient—the patient owes any deductible, copayment, or coinsurance directly to the physician. Depending on the physician’s exact billing arrangement, the remittances may be sent straight to the physician’s office or to a clearinghouse—an intermediary whom the physician has engaged to process her 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. Based on the information in the remittance, the physician can bill the patient for any amount they owe.

But the process is not always this smooth. Instead of approving the claim, the insurer may deny it, fully or in part, refusing payments for specific line items. The insurer may question the validity of the patient’s insurance coverage, the medical justification for a specific procedure, or whether the insurance contract covers the care provided. It may question whether the physician has submitted the correct codes, or authorize less payment than the doctor was expecting under the payment contract. In fact, the organization that manages

⁷The 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).

⁸See Clemens and Gottlieb (2017) for more details.

the Electronic Data Interchange standards maintains a list of around 350 codes for different reasons claims may be adjusted or denied.⁹

When a claim (or parts 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. 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 asking the patient to pay for amounts the insurer has not authorized. So in most cases the physician’s only option is to deal with the insurer directly.

Her next steps depend on why the claim was denied. If the insurer questions the medical necessity of the treatment, the physician may have to provide additional documentation about the patient’s condition, either through an online submission form or by fax. If there is an administrative error, such as a typo in the patient’s name or insurance details, the practice may need to submit a corrected claim. 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 remittance to convey the decision to the physician or her agent.

All of the processing and adjudication in this system absorb considerable resources. It also generates massive amounts of rich data, which allow us to investigate the interactions between physicians and insurers, and the implications of this process for physicians’ decisions.

2.2 Remittance Data

Our primary data source is IQVIA Real World Data—Remittance Claims. 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

⁹<http://www.x12.org/codes/claim%2Dadjustment%2Dreason%2Dcodes/>

drawn at the physician level.¹⁰ For the 108,531 unique physician covered in the sample, we observe their interactions with the full range of payers, including Medicaid, Medicare, and commercial insurance.

We see the remittances generated each time the insurer responds to a physician’s submission or resubmission—including those remittances indicating claim denial, nonpayment, or other complexity. This is a key difference from claims datasets used in much other research, which generally have exhaustive data from an insurer or set of insurers, but don’t see the full breadth of any physician’s business and often can’t link the same physician across insurers.

For each remittance, the data tell us the providing physician (including the National Provider Identification number), the practice submitting the bill, its zip code, and the payer 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 payer made its decision. We then see how the payer 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.

Inferring the Payer-Physician Contract. An inherent challenge in data of this form is that we naturally do not observe the allowed amounts for line items that are denied payment within a claim. For the line items for which these amounts are not observed, we use a three-step algorithm to impute the contractual amounts that would have been collected by the provider, had the claim been approved and processed smoothly, according to the payer’s contract with the physician.

Step 1: Whenever possible we impute the contractual amount as the average allowed

¹⁰Since the data provider includes remittance data from whichever clearinghouses it contracts with, rather than a systematic random sample, one may naturally worry about the samples representativeness. Upon introducing our data, (Gottlieb et al., 2018, online appendix) showed that physicians appear very representative of the covered specialties nationwide. This gives us a higher level of confidence on the nationwide representativeness of our results.

amount for claims processed smoothly by same insurer, when paying the same physician for the exact same procedure (HCPCS code). *Step 2:* When there are no claims available matching the criteria required for step 1, we impute the claim value based on the average markup between the payer’s allowed amounts to the provider and standard fee-for-service Medicare rates across all other HCPCS codes. We compute this markup and then impute the contractual amount to be the fee-for-service Medicare rate for the specific line item, multiplied by this payer-provider-specific markup. *Step 3:* In the few instances in which we lack the data required for either step 1 or 2, we compute the average discount from the billed charges to the allowed amounts specific to the payer-provider pair. Then, we impute the contractual amount by applying this payer-physician-specific discount to the observed billed charges for the specific line item.

Note on Terminology. In what follows, *line item value* refers to the contractual amount for a specific procedure for which the physician bills. This is the the allowed amount for all claims that are processed smoothly, and is otherwise the result of our imputation. The line item value is the amount that the provider would receive if there were no denials. 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. 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 88.8 million visits¹¹ we observe over the 2013-2015 period, the average initial claim value is \$154. For the bottom ten percent of visits this amount is lower than \$24, while for the top ten percent it exceeds \$238. Visits differ along several dimensions, including the number of line items included. On average, a visit contains 1.9 line items; ten percent of visits contain over four.

¹¹We drop Medigap and other secondary payers, claims with values of < \$0 or > \$1,000,000, the bottom and top one percent of line item values for CPT codes-payer-year combinations, and line items valued at < \$0.01.

A key variable for our analysis is the denial of a payment for at least one line item in a claim for a given visit. Table 1 shows that, on average, across all payers and all years in our sample, 7.5% 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 1.047. Patients are covered by different payers: 7.6% of visits in our sample are billed to Medicaid, 46.4% to Medicare, and 46% to commercial insurers.

The three types of payers differ across three 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 \$98.57, 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 \$84 on average. Medicare and commercial insurers have, on average, higher initial claim values (\$136 and \$179, respectively), and lower denial rates (7.3% and 4.8%). Accounting for resubmissions, the total revenue collected for Medicare patients averages \$131 per visit, and \$175 for patients covered by commercial plans.

Figure 2 summarizes the visit-level revenue graphically. The overall length of each bar represents the average claim value for each insurance type. We separate that length into the amount paid on initially submission and the amount initially denied. Some of that denied share is ultimately paid; this part is labeled “recovered” in the chart. This recovered plus the initially paid amount represent the physician's total gross revenue. But this overstates the net revenue: the office had to expend resources to collect that recovered amount. This piece is not directly observable in the data, but is the result of our estimation in section 3 below. We illustrate these collection costs as coming out of the recovered amount. These costs, plus the amount never recovered, combine to make up the total CIP shown on each bar. The figure illustrates the stark difference in Medicaid revenue compared with Medicare and commercial insurance—not only is the visit value lower, but a much larger share is dissipated in the costs of incomplete payments.

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 A.1 uses word clouds to summarize the explanations for all the denial reasons within each category.

In Table 3 we delve into the line item level rather than the visit. This allows us to illustrate in richer detail the differences in billing processes across payers, and how denial reasons relate to payment outcomes. We see remarkable differences across payers in reasons for denials. Administrative reasons comprise one quarter of denials in Medicaid, 16% in Medicare, and 14% in commercial insurance. Contractual reasons drive 30% of denials in Medicaid, 41% in Medicare, and 55% in commercial insurance.

Differences in 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, 62% in Medicare, and 40% in commercial insurance. After these billing processes end, providers ultimately recover 60% of revenues in Medicaid, 95% in Medicare, and 79% in commercial insurance.

Other reasons for denials lead to different outcomes. For example, coverage issues imply a 37% recovery rate in Medicaid, 69% in Medicare, and 88% 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 60% for both Medicare and commercial insurance.

Prices and billing processes vary not only across payers, but also across states. We will leverage these differences to study how providers respond to the financial incentives provided by both payment rates and the administrative burden of collecting payments. Figure 1 summarizes the variation across payers and states in initial claim values and share of these amounts that are ultimately collected (after accounting for denials and resubmissions). For Medicaid, the data show much lower values, and more variation across states, in both claim values and collection rates. This suggests that Medicaid is a relevant setting in which to consider whether providers respond not only to prices, but also to the difficulty and costs of collecting payments after care is provided.

2.3 Additional Data Sources

We complement our data with two additional sources, which are 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. Since MD-PPAS has the same physician identification number as the remittance data, merging the two to obtain physician characteristics is straightforward.

Finally, 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 major 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. SK&A also provides the National Provider Identification number that allows us to merge all of these

sources.

The resulting dataset contains 3.7 million provider-year observations over the 2009-2015 period. Physicians report accepting Medicaid patients 72.1% of the time, and accepting Medicare patients 84.1% of the time. In the same period, 1.5% of doctors move across different states and 27.3% of them work in a group that has locations in more than one state.

3 Estimating Costs of Incomplete Payments

3.1 A Model of the Provider Problem

The remittance data introduced above allow us to document and understand the incomplete payments that pervade medical billing. They imply that a physician's gain from providing care is smaller than in a complete-payments world. We can think of the physician's net revenue as the claim value minus two elements: the lost revenues and the billing costs necessary to recover payments after a claim is denied. This net revenue enters the physician's profit and any decision-making problem.

We directly measure lost revenues. To estimate billing costs, we rely on a simple intuition: if billing were costless, providers would always resubmit a denied claim hoping for a better outcome. This resubmission would have the potential to recover the missing revenue from the visit, or at least a part, at no cost. At the other extreme, if the cost of resubmitting a claim were higher than the maximum amount a provider could possibly recover, we would observe no resubmissions.

Expanding on this intuition, we use the following model in which risk neutral providers make optimal resubmission decisions when facing initial denials or incomplete payments from the insurer. This model allows us to estimate billing costs by rationalizing the observed variation in resubmissions and denials in the remittance data.

Periods are discrete, and indexed by $t = 0, 1, \dots$, and L is the set of line items contained in the initial claim for which the provider bills an insurer for the care provided. If payment

were complete, the visit revenues would be equal to the initial claim value equal to $\pi(L)$. Whenever we consider a (sub)set A of line items, $\pi(A)$ is the total contractual amount for the items in A .

Now consider the problem the provider (or billing office) faces when the payer denies payment for one or more line items on the initial claim. That is, instead of reimbursing all items in L , the payer denies payments for a set of items $D^1 \subset L$. The reason for denial is summarized by a reason code category ρ : administrative, contractual, coverage, duplicate, or information. As Figure 3 illustrates, the provider can stop the billing process at no additional cost, and forego any further payment for the visit. In this case, adopting the notation that $L - D^1$ means the subset of L *excluding* the items in D^1 , the visit revenue (or payoff) is $\pi(L - D^1)$.

Alternatively, the provider can pay an administrative cost to resubmit all or some of the denied line items. In our notation, the provider can choose any set $R^1 \subset D^1$, and submit a second claim requesting the payer to reimburse these line items that have been previously denied. Let the cost of this resubmission be $C(R^1, \rho) \geq 0$, equal to zero whenever $R^1 = \emptyset$ (no resubmission). Our goal is to estimate these costs, as they are the unobserved part of the broader costs of incomplete payment (CIP).

After resubmitting the line items in R^1 , the provider may receive the corresponding payments. This would lead to a visit payoff of $\pi(L - D^1) + \beta\pi(R^1) - C(R^1, \rho)$, where $\beta < 1$ is the intertemporal discount factor. Alternatively, as Figure 3 shows, payments for a subset of items $D^2 \subset R^1$ may be denied again. In this case, the provider must again choose whether to stop ($R^2 = \emptyset$, with payoff $\pi(L - D^1) + \beta\pi(R^1 - D^2) - C(R^1, \rho)$), or resubmit again a nonempty set of line items $R^2 \subset D^2$ at a cost $C(R^2, \rho)$. The process continues recursively.

In this model, the provider faces an optimal stopping, dynamic discrete choice problem under uncertainty. While the costs of resubmitting any subset of a line items R^t in any given period t are known to be $C(R^t, \rho)$, the returns from the resubmission are uncertain. These returns depend on the provider's expectations about the insurer's future denials and her own

future resubmissions. Crucially, the provider always has the option to stop and forego any further revenues for the visit.

Assuming providers have rational expectations about future payment probabilities and their own resubmission behavior, we can characterize the solution of the provider problem. We use $\sigma^*(D^t, \rho)$ to denote the optimal (stationary) strategy, i.e. the set of resubmitted items in period t when the items in D^t are denied for reason ρ . This solves:

$$\sigma^*(D^t, \rho) = \arg \max_{R^t \subset D^t} \mathcal{V}(R^t, \rho), \quad (1)$$

$$\mathcal{V}(R^t, \rho) = \underbrace{-C(R^t, \rho)}_{\text{Resubmission cost}} + \beta \underbrace{\mathbb{E} [\pi(R^t - D^{t+1}) + \mathcal{V}^*(D^{t+1}, \rho) | R^t, \rho]}_{\text{Expected future payoff after resubmission}}, \quad (2)$$

$$\mathcal{V}^*(D^t, \rho) = \mathcal{V}(\sigma^*(D^t, \rho), \rho). \quad (3)$$

The expectation in (2) is taken with respect to D^{t+1} . The distribution of $(D^{t+1}|R^t, \rho)$ is a key ingredient to solve (1)–(3), and it can be estimated using our remittance data.

We can now formally define the costs of incomplete payment, CIP, as the expected reduction in net revenues for a visit relative to the complete-payment counterfactual. Absent denials, the provider would collect $\pi(L)$. Incorporating denials and resubmission costs, CIP comprises two parts: lost revenues and resubmission costs. The following definition captures both parts:

$$CIP \equiv \pi(L) - \mathbb{E} \left[\sum_{\rho} \sum_{D^1 \subset L} \Pr[D^1, \rho] (\pi(L - D^1) + \mathcal{V}^*(D^1, \rho)) \right], \quad (4)$$

where $\Pr[D^1, \rho]$ is the probability that the line items in D^1 are denied for reason ρ . If there are no denials, $CIP = 0$, and the expected profitability of a patient after the first claim is submitted is $\pi(L)$. When denials are more common, CIP increases, which means expected profitability of a visit declines. This increase can occur through lost revenues, if the provider chooses not to resubmit denied claims, or resubmission costs if she chooses to resubmit.

We think of CIP as imposing an implicit tax τ^{CIP} on providers' revenues, defined as

$$\tau^{CIP} \equiv \frac{CIP}{\pi(L)}. \quad (5)$$

The provider expects net revenue of $(1 - \tau^{CIP}) \pi(L)$ rather than $\pi(L)$ for a visit. Our goals are to estimate CIP, and to study how physicians respond to both parts of expected revenue: $\pi(L)$ and τ^{CIP} .

