Offline Ad Slot Scheduling

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Abstract

We consider the *Offline Ad Slot Scheduling* problem, where advertisers must be scheduled to *sponsored search* slots during a given period of time. Advertisers specify a budget constraint, as well as a maximum cost per click, and may not be assigned to more than one slot for a particular search.

We give a truthful mechanism under the utility model where bidders try to maximize their clicks, subject to their personal constraints. In addition, we show that the revenue-maximizing mechanism is not truthful, but has a Nash equilibrium whose outcome is identical to our mechanism. As far as we can tell, this is the first treatment of sponsored search that directly incorporates both multiple slots and budget constraints into an analysis of incentives.

Our mechanism employs a descending-price auction that maintains a solution to a certain machine scheduling problem whose job lengths depend on the price, and hence is variable over the auction. The price stops when the set of bidders that can afford that price pack exactly into a block of ad slots, at which point the mechanism allocates that block and continues on the remaining slots. To prove our result on the equilibrium of the revenue-maximizing mechanism, we first show that a

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greedy algorithm suffices to solve the revenue-maximizing linear program; we then use this insight to prove that bidders allocated in the same block of our mechanism have no incentive to deviate from bidding the fixed price of that block.

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1. Introduction

Sponsored search is an increasingly important advertising medium, attracting a wide variety of advertisers, large and small. When a user sends a query to a search engine, the advertisements are placed into *slots*, usually arranged linearly down the page. These slots have a varying degree of exposure, often measured in terms of the probability that the ad will be clicked; a common model is that the higher ads tend to attract more clicks. The problem of allocating these slots to bidders has been addressed in various ways. The most common method is to allocate ads to each search independently via a *generalized second price* (GSP) auction, where the ads are ranked by (some function of) their bid, and placed into the slots in rank order. (See Lahaie et al. [19] for a survey of this area.)

There are several important aspects of sponsored search not captured by the original models. Most advertisers are interested in getting many clicks throughout the day on a variety of searches, not just a specific slot on a particular search query. Also, many advertisers have budget constraints, where they do not allow the search engine to spend more than their budget during the day. Finally, search engines may have some knowledge about the distribution of queries that will occur during the day, and so should be able to make more efficient allocation decisions than just simple ranking.

The *Offline Ad Slot Scheduling* problem is this: given a set of bidders with bids (per click) and budgets (per day), and a set of slots over the entire day where we know the expected number of clicks in each slot, find a schedule that places bidders into slots. The schedule must not place a bidder into two different slots at the same time. In addition, we must find a price for each bidder that does not exceed the bidder's budget constraint, nor their per-click bid. (See Section 1.3 for a formal statement of the problem.)

A good algorithm for this problem will have high revenue. Also, we would like the algorithm to be *truthful*; i.e., each bidder will be incented to report her true bid and budget. In order to prove something like this, we need a *utility function* for the bidder that captures the degree to which she is happy with her allocation. Natural models in this context (with clicks, bids and budgets) are *click-maximization*—where she wishes to maximize her number of clicks subject to her personal bid and budget constraints, or *profit-maximization*—where she wishes to maximize her profit (clicks $\times$ profit per click). In this paper we focus on click-maximization; see more detailed discussion on our model choice below.

We present an efficient mechanism for *Offline Ad Slot Scheduling* and prove that it is truthful. We also prove that the revenue-optimal mechanism for *Offline Ad Slot Scheduling* is not truthful, but has a Nash equilibrium (under the same utility model) whose outcome is equivalent to our mechanism; this result is strong evidence that our mechanism has desirable revenue properties. Our results generalize to a model where each bidder has a personal *click-through-rate* that multiplies her click probability.

Our utility function choice is in part motivated by the presence of budgets, which have a natural interpretation in this application: if an overall advertising campaign allocates a fixed portion of its budget to online media, then the agent responsible for that budget is incented to spend the entire budget to maximize exposure. From a different perspective, advertizers spread their Ad budget across several media. In each medium they want to ensure a certain price per eyeball (or click) and thus would spread out the budget according to market prices and viewing capacity. In contrast, under the profit-maximizing utility, a weak motivation for budgets is a limit on liquidity. Also, our choice of utility function is out of analytical necessity: Borgs et al. [5] show that under some reasonable assumptions, truthful mechanisms are impossible under a profit-maximizing utility.

The click-maximizing utility function also allows us to uncover appealing structural insights and strategic properties about ad allocation. The single-slot, budgets-only case is equivalent to an all-pay auction for a single divisible good. In this case, our mechanism is equivalent to the proportional sharing mechanism, where the good is divided proportionally according to budget. Truthfulness in the click-maximization model follows easily from monotonicity here, and Johari and Tsitsiklis [16] analyze this case in the profit maximization setting, giving a 3/4 price of anarchy result. However, allocating all the clicks from multiple slots (even without per-click limits) while respecting scheduling constraints requires allocations that are *not* proportional in budget, and thus proving monotonicity is much more difficult. Our mechanism provides such allocations, and we prove click monotonicity via structural insights on feasible allocations. Our mechanism also has the property that it divides the bidders and slots into blocks, and within each block the allocation is proportional sharing. Thus we feel confident that this mechanism has desirable properties under profit maximization as well, but this remains open.

