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## 2 **Combinatorial Auctions**

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### 7 **Introduction**

8 The advent of the Internet has led to the creation of  
9 global marketplaces in which sales of everything from  
10 low-cost used merchandise to billion dollar  
11 government procurements are conducted through  
12 auctions. This article concentrates on designs where  
13 many items are auctioned simultaneously and where  
14 bidders have the flexibility to combine the goods into  
15 packages. The discussion (1) highlights alternative  
16 combinatorial auction designs and provides the  
17 reader with multiple references and resources that  
18 describe more fully the underlying theory of these  
19 designs., and (2) describes the mechanisms used to  
20 evaluate the efficacy of such approaches in terms of  
21 their efficiency, equity, and cognitive complexity, and  
22 presents some examples of the use of combinatorial  
23 auctions for high-value government lease rights, as  
24 well as the use of such auctions for supply-chain  
25 procurement. These auctions require knowledge of  
26 both game theory and combinatorial optimization.

### 27 **General Concepts**

28 Governments throughout the world use auctions to  
29 lease the right to explore and extract minerals, fuel,

and lumber on government properties, to use the  
airwaves for mobile or broadcast communications, or  
to control emissions through cap and trade regulations.  
In addition, the use of business-to-business auctions  
(often called supply chain auctions) has become  
a billion-dollar industry. In each of these cases, the  
need to be able to bundle buys and sells has resulted  
in new auction theory and designs that enable the  
simultaneous selling or buying of items using  
mechanisms that allow participants to indicate their  
value for the entire package which may have  
a greater value than the sum of the items within that  
package. In addition, such auction designs allow users  
to specify quantity discounts, to indicate budget  
constraints on the total procurement, and to define  
other goals of the auction, e.g. social welfare goals in  
a government auction. These auction designs are  
computationally more complex for all participants  
and require languages that allow bidders to express  
their willingness to participate at a given price for  
a collection of objects. Such auctions have been  
termed combinatorial auctions. There are many books  
that describe the history of auctions, auction theory and  
its relationship to game theory, and others that are  
focused exclusively on combinatorial auction  
designs. For further reading on the subject, see:  
McMillan (2002) on the history of markets, Krishna  
(2002) on auction theory, Steiglitz (2007) on the  
success and pitfalls of EBAY auctions, Klemperer  
(2008) on auction theory and practice, and Milgrom  
(2004) and Cramton et al. (2005) on combinatorial  
auctions. In this review, only the major topics of the  
field are described, but multiple references are  
provided for further reading.

[\[Au1\]](#)

64 In what follows, one-sided auctions are considered  
 65 and are restricted to the case where there is a single  
 66 seller and multiple buyers (two-sided auctions are  
 67 often referred to as exchanges, see Milgrom (2007),  
 68 Parkes et al. (2001), and Hoffman and Menon (2010)  
 69 on exchange designs). Since the multiple-sellers/  
 70 single-buyer case and the multiple-buyers/  
 71 single-seller case are symmetric, the discussion  
 72 emphasizes the latter, but all results follow for either  
 73 case. The concentration is on auction designs where  
 74 that there are multiple items being sold. For at least  
 75 some of the buyers, a collection of items must be  
 76 procured to have a viable business plan;  
 77 consideration is given only to auction designs that  
 78 allow the packaging of collections of items. Such  
 79 designs can provide greater efficiency, as well as  
 80 greater revenue to the seller than the sequential  
 81 selling of items individually. These designs are  
 82 sufficiently general to allow bidders to express  
 83 a value on a package where the collection of items  
 84 may have a value greater than the individual items  
 85 (i.e. the goods are complements), as well as on  
 86 a package where a buyer can express a quantity  
 87 discount for buying more of the good (i.e. the goods  
 88 are substitutes).

89 Why are auctions such a popular mechanism for  
 90 buying and selling valuable objects? With the advent  
 91 of the Internet, auctions are capable of reaching many  
 92 more possible participants. Here, the potential buyers  
 93 wish to determine the minimum price that they must  
 94 pay given that they must compete with others for the  
 95 ownership of a good or collection of goods. From the  
 96 seller's perspective, submitting goods to an auction  
 97 may increase the number of buyers, thereby  
 98 increasing the potential for competitive bidding and  
 99 higher selling prices. Thus, an auction is a mechanism  
 100 to determine the market-based price, since the bidders  
 101 set the price through the competition among the bids.  
 102 This mechanism is dynamic and reacts to changes in  
 103 market conditions. The determination of selling prices  
 104 by an auction is perceived as fairer than if the price  
 105 were set by bilateral negotiations because all buyers  
 106 must adhere to the same set of rules. Most importantly,  
 107 if the rules are well designed, the result will have the  
 108 goods allocated to the entity that values them the most.

109 The two basic classes of auctions are described  
 110 next: (1) sealed bid auctions whereby there is only  
 111 a single opportunity to provide bids to the auction,  
 112 and (2) multi-round auctions where bids are taken

113 over a period of time and any high bid can be  
 114 overtaken whenever a new bid is received that  
 115 increases the overall revenue to the seller.

### Sealed Bid Auctions 116

117 One common auction mechanism is the first-price  
 118 (sealed bid) auction. In this design, all bidders submit  
 119 their bids by a specified date. The bids are examined  
 120 simultaneously and the auctioneer determines the set  
 121 of bidders that maximizes the revenue to the seller. The  
 122 optimization problem that determines a collection of  
 123 package bids that do not often overlap and produce the  
 124 maximum revenue is known as the Winner  
 125 Determination Problem (WDP). Mathematically, the  
 126 problem can be stated as follows:

$$WDP_{OR} : \text{Max} \sum_{b=1}^{\#Bids} BidAmount_b x_b \quad (1)$$

subject to :

$$Ax \leq 1$$

$$x \in \{0, 1\} \quad (2)$$

127 where  $x_b$  is a zero-one variable which indicates  
 128 whether bid  $b$  loses or wins, respectively.  $A$  is an  $n$   
 129  $x$   $m$  matrix with  $m$  rows, one for each item being  
 130 auctioned. Each of the  $n$  columns represents a bid  
 131 where there is a one in a given row if the item is  
 132 included in the bid and zero otherwise. Constraint set  
 133 (1) specifies that each item can be assigned at most  
 134 once. Set (1) constraints are equations when the seller  
 135 chooses to put a minimum price on each item and is  
 136 unwilling to sell any item below that price. In this case,  
 137 there is a set of  $m$  bids each with only a single item in  
 138 the package and a bid price at a price slightly below the  
 139 minimum opening bid price. In this way, the seller will  
 140 keep the item rather than allow it to be won by a bidder  
 141 at less than the opening bid price.

142 In this formulation of the WDP, the bidder can win  
 143 any combination of bids, as long as each item is  
 144 awarded only once; this is referred to as the "OR"  
 145 language. The problem with this language is that it  
 146 creates a type of exposure problem, that of winning  
 147 more than the bidder can afford. When multiple bids of  
 148 a single bidder can be winning, it is incumbent on the  
 149 software to highlight the maximum exposure to the



150 bidder. This calculation requires that a combinatorial  
 151 optimization problem be solved for each bidder that  
 152 calculates the dollar exposure, creating new  
 153 computational issues for the auctioneer and may  
 154 result in packages that are not best for the bidder.