3.2 Econometric Specification

To estimate our model, we augment our notation to account for observable differences across visits, and make a number of functional form and distributional assumptions.

Let j index visits and t the period in the dynamic billing process (i.e. the claim number for the same visit). Visit j includes a set of line items L_j in the initial claim, each indexed by $\ell \in L_j$. Visit characteristics include the payer k_j (Medicaid, Medicare, or commercial), the denial reason category ρ_j (null if there are no denials), and the state s_j . Each line item has an initial value π_ℓ . For any set of line items A , we define $\pi(A) = \sum_{\ell \in A} \pi_\ell$. For every visit j we observe $L_j, D_j^1, R_j^1, D_j^2, R_j^2, D_j^3, \dots$, and so on until the process ends. The denial and resubmission sets can be empty.

To estimate resubmission costs, we impose that, after the provider observes denials D_j^t , she makes her resubmission choice R_j^t according to equations (1)–(3):

$$R_j^t = \sigma^*(D_j^t, k_j, \rho_j, s_j) = \arg \max_{R^t \subset D_j^t} \mathcal{V}(R^t, k_j, \rho_j, s_j), \quad (6)$$

$$\begin{aligned} \mathcal{V}(R^t, k_j, \rho_j, s_j) &= -C_j(R^t, \rho_j) \\ &\quad + \beta \mathbb{E} [\pi(R^t - D^{t+1}) + \mathcal{V}^*(D^{t+1}, k_j, \rho_j, s_j) | R^t, k_j, \rho_j, s_j], \end{aligned}$$

where the expectation is taken with respect to D^{t+1} , conditional on R^t, k_j, ρ_j, s_j . That is, her resubmission strategy maximizes profit (revenue net of resubmission costs), accounting

for her expectations of how the insurer will respond to any given resubmission.

The conditional choice probability method introduced in Hotz and Miller (1993), and reviewed in Arcidiacono and Ellickson (2011), allows us to derive an estimate of \mathcal{V}^* analytically—with no need to solve (6) numerically. This approach is possible because the provider problem features a stopping option, or terminal choice: it is always possible to choose $R^t = \emptyset$, and doing so ends the billing process for the visit with no further uncertainty in payoffs.

To follow Hotz and Miller (1993), we make the following assumption about resubmission costs:

Assumption T1EV. *The resubmission costs $C_j(R, \rho)$ of a set of line items R for visit j are stochastic, with mean $\mu(R, k_j, \rho, s_j)$, and such that $C_j(R, \rho) = \mu(R, k_j, \rho, s_j) + \varepsilon$, where ε is iid across j , t , ρ , and R , following a Type 1 Extreme Value distribution. If $R = \emptyset$, $\mu(R, k, \rho, s) = 0$ for all k, ρ, s .*

Assumption T1EV has two important implications. First, a consistent estimate of \mathcal{V}^* is

$$\mathcal{V}^*(D^{t+1}, k, \rho, s) = -\ln(\Pr[R^{t+1} = \emptyset | D^{t+1}, R^t, k, \rho, s]) + \gamma, \quad (7)$$

where $\gamma \approx 0.5772$ is Euler's constant. This expression relies on $\Pr[R^{t+1} = \emptyset | D^{t+1}, R^t, k, \rho, s]$, the probability the physician will not submit any further claim—ending the billing process for the visit—if the line items $D^{t+1} \subset R^t$ are denied after resubmitting R^t . We can estimate this probability directly from the remittance data.

The second implication of Assumption T1EV is that the likelihood that R_j^t solves (6) is

$$\Pr[R_j^t = \sigma^*(D_j^t, k_j, \rho_j, s_j)] = \frac{\exp[-\mu(R_j^t, k_j, \rho_j, s_j) + \beta \times \text{ECV}(R_j^t, k_j, \rho_j, s_j)]}{\sum_{R \subset D_j^t} \exp[-\mu(R, k_j, \rho_j, s_j) + \beta \times \text{ECV}(R, k_j, \rho_j, s_j)]}, \quad (8)$$

where $\text{ECV}(R, k, \rho, s)$ is the expected continuation value from resubmitting R , defined by

$$\text{ECV}(R, k, \rho, s) \equiv \sum_{D^{t+1} \subset R} \Pr[D^{t+1}|R, k, \rho, s] (\pi(R - D^{t+1}) + \mathcal{V}^*(D^{t+1}, k, \rho, s)). \quad (9)$$

Equations (7)–(9) show that, after fixing β (which we set to 0.99),¹² the remittance data reveal empirical counterparts for almost all of the elements characterizing the likelihood of a resubmission. The only missing piece is the function μ , our estimand.

3.3 Maximum Likelihood Estimation

We impose two additional assumptions to avoid computational problems due to the curse of dimensionality. These assumptions allow us to obtain robust estimates of $\Pr[D^{t+1}|R, k, \rho, s]$ and $\Pr[R^{t+1} = \emptyset|D^{t+1}, R^t, k, \rho, s]$ in our sample, and therefore derive the likelihood for the observed resubmissions via (7)–(9) under Assumption T1EV.

Let $d(\pi, k, \rho, s)$ be a function describing the empirical probability that a previously-denied line item ℓ , worth $\pi_\ell = \pi$ (discretized in \$25-wide bins) is denied by payer k , for reason ρ , in state s , after being resubmitted.¹³ We then make the following two assumptions.

Assumption IND. *Denials of line items within a claim are conditionally independent, so*

$$\Pr[D^{t+1}|R^t, k, \rho, s] = \prod_{\ell \in D^{t+1}} d(\pi_\ell, k, \rho, s) \times \prod_{\ell \in R^t - D^{t+1}} (1 - d(\pi_\ell, k, \rho, s)).$$

Assumption IND simplifies the way in which providers can form beliefs about future denial

¹² 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 $\beta = 0.99$ 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.

¹³ We estimate this with our data as

$$\begin{aligned} d(\pi, k, \rho, s) &\equiv \Pr[\ell \in D_j^{t+1} | \ell \in R_j^t, \pi_\ell = \pi, k_j = k, \rho_j = \rho, s_j = s] \\ &= \frac{\sum_{j\ell} \mathbb{1} [\ell \in R_j^t \cap D_j^{t+1}; \pi_\ell = \pi; k_j = k; \rho_j = \rho; s_j = s]}{\sum_{j\ell} \mathbb{1} [\ell \in R_j^t; \pi_\ell = \pi; k_j = k; \rho_j = \rho; s_j = s]}. \end{aligned}$$

probabilities for subsets of line items. For this they treat each line item as independent from the rest of the claim.

Another simplification makes the number of line items and their total amount, jointly, a sufficient statistic for the expected stopping probability in future periods. That is, the provider's beliefs about future resubmission decisions depend only on these two parameters. Formally this is

Assumption SUF. *If D^{t+1} and \widehat{D}^{t+1} are such that $|D^{t+1}| = |\widehat{D}^{t+1}|$ and $\pi(D^{t+1}) = \pi(\widehat{D}^{t+1})$, then $\Pr[R^{t+1} = \emptyset | D^{t+1}, k, \rho, s] = \Pr[R^{t+1} = \emptyset | \widehat{D}^{t+1}, k, \rho, s]$.*

If two sets of line items that could be denied in the future have the same size and total value, the beliefs about future resubmissions are the same.

The last step to derive the likelihood for $\mu(R, k, \rho, s_j)$ is to parametrize it as

$$\mu(R, k, \rho, s) = \mathbb{1}[R \neq \emptyset] \times (\mu_{k,\rho,s}^1 + \mu_{k,\rho}^2 (|R| - 1)). \quad (10)$$

That is, the mean resubmission cost includes a payer-reason-state-specific effect and a linear term—with payer-reason-specific slope—in the number of resubmitted line items.

We estimate $\mu_{k,\rho,s}^1$ and $\mu_{k,\rho}^2$ solving

$$\max_{\mu_{k,\rho,s}^1, \mu_{k,\rho}^2} \prod_{jt} \Pr[R_j^t = \sigma^*(D_j^t, k_j, \rho_j, s_j)]$$

after replacing (10) in (8), and computing the ECV terms via (7) and (9). The resulting likelihood is analogous to that of a standard multinomial logit model, where each provider must choose which (sub)set of declined line items to resubmit, or to stop billing for the visit.

3.4 Identification of Resubmission Costs

To identify the parameters $\mu(R, k, \rho, s)$ governing resubmission costs, we exploit the joint variation in resubmission decisions, denied amounts, and expected repayment probabilities across visits, conditional on payer, state, and reason code category.

Ignoring the resubmissions in later periods, the payoff from resubmitting a claim is increasing in 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). Figure 4 illustrates this intuition. The top left panel shows the relationship between simulated resubmission decisions, claim value, and expected recovery rate conditional on state, diagnosis, and Charlson comorbidity index, when the resubmission cost is \$10 per claim; the top right panel when it increases to \$30. In each panel, the downward-sloping lines are level curves of constant resubmission probability; darker colors indicate areas of lower resubmission probability. The level curves are steeper and the darker areas more prevalent in Panel (b) because a claim of a given value requires a larger increase in collection probability to overcome the higher resubmission cost. The difference between Panels (a) and (b) highlights the mapping from the (unobserved) resubmission cost to the observed joint distribution of resubmissions, claim values, and recovery rates. The bottom panel of Figure 4 shows this joint distribution as observed in the actual remittance data.

Our approach to identify the parameters in $\mu(R, k, \rho, s)$ refines this intuition. In particular, we calculate the continuation values assuming that providers solve the dynamic discrete choice problem in (6). Figure 5 shows the empirical relationship between the probability that a set of denied line items is resubmitted, and the expected continuation value as defined in (9), estimated with the remittance data. This continuation value accounts not only for the next period's denials, but also for future resubmissions and potentially further denials. The extent to which providers make decisions consistent with revenue-maximizing behavior is striking. The sharp monotonic relationship between continuation values and probability of resubmission provides information about resubmission costs.

Note that physicians' decisions are not binary: they choose not only whether or not to resubmit a claim, but also which line items to include in the resubmission. The observable variables in the remittance data and our assumptions identify expected continuation values from resubmissions of any subset of (denied) lined items. We are then able to identify

resubmission costs varying by payer, state, reason for denial, and size of the claim, by analyzing how providers' discrete choices between viable resubmission options vary with the corresponding continuation values.

We illustrate this variation in Table 5, emphasizing differences across payers. In the top panel, we compare the maximum continuation value from resubmission of a claim between instances in which we observe a resubmission and instances in which we do not. The maximum is taken over all possible resubmission decisions available to the provider. When providers forego future visit revenues by deciding not to resubmit a claim, we estimate that the maximum continuation value from resubmitting would be, on average, \$10.10 in Medicaid, \$12.94 in Medicare, and \$12.21 in commercial insurance. Intuitively, providers' administrative costs for resubmitting claims must be higher than these amounts. When instead providers decide to resubmit, we estimate that the maximum continuation value from resubmitting would be \$21.43 in Medicaid, \$20.88 in Medicare, and \$34.90 in commercial insurance. Administrative costs for resubmitting a claim must be, on average, lower than these amounts.

Finally, the difference in resubmission costs for alternative sets of resubmitted line items is identified by comparing the estimated continuation value of the chosen options to the alternatives. The bottom panel of Table 5 focuses on instances in which we do observe a resubmission. It shows that the continuation values for the set of line items the physician resubmits are significantly higher than for the non-chosen alternatives.

3.5 Estimates of Resubmission Costs

Figure 6 provides a first look at our maximum-likelihood estimates of resubmission costs. For each payer we plot histograms of these costs, where the variation in each panel is across states and reason code categories. Since resubmission costs vary with the number of line-items in the claim, we show two different distributions for each insurer: one for claims with a single line item, and one for claims with three line items.

When haggling with Medicaid, providers face an average administrative cost of \$14 to

resubmit a claim with one line item, which increases to \$33 for claims with three line items. Medicare's distribution is lower, with average resubmission costs of \$10 and \$26 for one-line and three-line claims, respectively. Commercial insurance costs slightly more, at \$17 on average to resubmit a one-line claim and \$37 to resubmit a three-line claim. All of these costs are quite sizable relative to average claim value—especially in Medicaid, where the claim value is lowest. Crucially, the frequency with which claims are denied and enter this haggling process is quite different across insurers. As the summary statistics showed, the doctors incur these higher commercial resubmission costs only one-fifth as often as for Medicaid.

In Table 6 we report point estimates of the average (across states) cost of resubmitting one claim for different payers and reason categories. For the 66 percent of denials in the administrative, coverage, and information categories (Table 3), the cost of resubmitting a single-item claim to Medicaid is in the range of \$13 to \$15. When the claim is flagged as a duplicate, resubmission costs are higher, at \$21. When the reason is contractual, resubmitting a claim appears to require less administrative hassle, costing an estimated \$9.

There are meaningful differences in resubmission costs across payers and categories. Within each category, we estimate the lowest resubmission costs for Medicare. Administrative issues and duplicate claims denied by commercial payers have average resubmission costs of \$21 per claim, twice as large as for Medicare.

3.6 Estimates of the Costs of Incomplete Payments

With these estimates of resubmission costs, we now have estimates for all of the elements needed to compute the costs of incomplete payment (CIP), as defined in (4). We put these together to measure expected CIP and the implicit tax τ^{CIP} for each visit. These estimates do not follow directly from the resubmission costs summarized in Table 6, since the CIP depend also on the frequency of denials, composition of denials, likelihood of resubmission (which determines how often the resubmission costs occur), and recovery from those resubmissions.

