Phoning Home: The Procurement of Telecommunications for Incarcerated Individuals in the United States*

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Abstract

Incarcerated individuals in the U.S. purchase goods and services from monopoly vendors selected by their correctional authority. We study telecommunications, which have come under bipartisan scrutiny due to the high prices inmates pay for phone calls. Prospective providers are evaluated on their technical capabilities, the prices they would charge, and the "commission" they would pay the correctional authority. Using data from public records requests, we estimate a first-score auction model with evaluation uncertainty and multi-dimensional bidder heterogeneity. The model indicates that reducing the role of commissions in procurement lowers prices, whereas increasing competition among providers mainly raises commissions. Moreover, recent federal regulations that ban commissions and cap prices likely preserve providers' profitability.

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1 Introduction

What is the market price of a phone call? For decades, incarcerated individuals in the United States have paid what the Federal Communications Commission (FCC) refers to as "exorbitant" rates to monopoly telecommunications providers selected by their correctional authority (FCC, 2021a). In turn, the providers have shared the revenue they obtain with correctional authorities through commission payments. Thus, incarcerated individuals have funded their own incarceration.[1] For these reasons, the market for inmate communication services (ICS) has attracted significant bipartisan regulatory scrutiny, culminating in new federal regulations by the FCC that cap rates and ban commissions and ancillary fees (FCC, 2024).

This paper studies the ICS industry as it operated from 2000-2019. We focus on the procurement process, which resembles a first-score auction with evaluation uncertainty and multi-dimensional bidder heterogeneity. We develop an empirical model and use it to examine the interplay of commissions and rates. We also evaluate regulation, competition policy, and the interaction between the two. Our analysis contributes to a growing literature on "non-standard" auctions, such as scaling auctions where bidders submit a price per unit of quantity (e.g., Athey and Levin, 2001; Bajari et al., 2014; Bolotnyy and Vasserman, 2023) and scoring or multi-attribute auctions where contracts are awarded based on multiple aspects of the bid (e.g., Lewis and Bajari, 2011; Takahashi, 2018; Krasnokutskaya et al., 2020; Kong et al., 2022; Bhattacharya et al., 2022; Allen et al., 2024). By focusing on commission payments, we address an understudied aspect of procurement that arises in the ICS market and other settings.[2]

The empirical foundation of our study comprises public records requests that we submitted to all fifty states. We obtained and digitized requests for proposals (RFPs), the winning and losing bids submitted by ICS providers, how those bids were evaluated, and the ensuing contracts. Thus, we have nearly complete information for a sample of procurement events. Not all auctions in our data include commissions, but when they do, higher commission payments are associated with higher rates. We also find that auctions that place more weight on commissions in the scoring rule generate bids with larger commissions and higher rates. The empirical model connects these facts, as higher rates allow providers to make larger commission payments. Furthermore, natural experiments based on price reductions in two states support that incarcerated individuals respond to higher prices by reducing call volumes.

We estimate the model with the simulated method of moments, using established methods (e.g., Laffont et al., 1995; Asker and Cantillon, 2008) to bypass the computation of the

[1] There are more than two million incarcerated individuals in the United States (Bureau of Justice Statistics, 2021a,b), and the popular press has placed their total annual expenditures on phone calls at over one billion dollars (Shields, 2012). A nonprofit advocacy group estimated in 2019 that a typical 15-minute call costs about \$6.00 in local jails and about \$1.75 in state prisons (Prison Policy Initiative, 2019). For useful overviews of the industry, see Jackson (2005), Baker et al. (2020), and Raher (2020).

[2] One well-known example is that prescription drug companies pay rebates to pharmacy benefit managers (PBMs) in exchange for formulary placement (e.g., FTC, 2024; Ho and Lee, 2024).

symmetric Bayes-Nash equilibrium. We obtain distributions that characterize providers' technical capabilities and costs; the cost estimates are consistent with external sources (Bazelon et al., 2023). The model also performs well in out-of-sample validation checks. In counterfactual analyses, we show how the scoring rule affects outcomes and that banning commissions reduces rates. Furthermore, in the presence of commissions, we find that more competition increases commissions but may not lower rates. By contrast, under a commission ban, more competition lowers rates. We also examine regulations that fix rates and explore whether rate caps might reduce auction participation. Our analysis helps provide the evidentiary basis for regulation; the Order of the FCC cites an earlier draft of this paper twelve times (FCC, 2024).[3]

We begin the paper by discussing the institutional features of the ICS industry and summarizing the data (Section 2). In a prototypical ICS procurement process, the contracting entity evaluates bids received from providers using a scoring rule that considers proposed technical capabilities, the prices charged to inmates, and the commission payment. However, we observe that the price or commission is sometimes predetermined by the contracting entity. The average rate is \$1.65 (per 15-minute call) in our data. The average commission payment per inmate-month is \$11.34 and, conditional on some commission being paid, it constitutes 67% of the provider's revenue.[4] Commissions and rates are positively correlated among both all bids and winning bids. This empirical relationship helps motivate the study.

We provide three empirical analyses in Section 3. First, we relate proposed rates and commissions to their received scores. Lower rates and higher commissions are scored more favorably. However, the relationship for rates is weaker if commissions enter the scoring rule, consistent with procuring entities muting the incentive to propose low rates when commissions are valued.[5] Second, we regress the financial terms on the scoring rule weights. We find that if more weight is placed on the rate, then rates and commissions are lower (only the latter result is statistically significant). By contrast, if more weight is placed on the commission, rates and commissions are higher. Together, these first two analyses support that procuring entities and providers understand how the design of the scoring auction affects bidding incentives.

The third empirical analysis examines how significant policy-induced rate reductions in New York and New Jersey affected calling behavior. We document that the average number of calls per inmate-month increased from 8.82 to 15.86 in New York and 8.32 to 27.00 in New Jersey, corresponding to arc elasticities of 0.55 and 0.69, respectively. Despite greater usage, total expenditures fell by 40% in New York and 56% in New Jersey. We use these natural experiments to estimate a demand function that relates prices to calls; the demand function is one component of our empirical model. The price elasticity of demand that we estimate can

[3]One of us submitted the earlier draft of this paper ("The Price that Inmates Pay") to the FCC during its formal comment period in the rule-making process.

[4]Providers can also obtain revenue from ancillary fees, which we incorporate into the empirical model.

[5]As an analogy, a university instructor can specify that the midterm accounts for 30% of the final grade but nonetheless can diminish its importance by reducing the variance of midterm scores.

be viewed as consistent with a regular consumer surplus utility, suggesting that incarcerated individuals benefit from being able to make more calls.[6]

The empirical model features first-score auctions with multi-dimensional bidder heterogeneity and evaluation uncertainty (Section 4). An exogenous number of providers have private information about their costs and noisy signals about how their technical capabilities will be evaluated.[7] Our notion of cost is net of the ancillary fees that providers charge incarcerated individuals, which we take to be determined outside the model. The scoring rule is common knowledge. Providers submit a score to the procuring entity. The winning provider—the one that submits the highest score—must deliver a contract worth its bid. The contract specifies the commission and the rate incarcerated individuals pay for calls. Given the demand model, it determines the number of calls made and the provider's profit.

We assume providers employ strategies consistent with a symmetric Bayes-Nash equilibrium. For auctions in which commissions enter the scoring rule, we characterize equilibrium strategies following Asker and Cantillon (2008), relying on the observation that the contributions of the rate, the commission, and technical capabilities are additively separable in the scoring rule.[8] Each provider proposes the score that maximizes its expected profit given its information and the strategies of other firms; the winning supplier delivers a contract in which the rate maximizes the bilateral surplus of the provider and the procuring entity, and the commission is determined from the provider's submitted score. For auctions in which commissions do not enter the scoring rule, each provider proposes the score that maximizes its expected profit, which pins down the rate of the winning supplier. Thus, the model is flexible enough to capture the variability in scoring rules observed in the data, including how financial terms impact the evaluation process.

We discuss estimation in Section 5. The objects of interest are the distributions of costs and the technical scores and the informativeness of the signal about the technical score. We make parametric assumptions on the distributions to accommodate a small sample. We estimate the technical score distribution from the raw data. For the rest, we use simulated method of moments (e.g., Pakes and Pollard, 1989; McFadden, 1989). The moments require us to compute equilibrium objects for every candidate parameter vector. Thus, we focus on auctions where commissions enter the scoring rule because moments based on the bids of the winning provider can be obtained quickly from the revenue-equivalent second-score auction (e.g., Milgrom and

[6]Paragraph 26 of 2024 Order of the FCC states that "The record in this proceeding provides overwhelming evidence of the substantial burden excessive communications rates have on the ability of incarcerated people to stay connected and maintain the vital, human bonds that sustain families and friends when a loved one is incarcerated." Abdul-Razzak et al. (2024) finds that making calls free reduces misconduct among incarcerated individuals. Otsu (2023) finds that *visitation* in prison reduces recidivism due in part to improved employment outcomes after release.

[7]Our understanding is that providers are uncertain about how their capabilities will be evaluated, and incorporating uncertainty helps us fit the data better. In our application, uncertainty reduces the competitive advantage of firms with desirable technical capabilities, increasing competitive pressure.

[8]In this sense, our model is akin to the scaling auctions with quantity uncertainty that are studied in Athey and Levin (2001) and Bolotnyy and Vasserman (2023).

Weber, 1982; Laffont et al., 1995; Asker and Cantillon, 2008). We conduct two out-of-sample assessment exercises. We compute the full equilibrium and show that the model predicts losing bids. Then, we examine auctions where commissions do not enter the scoring rule, and approximate equilibrium following Bajari (2001) and Armantier et al. (2008). The model predicts that rates are lower for these auctions, consistent with what we observe in the data.

We use counterfactual simulations to analyze the economics of commissions (Section 6). First, we vary the relative weight placed on commissions and rates in the scoring rule, holding fixed the weight placed on technical capabilities. We find that expected equilibrium rates and commissions increase with the commission weight, reflecting that lower rates become less relevant for the procuring entity and that they support larger commission payments (which become more relevant). Second, we examine a ban on commissions. Although this requires the commission weight to be allocated to the rate and technical score components, we find that the ban lowers expected equilibrium rates under every possibility. Thus, the simulations support that the correlations in the raw data reflect causal relationships, and highlight how equilibrium commissions and rates are connected through the bidding incentives of providers.

We conduct three policy analyses in Section 7. First, we consider regulation that fixes rates but leaves commissions subject to competitive bidding. As the regulated rate falls, so does the expected equilibrium commission. For rates less than $0.18 (per 15-minute call), the sign on the equilibrium commission flips and the procuring entity ends up paying the provider for service. Profit *increases* modestly with more stringent regulation, as higher-cost providers are increasingly disadvantaged in the auction, reducing the competitive pressure on the lower-cost providers. Second, we consider regulation that bans commissions and caps rates at $0.90 per 15-minute call, consistent with the FCC Order.[9] We focus on whether such regulation would affect auction participation. Assuming that providers bid when the cap exceeds their costs, a representative auction with four potential bidders would receive at least three bids in 96% of our simulations. We also discuss how the ban on ancillary fees could shift our results.

Finally, we examine competition policy. To do so, we examine how outcomes vary with the number of providers.[10] We isolate the *competition effect* by rescaling the variances of the cost and technical score distributions such that their expected minimums and maximums do not change; thus, adding or subtracting firms does not affect the expected characteristics of the winner. With commissions, competition does not benefit incarcerated individuals. The reason is that providers can use the commission to adjust the aggressiveness of their bids, keeping the rates at the levels that maximize their bilateral surplus with the procuring entity. With a commission ban, however, providers must lower their rates to bid more aggressively, so competition

[9] Rate caps are a form of incentive regulation because firms benefit from cost reductions. The FCC has employed incentive regulation in the telecommunications industry before (e.g., Kaserman and Mayo, 2002; Sappington, 2002).

[10] Auction participation is exogenous in our model, so increasing the number of firms is a natural way to introduce competition. A large literature examines auction models with endogenous participation (e.g., Li and Zheng, 2009; Athey et al., 2011; Krasnokutskaya and Seim, 2011; Bhattacharya et al., 2014; Carril et al., 2022).

lowers rates. These results demonstrate an interaction of regulation and competition policy, as the regulatory structure helps determine who benefits from competition.[11]

The research closest to ours uses empirical auction models to examine government procurement practices. There are a number of recent contributions. Bhattacharya et al. (2022) show how incorporating contingency payments can reduce moral hazard in oil lease auctions. For federal procurement in the telecommunications and IT industries, Kang and Miller (2022) find that the benefit of soliciting another bidder tends to be modest because the procuring entity can extract informational rents. Bolotnyy and Vasserman (2023) examine how risk aversion leads firms to shade bids in procurement auctions run by the Massachusetts Department of Transportation. Allen et al. (2024) study scoring actions conducted by the FDIC to resolve insolvent banks, focusing on the uncertainty that bidders have about the scoring rule. Carril et al. (2022) examine procurement for defense contracts and find that both prices and *ex post* performance fall with the number of bidders; the latter occurs because marginal bidders tend to be less capable. All of these articles use bespoke models that incorporate salient features of the setting, and develop insights about how auction design can influence outcomes.[12]

Other recent studies have explored the interaction of price regulation and competition in oligopoly markets. Canzian et al. (2023) examine price caps in the European mobile telecommunications industry, Wang (2024) focuses on the effects of capping merchant fees in the payments industry, and Dubois et al. (2022) explore reference pricing for pharmaceuticals, which involves capping domestic prices based on prices abroad. Of these, the closest is Wang (2024), as capping merchant fees can affect who benefits from competition among payment networks, just as banning commissions changes how competition manifests in ICS. More distant is Byrne and de Roos (2019), which examines how regulating price transparency affected competitive outcomes in an Australian retail gasoline market.

2 Inmate Calling Services

2.1 Background

In this section, we describe the ICS industry in greater detail.[13] There are three main types of actors: incarcerated individuals and their social contacts, correctional authorities, and ICS providers. The correctional authority that handles procurement of ICS for most state-level

[11]If we do not rescale the variances of the cost and technical score distributions, then rates fall as the number of providers increases in the presence of commissions (albeit more gradually than under a commission ban). The reason is that the winning bidder is selected from a bigger pool and, therefore, tends to have lower costs simply due to the composition of the bidder pool.

[12]Also related, Slattery (2024) uses an auction model to study how state and local governments use tax incentives and other discretionary subsidies to attract firms.

[13]We draw on regulatory filings (e.g., FCC, 2012, 2013, 2015, 2021a, 2024), an article written by FCC economists (Baker et al., 2020), a small academic literature (e.g., Jackson, 2005; Raher, 2020; Bazelon et al., 2023), and our conversations with industry experts.

prison systems is the Department of Corrections (DOC); for county jails, it is often a sheriff's office. The providers are privately owned telecommunications companies specializing in ICS, such as Securus and Global Tel*Link (GTL).[14] Payments between these actors are governed by exclusive contracts that the correctional authority signs with a provider.

Most incarcerated individuals reside in a county jail before sentencing and in a state prison facility after sentencing.[15] Facility-specific rules determine their access to phones and who they can call, and a number of security measures are in place to ensure compliance. The rules also limit the duration of calls. A typical maximum call length is 15 minutes, but some facilities allow 20 or 30 minute calls. Payments from incarcerated individuals and their social contacts to the ICS provider are based on pricing schedules set during the procurement process. The overall expenditure required for a call can depend on a number of factors, including its length, whether it is intrastate or interstate, the payment type (i.e., whether it is a collect call), and whether there is a fixed connection charge.

