Phoning Home: The Procurement of Telecommunications Services for Prison Systems in the United States*

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Abstract

When incarcerated individuals in the United States purchase goods and services, they do so from monopoly vendors selected by their correctional authority. We study the case of inmate calling services (ICS), where the Federal Communications Commission has recently characterized prices as "exorbitant." We obtain and analyze data from public records requests that we submitted to all fifty states.

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1 Introduction

When the more than two million incarcerated individuals in the United States purchase goods and services, they do so from monopoly vendors selected by their correctional authority through public procurement.[1] These individuals use telephone calls to maintain contact with family, friends, and counsel. For this, they pay prices that the Federal Communications Commission (FCC) recently characterized as "exorbitant."[2] The popular press has placed the total annual expenditures of incarcerated individuals on phone calls at over one billion dollars.[3] This has attracted the scrutiny of regulators and policy-makers over the previous two decades, as well as public outcry. In the words of Raher (2020): "*In the eyes of a prison-retail firm, the numerous people entering or leaving jails, and the family members with whom they communicate, add up to a broad and lucrative pool of captive customers.*" However, little academic research has examined the economic incentives that generate the prices that arise or the likely efficacy of regulatory remedies.

This paper studies the procurement of inmate communications services (ICS) for state-level prison systems. The contract award process can be described as a first-score auction with evaluation uncertainty and multi-dimensional bidder types, as detailed below. Our analysis contributes to the empirical auction literature, in particular to the growing knowledge base on "non-standard" auctions. These include 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 on the basis of 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., forthcoming). This literature extends the econometric analysis of auctions beyond the one-dimensional price bid models that are much less "standard" in the real world.

Our second contribution is the collection and analysis of data from this understudied market. Our dataset is based on documents from public records requests that we submitted to all fifty states, covering the request for proposals (RFPs) issued by Departments of Corrections (DOCs). It contains all bids submitted by prospective ICS providers, how the bids were evaluated, and the ensuing contracts. Analyzing this data provides detailed insight into the procurement processes used. Second, it allows for the estimation of the auction model and recovery of firms' costs. We use the model estimates to simulate how the market would respond

[1] About two million people are incarcerated in US prisons and jails according to the Bureau of Justice Statistics; see the reports "Census of State and Federal Adult Correctional Facilities, 2019" and "Census of Jails 2005-2019".

[2] Federal Communications Commission, "Third Report and Order, Order on Reconsideration, and Fifth Further Notice of Proposed Rulemaking," released May 24, 2021. 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, as documented in the press release of the Prison Policy Initiative titled "State of Phone Justice: Local Jails, State Prisons, and Private Phone Providers," written by Peter Wagner and Alexi Jones, and dated February 2019.

[3] Todd Shields, "Prison Phones Prove Captive Market for Private Equity," *Bloomberg BusinessWeek* (October 4, 2012).

to various regulatory interventions.

A distinguishing feature of the auctions is that bids contain a non-negative commission to be paid to the buyer upon winning, rather than how much the bidder would be compensated for executing the services in the contract. Instead, the firm that wins the contract generates profits by becoming the monopoly provider of ICS services in the correctional facility. The second component of the bid is the call rate, which governs expected profits conditional on winning.[4] Existing models do not capture the interplay between the two and how changing the allocation mechanism or competitive environment would affect these equilibrium outcomes. In addition, the ICS service market has not been studied previously and may carry additional (security-related) costs relative to the regular telecom market. In this setting, increasing competition alone may not have the desired effect on procurement outcomes, as in settings with asymmetric bidders (e.g., Athey et al., 2013; Carril et al., 2022).

Besides the call rate and commission, points are given to a harder-to-quantify bid component interpretable as the firm's perceived technical capabilities. Our scoring auction model includes evaluation uncertainty to capture that this is hard to evaluate for bidders, too. Firms only observe a private signal about their technical score and we determine in estimation how informative this signal is. In this dimension, the model is particularly close to Takahashi (2018), who first assesses evaluation uncertainty in score auctions, although due to the quasi-linearity of our scoring rule in the commission our setting can be analyzed using the solution method of Asker and Cantillon (2008).[5]

To solve the model, we use the property that the realized score bid is separable from the rate and technical score bid conditional on winning, akin to scaling auctions with quantity uncertainty studied in Athey and Levin (2001) and Bolotnyy and Vasserman (2023). The separability property also underlies our estimation strategy, as in Bolotnyy and Vasserman (2023). Our unusually small and heterogeneous auction sample warrants a different estimation strategy based on the simulated method of moments (e.g., Pakes and Pollard, 1989; McFadden, 1989). We match simulated moments based on the rate and the commission to the data. As the rate maximizes the winning firm's profit conditional on the final score being as observed in the data, but independently of the number of other firms or their competitiveness, the rate moments are free of assumptions about what firms believe about their opponents. The commission moments are obtained using the approach in Laffont et al. (1995) based on the revenue equivalence theorem (e.g., Milgrom and Weber, 1982; Asker and Cantillon, 2008).

We organize the paper as follows. We first describe the procurement processes used for ICS

[4] The commission-rate structure is related to the cash-royalty auctions for oil drilling rights (e.g., Kong et al., 2022; Bhattacharya et al., 2022), although moral hazard is not an issue, all post-auction revenues accrue to the winning bidder, and the buyer favors lower call rates.

[5] We do use a solution technique similar to Takahashi (2018) in a model validation exercise based on auctions without commissions, relying on the necessary condition that bids are consistent with beliefs in equilibrium. As in Krasnokutskaya et al. (2020), we thus treat the non-price (technical score) component as exogenous, with one difference being that they model uncertainty in the weight placed on quality.

(Section 2). As mentioned above, a striking feature is that money flows from incarcerated individuals and their social contacts to the provider and, often, from the provider to the contracting authority. This may incentivize prospective ICS providers to propose higher call prices, all else equal, so they can afford larger commission payments. We also document that providers are differentiated in their technical capabilities—or, at least, in how their technical capabilities are perceived by contracting authorities—and two providers have most of the state-level contracts. Together, these facts indicate that market power also may distort market outcomes.

We next provide summary statistics and descriptive analyses (Section 3). Across the procurement events ("auctions") for which we received all requested documents, the average price of a 15-minute, collect phone call (the "rate") is \$1.62, close to the estimate of the nonprofit advocacy group cited above. We estimate that the average commission payment is \$11.34 per inmate-month. Among the auctions that result in a commission payment, this amounts to 67% of the revenue obtained from incarcerated individuals and their social contacts.