As far as we can tell, this is the first treatment of sponsored search that directly incorporates both multiple positions and budget constraints into an analysis of incentives (see Section 1.2 for a survey of related work). In its full generality, the problem of sponsored search is more complex than our model; e.g., since the query distribution is noisy, good allocation strategies need to be online and adaptive. Also, our mechanism is designed for a single query type, whereas advertisers are interested in enforcing their budget across multiple query types. However, the tools used in this paper may be valuable for deriving more general mechanisms in the future.

1.1. Methods and Results.

A natural mechanism for *Offline Ad Slot Scheduling* is the following: find a feasible schedule and a set of prices that maximizes revenue, subject to the bidders' constraints. It is straightforward to derive a linear program for this optimization problem, but unfortunately this is not a truthful mechanism (see Example 1 in Section 2). However, there is a direct truthful mechanism—the *price-setting* mechanism we present in this paper—that results in the same outcome as an equilibrium of the revenue-maximizing mechanism.

We derive this mechanism (and prove that it is truthful) by starting with the single-slot case in Section 2, where two extreme cases have natural, instructive interpretations. With only bids (and unlimited budgets), a winner-take-all mechanism works; with only budgets (and unlimited bids) the clicks are simply divided up in proportion to budgets. Combining these ideas in the right way results in a natural descending-price mechanism, where the price (per click) stops at the point where the bidders who can afford that price have enough budget to purchase all of the clicks.

Generalizing to multiple slots requires understanding the structure of feasible schedules, even in the special budgets-only case. In Section 3 we solve the budgets-only case by characterizing the allowable schedules in terms of the solution to a classical *machine scheduling problem* (to be precise, the problem $Q \mid pmtn \mid C_{\max}$ [13]). The difficulty that arises is that the lengths of the jobs in the scheduling problem actually depend on the price charged. Thus, we incorporate the scheduling algorithm into a descending-price mechanism, where the price stops at the point where the scheduling constraints are tight; at this point a block of slots is allocated at a fixed uniform price (dividing the clicks equally by budget) and the mechanism iterates. We present the full mechanism in Section 4 by incorporating bids analogously to the single-slot case: the price descends until the set of bidders that can afford that price has enough budget to make the scheduling constraints tight. A tricky case arises when a new bidder appears whose budget violates the scheduling constraints; in this case the budget of this "threshold" bidder is reduced to make them tight again. Finally in Section 4.2 we show that the revenue-optimal mechanism has a Nash equilibrium whose outcome is identical to our mechanism. This follows from the fact that if all the bidders in a block declare a bid (roughly) equal to the price of the block, nobody has an incentive to deviate, since every bidder is charged exactly her bid, and the clicks are divided up equally by budget.

1.2. Related Work.

There are some papers on sponsored search that analyze the *generalized second-price* (GSP) auction, which is the auction currently in use at Google and Yahoo. The equilibria of this auction are characterized and compared with VCG [9, 18, 2, 26]. Here the utility function is the *profit-maximizing* utility where each bidder attempts to maximize her clicks $\times$ profit per click, and budget constraints are generally not treated.

Borgs et al. [5] consider the problem of budget-constrained bidders for multiple items of a single type, with a utility function that is profit-maximizing, modulo being under the budget (being over the budget gives an unbounded negative utility). They give a truthful mechanism allocating some portion of the items that is revenue-optimal, and prove that in their model, under reasonable assumptions, truthful mechanisms that allocate all the units are impossible. Under an identical profit-maximizing model, Hafalir et al. [14] give what they term a "semi-truthful" mechanism, in which agents state their true budgets and do not understate their values, and they prove that this mechanism has an equilibrium that maximizes revenue over all Pareto-optimal mechanisms. Our work is different both because of the different utility function and the generalization to multiple slots with a scheduling constraint. Using related methods, Mahdian et al. [20] consider an online setting where an unknown number of copies of an item arrive online, and give a truthful mechanism with a constant competitive ratio guarantee.

Our mechanism can be seen as a generalization of Kelly's fair sharing mechanism [17, 16] to the case of multiple slots with a scheduling constraint. Nguyen and Tardos [23] generalize the results of Johari and Tsitsiklis [16] to polyhedral constraints, and also discuss the application to sponsored search. Both their bidding language and utility function differ from ours, and in their words their mechanism "is not a natural auction mechanism for this case." Nguyen and Vojnovic [24] extend the study of proportional sharing mechanisms by considering incentives of providers in oligopolies. It would be interesting to explore further the connection between these proportional sharing mechanisms and ours. We mention here that the special case of our price-setting mechanism for a single slot is reminiscent of the cost-sharing mechanism of Moulin and Shenker [22]. We thus hope that our techniques and mechanisms would be useful to mechanism design and analysis beyond the sponsored search application that inspired this work.

There is some work on algorithms for allocating bidders with budgets to keywords that arrive online, where the bidders place (possibly different) bids on particular keywords [21, 20]. The application of this work is similar to ours, but their concern is purely online optimization; they do not consider the game-theoretic aspects of the allocation. Abrams et al. [1] derive a linear program for the offline optimization problem of allocating bidders to queries, and handle multiple positions by using variables for "slates" of bidders. Their LP is related to ours, but again they do not consider game-theoretic aspects of their proposed allocations.

Bidder strategies for keyword auctions in the presence of budget constraints have also been considered [11, 25, 6, 4]. Generally these papers are not concerned with mechanism design, but there could be some interesting relationships between the models in these papers and the one we study here.