Three providers own most contracts for prison systems: Securus, GTL, and, to a lesser extent, IC Solutions. More providers have contracts with county jails, including smaller providers like NCIC and CPC. The industry's current configuration reflects a consolidation period during which GTL and Securus acquired many of the smaller providers. Most recently, GTL acquired Telmate in 2018, Securus abandoned the acquisition of IC Solutions after the Department of Justice expressed antitrust concerns, and IC Solutions acquired CenturyLink in 2020.[16]

Correctional authorities use procurement processes that resemble first-price scoring auctions to select their ICS provider. The broad contours are as follows: First, the correctional authority issues a request-for-proposal (RFP) that outlines the technical requirements that providers must meet, many of which relate to security measures. The RFP also specifies a binding scoring rule describing how the contracting authority will evaluate bids. Second, there is a formal question-and-answer period during which providers can gain additional information about the technical requirements and the facilities involved; prospective bidders can sometimes participate in formal visits ("walk-throughs") of the facilities. Providers also learn about their likely competitors through these interactions. Third, providers submit bids that describe their technical capabilities and propose financial terms. Finally, the correctional authority evaluates the bids according to the scoring rule, and the provider with the highest score wins the contract at the terms that they propose. Contracts are three or more years in duration.[17]

[14]GTL rebranded to ViaPath Technologies in 2022.

[15]The Federal Bureau of Prisons (FBP) and Immigration and Customs Enforcement (ICE) also operate facilities that house individuals charged or convicted of violating federal laws and immigration laws, respectively.

[16]The ICS industry began in the 1970s as prison systems relaxed rules restricting incarcerated individuals to a single phone call every three months. AT&T had a monopoly until the 1984 Consent Decree authorized its breakup. A number of providers entered the market in the following years, including large telecommunications companies like MCI and Sprint, as well as more specialized providers like GTL. In the 1990s, almost 30 ITS providers competed for prison and jail contracts. As a stylized fact, this increase in competition coincided with rising rates and commission payments. For a discussion of this history, see Jackson (2005).

[17]Many procurement processes differ from our description to some extent. For example, some authorities conduct

The technical capabilities of the provider receive considerable weight in the scoring rule. Correctional authorities prefer providers that offer robust security services, including live call monitoring, voice biometrics detection, three-way call prevention, and searchable databases. These capabilities are assessed directly by the authority. Inferences can also be made from the provider's demonstrated ability to win contracts for similar facilities or from reference letters that the provider submits with its bid. As the overall technical score combines multiple sources of information, including some that are qualitative, there can be significant evaluation uncertainty from a provider's perspective.

The other inputs to the scoring rule are financial terms. In many procurement processes, the correctional authority predetermines either the pricing schedule or the commission, allowing the other to be set through the bidding process. In other auctions, both the pricing schedule and the commission are subject to bidding, in which case they are usually evaluated separately. The commissions that correctional authorities receive are placed in "inmate welfare" funds that, in principle, support non-essential purchases of books, exercise equipment, and other amenities valued by incarcerated individuals. A report of the Prison Policy Initiative, a non-profit advocacy organization, claims that oversight is weak and that funds are sometimes under-utilized or misused, for example, to pay for operational expenses that would normally come from the general budget or, in extreme cases, perks for staff (Nam-Sonenstein, 2024).[18]

The large providers have two main revenue streams. The first comes from the prices charged for the phone calls that incarcerated individuals make. We refer to this as "non-fee revenue." The second comes from ancillary fees. The fees are obtained in a variety of ways. For example, providers can require that calls be made using prepaid calling cards and can levy fees when money is placed on those cards. Commissions are not paid on the revenue obtained from ancillary fees. Fee data are not always shared with the procuring authority and, therefore, are not always accessible with public record requests; in our data, we observe fees in some contracts but not others. The available evidence indicates that fee revenue is significant.[19]

There are at least two major costs associated with providing ICS. First, when providers start serving clients, they install their own phones and equipment (the telecommunication lines, though, typically do not need to be replaced). Second, providers operate and pay for data centers that store call recordings and associated metadata. Qualitatively, the cost of an "install" increases with the number and size of the facilities, and data center costs increase with the

the bidding in two rounds, with a subset of providers being asked to present more information—and possibly better financial terms—in the second round. Furthermore, losing bidders can contest the decision, which occasionally succeeds in changing the outcome and can lead to an entirely new procurement auction.

[18]The FCC's 2024 Order accounts for $0.02 per minute in facility costs for prisons (FCC, 2024), which is well less than the commission payments we observe in our data. Therefore, we interpret the commission payments as likely going beyond what would be required to compensate the procuring entity for incurred costs.

[19]The FCC determined that ancillary fees can raise the costs to incarcerated individuals and their social contacts by as much as 40%. See FCC Press Release, October 22, 2015, DOC-335984A1. Also notable is that one provider recently settled a class action lawsuit that alleged it had seized over $100 million from prepaid accounts following periods of inactivity. See Githieya v. Glob. Tel*Link Corp., USDC (N.D. Ga.), Case No. 1:15-CV-00986.

calls being made. As private equity companies own the large providers, high-fidelity financial information that breaks down the relative magnitude of these costs is not publicly available. However, one study conducts an accounting exercise and estimates the per minute average call cost to be $0.010-$0.012, depending on the size of the facility (Bazelon et al., 2023).

2.2 Regulatory History

The ICS industry has received considerable scrutiny at the federal and state levels. The history of federal regulation is detailed in FCC (2024). As a brief summary, the FCC adopted interim rate caps on interstate calls in 2013, and permanent rate caps on both intrastate and interstate calls in 2015. (Most calls are intrastate because incarcerated individuals tend to live near their families.) However, the 2015 rate caps were vacated in a 2017 court decision (*GTL vs. FCC*), in part on the grounds that the FCC lacked the statutory authority to regulate intrastate calls. The Martha Wright-Reed Act, enacted in 2023, explicitly granted the FCC the authority to ensure reasonable charges for communications used by inmates and led to the regulatory process that culminated in the 2024 Order. The new regulation places rate caps of $0.06 per minute ($0.90 for a 15-minute call) on ICS in prisons and bans commissions and ancillary fees. These rules phase in starting in November 2024.

Prior to July 2024, ten states passed laws to eliminate commissions in ICS contracts covering their state-level facilities, make calls free, or both.[20] Other states, including New York and New Jersey, have passed laws directing DOCs to place an emphasis on the lowest proposed cost to users when awarding telephone service contracts in correctional facilities. Most of these changes occurred after 2019, when our sample ends. At the time of the 2024 Order, commissions remained legal in 39 states, and many of the aforementioned changes applied only to state prison facilities but not county jails.

2.3 Data Collection and Summary Statistics

Our data comes from requests for public records that we submitted to all 50 states in the 2020-2021 academic year. Thus, data pertain to state prison systems rather than county jails. We targeted documents and data on ICS that span the previous two decades. In particular, we asked for the RFPs, all of the bids submitted by providers, how those bids were evaluated and scored, and the contracts with the winning providers. We also requested aggregated data on the number of calls and the total minutes of use, both at the monthly level and the average daily population (ADP) in the prison system.[21] Our empirical analysis is based on 37 procurement

[20]The states that eliminated commissions are Colorado, Illinois, Maryland, Nebraska, New Jersey, New Mexico, New York, Ohio, Rhode Island, and South Carolina. States that have implemented or scheduled implementation of free calls include Connecticut, California, Colorado, Minnesota and Massachusetts.

[21]Negotiating the public records requests and processing the files was an endeavor. The files were often not digitized and came in different formats. Responses were limited by the states' compliance requirements, their

events ("auctions") for which we received complete information (Appendix Table B.1).

Table 1 shows selected summary statistics at the auction level, on realized financial terms and the scoring rule weights placed on the rate, the commission, and the providers' technical capabilities. We measure the "rate" as the price of a 15-minute local collect call. For the commission, we use a measure of the payment from the provider per inmate-month that we describe later in this section. We use "technical capabilities" as a composite of the various considerations that relate to a bidder's ability to meet the buyer's technical requirements.[22] Across all auctions, the average rate is \$1.65, and the average commission payment per inmate-month is \$11.34. The average rate, commission, and technical weights are 0.22, 0.12, and 0.66, respectively. The rate and commission weights can be zero, reflecting that they are predetermined in some auctions. The average auction has 3.92 bidders.[23]

We allocate the auctions into subsamples based on whether both the rate and the commission are subject to bidding, whether only the commission is subject to bidding, and whether only the rate is subject to bidding. The average rate in these subsamples is \$2.55, \$1.91, and \$0.88, respectively. Two stylized facts are that rate tends to be the lowest in auctions for which it is the only financial term subject to bidding, and the commission tends to be the largest in auctions for which it is the only financial term subject to bidding. We also observe that the rate and commission receive similar weights in the scoring rule when both are subject to bidding, and the combined weight of the financial terms is similar across the subsamples.

Table 2 shows selected summary statistics at the bid level, based on the 155 bids that were submitted across all auctions. We examine the proposed rates and commissions, and the scores that were assigned. The statistics for rates and commissions are conditional in that we restrict the sample for rates and rate scores to bids in auctions that place a positive weight on rates and analogously for commissions and commission scores. The mean proposed rate is \$1.33, and the mean proposed commission is \$17.52. The scores have means of 0.71, 0.75, and 0.76 for rates, commissions, and technical capabilities, respectively, measured as a share of total awarded points.

Figure 1 explores the correlation between rates and commissions in the bid-level data. The left panel uses the full sample of 155 bids; the right panel focuses on the 37 winning bids. Both provide a scatter plot and a line of best fit. A positive empirical relationship between commissions and rates is evident, and we interpret that correlation as a third stylized fact. The slope coefficients in the lines of best fit are statistically significant at the one and ten percent

willingness to engage with our request, and their document retention practices. Still, we received at least some information from 43 states and obtained a complete set of documents and data on at least one procurement event from 26 states. Nine states provided a complete set of documents for multiple procurement events.

[22]For example, in 2016, North Dakota considered information technology, experience, qualifications, financial strength, and the presentation of each bidder. We treat all of these as part of a bidder's technical capabilities.

[23]All prospective providers submitted a single bid in 34 of the 37 auctions, so the average number of bids (4.19) is close to the average number of bidders. Our empirical model assumes that prospective providers submit a single bid. The conditions under which firms submit multiple bids in scoring auctions are explored in Allen et al. (2024).

Table 1: Selected Auction-Level Summary Statistics

	Mean	St. Dev.	10%	25%	50%	75%	90%
All Auctions							
Rate	1.62	1.32	0.27	0.58	1.65	2.25	3.12
Commission	11.34	10.53	0.00	0.05	10.74	19.61	28.27
Rate Weight	0.22	0.23	0.00	0.00	0.20	0.33	0.43
Commission Weight	0.12	0.19	0.00	0.00	0.00	0.15	0.32
Technical Weight	0.66	0.23	0.39	0.60	0.70	0.80	0.88
Number of Bidders	3.92	1.14	3.00	3.00	4.00	5.00	5.00
Rate and Commission in the Scoring Rule							
Rate	2.55	1.98	0.68	0.97	1.65	4.07	4.68
Commission	10.11	7.52	3.15	5.46	10.58	13.18	18.52
Rate Weight	0.19	0.14	0.04	0.10	0.20	0.22	0.32
Commission Weight	0.15	0.18	0.04	0.07	0.10	0.13	0.31
Technical Weight	0.66	0.31	0.40	0.68	0.70	0.80	0.92
Number of Bidders	3.29	0.95	2.60	3.00	3.00	3.50	4.40
Rate Predetermined, Commission in the Scoring Rule							
Rate	1.91	0.39	1.59	1.76	1.90	2.21	2.31
Commission	23.1	8.16	13.99	15.68	24.10	28.57	29.56
Commission Weight	0.33	0.20	0.14	0.20	0.30	0.34	0.48
Technical Weight	0.68	0.20	0.52	0.66	0.70	0.81	0.86
Number of Bidders	4.00	0.67	3.00	4.00	4.00	4.00	5.00
Rate in the Scoring Rule, Commission Predetermined							
Rate	0.88	0.77	0.19	0.33	0.60	1.24	2.06
Commission	4.58	6.34	0.00	0.00	0.62	8.49	13.11
Rate Weight	0.38	0.21	0.20	0.29	0.32	0.41	0.59
Technical Weight	0.62	0.21	0.41	0.59	0.69	0.72	0.80
Number of Bidders	4.17	1.38	2.70	3.00	4.00	5.00	6.00

Notes: The table provides selected summary statistics at the auction level for the 37 distinct auctions in the data. The rate is the cost of a 15-minute local collect call, and the commission is in dollars per inmate-month. Statistics are shown for the full sample and subsamples constructed based on which financial terms are subject to bidding. There are 37 auctions in the full sample and seven, ten, and 18 in the subsamples, respectively. Two auctions do not place any weight on financial terms in the scoring rule and are therefore omitted from the subsamples.

levels, respectively, and the bivariate correlation coefficients are 0.386 and 0.316.

We now return to our measure of commissions. We observe that commission payments are most commonly specified as a percentage of the non-fee revenue that the provider obtains. Among auctions with such terms, the average payment is 55% of non-fee revenue. Six auctions result in fixed commission payments that do not depend on revenue. We allocate these payments to the inmate-month level using data on ADP and contract duration. The average such payment is $13.57 per inmate-month. The commission measure that we report in Tables 1 and 2 combines the percentage and fixed commissions. We first calculate non-fee revenue using the data on rates and a demand function that returns the number of calls per inmate-month (Section 3.3). We then apply the commission percentage to non-fee revenue and adjust for any fixed commission payments, allocated to the inmate-month level.

Table 2: Selected Bid-Level Summary Statistics

	Mean	St. Dev.	10%	25%	50%	75%	90%
Rate	1.33	1.11	0.27	0.50	0.90	1.73	2.72
Commission	17.52	8.35	5.62	11.35	16.67	23.65	28.28
Rate Score	0.71	0.28	0.32	0.54	0.76	0.99	1.00
Commission Score	0.75	0.25	0.42	0.66	0.83	0.92	1.00
Technical Score	0.76	0.18	0.50	0.64	0.80	0.92	0.98

Notes: The table provides selected summary statistics at the bid level for the 155 bids in the data. The rate is the cost of a 15-minute local collect call, and the commission is in dollars per inmate-month. The scores are the fraction of the total points awarded to the bid. The statistics for rates and commissions are conditional, in that we restrict the sample for rates and rate scores to bids in auctions that place a positive weight on rates ($N = 106$), and analogously for commissions and commission scores ($N = 65$).

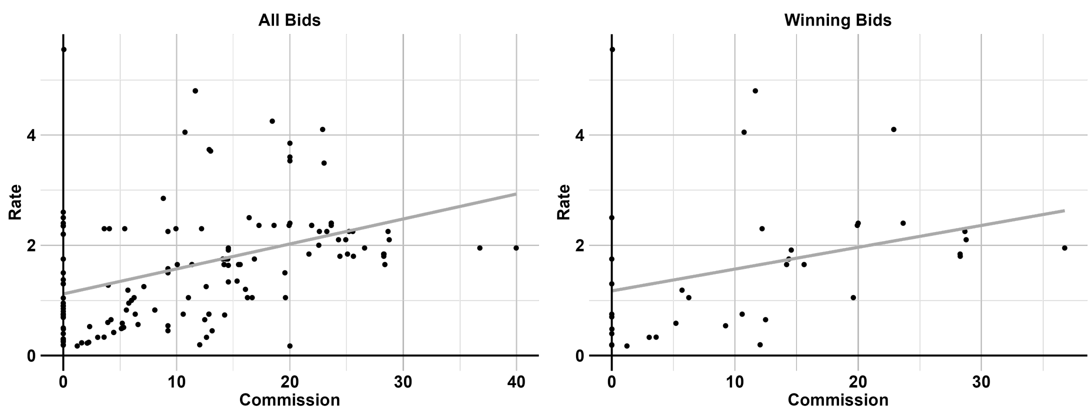

Figure 1: Empirical Relationship Between Rates and Commissions

Notes: The figure provides scatter plots of the commission and the rate in the bid data, using the full sample of 155 bids (left panel) and the 37 winning bids (right panel). Lines of best fit are also shown. The rate is in dollars per 15-minute local collect call. The commission is in dollars per inmate-month.