155 The most natural alternative to this “OR” language  
 156 is the “XOR” language. In this case, the user supplies  
 157 every possible combination of bids of interest along  
 158 with a maximum bid price that she is willing to pay for  
 159 that package. This language removes the dollar  
 160 exposure problem, since the maximum number of  
 161 bids that a bidder can possibly pay is the highest bid  
 162 amount of any of its bids. The problem with the XOR  
 163 language is that it places a new burden on the bidder:  
 164 the bidder is forced to enumerate all possible  
 165 combinations of packages of interest and their  
 166 associated values. Clearly, as the number of items in  
 167 an auction increase, the number of possible bids goes  
 168 up exponentially. When the XOR bidding language is  
 169 used the Winner Determination Problem ( $WDP_{XOR}$ )  
 170 becomes:

$$WDP_{xor} : Max \sum_{b=1}^{\#Bids} BidAmount_b x_b \quad (3)$$

subject to :

$$x = 1$$

$$\sum_{b \in S_B} x_b \leq 1 \text{ for each bidder } B \quad (4)$$

$$x_b \in \{0, 1\} \quad (5)$$

171 Where  $S_B$  is the set of bids of bidder  $B$ , and  
 172 constraint set (4) specifies that at most one of these  
 173 bids can be in the winning set.

174 Fujishima et al. (1999) proposed a generalization of  
 175 the OR language that does not require the enumeration  
 176 of all possible combinations. They label this language  
 177 OR\*. Here, each bidder is supplied dummy items  
 178 (these items have no intrinsic value to any of the  
 179 participants). When a bidder places the same dummy  
 180 item into multiple packages, it tells the auctioneer that  
 181 the bidder wishes to win at most one of these  
 182 collections of packages. This language is fully  
 183 expressive, as long as bidders are supplied sufficient  
 184 dummy items. This language is also relatively simple  
 185 for bidders to understand and use, as was shown in  
 186 a Sears Corporation supply-chain transportation

187 auction. In that auction, all bids were treated as “OR”  
 188 bids by the system. Some bidders cleverly chose  
 189 a relatively cheap item to place in multiple bids  
 190 thereby making these bids mutually exclusive,  
 191 Ledyard et al. (2002). There have been a number of  
 192 alternative bidding languages that have been proposed;  
 193 see Fujishima et al. (1999), Nisan (2000), Boutilier and  
 194 Hoos (2001), and Boutilier et al. (2002) for  
 195 descriptions of alternative languages.

196 One serious flaw in a first-price sealed-bid design is  
 197 that the bidder can experience what is referred to as the  
 198 winner’s curse, i.e., the winning bidder may pay more  
 199 than was necessary to win since the second highest bid  
 200 price was far less than the winning bid amount. For this  
 201 reason, sealed-bid first price auctions encourage  
 202 bidders to shave some amount off of the bid price.  
 203 From a game-theoretic perspective, one wants an  
 204 auction design that encourages straight-forward  
 205 honest bidding.

206 An alternative that overcomes this problem is the  
 207 second price (sealed bid) auction whereby the bidder  
 208 that has submitted the highest bid is awarded the object  
 209 (package), but the bidder pays only slightly more (or  
 210 the same amount) as that bid by the second-highest  
 211 bidder. In second price auctions with statistically  
 212 independent private valuations, each bidder has  
 213 a dominant strategy to bid exactly his valuation. The  
 214 second price auction also is often called a Vickrey  
 215 auction (1961).

216 In a second-price auction, one solves the same  
 217 winner determination problem as one does for the  
 218 first-price sealed-bid case, but the winners do not  
 219 necessarily pay what they bid. Instead, one  
 220 determines the marginal value to the seller of having  
 221 this bidder participate in the auction. To do this, for  
 222 each winning bidder, one calculates the revenue that  
 223 the seller would receive when that bidder participates  
 224 in the auction and when that bidder does not, i.e.  
 225 when none of the bids of this bidder are in the  
 226 winner determination problem. The difference in  
 227 the two objective function values is known as the  
 228 Vickrey-Clarke-Groves discount, named after the  
 229 three authors, Vickrey (1961), Clarke (1971), and  
 230 Groves (1973). Each of these authors wrote separate  
 231 papers producing certain attributes that this auction  
 232 design has as it relates to incentivizing bidders to  
 233 reveal their truth value of the goods demanded, and  
 234 the bidder pays the bid price minus the discount. When

235 winners pay this amount, the auction is known as the  
236 Vickrey-Clarke-Groves (VCG) Mechanism.

237 Although it can be shown that the VCG mechanism  
238 encourages truthful bidding, it is almost never used in  
239 practice. For a complete list of reasons for it being  
240 impractical, see Ausubel and Milgrom (2006) and  
241 Rothkopf (2007). In essence, the prices provided by  
242 this mechanism may be very low. Worse yet, when  
243 items have complementary values, i.e. the package is  
244 worth more to the bidder than the sum of the values of  
245 the individual items, the outcome may price the items  
246 so low that there is a coalition of bidders that would  
247 prefer to renege on the auction and negotiate privately  
248 with the seller, and the seller may respond by renegeing  
249 on the sale since both the seller and the coalition of  
250 buyers will be better off. Ausubel and Milgrom (2002)  
251 argue that prices should be set high enough so that no  
252 such coalitions exist. In game theoretic terms, the  
253 prices are set such that the outcome is in the core of  
254 a coalitional game. These authors introduced an  
255 auction design known as the ascending proxy auction  
256 in which the bidders provide all bids as if in  
257 a sealed-bid auction. Each bidder is provided with  
258 a proxy that bids for the bidder in a straightforward  
259 manner during an ascending auction. The proxy only  
260 announces bids to the auctioneer that maximize the  
261 bidder's profit, (i.e. bid price minus announced price)  
262 in any given round. The auction continues as an  
263 ascending package-bidding auction until, in some  
264 round, there are no new bids. Thus, the auction  
265 simulates, through proxy bidders, an ascending  
266 auction where the increment in each round is  
267 infinitesimally small and each bidder, through the use  
268 of its proxy, bids in a straight-forward manner. This  
269 auction design is very similar to the iBundle design of  
270 Parkes and Ungar (2000).

