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ABSTRACT

We empirically study bidding in the C Block of the US mobile phone spectrum auctions. Spectrum auctions are conducted using a simultaneous ascending auction design that allows bidders to assemble packages of licenses with geographic complementarities. While this auction design allows the market to find complementarities, the auction might also result in an inefficient equilibrium. In addition, these auctions have equilibria where implicit collusion is sustained through threats of bidding wars. We estimate a structural model in order to test for the presence of complementarities and implicit collusion. The estimation strategy is valid under a wide variety of alternative assumptions about equilibrium in these auctions and is robust to potentially important forms of unobserved heterogeneity. We make suggestions about the design of future spectrum auctions.

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1 Introduction

The US Federal Communications Commission (FCC) auctions licenses of radio spectrum for mobile phone service. Based on the recommendations of academic economists, the FCC employs an innovative simultaneous ascending auction. Bidding lasts for multiple rounds, and there is simultaneous bidding on all licenses in all rounds. The sale of all licenses closes when no more new bids for any license are forthcoming. Simultaneous ascending auctions allow bidders, mobile phone carriers in spectrum auctions, to assemble packages of licenses exhibiting the potential for substantial complementarities (or synergies) across licenses. For instance, a carrier that holds two geographically adjacent licenses can offer mobile phone users a greater geographically contiguous coverage area. The auction format's novelty and the economic importance of mobile phone markets have stimulated a large and vibrant theoretical literature. With the notable exception of the papers listed below, however, there is relatively little empirical work concerning the spectrum auctions.

We study data from the 1995–1996 auction of licenses for the C Block of the 1900 MHz PCS spectrum band, where the final bids totaled \$10.1 billion. The C block divided the United States into 493 small, geographically distinct licenses. The intent of auctioning small licenses was to allow a market mechanism rather than a regulator to determine the allocation of licenses so that the licenses are more likely to be used efficiently. Unfortunately, the auction might not maximize welfare from complementarities because the auction might possess inefficient equilibria. Efficiency might suffer if bidders implicitly collude through the threat of intimidatory bidding wars. For example, a bidder trying to add an additional license to a package to take advantage of complementarities might be punished by higher, retaliatory bids on its other licenses. Our contribution is to assess efficiency in these auctions and to determine whether implicit collusion prevented the efficient division of licenses into complementary packages.

In this paper, we propose and estimate a structural model of bidding in the C block spectrum auction. Our estimator has three novel features that contribute to the literature on the analysis of multiple unit auctions. First, like the estimator proposed by Haile and Tamer (2003), our estimator does not require the economist to make specific assumptions about which equilibrium was played in the data. There is no widely accepted theoretical model of bidding in spectrum auctions. Indeed, the theoretical problems of existence, uniqueness and characterization of equilibrium are far from resolved for dynamic, multiple unit auctions of the sort that we consider. Therefore, an estimation strategy that makes the minimal possible assumptions about the specific equilibrium being played in these markets is attractive for empirical work. Second, our estimates of bidder valuations will be consistent even if there is omitted heterogeneity in the form of license specific attributes that are valued equally by bidders but unobserved to the econometrician. Third, our estimation strategy allows for an extremely large, but discrete set of possible choices. This is crucial for our application since the number of possible packages that bidders can assemble is extremely large.

The C block auction is a unique experiment in modern business history. Only investors that were not associated with incumbent mobile phone carriers were allowed to bid in the C block. We choose to analyze data from the C block instead of the AB or DEF blocks for two other reasons. First, legal restrictions on incumbent phone companies make specification of the relevant choice sets quite complicated in the other spectrum auctions. Also, the number of firms that bid is larger in the C block than the AB block, yielding more observations for empirical work.

There are separate descriptive empirical literatures on complementarities and collusion in spectrum auctions. On complementarities, Ausubel, Cramton, McAfee and McMillan (1997) and Moreton and Spiller (1998) document that bidders purchased licenses that were geographically adjacent, and that winning bids are higher in markets where the second-highest bidder won adjacent licenses. For collusion, empirical research by Cramton and Schwartz (2000) and Cramton and Schwartz (2002) presents descriptive evidence that bidders in AB block did not aggressively compete for licenses and in the later DEF block auction used the last digits of numeric bids to signal rivals not to bid on other licenses.

Next, we turn to the problem of estimation. A main difficulty with estimation is, as discussed above, that there is no generally agreed upon model of bidding in spectrum auctions. While there is an extensive literature on structural estimation of auction models, most of these models assume that the econometrician has considerable information about the equilibrium to the game realized in the data. (See Donald and Paarsch (1993) and Donald and Paarsch (1996), Elyakime, Laffont, Loisel and Vuong (1994), Guerre, Perrigne and Vuong (2000), Campo, Guerre, Perrigne and Vuong (2000), Athey and Levin (2001), Campo (2001), Flambard and Perrigne (2002), Hortacsu (2002), Hendricks, Pinkse and Porter (2003), Bajari and Ye (2003), Jofre-Bonet and Pesendorfer (2003), Fevrier, Préget and Visser (2003), Cantillon and Pesendorfer (2003), Athey, Levin and Seira (2004) and Krasnokutskaya (2004).) In the spirit of Haile and Tamer (2003), we search for predictions that are robust across a wide range of theoretical models. One prediction that must hold in any equilibrium model (with pure strategies) is that at the end of the auction, a bidder's continuation value from the chosen action must be at least as large as the continuation value from actions that are not chosen. We use this system of revealed preference inequalities to form an estimate of a bidder's continuation value for bidding on a particular package.

An attractive feature of our estimator is that license-specific omitted variables that are valued equally by bidders are "differenced out" and do not bias estimates of the other structural parameters. Because we make weak assumptions about the data generating process, we are only able to recover information about within-auction continuation values, not the post-auction bidder valuations for alternative licenses. However, our estimates of the continuation values allow us to judge the relative importance of implicit collusion and complementarities in the packages that bidders assembled at the end of the auction.

First, we ask if geographic complementarities between licenses in a package are important determinants of continuation values. If strong complementarities are found, a more concentrated allocation of licenses than that observed in the auction might increase bidder surplus. Second, we ask whether the observed bidding appears to be collusive. If so, bidders are to some degree intimidated by the aggressiveness of rivals, and bidding may not produce a socially efficient assignment of packages of licenses to bidders. In particular, if bidders fear setting off a bidding war, they may not assemble packages that maximize the surplus from geographic complementarities.

Our continuation value estimates will provide evidence about these questions. For example, if complementarities present in a package of licenses enter significantly into bidder continuation values, this is evidence that a bidder's choices at the end of the auction are influenced by such complementarities. Our estimates will not allow us to say much about why complementarities are important determinants of continuation values. For example, a bidder might value a package with complementarities because it leads to increased profitability in its own operations or because it will lead to a higher resale value. Distinguishing between these two possibilities would require stronger assumptions about which equilibrium is being played within the auction and exactly how competition will proceed in the post-auction mobile phone industry. Such assumptions would be controversial given that the equilibria to these markets are not well understood.

Our results have implications for auction design. The United States government issues spectrum auctions for relatively small geographic areas (493 markets in the auction we study), while European countries often issue nationwide licenses. The US licensing system, together with the possibility of collusion, encourages more mobile phone carriers to win licenses at the risk that these companies are operating below the efficient scale because of the lack of geographic complementarities. Rules for the forthcoming Advanced Wireless Services (AWS) auction indicate that, for some spectrum blocks, the FCC is altering its licensing policy as it now plans to issue only twelve licenses for the entire United States. For other spectrum blocks in the AWS auction, the FCC is auctioning 734 distinct geographic licenses. Understanding the relative merits of small and large licenses requires systematic numbers about whether bidders do indeed have complementarities across licenses. In addition, auctioning larger licenses may inhibit the ability of bidders to implicitly collude by reducing the level of multi-market contact.

2 Background for the C Block Auction

2.1 FCC Spectrum Auctions for Mobile Phones

Wireless phones transmit on the publicly owned radio spectrum. In order to prevent interference from multiple radio transmissions on the same frequency, the Federal Communications Commission (FCC) issues spectrum users licenses to transmit on specified frequencies. Wireless phones in the United States transmit on two major regions of radio spectrum. The FCC assigned 800 MHz licenses in the 1980's using comparative worth regulatory hearings, lotteries, and induced partnerships among applicants. In the 1990's, Congress and the Clinton administration decided the mobile phone industry could support more competitors, and so the FCC allocated additional spectrum in the 1900 MHz (PCS) block to mobile phone carriers. For the PCS block of radio spectrum, the FCC assigned spectrum licenses using auctions.

There were three initial auctions of mobile phone spectrum between 1995 and 1997. The first auction (the AB blocks) sold 99 licenses for 30 MHz of spectrum for 51 large geographic regions and raised $7.0 billion for the US Treasury. The second auction (the C block) sold 493 30 MHz licenses in more narrowly defined geographic regions to smaller bidders that met certain eligibility criteria. The C block auction closed with winning bids totaling $10.1 billion, although some bidders were unable to make payments, and their licenses were later re-auctioned. The third auction (the DEF blocks) sold three licenses for 10 MHz in each of the same 493 markets as the C block. The bids totaled $2.5 billion in the DEF blocks.

There are a number of reasons to prefer to use data from the C block auction instead of the AB or DEF blocks. First, the number of observations is much larger in the C block: there are 255 bidders in the C block compared to only 30 in the AB blocks and 155 in the DEF blocks.[1] Furthermore, there were two licenses for sale for every geographic region in the AB blocks, and three licenses for every geographic region in the DEF blocks. An AB or DEF block bidder was thus guaranteed to be competing directly against at least one other winning carrier after the auction ended. This complicates the analysis of bidding behavior considerably. In the C block, each geographic region had only one license for sale.[2]

The C block auction took 184 rounds, lasting from December 1995 to April 1996. By issuing discounts to small businesses, the FCC effectively allowed only qualified entrepreneurs to bid.[3] This policy fulfilled a Congressional mandate to encourage smaller companies to offer wireless phone service. Bidding for the C block was more aggressive than in the AB block, with bids (for only half the spectrum sold in the AB blocks) totaling $10.1 billion. Figure 1 is a map of the licenses won by the Top 12 winning bidders. Figure 1 shows that the largest winner in the C block auction was NextWave, which spent a total of $4.2 billion for 56 licenses, including close to $1 billion for the New York City license.

Bidders were given an extended payment plan of 10 years. Many of the bidders planned to secure

[1] Moreover, many of the bidders in the AB and DEF blocks were incumbent mobile phone carriers, and for antitrust reasons were ineligible to bid in geographic markets where they already held licenses. In particular, parties owning more than a 40% interest in an existing wireless license in an area could not bid on another license in that area. Imposing the legal choice set of each bidder creates considerable additional complexity in estimation.

The C block, by comparison, featured only potential new entrants, so all bidders could potentially bid on all licenses. This policy may have lowered competition in the AB auction (Ausubel et al., 1997; Salant, 1997). The FCC limited any one bidder from winning more than 98 total licenses in the C and F entrepreneurs blocks. Only NextWave came close to meeting this limit. Ausubel et al. (1997) point out that because the limit was in total licenses rather than total population, NextWave had incentives to purchase licenses with the highest total population.

[2] After the auction, winning C block bidders were much more likely to compete against incumbent mobile phone carriers operating in the same geographic region than against other C block bidders.

[3] Plans to give additional advantages to women and minorities were dropped because of litigation. Small business ownership requirements were not overly strict. Two ownerships structures qualify bidders as small businesses. The first structure is a control group must hold 25% of the businesses' equity. Of that 25%, 15% (or 3/5) of the equity must be held by qualifying entrepreneurs. Of the remaining 75% of equity, no more than 25% can be controlled by any one entity. An alternative structure says the control group can be 50% of equity, with 30% being entrepreneurs. This allows the other 50% to be held by one outside entity, which in effect allows the company to partner with a major firm. The most famous case of partnering is Cook Inlet, an Alaskan native corporation that partnered with the incumbent carrier Western Wireless.

outside funding for both their license bids and other carrier startup costs after the auction. Securing licenses first and financing later was an extremely important part of the business plan of what was until the late 1990s the most successful American mobile phone carrier, McCaw Cellular.[4] McCaw grew from a regional cable provider to a multi-billion dollar mobile phone carrier by purchasing licenses and then using the licenses as collateral to secure loans. This strategy was based on McCaw's (correct) forecast of the revenue potential in mobile phones, which was higher than the forecasts of larger companies (Murray, 2001). It is possible that many of the C block bidders were trying to recreate McCaw's strategy. Without a license, a C block bidder is not necessarily a serious negotiating partner for financiers. With a scarce license, a small business bidder becomes a relevant player in the mobile phone industry, and can expect to hold serious discussions with financiers.

Compared to McCaw, the C block winners did not have an early-mover advantage. As it turns out, many C block winners were unable to meet their financial obligations to the FCC. These new carriers were unable to secure enough outside funding to both operate a mobile phone company and pay back the FCC. Many C block winners returned their licenses to the FCC, where they were re-auctioned. Others companies merged with with larger carriers (forming a large part of the licenses held by T-Mobile USA, for example), or were able to protect their licenses in bankruptcy court. NextWave is the most famous case of bankruptcy protection. NextWave was eventually able to settle with the FCC, and sell some of its licenses to other carriers for billions of dollars. Ex-post, the C block bidders, who were accused of bidding too aggressively at the time, underpredicted the eventual market value of the licenses. However, much of this value was to larger carriers, not small business entrants who could not secure the financing to operate as a mobile phone carrier. In 2004, only a few C block winners, such as GWI/MetroPCS, remain true independent carriers marketing service under their own brand.

The resale and merger activity suggests that a bidder's post-auction value for winning licenses was not only a function of the number of customers it planned to serve as a mobile phone carrier. Valuations might be a function of the bidder's beliefs about the expected value from resale of its licenses and the risk of bankruptcy.[5] Therefore, attempting to directly recover a bidder's value from operating a mobile phone carrier will be quite naive in this setting. We will favor a more nuanced interpretation of the estimates from our structural model. In addition, it is important to allow for an econometric approach that allows for unobserved heterogeneity from omitted license attributes, such as the anticipated resale value. The estimator that we propose is designed to accommodate a reasonably general form of unobserved heterogeneity.