Table 7 Panel (a) reports our estimated costs of incomplete payments. The first row shows that physicians can expect to lose 17.4 percent of Medicaid claim value to the incomplete payments tax, compared with 4.9 percent for Medicare and 2.8 percent for commercial insurance. These estimates include the amounts lost due to denials, and the resubmission costs necessary to recover revenues after denials. The second row shows the dollar values behind these implicit tax estimates. When treating a Medicaid patient, providers expect average CIP of \$12.09. The average for Medicare is \$4.07 per visit. Billing commercial insurers entails the lowest administrative burden, with an average CIP of \$2.69. Since Medicaid's contractual amounts are lower than other insurers', these differences get amplified when computing the implicit tax in row 1.

We can think of the CIP as comprising two parts: the revenues providers fail to collect, plus the costs of resubmission efforts. Figure 2 illustrates this decomposition. The former part—revenues never collected—is a raw (model-free) measure of the administrative burden imposed by payment denials. That is, we can ignore the resubmission costs, and simply calculate the lost revenues for a given visit, expressed as a share of the initial claim value (this is similar to the summary statistic presented in Gottlieb et al., 2018).

Panel (b) of Table 7 shows this estimate. Out of our estimated \$12.09 lost by providers due to payment uncertainty in Medicaid, \$9.36 (77 percent) is due to lost revenues, while the remaining \$2.73 is resubmission costs the physician incurs. For Medicare and Commercial payers, revenue losses account for around two-thirds of CIP.

We find a meaningful variation in CIP and τ^{CIP} across states, particularly in Medicaid. Figure 7 shows this. Expected CIP ranges from less than \$5 to more than \$30, while the implicit CIP tax τ^{CIP} is higher than 0.25 in California, Texas, Georgia, Illinois, and Pennsylvania, and lower than 0.1 in Colorado, Idaho, Washington, and Minnesota. In contrast, except for Medicare in Alaska, no state's τ^{CIP} exceeds 0.1 for either commercial insurance or Medicare.

4 Do Billing Hurdles Keep Physicians Away from Medicaid?

We now ask whether these costs of incomplete payments affect physicians' behavior. The logic for such a response is a simple application of upward-sloping supply curves. An extensive literature has examined how physicians respond to reimbursement rates for the care they receive, along a variety of margins. This work has used differences in the official reimbursement rates that insurers purport to offer physicians for their care—whether obtained from administrative documentation (Clemens and Gottlieb, 2014; Gottlieb et al., 2021), primary data collection (Alexander and Schnell, 2019), or secondary surveys (Gruber et al., 1999). These sources can all be thought of as measures of π in our framework,¹⁴ and the literature has shown that π affects intensity of care, investment decisions, and extensive margin participation decisions.

But we have seen that π overstates the net revenue physicians should actually expect to receive—in particular when caring for Medicaid patients. A visit that is purportedly worth π actually yields the physician only $(1 - \tau^{CIP})\pi$ in expectation, after accounting for collection costs and foregone revenue. So the standard economic logic that explains upward-sloping supply curves would predict that physicians should respond to $(1 - \tau^{CIP})\pi$ rather than π . In fact, canonical models would predict the same supply *elasticity* with respect to $1 - \tau^{CIP}$ as with respect to π . The importance of this implicit tax varies across settings, since τ^{CIP} differs across insurers.

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 it has the highest costs of incomplete payment, and physicians' low participation rates in Medicaid are notorious. The extensive margin is a natural focus because of the uncertainty inherent in the costs of incomplete payment. 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

¹⁴Henceforth we keep notation lighter, using π for $\pi(L)$ whenever there is no risk of confusion.

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.

We next describe how we summarize fees and CIP to analyze their impacts on physician behavior (section 4.1). Sections 4.2.1 and 4.2.2 then describe two empirical strategies to estimate the consequences of fees and CIP for physicians’ participation decisions. Section 4.3 presents the results.

4.1 Indices of Fees and CIP Across States

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 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:

$$\ln(\pi_{j\ell}) = \xi_{s,k} \cdot \mathbb{1}_s \times \mathbb{1}_k + \chi_h \cdot \mathbb{1}_h + \omega_i \cdot \mathbb{1}_i + \rho_1 \text{patient age} + \rho_2 \text{comorbidities} + u_i. \quad (11)$$

Each observation in this regression is one service line and $\pi_{j\ell}$ is the allowed amount for service ℓ in visit j . The key coefficients the regression estimates are the insurer-by-state fixed effects $\hat{\xi}_{s,k}$. 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 fee index. Since the dependent variable is in logs, we can interpret a 0.01 change in $\hat{\xi}_{s,k}$ as approximately a 1 percent change in the insurer/state’s fee.

In computing this index, the regression adjusts the raw value, $\pi_{j\ell}$, for the characteristics of that service and its claim. Most significantly, we control for fixed effects for the specific

procedure code $\mathbb{1}_h$ and for the physician $\mathbb{1}_i$. These controls ensure that our indices reflect differences between comparable medical care and don't reflect differences in physician composition, though our results are robust to excluding physician effects. In order to identify the state-by-insurer indices while controlling for physician, our data must have physicians who practice across multiple insurers, as well as some physicians who practice in multiple states. We treat commercial insurance as a single category and omit its indicator, so our index $\hat{\xi}_{s,k}$ is estimated relative to the national commercial average. We also control for patient characteristics, such as age and other diseases they have, in case these influence the cost of the service.

We estimate a similar index for CIP. Since visits are quite heterogeneous (as the wide variation in CIP seen in Figure 6 demonstrates), and we want to isolate the insurer's contribution, we again adjust the visit-level estimates for potential confounds. We follow the same logic as in equation (11), but replace the dependent variable with τ_j^{CIP} , the implicit tax from incomplete payments for visit j . We compute this following equation (4) using expected lost revenues and expected resubmission costs, conditional on that visit's characteristics. We then estimate:

$$\tau_j^{CIP} = \psi_{s,k} \cdot \mathbb{1}_s \times \mathbb{1}_k + \omega_i \cdot \mathbb{1}_i + \rho_1 \text{patient age} + \rho_2 \text{comorbidities} + u_i. \quad (12)$$

This regression also controls for the individual physician $\mathbb{1}_i$ and other visit characteristics that could affect payment difficulty. We weight it by the claim value so it reflects the average value of a physician's output, rather than the average visit. The estimated $\hat{\psi}_{s,k}$ coefficients serve as our index of the incomplete payments net-of-tax rate for each state-by-insurer. Unlike with fees, τ_j^{CIP} ranges from zero to one so we do not apply a log transformation. The resulting index $\hat{\psi}_{s,k}$ can be interpreted as capturing differences in implicit tax rates, with a 0.01 higher value representing a 1 percentage point higher implicit tax rate for the insurer-state pair.

Figure 8 shows the estimated Medicare and Medicaid indices across U.S. states, and Table 8 summarizes these distributions. Panel 8(a) shows the Medicaid fee index. Medicaid generally pays higher fees in the upper Midwest and northern Great Plains states, and lower fees in the Rust Belt and south. Panel 8(b) shows the implicit CIP tax, $\hat{\psi}_{s,\text{Medicaid}}$. Among high-fee states, such as the Dakotas, North Dakota has one of the highest index values while South Dakota is much lower. Among low-fee states, such as the lower Midwest, Illinois and Pennsylvania have relatively high implicit taxes while Wisconsin and Ohio are lower. These reflect each state's significant leeway in how to administer Medicaid. Helpfully for our purposes, it means that we have meaningful independent variation in both variables.

Panels 8(c) and (d) show the corresponding indices for Medicare. The Medicare fee index is overwhelmingly higher than for Medicaid, and its distribution more closely matches U.S. economic activity. Figure 9 shows a scatterplot relating the recovery rate index $\hat{\psi}_{s,k}$ and fee index $\hat{\xi}_{s,k}$ across states 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 pays Medicaid physicians 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.

The indices shown here reflect certain detailed choices about how to handle various data problems. When we present our empirical results in section 4.3, we also show robustness to other choices about data and index construction, such as which controls to include, whether to omit imputed contractual amounts, and whether to weight observations.¹⁵

¹⁵Appendix Table A.1 shows summary statistics for the weighted and unweighted indices, and for the indices that include and exclude the imputed contractual amounts.

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 eliminate variation 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, or altruism.

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 $\Delta \ln \text{Fee}_i = \hat{\xi}_{s', \text{Medicaid}} - \hat{\xi}_{s, \text{Medicaid}}$ as the difference between the fee indices estimated using equation (11) in the pre-move and post-move states' Medicaid programs. Similarly, $\Delta \tau_i^{\text{CIP}} = \hat{\psi}_{s', \text{Medicaid}} - \hat{\psi}_{s, \text{Medicaid}}$ is the difference in the log net-of-tax recovery rate that the physician can expect from Medicaid after moving, computed based on the estimates from (12).

Under the usual assumption that the timing 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 supply curve with respect to both fees and CIP, while controlling for time-invariant physician unobservables. For each mover, we use data starting up to 4 years prior to the move, through 4 years after the move, and estimate the following regression at

the physician-year level:

$$\begin{aligned} \text{Medicaid acceptance}_{i,t} = & \alpha + \beta \Delta \ln \text{Fee}_i \times \text{Post-Move}_t \\ & + \gamma \Delta \tau_i^{CIP} \times \text{Post-Move}_t \\ & + \phi_i \cdot \mathbb{1}_i + \vartheta \text{ Various controls}_{i,t} + \nu_{i,t} \end{aligned} \quad (13)$$

The dependent variable is a binary indicator for whether the physician reports accepting Medicaid patients. The critical controls here are individual physician fixed effects ϕ_i . This strategy identifies the supply parameters β and γ exclusively based on physicians who move. The key moment is the difference in those physicians' pre-move Medicaid acceptance and their post-move Medicaid acceptance, 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 (13), namely:

$$\begin{aligned} \text{Medicaid acceptance}_{i,t} = & \alpha + \sum_{\zeta \neq 0} \beta_\zeta \Delta \ln \text{Fee}_i \times \text{Year}_\zeta \\ & + \sum_{\zeta \neq 0} \gamma_\zeta \Delta \ln \tau_i^{CIP} \times \text{Year}_\zeta \\ & + \phi_i \cdot \mathbb{1}_i + \vartheta \text{ Various controls}_{i,t} + \nu_{i,t} \end{aligned} \quad (14)$$

where ζ denotes the year relative to that in which the physician moved. In both equations (13) and (14), we cluster standard errors by state.

4.2.2 Cross-State Groups

The movers strategy is appropriate if the key unobservables are physician-level, such as an individual doctor's preference for serving low-income patients or individual costs of dealing with bureaucratic hassle. But physicians increasingly operate in larger practices or major medical systems, which may have centralized billing that controls these costs. To

account for differences in groups' decision-making or billing efficiency, we introduce a second identification strategy to estimate states' impacts of Medicaid acceptance.

This strategy uses physician groups that span state boundaries. The idea is to identify the impact of state policies based on differences in acceptance decisions among physicians within the same practice, but facing different state policies. This eliminates any differences due to the practice, such as its skill at dealing with billing complexity, its history with a particular part of the market, or its altruism.

This strategy estimates a slightly different economic object than the movers approach. While movers yield a short-run physician-level estimate, this approach yields a long-run supply elasticity for a physician group in a given state. This strategy allows for 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 longer-run and the movers estimates as short-run.

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

$$\begin{aligned} \text{Medicaid acceptance}_{i,t} = & \alpha + \beta \hat{\xi}_{s(i), \text{Medicaid}} + \gamma \hat{\psi}_{s(i), \text{Medicaid}} \\ & + \theta_g \cdot \mathbb{1}_{g(i)} + \vartheta \text{ Various controls}_{i,t} + \epsilon_{i,t} \end{aligned} \quad (15)$$

The dependent variable is the same as in regression (13), a binary indicator for whether the physician reports accepting Medicaid patients. The state-level fee and CIP indices are the estimates from equations (11) and (12). The key controls are fixed effects $\mathbb{1}_{g(i)}$ for each physician group or system, defined based on the practice's tax identifier reported in MD-PPAS and health system reported by AHRQ. Given these fixed effects, we identify β and γ off of differences in Medicaid acceptance among physicians within the same practice. We again cluster standard errors by state.

This strategy's limitation is that it controls for unobservables at the group level but not

for the individual physician, as equation (13) does. Even within a group, physicians with a stronger preference for treating Medicaid patients could sort across states in ways correlated with their Medicaid policies.

Both of these strategies account for unobservable differences on the supply side of the market, i.e. among physicians and their practices. Other differences among states could confound the estimates of β and γ if they are correlated with Medicaid fees and CIP. To address this concern, we study selection on observables using Oster's (2019) assumption of proportional selection. We report the variants of equations (13) and (15) starting from raw correlations without controls, and then adding controls for local characteristics intended to capture other demand factors. We use the software provided by Oster (2019)¹⁶ to evaluate the changes in coefficients and predictive power observed as we add controls, and determine the likely extent of bias remaining in our estimates.

4.3 The Effect of Billing Hurdles on Medicaid Acceptance

Figure 10 shows our initial results from the movers strategy. Panel 10(a) shows the response to moving to a state with higher fees, while Panel 10(b) shows the response to moving to a state with higher costs of incomplete payments. Although the panels are shown separately, all coefficients in this figure come from the same regression, equation (14).

Note first that 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 incomplete payments and physicians' Medicaid acceptance decisions. After the move, we see clear positive coefficients for fees and negative for CIP. Higher fees lead to increased probability of Medicaid acceptance, while a higher implicit tax 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.

¹⁶ Available online at https://emilyoster.net/s/psacalc_0.zip

Table 9 shows the estimates of equation (13), which pools the pre-move and post-move years and estimates a single coefficient for each index. Column 1 shows the estimates without any additional controls; column 2 adds controls for insurance market conditions in the physician's county; column 3 adds controls for the physician's own demographics, and column 4 controls for local socioeconomic characteristics. Each column reports coefficients on both fee and CIP indices. The coefficient on log fees shows the effect of a 1 log point change in physicians' net revenue 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 half percentage point increase in physicians' propensity to accept Medicaid. The coefficient on $\Delta\tau^{CIP}$ can be thought of as the coefficient on a tax rate, so a 10 percentage point increase in τ^{CIP} reduces the probability of accepting Medicaid patients by 1 percentage point.