We use regressions to examine the scoring process in greater detail. First, we find that bids that receive higher scores tend to be proposals with lower rates and higher commissions, on average. Not all auctions include a commission, but in those that do the assigned scores appear less responsive to rates, all else equal. We also find that providers tend to submit bids with higher commissions when commissions receive more weight in the scoring rule, consistent with providers responding to their economic incentives. Providers also tend to propose lower rates when rates receive more weight and higher rates when commissions receive more weight, though only the latter relationship is statistically significant.

We also explore how calling patterns changed with sudden, drastic price reductions implemented in New York prisons in 2010 and New Jersey prisons in 2014. In both cases, we document that the average number of calls per inmate-month increased substantially (from 8.82 to 15.86 in New York and 8.32 to 27.00 in New Jersey). The average number of minutes of use increased similarly, even as total expenditures on ICS fell by 40% in New York and 56% in New Jersey. Interpreting the variation causally, we estimate a demand function for calls that we make use of in the empirical model of procurement. We develop the model in Section 4 and discuss the estimation strategy and results in Section 5. Section **??** clarifies the role of commissions as a key mechanism driving the effects of policy changes.

The counterfactuals (Section 6) will examine various regulatory remedies. Thus far, federal regulation of the ICS industry has taken the form of FCC Orders capping the rates for interstate phone calls. In 2013, the FCC instituted rate caps of \$0.25 per minute for collect calls and \$0.21 per minute for prepaid and debit calls. The Order was contested legally, and in 2017 the District of Columbia Court of Appeals ruled that the FCC does not have the statutory authority to regulate intrastate rates. As a result, the rate caps in the 2013 Order only applied to (less common) interstate calls. In 2021, the FCC further reduced interstate rate caps to \$0.12 per minute for prisons and $0.14 per minute for larger jails.[6] The FCC is currently in a rule-making stage regarding the implementation of the Martha Wright-Reed Act.

Ten states have recently passed laws to eliminate commissions in ICS contracts covering their state-level facilities.[7] Others have implemented or scheduled implementation of free calls: Connecticut declared prison phone calls would be free of charge in 2020, California made audio calls free in 2023, Colorado passed a law to make calls free by 2025, Minnesota declared costs to be free as of 2023, and later in 2023 Massachusetts followed suit.[8] 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.[9] Still, commissions remain legal in 39 states, and many of the aforementioned changes apply to state prison facilities but not county jails.

2 Inmate Calling Services

The ICS industry involves 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 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). The financial terms that determine the flow of funds between these actors are governed by exclusive contracts that the correctional authority signs with a provider. In this section, we describe the industry in greater detail, drawing on regulatory filings (e.g., FCC, 2013, 2015, 2021a), an article written by FCC economists (Baker et al., 2020), a small academic literature (e.g., Jackson, 2005; Raher, 2020; Bazeman et al., 2005), and our conversations with industry experts.

Most incarcerated individuals reside in a county jail before sentencing and in a state prison facility after sentencing.[10] 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 a pricing schedule that is set during the procurement process. The overall expenditure required for a call can depend on a number of factors, including its

[6] Federal Communications Commission, "Third Report and Order, Order on Reconsideration, and Fifth Further Notice of Proposed Rulemaking," released, May 24, 2021.

[7] The states are Colorado, Illinois, Maryland, Nebraska, New Jersey, New Mexico, New York, Ohio, Rhode Island, and South Carolina.

[8] These laws are respectively, Senate Bill 972 in Connecticut, Senate Bill 1008 in California, House Bill 23-1133 in Colorado, SF 2909 in Minnesota, and H. 1796 in Massachusetts.

[9] New York Consolidated Laws, Correction Law - COR Â§ 623 was passed in 2021 and New Jersey bill S-1880 in 2016.

[10] 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.

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 current configuration of the industry reflects a period of consolidation during which GTL and Securus acquired many of the smaller providers. Most recently, GTL acquired Telmate in 2018, the Department of Justice blocked the acquisition of IC Solutions by Securus in 2019 on antitrust grounds, and IC Solutions acquired CenturyLink in 2020.[11]

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 tend to be three or more years in duration.[12]

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 also can 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 the perspective of a provider.

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 others, both the pricing schedule and the

[11]The ICS industry began in 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 different 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).

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

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).

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. We understand that fee data are not typically shared with public entities (e.g., the procuring authorities) and cannot be obtained with public record requests. Still, the available evidence indicates that fee revenue is significant. The FCC determined that ancillary fees can raise the costs to incarcerated individuals and their social contacts by as much as 40%.[13]

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 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 (Bazeman et al., 2005).

3 Data and Empirical Analyses

3.1 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

[13]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.

population (ADP) in the prison system.[14] Our empirical analysis is based on 37 procurement 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.[15] 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.[16] There is significant variation across auctions in all of these measures.

Among the 37 auctions in our data, we observe 7 for which both the rate and the commission are subject to bidding, 10 in which only the commission is subject to bidding, and 18 in which only the rate is subject to bidding (in two auctions, neither is subject to bidding). Across these three subsamples, the average rates are $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 in these 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 ($N = 106$) and analogously for commissions and commission scores ($N = 65$). 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 commissions, and technical capabilities, respectively.

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.

[14] 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 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.

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

[16] The average auction received 4.19 bids from 3.92 bidders; all prospective providers submitted a single bid in 34 of the 37 auctions. Our empirical model assumes that prospective providers submit a single bid because that aligns with common practice. The conditions under which firms submit multiple bids in scoring auctions are explored in Allen et al. (forthcoming).

Table 1: Selected Auction-Level Summary Statistics

	Mean	St. Dev.	10%	25%	50%	75%	90%
All Auctions ($N = 37$)							
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
Rate and Commission in the Scoring Rule ($N = 7$)							
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
Rate Predetermined, Commission in the Scoring Rule ($N = 10$)							
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
Rate in the Scoring Rule, Commission Predetermined ($N = 18$)							
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

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. Two auctions do not place any weight on financial terms in the scoring rule and are therefore omitted from the subsamples.

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 bivariate correlation coefficients are 0.386 and 0.316, respectively.

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 3.4). 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 ($N = 65$).