2.2 Auction Rules and Bidder Characteristics

Similar rules govern all FCC auctions for mobile phone spectrum. Each auction operates using an ascending bid, simultaneous-close format. In other words, each auction lasts multiple rounds, where in

[4] McCaw was purchased by AT&T for $17.4 billion and renamed AT&T Wireless in 1993. AT&T Wireless was itself purchased by Cingular in 2004.

[5] The FCC's unjust enrichment regulation penalizes resale to carriers that do not qualify as eligible entrepreneurs.

each round all licenses are available for bidding. During a round, bidding on all licenses closes at the same time. Simultaneous bidding allows bidders to assemble a useful package of licenses from those available, without the risk of a necessary license to complete a package being unavailable because of an early close. These auction rules were explicitly designed to allow bidders to assemble packages exhibiting complementarities, while letting the bidders themselves and not the FCC determine where the true complementarities lie.

Each bidder pays an upfront amount of money for eligibility. A bidder's eligibility is expressed in units of total population. A bidder cannot bid on a package of licenses that exceeds the bidder's eligibility. For example, a bidder who pays to be eligible for 100 million people cannot bid on licenses that cover geographic areas that together contain more than 100 million residents. Eligibility cannot be increased after the auction starts. The eligibility payments were 1.5 cents per MHz-individual in a hypothetical license for the C block. Compared to the closing auction prices, these payments are trivial. From an empirical point of view, eligibility payments provide early evidence on a bidder's willingness to devote financial resources towards winning a large number of spectrum licenses. Because estimation requires at least one observable bidder characteristic, this paper does not consider strategic motives (such as intimidating rivals) for choosing eligibility levels.[6]

Table 1 lists characteristics of the 85 winning and 170 non-winning bidders in the continental United States.[7] The average winning bidder paid fees to be eligible to bid on licenses covering 10 million people, while the average losing bidder was eligible to bid on licenses covering only 5 million people. Bidders also had to submit financial disclosure forms (the FCC's Form 175) in order to qualify as entrepreneurs for the C block, which was limited to new entrants only. Here we see that the financial characteristics of winners and non-winners are similar, which leads us to believe that these disclosure forms did not represent the true resources of bidders. In our structural estimator, we use initial eligibility as an individual bidder characteristic instead of assets or revenues.

Table 1 lists the mean number of licenses bid on and won by winners and non-winners. On average, a winning bidder won 5 licenses and entered at least one bid on 39 licenses. Although not listed in the table, the top 15 winning bidders, in terms of number of licenses, were active bidders on many licenses. The top 15 winners won an average of 16 licenses and bid on an average of 123 (out of 493) licenses.[8] Most of the major winners and some of the non-winners were investors operating on a national scale. The role for idiosyncratic valuations of licenses due to local knowledge seems relatively low, as the

[6]The FCC is concerned with concluding the auction in a reasonable amount of time. Therefore, each bidder is required to make a certain number of bids, in terms of population, to prevent losing some of its eligibility. As the rounds progress, information is revealed about the demands of other bidders, and bidders drop their activity levels to an amount corresponding to the licenses they hope to win. By the close of the auction, a bidder's eligibility is generally only slightly higher than the licenses it wins.

[7]The C block also contains licenses for Alaska and Hawaii as well as Puerto Rico and several other island territories of the United States. The potential for complementarities between these licenses and licenses in the continental United States seems limited, so we restrict attention to the contiguous 48 states.

[8]One of the losing bidders submitted bids on all BTAs. This bidder withdrew from the auction because it felt that the prices were too high for its business plan.

bidding in the C block auction was dominated by national investors that were competing for licenses over the entire country.

2.3 Did the Auction Produce a Functioning Market?

In this section, we show that despite the many potential complications and the lack of solved theoretical models for this class of dynamic games, the C block auction generated closing bids where the underlying characteristics of licenses explain much of the variation in prices across licenses.

The most important characteristic of a license is the number of people living in it, who represent potential subscribers to mobile phone service. Figure 2 shows the winning bids by the population of the license, along with a fitted regression line. The slope of the regression line is $52.7. For the most part, the large population licenses, such as New York and Los Angeles, are only a little above or below the regression line.

Figure 2 is slightly misleading because most of the markets have fewer than five million residents, and are clumped together at the left-hand side of the figure. Figure 3 plots the winning bid per resident (instead of the total bid as before) for licenses with fewer than five million people. Here we see the mean winning bid per resident is well below $52.7, so that the implicit price of a resident is larger in especially large markets. Figure 3 shows that the final price per resident of more populated licenses is in fact greater. For example, there are no licenses with more than 1 million residents where the closing bid price is less than $20. This pattern of higher prices for larger licenses could be driven by other license characteristics (such as demographics), but is also consistent with increasing returns to operating scale in mobile phone carrier operation. Returns to operating scale create complementarities across licenses, as one way to increase scale is to win more licenses.

Figure 4 shows a map of the price per resident of licenses in the continental United States. Many of the licenses that sell for above $47 contain major metropolitan areas, such as Atlanta, Los Angeles, New York, Chicago, Dallas or Minneapolis. These major areas have dense population areas, which require fewer cellular towers per potential customer to serve. Ausubel et al. (1997) use proprietary consulting data on the population density of the expected build-out areas for C block mobile phone service. They have provided us the same data, which we plot in a US map in Figure 5. There seems to be positive correlation between the price per resident in Figure 4 and the population density of the buildout area in Figure 5. Indeed, the correlation between the two measures at the license level is 0.570.

Table 2 lists characteristics of winning packages. Only licenses in the continental United States are included in packages in Table 2. The average winning bidder agreed to pay $116 million and won a license covering 2.9 million people. The largest winner, NextWave, bid $4.2 billion for a package covering 94 million people. As discussed above, the major characteristic predicting the closing bid price of a license is the population of that license. It follows quite naturally that the income level of the potential customers in that license could also be a major determination of price. We use the percentage of households with incomes greater than $35,000 as our measure of package income. By this measure, the mean percentage of high income households in winning packages is 46%.[9]

2.4 Suggestive Evidence on Complementarities

Many aspects of the design of the FCC spectrum auctions focus on the possibility that a package of licenses might be worth more than the sum of the values of the licenses if won by different bidders. Licenses with these properties exhibit complementarities (synergies).

Before looking at the auction results, one's prior might be that complementarities are not important in the spectrum auctions. The FCC chooses market boundaries to be in sparsely settled areas in order to minimize complementarities across markets. Furthermore, 1900 MHz PCS wireless phone service is mainly deployed in urban areas and along major highways, so there might not even be PCS service along the boundaries of two markets.[10] Finally, companies can coordinate with contracts (roaming agreements) if the same company does not own the adjacent licenses.[11]

Researchers examining the auction results have generally concluded that complementarities were important. The map of the Top 12 winners (by the number of licenses) in Figure 1 shows several bidders win licenses in markets adjacent to each other.[12] For example, NextWave, the largest winner, purchases clumps of adjacent licenses in different areas of the country. GWI/MetroPCS fits the cluster pattern well, winning licenses in the greater San Francisco, Atlanta and Miami areas.

On the other hand, the majority of winning bidders won only a few licenses. Figure 1 emphasizes this by also plotting the 26 licenses in the continental United States that were the only license won by their winning bidders. We calculate that only 20 out of 89 C block winning bidders won packages of licenses where the population in adjacent licenses within the package was more than 1 million.[13] Aer Force is the prime example of a Top 12 bidder that did not seem overly concerned with complementarities. Figure 1 shows that Aer Force won 12 licenses in the continental United States, but that none of them are adjacent to each other. From the maps alone, it appears some winning bidders cared more about geographic complementarities than others.

Salant (1997), a consultant during the AB blocks auction for GTE, provides an insider's take on

[9] The cutoff level of household income of $35,000 is the same measure used in Ausubel et al. (1997). Magazine articles from that mid-1990s show that the level of penetration of mobile phones into lower-income groups that we see in 2004 was not predicted by many analysts, who considered higher-income groups to be the main market for mobile phones.

[10] To some extent, PCS licenses are primarily built out in urban areas because the FCC requires build outs to cover a certain fraction of the population of the market, rather than a fraction of the market's land area. 800 MHz carriers tend to cover both urban and rural areas because the FCC requires coverage as a large fraction of the land area of those licenses.

[11] The Coase Theorem suggests that, in a frictionless world, such contracts will implement the efficient outcome. Our paper uses revealed preference to investigate whether bidders thought the Coase Theorem would be operative in the post-auction mobile phone service industry.

[12] Ausubel et al. (1997) study in part the earlier AB auction and show several bidders win licenses adjacent to markets where the bidder is a mobile phone incumbent, or a landline telephone carrier. For example, Pacific Bell, at the time a California telephone company, won AB block licenses in California. Other bidders, such as the forerunners of Sprint PCS and AT&T Wireless, embarked on a strategy of winning licenses in as many markets as allowed.

[13] This complementarity measure is calculated over pairs of licenses. If a license is adjacent to two others in a package, its population will be counted twice. The 89 winners include four bidders who won licenses only outside of the continental United States.

bidder valuations. GTE did value complementarities, in that it wanted to acquire licenses in areas where it was a landline phone company, and in areas that would fill in holes in its existing wireless phone network. GTE was unwilling to bid on certain potentially lucrative licenses, such as Los Angeles, because GTE felt it would not be profitable to win such an expensive license.

Ausubel, Cramton, McAfee and McMillan (1997) and Moreton and Spiller (1998) examine whether adjacent licenses exhibited complementarities by regressing the log of winning bids on market and bidder characteristics. Ausubel et al. study the AB and C block auctions and find that the log of winning bids are positively related to whether the runner-up bidders won adjacent licenses, as one might expect in an ascending-bid auction. Moreton and Spiller have better measures of incumbency, and also find that winning bids are positively related to the runner-up bidder's measures of complementarities. The results are the most statistically significant for the C block auction.[14]

The previous authors also mention global complementarities or increasing returns to scale, the notion that a wireless network involves fixed costs that can be spread out among more customers in a larger carrier. We prefer the term operating scale economies for this concept. Scale economies can be represented as a valuation convex in package characteristics such as total population.

3 An Empirical Model of Spectrum Auctions

In this section, we propose an empirical model of bidding for spectrum licenses. FCC spectrum auctions are ascending-bid, multiple round auctions that can take more than a hundred days to complete. Formally speaking, a spectrum auction is a dynamic game, potentially with incomplete information. If bidders have finite valuations, they will cease bidding after a finite number of rounds, although the length of the auction is not known at the start.[15]

3.1 Basic Notation

We index rounds by t. There are $a = 1,...,N$ bidders who compete to win licenses $i = 1,...,L$. In the C block auction, N is 255 and L is 493. An FCC spectrum auction is a multiple unit auction and therefore bidders can submit bids on multiple licenses. While bidders submit bids on only individual licenses (there is no package bidding), a bidder is concerned about the package, or collection, of licenses it wins. We let $p_{at}(S)$ denote the vector of the bids submitted for the package of licenses S by bidder a in round t.

Ascending auctions differ from other dynamic games because a bidder's final payoff is based only upon the package it wins at the end of the auction, and the price paid for that package. Label a generic

[14] Ausubel et al. and Moreton and Spiller do not claim their price regressions correspond to hedonic estimates of bidder valuations. Rather, they specify descriptive or in-sample prediction regressions designed to summarize facts about the closing bid prices.

[15] The FCC gave itself reserve powers to end the auction if the normal course of bidding failed to do so. As these powers were not used, we do not model them.

terminal round to the game T. Then bidder a's profits from winning a package of licenses S is equal to

$$\pi_a(S) - \sum_{i \in S} p_{iT}, \tag{1}$$

where p_{iT} is the closing price for a license i in the package S. The term $\pi_a(S)$ is bidder a's valuation for the licenses in S. If a plans on marketing mobile phone services using these licenses then $\pi_a(S)$ would be equal to a's expected profits. Instead if a intends to resell the licenses or merge with a larger company, then $\pi_a(S)$ would represent the anticipated resale value of the licenses. Our broad interpretation of $\pi_a(S)$ is consistent with our discussion in Section 2.1, as there may be diverse factors that enter into a bidder's valuation.

The payoff function is additively separable in prices, which makes sense if we view the bidders as profit maximizers. We do not impose that $\pi_a(S)$ is additively separable in the license characteristics. Indeed, a notion of complementarities is that, for licenses i and j,

$$\pi_a(\{i,j\}) > \pi_a(\{i\}) + \pi_a(\{j\}),$$

or that the value of two licenses purchased together exceeds the sum of the valuations of the licenses if purchased separately. Obviously this violates additive separability.

At each round t, we denote the vector of state variables as s_t. At round t, s_t will include the highest bid and the identity of the highest bidder for each of the L licenses. Newly submitted bids must exceed the previous high bid by a certain minimum bid increment. If a bidder is currently the highest bidder on a license, without any action to withdraw the bidder remains the high bidder. The state space at $t+1$, s_{t+1}, is s_t including the new highest bids and bidders for licenses that had activity during round t.

The state space also includes a vector of bidder eligibilities. At round t, each bidder has an eligibility level, measured in the total population of licenses in a bidder's package. The sum of the population of licenses for a bidder's current highest bids and its new bids must be less than its eligibility. In order to speed the conclusion of the auction, the FCC reduces the eligibility of bidders that do not submit enough bids. The state space thus can be extended to include the vector of remaining eligibilities of all N bidders. The initial eligibility level is purchased by a bidder before the beginning of the auction.[16]

Certain Nash equilibria in a dynamic game may involve strategic interaction between players. In collusive equilibria, bidders enter special bids to signal to each other the licenses they are most interested in winning. Under collusion, bidders react to bid signals, so the history of past bids should also be included in the state space.

3.2 Assumptions for Efficiency

Milgrom (2000) proves that under two major assumptions a simultaneous ascending auction is equivalent to a tatonnement process that finds a competitive equilibrium of the economy. By the first welfare

[16] No one bidder can win more than 98 licenses between the C and F block entrepreneurial spectrum auctions.

theorem and the assumption that prices enter payoffs quasilinearly, the final assignment of licenses to bidders maximizes the total value in the economy. The outcome of the auction can then be analyzed as a two-sided matching (Shapley and Shubik, 1972) market where the two sides of the market are bidders and licenses, and the vector of license prices clears the market.