In our setting one is tempted to apply a *Fisher Market* model: here m divisible goods are available to n buyers with money B_i, and $u_{ij}(x)$ denotes i's utility of receiving x amount of good j. It is known [3, 10, 7] that under certain conditions a vector of prices for goods exists such that the *market clears*, in that there is no surplus of goods, and all the money is spent. Furthermore, this price vector can be found efficiently [8]. The natural way to apply a Fisher model to a slot auction is to regard the slots as commodities and have the utilities be in proportion to the number of clicks. However this becomes problematic because there does not seem to be a way to encode the scheduling constraints in the Fisher model; this constraint could make an apparently "market-clearing" equilibrium infeasible, and indeed plays a central role in our investigations.

1.3. Our Setting.

We define the *Offline Ad Slot Scheduling* problem as follows. We have $n > 1$ bidders interested in clicks. Each bidder i has a budget B_i and a maximum cost-per-click (max-cpc) m_i. Given a number of clicks c_i, and a price per click p, the utility u_i of bidder i is c_i if both the true max-cpc and the true budget are satisfied, and $-\infty$ otherwise. In other words, $u_i = c_i$ if $p \leq m_i$ and $c_i p \leq B_i$; and $u_i = -\infty$ otherwise. We have n' advertising slots where slot i receives D_i clicks during the time interval $[0, 1]$. We assume $D_1 > D_2 > \cdots > D_{n'}$.

In a *schedule*, each bidder is assigned to a set of (slot, time interval) pairs $(j, [\alpha, \beta))$, where $j \leq n'$ and $0 \leq \alpha < \beta \leq 1$. A *feasible schedule* is one where no more than one bidder is assigned to a slot at any given time, and no bidder is assigned to more than one slot at any given time. (Formally, the intervals for a particular slot do not overlap, and the intervals for a particular bidder do not overlap.) A feasible schedule can be applied as follows: when a user query comes at some time $\alpha \in [0, 1]$, the schedule for that time instant is used to populate the ad slots. If we assume that clicks come at a constant rate throughout the interval $[0, 1]$, the number of clicks a bidder is expected to receive from a schedule is the sum of $(\beta - \alpha)D_j$ over all pairs $(j, [\alpha, \beta))$ in its schedule.[2]

A *mechanism* for *Offline Ad Slot Scheduling* takes as input a declared budget B_i and declared max-cpc (the "bid") b_i, and returns a feasible schedule, as well as a price per click $p_i \leq b_i$ for each bidder. The schedule gives some number c_i of clicks to each bidder i that must respect the budget

[2]All our results generalize to the setting where each bidder i has a "click-through rate" γ_i and receives $(\beta - \alpha)\gamma_i D_j$ clicks (see Section 5). We leave this out for clarity.

at the given price; i.e., we have $p_i c_i \leq B_i$.

The *revenue* of a mechanism is $\sum_i p_i c_i$. We say a mechanism is *truthful* if it is a weakly dominant strategy to declare one's true budget and max-cpc; i.e., for any particular bidder i, given any set of bids and budgets declared by the other bidders, declaring her true budget B_i and max-cpc m_i maximizes her utility u_i. A (pure strategy) *Nash equilibrium* is a set of declared bids and budgets such that no bidder wants to change her declaration of bid or budget, given that all other declarations stay fixed. An ϵ-*Nash equilibrium* is a set of bids and budgets where no bidder can increase her utility by more than ϵ by changing her bid or budget.

Throughout the paper we assume some arbitrary lexicographic ordering on the bidders, that does not necessarily match the subscripts. When we compare two bids b_i and $b_{i'}$ we say that $b_i \succ b_{i'}$ iff either $b_i > b_{i'}$, or $b_i = b_{i'}$ but i occurs first lexicographically.

2. One Slot Case

In this section we consider the case $k = 1$, where there is only one advertising slot, with some number $D := D_1$ of clicks. We will derive a truthful mechanism for this case by first considering the two extreme cases of infinite bids and infinite budgets.

Suppose all budgets $B_i = \infty$. Then, our input amounts to bids $b_1 \succ b_2 \succ \ldots \succ b_n$. Our mechanism is simply to give all the clicks to the highest bidder. We charge bidder 1 her full price $p_1 = b_1$. We claim that reporting the truth is a weakly dominant strategy for this mechanism. Clearly all bidders will report $b_i \leq m_i$, since the price is set to b_i if they win. The losing bidders cannot gain from decreasing b_i. The winning bidder can lower her price by lowering b_i, but this will not gain her any more clicks, since she is already getting all D of them.

Now suppose all bids $b_i = \infty$. In this case, our input is just a set of budgets $B_1, \ldots, B_n$, and we need to allocate D clicks, with no ceiling on the per-click price. Here we apply a simple rule related to pricing schemes for network bandwidth (see, e.g., [17, 16]): Let $\mathcal{B} = \sum_i B_i$. Now to each bidder i, allocate $(B_i/\mathcal{B})D$ clicks. Set all prices the same: $p_i = p = \mathcal{B}/D$. The mechanism guarantees that each bidder exactly spends her budget, thus no bidder will report $B'_i > B_i$. Now suppose some bidder reports $B'_i = B_i - \Delta$, for $\Delta > 0$. Then this bidder is allocated $D(B_i - \Delta)/(\mathcal{B} - \Delta)$ clicks, which is less than $D(B_i/\mathcal{B})$, since $n > 1$ and all $B_i > 0$.