3 Descriptive Empirical Analyses

3.1 Analysis of Scoring Rules

In ICS procurement auctions, the score that is assigned to the providers' bids is a weighted average of a rate score, a commission score, and a score for technical capabilities. In this section, we examine the empirical relationships between rates and commissions and their respective scores. Our approach is to regress the score for the proposed financial term (rate or commission) on the financial term. The empirical relationships have implications for bidding incentives. For example, if a provider proposes a lower rate, then the effect on its overall score depends on both the weight placed on the rate score and how much its rate score would improve.

Table 3 summarizes the regression results. The columns on the left focus on rates. Column (i) shows the results of a univariate regression estimated on bids in auctions that place a positive weight on rates. The coefficient indicates that if the proposed cost of a 15-minute local collect call is $1.00 greater, then the associated rate score is 0.056 lower, on average. Columns (ii)

Table 3: Relationships Between Proposed Terms and Assigned Scores

Dependent Variable:	Rate Score					Commission Score		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Rate	-0.056	-0.040	-0.184	-0.250	-0.040			
	(0.023)	(0.022)	(0.041)	(0.036)	(0.021)			
Commission						0.008	0.010	0.018
						(0.004)	(0.005)	(0.009)
Provider Fixed Effects	no	yes	no	no	no	no	yes	no
Auction Fixed Effects	no	no	yes	yes	yes	no	no	yes
R^2	0.050	0.452	0.925	0.910	0.984	0.110	0.280	0.972
# of Observations	106	106	106	83	23	62	62	62

Notes: The table summarizes OLS regression results. The unit of observation is a bid. The dependent variable is the rate score in columns (i)-(v) and the commission score in columns (vi)-(viii). We measure the rate score and the commission score as the fraction of the maximum available points that is awarded to a bid. The independent variables are the rate, which we measure as the price of a 15-minute local collect phone call, and the commission, which we measure in terms of dollars per inmate-month. Columns (ii)-(iii) and (vii)-(viii) also include provider or auction fixed effects, as noted. The sample in columns (i)-(iii) includes bids in auctions that place a positive weight on rates in the scoring rule. The sample in column (iv) includes bids in auctions that place a positive weight on rates but not on commissions. The sample in column (v) includes bids in auctions that place a positive weight on both rates and commissions. The sample in column (vi)-(vii) includes bids in auctions that place a positive weight on commissions. Robust standard errors are in parentheses.

and (iii) show that a negative relationship also exists in the presence of provider and auction fixed effects, respectively. Thus, the results indicate that any given provider tends to receive lower rate scores when it proposes higher rates and that, in any given auction, the providers that propose higher rates tend to receive lower scores.

Columns (iv) and (v) use subsamples that differ based on whether a positive weight is placed on the commission in the auction's scoring rule (in addition to the rate). The coefficient on the rate is negative in both cases, but its magnitude is larger for auctions that do not consider commissions (column (iv)), and the difference is statistically significant. This raises the possibility that procuring entities that solicit commissions may implicitly reduce the role of rates in the scoring rule, even holding fixed the formal weight that is placed on pricing terms in the RFP. In our empirical model, such a practice would produce contracts that, in equilibrium, feature higher rates and larger commission payments.

Columns (vi)-(viii) focus on commissions.[24] The univariate regression of column (vi) shows that a $1.00 increase in the proposed commission payment (per inmate-month) is associated with a commission score that is 0.008 higher, on average. Columns (vii) and (viii) show that the relationship between commissions and commission scores is robust to the inclusion of provider and auction fixed effects. The strength of these relationships does not appear to depend on whether a positive weight is placed on rates in the auction's scoring rule.

[24]We omit from the sample three bids that receive a commission score of zero even with large proposed commissions. One was in the 2014 Utah auction, and the other two were in the 2019 Utah auction. We suspect the bidders were disqualified for other reasons. If we include these three bids, the coefficient in column (vi) decreases in magnitude and is no longer statistically significant, the coefficient in column (vii) is roughly unchanged, and the coefficient in column (viii) increases to 0.025 and remains statistically significant.

Table 4: Relationships Between Scoring Weights and Proposed Terms

Dependent Variable:	Rate			Commission		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Rate Weight	-0.056	-0.614	-0.324			-17.54
	(0.479)	(0.550)	(0.484)			(8.194)
Commission Weight			5.64	20.143	17.015	16.456
			(0.744)	(3.193)	(4.079)	(4.179)
Provider Fixed Effects	no	yes	yes	no	yes	yes
R^2	0.000	0.271	0.485	0.236	0.319	0.366
# of Observations	106	106	106	62	62	62

Notes: The table summarizes OLS regression results. The unit of observation is a bid. The dependent variable in columns (i)-(iii) is the rate, which we measure as the price of a 15-minute, local collect phone call. The dependent variable in columns (iv)-(vi) is the commission, which we measure in terms of dollars per inmate-month. The independent variables are the weights that the scoring rule places on the rate and the commission, respectively. Columns (ii)-(iii) and (v)-(vi) also include provider fixed effects. The sample in columns (i)-(iii) includes bids in auctions that place a positive weight on rates in the scoring rule. The sample in column (iv)-(vi) includes bids in auctions that place a positive weight on commissions. Robust standard errors are in parentheses.

Overall, there is statistical support for the scores being responsive to the financial terms proposed by bidders. Later, in the empirical model, we interpret the regressions as providing deterministic *scoring functions* that connect the scores and financial terms.

3.2 Auction Designs and Bids

Providers have an incentive to propose more generous financial terms (lower rates and higher commissions) when financial terms receive more weight in the scoring rule. In this section, we explore whether the empirical relationship between the auction weights and the financial terms that providers propose are consistent with those incentives. Our approach is to regress the rates and the commissions on the auction weights. The coefficients are identified by variation in weights across auctions, as bids into the same auction are subject to the same weights.

Table 4 summarizes the results. The columns on the left use the proposed rate as the dependent variable. Column (i) is a univariate regression on the rate weight, column (ii) adds provider fixed effects, and column (iii) also adds the commission weight as an explanatory variable. The coefficient on the rate weight is negative, consistent with our expectations, but not statistically different from zero. The magnitude of the coefficient in column (ii) corresponds to an increase in the rate weight by 25 percentage points being associated with proposed rates that are \$0.15 less expensive per 15-minute local collect call ($0.614 \times 0.25 = 0.154$). Interestingly, in column (iii), we find that higher commission weights are associated with higher proposed rates, and the relationship is statistically significant. The magnitude of the coefficient suggests an economically meaningful relationship, as an increase in the commission weight of 25 percentage points is associated with proposed rates that are \$1.41 higher.

There are at least two mechanisms that could explain the relationship between commission weights and proposed rates. First, as we discussed in the previous section, commissions appear to affect how procuring entities translate proposed rates into rate scores. Specifically, the empirical relationship between rates and rates scores is more modest if commissions receive weight in the scoring rule. Providers may infer that a higher commission weight implies that rates matter less in the auction, even holding the rate weight fixed. Second, a higher rate can provide more revenue to the provider, allowing it to pay a higher commission profitably. Thus, higher commission rates may induce providers to propose higher rates. These two mechanisms are not mutually exclusive, and both may contribute to the empirical variation in our data.

Columns (iv)-(vi) use the proposed commission as the dependent variable. The univariate regression of column (iv) shows that providers tend to submit bids with higher commissions when the auction weights commissions more heavily in the scoring rule. The coefficient indicates that an increase in commission weight of 25 percentage points is associated with proposed commissions per inmate-month that are \$5.03 higher. This relationship is robust to the inclusion of provider fixed effects (column (v)). Finally, column (vi) shows that commissions tend to be lower in auctions that place greater weight on rates. A plausible mechanism for this last effect is that a larger weight on rates induces providers to propose lower rates, and it may then be less profitable for the provider to propose the same level of commission.

3.3 The Demand for Calls

In this section, we explore how calling patterns change with price reductions that occur in two states and then exploit the variation to estimate the demand of incarcerated individuals for calls. The first state is New York. In 2010, it eliminated a per call connection charge of \$1.28 and reduced the per minute price from \$0.068 to \$0.048. The implied rate of a 15-minute call fell from \$2.30 to \$0.72. The second state is New Jersey, which implemented a series of price reductions from January 2014 to May 2015 that lowered the per minute price from \$0.33 to \$0.044 (from \$4.95 to \$0.66 for a 15-minute call).[25]

We examine four variables before and after these price changes: the number of calls per person/month, the minutes per call, the calling minutes per person/day, and the expenditure per person/month. Each variable is an average across all incarcerated individuals in the state prison system and is observed monthly. A visual inspection of the data reveals that each variable is reasonably stable before the price changes (Appendix Figure B.1). Afterwards, the number of calls and calling minutes increase, yet expenditures decrease. In New York, the minutes per call decreased slightly, consistent with incarcerated individuals substituting to shorter calls

[25]In both states, the same prices were charged for local, intrastate, and interstate calls, and for different payment methods (e.g., debit and collect). In New Jersey, the first change, which reduced the per minute price from \$0.33 to \$0.19, occurred in February 2014, on the direction of the DOC. We observe subsequent reductions to \$0.17 in March 2014, to \$0.15 in September 2014, and finally to \$0.044 in May 2015. The last change was due to a new state law. There was no per call connection charge in New Jersey before or after these changes.

Table 5: Calling Patterns Before and After Price Reductions

	New York				New Jersey			
	Before	After	Change	p-value	Before	After	Change	p-value
Number of Calls	8.82	15.86	7.04	0.000	8.32	27.00	18.68	0.000
Minutes per Call	20.81	18.87	-1.94	0.000	11.05	11.18	0.13	0.011
Minutes per Day	6.04	9.83	3.80	0.000	3.03	9.91	6.87	0.000
Expenditures	23.77	14.35	-9.43	0.000	30.36	13.24	-17.12	0.000

Notes: The table provides the average number of calls per inmate-month, average minutes per call, average minutes per inmate-day, and average expenditure per inmate-month (in dollars), both before and after price reductions in New York and New Jersey. It also provides the change and the p-value from a sample means test of the null hypothesis that the change equals zero. For New York, we use a "before" period of January-December 2009 and an "after" period of April 2010 - March 2011. For New Jersey, we use a "before" period of January-October 2013, as some data are unavailable for November-December 2013, and an "after" period of January-December 2016.

in response to the elimination of per call connection charges. In New Jersey, where per call connection charges did not exist, the minutes per call changed much less.

Table 5 summarizes the changes quantitatively, using "before" and "after" periods that we select based on our visual inspection of the data. The average number of calls per person/month increases from 8.82 to 15.86 in New York and 8.32 to 27.00 in New Jersey. Sample means tests indicate that these changes are statistically different from zero at the 1% level. Similar patterns are observed for the average minutes per inmate-day spent on the phone. Average expenditures per inmate-month decrease from \$23.77 to \$14.35 in New York and from \$30.36 to \$13.24 in New Jersey, and the changes again are statistically significant. Thus, the raw data are consistent with price being a meaningful determinant of phone usage.

As the empirical model of procurement requires a demand function, we extend our analysis and estimate a simple linear relationship between quantities and prices:

$$q_{it} = \beta_0 + \beta_1 r_{it} + u_{it} \tag{1}$$

where i and t index the state and time period, respectively, q is the number of calls per person/month, r is the price of a 15-minute phone call (the rate), and v captures seasonal and idiosyncratic factors. We estimate the model using OLS with observations at the state-month level. We assume that the rate is orthogonal to the error term so that OLS obtains unbiased coefficients. Our assumption would be violated if the state-level rate changes coincide with changes in prison policies that affect prisoners' access to phones. However, we have not seen evidence that such policy changes occurred.[26]

We estimate the model first by pooling the data from New York and New Jersey, and then by using subsample regressions for each state. Although these approaches produce similar results (see Appendix Table B.2), we interpret the subsample regressions as more reliably summa-

[26]Because variation in rates arises only due to the state-level policy changes, a 2SLS approach to estimation that uses state-level policy changes as instruments for price obtains identical point estimates.

rizing the variation in the data. To obtain the demand function that we use in the model of procurement, we average the two subsample regressions: $q = 24.47 - 4.41r$. The associated revenue-maximizing rate of a 15-minute call is \$2.78. The rate elasticities of demand evaluated at rates of \$1.00, \$2.00, \$3.00, and \$4.00 are 0.22, 0.56, 1.18, and 2.58, respectively. A rate that falls on the inelastic portion of the demand curve can maximize profit if the provider has fee revenue or if lower rates increase the likelihood of being selected by the procuring entity.[27]

4 Empirical Model

4.1 Setup

We model ICS procurement as a sealed-bid first-score auction with multi-dimensional bidder heterogeneity. We index procuring entities ("buyers") with i and prospective providers ("firms") with j. The number of firms, J_i, is exogenously determined. Firms differ in their costs and technical capabilities. The buyer specifies a scoring rule in the procurement process that converts technical capabilities, rates, and commissions into a single number (a "score"). Firms bid by submitting scores, and the firm with the highest score wins. When submitting bids, firms know their cost and have a noisy signal about how the buyer will assess their capabilities. Given the realized assessments, the winning provider must deliver a contract worth its bid.[28]

Consistent with observed industry practice, we assume that the scoring rule is additively separable in the rate, the commission payment, and the technical capabilities of the firm:

$$s_i(r_{ij}, k_{ij}, v_{ij}) = \omega_i^r s_i^r(r_{ij}) + \omega_i^k s_i^k(k_{ij}) + \omega_i^v v_{ij} \tag{2}$$

where r_{ij} is the rate, k_{ij} is the commission, $s_i^r(\cdot)$ and $s_i^k(\cdot)$ are *scoring functions* that translate these objects into numeric scores, v_{ij} is the score that the buyer assigns to the firm's technical capabilities (the "technical score"), and $(\omega_i^r, \omega_i^k, \omega_i^v)$ are weights that are non-negative and sum to one. The rate refers to the price of a 15-minute call and the commission is a payment per inmate. We assume that $s_i^r(\cdot)$ is strictly decreasing and $s_i^k(\cdot)$ is strictly increasing.

[27]The FCC has calculated arc elasticities using changes in rates that occur in other specific localities that are similar in flavor to what we observe in New York and New Jersey. The midpoint-adjusted arc elasticity is given by:

$$e = \left| \frac{Q_2 - Q_1}{(Q_2 + Q_1)} \right| \div \left| \frac{P_2 - P_1}{(P_2 + P_1)} \right|$$

The results "lead the Commission to conservatively conclude inmate calling services have a demand elasticity of at least 0.3." See paragraphs 197-198 of FCC (2021b). Using the same formula, we obtain midpoint-adjusted arc elasticities of 0.55 for New York and 0.69 for New Jersey.

[28]We assume that buyers bid scores rather than financial terms because it facilitates the analysis of equilibrium. In Asker and Cantillon (2008), this substitution is simply a change of variables because there is no evaluation uncertainty. With evaluation uncertainty about technical capabilities, the *ex post* realizations load onto win probabilities if firms bid rates and commissions, and onto those financial terms if firms bid scores. Due to this sensitivity, we focus our empirical analysis on the expected equilibrium rates and commissions rather than their full distributions.