The two main assumptions that Milgrom's efficiency theorem requires are

1. The licenses are mutual substitutes for all bidders, and

2. All bidders bid straightforwardly.

Unfortunately, neither one of the assumptions needed to prove that a simultaneous ascending auction is efficient appear to hold in the C block data.

For our purposes, if licenses are mutual substitutes they are not complements. The fact that many bidders win clusters of licenses, as seen in the map in Figure 1, is good evidence that licenses may not be mutual substitutes for all bidders. Other suggestive evidence on complementarities is discussed in Section 2.4.

Bidding straightforwardly means that a bidder submits new bids each period in order to maximize its payoffs, equation (1). One violation of straightforward bidding is jump bidding. When making a jump bid, a bidder enters a bid that exceeds the FCC's minimum bid for that round. Figure 3 shows that there was a non-trivial level of jump bidding during the C block auction. We define a jump bid to be any bid that is 2.5% greater than the FCC's minimum bid for that license and round.

When jump bidding, a bidder risks the chance that the jump bid will exceed the valuation of rival bidders, and be the final price. A jump bidder always has a nonzero probability of overpaying for a license.[17]

There are strategic reasons why a bidder might jump bid. Avery (1998) studies an ascending auction of a single item. Bidders have affiliated values and therefore a fear of the winner's curse, or paying too much for an item of uncertain true value. A jump bid of a significant amount can be a credible signal, as in expected value the jump bidder incurs a cost that the jump bid may be the final bid and close the auction at a price above the outcome from straightforward bidding. After signalling the jump bidder's aggressive intentions, other bidders may discontinue bidding, as they suspect that the winner after more bidding will overpay and suffer negative profits from the winner's curse.[18]

The multiple items sold in spectrum auctions give new opportunities for implicit collusion through repeated interaction and multi-market contact. Brusco and Lopomo (2002) present a theoretical model

[17] Daniel and Hirshleifer (1998) study a model of an ascending auction of a single item where bidding is costly. An equilibrium involves jump bidding to speed the conclusion of the auction. As bids in the C block auction totalled $10.1 billion, it is unlikely that bidders had a high opportunity cost of time and placed jump bids to speed the conclusion of the auction. Serious bidders employed teams of professionals to manage bidding activity.

[18] Theorists have shown that jump bidding can happen for non-collusive reasons. For example, in a simultaneous ascending auction where the bidding on each license can close at different times, which is not the FCC's rule, Zhèng (2005) shows that jump bidding can alleviate the exposure problem mentioned below. As we discuss below, the FCC auction rules have a more direct withdrawal mechanism to mitigate the exposure problem.

specifically designed to focus on collusion and complementarities in simultaneous ascending auctions. In a simultaneous ascending auction, there exist equilibria where bidders divide the items for sale amongst themselves. At the beginning of the auction, bidders enter bids to signal their preferred licenses. Then no colluding bidders place bids on items they are not designated to win in the collusive equilibrium. Bidders each win a small handful of items, but win them at very low prices and make a larger profit than through straightforward bidding. The collusive equilibrium is supported by the threat of reverting to straightforward bidding. The collusive outcome is not efficient, because the items are not necessarily assigned to the bidder with the highest valuation, and licenses with strong complementarities are not necessarily won by the same bidder. The signal in Brusco and Lopomo (2002) is a positive bid on a handful of licenses in the initial round, but not necessarily a jump bid. The logic in Avery (1998) suggests jump bids could be an effective signal, however.[19] [20]

Figure 3 shows jump bidding was prevalent towards the beginning of the auction, where the risk of overpaying is much lower. The number of total new bids dramatically slowed during the second half of the auction, and this slowdown is especially severe for jump bids. The presence of jump bids might represent attempts at intimidation, but jump bids are not evidence that intimidation was particularly effective. Attempts to collude may still have had serious implications for the final assignment of licenses to bidders, however. In our structural model, we will estimate whether bidder continuation values are a function of jump bids by rival bidders.

3.3 The Value Function

Multiple theoretical models have been proposed to study spectrum auctions. While each of these models gives us some insight into the incentives that bidders face, they offer potentially conflicting conclusions. Also, there is no consensus among theorists about the “correct” model of bidding in spectrum auctions. Therefore, it is highly desirable that an estimator does not require imposing a specific model of dynamic equilibrium (e.g. Milgrom (2000) or Brusco and Lopomo (2002)).

Given the diversity of models, we would like an estimator that allows us to learn which of several competing models might be most reasonable. The estimation approach that we propose is in the spirit of Haile and Tamer (2003) in that we try to only impose weak conditions of equilibrium that are required to hold in a wide range of models. As we describe below, the main condition that we will impose is the requirement that the continuation value from the observed actions exceeds the continuation value from

[19] Brusco and Lopomo also mention that complementarities might break implicit collusion. Counterintuitively, it is not the level of complementarities that prevents collusion, but the variability of complementarities across bidders.

Brusco and Lopomo (2002) discuss other reasons why collusion might fail. Having too many bidders relative to the number of items makes it harder to support a collusive equilibrium, as bidders not winning an item have no incentive to collude. Initial rounds of aggressive bidding might be needed to weed out bidders with low valuations in order to narrow down the remaining bidders into a implicitly colluding coalition.

[20] The collusive concerns described by Brusco and Lopomo (2002) applies to auctions of multiple discrete heterogeneous items. Ausubel and Cramton (2002) find a related result for sealed-bid (non-ascending, one shot) auctions of multiple identical items, such as electricity or treasury bonds. With multiple identical items, bidders usually have an incentive to shade their bids on marginal units to earn greater profits by paying a lower per-unit charge on inframarginal units.

actions that are not chosen at the end of the auction.[21]

In a pure-strategy, subgame perfect Bayes-Nash equilibrium of a simultaneous ascending auction, bidders maximize expected discounted payoffs at every state in the game tree. Payoffs are computed by taking expectations about the probability of reaching the various terminal nodes of the game tree as a function of bidder a's own strategy and the strategies of other players. In particular, at any state s_t, bidder a has a continuation value, or Bellman equation,

$$V_{at}(s_t, S) = \max_{p_{at}(S)} 0 + E\left[V_{at+1}(s_{t+1}, S) \mid p_{at}(S)\right].$$

We write "0+"to emphasize that there is no current-period payoff in an auction.[22] The expectation in the continuation value is taken knowing the optimal decision rule of bidder a at state s_t, $p_{at}(S)$, which is just the $p_{at}(S)$ that maximizes $E\left[V_{at+1}(S) \mid p_{at}(S)\right]$.[23]

The new state, s_{t+1}, evolves according to the submitted bids of all players. The uncertainty is over the distribution of future bids of other agents in the auction.[24] At a Nash equilibrium, the strategies of all bidders as a function of the unknown private information are known. For an individual bidder, the strategies of rivals are subsumed into the expectation operator.

In the data, the auction ended at some round we call T. Revealed preference implies that if a is the high bidder on a package of licences S at the end of the auction, then

$$V_{aT}(s_T, S) \geq V_{aT}\left(s_T, S'\right) \; \forall S' \supseteq S. \tag{2}$$

At the end of the auction, bids move very slowly and bidders do not submit bids much above the minimum required to be the highest bidder on a particular license. Therefore, we simplify a bidder's choice at the end of the auction to be the set of licenses that it wishes to be the high bidder on. We let $V_{aT}(s_T, S')$ be the continuation value that a receives from entering new bids to create a new package S' at the end of the auction. Revealed preference implies that the continuation value from the package of licenses that a won was superior to superset packages of licenses S' that a could have bid on.

The goal of our estimator will be to recover $V_{aT}(s_T, S)$. We will not attempt to recover the post-auction valuations $\pi_a(S)$. If we abstracted away from strategic behavior at the end of the auction so that bidders did not fear retaliation or other reactions from competitors, then we would have that $V_{aT}(s_T, S) = \pi_a(S) - \sum_{i \in S} p_{iT}$. This is because bidders should simply bid on their most preferred licenses at the end of the auction, subject to eligibility rules, if there are no strategic interactions.

[21] Haile and Tamer (2003) estimate bidder payoffs in private value auctions of a single good. The Haile and Tamer estimator is based in part off of the assumption that no bidder will let another win the good at a price below the first bidder's valuation of the good. This assumption of mostly straightforward bidding on all licenses is much less tenable in a multiple unit auction, where the fact that all bidders can bid on all licenses means that intimidation is real possibility.

[22] We ignore discounting, or impatience to end the auction.

[23] The set of licenses where new bids are entered must satisfy the eligibility rules.

[24] Alternatively, a rival bidder might be playing a mixing strategy, although we do not allow for mixed strategies in estimation.

Making this assumption, however, would make us unable to test for collusive behavior or other sources of inefficiency.

3.4 Our Continuation Value Identification Strategy

We use the revealed preferences of bidders at the end of an auction to identify continuation values. We make the following assumption.

Assumption 1. *The equilibrium bids in the final period of the auction are in pure strategies.*

The assumption of pure strategies is crucial for our estimator. If the bidding at the end of the auction is in mixed strategies, the bidders might have ex post regret. That is, if other players are randomizing, player *a*'s bids are a best response to its equilibrium beliefs about the distribution of other players' strategies, which would invalidate the revealed preference inequality in equation (2). Ciliberto and Tamer (2003) discuss ex-post regret in related problems.

In addition, we will make the following assumption:

Assumption 2. *At the terminal period T, the closing prices and past histories of play (in s_T) are such that*

$$V_{aT}\left(s_T, S_a\right) \geq V_{aT}\left(s_T, S'\right) \; \forall \, a, S' \neq S_a. \tag{3}$$

Assumption 2 states that a bidder's continuation value for its winning package is greater than its continuation value for any other package, at the realized final state of the game. This includes packages that may violate the eligibility rules of the auction. In principle we could incorporate the eligibility rules into our estimation strategy. However, this would be at the cost of increasing the computational complexity of programming our estimator. Further, imposing eligibility constraints would limit the empirical content of revealed preferences, as it is likely that a bidder with a high continuation value for another license would have bid on that license 10, 20 or 50 rounds before the end of the auction. As bidding slowed down at the end of the auction, we believe it is reasonable to assume that giving bidders additional eligibility would not have changed behavior very much if at all.

Assumption 2 also rules out the exposure problem that can arise from complementarities. In the exposure problem, a bidder places a bid on a package of licenses with significant complementarities, but eventually only wins a subset of the licenses. If the total package payoffs are dominated by the complementarities, the bidder may end up overpaying for the licenses it does win. We rule out the exposure problem because we think it is not a major issue in this auction because the FCC's auction rules allow a bidder to withdraw a standing high bid. When the bidder withdraws a standing high bid, the bidder is potentially liable for a penalty equal to the difference between the withdrawn bid and the final closing price of the license. If the withdrawn bid is lower than the eventual closing price, the bidder faces no penalty.[25] Penalties in the C block option were not large. The median maximum potential penalty, the penalty if no other bidders entered new bids on that license after a withdrawal, was \$93,530. Because almost all licenses had higher bids posted after a withdrawal, only around \$5 million in penalties were eventually paid after the auction ended, a relatively small amount compared to the \$10.1 billion in winning bids. The largest penalty was faced by a bidder who added an extra "0" to the end of its bid by mistake.

Sixteen different bidders used the withdrawal option. Those sixteen bidders withdrew a total of fifty bids on individual licenses during the C block auction, representing 0.17% of the 29,865 bids entered during the 184 rounds of the auction. Seven bids were withdrawn in the first round. There is some evidence that those withdrawing bids had made many unsuccessful bids at the same time as the withdrawn bid. Bidders submitted an average of twenty bids the round a withdrawn bid was first entered and the bidders were the highest bidder after that round on an average of three licenses. This is consistent with the withdrawal option being used to mitigate an exposure problem. With so little use of the withdrawal option, probably few bidders were stuck with licenses they preferred not to win at the closing prices.

The summary of this discussion is that Assumption 2 is motivated by revealed preference. If bidders would have higher continuation values from more bidding, to a first approximation they should have done so. If bidders were standing high bidders on the wrong licenses, they would face low penalties from withdrawing, and should have done so.

3.5 Combinatorics of Auction Outcomes

The revealed preference inequality in equation (3) forms the basis for our estimator of continuation values. Even this simple inequality presents immense computational challenges to estimation. The total number of packages that could be won by an individual bidder in the C block auction includes all subsets of the 493 licenses with 98 or fewer total licenses. There are $3.58\text{x}10^{105}$ such packages.[26] Therefore, the number of packages that could be won by a bidder is larger than the number of atoms in the universe.[27] Any estimation method that requires evaluating the revealed preference inequalities at all possible packages will be infeasible. This dimensionality problem will motivate our estimation approach which we describe in detail in Section 5.

[25] Cramton and Schwartz (2000) suggest that the withdrawal rule may be another tool for implicit collusion. A bidder can submit a bid on a rival bidder's license to signal to the rival that punishment is forthcoming if the rival doesn't cease bidding on another license. Then the signalling bid is withdrawn, leaving little risk to the original bidder.

[26] The power set of all packages, ignoring the FCC's rule of no more than 98 licenses per package, has size $2^{493} = 2.557\text{x}10^{148}$.

[27] Physicists estimate that the total number of atoms in the universe ranges from 10^{79} to 10^{81}, clearly a good deal fewer than the $3.58\text{x}10^{105}$ packages in the C block auction.

4 Empirical Proxies for Attempted Collusion and Complementarities

This section focuses on an intuitive discussion of identification of continuation values in the C block spectrum auction, by relating observed variables to the economic questions about collusion and complementarities outlined in the introduction. All of the following observables enter as covariates into our parameterizations of continuation values.

4.1 Jump Bids as Proxies for Attempted Intimidation

Brusco and Lopomo (2002) suggest that there are many collusive equilibria in an ascending bid auction. Cramton and Schwartz (2000) and Cramton and Schwartz (2002) document cases of intimidation in spectrum auctions, particularly in the AB and DEF block auctions. Our strategy for investigating the possibility of intimidation is to parameterize continuation values as functions of observable proxies for intimidation. Jump bidding is our main proxy for potential intimidation. A bidder bidding straightforwardly would enter a bid equal to no higher than the minimum bid, in the hope that the minimum bid exceeds the valuation of rival bidders. A non-strategic bidder loses nothing by always bidding the minimum bid when his valuation for the license exceeds the minimum bid.