2.1. Greedy First-Price Mechanism.

A natural mechanism for the general single-slot case is to solve the associated "fractional knapsack" problem, and charge bidders their bid; i.e., starting with the highest bidder, greedily add bidders to the allocation, charging them their bid, until all the clicks are allocated. We refer to this as the *greedy first-price* (GFP) mechanism. Though natural (and revenue-maximizing as a function of bids) this mechanism is easily seen to be not truthful:

Example 1. *Suppose there are two bidders and* $D = 120$ *clicks. Bidder 1 has (*$m_1 = \$2$*,* $B_1 = \$100$*) and bidder 2 has (*$m_2 = \$1$*,* $B_2 = \$50$*). In the GFP mechanism, if both bidders tell the truth, then bidder 1 gets 50 clicks for* $\$2$ *each, and 50 of the remaining 70 clicks go to bidder 2 for* $\$1$ *each. However, if bidder 1 instead declares* $b_1 = \$1 + \epsilon$*, then she gets (roughly) 100 clicks, and bidder 2 is left with (roughly) 20 clicks.*

The problem here is that the high bidders can get away with bidding lower, thus getting a lower price. The difference between this and the unlimited-budget case above is that a lower price now results in more clicks. It turns out that in equilibrium, this mechanism will result in an allocation where a prefix of the top bidders are allocated, but their prices equalize to (roughly) the lowest bid in the prefix (as in the example above).

2.2. The Price-Setting Mechanism.

An equilibrium allocation of GFP can be computed directly via the following mechanism, which we refer to as the *price-setting (PS) mechanism*. Essentially this is a descending price mechanism: the price stops descending when the bidders willing to pay at that price have enough budget to purchase all the clicks. We have to be careful at the moment a bidder is added to the pool of the willing bidders; if this new bidder has a large enough budget, then suddenly the willing bidders have *more* than enough budget to pay for all of the clicks. To compensate, the mechanism decreases this "threshold" bidder's effective budget until the clicks are paid for exactly. We formalize the mechanism as follows:

Price-Setting (PS) Mechanism (Single Slot)

- Assume wlog that $b_1 \succ b_2 \succ \ldots \succ b_n \geq 0$.
- Let k be the first bidder such that $b_{k+1} \leq \sum_{i=1}^{k} B_i/D$. Compute price $p = \min\{\sum_{i=1}^{k} B_i/D, b_k\}$.
- Allocate B_i/p clicks to each $i \leq k-1$. Allocate $\hat{B}_k/p$ clicks to bidder k, where $\hat{B}_k = pD - \sum_{i=1}^{k-1} B_i$.

Example 2. *Suppose there are three bidders with* $b_1 = \$2$, $b_2 = \$1$, $b_3 = \$0.25$ *and* $B_1 = \$100$, $B_2 = \$50$, $B_3 = \$80$, *and* $D = 300$ *clicks. Running the PS mechanism, we get* $k = 2$ *since* $B_1/D = 1/3 < b_2 = \$1$, *but* $(B_1 + B_2)/D = \$0.50 \geq b_3 = \$0.25$. *The price is set to* $\min\{\$0.50, \$1\} = \$0.50$, *and bidders 1 and 2 get 200 and 100 clicks at that price, respectively. There is no threshold bidder.*

Example 3. *Suppose now bidder 2 changes her bid to* $b_2 = \$0.40$ *(everything else remains the same as Example 2). We still get* $k = 2$ *since* $B_1/D = 1/3 < b_2 = \$0.40$. *But now the price is set to* $\min\{\$0.50, \$0.40\} = \$0.40$, *and bidders 1 and 2 get 250 and 50 clicks at that price, respectively. Note that bidder 2 is now a threshold bidder, does not use her entire budget, and gets fewer clicks.*

Note that this mechanism reduces to the given mechanisms in the special cases of infinite bids or budgets (with the proper treatment of infinite bids/budgets).

Theorem 1. *The price-setting mechanism (single slot) is truthful.*

Proof. For the purposes of this proof, let bidders $\{1, \ldots, n\}$ be such that $b_1 \succ \ldots \succ b_n = 0$, and consider a new bidder (call her Alice) with true max-cpc m and true budget B^*.

We first show that reporting the true budget is a weakly dominant strategy for Alice, for any fixed bid $b > 0$. Let ℓ be the first bidder with $b \succ b_\ell$, so $b_1 \succ \ldots \succ b_{\ell-1} \succ b \succ b_\ell \succ \ldots \succ b_n$. Let $\mathcal{B} = \sum_{i=1}^{\ell-1} B_i$. If $\mathcal{B} \geq bD$ then the mechanism will not allocate any clicks to Alice, regardless of the reported budget, since the price will stop before reaching b. If $\mathcal{B} < bD$, we will argue that Alice's clicks c are non-increasing in B. Define $\hat{B} = bD - \mathcal{B} > 0$.

- If Alice declares $B \in [\hat{B}, \infty]$, then the price will stop at b. She will spend $\hat{B}$ and receive $c = \hat{B}/b$ clicks.

- If Alice declares $B \in [0, \hat{B})$, then the price will be lower than b, and she will spend all of her budget. Her final number of clicks will be $c = (B/(B + \mathcal{B} + R))D$, where R is the total spend of bidders $\{\ell, \ldots, n\}$. Since R is non-increasing in B, we can conclude that c is non-decreasing in B.

Putting together these intervals, we see that c is non-decreasing in B overall, and since Alice's total spend is $\min\{B, \hat{B}\}$, we may conclude that it is weakly dominant to declare $B = B^*$.