The profit of the selected firm depends on the rate and commission in the contract it delivers, and on its costs. Letting firm j be the selected firm, profit is given by

$$\pi(r_{ij}, k_{ij}, c_{ij}, M_i) = [(r_{ij} - c_{ij})q(r_{ij}) - k_{ij}]\, M_i \tag{3}$$

where c_{ij} is the average cost of a call, $q(\cdot)$ is a demand function that determines the number of calls per inmate, and M_i is the population of the prison system. We apply the normalization $M_i = 1$. The average cost of a call reflects data center and installation expenses, both of which scale with demand, offset by any ancillary fee revenue. Thus, the average cost can be negative if ancillary fees exceed the explicit cost of service.[29] The technical capabilities of the firm do not enter the demand function because they primarily reflect the ability of the firm to provide security services, which we assume are not valued by incarcerated individuals.

The auction weights, scoring functions for rates and commissions, number of bidders, and demand function are common knowledge. We assume that when bids are submitted, each firm knows its cost, c_{ij}, and has a signal, ξ_{ij}, of the technical score it will receive. As these objects will determine equilibrium strategies, the vector (c_{ij}, ξ_{ij}) characterizes the multidimensional *type* of the firm. We also assume that the technical score becomes common knowledge after firms submit bids, and is weakly increasing in the signal. Formally,

ASSUMPTION 1 (Information). *The cost, c_{ij}, and the signal about the technical score, ξ_{ij}, are the private information of firm j, with $c_{ij} \sim^{i.i.d.} F_C$ and $\xi_{ij} \sim^{i.i.d.} F_S$. The corresponding probability distribution functions, f_C and f_S, are absolutely continuous with support over $[\underline{c}, \bar{c}] \in \mathbb{R}$ and $[\underline{\xi}, \bar{\xi}] \in \mathbb{R}$. The distributions F_C and F_S are common knowledge, and $c_{ij} \perp \xi_{ij}\ \forall ij$.*

ASSUMPTION 2 (Technical Scores). *The distribution of technical scores conditional on the signal realization ξ is given by $F_{V|S}(v|\xi)$. For any $\xi' \geq \xi$ it holds that $F_{V|S}(v|\xi') \leq F_{V|S}(v|\xi)$.*

The firm that submits the highest bid wins the auction. We assume that it chooses the rate and commission that maximize its profit, while also making the contract worth its bid. Letting firm j be the winner, and $\hat{s}_{ij}$ be its bid, the requirement is $s_i(r^*_{ij}, k^*_{ij}, v_{ij}) = \hat{s}_{ij}$, where r^*_{ij} and k^*_{ij} are solutions for the rate and commission, respectively. As we discuss later, these solutions exist under our maintained parametric assumptions. Thus, the profit of the winning firm can be expressed as an implicit function of the score that it bids, its cost, and its technical score: $\pi(r^*_{ij}, k^*_{ij}, c_{ij}) = \pi(\hat{s}_{ij}, c_{ij}, v_{ij})$.

4.2 Equilibrium

Our equilibrium concept is symmetric Bayes-Nash equilibrium. Each firm submits a score according to a strategy, $\sigma_{ij}(c_{ij}, \xi_{ij})$, that maximizes its expected profit, conditional on the strate-

[29] At the time the auction occurs, c_{ij} can be interpreted as the marginal cost associated with winning the contract, measured on a per inmate-month basis. Once installation expenses have been incurred, they are sunk, so c_{ij} is not the marginal cost of an individual call.

gies of other firms. Under symmetry, all firms use the same strategy, so we have $\sigma_{ij}(c_{ij}, \xi_{ij}) = \sigma_i(c_{ij}, \xi_{ij})$ for all j. The equilibrium strategy satisfies the following condition:

$$\hat{s}_{ij} = \sigma_i(c_{ij}, \xi_{ij}) = \arg\max_{\hat{s}} Pr(\hat{s} \geq \max_{k=1,\ldots,J_i} \{\sigma_i(c_{ik}, \xi_{ik})\}) \int \pi\left(\hat{s}, c_{ij}, v\right) dF_{V|S}(v|\xi_{ij}) \tag{4}$$

where we use $Pr(\cdot)$ to refer to the probability of an event. The first term in the maximand is the probability that firm j wins the auction given the bid, and the second term is the expected profit associated with the bid. Firms balance that submitting a higher score increases their probability of winning but decreases their expected profit conditional on winning.

We distinguish two types of auctions in our data that require different treatments. In the first set, commissions enter the scoring rule ($\omega_i^k > 0$). For these auctions, we obtain an analytical expression of the equilibrium (Section 4.3) that forms the basis for our estimation approach (Section 5.3). In the second set, buyers predetermine the commission ($\omega_i^k = 0$). If firm j wins auction i with a score bid of $\hat{s}_{ij}$, the rate is pinned down by the equation $s_i(r_{ij}, v_{ij}) = \hat{s}_{ij}$, as the firm must deliver a contract worth its bid. A unique solution exists because $s_i(\cdot)$ is strictly decreasing in r. The equilibrium strategy itself solves a series of differential equations, one for each cost and signal combination (akin to, e.g., Bajari, 2001; Campo et al., 2003; Carril et al., 2022).[30] Analytical and numerical solutions are unavailable except for special cases. In our model, the complications include evaluation uncertainty, multi-dimensional heterogeneity, and that the rate is not a transfer between the firm and the buyer. We use this set of auctions to validate our estimation results, approximating the equilibrium using methods developed in Bajari (2001) and Armantier et al. (2008). We describe these methods later (Section 5.4.2).

4.3 Equilibrium with Commissions in the Scoring Rule

If commissions enter the scoring rule, then our empirical model falls into a class of scoring auctions studied in Asker and Cantillon (2008), given that the following key assumptions hold:

ASSUMPTION 3 (Quasi-linear scoring rule). *There exists an order-preserving transformation of $s_i(r, k, v)$, denoted $\phi_i(r, k, v)$, that satisfies $\phi_i(r, k, v) = \psi_i(r, v) + k$.*

ASSUMPTION 4 (Bilateral Surplus). *The bilateral surplus of the buyer and the winning supplier, $\psi_i(r, v) + (r - c)q(r)$, is bounded and strictly concave in r.*

Assumption 3 holds if $\omega_i^k > 0$ due to equation (2) and our earlier assumption that the commission scoring function, $s_i^k(\cdot)$, is strictly increasing. If the scoring rule, $s_i(\cdot)$, reflects the buyer's preferences, then the transformation, $\phi_i(\cdot)$, expresses those preferences in currency units. The assumption also implies that any bid, $\hat{s}_{ij}$, has an equivalent bid, $\tilde{s}_{ij} \equiv \tilde{s}_i(\hat{s}_{ij})$, expressed in

[30] Bidders with higher technical score signals are more competitive in expectation, even though they draw costs from the same distribution. As they also submit single-dimensional rate bids, it renders the setting with $\omega_i^k = 0$ close to asymmetric private value first-price auction models.

currency units, where $\tilde{s}(\cdot)$ is strictly increasing. Assumption 4 holds under the parametric restrictions we introduce later (Section 5.1). The commission is a transfer that does not affect bilateral surplus.

Under assumptions 3 and 4, the rate and commissions that maximize the profit of firm j, conditional on winning with a bid of $\hat{s}_{ij}$ and subject to $s_i(r_{ij}, k_{ij}, v_{ij}) = \hat{s}_{ij}$, can be characterized as follows. The rate is set to maximize bilateral surplus given the firm's cost:

$$r^*_{ij} = r^*_i(c_{ij}) = \arg\max_r \big(\psi_i(r, v_{ij}) + (r - c_{ij})q(r)\big) \tag{5}$$

Assumption 4 ensures that a unique solution exists. If the buyer predetermines the rate, let r^*_{ij} correspond to the predetermined rate. In either case, the commission must then satisfy:

$$s_i(r^*_{ij}, k^*_{ij}, v_{ij}) = \hat{s}_{ij} \tag{6}$$

A unique solution exists because the scoring rule is additively separable, and the scoring function for commissions, $s^k_i(\cdot)$, is strictly increasing. Putting these equations together, the winning firm sets a rate that maximizes the size of the "pie" it creates for itself and the buyer, and a commission that provides "slices" based on the scoring rule and its bid. A firm that wins with a more aggressive bid must provide a larger slice to the buyer, all else equal.

A few observations can be made. Equations (5) and (6) show that the rate and commission of the winning firm, conditional on its bid, are unaffected by the bids of other firms. This allows equilibrium strategies to be expressed in terms of the single-dimensional score bid, $\sigma_i(c_{ij}, \xi_{ij})$, even with multidimensional bidder types and bid components. Other empirical models of scoring or scaling auctions share a similar property (e.g., Athey and Levin, 2001; Lewis and Bajari, 2011; Bajari et al., 2014; Bolotnyy and Vasserman, 2023). In our context, the simplification is due to the quasi-linearity of the scoring rule (Assumption 3). Another observation is that the additive separability of the scoring rule in r and v implies that r^* does not depend on v, even though $\psi_i(\cdot)$ does. Thus, a firm's technical score matters for the commission but not the rate.

We now turn to the equilibrium bidding strategy. Let the *pseudotype* of the firm, x_{ij}, be the maximum bilateral surplus the firm expects to generate if it wins the auction:

$$x_{ij} = x_i(c_{ij}, \xi_{ij}) = (r^*_{ij} - c_{ij})q(r^*_{ij}) + \int \psi_i(r^*_{ij}, v)dF_{V|S}(v|\xi_{ij}) \tag{7}$$

Asker and Cantillon (2008) establish that firms that have the same pseudotype adopt the same strategies in equilibrium, so we have $\sigma_i(c_{ij}, \xi_{ij}) = \sigma_i(x_{ij})$. They also establish that the equilibrium score increases monotonically in the pseudotype, so the firm with the highest pseudotype wins the auction. Applying a change of variables to equation (4), using equation (7), we obtain an expression for the equilibrium bidding strategy:

$$\sigma_i(x_{ij}) = \arg\max_{\tilde{s}} Pr(\tilde{s} \geq \max_{k=1,\dots,J_i} \{\sigma_i(x_{ik})\})(x_{ij} - \tilde{s})) \tag{8}$$

where, again, $\tilde{s}$ is a bid expressed in currency units; in a slight abuse of notation, the strategies are also in currency units. The first term in the maximand is the probability of winning, and the second term is the portion of bilateral surplus the firm expects to retain as profit if it wins.

The probability that a firm wins with a bid of $\tilde{s}$ equals the probability that $J_i - 1$ bidders have a pseudotype below $\sigma_i^{-1}(\tilde{s})$, relying on symmetry and monotonicity of the equilibrium:

$$Pr(\tilde{s} \geq \max_{k=1,\dots,J_i} \{\sigma_i(x_{ik})\}) = T_i \left(\sigma_i^{-1}(\tilde{s})\right)^{J_i-1} \tag{9}$$

where $T_i(\cdot)$ is the distribution of pseudotypes, given as

$$T_i(x) = \int\int \mathbb{1}\big(x_i(c,\xi) \leq x\big) dF_C(c) dF_S(\xi) \tag{10}$$

Denoting the support of $T_i(\cdot)$ by $[\underline{t}, \bar{t}]$ and adding the boundary condition that $\sigma_i(\underline{t}) = \underline{t}$, the equilibrium (score) bidding strategy is given by

$$\sigma_i(x_{ij}) = x_{ij} - \frac{\int_{\underline{t}}^{x_{ij}} T_i(u)^{J_i-1} du}{T_i(x_{ij})^{J_i-1}} \tag{11}$$

Equation (11) characterizes the unique symmetric Bayes-Nash equilibrium score for any auction in which commissions receive weight in the scoring rule (Asker and Cantillon, 2008). The rate of the winning bidder is set according to equation (5) if it is subject to bidding and at the predetermined level otherwise. The commission of the winning bidder is determined by equation (6) after plugging in for the equilibrium score.

5 Estimation

We estimate the model in parts. We discuss the scoring functions and demand, then the technical score distribution, then the cost distribution and the informativeness of the technical score signal. We place parametric restrictions on the model throughout to accommodate estimation with a small sample. We also conduct assessment exercises comparing the model's equilibrium predictions to out-of-sample outcomes.

5.1 Scoring Functions

We assume that the scoring functions for rates and commissions are linear in their arguments and that they are common knowledge to the bidders. The scoring functions take the following form:

$$s_i^r(r_{ij}) = \alpha_{0i}^r + \alpha_1^r r_{ij} \tag{12}$$
$$s_i^k(k_{ij}) = \alpha_{0i}^k + \alpha_1^k k_{ij} \tag{13}$$

We account for unobserved heterogeneity through the fixed effects of the scoring functions. We estimate the scoring functions as described in Section 3.1. The slope coefficients are in columns (iv), (v), and (viii) in Table 3. Accounting for unobserved auction-level heterogeneity affects the slopes (e.g., compare columns (i) and (iii)). This matters for the parameters of the cost distribution that we estimate later; failing to account for this type of unobserved heterogeneity overestimates the variance, consistent with the empirical results of Krasnokutskaya (2011).[31]

For auctions in which commissions enter the scoring rule ($\omega_i^k > 0$), the linearity of demand and the scoring functions ensures that assumptions 3 and 4 hold. Furthermore, substituting into equation (2) and rearranging yields an analytical solution for the transformed scoring rule:

$$\psi_{ij} \equiv \psi_i(r_{ij}, v_{ij}) = \frac{\omega_i^r \alpha_1^r}{\omega_i^k \alpha_1^k} r_{ij} + \frac{\omega_i^v}{\omega_i^k \alpha_1^k} v_{ij} + \frac{\omega_i^k \alpha_{0i}^k + \omega_i^r \alpha_{0i}^r}{\omega_i^k \alpha_1^k} \tag{14}$$
$$\phi_{ij} \equiv \phi_i(r_{ij}, k_{ij}, v_{ij}) = \psi_{ij} + k_{ij} \tag{15}$$

The objects in these equations are data or estimated parameters. We also obtain a closed-form solution for equilibrium rates in these auctions. Substituting these objects into equation (5), the first order conditions yield

$$r_{ij}^* = \frac{1}{2}\left(-\frac{\beta_0}{\beta_1} + c_{ij} - \frac{1}{\beta_1}\frac{\omega_i^r \alpha_1^r}{\omega_i^k \alpha_1^k}\right) \tag{16}$$

As already noted, equilibrium rates are invariant to the number of competitors in this setting. Given the additive separability of $s_i(\cdot)$ in r and v, they are also independent of the firm's technical capabilities. They depend on the auction weights only through the ratio of $\omega_i^r \alpha_1^r$ to $\omega_i^k \alpha_1^k$, so changes to the weight placed on technical capabilities do not affect rates if the relative weight placed on rates and commissions is unchanged. Finally, the equilibrium rate is lower than the rate set by a profit-maximizing monopolist.

For auctions in which commissions do not enter the scoring rule ($\omega_i^k = 0$), the linearity of demand and the scoring functions implies that the rate that solves $s_i(r_{ij}, k_i, v_{ij}) = \hat{s}_{ij}$ has the following analytical solution:

$$r_{ij}^* = \frac{1}{\omega_i^r \alpha_1^r}\left(\hat{s}_{ij} - \omega_i^r \alpha_0^r - \omega_i^v \left(\xi_{ij} + \epsilon_{ij}\right)\right)$$

[31] We treat the scoring functions as deterministic and do not explicitly incorporate the regression residuals in the model. As a practical matter, the R^2 values that we obtain are high, indicating that the residuals do not matter much for outcomes. Were we to incorporate the scoring function residuals as stochastic shocks realized after bids are placed, then they would enter in the same way as the shock to the technical score.

This rate is invariant to the number of competitors, conditional on the score bid, $\hat{s}_{it}$. However, competition affects the equilibrium bids in these auctions, so it also matters for rates.