To put these magnitudes in context, we note from Table 8 that the fee index has a cross-state standard deviation of 0.21, while the CIP index has a standard deviation of 0.11. So, according to column 1, moving to a state with one standard deviation higher fees increases the probability of accepting Medicaid patients by 1.2 percentage points, while moving to a state with one standard deviation higher implicit tax reduces the probability by the same amount. Based on this calculation, CIP is almost exactly as important for understanding the variation in physicians' willingness to treat Medicaid patients as reimbursement rates are.

From a physician's perspective, a 10 percent increase in revenue has the same impact whether it comes from 10 percent higher fees or an equivalent reduction in implicit taxes. So it would be natural if they respond comparably to these two sorts of changes. The *p*-values below the coefficients in Table 9 test this. Since one coefficient is in logs, while the other is in percentage points, we must multiply the coefficient on $\Delta\tau^{CIP}$ by one minus the average implicit tax rate to make the two comparable. We perform this scaling and then report a test for equality of the fee and scaled implicit tax coefficients. We fail to reject equality with

$p > 0.1$ in all columns.

The next rows report the results of Oster's (2019) test for coefficient stability. We report Oster's δ using the recommended $R_{max} = 1.3\tilde{R}$ (within physician), i.e. the amount of unobservable selection relative to observed selection that would be necessary to drive our estimates to zero. We find estimates ranging from $\delta = 1$ to $\delta = 2$ across the columns. This is close to the "appropriate upper bound" of $\delta = 1$ that (Oster, 2019, p. 188) recommends, implying the coefficients are reasonably stable.

Table 10 reports the results from our second strategy, which aims to capture long-run responses using groups that cross state boundaries. We obtain slightly higher coefficients, as might be expected from longer-run, more static responses. Indeed, the coefficients around 0.1 on log fees in columns 2–5 are very similar to the point estimate for year 4 after the move from Figure 10(a). 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 1.1 (column 4) to 3.9 percentage points (column 1) less likely to accept Medicaid patients. CIP is again just as important as reimbursements.

Except for column 1, we again find no statistical difference between the scaled coefficient on τ^{CIP} and the coefficient on log fees. Physicians appear to respond similarly to increased expect revenue from the two channels. Oster's coefficient stability test is somewhat less reassuring with this approach than for movers, with $\delta = 1.4$ for fees and $\delta = 0.6$ for CIP.

The appendix reports robustness to many different choices of how to compute our indices. The columns of Appendix Table A.2 vary the sample of visits used to compute the CIP index. Across the horizontal panels, we vary details of how we calculate the fee index. In the top panel, the fee index is unchanged, and column 1 uses the same CIP index as in our main results. Column 2 computes CIP indices by looking only at the first visit in our data of any physician/patient pair, to avoid concerns that subsequent visits may be selected depending on the billing success of the first visit. Column 3 is the complement: it excludes the first visit,

instead focusing on visits where the physician has already had an opportunity to resolve any patient-specific billing problems. Column 4 includes a control for local income in the index-calculation regressions. Column 5 adds diagnosis fixed effects to those regressions. Column 6 estimates the index only off of pregnant patients, as pregnant women have more similar eligibility for Medicaid across states. The last column removes physician fixed effects from these index regressions. In all cases, the results remain quantitatively similar and statistically significant.

The subsequent panels show these same various CIP indices but with alternative approaches to the estimation of the fee index. The second panel eliminates the regression weights. The third panel adds to the regression sample observations for which we have to impute the claim value. We eliminate those from the baseline index calculation, but this panel shows that the results are stable when including them. The fourth panel includes the imputations and removes the regression weights. Table A.3 repeats the same exercise for the cross-state group strategy. Once again, results are robust and stable across the various choices.

Appendix Tables A.4 and A.5 measure the CIP as simply the revenue providers are unable to collect; that is, the difference between the claim value and the amount ultimately collected. The results in this table thus neglect the costs of resubmission, costs which enable providers to recover some of the revenue initially denied. Even so, we find similar and robust estimates.

To summarize, these results demonstrate the profound importance of administrative hassles for Medicaid patients' access to care. Physicians appear to treat the implicit tax from incomplete payments 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 implicit taxes. This suggests an important new dimension of health insurance that has been largely overlooked in policy discussions.

While billing hassles could have benefits we don't measure, they clearly deter physicians from participating in Medicaid. The quality of administrative processes should be a first-order concern for anyone interested in the quality of Medicaid or equity in healthcare access.

5 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 willingness to participate in Medicaid responds just as much to billing difficulty as to the reimbursement rate. This result is robust to two identification strategies, and the impact appears larger in the long run than in the short run.

Our findings demonstrate the importance of well functioning business operations in the healthcare setting. Difficulty with payment collection has meaningful impacts on 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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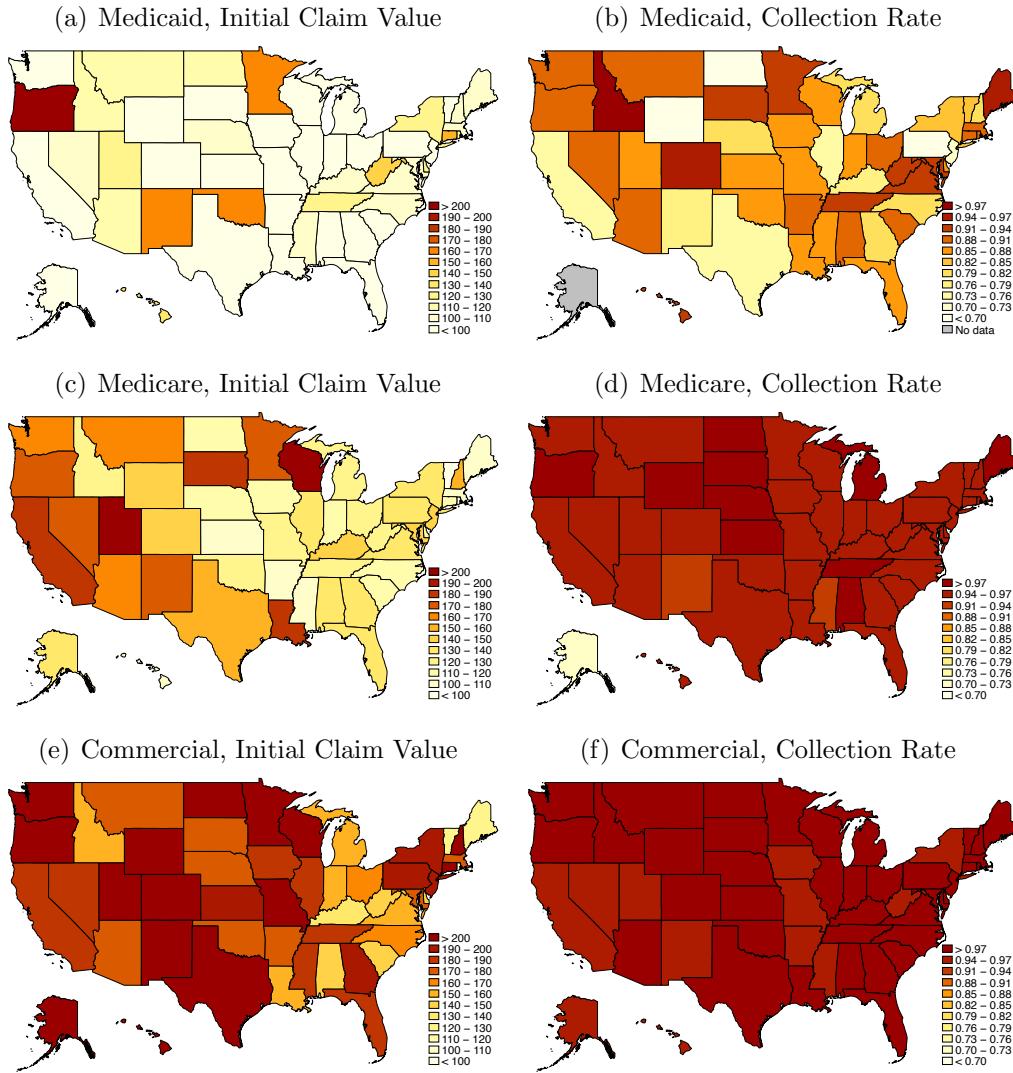
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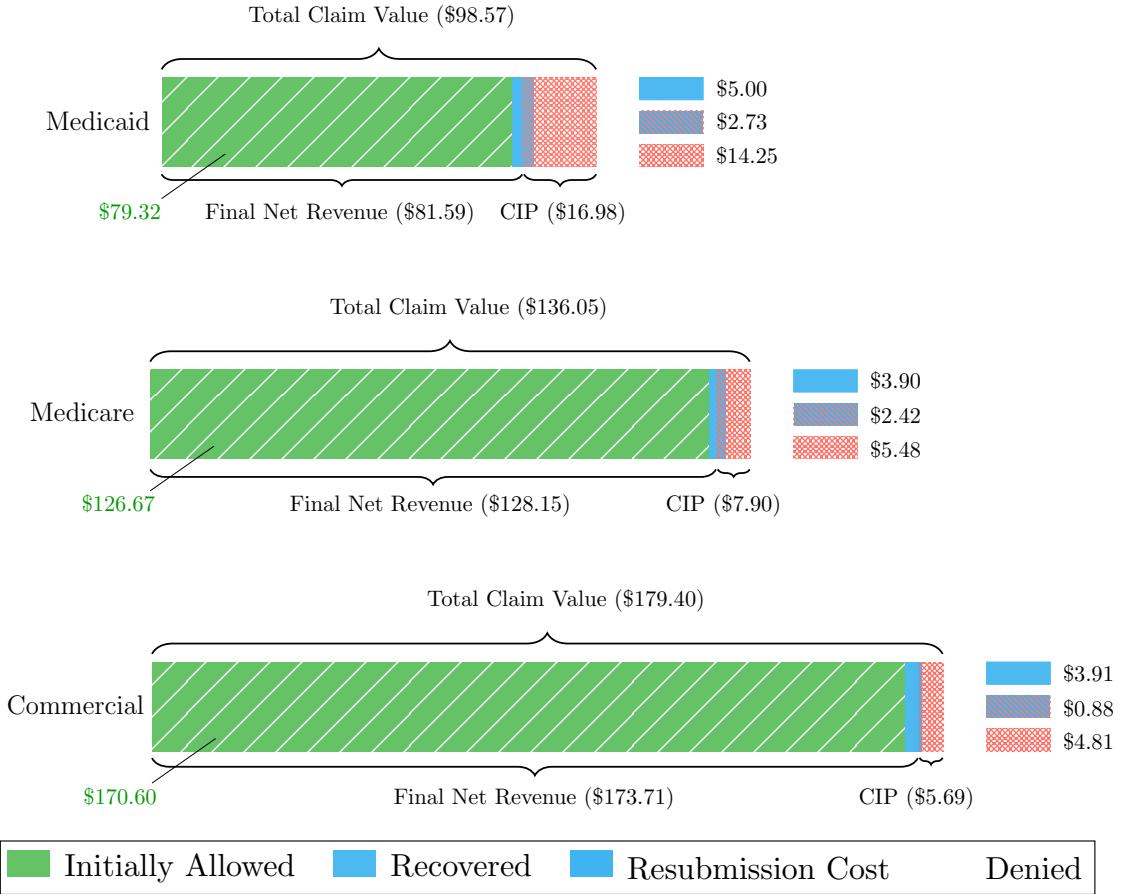
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Figure 1: Initial Claim Values and Collection Rates across States and Payers



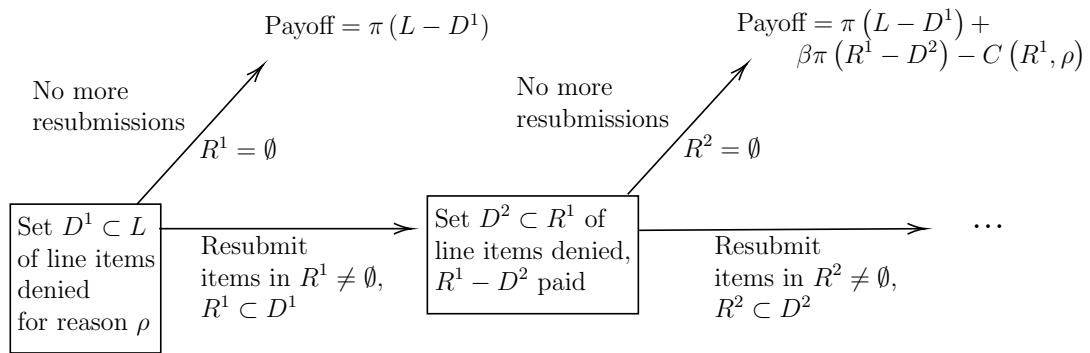
Note: The left column illustrates the variation across states and payers in the initial claim value visits observed in the IQVIA sample. The right column illustrates the variation across states and payers in the share of initial claim value that is ultimately collected by the provider after accounting for denials and resubmissions.