Definitively establishing collusion using bid data is extremely difficult. We will be able to determine whether jump bids on licenses early in the auction generated lower continuation values for those licenses at the end of the auction. Even if this is true, given how little is understood about the equilibrium to spectrum auction games, one should be cautious in interpreting this evidence as definitive proof of collusion. However, if the impact of jump bids on the valuations is large, auction designers might wish to consider whether the potential for intimidation could be alleviated through an improved licensing scheme.

Table 3 lists statistics for the population-weighted mean numbers of jump bids for the 85 winning packages. A typical license in a package has 2.6 jump bids submitted by non-winning bidders over the course of the auction. Although not listed in the table, five of the 85 winning packages have no jump bids entered by rival bidders at all. One winning package, which consists of the single license for Milwaukee, has fifteen jump bids by rival bidders.[28]

4.2 Proxies for Potential Complementarities

The FCC's simultaneous ascending auction is designed to allow bidders to assemble a package of licenses with complementarities. Mobile phones are a network good with substantial fixed costs, such as providing customer service, marketing, and the development and implementation of new technologies. On the demand side, mobile phone users may wish to use their phone in geographic locations other than their home area, and may value carriers that have greater coverage areas. We measure the impor-

[28] In the empirical application, when calculating the continuation value for a given bidder and package combination, we always remove the jump bids made by that bidder on licenses in that package.

tance of economies of operating scale and geographic scope in continuation values by collecting data on variables that proxy for potential complementarities.

Our main method of estimating the size of economies of operating scale is including a quadratic terms in population into continuation value functions. The main package characteristic a mobile phone carrier cares about is the total population of the licenses in the package. If the coefficient on the square of population is positive, then valuations are convex in total population, and it appears likely that bidders value operating scale economies. In other words, they have increasing returns to scale. If instead the coefficient on the square of population is negative, then continuation values are concave in population, and it appears that there are decreasing returns to operating scale.

For mobile phone carriers, geographic scope economies arise when serving related markets makes the total profit from serving those markets greater than than the total profits if separate companies served each market. We use three proxies for geographic scope, in order to examine the robustness of our estimates to different measures.[29]

Our first proxy for geographic scope is based on the geographic distance between pairs of licenses within a package.[30] For a package S, potential complementarities are

$$\frac{1}{\sum_{i \in S} \text{population}_i} \sum_{i \in S} \text{population}_i \sum_{j \in S \setminus \{i\}} \frac{\text{population}_j}{\text{distance}\,(i,j)},$$

where population is measured in millions and distance is measured in kilometers. This measure is just the population-weighted mean across licenses of the number of other residents, divided by their distances.[31] Table 4 shows sample statistics on the geographic complementarities for the 85 winning packages. Counting the population-weighted means over all the pairwise combinations of licenses in a package, licenses in the 85 winning packages have a mean 6 million $(0.006 \cdot 1000)$ pairwise combinations of residents in different markets a normalized distance of 1000 km (620 miles) from each other.

[29]The previous literature emphasizes the geographic adjacency of two markets. Visually, geographic adjacency is interesting because it is evident from looking at a map of winning bids that some bidders purchase clusters of adjacent licenses. However, in the western United States many markets are geographically adjacent only because large regions of desert have been added to the corresponding geographic markets. Adjacency says, for example, that the Reno license is next to Los Angeles license, while those two cities are actually 615 km apart. Our population-weighted centroid measure says the Reno license is 510 km away from the Los Angeles license. Note that the previous descriptive empirical work only considered observed winning packages, and as Reno and Los Angeles were won by different bidders, this example is not relevant for their analysis.

[30]We measure distance between two licenses using the population-weighted centroid of each license. The population-weighted centroid is calculated using a rasterized smoothing procedure using county-level population data from the US Census Bureau.

[31]This geographic complementarity proxy can be motivated as follows. Consider a mobile phone user in a home market i. That mobile phone user potentially wants to use his phone in all other markets. He is more likely to use his phone if there are more people to visit, so his visit rate is increasing in the population of the other license, j. The user is less likely to visit j if j is far from his home market i, so we divide by the distance between i and j. We care about all users equally, so we multiply the representative user in i's travel experience by the population of i. Finally, we want an average rather than a total measure as we already include total population as a measure of operating scale in continuation valuation. Therefore, we take the population-weighted mean by dividing by the total population in the package.

Geographic measures of distance may not capture the returns to scope that carriers are concerned about. Mobile phone customers may travel by means other than ground transportation. For example, many business users travel by air between Los Angeles and New York. In fact, the C block bidder NextWave won both the New York and Los Angeles licenses. In addition, distance is not the only factor affecting even ground travel.

We have two complementarity proxies based upon travel between two licenses. The first measure, from the 1995 American Travel Survey (ATS), is proportionate to the number of trips longer than 100 km between major cities. All forms of transportation are covered. The downside of this measure is that for privacy reasons the ATS does not provide enough information about rural origin and destinations to tie rural areas to particular mobile phone licenses. Our second measure, from the Airline Origin and Destination Survey for the calendar year 1994, is the projected number of passengers flying between two mobile phone license areas.[32] The drawback of the air travel measure is that it assumes all passengers stay in the mobile phone license area where their destination airport is located.[33] Both travel measures for a package S are population-weighted means across licenses, and take the form

$$\frac{1}{\sum_{i \in S} \text{population}_i} \sum_{i \in S} \text{population}_i \sum_{j \in S \setminus \{i\}} \text{trips}\left(\text{origin is } i, \text{destination is } j\right),$$

where our ATS measure uses the count of raw trips in the survey, and the air travel count is inflated to approximate the total number of trips during 1994.[34] The ATS data in Table 4 show a license in a wining package has a mean of 53.2 trips between a license and the other licenses in the package. The airline data show a typical license has 26,100 plane trips a year between that license and others in the same winning package.

For all geographic scope proxies, some fraction of the winning packages has a value of 0. For example, 26 out of the 85 winning packages contain only one license in the continental United States. Therefore, looking at only the actions of a few large carriers may distort one's impression of how important scope economies are. The fact that singleton packages are observed suggests that other factors influence wireless industry structure.

[32] Intermediate stops are not counted for either dataset. For both datasets, geographic information software (GIS) was used to match origins and destinations with mobile phone licenses. For airports, the origin and destination license areas are easy to calculate. For the MSAs (Metropolitan Statistical Areas) used in the ATS, the equivalent C block license area was found using the centroid of the origin or destination MSA. The C block license boundaries for urban areas roughly follow MSAs.

[33] We effectively code that there are zero potential complementarities between rural licenses for both travel measures.

[34] Our airline passenger measure does not distinguish between origins and destinations, so we simply divide the formula for the complementarity proxy by 2. If all airline travel is round-trips during the same calendar year, this measure should be exactly correct.

5 Estimator for Multiple Item Auctions

5.1 Revealed Preferences and an Estimation Inequality

We will model which licenses to bid on at the end of the auction as an equilibrium discrete choice problem. As we discussed in Section 3.5, the number of choices available to a bidder is very large, which makes most approaches to estimating discrete choice models impractical. In this section, we reduce the computational complexity of the estimation problem by demonstrating that, under appropriate regularity conditions, static equilibrium in the final round of the auction implies that a version of a social planner's problem is solved. The preferences in the static social planner's problem are given by the continuation values from the dynamic auction game. We can then estimate based upon much lower dimensional inequalities that are necessary, but not sufficient, conditions for the auction's outcome to be a solution of the static social planner's problem.

Consider two bidders, a and b. In the data, bidder a wins the package of licenses S_a, and bidder b wins the package of licenses S_b. The physical constraint that any license can be won only once means $S_a \cap S_b = \emptyset$. Let license $i \in S_a$ and let license $j \in S_b$. By Assumption 2 applied to each bidder separately, it follows that

$$V_{aT}(s_T, S_a) + V_{bT}(s_T, S_b) \geq V_{aT}(s_T, (S_a \setminus \{i\}) \cup \{j\}) + V_{bT}(s_T, (S_b \setminus \{j\}) \cup \{i\}). \tag{4}$$

That is, the sum of the equilibrium continuation values for a and b is greater than the sum of the continuation values where a wins j and b wins i, and all other assignments of licenses to bidders remain unchanged.

Next, we will assume that the continuation values satisfy the following parametric functional form.

Assumption 3. *For bidder a at the auction's terminal node T, a's continuation value for an arbitrary package S satisfies*

$$V_{aT}(s_T, S) = V_a(S \mid \beta) + \sum_{i \in S} \xi_i - \sum_{i \in S} p_{iT}.$$

We will assume that the continuation value for winning the package of licenses S is an additive function of three terms. The final term is the sum of the final prices p_{iT} of the licenses in S. The term $V_a(s_T, S) + \sum_{i \in S} \xi_i$ is the non-price component of a's continuation value for winning the licenses in S. We decompose the non-price continuation values into two components. $V_a(S \mid \beta)$, is a bidder-specific continuation value term that is parameterized by a vector of parameters β. $V_a(S \mid \beta)$ captures bidder-specific valuations as well as the nonlinear interactions between the characteristics of different licenses that create complementarities.

The second term $\sum_{i \in S} \xi_i$ is the sum of the license characteristics that are valued the same by all bidders. As all bidders receive these benefits, each ξ_i is likely to affect the closing prices, but does not affect the equilibrium assignment of bidders to licenses. While letting each ξ_i enter only linearly rules out possibly interesting interactions between the unobservable components of licenses, we shall show now that this assumption allows ξ_i to be a function of characteristics that are observed to the bidders but not the econometrician.

Under assumption 3 equation (4) becomes

$$V_a(S_a \mid \beta) + \sum_{k \in S_a} \xi_k - \sum_{k \in S_a} p_{kT} + V_b(S_b \mid \beta) + \sum_{k \in S_b} \xi_k - \sum_{k \in S_b} p_{kT} \geq$$
$$V_a((S_a \backslash \{i\}) \cup \{j\} \mid \beta) + \sum_{k \in (S_a \backslash \{i\}) \cup \{j\}} \xi_k - \sum_{k \in (S_a \backslash \{i\}) \cup \{j\}} p_{kT}$$
$$+ V_b((S_b \backslash \{j\}) \cup \{i\} \mid \beta) + \sum_{k \in (S_b \backslash \{j\}) \cup \{i\}} \xi_k - \sum_{k \in (S_b \backslash \{j\}) \cup \{i\}} p_{kT}.$$

Notice that the same set of licenses, $S_a \cup S_b$, appears on the left and right hand sides, because the inequality involves bidders a and b exchanging licenses. Subtraction simplifies the inequality to

$$V_a(S_a \mid \beta) + V_b(S_b \mid \beta) \geq V_a((S_a \backslash \{i\}) \cup \{j\} \mid \beta) + V_b((S_b \backslash \{j\}) \cup \{i\} \mid \beta). \quad (5)$$

Thus, the additivity in Assumption 3 causes the prices p_{kT} and unobserved license characteristics ξ_k to drop out of our revealed preference inequality. In the context of a market where an unlimited number of people can purchase the same item, Berry (1994) and Berry, Levinsohn and Pakes (1995) argue that the presence of product characteristics that are unobserved to the econometrician but are observed to market participants and are correlated with observed variables may generate severe biases in estimating demand and supply parameters. In demand estimation, the main concern is that greater quality items have higher prices. In the inequality in our equation (5), we difference out the prices and the unobserved license characteristics. As we difference out prices anyway, our main concern in eliminating the ξ_k's is that unobserved product characteristics may be correlated with included license and bidder characteristics.[35]

The inequality in equation (5) is the basis for our estimator. The inequality is easy to compute and differences out endogenous prices, p_{kT}, and unobserved license characteristics, ξ_k. We view the robustness of our estimator to the bidder-invariant unmeasured characteristics of licenses included in the ξ_k's to be a major advantage. Our policy interests focus on complementarities and implicit collusion. Both concerns deal with the interaction of bidder characteristics and license characteristics. Empirical work in the social sciences often has problems with omitted variables. In our approach, differencing out unobserved heterogeneity in licenses and focusing on only aspects of license valuations that are directly related to our policy interests makes our identification strategy much less contaminated by unmeasured variables.

Demange, Gale and Sotomayor (1986) and Hatfield and Milgrom (2003), among others, have pointed out that a generalization of an auction of multiple heterogeneous items is a two-sided matching

[35] It is difficult to find instruments for price, so in practice Berry et al. (1995) assume that unobserved product characteristics are not correlated with non-price, observed product characteristics. We do not need to assume that observed and unobserved characteristics are uncorrelated.

game. In a spectrum auction, the two sides of the market are bidders and licenses. The C block auction has 255 bidders and 493 licenses. Each license can only make one "match" to a single bidder. We now prove that the spectrum auction's final round is in a static equilibrium when static preferences are given by continuation values, and where all licenses are won by only one bidder and no bidders would prefer to match with other licenses.[36]

Result 1. *Define a static equilibrium for the final round of the spectrum auction to be a set of prices and an assignment of licenses to bidders such that 1) Each license is won by only one bidder; 2) No bidder would receives a higher continuation value from removing an individual license from its final package, and 3) No bidder would prefer to win a different package of licenses. If Assumptions 1 and 2 are satisfied for all bidders, the outcome of the auction is a static equilibrium for the continuation values in the final auction round.*

Proof. 1) Each license is won by only one agent because the auction must clear markets license by license. 2) Assumption 2 is satisfied for packages that contain fewer items than the packages won in the auction. 3) This is a restatement of Assumption 2.

□

Next, we show that the outcome of the final round of the auction solves an appropriately defined social planning problem in continuation values. We will refer to an allocation of licenses, S_a for the $a = 1, \ldots, N$ bidders, as feasible if each license is allocated to a single bidder.

Result 2. *If Assumptions 1 and 2 are satisfied for all bidders, the observed allocation of the licenses maximizes the sum of the continuation values $\sum_{a=1}^{N} V_{aT}(s_T, S_a)$ among all feasible allocations. Furthermore if Assumption 3 is also satisfied, then the decentralized auction outcome maximizes the sum of $\sum_{a=1}^{N} V_a(S_a \mid \beta)$ among all feasible allocations.*

Proof. Compare the outcome of the auction, where a bidder a has winning package S_a, to some other auction outcome where bidder a wins S'_a. If there are N bidders, the outcome of the auction maximizes continuation values if

$$\sum_{a=1}^{N} V_{aT}(s_T, S_a) \geq \sum_{a=1}^{N} V_{aT}\left(s_T, S'_a\right) \tag{6}$$

for all alternative feasible allocations of the form $\{S'_a\}_{a=1}^{N}$. By Assumption 2, for each a the term $V_{iT}(s_T, S_i)$ is weakly greater than $V_{aT}(s_T, S'_a)$, so the entire sum in the left hand side is greater than the sum on the right hand side.