5.2 Distribution of Technical Scores

We observe the technical scores (v_{ij}) but not the signals (ξ_{ij}). For the unconditional distribution of technical scores, we assume a normal distribution with auction-specific means ($\bar{v}_i$) and a variance that is common across auctions, so that $\left(v_{ij} - \bar{v}_i\right) \sim^{i.i.d.} N(0, \sigma_v^2)$. We estimate the auction-specific means by regressing the technical scores on auction fixed effects using the full sample of 155 bids. We estimate the variance parameter (σ_v^2) using the variance of the residuals. Thus, we use within-auction variation to determine the extent of provider differentiation. This isolates the more relevant variation for bidding incentives. The standard deviation of the residuals is 0.12. Appendix Figure B.2 plots the empirical distribution of residuals and the (re-centered) unconditional technical score distribution we estimate.

We assume that the evaluation noise (denoted by ϵ) is additive to the signal and that $\epsilon \sim^{i.i.d.} N(0, \sigma_\epsilon^2)$. By properties of the sums of normal distributions, this implies that the variance of the signal is given by $\lambda\sigma_v^2$, where $\lambda \in [0, 1]$ is a natural measure of the relative variances of signal and noise as given by

$$\lambda = \frac{\sigma_\xi^2}{\sigma_\xi^2 + \sigma_\epsilon^2} = \frac{\sigma_\xi^2}{\sigma_v^2} \tag{17}$$

Lower values of λ imply that the signal is less informative; $\lambda = 0$ implies that the signal contains no information, whereas $\lambda = 1$ implies no evaluation uncertainty. We assume that the auction-specific conditional technical score distribution, $F_{V|S}(\cdot; \xi_{ij})$, is normally distributed with mean $\bar{v}_i + \xi_{ij}$ and variance $(1-\lambda)\sigma_v^2$. We estimate λ and the cost parameters using simulated method of moments, as discussed in the next section.

5.3 Cost Distribution and Informativeness of the Signal

We assume the cost distribution is normal with mean μ_c and standard deviation σ_c. We estimate the mean and standard deviation, along with the λ, which characterizes the informativeness of the signal, using simulated method of moments (e.g., Pakes and Pollard, 1989; McFadden, 1989). The identifying assumption is that differences between observed auction outcomes and those implied by the true parameters are orthogonal to a set of instruments. Implementation requires computing the symmetric Bayes-Nash equilibrium for every candidate parameter vector. To reduce the computational burden, we take two steps. First, we focus on auctions for which commissions enter the scoring rule so that we can use the framework of Asker and Cantillon (2008). Second, we construct moments using the bids of the winning firms, which can be calculated instantaneously by analyzing the revenue-equivalent second-score auction (e.g., Laffont et al., 1995).[32] Thus, we sidestep the integration required to solve equation (11).

The equilibrium outcomes that enter the moments are the winning firm's rate and commission. Letting $l = 1, \ldots, L$ denote simulated auctions, each of which comprises draws on cost, signals, and technical scores for the auction-specific number of bidders, the empirical moments take the form

$$\mathbf{m}_r(\boldsymbol{\theta}) = \frac{1}{I}\sum_i \left(r_i^{(1)} - \frac{1}{L}\sum_{l=1}^{L} \tilde{r}_{il}^{(1)}(\boldsymbol{\theta}) \right) g\left(\mathbf{Z}_i\right) \tag{18}$$

$$\mathbf{m}_k(\boldsymbol{\theta}) = \frac{1}{I}\sum_i \left(k_i^{(1)} - \frac{1}{L}\sum_{l=1}^{L} \tilde{k}_{il}^{(1)}(\boldsymbol{\theta}) \right) g\left(\mathbf{Z}_i\right) \tag{19}$$

where $\boldsymbol{\theta} = (\mu_c, \sigma_c, \lambda)$ is a vector of parameters, I is the number of auctions, the superscript $^{(1)}$ identifies the winning bidder, $\tilde{r}_{il}^{(1)}(\boldsymbol{\theta})$ and $\tilde{k}_{il}^{(1)}(\boldsymbol{\theta})$ are simulated outcomes for the rate and the expected commission of the winning bidder, and $g\left(\mathbf{Z}_i\right)$ is a function of instruments.

The variables we include in $\mathbf{Z}_i$ are the number of bidding firms and the auction weights on rates and commissions. We specify a second-order polynomial of these variables to construct the $g(\cdot)$ function. As the polynomial exhibits collinearity, we apply principal components analysis and isolate four principal components that account for 99.4% of the variance. We let $g\left(\mathbf{Z}_i\right) = \tilde{\mathbf{Z}}_i$, where $\tilde{\mathbf{Z}}_i$ includes the four principal components and a constant. The parameter estimates are given by

$$\hat{\boldsymbol{\theta}} = \underset{\theta \in \Theta}{\arg\min} \left(\mathbf{M}(\boldsymbol{\theta})' \mathbf{A}^{-1} \mathbf{M}(\boldsymbol{\theta}) \right) \tag{20}$$

where the vector $\mathbf{M}(\boldsymbol{\theta})$ contains the empirical moments and $\mathbf{A}$ is some positive definite weighting matrix. We use the standard two-step estimation procedure (Hansen, 1982). In the first step, we set $\mathbf{A} = \tilde{\mathbf{Z}}'\tilde{\mathbf{Z}}$. In the second step, we use an estimate of the optimal weighting matrix. Asymptotic consistency obtains as the number of auctions and simulations grows large. We simulate each of the auctions in the sample 1,000 times.

Table 6 summarizes the results. We estimate the mean and standard deviation of the cost distribution to be 0.22 and 0.52, respectively. The cost of the winning firm, averaging across auctions and simulation draws, is -0.08. Thus, the results are consistent with ancillary fee revenue largely offsetting the explicit cost of service for the firms most likely to win. Observing contracts that specify a rate less than \$0.50 (Appendix Table B.1) corroborates that costs (net of fees) are unlikely to be large for winning firms.[33] Our results are also consistent with Bazelon et al. (2023), which places explicit costs in the \$0.15-\$0.18 range for a 15-minute call.

[32] In the revenue-equivalent second-score auction, the dominant strategy is to propose a score that equals expected bilateral surplus (i.e. the pseudotype). The second-best pseudotype pins down the value of the contract that the winning firm must deliver. Given a set of simulated draws (c_{ij}, ξ_{ij} for $j = 1 \ldots, J$), we calculate the pseudotype of each firm, determine the value of the winning contract, and calculate the expected rate and commission.

[33] See Florida in 2017, Minnesota in 2016 and 2019, Nebraska in 2016, New Jersey, West Virginia, and Wisconsin in 2018. The rates are \$0.19, \$0.33, \$0.33, \$0.19, \$0.40, \$0.48, and \$0.17 respectively.

Table 6: Cost Distribution and Informativeness of Signal

		Estimate	St. Error
Estimation Results			
Mean of Costs	μ_c	0.22	(0.04)
Standard Deviation of Costs	σ_c	0.52	(0.12)
Informativeness of Signal	λ	0.16	(0.07)
Derived Equilibrium Statistics			
Rate	$r_i^{(1)}$	2.10	
Commission	$k_i^{(1)}$	20.30	
Profit	$\pi_i^{(1)}$	12.32	

Notes: Estimation is with simulated method of moments. The unit of observation is an auction and the sample comprises 16 auctions in our data that place a positive weight on commissions. We exclude Vermont because the commission weight is only two percent. Point estimates and standard errors are shown. We also report the winning firm's expected rate, commission, and profit, averaging across simulation draws and auctions. The rate is for a 15-minute call. The commission and profit are per inmate-month.

We estimate that the signal accounts for 16% of the variance in the technical score ($\lambda = 0.16$). The precision with which the parameter is estimated allows us to reject the extreme cases of an uninformative signal or no evaluation uncertainty (standard error of 0.07). Further, we obtain standard deviations of the signal and the evaluation noise of $\sigma_\xi = 0.05$ and $\sigma_\epsilon = 0.11$, respectively, using equation (17). Our results are consistent with firms having significant uncertainty about how buyers evaluate their technical capabilities.[34]

Evaluation uncertainty has meaningful implications for economic outcomes. There are two main mechanisms at play. First, a more informative signal means that firms with desirable technical capabilities perceive a higher probability of winning and bid less aggressively. The opposite holds for firms with undesirable capabilities, but such firms are less likely to win, so if this mechanism dominates, then equilibrium profit tends to increase with the informativeness of the signal. Furthermore, as the auction winner is less likely to be a low-cost firm, equilibrium rates are higher on average. Second, a more informative signal strengthens the marginal effect of the bid on the probability of winning (i.e., by reducing "luck"), causing all firms to bid more aggressively. In our application, the first mechanism dominates, as equilibrium rates and profit increase with the informativeness of the signal (Appendix Figure B.3).[35]

Table 6 also reports equilibrium statistics obtained by averaging across auctions and simulation draws. The mean rate implied by the model is $2.10 per 15-minute call, and the mean

[34] We conduct an additional empirical analysis to investigate this point, based on the idea that if firms can (mostly) anticipate their technical scores, then the technical scores should be correlated with rates and commissions. We do not see such correlations in the bid-level data. If we add the technical score as an explanatory variable to the regressions of Table 4, its coefficient never approaches statistical significance. In the column (i) regression, its p-value is 0.77.

[35] In that sense, our results differ from those of Takahashi (2018), who finds that the second mechanism dominates in a sample of design-build auctions where the firm with the lowest price per quality score ratio wins the contract.

commission is \$20.30 per inmate-month. These are close to the empirical means of \$2.27 and \$18.51 that we calculate for the auctions in the sample. The equilibrium rates imply that average non-fee revenue is \$31.16 per inmate-month. Thus, on average, the commission accounts for 59% of non-fee revenue. Also factoring in the explicit cost of service and fee revenue, the model implies that the profit of the winning firm is \$12.46 per inmate-month on average.

5.4 Model Assessments

The simulated method of moments uses data on the winning bids in auctions for which commissions enter the scoring rule. In this section, we examine model predictions for (1) the full set of bids, including losing bids, in the same set of auctions and (2) outcomes in auctions for which commissions do not enter the scoring rule. These analyses incorporate out-of-sample data and can be used to assess the empirical model and the parameter estimates.

5.4.1 Analysis of Winning and Losing Bids

We compute the equilibrium (score) bids that arise in each simulated auction used in estimation by applying equation (11), given the estimated parameters. We rank the bids as first-best, second-best, third-best, and fourth-best and then average them across simulations. We then compare these measures—the ranked expected scores—to the scores observed in the data. The first-best bids are used in estimation, but the other bids are not, so the exercise involves in-sample and out-of-sample fits. Figure 2 provides the corresponding scatter plots. The model predictions and the data are highly correlated in each plot; the bivariate correlation statistics are 0.92, 0.90, 0.81, and 0.75, respectively, for the first-best, second-best, third-best, and fourth-best bids. Furthermore, the lines of best fit are not far from the 45-degree lines. We interpret the exercise as supporting the reasonableness of the empirical model and the parameter estimates.

5.4.2 Auctions Without Commissions in the Scoring Rule

We now use the data from auctions where the commission does not enter the scoring rule. We use an iterative procedure to approximate equilibrium bidding strategies. The basic idea is to parameterize a function determining how firms believe their competitors will bid, compute the best responses to those beliefs, update beliefs, and iterate until the beliefs are close to the best responses (e.g., Bajari, 2001; Armantier et al., 2008).[36] The question is whether the empirical model generates rates similar to those in the out-of-sample data.

[36]Direct approaches to solving the system of differential equations have been developed in the literature, but they can be slow and unstable (e.g., Marshall et al., 1994; Bajari, 2001; Li and Riley, 2007; Fibich and Gavish, 2011; Hubbard et al., 2012). Other approaches are possible. Carril et al. (2022) assume a distribution on equilibrium *bids* and estimate the parameters of that distribution, matching simulated moments to data and guaranteeing that actions are consistent with beliefs at the solution. See also Richert (2024). Other empirical applications have used approximations that are similar to ours (e.g., Eklöf, 2005; Armantier and Sbaï, 2006; Takahashi, 2018).

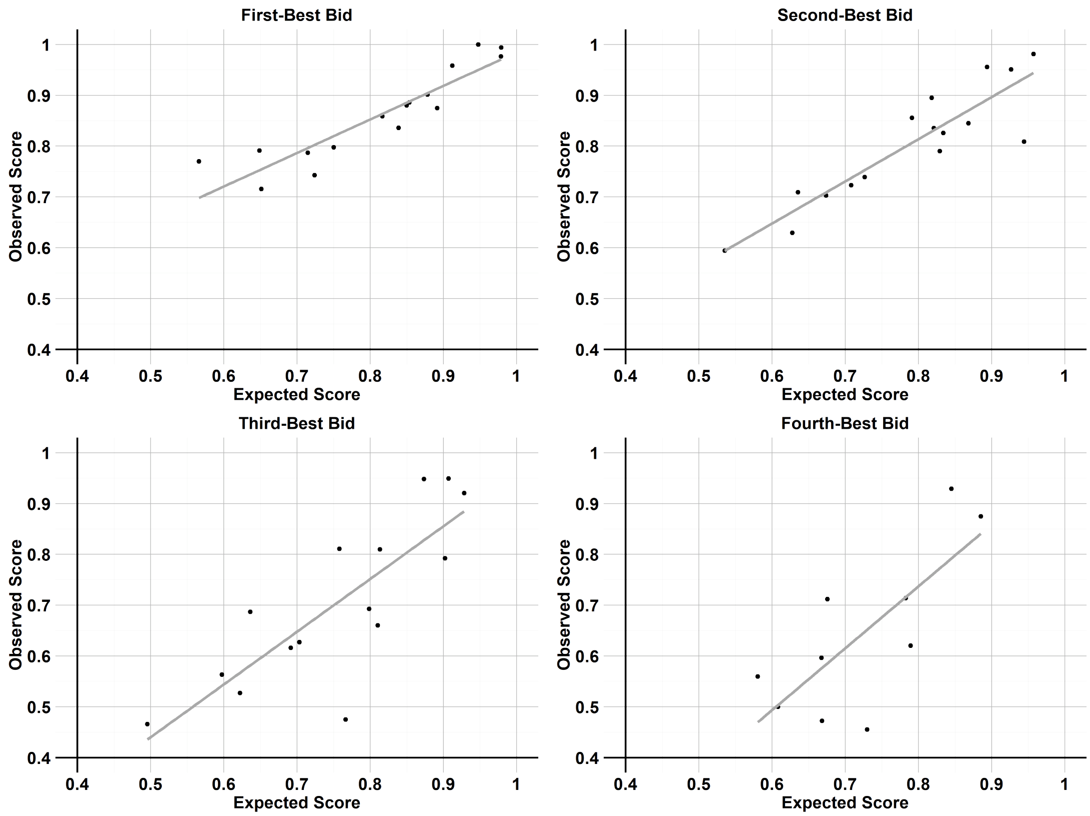

Figure 2: Fit of the Model to Observed Scores

Notes: The figure provides scatter plots of the expected score (horizontal axis) and the observed score (vertical axis) for the 16 auctions used to estimate the cost distribution. Separate panels are provided for the first-best, second-best, third-best, and fourth-best bidders. All the auctions have at least two bidders, 15 have three bidders, and 10 have four or more bidders. Lines of best fit are also shown.