Figure 2: Decomposition of Average Claim Values



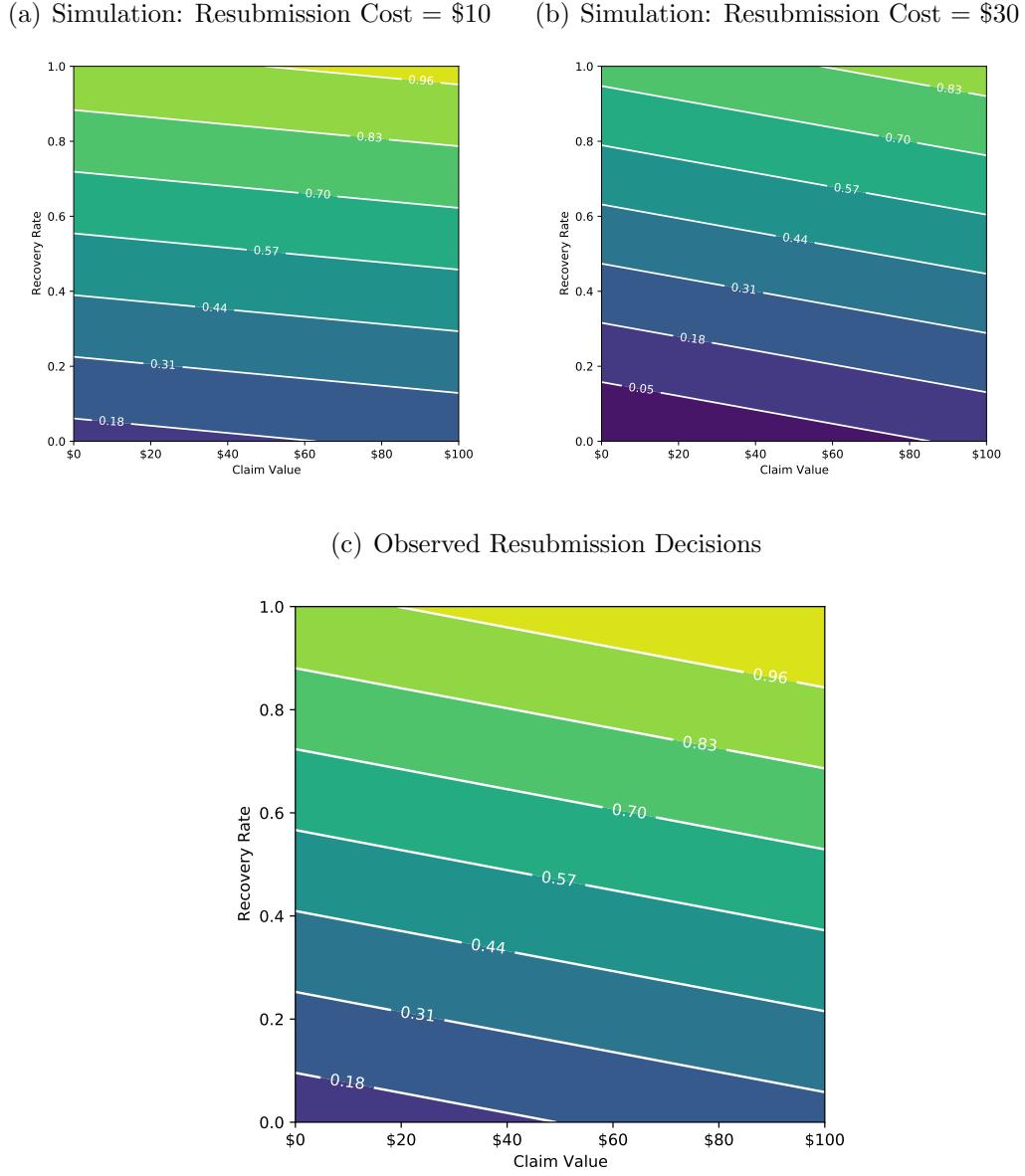
Note: The figure illustrates the how value of the average claim for Medicaid, Medicare and commercial insurers is allocated. The length of each bar shows the total value of the average claim, computed based on the contracts we infer according to the method in section 2.2. The leftmost region (green, with diagonal lines sloping up) shows the average payment upon initial submission. The remainder is initially not paid. The blue region is ultimately paid following subsequent submissions, while region marked in red cross-hatches is not ever paid. The part of the blue region covered with diagonal red lines sloping down represents the part of recovered revenue that is spent on the recovery process, according to our estimation in section 3. The costs of incomplete payment (CIP) include the red region indicating denied amounts never recovered plus the part of recovered revenue that is spent on the recovery.

Figure 3: Provider Resubmission Problem Following the Initial Denial



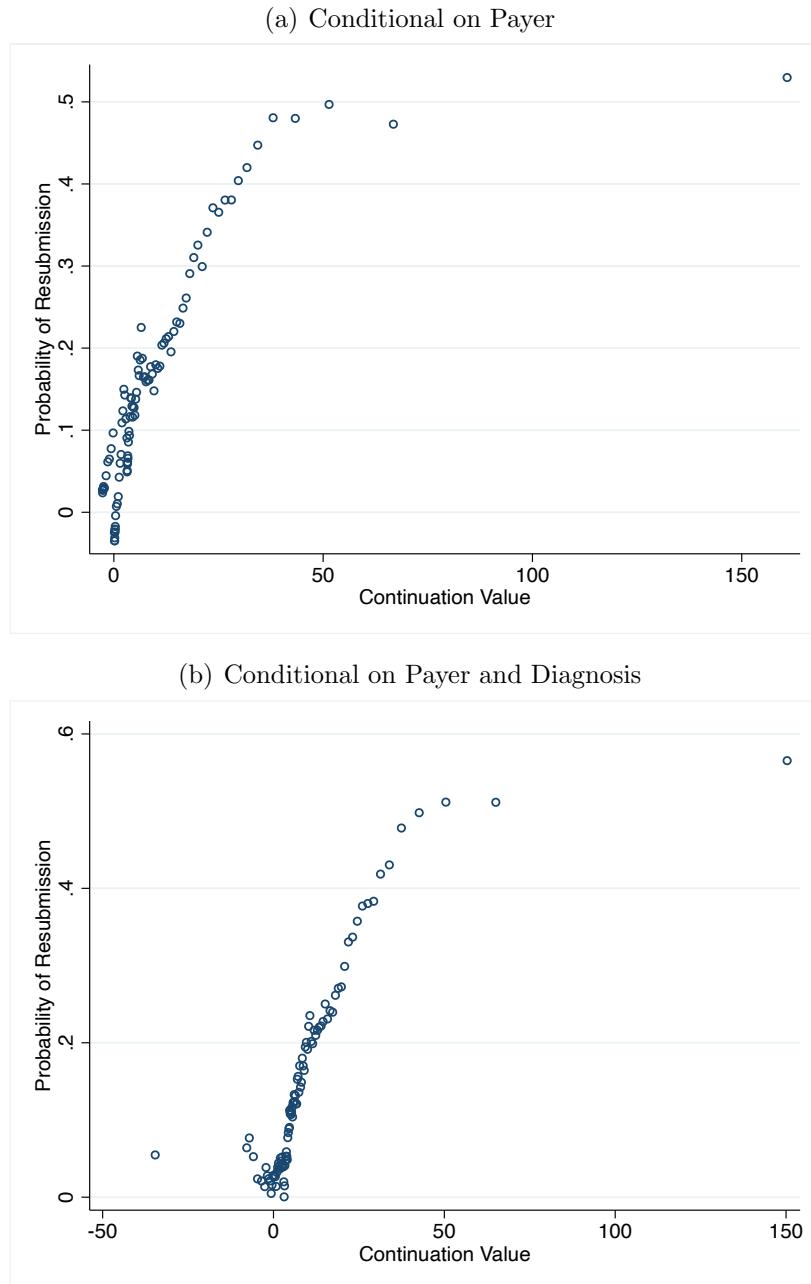
Note: The figure provides a schematic of the decision tree for the provider dynamic discrete choice problem following a denied claim.

Figure 4: Intuition for Identification of Resubmission Costs



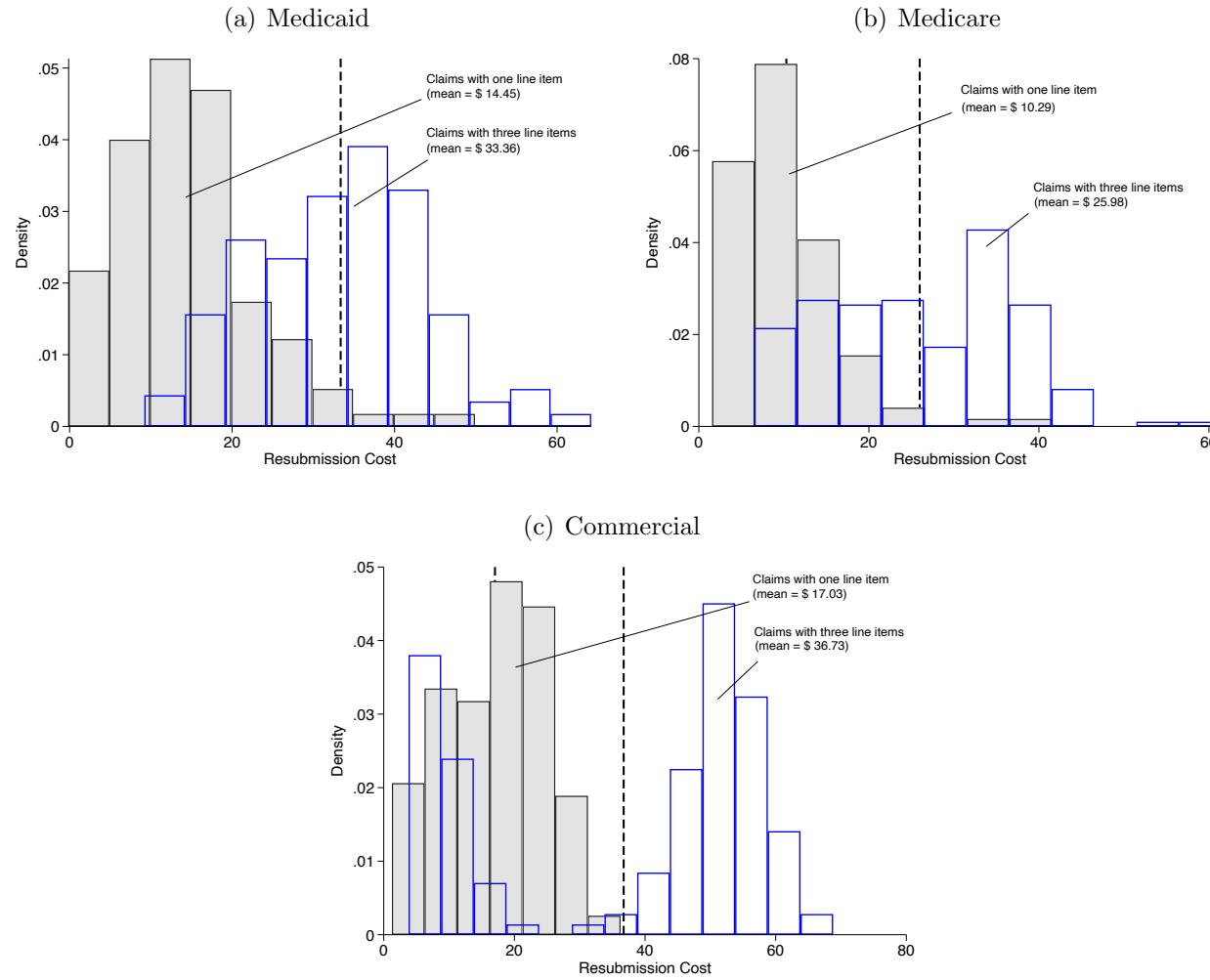
Note: The figure illustrates the intuition for identification of resubmission costs. In each panel, for any given combination of recovery rate for a resubmitted claim (vertical axis) and claim value (horizontal axis) the color corresponds to the fitted probability of claim resubmission, fitted with a linear model. (We regress resubmissions on a constant, the claim value, and the recovery rate.) Panel (a) is drawn using simulated resubmissions imposing a resubmission cost of \$10 per claim and a normal error term with mean zero and standard deviation \$10, and Panel (b) is drawn using simulated resubmission imposing a resubmission cost of \$30 per-claim, with the same error term. Different resubmission costs imply a different joint distribution of claim value, recovery rate, and resubmissions. Panel (c) is drawn using this joint distribution as observed in our remittance data. The shape of this distribution, conditional on reason code, payer, and state, is the main source of identification of the parameters governing resubmission costs.