It remains to show that it is weakly dominant for Alice to declare a bid $b = m$, given that she declares a budget $B = B^*$. Let $R(b)$ be the total spend of bidders $\{1, \ldots, n\}$ given that Alice declares b. Note that $R(b)$ is non-increasing in b. Let p_1 be the price that would result if $b = \infty$, and let p_2 be the price that would result if $b = 0$. Note that $p_2 \leq p_1$.

- If $b \in [0, p_2)$ then the price stops at p_2 and Alice receives zero clicks.
- If $b \in (p_1, \infty]$, then the price stops at p_1, and Alice receives B/p_1 clicks.
- If $b \in [p_2, p_1]$, then the price stops at b. To see this, note that if Alice had bid zero, then the price would have gone down to p_2, so it certainly stops at b or lower. But at price b, the set of bidders that can afford this price consists of at least all the bidders that could afford price p_1, and so we must have $B + \sum_{i:b_i \succ b} B_i \geq B + \sum_{i:b_i \geq p_1} B_i \geq p_1 D \geq bD$. Alice thus receives
$$\max\left\{0, D - \left(\sum_{i:b_i \succ b} B_i/b\right)\right\} \tag{1}$$
clicks, and we may conclude that in this interval, clicks are non-decreasing with b.

Note that in the expression (1), plugging in p_1 for b yields $c = B/p_1$. Thus we have that in the interval $[p_2, \infty]$, clicks are non-decreasing with b, and the price is always $\min\{b, p_1\}$. We conclude that bidding $b = m$ is a weakly dominant strategy. $\square$

2.3. Price-Setting Mechanism Computes Nash Equilibrium of GFP.

Consider the greedy first-price auction in which the highest bidder receives B_1/b_1 clicks, the second B_2/b_2 clicks and so on, until the supply of D clicks is exhausted. It is immediate that truthfully reporting budgets is a dominant strategy in this mechanism, since when a bidder is considered, her reported budget is exhausted as much as possible, at a fixed price. However, reporting $b_i = m_i$ is *not* a dominant strategy. Nevertheless, it turns out that GFP has an equilibrium whose outcome is (roughly) the same as the PS mechanism. One cannot show that there is a plain Nash equilibrium because of the way ties are resolved lexicographically; the following example illustrates why.

Example 4. *Suppose we have the same instance as example 1: two bidders, $D = 120$ clicks, ($m_1 = \$2$, $B_1 = \$100$) and ($m_2 = \$1$, $B_2 = \$50$). But now suppose that bidder 2 occurs first lexicographically. In GFP, if bidder 2 tells the truth, and bidder 1 declares $b_1 = \$1$, then bidder 2 will get chosen first (since she is first lexicographically), and take 50 clicks. Bidder 2 will end up with the remaining 70 clicks. However, if bidder 1 instead declares $b_1 = \$1 + \epsilon$ for some $\epsilon > 0$, then she gets $100/(1 + \epsilon)$ clicks. But this is not a best response, since she could bid $1 + \epsilon/2$ and get slightly more clicks.*

Thus, we prove instead that the bidders reach an ϵ-Nash equilibrium:

Theorem 2. *Suppose the PS mechanism is run on the truthful input, resulting in price p and clicks $c_1, \ldots, c_n$ for each bidder. Then, for any $\epsilon > 0$ there is a pure-strategy ϵ-Nash equilibrium of the GFP mechanism where each bidder receives $c_i \pm \epsilon$ clicks.*

Proof. We will show that for sufficiently small $\epsilon' > 0$, if each bidder truthfully reports her budget and bids $b_i = \min\{m_i, p + \epsilon'\}$ in the GFP mechanism, then the conditions in the theorem hold.

There are two ways that the PS mechanism (under truthful input) can reach its last allocated bidder k and final price p: if $m_k > p \geq m_{k+1}$ and then $pD = \sum_{i=1}^{k} B_i$ (no threshold bidder), or if $p = m_k$ (k is a threshold bidder).

In the first case, we have that bidders $i \leq k$ all have $m_i > p$. Thus in the supposed equilibrium of GFP, all these bidders are bidding $p + \epsilon'$, and all bidders $i > k$ are bidding $m_i \leq p$. Therefore in GFP, each $i \leq k$ will receive $B_i/(p + \epsilon')$ clicks, and the total number of clicks allocated by GFP to bidders $1 \ldots k$ is $\sum_{i \leq k} B_i/(p + \epsilon') = (\frac{p}{p+\epsilon'})D$. The remaining $D' = (1 - \frac{p}{p+\epsilon})D$ clicks, are allocated to bidders $i > k$. Bidders $1 \ldots k$ lose clicks by increasing their bid, and can gain at most D' clicks by lowering their bid. Bidders $i > k$ will never raise their bid (since they are bidding m_i), and cannot gain more clicks by lowering their bid. Since D' can be made arbitrarily small, we have an ϵ-Nash equilibrium.