271 Hoffman et al. (2006) provide a computational  
272 approach toward speeding up the calculations  
273 associated with this proxy auction design, and Day  
274 and Raghavan (2007) provide an elegant mechanism  
275 to obtain minimal core prices directly. The direct  
276 mechanism of Day and Raghavan sequentially solves  
277 winner determination problems to determine losing  
278 coalitions that could supply more revenue to the  
279 seller at the current prices. When the solution to this  
280 optimization problem yields revenue greater than what  
281 the VCG mechanism would provide, the prices of the  
282 winning bid set are raised so that the total price paid by  
283 winning bidders is equal to this new revenue. To

284 determine these new prices, one must be sure that any  
285 winning bidder that forms part of this blocking  
286 coalition does not have its price raised from its prior  
287 price since it would not be willing to join a coalition if  
288 it were to lose revenue relative to its prior offer by the  
289 seller. The algorithm is an iterative cutting plane  
290 algorithm that forces the prices higher at each  
291 iteration until one can find no coalition that can  
292 increase revenue to the seller. Therefore, the  
293 algorithm finds prices for each winning bidder that  
294 are in the core. Since there may be many such  
295 minimum core prices, Day and Milgrom (2008)  
296 suggest that, in order to encourage sincere bidding,  
297 one choose the minimum core prices that are closest  
298 in Euclidean distance from the VCG prices.  
299 Alternatively, Erdil et al. (2009) argue for a different  
300 set of minimum core prices that are based "on a class of  
301 'reference rules' in which bidders' payments are,  
302 roughly speaking, determined independently of their  
303 own bids as far as possible."

304 These core-selecting second-price sealed-bid  
305 mechanisms have the following properties: They are  
306 in the core, they eliminate the exposure problem, and  
307 they encourage bidders to bid sincerely. As with all  
308 sealed-bid auctions, they make collusion and  
309 punishment for not adhering to tacit agreements  
310 extremely difficult.

311 There are, however, negatives associated with this  
312 auction, as well as for all sealed-bid auction designs, in  
313 that it puts a significant burden on the bidders. Each  
314 bidder needs to assess, for every possible combination  
315 of items, whether it is a package of interest and then,  
316 for all such packages, determine the maximum it is  
317 willing to pay. In addition, such mechanisms do not  
318 provide any information about how the packages  
319 submitted might fit with packages submitted by other  
320 bidders. To overcome these problems, a number of  
321 authors have suggested simultaneous ascending  
322 combinatorial auction designs that allow users price  
323 information during the auction.

## 324 Multi-round Auctions

325 Often the value of the good or package of goods being  
326 auctioned is not completely known and/or private.  
327 Instead, there is a common component to the bid  
328 value, that is, the value of the item is not independent  
329 of the other bidders, but rather there is a common



330 underlying value as well. In such situations, each  
331 agent has partial information about the value. Many  
332 high-stakes auctions, such as government auctions for  
333 spectrum, oil exploration, and land use, fall into this  
334 class. In the case of package-bidding auctions, when  
335 there is a common component and bidders want to  
336 assess how much others are willing to pay for that  
337 item or package of items, the auction is usually an  
338 ascending auction with multiple rounds. A round  
339 consists of a given time period where bidders have  
340 the opportunity to submit new bids. When the round  
341 ends, all bids are collected and the winner  
342 determination problem is solved. This optimization  
343 problem determines the packages that provide the  
344 seller with the maximum revenue. The bids that are  
345 in the winning set are labeled “provisionally winning,”  
346 i.e. they would be winning if the auction ended in this  
347 round. Thus, in an ascending combinatorial auction, all  
348 items are sold simultaneously and a bidder can bid on  
349 any collection of items in a given round. To overcome  
350 the current set of provisionally winning bids, a bidder  
351 must submit a bid that increases the total revenue to the  
352 seller.

353 There are a number of design question that must be  
354 answered to have a complete combinatorial auction  
355 design:

- 356 1. How does the auction end?
- 357 2. Must bidders participate in every round?
- 358 3. Are bids from previous rounds part of the bids  
359 considered by the winner determination problem?
- 360 4. How are the prices set in each round?
- 361 5. What do bidders know about the bids of other  
362 bidders?
- 363 6. What other rules might be necessary to ensure that  
364 collusion is avoided, to make reneging costly, and  
365 to encourage bidders to act truthfully?

366 Of importance is how to assure that the auction ends  
367 in a reasonable period of time and that price discovery  
368 (the main reason for a multi-round auction) is  
369 accomplished. Most package-bidding auctions have  
370 discrete time periods, called rounds, and in each  
371 round, the auctioneer provides a price to the user that  
372 is the minimum price that the bidder must supply in  
373 order to place a new bid. One can choose either a fixed  
374 stopping rule or a stopping rule that is determined  
375 dynamically. A fixed time stopping rule specifies that  
376 the auction will end at a given time. With a fixed  
377 stopping time, bidders are encouraged to not provide  
378 any bids until the very last seconds of the auction,

379 called sniping. The purpose of sniping is to give other  
380 bidders no chance of responding to an offer. In this  
381 way, a bidder can acquire price information from other  
382 bidders but does not reciprocate, since throughout  
383 most of the auction, the bidder is silent. If all bidders  
384 chose to snipe and provide no bids until the end of the  
385 auction, the auction essentially becomes a first-price  
386 sealed-bid auction. To overcome the problem of  
387 sniping and to encourage price discovery, most  
388 package bidding auctions use an alternative stopping  
389 criteria whereby the auction ends when no new bids are  
390 presented within a round.

391 Often, for high-stakes multi-round auctions, there  
392 are also activity rules that require a bidder to bid in  
393 a consistent way throughout the auction. Activity rules  
394 force bidders to maintain a minimum level of bidding  
395 activity to preserve their eligibility to bid in the future.  
396 Thus, a bidder desiring a large quantity at the end of the  
397 auction (when prices are high) must bid for a large  
398 quantity early in the auction (when prices are low). If  
399 the bidder cannot afford to bid on a sufficient number  
400 of items to maintain current eligibility, then eligibility  
401 will be reduced so that it is consistent with current  
402 bidding. Once eligibility is decreased, it can never be  
403 increased. As the auction progresses, the activity  
404 requirement increases, reducing a bidder’s flexibility.  
405 The lower activity requirement early in the auction  
406 gives the bidder greater flexibility in shifting among  
407 packages early on when there is the most uncertainty  
408 about what will be obtainable. Precisely how the  
409 activity and eligibility rules are set matters and must  
410 be depend upon the type of auction – the value of the  
411 items being auctioned, the projected length of the  
412 auction, the number of participants, etc. In many  
413 high-stakes auctions, such as spectrum or electricity,  
414 these activity rules have proven highly successful,  
415 Klemperer (2002), McMillan (2002), and Milgrom  
416 (2004).

417 In an ascending multi-round auction design, the  
418 auctioneer must provide information about the  
419 current value of each package. This information is  
420 used for two related purposes: (1) to specify the  
421 minimum bid for each item or package in the next  
422 round and (2) to provide valuation information to  
423 bidders so that they can determine what might be  
424 required for a bid to be winning in a subsequent  
425 round. While pricing information is easy to ascertain  
426 in single item auctions or in simultaneous multi-round  
427 auctions without package bidding, (i.e. where bids can

428 be placed on only single items), pricing information for  
429 combinatorial auctions is not well defined. Bidders  
430 provide only aggregate package prices without  
431 providing the information about how each of the  
432 individual components that made up the bundle  
433 contributes to the overall price. Attempting to  
434 disaggregate these bundles into single item prices  
435 unambiguously is not possible. Also, since there are  
436 many ways that some bundle might partner with other  
437 packages to create a winning set, determining the  
438 minimal cost partnering for a given package by  
439 a given bidder is a complex problem.