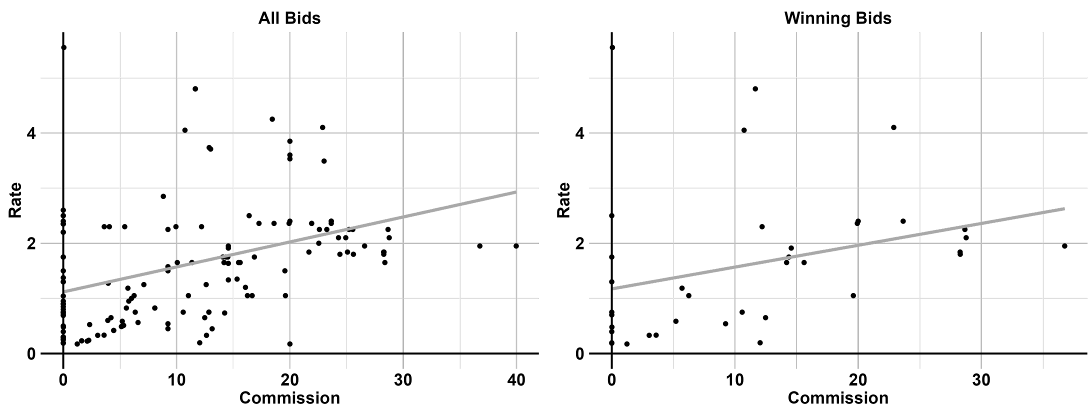

Figure 1: Empirical Relationship Between Rates and Commissions

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 also are shown. The rate is in dollars per 15-minute local collect call. The commission is in dollars per inmate-month.

3.2 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) and (iii) show that a negative relationship also exists in the presence of the provider and the

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			
	(0.024)	(0.023)	(0.040)	(0.050)	(0.039)			
Commission						0.008	0.010	0.018
						(0.003)	(0.003)	(0.006)
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. Standard errors are in parentheses.

auction fixed effects, respectively. Thus, the results indicate that providers tend to receive lower rate scores in auctions for which they propose 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 receive 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.[17] 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.

Overall, there is statistical support for the scores being responsive to the financial terms

[17]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 been 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.

proposed by bidders. Later, in the empirical model, we interpret the regressions as providing deterministic *scoring functions* that connect the scores and financial terms.

3.3 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 fixed the rate weight. Second, a higher rate can provide more revenue to the provider, allowing it to pay a higher commission. 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

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
	(0.588)	(0.621)	(0.527)			(9.527)
Commission Weight			5.64	20.143	17.015	16.456
			(0.962)	(4.673)	(5.369)	(5.247)
Constant	1.347		0.751	12.08		14.472
	(0.226)		(0.912)	(1.532)		(8.011)
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. Standard errors are in parentheses.

be less profitable for the provider to propose the same level of commission.

3.4 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).[18]

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

[18] 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:

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

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.[19]

Table 6 summarizes the regression results. We estimate the model with pooled data (column (i)), with pooled data and state-specific intercepts (column (ii)), and with separate subsamples for the two states (columns (iii) and (iv)). The results across all the columns are similar, but we

[19]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 results.

Table 6: Demand for Calls

	(i)	(ii)	(iii)	(iv)
Price	-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 dependent variable is the average number of calls per inmate-month. Observations are at the state-month level. The sample for New York includes January-December 2009 and April 2010 - March 2011. The sample for New Jersey includes January-October 2013 and January-December 2016.

interpret columns (ii)-(iv) as most reliably summarizing the variation in the data. To obtain the demand function that we use in the model of procurement, we average the final two columns: $q = 24.47 - 4.41r$. 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.[20]

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. We assume that the number of bidders, J_i, is exogenously determined. Under a change-of-variables proposed in Asker and Cantillon (2008) and used elsewhere in the literature, firms submit scores, $\hat{s}_{ij}$, and the firm with the highest score is selected. The provider must then de-

[20]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.

liver a contract to the buyer that specifies financial terms and has a value equal to the submitted score. Buyers evaluate contracts using a binding scoring rule, although some uncertainty about how buyers assess firms' technical capabilities will be incorporated.

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 increasing and $s_i^k(\cdot)$ is strictly decreasing.

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.[21] 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 at the time 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 $c_{ij} \perp \tilde{\xi}_{ij}\ \forall ij$.*

ASSUMPTION 2 (Technical Scores). *The distribution of technical scores conditional on the signal*

[21] 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.

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 model accommodates that, in some auctions, the rate or the commission is predetermined by the procuring entity. This corresponds to weights in the scoring rule of $\omega_i^r = 0$ or $\omega_i^k = 0$, respectively. Where the rate and commission are choice variables of the winning firm, however, we assume they are selected to maximize profit, subject to $s_i(r_{ij}, k_{ij}, v_{ij}) = \hat{s}_{ij}$, where again we let firm j be the winning firm. Assumptions that we introduce later ensure that the profit-maximizing rates and commissions exist. Taking these as given, the profit of the winning bidder can be expressed as an implicit function of the score that it bids, its cost, and its technical score: $\pi(r_{ij}^*, k_{ij}^*, c_{ij}) = \pi(\hat{s}_{ij}, c_{ij}, v_{ij})$.

We assume that each firm submits a score according to a strategy, $\sigma_i(c_{ij}, \xi_{ij})$, that maximizes its expected profit, conditional on the strategies of other firms. Given evaluation uncertainty, the expected profit is:

$$\Pi_{ij}(\hat{s}_{ij}; c_{ij}, \xi_{ij}) = P_i(win|\hat{s}_{ij}) \int \pi(\hat{s}_{ij}, c_{ij}, v) dF_{V|S}(v|\xi_{ij}) \tag{4}$$

where the first term is the probability that firm j wins the auction (this implicitly incorporates other firms' strategies) and the second term is the profit conditional on winning.[22] Firms must balance that submitting a higher score increases their probability of winning but decreases their profit conditional on winning. In the next sections, we characterize the bidding strategies that arise in symmetric Bayes-Nash equilibrium.

4.2 Equilibrium with Commissions

The characterization of equilibrium strategies depends on whether the commission is a strategic variable (equivalently, whether $\omega_i^k > 0$). We first consider auctions that feature commissions, for which the model falls into a class of scoring auctions studied in Asker and Cantillon (2008). Two additional assumptions are necessary:

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

ASSUMPTION 4 (Surplus properties). *$\psi_i(r, v) + (r - c)q(r)$ is bounded and strictly concave in r.*

If the scoring rule, $s_i(\cdot)$, reflects the preferences of the buyer, then the transformation, $\phi_i(\cdot)$, expresses those preferences in units of currency, and $\psi_i(\cdot) + (r - c)q(r)$ is the social surplus that accrues to the buyer and the selected supplier.[23] Because the commission is a transfer between the buyer and provider, it cancels from the social surplus measure.

[22]A more mathematical expression of the win probability is: $P_i(win|\hat{s}) = P_i\left(\hat{s}_{ij} \geq \max_{k=1,\ldots,J_i} \{\hat{s}_{ik}\}\right)$.