In the second case, $p = m_k$. Let $k' < k$ be the last bidder bidding more than p. In the supposed GFP equilibrium, bidders $1 \dots k'$ are bidding $p + \epsilon'$, and bidders $(k'+1, \dots, k)$ are bidding $m_k = p$. Thus GFP allocates $B_i/(p+\epsilon')$ clicks to bidders $1 \dots k'$, B_i/p clicks to bidders $(k'+1, \dots, k-1)$ (if any such bidders exist) and the remaining clicks to bidder k. As in the previous case, no bidder can gain from raising her bid, the number of clicks that a bidder $i \leq k'$ can gain from lowering her bid can be made arbitrarily small, and no other bidder can gain from lowering her bid. $\square$

3. Multiple Slots: Bids or Budgets Only

Generalizing to multiple slots makes the scheduling constraint nontrivial. Now instead of splitting a pool of D clicks arbitrarily, we need to assign clicks that correspond to a feasible schedule of bidders to slots. The conditions under which this is possible add a complexity that we characterize and incorporate into our mechanism in this section.

As in the single-slot case it will be instructive to consider first the cases of infinite bids or budgets. Suppose all $B_i = \infty$. In this case, the input consists of bids only $b_1 \succ b_2 \succ \dots \succ b_n$. Naturally, what we do here is rank by bid, and allocate the slots to the bidders in that order. Since each budget is infinite, we can always set the prices p_i equal to the bids b_i. By the same logic as in the single-slot case, this is easily seen to be truthful. In the other case, when $b_i = \infty$, there is a lot more work to do, and we devote the remainder of the section to this case.

Without loss of generality, we may assume the number of slots equals the number of bids (i.e., $n' = n$); if this is not the case, then we add dummy bidders with $B_i = b_i = 0$, or dummy slots with $D_i = 0$, as appropriate. We keep this assumption for the remainder of the paper.

3.1. Assigning slots using a classical scheduling algorithm.

First we give an important lemma that characterizes the conditions under which a set of bidders can be allocated to a set of slots, which turns out to be just a restatement of a classical result [15] from scheduling theory.

Lemma 1. *Suppose we would like to assign an arbitrary set $\{1, \dots, k\}$ of bidders to a set of slots $\{1, \dots, k\}$ with $D_1 > \dots > D_k$. Then, a click allocation $c_1 \geq \dots \geq c_k$ is feasible iff*

$$c_1 + \dots + c_\ell \leq D_1 + \dots + D_\ell \quad \textit{for all } \ell = 1, \dots, k. \tag{2}$$

Proof. In scheduling theory, we say a *job* with *service requirement* x is a task that needs x/s units of time to complete on a *machine* with *speed* s. The question of whether there is a feasible allocation is equivalent to the following scheduling problem: Given k jobs with service requirements $x_i = c_i$, and k machines with speeds $s_i = D_i$, is there a schedule of jobs to machines (with preemption allowed) that completes in one unit of time?

As shown in Horvath et al. [15], the optimal schedule for this problem (a.k.a. $Q|pmtn|C_{\max}$) can be found efficiently by the *level algorithm*,[3] and the schedule completes in time $\max_{\ell \le k}\{\sum_{i=1}^{\ell} x_i / \sum_{i=1}^{\ell} s_i\}$. Thus, the conditions of the lemma are exactly the conditions under which the schedule completes in one unit of time. □ □

3.2. A multiple-slot budgets-only mechanism.

Our mechanism will roughly be a descending-price mechanism where we decrease the price until a prefix of budgets fits tightly into a prefix of positions at that price, whereupon we allocate that prefix, and continue to decrease the price for the remaining bidders.

The following subroutine, which will be used in our mechanism (and later in the general mechanism), takes a set of budgets and determines a prefix of positions that can be packed tightly with the largest budgets at a uniform price p. The routine ensures that all the clicks in those positions are sold at price p, and all the allocated bidders spend their budget exactly.

[3] In later work, Gonzalez and Sahni [12] give a faster (linear-time) algorithm.

Routine "Find-Price-Block"

Input: Set of n bidders, set of n slots with $D_1 > D_2 > \cdots > D_n$.

• If all $D_i = 0$, assign bidders to slots arbitrarily and exit.

• Sort the bidders by budget and assume wlog that $B_1 \geq B_2 \geq \ldots \geq B_n$.

• Define $r_\ell = \sum_{i=1}^{\ell} B_i / \sum_{i=1}^{\ell} D_i$. Set price $p = \max_\ell r_\ell$.

• Let ℓ^* be the largest ℓ such that $r_\ell = p$. Allocate slots $\{1, \ldots \ell^*\}$ to bidders $\{1, \ldots, \ell^*\}$ at price p, using all of their budgets; i.e., $c_i := B_i/p$.

Note that in the last step the allocation is always possible since for all $\ell \leq \ell^*$, we have $p \geq r_\ell = \sum_{i=1}^{\ell} B_i / \sum_{i=1}^{\ell} D_i$, which rewritten is $\sum_{i=1}^{\ell} c_i \leq \sum_{i=1}^{\ell} D_i$, and so we can apply Lemma 1. Now we are ready to give the mechanism in terms of this subroutine; an example run is shown in Figure 1.

Price-Setting Mechanism (Multiple Slots, Budgets Only)

• Run "Find-Price-Block" on bidders $1, \ldots, n$, and slots $1, \ldots, n$. This gives an allocation of ℓ^* bidders to the first ℓ^* slots.

• Repeat on the remaining bidders and slots until all slots are allocated.