440 To further complicate the pricing issue, bidders may  
441 view certain items as substitutes and other items as  
442 complements. In the case where items are substitutes,  
443 bidders are likely to express sub-additive values for  
444 their packages. That is, the value of a package of items  
445 is less than or equal to the sum of the values of the  
446 items that make up the package. In the complementary  
447 case, bidders are likely to express super-additive  
448 values for packages. In this case, the value of  
449 a package of items is greater than or equal to the sum  
450 of the values of the items that make up the package.  
451 When items can be both substitutes and complements  
452 for bidders, providing unambiguous, complete and  
453 accurate price information is an unsolved problem.  
454 The non-convex nature of the problem means that the  
455 linear prices (i.e. the sum of a package is equal to the  
456 sum of the individual items that make up the package)  
457 that can be obtained from dual prices from the linear  
458 relaxation of the WDP problem will overestimate the  
459 true values of the items. In most auctions, one adjusts  
460 the dual prices so that the prices are modified so that  
461 when one sums the items in each of the winning  
462 packages, the prices on those packages exactly equal  
463 the prices bid by the provisionally winning bidders (i.e.  
464 the winners at the end of the current round). Rassenti  
465 et al. (1982) terms these prices pseudo-dual prices.  
466 (For theoretical issues with duals associated with  
467 non-convex problems see Wolsey(1981), and for  
468 non-anonymous non-linear prices see deVries and  
469 Vohra (2003) and Bikhchandani and Ostroy (2001).)

470 Although linear pricing cannot accommodate all  
471 aspects of the pricing associated with the non-linear,  
472 non-convex, winner determination problem, there are  
473 still good reasons for considering its use for  
474 determining future bid requirements. First, even  
475 perfect pricing is only correct when all other aspects  
476 of the problem remain fixed, i.e. when bid amounts

477 remain the same on all other bids and when no new  
478 bids are submitted. Second, a dual price associated  
479 with a given constraint is only correct when one  
480 changes this single restriction (the right-hand-side of  
481 the associated constraint) by a very small amount. In  
482 the case of combinatorial auctions, the item is either  
483 won or it is not. Changes to a constraint would either  
484 remove the item entirely from consideration or create  
485 a second identical item. Thus, even non-linear,  
486 non-anonymous pricing has serious limitations in the  
487 context of the winner determination problem since  
488 the removal of a single item from the auction (e.g.  
489 the removal of the New York City market from  
490 consideration in a nationwide spectrum auction) may  
491 change the willingness of bidders to participate.

492 Finally, in an ascending bid auction, bidders need  
493 pricing information that is easy to use and understand,  
494 and is perceived to be fair. In this situation, easy to use  
495 means that bidders can quickly compute the price of  
496 any package, whether or not it had been previously bid.  
497 Often, bidders want to know what it would take for  
498 such a bid to be competitive, i.e. have some possibility  
499 of winning in the next round. Bidders may also  
500 perceive such prices to be fair since all bidders must  
501 act on the same information. Linear prices are likely to  
502 move the auction along and deter such gaming  
503 strategies as parking (parking is an approach whereby  
504 the bidder bids on packages that currently have very  
505 low prices knowing that these packages have  
506 a very low probability of winning). Bidding on such  
507 low-priced packages allows a bidder to maintain  
508 eligibility (by maintaining activity), while hiding  
509 interest in the packages that are really desired until  
510 later in the auction). Thus, virtually all ascending  
511 combinatorial auctions use pseudo-dual pricing. For  
512 more on alternative pricing within this general  
513 framework and the testing thereof, see (Dunford et al.  
514 (2003), Bichler et al. (2009) and Brunner et al. (2011).

515 In 1999, DeMartini et al. proposed an auction  
516 design labeled The Resource Allocation Design or  
517 RAD where the WDP is solved each round and all  
518 losing bidders can only bid on packages where the  
519 package price is the sum of the pseudo-dual prices  
520 plus some increment (as announced by the  
521 auctioneer). There is no activity rule for this auction  
522 design. In 2002, the Federal Communications  
523 Commission (FCC) announced a similar package  
524 bidding design but proposed refinements to the  
525 pseudo-price calculations that attempts to limit

526 fluctuations (both positive and negative) in prices.  
527 A related design was proposed by Bichler et al.  
528 (2009) and is called the Approximate Linear Pricing  
529 Scheme (ALPS). It also uses similar rules but chooses  
530 the ask price to better balance prices across items. Note  
531 that all of these pricing procedures allow prices to both  
532 increase and decrease depending upon the packages  
533 that are in the winning set. In virtually all of these  
534 designs, any bid submitted in any round is considered  
535 active throughout the auction. This rule works well  
536 with the XOR language since only one bid of  
537 a bidder can be in an optimal set and bidders should  
538 be willing to win bids placed in early rounds of the  
539 auction, when prices were low. This rule forces bidders  
540 to provide sincere bids throughout the auction.

541 A very different ascending package bidding design  
542 was proposed by Porter et al. (2003). It is called the  
543 combinatorial clock auction. In this design, the  
544 auctioneer provides prices for each unique good  
545 (if there are multiple identical items, then the bidder  
546 indicates that number of units of that item they desire)  
547 based solely on whether there is more demand for the  
548 item than for supply; no WDP problem is solved. There  
549 is no concept of a provisionally winning bidder.  
550 Instead, prices increase whenever demand for a given  
551 item is greater than supply. Bidders indicate the single  
552 package bid that is best given the per-unit prices  
553 announced by the auctioneer. All bidders must rebid  
554 on any item that they wish to procure in each round.  
555 The only information provided to bidders at the end of  
556 each round is the quantity demanded for each item and  
557 the price for the next round. As long as demand  
558 exceeds supply for at least one item, the price is  
559 increased for those items with excess demand. If  
560 there are no new bids in a round and supply equals  
561 demand, then the auction ends. However, it may  
562 happen that when there are no new bids, demand has  
563 been reduced to below supply. If this occurs, a WDP is  
564 solved using all bids from all rounds. If the computed  
565 prices do not displace any bids from the last round,  
566 then the auction ends. Otherwise, the auction resumes  
567 with the prices determined by using the pseudo-prices  
568 calculated from the WDP. Thus, for most rounds, the  
569 computation has been drastically reduced to merely  
570 increasing prices by a given increment. Only, when  
571 demand has dropped below supply is the WDP solved.