[23]This measure is unlikely to reflect total social surplus for a number of reasons, including that, to the extent it reflects the preferences of incarcerated individuals, it is only through the rate component of the score.

Under assumptions 3 and 4, the rate and commissions that maximize the profit of firm j, conditional on winning 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 social 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 rate is predetermined by the contracting entity, let r^*_{ij} correspond instead to the predetermined rate. The commission is set to satisfy:

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

where, in a slight abuse of notation, we assume that $\hat{s}_{ij}$ is expressed in units of currency. Putting these equations together, the winning firm can be conceptualized as setting a rate that maximizes the size of the "pie" it creates and a commission that provides "slices" to itself and the buyer based on the scoring rule and its bid.

A few observations can be made. Equations (5) and (6) show that the rate and commission are *non-strategic*, in the sense that they are determined independently of the competition, conditional on the firm's bid, $\hat{s}_{ij}$. This clarifies why equilibrium strategies can 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_{ij}, 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 (score) bidding strategy. Let the *pseudo-type* of the firm, x^*_{ij}, be the maximum social surplus that the firm expects to be able to generate if it wins the auction:

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

Firms that have the same pseudo-type adopt the same bidding strategies in equilibrium (Asker and Cantillon, 2008), so we have $\sigma_i(c_{ij}, \xi_{ij}) = \sigma_i(x^*_{ij})$. Furthermore, the equilibrium score that firms bid increases monotonically in the pseudo-type, so the firm with the highest pseudo-type wins the auction. Applying a change of variables to equation (4), using equation (7), we obtain an expression for the equilibrium bidding strategy:

$$\sigma_i(x^*_{ij}) = \arg\max_{\hat{s}} P_i(win|\hat{s})(x^*_{ij} - \hat{s}) \tag{8}$$

The first term in the maximand is the probability of winning, as before. The second term is the portion of social surplus that the firm expects to retain as profit if it wins.

The probability of winning equals the probability that $J_i - 1$ bidders have a pseudo-type below $\sigma_i^{-1}(\hat{s})$, relying on symmetry and monotonicity of the equilibrium:

$$P_i(win|\hat{s}) = T_i\left(\sigma_i^{-1}(\hat{s})\right)^{J_i-1} \tag{9}$$

where $T_i(\cdot)$ is the distribution of pseudo-types, given as

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

A closed-form solution for the equilibrium bids now can be derived. 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

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

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.[24]

4.3 Equilibrium without Commissions

The solution technique of Asker and Cantillon (2008) does not apply if the commission is not a choice variable of the firm (i.e., if $\omega_i^k = 0$). However, a similar change-of-variables can be adopted to address multi-dimensional types (consisting of c_{ij} and ξ_{ij}) and the evaluation uncertainty. The symmetric Bayes-Nash equilibrium comprises strategies, $\sigma_i(c_{ij}, \xi_{ij})$, that maximize the expected profit function of each firm, conditional on other firms using the same strategy. If firm j wins auction i with a score bid of $\hat{s}_{ij}$, the rate it sets, r_{ij}^*, solves the equation $s_i(r_{ij}, k_i, v_{ij}) = \hat{s}_{ij}$, given a commission k_i that is pre-determined by the buyer. A solution exists because $s_i(\cdot)$ is strictly increasing in r. The rate pins down profit. Formally, the equilibrium (score) bidding strategy is

$$\hat{s}_{ij}^* = \sigma_i(c_{ij}, \xi_{ij}) = \arg\max_{\hat{s}} P_i(win|\hat{s}) \int \pi\left(\hat{s}, c_{ij}, k_i, v\right) dF_{V|S}(v|\xi_{ij}) \tag{12}$$

[24] In estimation, we use the commission that a firm expects to pay if it wins. The expected commission differs from equation (6) due to evaluation uncertainty and is given by

$$\bar{k}_{ij}^* = \bar{k}_{ij}^*(\hat{s}_{ij}, c_{ij}, \xi_{ij}) = \hat{s}_{ij} - \int \psi_i(r_{ij}^*, v) dF_{V|S}(v|\xi_{ij})$$

where, again, the first term is the probability that firm j wins the auction (this implicitly incorporates other firms' strategies) and the second term is the profit conditional on winning. A higher score bid increases the probability of winning, all else equal, but reduces profit conditional on winning because it implies a lower rate.

The equilibrium score bid decreases in cost and increases in the signal of the technical score. For intuition on the latter property, consider that a bidder with a higher signal about its technical score has a lower expected implicit cost of delivering a contract worth any given score (meaning that they expect to set a higher rate and retain more profits). Bidders with higher signals are, therefore, more competitive in expectation, even though they draw costs from the same distribution. As they also submit single-dimensional score bids, it renders the setting with $\omega_i^k = 0$ close to asymmetric private value first-price auction models (e.g., Campo et al. (2003), Carril et al. (2022)). We use an approximation of the equilibrium defined by equation (12) in simulated sets of auctions to validate our parameter estimates, as detailed below.

5 Estimation

We estimate the model in parts. We first discuss the scoring functions and demand, then the (unconditional) technical score distribution, and 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.

5.1 Scoring Functions and Demand Function

We assume that the scoring functions for rates and commissions and the demand function are linear in their arguments. The scoring functions take the following form:

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

$$s_i^k(k_{ij}) = \alpha_{0i}^k + \alpha_1^k k_{ij} \tag{14}$$

We account for unobserved heterogeneity in the way bids are scored through the fixed effects of the scoring functions. We do, however, assume that the slopes are common across auctions. We estimate the scoring functions as described in Section 3.2. The slope coefficients are in columns (iv), (v), and (viii) in Table 3. Accounting for unobserved scoring function 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).[25]

[25] 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

For the demand function, we estimate equation (1) as described in Section 3.4. We use an average of columns (iii) and (iv) in Table 6.

Linearity ensures that assumptions 3 and 4 hold for any auction in which the commission is a strategic variable (equivalently, $\omega_i^k \alpha_1^k \neq 0$). Furthermore, substituting into equation (2) and rearranging yields an analytical solution for the transformed scoring rule:

$$\begin{aligned} \psi_{ij} &\equiv \psi_i(r_{ij}, v_{ij}) = \frac{\omega_i^r \alpha_1^r}{\omega_i^k \alpha_1^k} r_{ij} + \frac{\omega_i^v}{\omega_i^k \alpha_1^k} v_{ij} + \frac{\omega_i^k \alpha_{0i}^k + \omega_i^r \alpha_{0i}^r}{\omega_i^k \alpha_1^k} && (15) \\ \phi_{ij} &\equiv \phi_i(r_{ij}, k_{ij}, v_{ij}) = \psi_{ij} + k_{ij} && (16) \end{aligned}$$

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

$$r_{ij}^* = \frac{1}{2}\left(-\frac{\beta_0}{\beta_1} + c_{ij} - \frac{1}{\beta_1}\frac{\omega_i^r \alpha_1^r}{\omega_i^k \alpha_1^k}\right) \quad (17)$$

As we have 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 technical capabilities of the firm. As they depend on the auction weights only through the ratio of $\omega_i^r \alpha_1^r$ to $\omega_i^k \alpha_1^k$, 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 that would be set by a profit-maximizing monopolist.