Let $p_1, p_2, \ldots$ be the prices used for each successive block assigned by the algorithm. We claim that $p_1 > p_2 > \ldots$; to see this, note then when p_1 is set, we have $p_1 = r_k$ and $p_1 > r_\ell$ for all $\ell > k$, where k is the last bidder in the block. Thus for all $\ell > k$, we have $p_1 \sum_{j \leq \ell} D_j > \sum_{i \leq \ell} B_j$, which gives $p_1 \sum_{k<j\leq\ell} D_j > \sum_{k<i\leq\ell} B_j$ using $p_1 = r_k$. This implies that when we apply Find-Price-Block the second time, we get $r'_\ell = \sum_{k<i\leq\ell} B_j / \sum_{k<j\leq\ell} D_j < p_1$, and so $p_2 < p_1$. This argument applies to successive blocks to give $p_1 > p_2 > \ldots$.

Theorem 3. *The price-setting mechanism (multiple slots, budgets only) is truthful.*

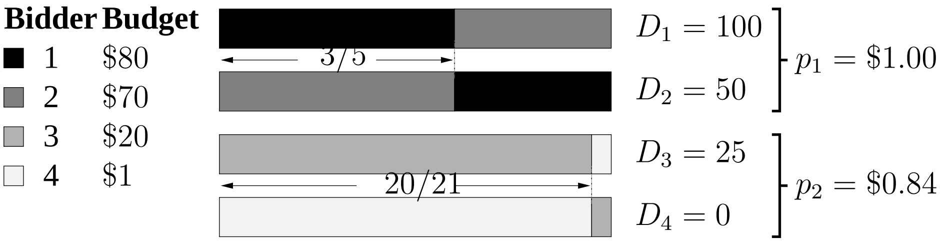

Figure 1: An example of the PS mechanism (multiple slots, budgets only). We have four slots with $D_1, \ldots, D_4$ clicks as shown, and four bidders with declared budgets as shown. The first application of Find-Price-Block computes $r_1 = B_1/D_1 = 80/100, r_2 = (B_1+B_2)/(D_1+D_2) = 150/150, r_3 = (B_1+B_2+B_3)/(D_1+D_2+D_3) = 170/175$, $r_4 = (B_1 + B_2 + B_3 + B_4)/(D_1 + D_2 + D_3 + D_4) = 171/175$. Since r_2 is largest, the top two slots make up the first price block with a price $p_1 = r_2 = \$1$; bidder 1 gets 80 clicks and bidder 2 gets 70 clicks, using the schedule as shown. In the second price block, we get $B_3/D_3 = 20/25$ and $(B_3 + B_4)/(D_3 + D_4) = 21/25$. Thus p_2 is set to $21/25 = \$0.84$, bidder 3 gets $500/21$ clicks and bidder 4 gets $25/21$ clicks, using the schedule as shown.

In order to prove Theorem 3, we first need to establish the following Lemma:

Lemma 2. *In Find-Price-Block, if $B_i = B_{i+1}$, then i cannot be the last slot of the computed price block.*

Proof. Suppose the contrary, namely that i is the last slot of the first price block and $(i + 1)$ is the first slot in the second price block. Denote $B = B_1 + ... + B_{i-1}$ and $D = D_1 + ... + D_{i-1}$. Then the price of the first price block satisfies (1) $p_1 = \frac{B+B_i}{D+D_i} \geq \frac{B}{D}$ and (2) $p_1 = \frac{B+B_i}{D+D_i} > \frac{B+B_i+B_{i+1}}{D+D_i+D_{i+1}}$. The first condition is equivalent to $\frac{B_i}{D_i} \geq \frac{B+B_i}{D+D_i}$, and the second condition is equivalent to $\frac{B+B_i}{D+D_i} > \frac{B_{i+1}}{D_{i+1}}$. The latter two inequalities imply $\frac{B_i}{D_i} > \frac{B_{i+1}}{D_{i+1}}$, which is a contradiction to the fact that $B_i = B_{i+1}$ and $D_i > D_{i+1}$. $\square$

Proof. Theorem 3 Suppose bidders $1, \ldots, n$ declare budgets $B_1 \geq \cdots \geq B_n$, and Alice declares budget B. Let ℓ_B be the rank of Alice by budget (and lexicographic order in case of ties) if she bids B. We will prove that the number of clicks Alice receives is non-increasing as she lowers her declared budget B, which immediately implies that truthful reporting of budgets is weakly dominant in the PS mechanism.

Let r_j^B be the ratio r_j assuming Alice bids B; so $r_k^B = (B + \sum_{i=1}^{k-1} B_i)/\sum_{i=1}^{k} D_i$ if $\ell_B \leq k$, and $r_k^B = \sum_{i=1}^{k} B_i/\sum_{i=1}^{k} D_i$ otherwise. For a declared budget B, let k_B be the last slot in the first price block chosen by the mechanism. So, $k_B = \arg\max_k r_k^B$ (if there are multiple maxima, then k_B is the largest lexicographically).

For sufficiently large $B > B_1$, we get that $r_1^B > r_k^B$ for all k and so $k_B = 1$. For any such B Alice receives D_1 clicks, the most possible. Now as we lower B, two significant events could occur; we could drop to another bidder's budget B_i, or we could have a change in k_B, thus changing the set of bidders in the first block. If neither of these events occur, then Alice remains in the first price block, but gets a smaller share of the clicks. Thus it remains to cover these two events.

If $B = B_i$ for some i, then note that by Lemma 2, Alice cannot be the last bidder in the block, so i is in the same block as Alice. Therefore we may exchange the roles of Alice and bidder i lexicographically (i.e., increase Alice's rank by one) and nothing changes.