572 Other approaches are the auction designs that  
573 simplify the problem by only allowing a few  
574 pre-defined packages (Harstad et al. 1998) for which

the WDP is polynomially solvable. This idea of only  
575 allowing a certain pre-determined set of packages  
576 (called hierarchical packages, Goeree and Holt 2010)  
577 was used in the 2009 FCC auction for broadband  
578 spectrum that brought over \$19B into the U.S.  
579 Treasury. In that design, all bids were additive  
580 (the OR language applied) and the WDP was solved  
581 in linear time. When it is possible, in advance, to  
582 understand the needs of the bidders and when the  
583 packages most desired can be represented in  
584 a hierarchical fashion, then one obtains an auction  
585 design that is both simpler and quite efficient.  
586 However, if the demand for packages does not take  
587 on this hierarchical structure, then imposing such  
588 structure on the problem for the sake of  
589 computability will likely lead to less efficient  
590 outcomes. 591

### 592 Hybrid Designs

Ausubel et al. (2006) have argued for a hybrid design  
593 that reduces the computational burden on both the  
594 bidder and the auctioneer. Here, one first uses  
595 a combinatorial clock design followed by a last round  
596 second-price sealed-bid approach. The combinatorial  
597 clock is similar to that proposed by Porter et al. (2003)  
598 with the further enhancement that bidders who find the  
599 increment too high are able to place a bid at a price  
600 between the old price and the new price that indicates  
601 the maximum amount the bidder is willing to pay for  
602 that combination of items. In this way, the efficiency  
603 loss due to increment size is lessened. This phase of the  
604 auction ends when demand is less than or equal to  
605 supply or when demand on most items has trailed off.  
606 When demand does not exactly equal supply on all  
607 items, a sealed-bid phase is initiated. Here, the  
608 ascending proxy auction of Ausubel and Milgrom  
609 (2001) is imposed. When these two auction designs  
610 are merged, one must be careful that the activity rules  
611 work well for both phases of the auction. One wants  
612 tight activity rules in the ascending phase of the  
613 auction to ensure that the bidders are forced to bid  
614 sincerely. However, these rules may need to be  
615 relaxed or altered during the final sealed-bid phase or  
616 a straightforward bidder may be precluded from  
617 providing all of the packages that bidder values  
618 during the sealed-bid round. Also, theory dictates that  
619 in order to guaranteed an efficient outcome, losing  
620



621 bidders (i.e. bidders who dropped out prior to the final  
622 phase) must also provide all of the bids that they value  
623 in the final phase. Thus, although this hybrid auction is  
624 promising in that it is likely to speed up combinatorial  
625 auctions, research is still necessary to better  
626 understand how the rules of these two disparate  
627 auctions should be set so that they mesh well. For  
628 more on testing of this design, see Bichler et al. (2011).

## 629 **Complexity of Combinatorial Auctions**

630 As the previous discussion illustrates, most  
631 combinatorial auction designs requires considerable  
632 computation and most of the computational burden  
633 falls to the auctioneer. This seems appropriate since  
634 the auctioneer wants an auction that allows much  
635 participation; bidders should not be required to  
636 understand combinatorial optimization in order to  
637 participate. In terms of these computations,  
638 commercial software, such as CPLEX, GUROBI, or  
639 XPRESS have shown their ability to solve such  
640 problems in reasonable times (less than 30 minutes).  
641 Thus, although there is much in the literature that  
642 argues against combinatorial auctions because of the  
643 computational burden, the optimization software has  
644 proven up to be capable of handling the problems that  
645 are currently being considered applicable for this type  
646 of auction. For more on the computational issues in  
647 computing winner determination problems, see  
648 Leyton-Brown et al. (2005) and Bichler et al. (2010).

649 Since multi-item auctions are complex and require  
650 bidders to consider multiple alternative bid options, it  
651 is important that the computer software used for  
652 communication between the bidder and the  
653 auctioneer be easy to use and understand. Good  
654 graphical user interfaces help bidders to feel  
655 comfortable that they understand the current state of  
656 the auction (they have been able to find the current  
657 price information, the items they are winning, the  
658 amount of bidding necessary to remain eligible, their  
659 dollar exposure based on what they have bid, etc.). The  
660 system must also provide easy ways for bidders to  
661 input their next moves and confirm that they have  
662 provided the system with the correct information. As  
663 the use of auctions is spreading, computer interfaces  
664 for such processes continue to improve and to provide  
665 better ways of displaying information to the users

through charts, graphs and pictures. There is likely to  
666 be continued improvement in this area. 667

668 These tools do not, however, help the bidder  
669 determine the optimal combination of items to bundle  
670 as a package and the optimal number of packages to  
671 supply to the system. Since bidders face the serious  
672 problem of determining which bids are most likely to  
673 win at prices that are within their budgets, tools that  
674 assist bidders in understanding the state of the auction  
675 is important. In both supply-chain auctions and in  
676 high-stakes government auctions (such as spectrum  
677 auctions), bidder-aided tools are often developed to  
678 assist the bidder in determining the package or  
679 packages to submit in any given round. In the case of  
680 supply-chain auctions, the auctioneer often suggests  
681 packages to the suppliers that will fit well with other  
682 bidder's bids (e.g. by either adding or removing  
683 a single item from the package, or by considering  
684 a quantity discount for supplying more of an item).  
685 Such tools have been found to be very useful and also  
686 computationally tractable; see Elmaghraby et al.  
687 (2002), Dunford et al. (2003), and Boutilier et al.  
688 (2004). Day and Raghavan (2005) and Parkes (2005)  
689 provide alternative ways for bidders to express  
690 preferences that do not require that the bidder  
691 specifying particular packages to the auctioneer. AU2

## 692 **Applications of Combinatorial Auctions**

693 There are many examples of governments' using  
694 auctions for the allocation of valuable assets. In most  
695 of these auctions, the government is allocating a good  
696 and uses auctions to determine both the price and the  
697 allocation. Since 1994, governments throughout the  
698 world have been using simultaneous multi-round  
699 auctions for the allocation of spectrum. For spectrum,  
700 a government has the goal of allocating the good to the  
701 entities that value it the most with the hope that the bid  
702 cost will encourage the build-out of the services. To  
703 assure that there is sufficient competition in the  
704 telecommunications industry, the U.S. government  
705 has, in the past, set spectrum caps for each region.  
706 These auctions have been copied globally and are  
707 now the standard way that spectrum is allocated.  
708 Recently, a number of different package-bidding  
709 designs are being tried including the hierarchical  
710 ascending auction, the combinatorial clock auction,  
711 or the clock-proxy design. As of 2005, these auctions

712 have resulted in revenues in excess of \$200 billion  
713 dollars worldwide (Cramton 2005).

714 Within the power industry, there has also been  
715 an evolutionary movement toward auctions for the  
716 determination of who can supply power to the  
717 electricity grid and at what price. Most of  
718 the allocation is determined one day ahead of the  
719 demand. The auction reflects the unique  
720 characteristics (both physical and structural) of the  
721 industry. The allocation is determined by  
722 a complicated optimization that evaluates the  
723 demands at various nodes of the networks and prices  
724 power generation at each such node. The spot market  
725 corrects this allocation for any last minute changes due  
726 to weather, plant outages, etc. Long term contracts  
727 make this process work.

728 Similarly, auctions have been used to bring  
729 market-based forces to control air pollution. Here,  
730 a government entity (either nationally run or  
731 regionally administered) establishes a fixed number  
732 of tradable allowances each of which represents the  
733 legal right for its owners to emit a fixed quantity of  
734 pollution. A firm holding an allowance can emit the  
735 fixed quantity and surrender the allowance to the  
736 government, or if the firm can abate its emissions, it  
737 can profit by selling the allowance to another polluter  
738 than cannot so inexpensively abate emissions. The  
739 establishment of the fixed quantity is the cap. The  
740 exchange of allowances (credits) between polluters is  
741 the trade. See Ellerman et al. (2003) and Tietenberg  
742 (2006) for a general overview of cap and trade ideas.