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 variation that is more relevant for bidding incentives and is consistent with our treatment of the scoring functions. The standard deviation of the residuals is 0.12. Appendix Figure B.2 plots the empirical distribution of residuals along with the (re-centered) unconditional technical score distribution that 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

are placed, then they would enter in the same way as the shock to the technical score.

and noise as given by

$$\lambda = \frac{\sigma_\xi^2}{\sigma_\xi^2 + \sigma_\epsilon^2} = \frac{\sigma_\xi^2}{\sigma_v^2} \tag{18}$$

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, $F_{V_i|S}(\cdot; \xi_{ij})$, 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 we discuss in the next section.

5.3 Cost Distribution and Informativeness of the Signal

We assume that 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 that we compute the symmetric Bayes-Nash equilibrium for every candidate parameter vector. As is well-known, direct solutions to equations (11) and (12) are computationally burdensome to obtain, and this shapes our approach to estimation.

We obtain estimates with data from auctions for which the commission is a strategic variable, using the approach of Laffont et al. (1995). The main idea is that some equilibrium objects from these auctions, including the winning firm's rate and expected commission, are theoretically identical to those that arise in a revenue-equivalent second-score auction. As equilibrium in the second-score auction features dominant strategies, equation (6) can be bypassed.[26] This facilitates estimation because the targeted equilibrium objects can be obtained quickly and repeatedly. We also use data from auctions for which the commission is *not* a strategic variable, but do so in the context of an out-of-sample model assessment exercise (next section) rather than directly in the estimation procedure.

The equilibrium outcomes that enter the moments are the winning firm's rate and expected 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

[26]In the second-score auction, the dominant strategy is to propose a score that equals the expected social surplus (i.e. the pseudo-type). The second-best pseudo-type 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 pseudo-type of each firm, determine the value of the winning contract that must be delivered, and calculate the rate and expected commission that the winning firm would select to fulfill that contract.

moments take the form

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

$$\mathbf{m}_k(\boldsymbol{\theta}) = \frac{1}{I}\sum_i \left(\bar{k}_i^{(1)} - \frac{1}{L}\sum_{l=1}^{L} \tilde{\bar{k}}_{il}^{(1)}(\boldsymbol{\theta}) \right) g\left(\mathbf{Z}_i\right) \tag{20}$$

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 $\tilde{\bar{k}}_{il}^{(1)}(\boldsymbol{\theta})$ 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 instruments that we include are a constant, the number of bidding firms, and the auction weights on rates and commissions. To construct the $g(\cdot)$ function, we specify a second-order polynomial of the instruments. 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

$$\hat{\boldsymbol{\theta}} = \underset{\theta \in \Theta}{\arg\min} \left(\mathbf{M}(\boldsymbol{\theta})' \mathbf{A}^{-1} \mathbf{M}(\boldsymbol{\theta}) \right) \tag{21}$$

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. The sample includes 16 auctions, and we simulate each 1,000 times.

Table 7 summarizes the results. We estimate the mean and standard deviation of the cost distribution to be 0.23 and 0.51, respectively. This implies a fair amount of cost-based heterogeneity among firms which, together with the heterogeneity in technical score, fits with the empirical reality that Securus and GTL win many more prison-system contracts than other providers. The cost of the winning firm, averaging across auctions and simulation draws, is -0.06. Thus, the results are consistent with ancillary fee revenue largely offsetting the explicit cost of service for the firms most likely to win a contract. Observing a number of 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.[27] Our results are also consistent with Bazeman et al. (2005), which places explicit costs in the \$0.15-\$0.18 range for a 15-minute call.

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 0.04). Further,

[27] 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 7: Cost Distribution and Informativeness of Signal

		Estimate	St. Error
Estimation Results			
Mean of Costs	μ_c	0.23	(0.04)
Standard Deviation of Costs	σ_c	0.51	(0.11)
Informativeness of Signal	λ	0.16	(0.04)
Derived Equilibrium Statistics			
Rate	$r_i^{(1)}$	2.10	
Commission	$\bar{k}_i^{(1)}$	20.07	
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 weights commissions by only two percent. Point estimates and standard errors are shown. We also report the rate, expected commission, and profit of the winning firm, averaging across simulation draws and auctions. The rate is for a 15-minute call. The commission and profit are per inmate-month.

we obtain standard deviations of the signal and the evaluation noise of $\sigma_\xi = 0.05$ and $\sigma_\epsilon = 0.11$, respectively, making use of equation (18). Our results are consistent with firms having significant uncertainty about how buyers will evaluate their technical capabilities.[28]

We also report equilibrium statistics that we obtain by averaging across auctions and simulation draws. The mean rate implied by the model is $2.10 per 15-minute call, and the mean commission is $20.07 per inmate month. These are close to the empirical means of $2.27 and $18.51, respectively, that we calculate for the auctions in the sample. The equilibrium rates imply that average non-fee revenue is $31.18 per inmate-month. Thus, the commission accounts for 59% of non-fee revenue on average. Also factoring in the explicit cost of service and fee revenue, the model implies that the profit of the winning firm is $12.32 per inmate on average.