Figure 5: Probability of Resubmission and Continuation Value



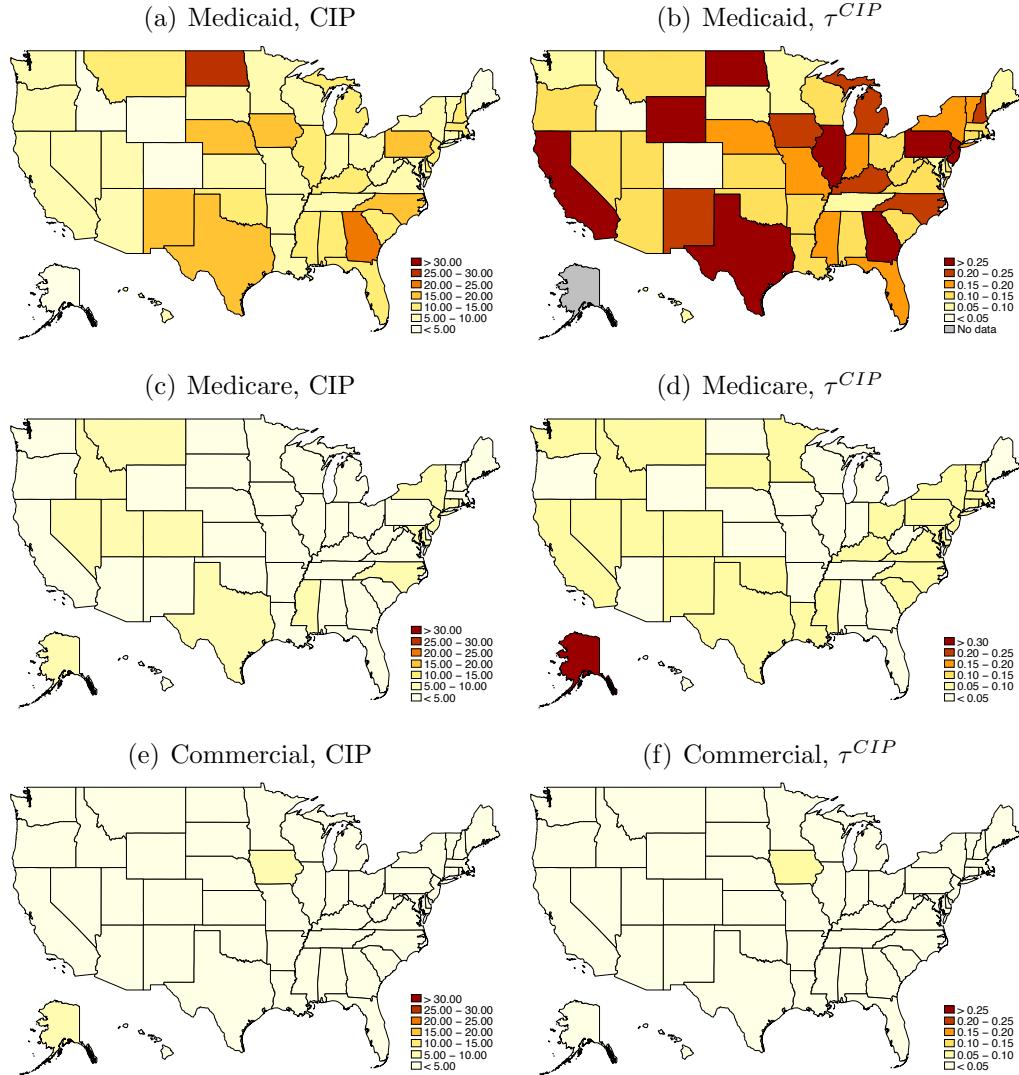
Note: The figure shows a binscatter of the probability that a set of line items is resubmitted (vertical axis) plotted against the continuation value estimated with the remittance data, accounting for future payments, denials, and the probability of submitting further claims. The top panel is plotted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

Figure 6: Estimated Resubmission Costs



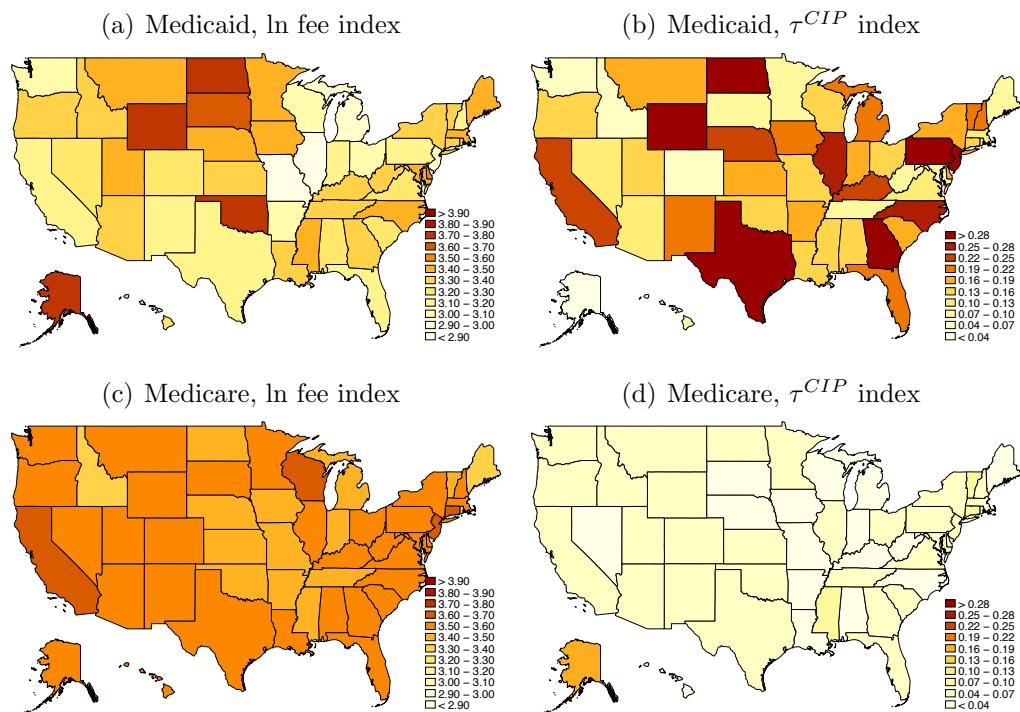
Note: The figure plots histograms across state-by-reason code categories of our estimates of the billing cost providers have to pay to resubmit a claim. Since we estimate resubmission costs varying with the number of line items in a claim, we illustrate the estimates for two examples. The shaded bars correspond to the resubmission costs for claims with one line item (the vast majority in our data), the blue hollow bars to resubmission costs for claims with three line items.

Figure 7: Costs of Incomplete Payments Estimated Across States and Payers



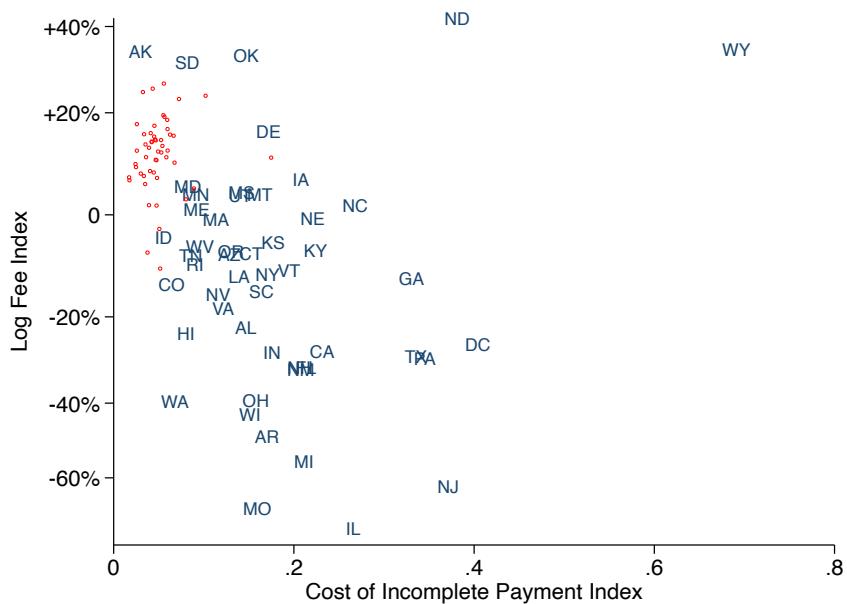
Note: The left column shows the mean estimated costs of incomplete payments (CIP) by state and payer. The right column show the mean implicit tax (CIP as a share of visit value) by state and payer.

Figure 8: Estimated Indices for Medicaid and Medicare across States



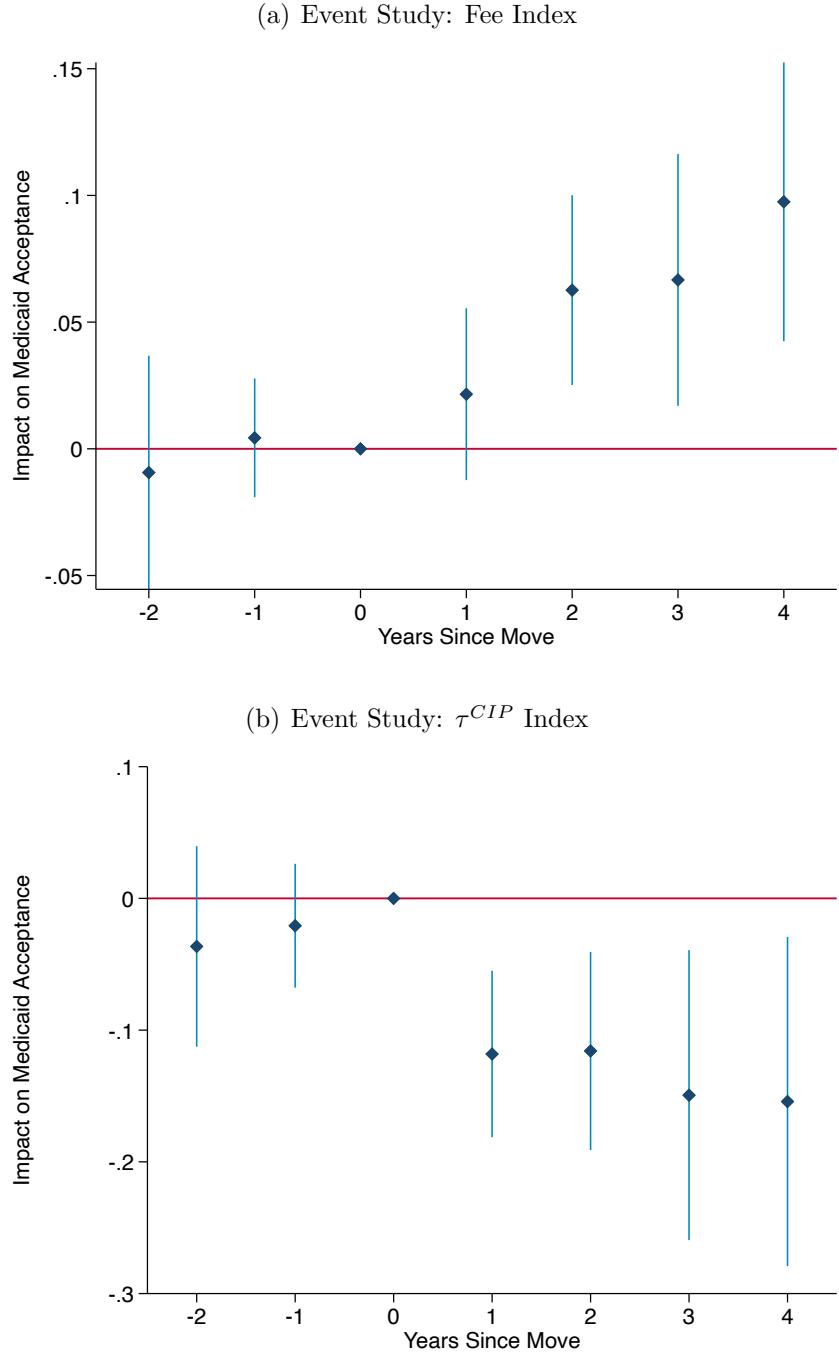
Note: The top two maps show the estimated indices for Medicaid by state. The bottom two show the estimated indices for Medicare by state. The fee and CIP indices are estimated according to equations (11) and (12).

Figure 9: Variation in Fee and CIP-Tax Indexes



Note: The scatter plot shows the variation across states in the ln fee index (vertical axis) and τ^{CIP} index (horizontal axis), as estimated via equations (11) and (12). Blue state abbreviations correspond to the respective's state Medicaid program, while red circles correspond to Medicare.

Figure 10: Movers Event Studies



Note: The figure plots the coefficients of the movers event study as specified in equation (14). The top panel shows the coefficients β_ζ , capturing the effect of the fee index on the probability to accept Medicaid patients, where ζ (year relative to move) varies on the horizontal axis. The bottom panel shows the corresponding plot for the coefficient γ_ζ , capturing the effect of the implicit tax due to the cost of incomplete payments.

Table 1: Remittance Data Summary, Visit Level

	Mean	SD	10th Percentile	90th Percentile	Observations
Initial claim value	153.17	433.09	23.90	237.92	88827331
Number of line items	1.888	1.61	1.00	4.00	88827331
Some items denied (=1)	0.075	0.26	0.00	0.00	88827331
Denied value in initial claim	9.863	122.37	0.00	0.00	88827331
Total denied amount	5.837	89.08	0.00	0.00	88827331
Total claims submitted	1.047	0.26	1.00	1.00	88827331
Medicaid patient (=1)	0.076	0.26	0.00	0.00	88827331
Medicare patient (=1)	0.464	0.50	0.00	1.00	88827331
Private patient (=1)	0.460	0.50	0.00	1.00	88827331
Year	2014	0.79	2013	2015	88827331

Note: The table summarizes the IQVIA remittance data at the visit level. Initial claim value is the total amount the provider would receive if all line items in the first claim after the visit were paid. Line items in initial claim is the total number of line items for which the provider requests a payment after the visit. Some items denied is an indicator for claims in which at least one item is not paid. Denied value in initial claim is the sum of the line item values for line items not paid after the initial claim submission. Total denied amount is the sum of the line item values that are ultimately not paid for the visit. The difference between denied claim value in initial claim and total denied amount is the amount recovered by the provider through resubmissions of claims for the same visit. The bottom rows summarize indicators for the patient's primary payer and the year in which the visit took place.

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

	Medicaid	Medicare	Commercial
Initial claim value	98.57	136.05	179.40
Some items denied (=1)	0.250	0.073	0.048
Denied value in initial claim	19.26	9.38	8.80
Total denied amount	14.25	5.48	4.81
Collected visit revenue	84.32	130.57	174.59

Note: The table summarizes initial claim values and the outcome of the billing processes across payers, as observed in the IQVIA remittance data. For each payer, the initial claim value is the total amount the provider would receive if all line items in the first claim after the visit are paid. Some items are denied is an indicator taking value one if at least one item is not paid. Denied value in initial claim is the sum of the line item values for line items not paid after the initial claim is submitted. Total denied amount is the sum of the line item values that are ultimately not paid for the visit. Collected visit revenue is the total amount collected by the provider for the visit.