[36] Hatfield and Milgrom (2003) present counterexamples for general two-sided matching games that shows that there might not be a static equilibrium when at least one agent has payoffs that feature complementarities across multiple matches. The Hatfield and Milgrom counterexample uses the freedom to choose any set of preferences, so it is not a proof that there does exist equilibria in the C block spectrum auction. We must impose Assumption 2, rather than motivating it from sufficient primitive conditions about the lack of complementarities. The failure to find a general existence theorem when there are complementarities is also found in standard Walrasian competitive markets, as the second welfare theorem (there exists a competitive equilibrium that generates each Pareto optimum) rules out complementarities. The lack of a general existence theorem under complementarities is not a problem specific to multiple unit auctions or to matching.

Under Assumption 3, equation (6) becomes

$$\sum_{a=1}^{N} V_a(S_a \mid \beta) \geq \sum_{a=1}^{N} V_a(S'_a \mid \beta)$$

as the prices in s_T and the unmeasured license characteristics of the form ξ_i difference out on both sides, as the identities of the licenses for sale are the same on both sides of the inequality.

□

We note that this result is similar to the equivalence of the pairwise stable match solution to a social planning problem in matching games where prices enter payoffs quasilinearly (Koopmans and Beckmann, 1957; Shapley and Shubik, 1972; Becker, 1973; Sotomayor, 1992). The social planning result shows that, given the continuation values in the final round of the auction, the static equilibrium assignment of bidders to licenses in the final round is likely to be unique. If the continuation values take random values over the entire real line, the probability that any two feasible allocations have the same sum $\sum_{a=1}^{N} V_a(S_a \mid \beta)$ is 0.

As is typical in the discrete choice literature, we need to add random stochastic shocks so that the econometric model can fit any arbitrary assignment of licenses to bidders. The shocks are observed by the agents, but not the econometrician, so from the econometrician's viewpoint matches between licenses and bidders happen with some probability. For any two sets of bidders a and b and any two packages of licenses S_a and S_b, let $P_{ab}(S_a, S_b \mid X, \beta)$ be the probability that bidder a wins package S_a and bidder b wins package S_b when the parameter vector in continuation values is β and X is a matrix of observable covariates.[37]

A formal theoretical assumption that is required for our semiparametric estimator to be consistent is that match probabilities for two bidders are *rank ordered* by the deterministic portions of continuation values. This assumption is a stochastic version of equation (5), a necessary condition for the deterministic social planner's problem.

Assumption 4. *Consider two licenses $i \in S_a$ and $j \in S_b$, and two bidders a and b, where $S_a \cap S_b = \emptyset$. Assume that*

$$V_a(S_a \mid \beta, X) + V_b(S_b \mid \beta, X) > V_a((S_a \setminus \{i\}) \cup \{j\} \mid \beta, X) + V_a((S_b \setminus \{j\}) \cup \{i\} \mid \beta, X)$$

if and only if

$$P_{ab}(S_a, S_b \mid X, \beta) > P_{ab}((S_a \setminus \{i\}) \cup \{j\}, (S_b \setminus \{j\}) \cup \{i\} \mid X, \beta).$$

Assumption 4 does not impose a known parametric functional form for the error terms (as in logit and probit models), so the estimator based upon rank ordering matching probabilities is semiparametric.

[37] X is the matrix of the bidder and license characteristics for all bidders and licenses in the C block auction, not just bidders a and b and the licenses in S_a and S_b. This is important for the asymptotic theory in Fox (2005a). The probability $P_{ab}(S_a, S_b \mid X, \beta)$ is the sum of the probability of the subset of the $255^{493} = 2.65\text{x}10^{1186}$ or so possible auction outcomes where bidder a wins package S_a and bidder b wins package S_b.

We focus on the probability of two packages being won by given bidders simultaneously because such terms appear in the probability limit of the matching estimator introduced below.[38] The rank ordering property is an extension of a single-agent rank ordering property introduced by Manski (1975), which states that a single-agent chooses a discrete action i with greater probability than j if the deterministic part of the utility from i is greater than from j. Manski (1975) and Fox (2005b) discuss how a sufficient condition for the single-agent rank ordering property is that the error terms in the random utility model have an exchangeable joint density.

In a matching market, Fox (2005a) discusses several frameworks that can motivate Assumption 4. The most mathematically straightforward story is that random errors prevent the market from forming the exact static equilibrium that maximizes continuation values in the final round. In a market with transferable utility, the equivalent of the single agent from Manski (1975) is the social planner. A mathematically equivalent alternative to computing a decentralized equilibrium in the final round is to have the social planner make a discrete choice between the $255^{493} = 2.65\text{x}10^{1186}$ auction outcomes in the C block, given the continuation values at the end of the auction. Fox (2005a) proves that a sufficient condition that will generate Assumption 4 is that the social planner's error terms have an exchangeable joint density.

Another story is that bidders have idiosyncratic bidder-license payoffs ε_{ai}, so that the continuation value of a bidder has the random utility form $V_a(S_a \mid \beta, X) + \sum_{i \in S_a} \varepsilon_{ai}$ for bidder a and package S_a. However, to be clear, Fox (2005a) shows that it is not a theorem that the rank order property holds when the density for the vector of ε_{ai}'s is exchangeable.[39] However, the rank order property might hold if the variance of the error terms is small. Section 2.2 shows that most major winners in the C block were large scale investors that operated on a national scale. The major players were not local businessmen exploiting idiosyncratic knowledge but investors concerned with the national industry structure. Therefore, on a priori grounds we feel it is likely that the role for the bidder-license specific error is indeed low. Our structural estimates reported below fit the data very well, so we are ex post comfortable that our included covariates are good proxies for the major components of continuation values.

5.2 The Maximum Score Estimator for Multiple-Unit Auctions

Fox (2005a) introduces a matching games estimator based on the social planning problem, or equivalently the set of physical pairings in a decentralized static equilibrium.[40] The matching estimator

[38]Fox (2005a) proves that the matching estimator is consistent using a general consistency theorem from Newey and McFadden (1994). Part of proving an extremum estimator is consistent is showing that the probability limit of the objective function is uniquely maximized at the true parameter value, and Assumption 4 concerns terms appearing in the probability limit that make such a proof possible.

[39]The reason is each of the social planner's auctionwide outcomes has many component matches between bidders and licenses, and the outcomes with some overlap of individual license assignments have correlated composite errors. A counterexample to Manski's rank ordering property for single-agent discrete choice models is when there is correlation across in the error terms for choices such that the resulting joint density of the error terms is not exchangeable.

[40]The equivalence of the social planning and decentralized equilibrium solutions is also employed for estimation in a

is computationally simple, because it relies on the payoff maximizing property of the equilibrium, rather than computing an equilibrium. As the set of physical pairings in a stable match is a qualitative outcome, the estimation strategy builds on results in the single-agent discrete choice literature. The matching games estimator in Fox (2005a) is an evolution of the single-agent discrete choice maximum score estimators of Manski (1975), Matzkin (1993) and Fox (2005b).

We are ready to write down the estimator. We use notation that emphasizes what the objective function looks like for our sample, rather than notation that makes it easier to compute the objective function's probability limit. The matching estimator is any parameter vector $\hat{\beta}$ that maximizes the objective function

$$\sum_{i=1}^{480} \sum_{j=1, S_i \neq S_j}^{480} 1 \left[V_{a(i)}\left(S_i \mid \beta, X\right) + V_{a(j)}\left(S_j \mid \beta, X\right) > \right.$$
$$\left. V_{a(i)}\left(\left(S_i \backslash \{i\}\right) \cup \{j\} \mid \beta, X\right) + V_{a(j)}\left(\left(S_j \backslash \{j\}\right) \cup \{i\} \mid \beta, X\right) \right]. \quad (7)$$

The function $1[\cdot]$ is the indicator function, which is equal to 1 if the inequality in brackets is true, and 0 otherwise. The number 480 is the total number of licenses for sale in the continental United States. As there are two summations, the objective function considers two licenses, i and j, at a time. Only pairs of licenses with different winners are considered. The objective function then considers the winning package that contains i, S_i, and the winning package that contains the license j, S_j. One bidder in the data, $a(i)$, won the package S_j, and another bidder, $a(j)$, won S_j. The objective function considers a counterfactual situation where instead bidder $a(i)$ won license j and bidder $a(j)$ won license i. The sum of the continuation values for the two bidders at the round the auction ended in the data under this alternative outcome is

$$V_{a(i)}\left(\left(S_i \backslash \{i\}\right) \cup \{j\} \mid \beta, X\right) + V_{a(j)}\left(\left(S_j \backslash \{j\}\right) \cup \{i\} \mid \beta, X\right),$$

where the set operators show that i is added to $a(i)$'s package and subtracted from $a(j)$'s package, and similarly for j. The objective function's score of correct predictions according to Assumption 4, equation (7), only increases by 1 when the observed outcome gives a greater sum of deterministic continuation values than the alternative where licenses i and j exchange winning bidders.

Because Assumption 4 considers exchanging only two licenses at a time, the matching maximum score estimator does not need to consider all possible combinations of licenses. Therefore, the matching estimator does not have a computational curse of dimensionality in the size of the market. Considering only a subset of license exchanges is a strong advantage, as the number of number of packages of multiple C block licenses is the number of elements of the power set of all licenses in the continental

marriage market setting by Choo and Siow (2003). The parametric error term assumptions of Choo and Siow act like a single-agent discrete choice problem, and do not enforce the physical constraint that each man can marry only one woman, or each license can be won by only one bidder.

United States, or 2^{480}. We focus on exchanges of only one license for each bidder in order to make the estimator use a local notion of identification, rather than out-of-sample extrapolations. Also, using a simple rule, all exchanges of one license, makes the results replicatable as no extra randomization contributes to the reported estimates.[41]

Exchanging only two licenses at a time involves relatively small counterfactuals. In the C block, NextWave won the New York City license and a smaller winner named Americal won the Corpus Christi, Texas license. Our identification strategy asks why this outcome was likely to have a jointly higher continuation value than if instead Americal won New York City and NextWave won Corpus Christi. By considering only small changes to packages, we are exploiting variation in the outcomes that was more likely possible towards the end of the auction. Note that all of our counterfactual possibilities in the estimator involve bidders winning packages with the same number of licenses. We do not consider wildly out of sample counterfactuals, such as Americal winning a package of 50 licenses in large metropolitan areas and NextWave winning only one license in a rural area. This is our attempt to impose some sort of budget constraint. It is unlikely Americal had the financial resources to even consider bidding on such an out-of-sample package.[42]

If Assumption 4 holds, Fox (2005a) proves the matching maximum score estimator used in this paper is consistent, as the number of matching markets (auctions) goes to infinity. Observing many similar economic situations, in this case auction markets, is a key part of almost any consistency argument. By contrast, this paper uses data on only the C block spectrum auction. The C block was a unique market experiment in economic history. The C block attracted only new entrants to the mobile phone industry. These potential new carriers were mainly investors not tied beforehand to any region of the country. The outcome of the \$10.1 billion auction shows how these bidders sorted themselves into packages of winning licenses. If we properly control for implicit collusion, the C block experiment allows us to see how a segment of an industry simultaneously decided to organize itself. So while observing a large number of similar auctions is necessary for the consistency argument, we choose to use the estimator for a finite sample of one very large auction in order to focus our attention on a unique market experiment.

5.3 Continuation Value Functional Form

We have discussed the matching games estimator for a general parametric functional form for continuation values. Now we introduce the actual functional form that we will estimate.[43] The functional

[41] We discuss later that empirical experimentation shows that the point estimates when the objective function includes exchanges of two licenses per bidder (four total) are qualitatively similar.

[42] The formal theory of matching imposes quotas on the number of matches each agent can make. Our estimator keeps the number of licenses in each winner's package the same, so we do not violate any such quotas. Unfortunately, standard models of matching do not allow for monetary budget constraints. We could consider only inequalities that keep the total expenditure of a bidder under the sum of the prices of its winning licenses in the data. We are concerned that the endogenous prices are correlated with unobserved variables, and we have not proved the consistency of the matching estimator for this case.

[43] Introducing a parametric functional form for continuation values simplifies numerical optimization, as the computer needs to search only over a finite dimensional parameter space. Fox (2005a) presents a fully nonparametric analysis of

form is motivated by the fact that the bidders in the C block spectrum auction are potential mobile phone carriers. These carriers want to offer mobile phone service to customers. Our functional form emphasizes that the quality-adjusted population, q, is the most important package characteristic, as a mobile phone carrier needs potential customers for its service. Indeed, Figure 2 shows that population is by far the most important characteristic in the price of licenses. Other characteristics of a package of licenses should only adjust the value of a single resident up or down a little.

As before, let $V_a(S \mid \beta, X)$ be the portion of the parametric form that depends on the unknown parameters β and that enters the estimator. For a package of licenses S, bidder a has a continuation value

$$V_a(S \mid \beta, X) = \gamma \log(\text{eligibility}_a) \left\{ q(S) + \beta_{\text{sq}} (q(S))^2 \right\}. \tag{8}$$

Quality-adjusted population $q(S)$ is the main package characteristic affecting continuation values. It enters the continuation value, equation (8), as a quadratic. The parameter β_{sq} controls the importance of operating scale. If $\beta_{\text{sq}} > 0$, payoffs are convex in quality-adjusted population, and therefore there are increasing returns to operating scale. Scale economies are one reason licenses might be complements.

Quality-adjusted population is defined to be, for some example covariates,

$$q(S) = \text{population}_S \times (1 + \beta_{\text{inc}} \text{income}_S) \left(1 + \beta_{\text{syn}} \text{synergy}_S\right) \left(1 + \beta_{\text{jump}} \text{jump bids}_S\right),$$

where the listed characteristics are observable characteristics of a package. For example, income_S is the percentage of high-income customers in a package. If $\beta_{\text{inc}} > 0$, then a bidder values the total population of a package with richer residents more than a package with poorer residents. If $\beta_{\text{syn}} > 0$, then there are returns to the geographic scope proxy synergy_S, which can be geographic distance or a measure of travel between licenses.