5.4 Model Assessment

We now use the data from auctions in which the commission is not a strategic variable to conduct an out-of-sample assessment of the model and our parameter estimates. The exercise involves computing the Bayes-Nash equilibrium, taking as given the estimated parameters, and comparing the equilibrium rates to those in the data. The exercise is ambitious because auctions without commissions tend to be quite different from those with commissions (Section 3.1). The key statistic for present purposes is the average rate, which is $2.27 among the auctions in the

[28] We conduct an additional empirical 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.

estimation sample but \$0.76 among the auctions in the validation sample.[29]

Computing equilibrium for these auctions is challenging, and we cannot use the revenue equivalence theorem to bypass solving for the full solution to equation (12) because the only strategic variable—the rate—is not a transfer between the winning firm and the buyer (it also affects the number of calls and thus the amount of "social surplus"). Our approach is to specify an initial set of beliefs that firms have about how competitors will bid, under which the scores that firms actually bid solve single-agent optimization problems. To find beliefs that are consistent with equilibrium behavior, we update the initial set of beliefs based on the solutions to the firms' optimization problems, obtain new solutions, and iterate on this process until the beliefs and solutions converge. What is obtained is a simulated approximation of the symmetric Bayes-Nash equilibrium in (12).[30]

To add detail, in each iteration $h = 0, 1, \ldots$, we assume that firms believe that their competitors will bid scores according to a linear function of auction and firm observables:

$$\hat{s}_{ij}^{(h)} = \mathbf{x}_{ij}' \gamma^{(h)}. \tag{22}$$

where the vector $\gamma^{(h)}$ contains what we refer to as the "belief coefficients" in iteration h. We include five observables in $\mathbf{x}_{ij}$: a constant, the auction-specific constant in the scoring function for rates (α_{0i}^r), the auction-specific mean technical score ($\overline{v}_i$), the scoring rule weight on rates (ω_i^r), the number of bidders (J_i), the predetermined commission (k_i), cost (c_{ij}), and the technical score signal (ξ_{ij}).

We solve numerically for the scores that a number of simulated firms would bid in each auction, given these beliefs. The simulated firms are defined by cost and signal draws, and we incorporate their uncertainty about their competitors' costs and signals.[31] We regress the profit-maximizing score bids of the simulated firms on the same determinants to obtain regression coefficients, $\hat{\gamma}^{(h)}$, 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 $\rho^{(h)} \in [0, 1]$ is a tuning parameter that controls the step sizes, and repeat.

Beliefs are consistent with equilibrium play if they align with how firms would actually set their bids given the beliefs. Our empirical measure of alignment is the mean squared error (MSE) between the belief coefficients and the regression coefficients. We calculate the MSE at

[29] We include all auctions for which rates enter the scoring rule but commissions do not, except for New Hampshire in 2013, which places 100% of the scoring rule weight on rates. In total, 17 auctions are included.

[30] Our procedure is in the spirit of Takahashi (2018), although the implementation details differ. Other approaches are possible. For example, Carril et al. (2022) assume a distribution on equilibrium *bids* and estimate the parameters of that distribution, matching simulated moments to data and thereby also guaranteeing that actions are consistent with beliefs at the solution. See Bajari (2001) and Richert (2024) for alternative indirect inference methods.

[31] We detail the simulation techniques we use in Appendix A.1.

iteration h according to

$$MSE^{(h)} = \frac{1}{M}\sum_{m}\left(\gamma_m^{(h)} - \hat{\gamma}_m^{(h)}\right)^2 \tag{24}$$

where the subscript $m = 1, \ldots, M$ denotes the m^{th} element of the coefficient vector. To our knowledge, convergence is not guaranteed. We use one iteration with $\rho = 1$, and thirty iterations each with $\rho = 0.50$, $\rho = 0.25$, $\rho = 0.10$, and $\rho = 0.01$. We obtain an MSE of 5e-10.[32]

Table 8 summarizes the results. The headline result is that the expected rate of the winning bidder, averaging across auctions, is \$0.82, which is close to the \$0.76 that we observe as the empirical average. The expected profit of the winning firm, at \$6.72 per inmate-month, is less than what we estimate for auctions that feature commissions in the scoring rule (\$12.32, see Table 7). Thus, the lower rates that we observe in the validation sample have a larger effect on profit than the smaller, predetermined commissions. The coefficients take the expected signs and are precisely estimated. The R^2 of 0.99 does not point to a meaningful role for excluded determinants or non-linearity. Overall, we interpret the result as corroborating the usefulness of the model in our setting.[33]

6 Policy Implications

6.1 Rate Regulation

We first explore the economic effects of rate regulation. To do so, we simulate equilibrium outcomes for a range of predetermined rates, holding everything else about the auction environment fixed. The policy experiment bears the FCC's regulation of the ICS industry to date, which involve rate caps for interstate calls. It also bears on recently passed state laws in Connecticut, California, Colorado, Minnesota, and Massachusetts that make calls free. We use an auction with four bidders and scoring rule weights of $\omega^k = 0.33$ and $\omega^v = 0.67$. We consider rates ranging from \$0.00 to \$2.00 per 15-minute call.

Figure 2 presents the results. The top left panel focuses on the commission and the profit of the winning firm. With a \$2.00 regulated rate, the commission payment is \$25.21 per inmate-month. As the regulated rate falls, 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 buyer pays the provider \$4.15 per inmate month.[34]

[32]Running the 151 iterations takes about 16 hours (using a single processor). We use starting values that create variation for the initial regression: -0.5, 0.5, 0.5, 0.5, 0.5, -0.5, -0.5, and 0.5 for the six coefficients, respectively.

[33]As a caveat, the model does not match cross-auction variation in rates *within* the auctions used in the assessment exercise. Therefore, we view the model as more appropriate for drawing representative conclusions that characterize the industry generally than for evaluating any single, specific auction setting.

[34]Benchmarking this against the lowest rates in our data (Appendix Table B.1), a commission is paid in two of four contracts with rates below \$0.20. Our understanding is that some states now pay for ICS with free calls. For example, Connecticut Senate Bill 972 (2021) states: "The annualized cost for paying the [ICS] vendor for telephone

Table 8: Model Assessment Exercise

		Coefficient	St. Error
Determinants of Firm's Beliefs			
Constant	1	-0.1757	(0.0002)
Constant in Scoring Function for Rates	α_{0i}^r	0.4398	(0.0002)
Mean Technical Score	$\overline{v}_i$	0.6250	(0.0002)
Scoring Rule Weight on Rates	ω_i^r	0.1699	(0.0002)
Number of Bidders	J_i	0.0013	(0.0002)
Predetermined Commission	k_i	0.00004	(0.00001)
Cost	c_{ij}	-0.0729	(0.0001)
Technical Signal	ξ_{ij}	0.4518	(0.0006)
Coefficient MSE		2e-10	
R^2		0.99	
Derived Equilibrium Statistics			
Expected Rate of Winning Bidder		0.82	
Expected Profit of Winning Firm		6.72	

Notes: We approximate symmetric Bayes-Nash equilibrium bidding strategies by computing how 100 "focal firms" bid in each of 17 auctions, given a belief that competitor's bids are a linear function of the determinants in the table. We then regress the focal firms' bids on the determinants and update beliefs. The table shows the regression after 151 iterations. The MSE describes the distance between the belief and regression coefficients. The derived equilibrium statistics are the expected rate and profit of the winning bidder, averaging over the 17 auctions in the validation sample. Appendix A.1 provides details on the simulation methods.