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

Reason Code Category	Share of Denials	Mean Line Item Value	Mean Pr. of Resubmission	Mean # of Resubmissions	Mean Recovery Rate
Panel (a): Medicaid					
Administrative	0.251	53.61	0.39	0.51	0.60
Contractual	0.297	44.29	0.35	0.42	0.92
Coverage	0.251	56.54	0.25	0.34	0.37
Duplicate	0.041	60.74	0.19	0.24	0.15
Information	0.160	63.53	0.41	0.57	0.29
Panel (b): Medicare					
Administrative	0.163	91.57	0.62	0.72	0.95
Contractual	0.406	84.02	0.80	0.87	0.98
Coverage	0.231	81.37	0.49	0.60	0.69
Duplicate	0.102	82.57	0.47	0.60	0.50
Information	0.098	89.14	0.61	0.79	0.61
Panel (c): Commercial					
Administrative	0.139	104.03	0.40	0.49	0.79
Contractual	0.550	102.33	0.80	0.87	0.99
Coverage	0.127	110.60	0.70	0.83	0.88
Duplicate	0.087	104.25	0.24	0.29	0.27
Information	0.097	146.44	0.61	0.76	0.63

Note: The table summarizes the remittance data for line items that are denied after the first submission. Each panel corresponds to a different payer, while rows indicate the reason code category used to justify the denial in response to the initial claim. The first column shows the share of line items denied for a specific reason, relative to all denied line items. The second column shows the average line item value. The third column shows the average probability that the line item is resubmitted in a second claim following the initial denial. The fourth column shows the average number of times that a line item is resubmitted following the initial denial. The last column shows the average probability that the line item value is ultimately paid.

Table 4: Physicians Survey Summary

	Mean	SD	10th Percentile	90th Percentile	Observations
Accepts Medicaid (0,1)	0.721	0.45	0.00	1.00	3688970
Accepts Medicare (0,1)	0.841	0.37	0.00	1.00	3688970
Cross-State Mover (0,1)	0.015	0.12	0.00	0.00	2528500
Cross-State Group (Tax ID; 0,1)	0.273	0.45	0.00	1.00	3688970
Year	2012	1.93	2009	2015	3688970

Note: The table summarizes the physician-year level data from MD-PPAS augmented with the SK&A survey.

Table 5: Estimated Value of Resubmissions and Observed Resubmission Decisions

	Medicaid	Medicare	Commercial
Panel (a): Maximum Continuation Value of Claims			
Instances in which providers do not resubmit claims	10.10	12.94	12.21
Instances in which providers resubmit claims	21.43	20.88	34.90
Panel (b): Continuation Value of Resubmission			
Not resubmitted set of line items	5.16	7.57	10.82
Resubmitted set of line items	20.25	19.77	33.47

Note: The table summarizes the variation in continuation values from resubmission across observed and counterfactual resubmission decisions. It highlights that the remittance data are consistent with providers being forward-looking and profit-maximizing, and it showcases the variation we leverage to identify resubmission costs. Panel (a) shows the maximum continuation value across all viable resubmission options, which includes the option not to resubmit. That is, Panel (a) compares the maximum continuation value from resubmission between instances in which the provider chooses to resubmit a set of denied line items, and instances in which the provider chooses to forego visit revenues for the denied items. Panel (b) shown the continuation value conditional on instances in which providers resubmit claims. That is, Panel (b) compares the sets of line items that are resubmitted to their feasible alternatives for instances in which a resubmission is observed.

Table 6: Estimated Resubmission Costs by Reason Code Categories

Reason Code Category	Medicaid	Medicare	Commercial
Administrative	15.39 (0.558)	10.01 (0.145)	21.18 (0.334)
Contractual	9.19 (0.191)	7.43 (0.108)	8.40 (0.146)
Coverage	14.66 (0.261)	12.14 (0.177)	18.33 (0.329)
Duplicate	21.00 (0.604)	11.40 (0.640)	20.62 (0.534)
Information	13.24 (0.381)	10.49 (0.272)	17.36 (0.615)

Note: The table reports the average across states of the parameter $\mu_{k,\rho,s}^1$ for a given k, ρ pair. This is equal to the resubmission cost for a claim with one line item, denied by payer k for reason ρ . Standard errors are reported in parentheses.

Table 7: Estimates of CIP and Implicit CIP Tax

	Medicaid	Medicare	Commercial
Panel (a): Estimates including Resubmission Costs			
τ^{CIP}	0.174	0.050	0.028
Average CIP	12.09	4.07	2.69
Panel (b): Estimates excluding Resubmission Costs			
$\tau^{\text{Share Lost}}$	0.139	0.033	0.019
Average Denied Amount	9.36	2.59	1.81

Note: The table reports our estimates of average costs of incomplete payments (CIP) and implicit CIP tax for each payer. These estimates are computed by taking the average across visits. The first panel computes CIP and τ^{CIP} following equations (4) and (5). These calculations include both lost revenues due to denials and resubmission costs. The second panel shows the amount of lost revenues, and the corresponding implicit tax, as calculated directly from the remittance data, ignoring the estimated resubmission costs. All statistics are computed using the entire sample for each payer, after excluding the visits in the top 1 percentile of CIP values. Omitting these visits yields smaller average CIP values for each payer and lower estimates of τ^{CIP} .

Table 8: Summary of Medicaid Indices

	Mean	SD	10th Percentile	90th Percentile	Observations
Panel (a): Medicaid Indices Across States					
ln(fee) Index	3.3121	0.21	3.06	3.57	51
τ^{CIP} Index	0.1836	0.11	0.08	0.34	51
Panel (b): Changes in Medicaid Indices for Movers					
$\Delta \ln(\text{fee})$ Index	0.0090	0.25	0.01	0.31	23953
$\Delta \tau^{CIP}$ Index	-0.0023	0.13	-0.17	0.17	23953

Note: These tables summarize the Medicaid fee and CIP indices. Panel (a) summarizes the cross-state variation of the indices estimated via equations (11) and (12). Panel (b) summarizes the differences of the same indices across physician movers. For each physician we observe moving across state borders between 2009 and 2015, the difference is simply the index value in the post-move state minus the index value in the pre-move state.

Table 9: Movers Regression

Dependent Variable	Accepting Medicaid Patients?			
	(1)	(2)	(3)	(4)
Post-Move $\times \Delta \ln \text{Fee}$	0.0560*** (0.0159)	0.0427** (0.0172)	0.0298** (0.0137)	0.0277** (0.0127)
Post-Move $\times \Delta \tau^{CIP}$	-0.1056*** (0.0282)	-0.1033*** (0.0261)	-0.0587** (0.0237)	-0.0542** (0.0234)
δ s.t. $\hat{\beta} = 0$	1.914	1.403	0.970	0.966
δ s.t. $\hat{\gamma} = 0$	1.853	2.616	0.912	0.913
R^2 Within Physician	0.008	0.010	0.014	0.017
R^2_{max}	0.010	0.012	0.018	0.022
N	56886	56886	56886	56886
R^2	0.600	0.600	0.602	0.603
p -value for adjusted coefficient equality	0.282	0.116	0.459	0.487
Phys. FE	Yes	Yes	Yes	Yes
Group FE	No	No	No	No
Number of Physicians	23953	23953	23953	23953
Provider Controls	No	Yes	Yes	Yes
Insurance Market Controls	No	No	Yes	Yes
Socioeconomic Controls	No	No	No	Yes

Note: The table reports OLS estimates of β (coefficient on $\Delta \ln \text{fee}$ index) and γ (coefficient on $\Delta \tau^{CIP}$ index) from equation (13), estimated over the subset of physicians who move across states between 2009-2015, as recorded in the MD-PPAS data (section 2.3). Insurance market controls are: average Medicare HCC risk score (at county-year level); Medicare Advantage penetration, number of people eligible for Medicaid, number of people eligible for Medicare, share of uninsured among those younger than 65, share of dually eligible for Medicaid and Medicare, people enrolled in Medicare (at county level); fraction of people covered by Medicare, fraction of people covered by Medicaid, fraction of people uninsured (at state-year level). Provider controls are: number of practicing physicians, physicians per capita (at county-year level). Socioeconomic controls are: median household income, share of people living in poverty, population, share of people identifying as white (at county-year level). Standard errors are in parentheses, clustered at the state level. The table also reports the p -value of the test again the null hypothesis that $\beta = -\gamma \times (1 - \bar{\tau}^{CIP})$, where $\bar{\tau}^{CIP} = 0.174$, from Table 7, and the δ values corresponding to Oster's (2019) test for coefficient stability.

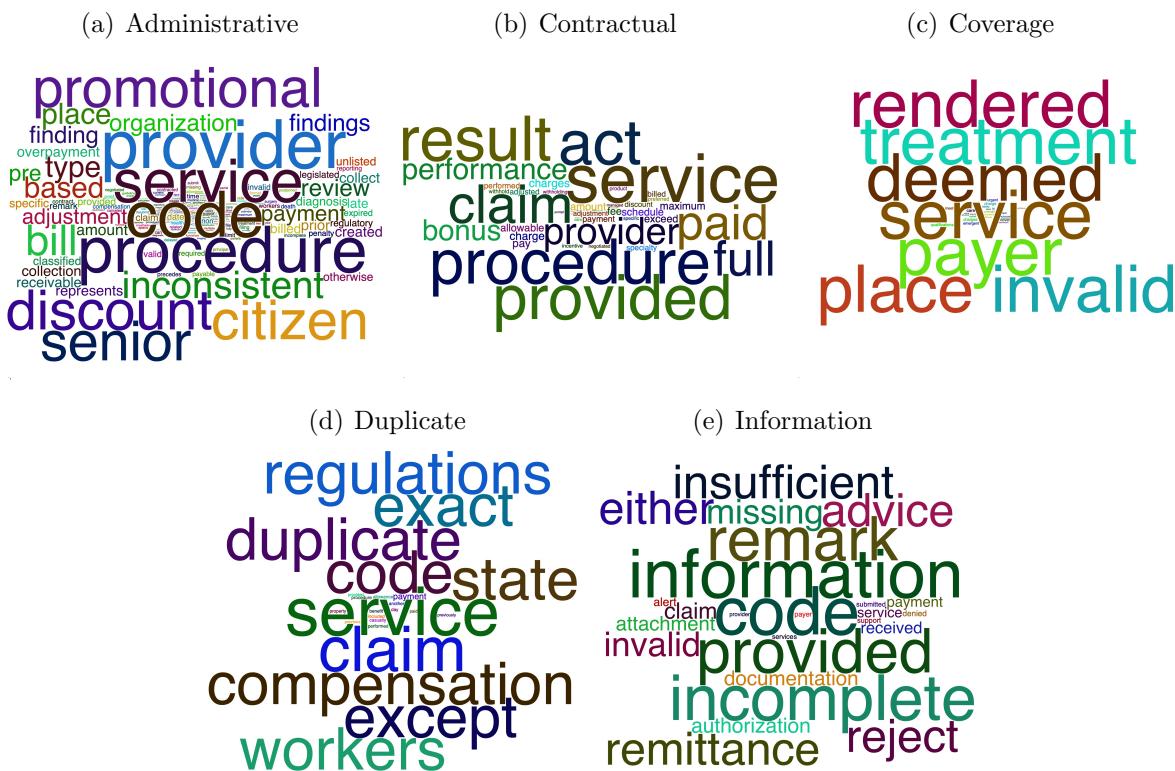
Table 10: Cross-State Regression

Dependent Variable	Accepting Medicaid Patients?				
	(1)	(2)	(3)	(4)	(5)
ln Fee	0.1036*	0.1021***	0.0965**	0.1049***	0.0923***
	(0.0563)	(0.0361)	(0.0364)	(0.0275)	(0.0238)
τ^{CIP}	-0.3082**	-0.1697**	-0.1634**	-0.1208*	-0.0977*
	(0.1252)	(0.0662)	(0.0661)	(0.0660)	(0.0579)
δ s.t. $\hat{\beta} = 0$	/	0.136	0.185	0.703	1.354
δ s.t. $\hat{\gamma} = 0$	/	0.141	0.161	0.341	0.570
R^2 Within Group	/	0.008	0.008	0.008	0.009
R^2_{max}	/	0.010	0.010	0.011	0.012
N	1,472,527	1,472,527	1,472,527	1,472,527	1,472,527
R^2	0.010	0.323	0.323	0.326	0.328
p-value for adjusted coefficient equality	0.220	0.577	0.568	0.928	0.823
Group	AHRQ and Tax ID				
Phys. FE	No	No	No	No	No
Group FE	No	Yes	Yes	Yes	Yes
Number of Physicians	521,030	521,030	521,030	521,030	521,030
Provider Controls	No	No	Yes	Yes	Yes
Insurance Market Controls	No	No	No	Yes	Yes
Socioeconomic Controls	No	No	No	No	Yes

Note: The table reports OLS estimates of β (coefficient on ln fee index) and γ (coefficient on τ^{CIP} index) from equation (15), estimated over the subset of physicians who work in physician groups operating in multiple states between 2009-2015, as recorded in the MD-PPAS data (described in section 2.3). Insurance market controls are: average Medicare HCC risk score (at county-year level); Medicare Advantage penetration, number of people eligible for Medicaid, number of people eligible for Medicare, share of uninsured among those younger than 65, share of dually eligible for Medicaid and Medicare, people enrolled in Medicare (at county level); fraction of people covered by Medicare, fraction of people covered by Medicaid, fraction of people uninsured (at state-year level). Provider controls are: number of practicing physicians, physicians per-capita (at county-year level). Socioeconomic controls are: median household income, share of people living in poverty, population, share of people identifying as white (at county-year level). Standard errors are in parentheses, clustered at the state level. The table also reports the p-value of the test again the null hypothesis that $\beta = -\gamma \times (1 - \bar{\tau}^{CIP})$, where $\bar{\tau}^{CIP}$ corresponds to 0.174 as per Table 7 and the values of δ 's corresponding to Oster's (2019) test for coefficients stability.

A Appendix: Additional Tables and Figures

Figure A.1: Frequent Words in the Reasons for Denial, by Category



Note: Each word cloud summarizes the text description of the reasons for denials observed in the IQVIA remittance data. We observe over 350 different reason codes, each associated with a brief description of the issue raised by the payer. After grouping these codes in the five categories that we use for our analysis, we count the frequency of each (non elementary) word in the corresponding descriptions. The word clouds weight each such word by the frequency in which it appears in the descriptions of the corresponding category.