743 The use of combinatorial auctions for the  
744 procurement of goods in services has also been  
745 growing. Some of these auctions are sealed-bid  
746 auctions, while most are moving toward multi-round  
747 auction designs. In such auctions, the providers of the  
748 goods and services are pre-screened and are then  
749 allowed to provide bids for collections of good and/or  
750 services as all or nothing packages. For a general  
751 survey of supply-chain auctions, see Bichler et al.  
752 (2005). The three applications described next  
753 highlight a few examples to show how such auctions  
754 differ from government auctions.

755 1. The first use of a combinatorial auction within the  
756 transportation industry was an auction conducted by  
757 Sears. Here, suppliers of freight delivery were  
758 allowed to bundle multiple lanes together into  
759 a single bid thereby allowing carriers to coordinate  
760 multiple businesses and reduce empty or low value

761 backhaul movements. It also provided a means to  
762 incorporate surge demand contingencies into the  
763 longer (3-year) contracts, thereby lessening the  
764 need to renegotiate contracts whenever demands  
765 changed; Ledyard et al. (2002).

766 2. Mars Incorporated used a combinatorial auction  
767 mechanism to procure the necessary goods from  
768 multiple suppliers allowing bidders to specify  
769 complex bid structures that indicated quantity  
770 discounts, minimum supply, and multiple goods  
771 collected within a single bid. No bidder was  
772 allowed to supply more than a certain percentage  
773 of the overall quantity needed and newer suppliers  
774 were limited more severely than their suppliers they  
775 had used over a number of years. The algorithm also  
776 assured that there were multiple suppliers in the  
777 solution for each critical entity. These auctions are  
778 not simple, but work to match the needs of  
779 the procurer, Mars, with the capabilities of the  
780 suppliers (often farmers). The allocation considers  
781 geographic, volume and quality factors. The  
782 suppliers liked the auction mechanism because of  
783 its transparency, shorter negotiation time and  
784 fairness; Honer et al. (2003).

785 3. Motorola Corporation used auctions for the  
786 procurement of the multitude of parts needed for  
787 cellular devices. Motorola needed to reduce both  
788 the time and the effort required to prepare for and  
789 conduct negotiations with its suppliers, simplify  
790 their coordination, and optimize contract awards  
791 across sectors, in order to save costs; Metty et al.  
792 (2005).

793 Governments are moving toward procuring their  
794 goods and services in a similar fashion. One such  
795 example is the use of auctions to determine the  
796 suppliers of lunches in a large school system. Chile  
797 spends around US\$180 million a year to feed  
798 1,300,000 students from low income families. To  
799 improve the quality of the goods and services being  
800 provided to the school system and to save money, the  
801 government chose to assign catering contracts in  
802 a single-round sealed-bid combinatorial auction. This  
803 auction resulted in a transparent and objective  
804 allocation approach, thereby generating competition  
805 among firms. It also allowed the companies to build  
806 flexible territorial bids to include their scale of  
807 economies, leading to more efficient resource  
808 allocation. This new methodology improved the

809 price-quality ratio of the meals with yearly savings of  
 810 around US\$40 million, equivalent to the cost of  
 811 feeding 300,000 children during one year; Epstein  
 812 et al. (2002).

813 In supply-chain auctions, rules are designed to  
 814 assure a certain diversification in suppliers and to  
 815 assure the reliability of the supply chain. In each  
 816 case, are goals other than revenue maximization or  
 817 efficiency that drove the auction design. In addition,  
 818 the auction design must consider the nature of the  
 819 investment. For spectrum, where there was both  
 820 uncertainty in the long-term use of the technologies  
 821 and where the cost of build-out are high, long-term  
 822 leases were chosen. For energy, auctions are used for  
 823 a much shorter decision problem. The U. S. Treasury  
 824 uses multiple auctions for short, medium and  
 825 long-term debt allocation. Oil and gas exploration  
 826 must have a relatively long-term horizon where  
 827 payments for wildcatting are based on the bid price  
 828 and a yearly rent, whereas payments for extraction are  
 829 based on bid price and royalties.

830 Thus, one must consider carefully the application  
 831 when designing the allocation mechanism and the  
 832 payment scheme. Auction theory and its use is  
 833 growing because of its proven value. It provides price  
 834 discovery and signals where more capacity is needed.  
 835 It is often a fairer and more transparent process for the  
 836 allocation of goods and services.

837 **Conclusions**

838 Combinatorial auctions are appropriate for problems  
 839 where the bidders need to procure a collection of items  
 840 that contribute to their having a viable business plan.  
 841 When evaluating alternative designs, one is likely to  
 842 want to satisfy the following goals:

- 843 1. The property rights are well-defined
- 844 2. Bidders are able to, through their bids, announce  
 845 the entire collection of objects that they need for  
 846 a given business plan
- 847 3. The auction results in maximum revenue to the  
 848 seller
- 849 4. The auction results in an efficient outcome i.e. all  
 850 items are collectively allocated to the bidders that  
 851 value these items the most
- 852 5. The auction is perceived as fair to all bidders
- 853 6. The auction ends in a reasonable amount of time

7. The auction has limited transaction costs, i.e. the 854  
 rules are not so difficult or the bidding so 855  
 complicated that a straightforward bidder finds it 856  
 difficult to participate 857
8. The auction cannot be gamed, i.e. truthful bidding 858  
 is an optimal strategy for all bidders 859
9. The auction allows price discovery 860
10. The auction is computationally feasible and scalable 861

862 It is not possible to have all such attributes obtain  
 863 simultaneously. For each applications, some of these  
 864 goals will be more important than others. One should,  
 865 however, keep all of these goals in mind when  
 866 evaluating a mechanism.

867 In addition, the auction mechanism should consider  
 868 any application-specific issues that might arise. For  
 869 example, in government auctions one might want to  
 870 consider how market power impacts the outcome,  
 871 whether there will be sufficient participation, and  
 872 whether the outcome will limit future competition in  
 873 the industry. In certain situations, there may need to be  
 874 a transition period that allows the market to adjust to  
 875 a change in the way rights are allocated; One may have  
 876 to consider the associated rights that a bidder would  
 877 need to be able to use the right being sold or leased in  
 878 the auction; The seller needs to determine if the rights  
 879 are paid for over time or at the end of the auction; The  
 880 money obtained may need to be designated for  
 881 a specific use in order for the government to obtain  
 882 the approval of all constituents. The auction design  
 883 may also need to satisfy other social goals specific to  
 884 the application (e.g. reducing emissions, increasing  
 885 competition, incentivizing innovation, improving  
 886 multi-modal transportation). Similarly, in supply  
 887 chain auctions, a variety of goals need to be  
 888 considered– quality of the goods, price, historical  
 889 dependability of the supplier, among others.