We find that a linear belief function performs well in the iterative procedure. In iteration $h = 0, 1, \ldots$, we assume firms believe that competitor j in auction i will bid according to

$$\hat{s}_{ij}^{(h)} = \mathbf{x}_{ij}' \gamma_i^{(h)} \tag{21}$$

where the auction-specific vector $\gamma_i^{(h)}$ contains "belief coefficients" and the vector $\mathbf{x}_{ij}$ includes a constant and the cost and technical signal of the competitor. The auction-specific constants absorb the auction weights and the number of competitors. Given these beliefs, we compute the best responses of $f \in (1, \ldots, F)$ simulated "focal" firms. We use $\hat{s}_{if}^{(h)BR}$ to denote the best response score of firm f in auction i and iteration h. It obtains from (4), replacing the equilibrium strategy of competitor k with the belief $(\hat{s}_{ik}^{(h)})$, as in

$$\hat{s}_{if}^{(h)BR} = \arg\max_{\hat{s}} Pr(\hat{s} \geq \max_{k=1,\ldots,J_i} \{\hat{s}_{ik}^{(h)}\}) \int \pi(\hat{s}, c_{ij}, \nu) dF_{V|S}(\nu|\xi_{ij}) \tag{22}$$

The win probability relies on Monte Carlo integration over the realizations of $r \in (1, \ldots, R)$ cost and signal draws of the J_i competitors of firm f. For each auction, we regress the F best responses on the costs and signals of the simulated firms to obtain regression coefficients, $\hat{\gamma}_i^{(h)}$, that are analogous to the belief coefficients. We then update the belief coefficients according to

$$\gamma^{(h+1)} = \rho^{(h)} \hat{\gamma}^{(h)} + \left(1 - \rho^{(h)}\right) \gamma^{(h)} \tag{23}$$

where $\rho^{(h)} \in [0, 1]$ controls the step size. We interpret beliefs as consistent with equilibrium play if the mean squared error between the belief and regression coefficients is small.[37]

The headline result of the assessment exercise is that the expected equilibrium rate is similar to what is observed in the data, averaging across the auctions for which the commission does not enter the scoring rule ($0.96 versus $0.76). We interpret these numbers as similar because both are much lower than the average rate of $2.27 that we observe for the auctions used to estimate the model. That is, the assessment exercise requires significant projection outside the range of data in the estimation sample, yet the model predictions are reasonably accurate. A caveat is that the model does not match well the variation in rates within the assessment sample; the correlation coefficient is 0.05. We also find an expected profit of $8.93 per inmate-month, which is less than the $12.32 that we estimate for auctions that feature commissions in the scoring rule. Our results are consistent with firms earning more profit on average when commissions enter the scoring rule.

6 The Economics of Commissions

In this section, we use two numerical experiments to tease out the economic implications of commission payments in the context of the empirical model. The first experiment considers an auction in which the commission receives weight in the scoring rule. We fix the technical weight at 0.67 and assume four firms, based on the empirical means (e.g., Table 1). We compute expected equilibrium outcomes under different rate and commission weights, varying the commission weight from just above zero to 0.33 and letting the rate weight be the residual.

Figure 3 summarizes the results. The left panel shows that the expected equilibrium rate increases with the commission weight (dashed line). This can be understood from the closed-form solution for rates in equation (16), in which the ratio ω_i^r / ω_i^k determines the discount from the monopoly price. This ratio decreases as we increase the commission weight, and in our experiment, it reaches zero at the highest commission weight. Therefore, moving from left to right, the rate converges to the monopoly level as the marginal increase in rates becomes less consequential for the probability of winning the auction.

[37] We use 31 iterations and find that the mean squared error is near zero at the end; the average across auctions is 1e-5. The average R^2 from the regressions is 0.88, which does not indicate a substantial role for non-linearities in the belief function. We provide more detail on the methodology and results in Appendix A.

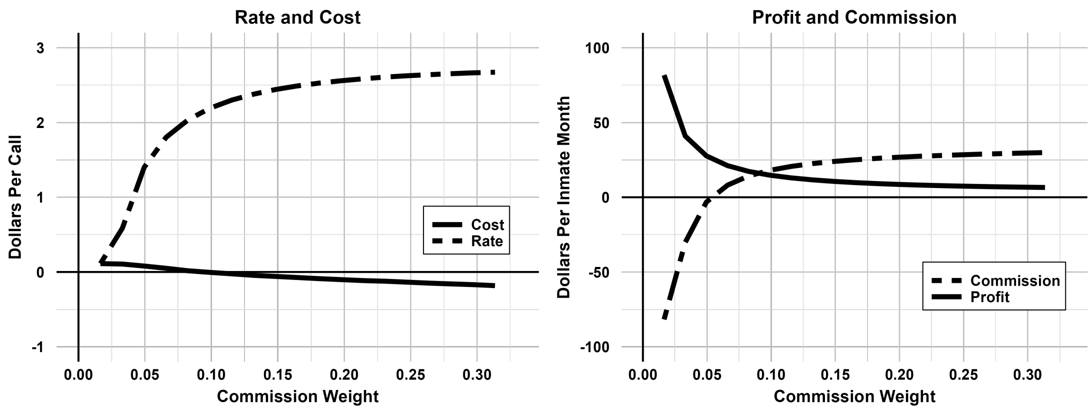

Figure 3: The Effect of the Commission Weight on Equilibrium Outcomes

Notes: The figure plots the expected cost and expected equilibrium rate, commission, and profit of the winning firm in simulated auctions with commissions. All auctions feature four bidders and a technical weight of 0.67. We vary the commission weight from 0.02 to 0.33, letting the rate weight be the residual.

The left panel also shows that the expected cost of the winning firm decreases with the commission weight (solid line). Thus, the increase in rates does not reflect a pass-through of higher costs; in fact, costs fall. As the commission weight increases relative to the technical weight, the procuring entity tends to award contracts to the firms that can provide the largest commissions rather than those with the most preferred technical capabilities. This selection favors firms with low costs of service or high ancillary fees (recalling that cost in our model is net of the two). Although we treat fees as exogenous, were we to relax that assumption, higher commission weights would create incentives for higher fees.

The right panel shows that the expected equilibrium commission increases with the commission weight (dashed line), and the expected equilibrium profit decreases (solid line). Although the first pattern may be unsurprising, it is worth noting that for commission weights that are low enough, the flow of funds reverses, with the procuring entity paying a fixed sum to the winning firm for service. That profit approaches zero as the commission weight grows large relative to the rate weight indicates that, even as the winning firm sets rates at the monopoly level, the procuring entity extracts nearly all profit in the form of the commission payment. Therefore, in the extreme case, the procuring entity is the beneficiary of the monopoly rates.

The second experiment contemplates a commission ban. We start with a prototypical auction with four bidders, a technical weight of 0.67, and rate and commission weights of 0.165. In this auction, the equilibrium rate is \$2.49, and the equilibrium commission and profit are \$25.04 and \$9.83 per inmate-month, respectively. We then eliminate the commission weight and shift it to the rate weight, technical weight, or some combination of the two, and approximate equilibrium for each possibility using the methodology described in Section 5.4. Thus, the possible rate weights after the ban range from 0.165 to 0.33, corresponding to complete transfers of the commission weight to the technical weight and the rate weight, respectively.

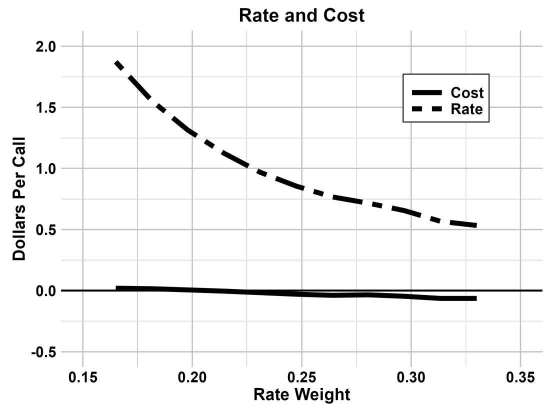

Figure 4: Economic Outcomes After a Ban on Commissions

Notes: The figure plots the expected cost and expected equilibrium rate of the winning firm in simulated auctions without commissions. All auctions feature four bidders. We vary the rate weight from 0.165 to 0.33, letting the technical weight be the residual. This mimics a ban on commissions in an auction that initially had a technical weight of 0.67 and rate and commission weights of 0.165, as the commission weight would need to be reallocated. We obtain our results by approximating the equilibrium; beliefs are recomputed for each set of auction weights.

Figure 4 summarizes the results. The horizontal axes contain the possible rate weights after the ban on commissions. The expected equilibrium rate decreases with the rate weight (dashed line). For *every* possible rate weight, however, it is less than the $2.49 that obtains before the commission ban. Thus, banning commissions lowers rates, with bigger effects if more commission weight is transferred to the rate weight. We also plot the expected net cost of the winning bidder, which decreases with the rate weight (solid line). Placing more weight on rates advantages low-cost or high-fee providers in the auction. This selection effect is the opposite of what obtains with commissions (e.g., see Figure 3, where the rate weight decreases going from left to right); however, it does not appear meaningful in the numerical example.

7 Counterfactual Policy Analyses

We consider three policy analyses: First, we examine regulation that predetermines rates but allows competition to determine the magnitude of commission payments. Second, we examine regulation that caps competitively determined rates; among our analyses, this comes the closest to the 2024 Order of the FCC. Third, to inform competition policy, we examine how outcomes vary with the number of competitors with and without commissions.

7.1 Rate Regulation

We first explore regulation that determines rates; the procuring entity still conducts a scoring auction that determines the commission payment. We examine how outcomes vary with the regulated rate. The analysis can be motivated by recently passed state laws in Connecticut, California, Colorado, Minnesota, and Massachusetts that make calls free for incarcerated individuals; these states pay or will pay for ICS, which could be interpreted as a negative commission.[38] Our starting point is an auction with four bidders and scoring rule weights of $\omega^k = 0.33$ and $\omega^v = 0.67$. We compute equilibrium for rates from \$0.00 to \$1.00 per 15-minute call.

Figure 5 presents the results. The top panel plots the expected equilibrium commission and profit. With a \$1.00 regulated rate, the commission payment is \$16.33 per inmate-month. As the regulated rate falls (from right to left), the commission decreases because the winning firm obtains less revenue from calls and so can pay less in commission. For regulated rates less than \$0.175, the commission is negative, such that the flow of funds reverses and the buyer pays the provider. With free calls, the procuring entity pays the provider \$3.75 per inmate-month. In our data, we do not observe payments from the procuring entity to the provider, but they are standard in many procurement settings outside ICS, including school milk and meals (Porter and Zona, 1999; Olivares et al., 2012) and public transportation (Cantillon and Pesendorfer, 2007; Marra and Oswald, 2024).

Profit increases as the regulated rate falls. Mechanically, the loss of revenue from rates and fees is more than offset by smaller commission payments. This occurs because rate regulation increases the market power of the winning provider by disadvantaging higher-cost providers in the bidding process—keeping in mind that "low cost" in our model can be due to high fees. Although all firms lose profit from calls as regulated rates fall, this effect is amplified for high-cost firms. These disadvantaged firms bid less aggressively, enabling the winning provider to obtain better financial terms from the buyer. As regulated rates fall, however, the revenue of the winning provider increasingly comes from the buyer via a fixed payment rather than from incarcerated individuals via the rate.

The bottom panels of Figure 5 illustrate the competitive effects of rate regulation. In the bottom left panel, we show that the expected cost of the winning firm decreases as regulated rates fall (solid line). The expected technical signal also decreases, but more modestly (dashed line). This reflects that, as rates fall, profit increasingly depends on low costs or high fees. Firms with higher costs but better technical capabilities become less likely to bid aggressively enough to win. The bottom right panel plots the expected pseudotypes of the first-best firm (solid line) and second-best firm (dashed line). Both decrease as regulated rates fall because less profit is obtained from the rate. However, the pseudotype of the second-best firm decreases more rapidly because, on average, it has higher costs. Quantitatively, the gap is 8.97 at a regulated rate of \$1.00 and 10.55 with free calls. At each regulated rate, the gap between the first- and second-best pseudotypes equals the profit of the winning bidder shown in the top panel.

Thus, in the model, rate regulation shifts the burden of paying for ICS from incarcerated individuals and their social contacts to the procuring entity. Enacted in isolation, it also in-

[38] For example, Connecticut Senate Bill 972 (2021) states: "The annualized cost for paying the [ICS] vendor for telephone services is approximately \$4.5-\$5.5 million per year...."

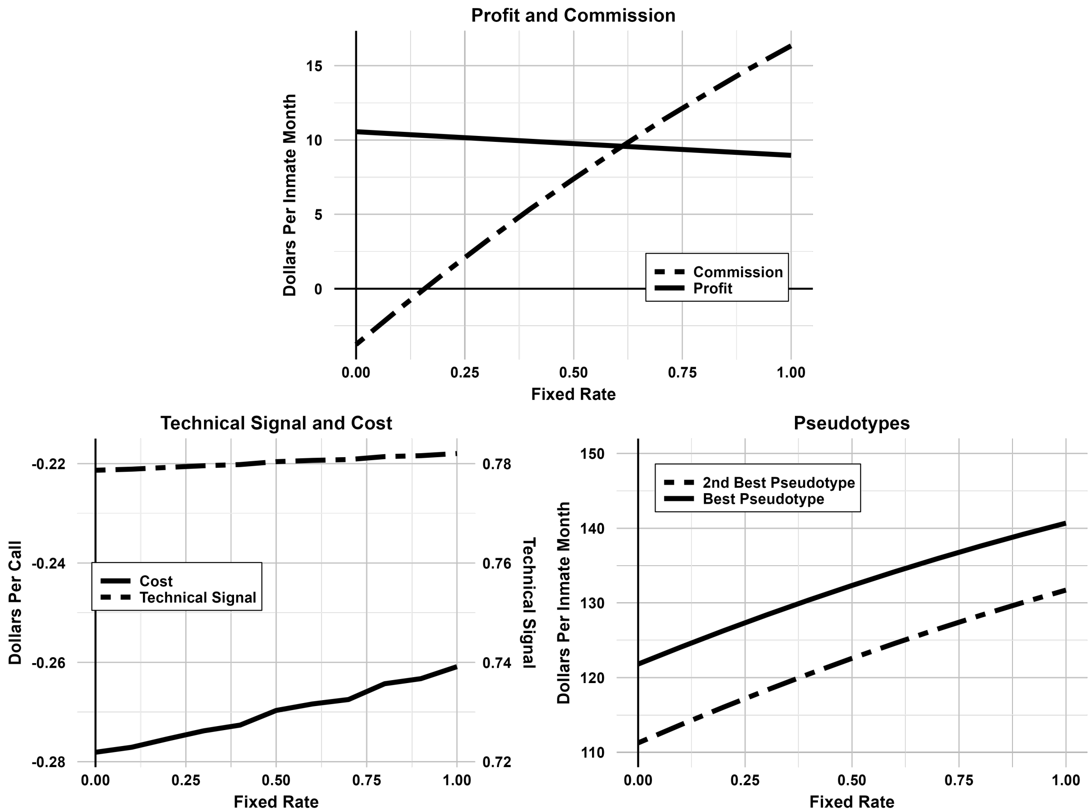

Figure 5: The Economic Effects of Rate Regulation

Notes: The figure is based on 1,000 simulations of an auction with four bidders, scoring rule weights of $\omega^k = 0.33$ and $\omega^v = 0.67$, and regulated rates between \$0.00 and \$1.00 per 15-minute call (horizontal axis). The top panel shows the expected equilibrium commission payment and profit. The bottom left panel shows the expected cost and technical signal of the winning firm. The bottom right panel shows the expected first-best and second-best pseudotypes.

creases the market power and profit of the winning firms by placing prospective providers with relatively high costs (or low fees) at a disadvantage in the auction process.