The top left panel also shows modest profit *increases* as regulated rates fall. This reflects that the loss of rate revenue is more than offset by the change in the commission payment and a gain in fee revenue. The reason this occurs is that 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 correspond with "high fees"). Although all firms lose profit from call prices as regulated rates fall, this effect is larger for high-cost firms. In equilibrium, the disadvantaged firms bid less aggressively and exert weaker competitive pressure, 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 rather than incarcerated individuals.

The remaining panels in the figure illustrate some of these effects. In the top right panel, we show that the expected cost of the winning firm decreases as regulated rates fall. The expected technical score signal also decreases, but more modestly. This reflects that, as rates fall, profit is increasingly dependent on having low costs (or high fees). Firms with higher costs and better technical capabilities become less likely to bid aggressively enough to win. The bottom left panel shows that the pseudo-types of the first-best and second-best firms decrease as regulated rates fall (this occurs because less profit is obtained from call prices). However, the pseudo-type

services is approximately \$4.5-\$5.5 million per year...."

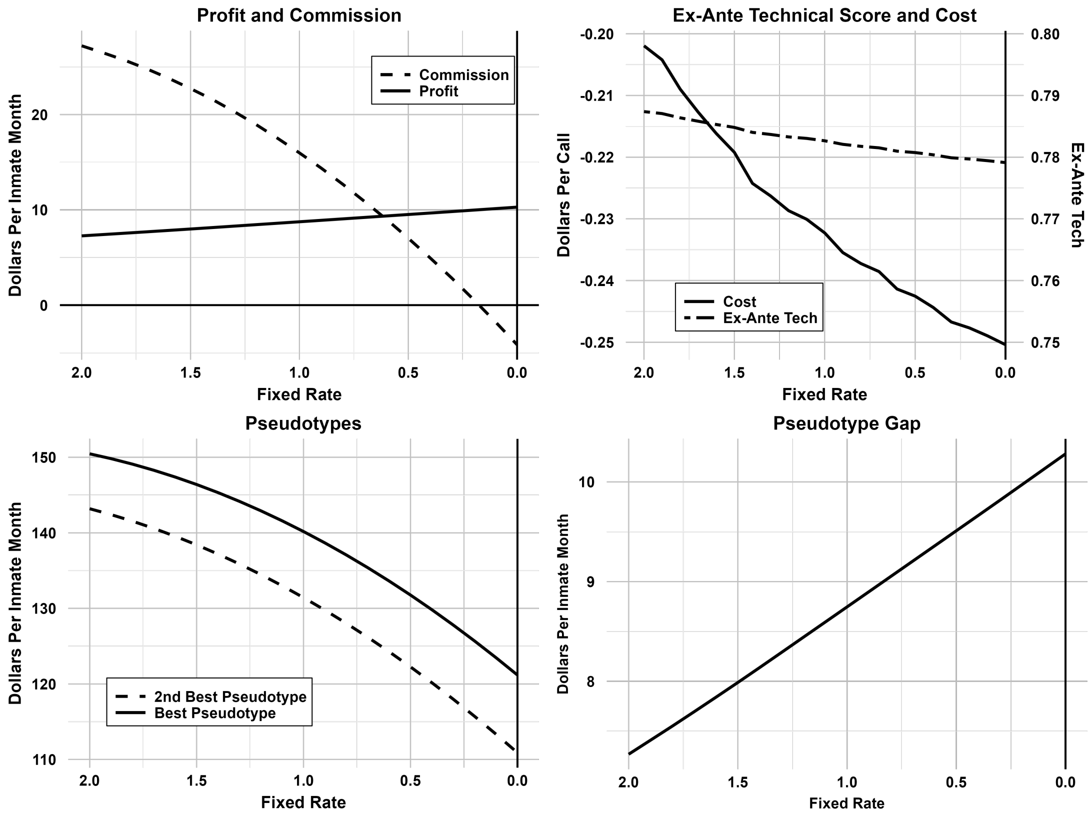

Figure 2: The Economic Effects of Rate Regulation

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 \$2.00 per 15-minute call (horizontal axis). The top left panel shows the expected commission payment and the profit of the winning bidder. The top right panel shows the expected cost and technical score signal of the winning bidder. The bottom left panel shows the expected first-best and second-best pseudo-types, and the bottom right panel shows their difference.

of the second-best firm falls more rapidly because, on average, it has higher costs. Because the widening gap in pseudo-types may be difficult to see, we plot the "pseudo-types gap" in the bottom right panel. It is precisely the difference between the pseudo-types of the first- and second-best firms that determines the market power. Indeed, the pseudo-type gap equals the profit of the winning bidder (e.g., compare the bottom right and top left panels).

Thus, in the model, rate regulation can shift the burden of paying for ICS from incarcerated individuals and their social contacts to the correctional authority. Enacted in isolation, it also increases the market power and profit of the winning firms by placing prospective providers that have relatively high costs or low fees at a disadvantage in the auction process.[35]

[35]Whether these results would hold if rate regulation were implemented in conjunction with a fee ban would depend on the extent to which fee policies are heterogeneous across firms. If the cost heterogeneity in our model is due to differences in the explicit cost of service, rather than differences in fees, then the results extend. See Appendix Figure B.3, where we simulate regulated rates with a cost distribution that is shifted up by \$0.50, to mimic a uniform loss of fees. The commission line shifts but the profit line is unchanged. On the other hand, if

firms differ in their fee policies, then banning fees would disproportionately affect firms on the low end of the cost distribution, increasing competitive intensity in the market by making firms more similar. Another possibility that we do not explore is that fee regulation could encourage firms set higher fees in response.

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Appendix

A Methodological Details

A.1 Simulation Techniques for Auctions without Commissions

We provide additional details on our implementation of the model assessment exercise described in Section 5.4. We take 10 evenly-spaced draws from both the cost distribution and the signal distribution. As the cost and the signal distributions are independent (by assumption), the combination of these draws provides 100 representative "focal firms" for which we can obtain profit-maximizing bids in each auction, given a set of beliefs. As there are 17 auctions in the validation sample, we compute 1700 profit-maximizing bids during each iteration on beliefs, and there are 1700 observations in our regressions of bids on belief determinants.

We compute each profit-maximizing bid numerically. For a candidate bid from a focal firm with a known cost and signal, and in a given auction, we compute the implied rate and profit (conditional on winning) for each of 999 evenly-spaced draws on the evaluation noise. We obtain the (perceived) probability of winning by determining the fractions of times that the focal firm's 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; the numbers of competitors in the sets are auction-specific. 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 in hand, we obtain the expected profit that a candidate bid obtains (given the auction and focal firm).