The log of bidder a's eligibility, as described in Table 1, multiplies the quadratic in $q(S)$. This is because the matching estimator asks why bidder a won license i and bidder b license j rather than the reverse. Only portions of payoffs that are interacted with observable bidder characteristics, in this case initial eligibility, are identifiable, as the auctionwide sum of continuation values from interacted characteristics changes if the license is assigned to another bidder. The parameter γ in equation (8) translates the identifiable portion of continuation values into monetary units. The matching estimator does not use the price data, so the scale of payoffs in monetary units is not identifiable. We impose the scale normalization that $\gamma = +1$, or that bidders with more eligibility value quality-adjusted population more than those who chose not to commit many resources to the auction.[44] The correlation between a bidder's initial eligibility and the population of its winning package is 0.76. Note that our use of only

identification and maximum score estimation, where the functional form of $V_a(S \mid \beta, X)$ is unspecified within a large class of possible continuation value functions.

[44] The sign of γ, but not its scale, can be superconsistently estimated in the maximum score framework. It is a standard result in semiparametric discrete choice estimation that location and scale normalizations must be imposed on the unknown parameter vector, and qualitative outcome data do not impose particular cardinalizations for utility functions (Horowitz, 1998). Only the ordinal ranking of payoffs are identifiable from qualitative data such as matches of bidders to licenses.

the qualitative outcome data on which bidders won which licenses differentiates this paper from many other structural auction papers, which focus on variation in bids.

The fact that our empirical proxies, such as the complementarities between licenses, are non-additive functions of the characteristics of all licenses also provides identification. The complementarities from adding Orlando, FL to a package containing Miami and Tampa, FL is presumably more than a package containing San Francisco and Los Angeles, CA.

6 Estimates of Complementarities and Implicit Collusion

We will use our estimates of continuation values to gain some insight into whether bidders value complementarities and whether bidders fear setting off a price war.

Table 5 lists estimates of β in continuation values, equation (8), from using the two-sided matching games estimator.[45] The numbers reported are 95% confidence intervals from subsampling.[46] Column 1 is a simple specification that only includes the percentage of high-income households as a package characteristic. Consider a bidder with fixed level of initial eligibility. Increasing the percentage of high income households in a package by 1% will increase the continuation value of the package by 6%. Now consider two bidders, one whose initial eligibility is twice that of another (whose log eligibility is the log of 2 or 0.69 points higher). The bidder with twice the initial eligibility will value the 1% increase in the high-income household percentage $0.69 \cdot 0.06 = 4\%$ more than the lower eligibility bidder.

Columns (2)–(4) are much more interesting specifications that attempt to address the key questions raised in the paper by including proxies for implicit collusion (jump bidding), and two types of complementarities, operating scale (the quadratic term in quality-adjusted population), and geographic scope. Column (2) contains a specification where the geographic scope proxy is a measure of the population of two licenses divided by the distance between them. All the coefficients are statistically different from 0.

From Table 4, the mean value of this geographic distance measure is 0.006. Doubling this figure to 0.012 results in a $0.006 \times 26.93 = 16.2\%$ increase in a bidder's valuation. This is a very substantial role for the economies of geographic scope, and thus for complementarities. Understanding the total role of complementarities requires looking at the coefficient on the quadratic in quality-adjusted population,

[45]The objective function was numerically maximized using the global optimization algorithm known as differential evolution (Storn and Price, 1997). More than ten runs were performed for all specifications. The reported point estimates are the best found maxima, although care was taken to ensure that runner up computed maxima were qualitatively the same as the best found values.

[46]Subsampling is a resampling procedure discussed in Politis, Romano and Wolf (1999). Subsampling does not require the objective function to be continuous, and has been proved to be consistent for single-agent binary choice maximum score estimators by Delgado, Rodríguez-Poo and Wolf (2001). We use fake data sets of 100 licenses. Our subsampling procedure is somewhat ad hoc from an asymptotic theory standpoint, as the formal asymptotics in Fox (2005a) are in the number of markets going to infinity instead of the number of licenses in a market, and in this paper we data on only one market, the C block spectrum auction. Also, subsampling has not been extended to allow for spatial autocorrelation, so we do not adjust for such correlation, although see Politis and Romano (1993) for results on the bootstrap, which is inconsistent for maximum score estimators.

which is estimated to be -0.00440. The coefficient is negative, meaning the model estimates that there are decreasing returns to operating scale. For a package of 10 million people evaluated at typical values for the other characteristics, the decreasing returns to scale decrease the package's value by 1.7%.[47] However, for a package with 50 million people (1/5 of the US population), the decreasing returns to scale blow up and decrease the package's total value by 9.4%. The point estimates show important positive returns to geographic scope, and somewhat less important negative returns to operating scale.

It is interesting that including other covariates dramatically changes the point estimate for income from 6.12 to -1.21. Now a 1% increase in the high income household percentage decreases the valuation by 1.21%, instead of raising it by 6% without other controls. The change in the sign of a coefficient once other variables are controlled for means that simply staring at a map with only one characteristic plotted is a poor substitute for a multivariate analysis, just as multiavariate least squares produces different slope coefficient estimates than univariate least squares applied to each regressor separately. Note that in many other specifications, including linear price regressions, measures of income had negative signs once other regressors were included. The negative sign is not an artifact of the matching estimator alone.

Another important question we examine is the importance of attempts at implicit collusion in continuation values. We proxy for attempts at intimidation with the presence of jump bids. A typical license in a package has 2 jump bids by bidders who eventually do not win the license. A package with 2 jump bids per license has a continuation value that is 6.5% lower than one with only 1 jump bid. So the mean package's complementarities (16.2%) has an effect roughly equal to two jump bids (13.0%). We return to this point in the discussion of the policy implications of our results.

As for data fit, 105,896 (95.2%) of the 111,192 pairwise combinations of licenses won by different bidders that enter the objective function are predicted correctly according to Assumption 4. The assumption rank orders match probabilities by the sums of pairs of continuation values. There is not much more variation left in the license assignments to explain, with just four covariates included in the model.

Column (3) replaces geographic distance complementarities with the measure based upon air travel. In Column (3), the estimated coefficient on jump bids is statistically the same as in Column (2). The coefficient on income changes from -1.21 to -1.02, so that a 1% increase in income decreases the quality-adjusted population by 1%. The coefficient on air travel is statistically not different than 0 and economically small. The mean level of within-package air travel of 26.1 (in thousands of passengers) raises the quality-adjusted population value by 0.16% over a package with no air travel. Air travel does not have a large contribution towards the economics of geographic scope. Note also that the column with air travel has a lower number of correct predictions: 83.5% of license combinations are predicted

[47] The number 1.7% is calculated as follows. The quality-adjusted population for a package with 10 million people and other characteristics at their mean values is $10 \cdot (1+0.006 \cdot 26.93)\,(1-2.6 \cdot 0.0646)\,(1-0.46 \cdot 1.21) = 4.29$. Total normalized package value (before multiplication by a bidder's characteristic) is then $4.29 - 0.0040 \cdot 4.29$, and the ratio of $-0.0040 \cdot 4.29$ is -0.017.

correctly at the estimated parameter values. Air travel fits the data poorly, compared to geographic distance between licenses. The returns to operating scale in Column (3) are negative, but smaller in magnitude than the negative returns to scale with the geographic distance complementarity measure in Column (2). The returns to scale decrease package value by 0.6% for a package of 10 million people, and 3.5% for a package with 50 million people.

Column (4) switches to the third geographic scope proxy: the number of trips between licenses in a package, as recorded by the American Travel Survey (ATS). According to the sample statistics in Table 4, the mean winning package has 53 such trips, and the standard deviation is 310. Doubling the mean number of trips, results in a $53 \cdot 0.000934 = 5.0\%$ increase in the quality-adjusted population that enters continuation values. The signs and magnitudes of the coefficients on income, the mean number of jump bids and the quadratic in resident quality are similar to the results in Column (2).

7 Implications for the Geographic Size of Spectrum Licenses

We prefer the point estimates in Column (2) of Table 5 as our final results. With 95.2% of the license switches correctly predicted according to the rank order property in Assumption 4, we feel our covariates are able to robustly fit the data. There are two main results from our preferred specification. First, we find that our proxy for attempts at implicit collusion, the number of jump bids by rival bidders, does decrease the continuation value of a package of licenses. A package with an extra jump bid per license in it has its value reduced by 6.5%. Second, we find that our proxy for geographic complementarities, based on the population of other licenses in a package divided by geographic distance, is strongly positively correlated with continuation values. Using the sample statistics from Table 4, we find that a one standard deviation increase in our complementarity proxy raises total package value by 41%.[48] The point estimate of a large return to geographic scope is offset somewhat by a negative point estimate for the returns to operating scale, although the positive scope effect is several times larger at typical covariate values.

In the introduction, we mentioned that the FCC is considering policy changes where it will auction some a block of Advanced Wireless Service licenses for mobile phone carriers that each cover one-twelfth of the United States, although another block will be split into 734 geographic license. These licensing schemes bracket the 493 markets seen in the C block. The spectrum block with twelve geographic licenses moves the United States closer to the European system, where countries often issue nationwide spectrum licenses.

Our findings of large complementarities support the idea that larger licenses will ensure that more winning carriers will be able to operate on a more efficient scale. Larger licenses leave less of a chance for auction idiosyncrasies to cause an inefficient assignment. The fact that our included covariates are able to predict 95.2% of the licenses decisions correctly suggests that the role for the error terms in

[48] This number is $26.93 \cdot 0.0151$.

these auctions is low. Perhaps bidders do not have strong preferences for certain licenses, meaning that auctioning larger licenses might not cause a great destruction in the idiosyncratic or regional knowledge of certain carriers that would be best captured by offering small licenses. The role of complementarities does justify using a simultaneous ascending bid auction, which is designed to allow bidders to assemble packages of licenses exhibiting complementarities.

Consistent with earlier descriptive empirical work on spectrum auctions by Cramton and Schwartz (2000), and with the theoretical analysis of Brusco and Lopomo (2002), we find that attempts at intimidation through jump bidding affect the assignment of licenses. The presence of intimidation likely means that the C block auction was at least partially inefficient in its final assignment.

Under a system of larger licenses, there might be less scope for intimidation. In the extreme case of offering only one nationwide license, there would be little to gain from colluding with rivals, as only one carrier can walk away with the license. On the other hand, entry in auctions is important to prevent intimidation from a small number of bidders. Offering only one nationwide license would discourage participation from all but a few larger players. A small number of bidders could collude before or during the auction to depress the revenue earned by the US Treasury.

As we discussed in Section 2.1, the C block auction fulfilled a Congressional mandate to open the wireless phone industry to small business entrants. Not all of the C block bidders were truly small businesses. However, real small businesses cannot hope to start nationwide mobile phone carriers from scratch. Our finding of strong geographic complementarities suggests that encouraging small businesses to offer mobile phone service does not maximize societal output.

8 Wider Discussion

8.1 Robustness of the Matching Estimator to Choice of Inequalities

The reported estimates in Table 5 use inequalities with exchanges of only one license per bidder, for two total. This deterministic rule aids replication as randomization plays no rule in the objective function. Alternatively, we could have proceeded by randomly choosing inequalities where bidders exchanges two licenses, for four total. When the estimator includes exchanges of mainly two licenses per bidder, estimates for the specification with geographic distance complementarities (column (2) in Table 5) are -1.40 for income, 21.89 for geographic distance, -0.075 for jump bids, and -0.00882 for the quadratic term in quality-adjusted population.[49] We have performed other robustness checks and feel that the coefficient estimates are qualitatively robust to the set of inequalities used in estimation.

[49]These estimates come from a specification where the inequalities overweight exchanges of pairs of adjacent licenses. When a large bidder wins multiple clusters of licenses, the pair of licenses being exchanged is more likely to be licenses in the same cluster rather than different clusters. For bidders who win only one license, only one license is exchanged for that bidder.

8.2 Matching vs. Other Estimators

We feel that the matching estimator best fits the economic primitives of a spectrum auction. As in a matching game, a spectrum auction has a finite number of bidders, a finite number of licenses for sale, and all bidders and licenses are observably heterogeneous both to the econometrician and to other bidders in the auction. Although the estimator does not use price data, the estimator is only consistent for a matching model with endogenous prices, just as a spectrum auction elicits a vector of prices that end the auction.

As discussed in Section 3.5, a major problem in estimation using discrete choice methods is that the number of possible outcomes for a single agent, the number of distinct packages of licenses, is unfathomable. The number of auction-wide outcomes is the number of combinations of feasible outcomes for all bidders, which is even larger. The matching estimator addresses the computational concern by using only weak implications of the theory. It uses restrictions involving only small deviations of two licenses exchanging ownership.

However, throughout the course of our empirical work, we have implemented other estimators that are consistent under different assumptions about competition. The only two known single-agent discrete choice estimators that are consistent when using covariate data on only a subset of the possible winning packages are the McFadden (1978) subset logit estimator and the single-agent maximum score estimator of Fox (2005b). Single-agent methods suffer because the revealed preference of an agent to stop bidding is a function of the vector of closing prices, but the prices are functions of valuations for all 255 bidders. The single-agent discrete choice methods cannot elegantly handle the complex endogeneity of prices in a multiple-unit auction. The matching model solves the price endogeneity problem by finding equilibrium restrictions that hold because of the presence of prices, but which do not use price data.

We have also estimated the hedonic model of Bajari and Benkard (2003). This method treats packages of licenses as a bundle of continuous characteristics in covariate space. The hedonic estimator uses nonparametric methods to regress the closing prices of the 85 winning prices on characteristics of those packages. In a second stage, bidder-specific random coefficients in continuation values are backed out from first-order conditions relating the price gradient to the marginal benefit of each characteristic. The hedonic method relies critically on the researcher's ability to correctly estimate the slope of the hedonic price function at every point in a multivariate package characteristics space. That is difficult with data on only 85 winning packages. The matching estimator in this paper ignores entirely variation in price, and works more directly with the characteristics of bidders and packages.