Table A.1: Summary of Medicaid Indices

	Mean	SD	10th Percentile	90th Percentile	Observations
Panel (a): Medicaid Indices Across States					
ln(fee) Index (baseline)	3.3121	0.21	3.06	3.57	51
ln(fee) Index (full sample)	3.3029	0.20	3.07	3.56	51
ln(fee) Index (full sample, weighted)	4.5759	0.24	4.30	4.85	51
ln(fee) Index (weighted)	4.5805	0.24	4.30	4.87	51
τ^{CIP} Index (baseline)	0.1836	0.11	0.08	0.34	51
τ^{CIP} Index (weighted)	0.1505	0.09	0.07	0.26	51
Panel (b): Changes in Medicaid Indices for Movers					
Δ ln(fee) Index (baseline)	0.0090	0.25	-0.29	0.31	23953
Δ ln(fee) Index (full sample)	0.0078	0.24	-0.29	0.30	23953
Δ ln(fee) Index (full sample, weighted)	0.0049	0.28	-0.36	0.38	23953
Δ ln(fee) Index (weighted)	0.0051	0.29	-0.38	0.38	23953
$\Delta\tau^{CIP}$ Index (baseline)	-0.0023	0.13	-0.17	0.17	23953
$\Delta\tau^{CIP}$ Index (weighted)	-0.0023	0.11	-0.13	0.13	23953

Note: These tables summarize Medicaid indices. Panel (a) summarizes the cross-state variation of the indices estimated via equations (11) and (12). The baseline fee index is estimated using only non-imputed fee values. The baseline fee index is estimated using only non-imputed fee values. We estimate a second fee index using the entire sample. Summary statistics are shown for indices estimated without regression weights and using the claim value π as a regression weight for the CIP index and the visit's Medicare RVUs as a regression weight for the fee index. Panel (b) summarizes the differences of the same indices across physician movers. For each physician we observe moving across state borders between 2009 and 2015, the difference is simply the index value in the post-move state minus the index value in the pre-move state.

Table A.2: Robustness of Mover Regression Results

	Standard Index	First Visit Only	First Visit Excluded	Local Income Control	Index w/ Diagnosis FE	Pregnant Patients Only	Index w/o Physician FE
Panel (a): Fee index without imputations, unweighted regressions							
Post-Move $\times \Delta \log \text{Fee}$	0.0277** (0.0127)	0.0295** (0.0126)	0.0265** (0.0128)	0.0277** (0.0127)	0.0255** (0.0126)	0.0325** (0.0122)	0.0253* (0.0126)
Post-Move $\times \Delta \tau^{CIP}$	-0.0542** (0.0234)	-0.0577** (0.0247)	-0.0506** (0.0219)	-0.0541** (0.0233)	-0.0577*** (0.0209)	-0.0565** (0.0218)	-0.0576*** (0.0207)
Panel (a): Fee index without imputations, weighted regressions							
Post-Move $\times \Delta \log \text{Fee}$	0.0207* (0.0106)	0.0217** (0.0104)	0.0196* (0.0107)	0.0207* (0.0106)	0.0188* (0.0105)	0.0248** (0.0102)	0.0191* (0.0105)
Post-Move $\times \Delta \tau^{CIP}$	-0.0544* (0.0294)	-0.0530* (0.0301)	-0.0545* (0.0271)	-0.0544* (0.0294)	-0.0595** (0.0232)	-0.0693* (0.0388)	-0.0558** (0.0229)
Panel (a): Fee index with imputations, unweighted regressions							
Post-Move $\times \Delta \log \text{Fee}$	0.0287** (0.0130)	0.0303** (0.0129)	0.0280** (0.0132)	0.0287** (0.0130)	0.0275** (0.0130)	0.0346*** (0.0126)	0.0273** (0.0130)
Post-Move $\times \Delta \tau^{CIP}$	-0.0566** (0.0240)	-0.0596** (0.0252)	-0.0530** (0.0223)	-0.0564** (0.0238)	-0.0606*** (0.0210)	-0.0604*** (0.0224)	-0.0605*** (0.0208)
Panel (a): Fee index with imputations, weighted regressions							
Post-Move $\times \Delta \log \text{Fee}$	0.0210* (0.0107)	0.0217** (0.0106)	0.0203* (0.0108)	0.0210* (0.0107)	0.0199* (0.0106)	0.0257** (0.0105)	0.0201* (0.0107)
Post-Move $\times \Delta \tau^{CIP}$	-0.0569* (0.0301)	-0.0552* (0.0308)	-0.0570** (0.0275)	-0.0569* (0.0301)	-0.0621** (0.0235)	-0.0743* (0.0400)	-0.0585** (0.0233)

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Note: The table shows robustness to different versions of the estimates in Table 9—exploiting physicians moving across states—of the effect of the ln fee index and τ^{CIP} index on Medicaid acceptance, resulting from alternative ways to calculate these indexes. Different row panels correspond to alternative fee indices, while different columns correspond to alternative CIP indices. Standard errors are in parentheses, clustered at the state level.

Table A.3: Robustness of Cross-State Regressions Results

	Standard Index	First Visit Only	First Visit Excluded	Local Income Control	Index w/ Diagnosis FE	Pregnant Patients Only	Index w/o Physician FE
Panel (a): Fee index without imputations, unweighted regressions							
Index of ln Fee	0.0923*** (0.0238)	0.0960*** (0.0243)	0.0902*** (0.0236)	0.0922*** (0.0238)	0.0928*** (0.0243)	0.1005*** (0.0254)	0.0926*** (0.0242)
τ^{CIP}	-0.0977* (0.0579)	-0.0747 (0.0626)	-0.0980* (0.0494)	-0.0983* (0.0578)	-0.0760 (0.0555)	-0.0593 (0.0627)	-0.0769 (0.0557)
Panel (b): Fee index without imputations, weighted regressions							
Index of ln Fee	0.0645*** (0.0199)	0.0678*** (0.0203)	0.0630*** (0.0196)	0.0722*** (0.0205)	0.0634*** (0.0198)	0.0729*** (0.0213)	0.0631*** (0.0197)
τ^{CIP}	-0.1372* (0.0736)	-0.0836 (0.0738)	-0.1504** (0.0648)	-0.1372* (0.0736)	-0.1270* (0.0665)	-0.0465 (0.1150)	-0.1272* (0.0661)
Panel (c): Fee index with imputations, unweighted regressions							
Index of ln Fee	0.0977*** (0.0235)	0.1008*** (0.0365)	0.0963*** (0.0234)	0.0976*** (0.0235)	0.0984*** (0.0240)	0.1064*** (0.0252)	0.0982*** (0.0240)
τ^{CIP}	-0.1029* (0.0584)	-0.0778 (0.0627)	-0.1040** (0.0501)	-0.1034* (0.0583)	-0.0841 (0.0566)	-0.0694 (0.0645)	-0.0851 (0.0569)
Panel (d): Fee index with imputations, weighted regressions							
Index of ln Fee	0.0676*** (0.0196)	0.0703*** (0.0201)	0.0668*** (0.0193)	0.0676*** (0.0196)	0.0670*** (0.0195)	0.0758*** (0.0213)	0.0668*** (0.0194)
τ^{CIP}	-0.1420* (0.0753)	-0.0875 (0.0752)	-0.1555** (0.0665)	-0.1420* (0.0753)	-0.1335* (0.0683)	-0.0595 (0.1181)	-0.1337* (0.0679)

Note: The table shows robustness to different versions of the estimates in Table 10—exploiting physician groups operating in multiple states—of the effect of the ln fee index and τ^{CIP} index on Medicaid acceptance, resulting from alternative ways to calculate these indexes. Different row panels correspond to alternative fee indices, while different columns correspond to alternative CIP indices. Standard errors are in parentheses, clustered at the state level.

Table A.4: Effect of Fees and CIP Measured as Uncollected Revenue Only (Mover Strategy)

	Standard Index	First Visit Only	First Visit Excluded	Local Income Control	Index w/ Diagnosis FE	Pregnant Patients Only	Index w/o Physician FE
Panel (a): Fee index without imputations, unweighted regressions							
Post-Move $\times \Delta \log \text{Fee}$	0.0248* (0.0128)	0.0263** (0.0126)	0.0240* (0.0130)	0.0248* (0.0128)	0.0226* (0.0129)	0.0302** (0.0120)	0.0224* (0.0129)
Post-Move $\times \Delta \tau^{CIP}$	-0.0623*** (0.0229)	-0.0685*** (0.0246)	-0.0566** (0.0212)	-0.0620*** (0.0228)	-0.0675*** (0.0207)	-0.0792*** (0.0247)	-0.0676*** (0.0206)
Panel (b): Fee index without imputations, weighted regressions							
Post-Move $\times \Delta \log \text{Fee}$	0.0194* (0.0107)	0.0202* (0.0105)	0.0186* (0.0107)	0.0194* (0.0107)	0.0179* (0.0106)	0.0231** (0.0102)	0.0181* (0.0106)
Post-Move $\times \Delta \tau^{CIP}$	-0.0596* (0.0304)	-0.0603* (0.0320)	-0.0584** (0.0267)	-0.0596* (0.0304)	-0.0637*** (0.0237)	-0.1156*** (0.0383)	-0.0609** (0.0234)
Panel (c): Fee index with imputations, unweighted regressions							
Post-Move $\times \Delta \log \text{Fee}$	0.0262* (0.0132)	0.0273** (0.0130)	0.0260* (0.0134)	0.0262* (0.0132)	0.0251* (0.0132)	0.0330** (0.0124)	0.0249* (0.0132)
Post-Move $\times \Delta \tau^{CIP}$	-0.0651*** (0.0234)	-0.0713*** (0.0252)	-0.0593*** (0.0214)	-0.0648*** (0.0233)	-0.0705*** (0.0205)	-0.0838*** (0.0251)	-0.0705*** (0.0203)
Panel (d): Fee index with imputations, weighted regressions							
Post-Move $\times \Delta \log \text{Fee}$	0.0200* (0.0108)	0.0205* (0.0107)	0.0196* (0.0108)	0.0200* (0.0108)	0.0191* (0.0107)	0.0247** (0.0104)	0.0192* (0.0107)
Post-Move $\times \Delta \tau^{CIP}$	-0.0628** (0.0309)	-0.0635* (0.0326)	-0.0612** (0.0270)	-0.0628** (0.0309)	-0.0666*** (0.0239)	-0.1216*** (0.0391)	-0.0639*** (0.0236)

Note: The table shows robustness to different versions of the estimates in Table 9—exploiting physicians moving across states—of the effect of the ln fee index and τ^{CIP} index on Medicaid acceptance, when measuring the latter as simply the share of revenue not collected. That is, the definition of CIP in this table does not include the estimated cost of the resubmission process. The table shows estimates resulting from various ways to calculate these indexes. Different row panels correspond to alternative fee indices, while different columns correspond to alternative CIP indices. Standard errors are in parentheses, clustered at the state level.

Table A.5: Effect of Fees and CIP Measured as Uncollected Revenue Only (Cross-State Strategy)

	Standard Index	First Visit Only	First Visit Excluded	Local Income Control	Index w/ Diagnosis FE	Pregnant Patients Only	Index w/o Physician FE
Panel (a): Fee Index without imputations, unweighted regressions							
Index of ln Fee	0.0879*** (0.0229)	0.0920*** (0.0234)	0.0870*** (0.0230)	0.0879*** (0.0229)	0.0897*** (0.0236)	0.0992*** (0.0250)	0.0894*** (0.0236)
τ^{CIP}	-0.1124* (0.0610)	-0.0922 (0.0689)	-0.1068** (0.0504)	-0.1124* (0.0606)	-0.0897 (0.0600)	-0.0725 (0.0671)	-0.0911 (0.0601)
Panel (b): Fee Index without imputations, weighted regressions							
Index of ln Fee	0.0613*** (0.0190)	0.0648*** (0.0196)	0.0614*** (0.0190)	0.0612*** (0.0190)	0.0609*** (0.0189)	0.0725*** (0.0210)	0.0607*** (0.0189)
τ^{CIP}	-0.1618** (0.0794)	-0.1099 (0.0852)	-0.1627** (0.0660)	-0.1613** (0.0785)	-0.1471** (0.0729)	-0.0875 (0.1241)	-0.1481** (0.0725)
Panel (c): Fee Index with imputations, unweighted regressions							
Index of ln Fee	0.0936*** (0.0226)	0.0969*** (0.0231)	0.0936*** (0.0227)	0.0936*** (0.0226)	0.0954*** (0.0233)	0.1052*** (0.0247)	0.0951*** (0.0233)
τ^{CIP}	-0.1194* (0.0616)	-0.0974 (0.0692)	-0.1144** (0.0511)	-0.1193* (0.0613)	-0.0998 (0.0613)	-0.0850 (0.0699)	-0.1012 (0.0613)
Panel (d): Fee Index with imputations, weighted regressions							
Index of ln Fee	0.0649*** (0.0187)	0.0675*** (0.0194)	0.0658*** (0.0186)	0.0649*** (0.0186)	0.0650*** (0.0185)	0.0757*** (0.0210)	0.0648*** (0.0185)
τ^{CIP}	-0.1685** (0.0813)	-0.1162 (0.0868)	-0.1694** (0.0677)	-0.1679** (0.0803)	-0.1549** (0.0747)	-0.1039 (0.1288)	-0.1558** (0.0743)

Note: The table shows robustness to different versions of the estimates in Table 10—exploiting physician groups operating in multiple states—of the effect of the ln fee index and τ^{CIP} index on Medicaid acceptance, when measuring the latter as simply the share of revenue not collected. That is, the definition of CIP in this table does not include the estimated cost of the resubmission process. The table shows estimates resulting from various ways to calculate these indexes. Different row panels correspond to alternative fee indices, while different columns correspond to alternative CIP indices. Standard errors are in parentheses, clustered at the state level.