We use the optimize function in R to conduct the optimization. This requires that we specify lower and upper bounds for the bids. As the lower bound, we use the score that corresponds to the monopoly price with the lowest possible technical score for focal firm (given the evaluation noise draws). As the upper bound, we use the score that corresponds to at-cost rates with the highest possible technical score. Given the finite number of simulated sets of competitors, some focal firms perceive there to be no probability of winning, and for those, we impute the bid using the beliefs. Omitting those observations from the regression obtains nearly identical results. We update beliefs as described in Section 5.4.

B Additional Figures and Tables

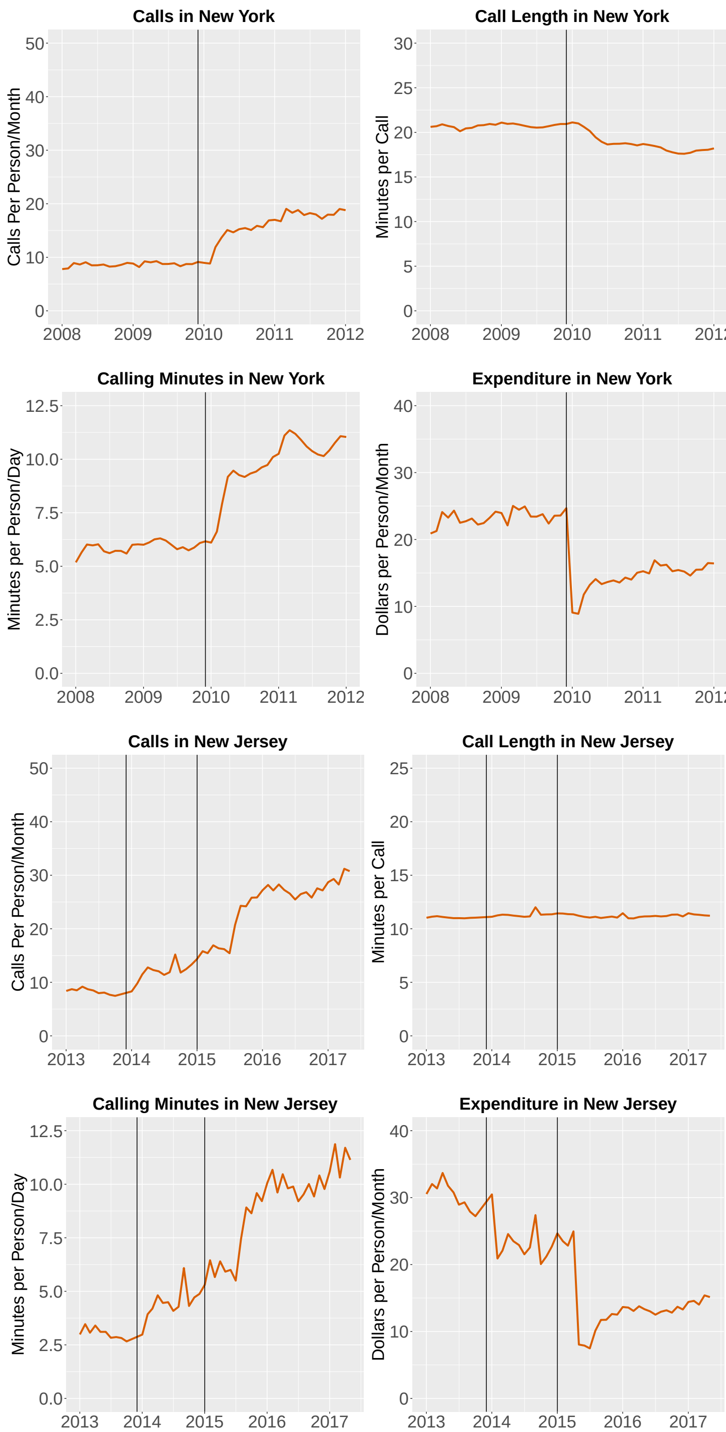

Figure B.1: Calling Patterns Before and After Price Reductions

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.

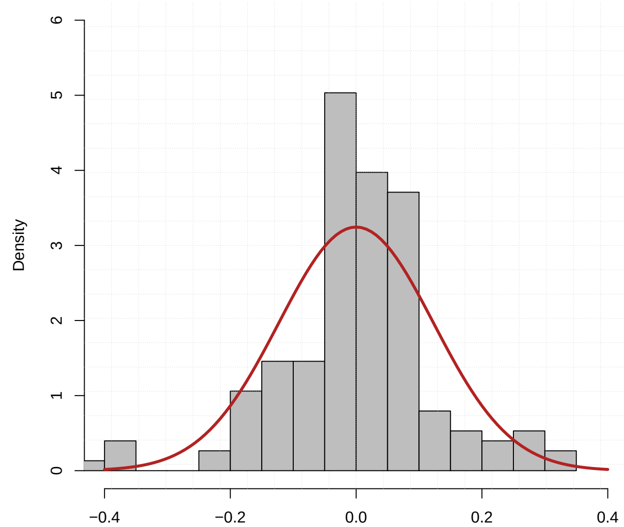

Figure B.2: Distribution of Technical Score Residuals

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.

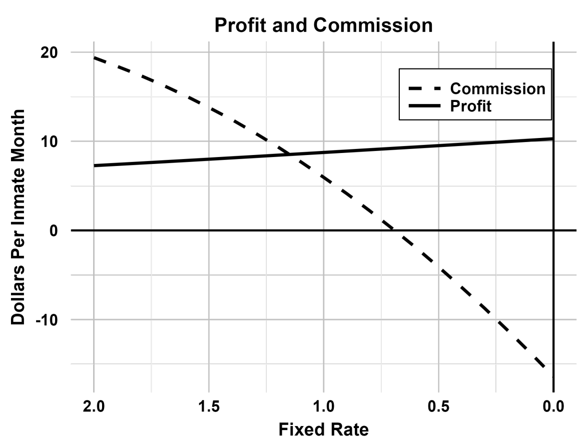

Figure B.3: Rate Regulation with a Ban on Fees

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 \$2.00 per 15-minute call (horizontal axis). The estimated cost distribution is shifted up by \$0.50 to incorporate a "ban on fees; such a shift approximates a fee ban if firms have the same fee policies. The figure shows the expected commission payment and the profit of the winning bidder. The expected commission equals zero at a regulated rate of \$0.692.

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 the 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.