8.3 Complementarities vs. Correlated Preferences

The FCC spectrum auction design allows bidders to assemble a package of licenses that have the potential for complementarities. The C block bidder Carolina PCS won a package of licenses for most of South Carolina. Our estimates in Table 5 attribute this bidder's payoffs to complementarities, as our matching estimator does not allow errors to be idiosyncratically correlated (non-exchangeable) across licenses. Another explanation is that Carolina PCS has preferences for licenses in the southeastern United States.[50]

We recognize that any choice data can be explained by an arbitrarily complex distribution of stochastic errors without regard to deterministic payoff terms. However, we can limit ourselves to a reasonable class of correlated payoffs, based upon the notion that each bidder has a spatial bliss point. If each bidder has a bliss point, we expect bidders to win licenses mainly in the same region of the United States. Only two of the top ten winning C block bidders by population won licenses in only one region. ChaseTel purchased licenses to cover all of Tennessee and some bordering areas, and another bidder (Carolina PCS) won licenses for most of South Carolina.[51] The other top ten bidders (in terms of population) that did win licenses in clusters did so in multiple areas of the country. For example, the carrier GWI/MetroPCS won licenses in southern Florida, the greater Atlanta area, and northern California. While it is possible GWI/MetroPCS had correlated payoffs for only those three regions, we (subjectively) feel complementarities are a much more likely explanation for GWI/MetroPCS's license clusters.[52]

8.4 Bankruptcy and Moral Hazard / Adverse Selection

This paper stops at the C block auction and does not consider the outcomes of bidders after they won their licenses and became mobile phone carriers. In fact, as we discuss in Section 2.1, many winners were unable to both repay the FCC and fund the enormous capital investments needed to operate a mobile phone network. Zhèng (2001) analyzes a first-price sealed-bid auction and suggests that bidders may strategically anticipate the possibility of default. In an equilibrium with default and low interest rates, bidders with less collateral bid more aggressively because they will have less at risk in a state of the world where default occurs. Default then leads to an adverse selection problem where bidders with fewer financial resources win more licenses. Zhèng's story has similar observable implications to the winners' curse in common value auctions, where the winning bidder is always the bidder who has an overly ambitious signal about the value of the item for sale. We find evidence that bidders with a stronger initial commitment to the auction won larger packages of licenses, which is consistent but not confirmatory of theories about the winner's curse and moral hazard due to bankruptcy protection.[53]

[50] Distinguishing between true complementarities and correlated preferences is important for auction design. Without complementarities and ignoring strategic behavior, a sequence of separate ascending-bid auctions for each license ensures that all licenses are awarded to the bidders with the highest idiosyncratic payoff. The simultaneous auctioning of all licenses, as implemented by the FCC, is important mainly because of the potential for true complementarities between licenses in a package.

[51] Both ChaseTel and Carolina PCS sold their licenses to national carriers before establishing serious market positions as independent carriers. A third top ten bidder won licenses in a narrow, geographically contiguous band stretching from Detroit to Dallas, although this area is so diverse it is hard to explain with a geographic preferences explanation.

[52] Most of the winning bidders were large-scale investors willing to operate outside their home regions. For example, one of the largest winners in the continental United States was based in Puerto Rico.

[53] In a common values auction, bidders are unsure about the true value of the good. An ascending bid auction reveals a lot of information about the signals other bidders have about the value of the good. By the end of the auction, bidders should

9 Conclusions

The FCC auctions licenses to operate mobile phone carriers in geographic markets. An important policy question is whether the geographic size of these licenses should be enlarged for future auctions. Enlarging the size of geographic licenses will ensure that auction irregularities such as attempts at implicit collusion do not dramatically restrict the ability of winning carriers to achieve economies of operating scale and geographic scope.

We empirically examine the C block spectrum auction, where bids for the 89 winning bidders totaled \$10.1 billion. We estimate whether bidders' continuation values are functions of proxies for potential complementarities between multiple licenses in a winning package, and whether a proxy for attempts at collusion make a package of licenses less attractive. Our main proxy for potential complementarities is a measure of the population-weighted distance between licenses in a package, and our main proxy for attempts at intimidation is the history of jump bids on a license.

The C block spectrum auction is a simultaneous ascending auction that lasted 184 rounds, had 255 bidders, and offered 493 licenses for sale. The equilibrium in such a complex dynamic game with repeated interaction and multiple-market contact is not known and is not computable. Therefore, we base identification on relatively weak conditions about the behavior of agents at the end of the auction. We assume that the auction creates a vector of prices where no bidder would prefer to withdraw from its winning licenses and bid on others at the end of the auction. Justifying this assumption is the presence of a rarely used withdrawal option in the FCC's rules.

We estimate bidders' continuation values using a two-sided matching estimator. The estimator is for a matching market with endogenous prices, but does not use data on prices. Instead, the estimator uses the revealed preference argument to state that the economy-wide sum of continuation values is maximized at the closing set of license assignments. The estimator uses data on the characteristics of winning bidders, winning packages, and hypothetical winning packages where the ownership of two licenses has been exchanged between two bidders. Thus, identification comes from the joint incidence of winning licenses within a package and the identities of bidders. The objective function is computationally simple, and the estimator is semiparametric, as it does not rely on specifying a parametric distribution for the error terms.

We find that our proxies for geographic scope and attempts at implicit collusion contribute strongly to continuation values. Packages with one more previous jump bid for a license have a 7% lower continuation values. A one standard deviation increase in our complementarity proxy raises total package value by 33%. The fact that intimidation has the potential to affect final license assignments means that

be pretty informed about the common value component, and what is left of the winner's curse probably reflects an aggregate information shock, or raw uncertainty about the prospects for new entrants in the mobile phone industry that cannot be averaged out in an auction. Hong and Shum (2003) estimate the rate of learning of bidders in the AB block spectrum auction and find that bidders do shade their bid curves as rival bidders drop out of bidding in the ascending auction. This shows that bidders do learn. Hong and Shum interpret their results as suggesting bidders are symmetric, as their informational draws are consistent with a pattern of arising from the same underlying distribution.

the auction may not succeed in producing an efficient outcome in final structural payoffs (as opposed to continuation values). Increasing the size of geographic licenses offered for sale may ensure that the mobile phone industry realizes potential returns to geographic scope without the need for costly post-auction reorganization through mergers and resale.

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Figure 1: Map of the Licenses Won by The Top 12 Winning Bidders and Bidders Who Won Only One License

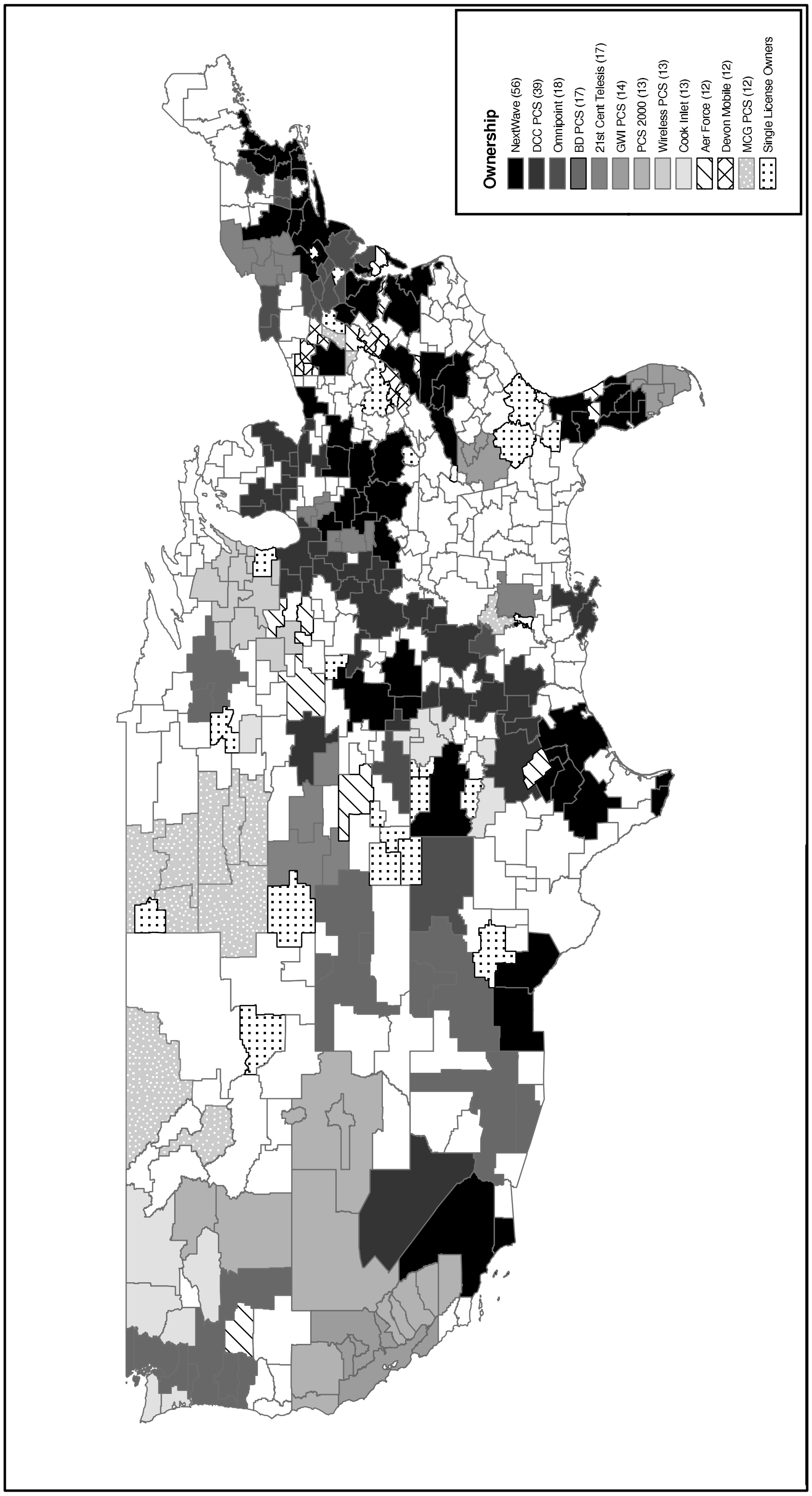

Figure 2: Winning Bids by the Population of the 493 C Block Licenses

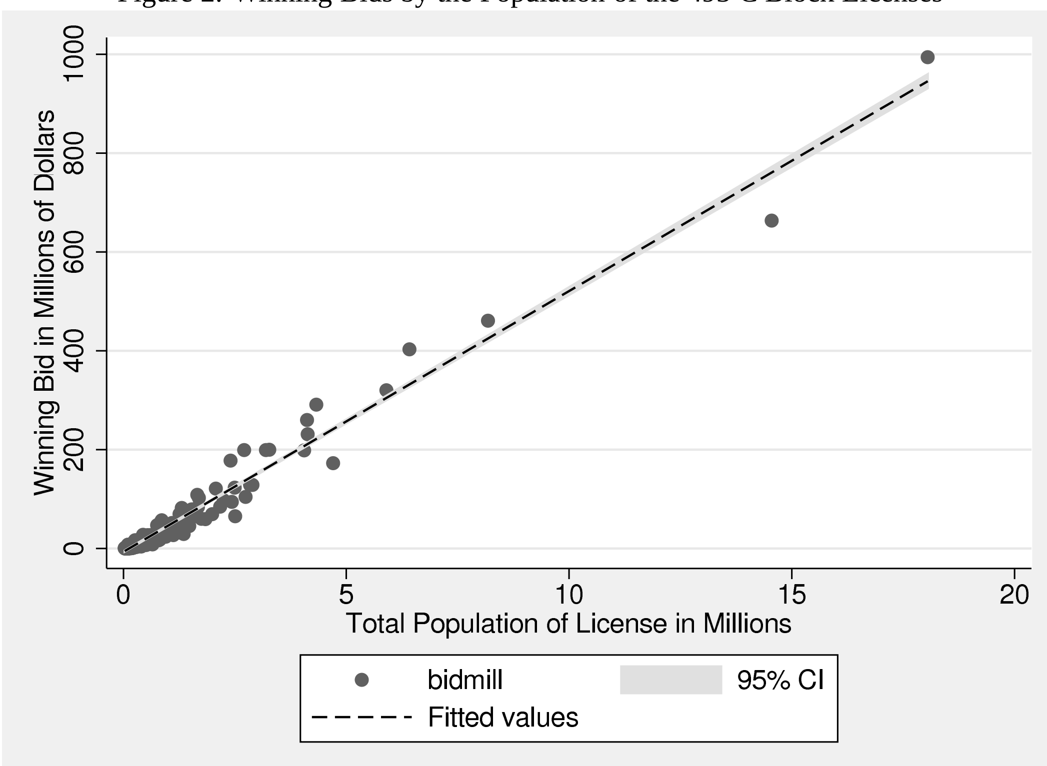

Figure 3: Winning Bids per Resident by the Population of Licenses with Fewer than 5 Million Residents