**See**

- ▶ Auction and Bidding Models 890
- ▶ Integer and Combinatorial Programming 891

**References**

892  
 Ausubel, L. M., Cramton, P., & Milgrom, P. (2005). The clock 893  
 proxy auction. In P. Cramton, Y. Shoham, & R. Steinberg 894  
 (Eds.), *Combinatorial auctions* (pp. 113–136). MIT Press. 895



896 Ausubel, L. M., & Milgrom, P. (2002). Ascending auctions with  
 897 package bidding. *Frontiers of Theoretical Economics*, 1,  
 898 1–42.

899 Ausubel, L. M., & Milgrom, P. (2006). The lovely but lonely  
 900 Vickrey auction. In P. Cramton, Y. Shoham, & R. Steinberg  
 901 (Eds.), *Combinatorial auctions*. Cambridge, MA: MIT Press.

902 Bichler, M. (2011). Auctions: Complexity and algorithms. In  
 903 *Wiley encyclopedia of operations research and*  
 904 *management science*. John Wiley and Sons.

905 Bichler, M., Shabalin, P., & Wolf, J. *Efficiency, auction revenue,*  
 906 *and bidding behavior in the combinatorial clock auction*.  
 907 Technical Report available from M. Bichler.

908 Bichler, M., Davenport, A., Hohner, G., & Kalagnanam, J.  
 909 (2006). Industrial procurement auctions. In P. Crampton, Y.  
 910 Shoam, & R. Steinberg (Eds.), *Combinatorial auctions*  
 911 (pp. 593–612). MIT Press.

912 Bichler, M., Shabalin, S., & Pikhovskiy, A. (2009).  
 913 A computational analysis of linear price iterative  
 914 combinatorial auction formats. *Information Systems*  
 915 *Research*, 20(1), 33–59.

916 Bikhchandani, S., DeVries, S., Schummer, J., & Vohra, R.  
 917 (2002). Linear programming and Vickrey auctions. In B.  
 918 Dietrich & R. Vohra (Eds.), *Mathematics of the internet: E-*  
 919 *auctions and markets* (pp. 75–115).

920 Bikhchandani, S., & Ostroy, J. M. (2002). The package  
 921 assignment model. *Journal of Economic Theory*, 107,  
 922 337–406.

923 Boutilier, C., & Hoos, H. H. (2001). Bidding languages for  
 924 combinatorial auctions. *Seventh International Joint*  
 925 *Conference on Artificial Intelligence (IJCAI-01)*, 1211–1217.

926 Boutilier, C., Sandholm, T., & Shields, R. (2004). Eliciting  
 927 bid taker non-price preferences in “Combinatorial  
 928 Auctions”. In V. Khu-Smith & C. J. Mitchell (Eds.),  
 929 *Proceedings of the national conference on artificial*  
 930 *intelligence* (pp. 204–211). San Jose, CA.

931 Brunner, C., Goeree, J. K., Holt, C. H., & Ledyard, J. O. (2011).  
 932 An experimental test of flexible combinatorial spectrum  
 933 auction formats. *American Economic Journal:*  
 934 *Microeconomics*, 2, 39–57.

935 Cason, T. N. (1993). Seller incentive properties of EPA’s  
 936 emission trading auction. *Journal of Environmental*  
 937 *Economics and Management*, 25, 177–195.

938 Clarke, E. (1971). Multipart pricing of public goods. *Public*  
 939 *Choice*, 8, 19–33.

940 Cramton, P. (2005). Simultaneous ascending auctions. In P.  
 941 Cramton, Y. Shoham, & R. Steinberg (Eds.), *Combinatorial*  
 942 *auctions* (pp. 99–114). MIT Press.

943 Cramton, P., Shoham, Y., & Steinberg, R. (Eds.). (2005).  
 944 *Combinatorial auctions* (pp. 99–114). MIT Press.

945 Day, R., & Milgrom, P. (2008). Core-selecting package auctions.  
 946 *International Journal of Game Theory*, 36(3), 393–407.  
 947 Springer.

948 Day, R., & Raghavan, S. (2005). *Assignment preferences and*  
 949 *combinatorial auctions*. Working paper, Operations and  
 950 information management school of business, University of  
 951 Connecticut. <http://users.business.uconn.edu/bday/index.htm>

952 DeMartini, C., Kwasnica, A. M., Ledyard, J. O., & Porter, D.  
 953 (1999). *A new and improved design for multi-object iterative*  
 954 *auctions*, Social Working Paper. Pasadena, CA: Division of  
 955 the Humanities and Social Sciences, California Institute of  
 956 Technology.

DeVries, S., & Vohra, R. (2003). Combinatorial auctions: 957  
 A survey. *INFORMS Journal on Computing*, 15(3), 284–309. 958

Dunford, M., Hoffman, K., Menon, D., Sultana, R., & Wilson, T. 959  
 (2003). *Price estimates in ascending combinatorial auctions*,  
 960 Technical Report. Fairfax, VA: George Mason University,  
 961 Systems Engineering and Operations Research Department.

962 Ellerman, A. D., Joskow, P. L., Montero, J., Schmalensee, R., &  
 963 Bailey, E. M. (2000). *Markets for clean air: The U.S. acid*  
 964 *rain program*. Cambridge University Press. 965

966 Epstein, R., Henriquez, L., Catalan, J., Weintraub, G., &  
 967 Martinez, C. (2002). A combinatorial auction improves  
 968 school meals in Chile. *Interfaces*, 32(6), 1–14. 968

969 Erdil, A., Klemperer, P., Cramton, P., Dijkstra, G., Goeree, J.,  
 970 Marszalec, D., Meyer, M., Milgrom, P., Pagnozzi, M., &  
 971 Parkes, D. C. (2009). *A new payment rule for core-selecting*  
 972 *package auctions*. Technical report available on Paul  
 973 Klemperer’s website. 973

974 Friedman, D., & Rust, J. (Eds.). (1993). *The double auction*  
 975 *market: Institutions, theories and evidence* (Santa Fe  
 976 Institute studies in the sciences of complexity, Vol. XIV).  
 977 Addison Wesley. 977

978 Fujishima, Y., Leyton-Brown, K., & Shoham, Y. (1999).  
 979 Taming the computational complexity of combinatorial  
 980 auctions: Optimal and approximate approaches.  
 981 *Proceedings of IJCAI 1999*, 548–553. 981

982 Goeree, J. K., & Holt, C. A. (2010). Hierarchical package  
 983 bidding: A paper & pencil combinatorial auction. *Games*  
 984 *and Economic Behavior*, 70(1), 146–169. 984

985 Groves, T. (1973). Incentives in teams. *Econometrica*, 41,  
 986 617–631. 986

987 Harstad, R., Pekec, A., & Rothkopf, M. H. (1998).  
 988 Computationally manageable combinatorial auctions.  
 989 *Management Science*, 44, 1131–1147. 989

990 Hoffman, K., Menon, D., van den Heever, S. A., & Wilson, T. Au3  
 991 Observations and near-direct implementations of the  
 992 ascending proxy auction. In P. Cramton, Y. Shoham, &  
 993 R. Steinberg (Eds.), *Combinatorial auctions* (pp. 415–450).  
 994 MIT Press. 994