7.2 Rate Caps

We now consider regulation that caps competitively determined rates at \$0.90 per 15-minute call, a level that we select to be consistent with the 2024 Order of the FCC. Such a cap directly affects equilibrium rates whenever those rates exceed the cap; it can also have indirect effects if it screens out firms with costs above the cap. Our previous findings raise the prospect that the rate cap may not bind equilibrium rates, given that the FCC Order also bans commissions (e.g., Section 5.4 and Section 6, where equilibrium rates often are less than \$0.90). That is, banning commissions may decrease rates below the cap, eliminating the direct effect and making the cap redundant, at least in some auctions.

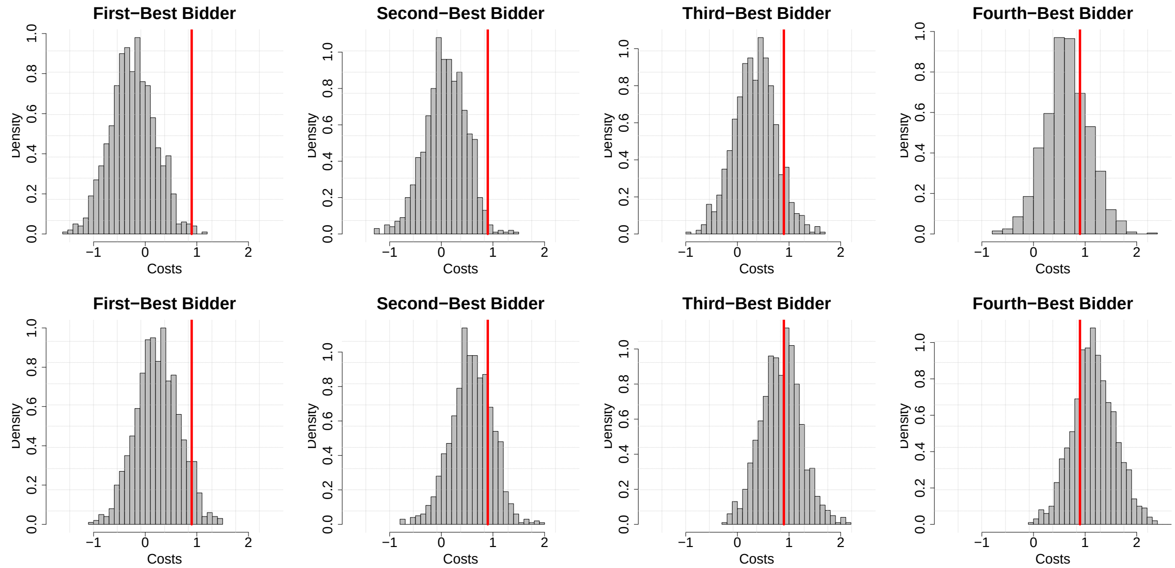

Figure 6: The Cost Distribution and the Rate Cap by Bidder

Notes: From left to right, the figure provides histograms of the cost distribution for the winning firm, the second-best firm, the third-best firm, and the fourth-best firm. The vertical line plots the 2024 imposed rate caps by the FCC of \$0.90 per 15-minute call. The top panels are based on 1,000 simulations of an auction with four bidders and scoring rule weights of $\omega^r = 0.33$ and $\omega^v = 0.67$. The bottom panels incorporate a \$0.50 rightward shift in the cost distribution but otherwise are based on the same assumptions.

In this section, we analyze the indirect effects. As auction participation is exogenous in our model, we examine the distribution of costs in an auction without commissions and determine how frequently costs exceed the cap. We use an auction with a technical weight of 0.67, a rate weight of 0.33, and four bidders. The results are summarized in the top panels of Figure 6, which provide histograms of the cost distributions of the first-best firm (the winner) and each of the other firms. We obtain the distributions using 1,000 simulations. The vertical red line in each panel is the rate cap. Taking the firms in turn, the fraction of simulations in which their cost is below the cap is 99.5%, 98.8%, 91.5%, and 72.9%, respectively. If a firm bids when its cost is below the cap, then 95.5% of the auctions would have at least three bidders.[39] As the fourth-best firm is the least competitively significant, the exercise suggests that the rate cap may have limited indirect effects through auction participation, assuming still that bidders observe their costs before entry (e.g., as in the canonical entry model of Samuelson, 1985).

However, the FCC Order also bans fees. In our model, this would increase costs (which are net of fees). To examine the sensitivity of our results to the fee ban, we shift the distribution of costs up by \$0.50 and recompute equilibrium in 1,000 simulations. The histograms of the cost distributions are in the lower panels of Figure 6. Taking the firms in turn, the fraction of simulations in which they have costs below the cap are 93.5%, 78.5%, 54.0%, and 24.9%, respectively.

[39]The fourth-best bidder can have lower costs than the third-best bidder, for example, as there is heterogeneity in the technical signal that affects relative equilibrium bids.

Only 51.8% of auctions would have at least three bidders if firms bid when their costs are below the cap. Thus, when paired with a fee ban, the rate cap could affect participation. However, our analysis of this point is no more than suggestive because we cannot separately identify fees from the cost of service. For example, if high-cost firms in our model are high-cost *because* their fees are low, then shifting the cost distribution of all firms by the same amount may not capture the ban on fees well.

7.3 Competition Policy

Our final analysis examines how outcomes vary with the number of competitors. We motivate the exercise from the extended period of consolidation in the industry and the recent decision of the Department of Justice to block the merger of Securus and ICS. In our empirical model, adding a firm affects outcomes for two reasons. First, it lowers the probability that any given firm wins and thereby induces more aggressive bidding. Second, it improves the expected characteristics of the winner (in our model, this implies lower cost and better technical capabilities). We refer to these as a *competition effect* and a *composition effect*, respectively.

We first consider an auction with commissions in the scoring rule. In that context, our description of the composition and competition effects effects can be sharpened. The composition effect occurs because the expected first-best pseudotype increases with the number of firms, whereas the competition effect occurs because the expected second-best pseudotype increases. We consider an auction with a technical weight of 0.67 and rate and commission weights of 0.165 and compute expected equilibrium outcomes with different numbers of competitors. We report "unadjusted" results that combine the competition and composition effects. We also report "adjusted" results that we produce by rescaling the variances of the cost and technical score distributions such that their expected minimums and maximums do not change with the number of firms; this isolates the competition effect.[40]

Figure 7 shows the results. The left panel focuses on the expected equilibrium rate. As we increase the number of firms from two to ten, the unadjusted rate falls from \$2.49 to \$2.25, but the adjusted rate is flat. Thus, changes in the rate are due to the composition effect. This makes sense given that in these score auctions, the winning firm chooses rates based on its cost but not the identity or number of competitors (equation (16)). The right panel shows that the expected equilibrium commission increases with the number of firms. The full effect is weaker than the competitive effect because a winning firm with a better technical score—due to the composition effect—can out-score the second-best firm with a lower commission payment. Overall, our results indicate that adding more firms benefits the procuring entity, but whether incarcerated individuals gain depends on the cost structure of the new firms.

Figure 8 considers auctions in which commissions are not in the scoring rule. In that setting,

[40]We rescale so that the expected minimums/maximums coincide with those of our estimated distributions in the duopoly case. Thus, the adjusted and unadjusted outcomes are the same when there are two firms.

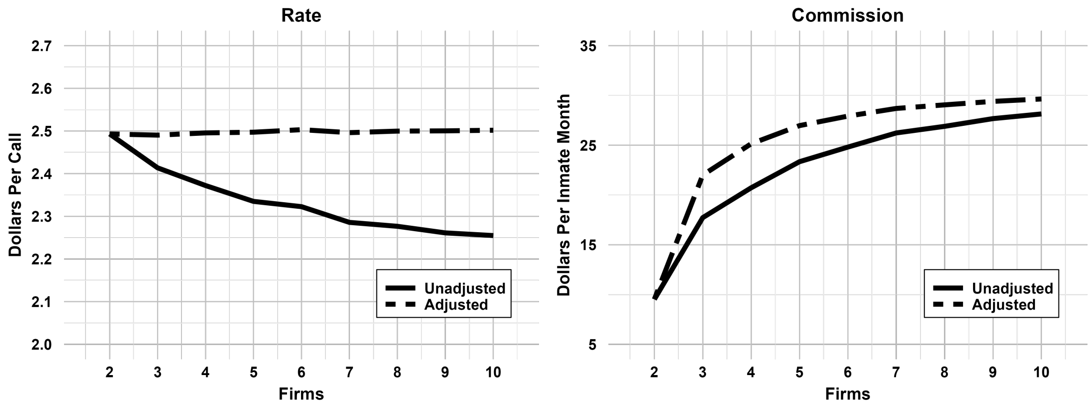

Figure 7: The Effect of Competition with Commissions

Notes: The graphics depict simulated rates, commissions, and retained profit under two conditions. The unadjusted trends do not correct for the effect of additional draws from the cost and quality distributions as competition increases. In adjusted trends the distributions are altered such that the expected best cost and quality remain constant.

the rate is the only financial term subject to competition, and adding firms unambiguously improves outcomes for incarcerated individuals. In our experiments, we assume a technical weight of 0.67 and a rate weight of 0.33. As shown, both the unadjusted and adjusted expected equilibrium rates decrease from \$1.60 to about \$0.38 as we raise the number of firms from two to ten, though the change happens earlier for the unadjusted rate. Pairing this with our earlier results, we find that the link between competition and rates is more robust when commissions are not determined in the bidding process.

8 Conclusion

We have investigated the auction mechanisms that shape contractual agreements between correctional facilities and providers of inmate calling services (ICS). The relevant financial terms include the prices that incarcerated individuals pay to the ICS provider to make phone calls and the commission—a payment from the provider to the correctional authority. Prospective ICS providers are often evaluated based on the commission they propose and thus have an incentive to charge higher prices to support larger commission payments. This distortion interacts with providers' market power in interesting and novel ways, with regulatory and competition policy implications for an industry that has recently received considerable scrutiny.

The empirical foundation of the paper is a new dataset that documents each step of the procurement process as implemented in many states, obtained through public records requests. Our empirical analysis demonstrates that procuring entities prefer lower rates and higher commissions, and providers bid accordingly; it also shows that providers bid higher rates in auctions that also solicit commissions. We estimate an empirical model of the industry that features

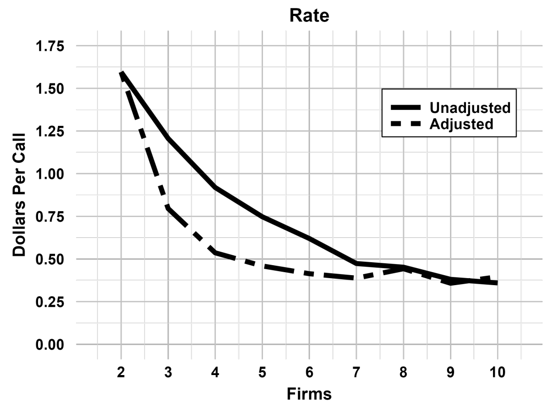

Figure 8: The Effect of Competition Without Commissions

Notes: The figure depicts simulated rates and profit under two conditions. The unadjusted trend does not correct for the effect of additional draws from the cost and quality distributions as competition increases. The adjusted trend alters the distributions such that the expected best cost and quality remain constant.

sealed-bid, first-score auctions with multi-dimensional bidder heterogeneity and evaluation uncertainty. The model allows us to causally connect auction features, such as the evaluation of commissions, to relevant economic outcomes. For example, simulations indicate that a ban on commissions would lower the prices that incarcerated individuals pay to make calls. We also use the model to examine two regulatory remedies—fixed rates and rate caps—and the conditions under which adding more competition would benefit incarcerated individuals.

There is significant scope for future research. First, there has been a raft of state-level efforts to reduce rates and eliminate commission payments in the last few years. These efforts, as well as recently-promulgated FCC regulations, should create opportunities to examine empirically how regulation and policy changes affect outcomes; such research would complement our model-based approach. Second, future research could examine how prison phone prices affect broader social outcomes, such as recidivism and the ability of incarcerated individuals to obtain employment after release. One paper along these lines is Abdul-Razzak et al. (2024). Finally, while we have focused on ICS, Raher (2020) highlights that, for many of the same reasons, prices are inflated for incarcerated individuals more generally, and future research could explore this.

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Appendix

A Approximation for Auctions without Commissions

We provide additional details on the model assessment exercise described in Section 5.4.2. The sample comprises 17 auctions for which the commission does not enter the scoring rule; we exclude New Hampshire in 2013, which places 100% of the scoring rule weight on rates. We apply the iterative procedure separately in each of these auctions.

We take ten evenly-spaced draws from both the cost distribution and the signal distribution.[41] The combination of these draws provides 100 representative "focal firms" for which we obtain best responses given a set of beliefs. We compute the best responses of these focal firms numerically. For a candidate score bid from a focal firm with a known cost and signal, we compute the implied rate and profit (conditional on winning) for 999 evenly-spaced draws on the evaluation noise; this allows us to calculate the expected profit conditional on winning. We obtain the probability of winning by determining the fraction of times that the focal firm's candidate score bid exceeds the bids of all its competitors, using 1000 simulated sets of competitors (each defined by cost and signal draws) and obtaining competitor bids from the beliefs. We draw the simulated sets of competitors using 999 evenly-spaced cost draws and 999 evenly-spaced signal draws, matched randomly. Thus, we consider a full range of possible competitors; the focal firms are not restricted to competing only with each other. With the conditional profit and the probability of winning, we obtain the expected profit of each candidate bid. The candidate bid that maximizes expected profit is the best response.[42]

We update beliefs as described in Section 5.4.2. We set $\rho = 1$ for the first iteration, and $\rho = 0.50$ for 10 iterations, $\rho = 0.10$ for 10 iterations, $\rho = 0.01$ for 10 iterations. Adding more iterations does not always reduce the mean squared error. Thus, while we find that mean squared error tends to be very small after 31 iterations, we have not been able to make it arbitrarily small, even with smaller step sizes. The process is not a contraction mapping.

Table B.3 shows the regression results obtained in the final iteration. The dependent variable is the best response of the focal firms; the regressors are the cost and technical signal of

[41] That is, we take the 5th percentile, 15th percentile, 25th percentile, and so on, up to the 95th percentile. Thus, the draws are evenly distributed in probability space.

[42] We use the optimize function in R to find the best responses. The function requires us to specify lower and upper bounds. As the lower bound, we use the score corresponding to the monopoly price with the lowest possible technical score signal for the focal firm. As the upper bound, we use the score corresponding to at-cost rates with the highest possible technical score.

the focal firms. Each row shows the results for a single auction. In each auction, the score bids of the focal firms decrease with their costs and increase with their technical signal, which comports with profit-maximizing behavior. The results show that the best responses can be well approximated with a simple linear function: the lowest R^2 value is 0.8034.

The heterogeneity in the belief coefficients across auctions reflects differences in auction design and the number of competitors. To illustrate, we regress the belief coefficients on the auction weights and the number of firms. The results appear in Table B.4. The first column shows that the best responses tend to be more sensitive to the focal firm's costs if the rate weight is larger and there are more competitors (the belief coefficient on costs becomes more negative). The second column shows that the best responses tend to become more sensitive to the focal firm's technical signal if the technical weight is larger and there are more competitors (the belief coefficient on the technical signal becomes more positive). The third column shows that bids are higher (more competitive, implying lower rates) if the rate weight is larger. All of these results comport with the comparative statics of the model and are accounted for in the assessment exercise because we use auction-specific regressions.