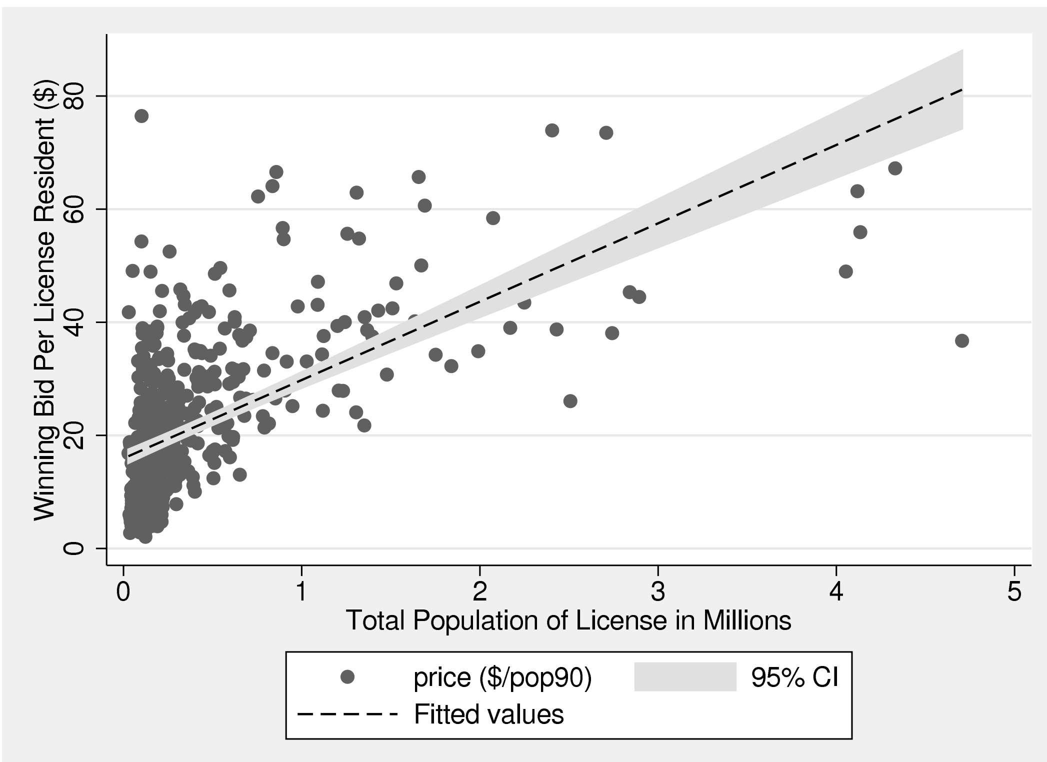

Figure 4: Map of the Price per Resident for Licenses

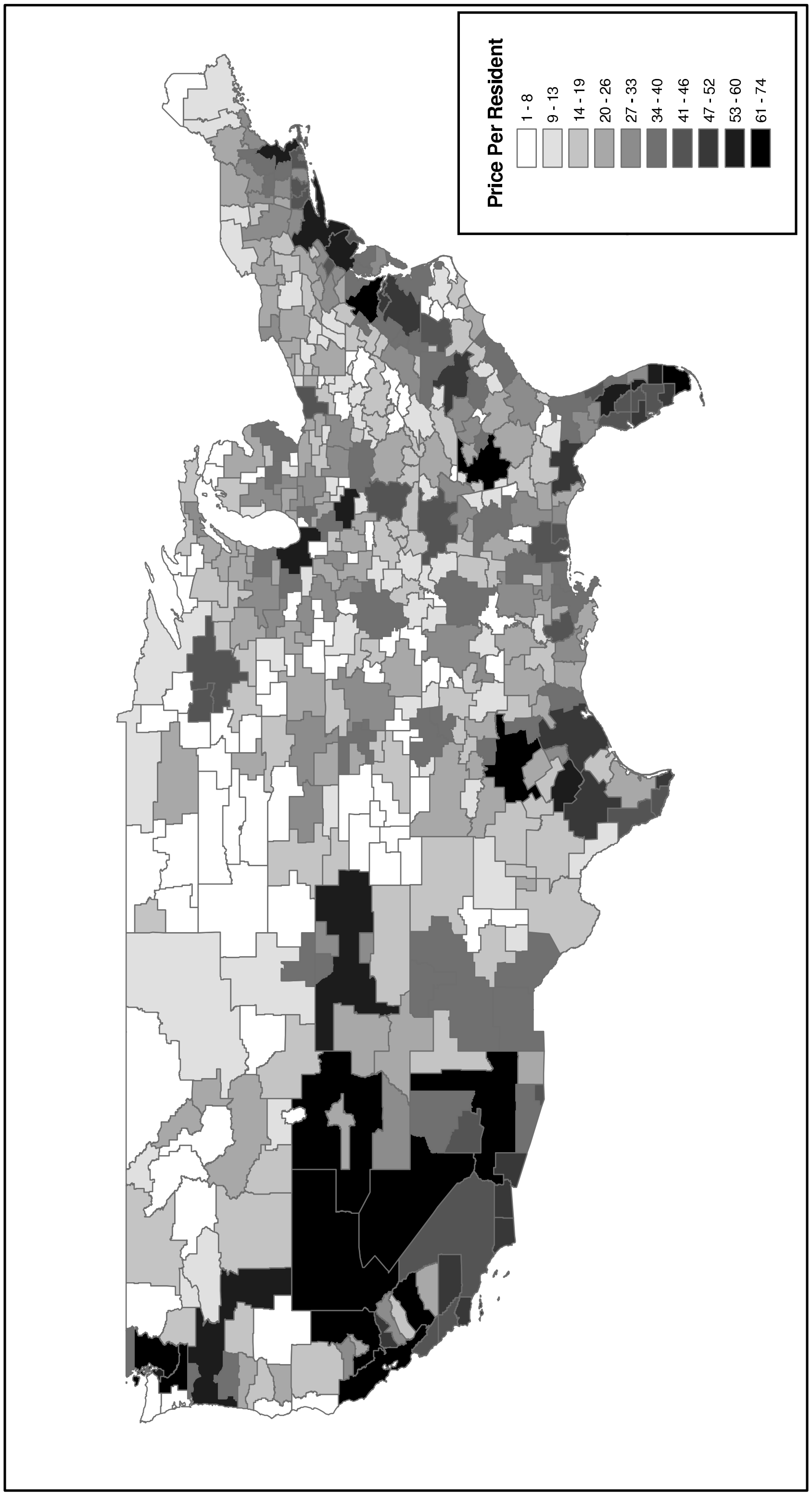

Figure 5: Map of the Population Density (residents/km) of the Expected C Block Buildout Area

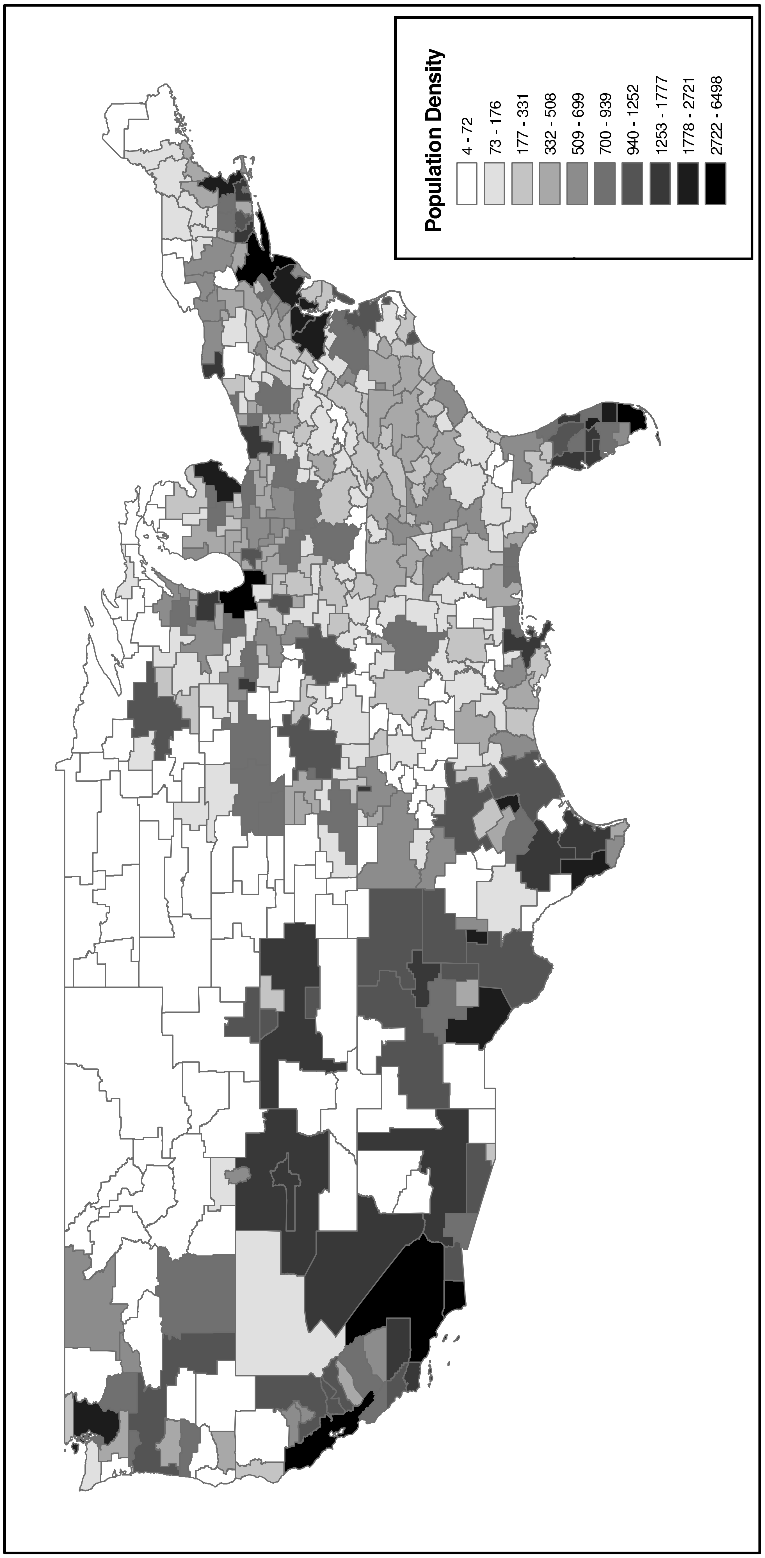

Figure 6: The Number of Jump Bids per Round

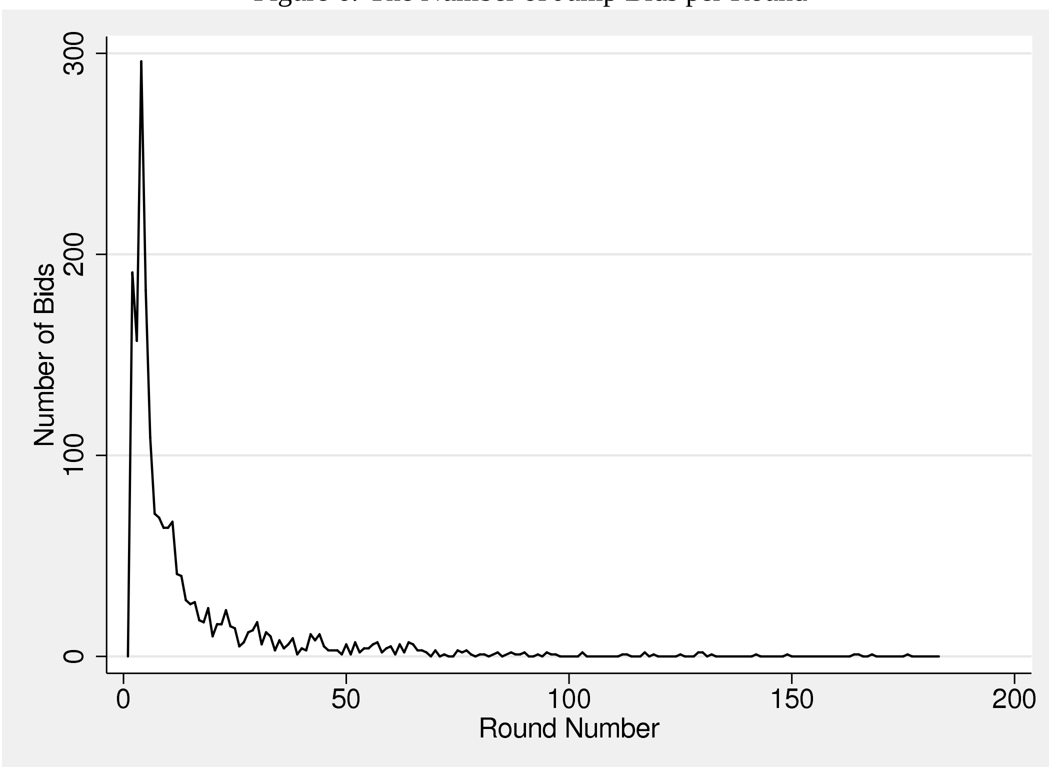

Table 1: Characteristics of Winners and non-Winners of Packages in the Continental United States

	Winners		non-Winners	
Characteristic	Mean	Stand. Dev.	Mean	Stand. Dev.
Initial Eligibility (millions of residents)	9.77	27.2	5.15	18.5
Assets ($ millions)	13.1	21.8	12.3	18.8
Revenues ($ millions)	40.7	67.8	39.9	72.3
# of licenses won	5.3	7.1	0	0
# of licenses ever bid on	38.5	70.6	14.8	44.2
# of bidders	85		170	

Table 2: Total Closing Prices and Population Characteristics of 85 Winning Packages

Characteristic	Mean	Standard Deviation	Min	Max
Total price ($millions)	116.2	496.1	0.102	4,201
Total population in 1994 (millions)	2.91	10.93	0.027	93.8
% of Households with Income > $35K	46.0	6.9	28.9	62.5

Table 3: Within-Package Weighted Mean Number of Jump Bids of Rival Bidders

Characteristic	Mean	Standard Deviation	Min	Max
Jump bids (#)	2.60	2.43	0	15

Table 4: Within-Package Population Weighted Means of Geographic Scope Proxies

Characteristic	Mean	Standard Deviation	Min	Max
Population / distance two markets in a package (millions of people/distance in km)	0.00601	0.0151	0	0.115
Trips between markets in a package in the American Travel Survey	53.2	311	0	2660
Total trips between airports in markets in a package (thousands)	26.1	112	0	912

Table 5: Matching Estimates of Continuation Value Parameters with 95% Confidence Intervals

Characteristic	(1)	(2)	(3)	(4)
Total population in 1994 (millions)	1	1	1	1
Households with income >$35K (%) (β_{inc})	6.12 (4.59,18.1)	-1.21 (-1.27,-0.87)	-1.02 (-1.11,-0.876)	-1.24 (-1.31,-1.09)
Population-weighted mean of distance synergies (millions/kilometers) (β_{syn})		26.93 (22.7,44.4)		
Population weighted mean of within-package airline travel (thousands per year) (β_{syn})			0.0000616 (-0.0000250,0.0000218)	
Population weighted mean of within-package household trips from the ATS (β_{syn})				0.000934 (0.000415,0.00267)
Population weighted mean jump bids (#) (β_{jump})		-0.0646 (-0.0755,-0.0544)	-0.0697 (-0.101,-0.0653)	-0.0835 (-0.184,-0.0782)
Quadratic term in resident quality (β_{sq})		-0.00440 (-0.00580,-0.00350)	-0.00145 (-0.00614,0.00899)	-0.00593 (-0.00844,0.000626)
% Score of Correct Predictions in Objective Function	36.9%	95.2%	83.5%	85.4%