995 Hoffman, K., & Menon, D. (2010). A practical combinatorial  
 996 clock exchange for spectrum licenses. *Decision Analysis*,  
 997 7(1), 58–77. 997

998 Hoffman, K., Menon, D., & van Den Heever, S. A. (2008).  
 999 A package bidding tool for the FCC’s spectrum auctions  
 1000 and its effect on auction outcomes. *Telecommunications*  
 1001 *Modeling Policy and Technology: Operations Research/*  
 1002 *Computer Sciences Interfaces Series*, 44, 153–189. 1002

1003 Holt, C. A., Shobe, W., Burtraw, D., Palmer, K., & Goeree, J.  
 1004 (2007). *Auction design for selling CO<sub>2</sub> emission allowances*  
 1005 *under the regional greenhouse gas initiative. Regional*  
 1006 *greenhouse gas initiative*. Technical Report to RGGI. 1006

1007 Honer, G., Rich, J., Ng, E., Reid, G., Davenport, A.,  
 1008 Kalagnanam, J., Lee, H. S., & An, C. (2003).  
 1009 Combinatorial and quantity discount procurement auctions  
 1010 benefit mars, incorporated and its suppliers. *Interfaces*,  
 1011 33(1), 23–35. 1011

1012 Klemperer, P. (1999). Auction theory: A guide to the literature.  
 1013 *Journal of Economic Surveys*, 13(3), 227–286. 1013

1014 Klemperer, P. (2002). What really matters in auction design.  
 1015 *Journal of Economic Perspectives*, 16, 169–189. 1015

- 1016 Klemperer, P. (2004). *Auctions: Theory and practice* (The  
 1017 toulouse lectures in economics). Princeton, NJ: Princeton  
 1018 University Press.
- 1019 Koboldt, C., Maldoom, D., & Marsden, R. (2003). *The first*  
 1020 *combinatorial spectrum auction*. Ofcom Technical Report  
 1021 describing the results of the 2003 Nigerian Spectrum  
 1022 Auction, available on of com website.
- 1023 Krishna, V. J. (2002). *Auction theory*. Academic Press, 200pp.
- 1024 Kwasnica, A. M., Ledyard, J. O., Porter, D., & DeMartini, C.  
 1025 (2005). A new and improved design for multi-object iterative  
 1026 auctions. *Management Science*, 51, 419–4234.
- [Au4] 1027 Ledyard, J. O., Olson, M., Porter, D., Swanson, J. A., & Torma,  
 1028 D. P. (2002) The first use of a combined value auction for  
 1029 transportation services. 32, 4–12.
- 1030 Lehmann, D., Mueller, R., & Sandholm, T. (2005). The winner  
 1031 determination problem. In P. Cramton, Y. Shoham, & R.  
 1032 Steinberg (Eds.), *Combinatorial auctions*. Cambridge, MA:  
 1033 MIT Press.
- 1034 Leyton-Brown, K., Nudelman, E., & Shoham, Y. (2005).  
 1035 Empirical hardness models. In P. Cramton, Y. Shoham, &  
 1036 R. Steinberg (Eds.), *Combinatorial auctions* (pp. 479–503).  
 1037 MIT Press.
- 1038 McMillan, J. (2002). *Reinventing the bazaar: A natural history*  
 1039 *of markets*. Norton Press, 278pp.
- 1040 Metty, T., Harlan, R., Samelson, Q., Moore, T., Morris, T., &  
 1041 Sorenson, R. (2005). Reinventing the supplier negotiation  
 1042 process at motorola. *Interfaces*, 35(1), 7–23.
- 1043 Milgrom, P. (2004). *Putting auction theory to work*. Cambridge  
 1044 Press, 368pp.
- 1045 Milgrom, P. (2007). Package auctions and exchanges.  
 1046 *Econometrica*, 75(4), 935–965.
- 1047 Nisan, N. (2000). Bidding and allocation in combinatorial  
 1048 auctions. *Proceedings of the 2nd ACM Conference on*  
 1049 *Electronic Commerce*, 1–12.
- 1050 O’Neill, R. P., Helman, U., Hobbs, B., Stewart, W. R., &  
 1051 Rothkopf, M. (2007). The joint energy and transmission  
 1052 rights auction: A general framework for RTO market  
 1053 designs. *Power Engineering Review, IEEE*, 22(10), 59–68.
- Parkes, D. C. (2005). Auction design with costly preference 1054  
 elicitation. *Annals of Mathematics and AI*, 44, 269–302. 1055
- Parkes, D. C., Kalagnanam, J., & Eso, M., (2001). Achieving 1056  
 budget-balance with Vickrey-based payment schemes in 1057  
 combinatorial exchanges. *Proceedings of the 17th*  
*International Joint Conference on Artificial Intelligence*  
 1058 *(IJCAI-01)*, 1161–1168. 1059  
 1060
- Parkes, D. C., & Ungar, L. H. (2000). Iterative combinatorial 1061  
 auctions: Theory and practice. *Proceedings of the 17th*  
*National Conference on Artificial Intelligence (AAAI-00)*,  
 1062 74–81. 1063  
 1064
- Pecek, A., & Rothkopf, M. H. (2006). Non-computational 1065  
 approaches to mitigating computational problems in 1066  
 combinatorial auctions. In P. Cramton, Y. Shoham, &  
 1067 R. Steinberg (Eds.), *Combinatorial auctions*. M.I.T. Press. 1068
- Porter, D., Rassenti, S., Roopnarine, A., & Smith, V. (2003). 1069  
 Combinatorial auction design. *Proceedings of the National*  
*Academy of Sciences*, 100(19), 11153–11157. 1070  
 1071
- Porter, D., & Smith, V. (2006). FCC license experiment design: 1072  
 A 12-year experiment. *Journal of Law Economics and*  
*Policy*, 3, 63–80. 1073  
 1074
- Rassenti, S., Smith, V., & Bulfin, R. I. (1982). A combinatorial 1075  
 mechanism for airport time slot allocation. *Bell Journal of*  
*Economics*, 13, 402–417. 1076  
 1077
- Rothkopf, M. H. (2007). Thirteen reasons why the 1078  
 Vickrey-Clarke-Groves process is not practical. *Operations*  
*Research*, 55(2), 191–197. 1079  
 1080
- Steiglitz, K. (2007). *Snipers, shills and sharks: eBay and human*  
*behavior*. Princeton University Press, 298pp. 1081  
 1082
- Tietenberg, T. H. (2006). *Emissions trading: Principles and*  
*practice* (2nd ed.). Washington: RFF Press. 1083  
 1084
- Vickrey, W. (1961). Counter-speculation, auctions and 1085  
 competitive sealed tenders. *Journal of Finance*, 16, 8–37. 1086
- Wolsey, L. A. (1981). Integer programming duality: Price 1087  
 functions and sensitivity analysis. *Mathematical*  
*Programming*, 20(1), 173–195. 1088  
 1089
- Wurman, P. R., & Wellman, M. P. (1999). *Equilibrium prices in*  
*bundle auctions*, Sante Fe Institute Working Papers (Paper:  
 1090 99-09-064). 1091  
 1092

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