B Additional Figures and Tables

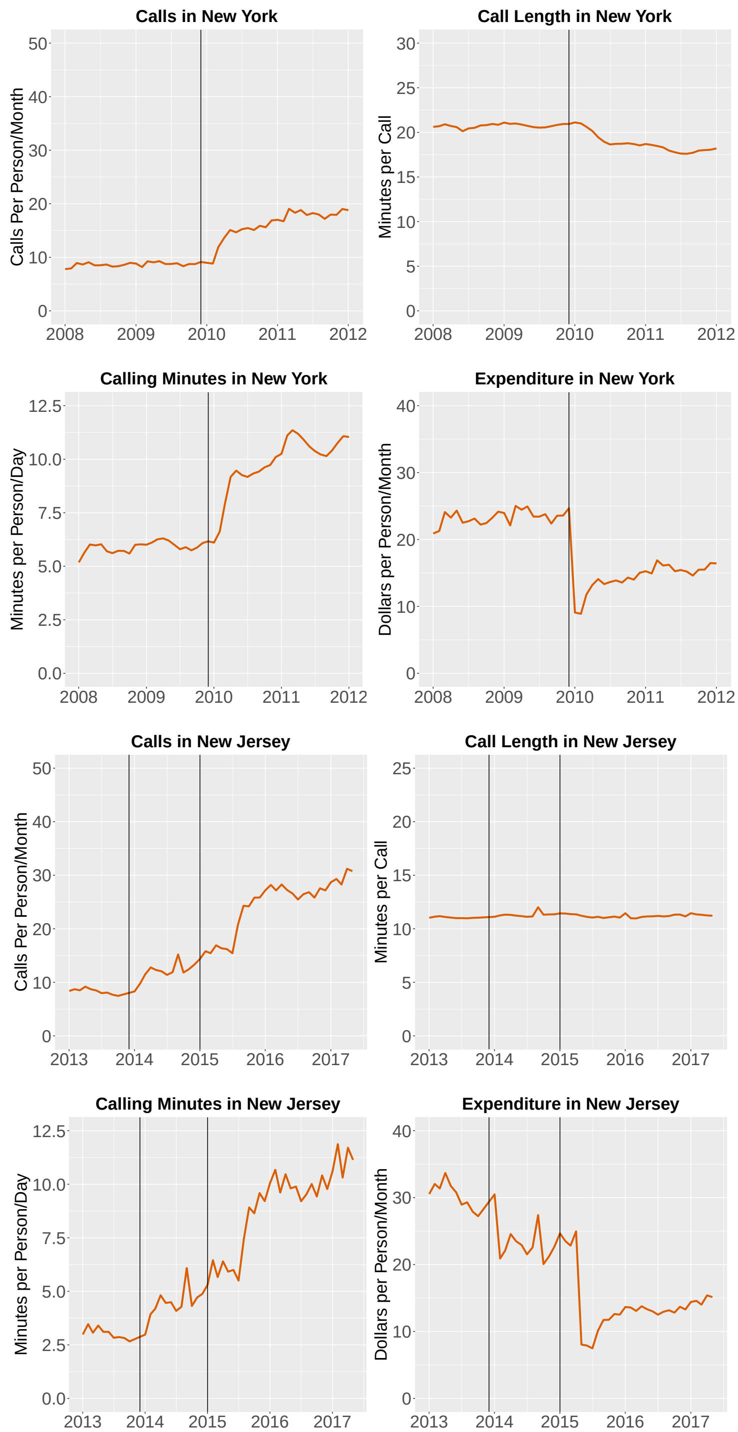

Figure B.1: Calling Patterns Before and After Price Reductions

Notes: The figure plots calls per person/month, minutes per call, minutes per person/day, and expenditure per person/month over time in New York (top four panels) and New Jersey (bottom four panels). The data points are monthly averages. The vertical black lines show the timing of price changes.

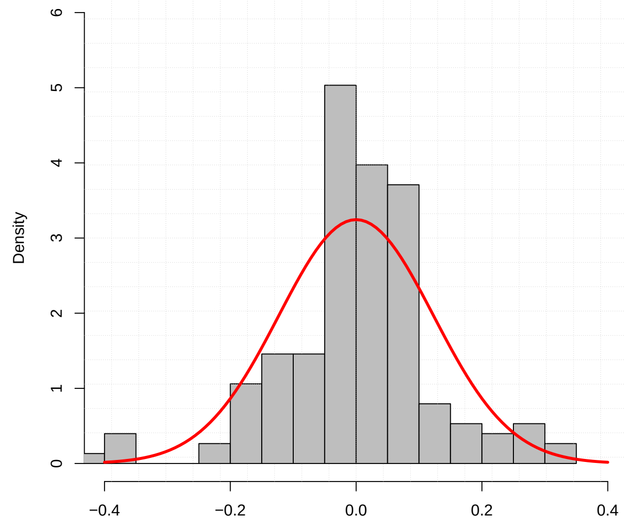

Figure B.2: Distribution of Technical Score Residuals

Notes: The figure provides a histogram of the residuals we obtain from a regression of technical scores on auction fixed effects. We measure the technical score as the score of the bidder divided by the maximum possible score (for all elements of the bid related to technical capabilities or subjective assessments of the provider). The figure also plots the probability density function of the technical score distribution that we estimate (red line). The probability density function is re-centered around zero.

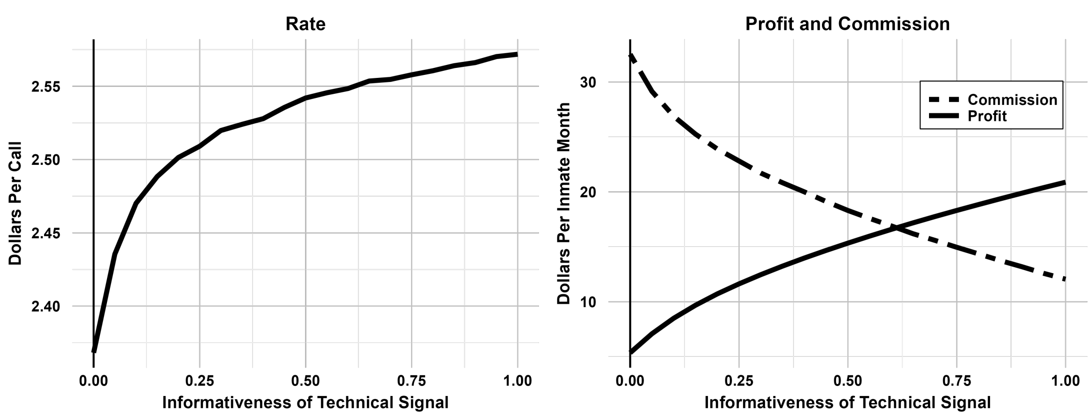

Figure B.3: The Effect of Evaluation Uncertainty on Equilibrium Outcomes

Notes: The figure considers a hypothetical auction defined by $\omega_i^r = 0.165$, $\omega_i^k = 0.165$, $\omega_i^v = 0.67$, and $J = 4$. We compute equilibrium for $\lambda \in [0, 1]$, holding everything else constant. The left panel plots the average equilibrium rate, and the right panel plots the average equilibrium commission and profit.

Table B.1: Summary of the Bid Data

	State	Year	Rate Weight	Quality Weight	Comm. Weight	# of Bids	# of Bidders	Winning Bidder	Contract Rate	Contract Commission Percentage	Contract Commission Fixed	Contract Commission Total
1	Alaska	2016	0	0.56	0.44	4	4	Securus	1.05	0.94	0	19.61
2	Arizona	2014	0	0.17	0.83	4	4	CenturyLink	1.84	0.94	0	28.27
3	Arkansas	2014	0	1	0	4	4	Securus	4.80	0.73	0	11.65
4	Florida	2013	0.05	0.90	0.05	3	3	GTL	0.75	0.67	0	10.58
5	Florida	2017	0.17	0.83	0	3	3	Securus	0.19	0	0	0
6	Georgia	2015	0	0.65	0.35	3	3	Securus	1.95	0.97	6.73	36.76
7	Idaho	2014	0.20	0.80	0	5	5	CenturyLink	2.40	0	20.00	20.00
8	Illinois	2012	0.45	0	0.55	3	3	Securus	4.10	0.87	0	22.89
9	Indiana	2010	0.22	0.67	0.11	3	3	PCS	4.05	0.40	0	10.74
10	Kentucky	2012	0	0.74	0.30	5	5	GTL	2.25	0.88	0	28.66
11	Kentucky	2017	0	0.86	0.14	3	3	GTL	1.65	0.50	0	14.19
12	Maine	2015	0.15	0.70	0.15	4	4	Legacy	1.65	0.55	0	15.61
13	Massachusetts	2013	0	0.86	0.14	6	4	GTL	2.36	0.60	0	19.93
14	Michigan	2018	0	1	0	3	3	GTL	2.40	0	23.65	23.65
15	Minnesota	2005	0	0.84	0.16	4	4	MCI	1.75	0.49	0	14.37
16	Minnesota	2016	0.40	0.60	0	8	4	GTL	0.33	0.47	0	3.60
17	Minnesota	2019	0.30	0.70	0	4	4	GTL	0.33	0.40	0	3.04
18	Missouri	2000	0.75	0.25	0	2	2	MCI	1.30	0	0	0
19	Missouri	2006	0.52	0.48	0	5	5	PCS	2.50	0	0	0
20	Missouri	2011	0.42	0.58	0	10	7	Securus	1.75	0	0	0
21	Missouri	2018	0.28	0.72	0	3	3	Securus	0.75	0	0	0
22	Montana	2017	0.20	0.80	0	5	5	CenturyLink	0.54	0	9.24	9.24
23	Nebraska	2008	0.33	0.67	0	6	6	PCS	0.70	0	0	0
24	Nebraska	2016	0.41	0.59	0	6	5	GTL	0.19	0	0	0
25	New Hampshire	2013	1	0	0	4	4	IC Solutions	0.65	0.20	9.67	12.48
26	New Hampshire	2018	0.35	0.65	0	4	4	GTL	0.19	0.20	11.12	12.04
27	New Jersey	2014	0.40	0.60	0	2	2	GTL	0.40	0	0	0
28	North Dakota	2016	0.23	0.68	0.09	5	5	Securus	1.19	0.25	0	5.70
29	Oklahoma	2018	0.30	0.70	0	4	4	Securus	1.91	0	14.57	14.57
30	Utah	2014	0	0.70	0.30	4	4	CenturyLink	2.10	0.90	0	28.76
31	Utah	2019	0	0.70	0.30	4	4	GTL	1.80	0.95	0	28.28
32	Vermont	2010	0	0.70	0.30	5	5	PCS	2.30	0.37	0	12.20
33	Vermont	2016	0.03	0.95	0.02	3	3	GTL	0.58	0.41	0	5.21
34	Virginia	2005	0.20	0.70	0.10	2	2	MCI	5.55	0.41	0	0.05
35	West Virginia	2014	0.30	0.70	0	3	3	CenturyLink	0.48	0	0	0.01
36	Wisconsin	2008	0.30	0.70	0	6	6	Embarq	1.05	0.30	0	6.25
37	Wisconsin	2018	0.20	0.80	0	3	3	CenturyLink	0.17	0.30	0	1.23

Notes: The table summarizes the auction-level data. Rate is the cost of a 15-minute local collect phone call. The commission percentage is the percentage of the non-fee revenue that the provider pays to the state. The fixed commission is a fixed amount of money that the provider pays to the state, converted to be in dollars per inmate-month. The total commission combines these two forms of payments and is in dollars per inmate-month.

Table B.2: Demand for Calls

	(i)	(ii)	(iii)	(iv)
Rate	-3.30	-4.37	-4.46	-4.35
	(0.38)	(0.07)	(0.27)	(0.07)
Constant	22.00		19.07	29.86
	(1.35)		(0.61)	(0.29)
NJ Constant		29.90		
		(0.28)		
NY Constant		18.93		
		(0.27)		
R^2	0.53	1.00	0.93	0.99
# of Observations	46	46	24	22
Sample	NJ/NY	NJ/NY	NJ	NY

Notes: The table summarizes OLS regression results. Observations are at the state-month level. The dependent variable is the average number of calls per inmate-month. The main independent variable is the price of a 15-minute call. The sample for New York includes the months January-December 2009 and April 2010 - March 2011. The sample for New Jersey includes the months January-October 2013 and January-December 2016.

Table B.3: Belief Regressions

State	Year	Constant: $\gamma_0^{(31)}$		Cost: $\gamma_1^{(31)}$		Tech Signal: $\gamma_2^{(31)}$		R^2
Florida	2017	0.7611	(0.0004)	-0.0368	(0.0009)	0.5913	(0.0092)	0.9842
Indiana	2014	0.6647	(0.0008)	-0.0455	(0.0017)	0.7111	(0.0185)	0.9572
Minnesota	2016	0.7252	(0.0026)	-0.0945	(0.0055)	0.6257	(0.0594)	0.8058
Minnesota	2019	0.5756	(0.0013)	-0.0649	(0.0028)	0.5833	(0.0299)	0.9048
Missouri	2000	1.0691	(0.0011)	-0.0923	(0.0023)	0.1181	(0.0250)	0.9427
Missouri	2006	0.8848	(0.0029)	-0.1268	(0.0062)	0.5312	(0.067)	0.8309
Missouri	2011	0.9356	(0.0043)	-0.1652	(0.0093)	1.1118	(0.1001)	0.8185
Missouri	2018	0.9423	(0.0011)	-0.0529	(0.0024)	0.5344	(0.0258)	0.9041
Montana	2017	0.7430	(0.0006)	-0.0573	(0.0012)	0.6319	(0.0129)	0.9796
Nebraska	2008	0.6594	(0.0026)	-0.1017	(0.0056)	0.9039	(0.0601)	0.8513
Nebraska	2016	0.7114	(0.0039)	-0.1332	(0.0083)	0.9151	(0.0887)	0.7906
New Hampshire	2018	0.7676	(0.0010)	-0.0796	(0.0022)	0.5081	(0.0235)	0.9486
New Jersey	2014	0.5558	(0.0015)	-0.0549	(0.0032)	0.3339	(0.0340)	0.8034
Oklahoma	2018	0.6558	(0.0010)	-0.0761	(0.0021)	0.5272	(0.0228)	0.9494
Wisconsin	2008	0.7134	(0.0014)	-0.0800	(0.0030)	0.7502	(0.0325)	0.9269
Wisconsin	2018	0.7845	(0.0006)	-0.0414	(0.0012)	0.5614	(0.0132)	0.9682
West Virginia	2014	0.9286	(0.0013)	-0.0581	(0.0027)	0.4971	(0.0290)	0.8862

Notes: For auctions in which the commission does not enter the scoring rule, we approximate symmetric Bayes-Nash equilibrium by computing how 100 "focal firms" would bid, given a belief that competitor's bids are a linear function of their costs and technical signal. We regress the best responses of the focal firms (e.g., their score bid) on their costs and signals, update beliefs, and iterate, as formalized in equation (21). The table summarizes the regression results for each auction after 31 iterations. We provide the coefficients, the standard errors (in parentheses), and the R^2 for each state-specific regression.

Table B.4: Determinants of Belief Coefficients

	Dependent Variable		
	$\gamma_1^{(31)}$	$\gamma_2^{(31)}$	$\gamma_0^{(31)}$
Rate Weight	-0.1722		0.4742
	(0.0274)		(0.2326)
Technical Weight		0.3623	
		(0.1901)	
# of Bidders	-0.0175	0.1341	-0.0069
	(0.0027)	(0.0189)	(0.0231)
R^2	0.8372	0.8069	0.2421

Notes: The table summarizes how the belief coefficients (after 31 iterations) correlate with selected auction features. The belief coefficients ($\gamma_1, \gamma_2, \gamma_3$) correspond to the coefficient on the cost, the technical signal, and the constant in the belief regressions (reported in Appendix Table B.3). Here, we regress the belief coefficients on the rate weight, the technical weight, and the number of bidders. The unit of observation is an auction, and there are 17 observations. The technical weight equals one less the rate weight, as the commission does not enter the scoring rule for these auctions. Each regression also includes a constant. Standard errors are in parentheses.