Now suppose B reaches a point where r_k changes because $\arg\max_k r_k^B$ changes from k_B to k'. We use $k^* = k_B$ for the remainder of the proof for ease of notation. At the bid B we have $r_{k^*}^B = r_{k'}^B$. We claim that either $k' > k^*$ or $k' < \ell_B$. To see this note that for any k between ℓ_B and k^* we have that r_k^B decreases at a rate of $1/(\sum_{i=1}^k D_i)$, which is faster than the rate of the highest ratio $r_{k^*}^B$.

If $k' > k^*$ then Alice remains in the first block, but it expands from ending at k^* to ending at k'. Both before and after the change in r_k, Alice is spending her entire budget at price $r_{k^*}^B = r_{k'}^B$, so her clicks remain the same.

If $k' < \ell_B$ then Alice would remain in a block ending at slot k^*, since $r_{k^*}^B$ remains maximum among $r_{\ell_B}^B, ..., r_n^B$ (by the same reasoning about "rate" as above). Since $r_{k^*}^B = r_{k'}^B$ we have that the price of Alice's block and the first block will be the same. Since Alice is spending her entire budget before and after the change in r_k at the same price, her clicks remain the same. As we continue to decrease B beyond this point, we simply remove the bidders and slots from the first price block, and imagine that we are again in the first price block of a reduced instance. $\square$

4. Main Results

In this section we give our main results, presenting our price-setting mechanism in the general case, building on the ideas in the previous two sections. We begin in Section 4.1 by stating the mechanism and showing some examples, then proving that the mechanism is truthful. In Section 4.2 we analyze the revenue-optimal schedule, and show that it can be computed with a generalization of the *greedy first-price (GFP)* mechanism. We then show that GFP has an ϵ-Nash equilibrium whose outcome is identical to the general PS mechanism.

4.1. The Price-Setting Mechanism (General Case).

The generalization of the PS mechanism combines the ideas from the bids-and-budgets version of the single slot mechanism with the budgets-only version of the multiple-slot mechanism. As our price descends, we maintain a set of "active" bidders with bids at or above this price, as in the single-slot mechanism. These active bidders are kept ranked by *budget*, and when the price reaches the point where a prefix of bidders fits into a prefix of slots (as in the budgets-only mechanism) we allocate them and repeat. As in the single-slot case, we have to be careful when a bidder enters the active set and suddenly causes an over-fit; in this case we again reduce the budget of this "threshold" bidder until it fits. We formalize this as follows:

Price-Setting Mechanism (General Case)
(i) Assume wlog that $b_1 \succ b_2 \succ \ldots \succ b_n = 0$.
(ii) Let k be the first bidder such that running Find-Price-Block on bidders $1, \ldots, k$ would result in a price $p \geq b_{k+1}$.
(iii) Reduce B_k until running Find-Price-Block on bidders $1, \ldots, k$ would result in a price $p \leq b_k$. Apply this allocation, which for some $\ell^* \leq k$ gives the first ℓ^* slots to the ℓ^* bidders among $1 \ldots k$ with the largest budgets.
(iv) Repeat on the remaining bidders and slots.

An example run of this mechanism is shown in Figure 2. Since the PS mechanism sets prices per slot, it is natural to ask if these prices constitute some sort of "market-clearing" equilibrium in the spirit of a Fisher market. The quick answer is no: since the price per click increases for higher slots, and each bidder values clicks at each slot equally, then bidders will always prefer the bottom

Bidder	Budget	Bid
■ 1	\$80	\$3
■ 2	\$70	\$0.75
■ 3	\$20	\$1
□ 4	\$1	\$0.50

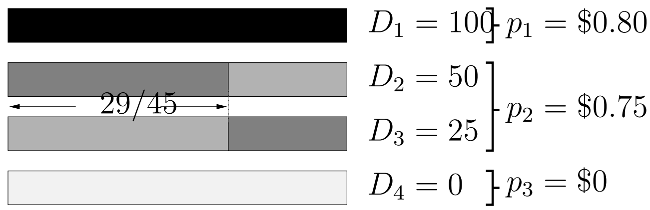

Figure 2: Consider the same bidders and slots as in Figure 1, but now add bids as shown. Running Find-Price-Block on only bidder 1 gives a price of $r_1 = 80/100$, which is less than the next bid of \$1. So, we run Find-Price-Block on bidders 1 and 3 (the next-highest bid), giving $r_1 = 80/100$ and $r_2 = 100/150$. We still get a price of \$0.80, but now this is more than the next-highest bid of \$0.75, so we allocate the first bidder to the first slot at a price of \$0.80. We are left with bidders 2-4 and slots 2-4. With just bidder 3 (the highest bidder) and slot 2, we get a price $p = 20/50$ which is less than the next-highest bid of \$0.75, so we consider bidders 2 and 3 on slots 2 and 3. This gives a price of $\max\{70/50, 90/75\} = \$1.40$, which is more than \$0.50. Since this is also more than \$0.75, we must lower B_2 until the price is exactly \$0.75, which makes $B_2' = \$36.25$. With this setting of B_2', Find-Price-Block allocates bidders 2 and 3 to slots 2 and 3, giving $75(36.25/56.25)$ and $75(20/56.25)$ clicks respectively, at a price of \$0.75 per click. Bidder 4 is allocated to slot 4, receiving zero clicks.

slot. Note that by the same logic as the budgets-only mechanism, the prices $p_1, p_2, \ldots$ for each price block strictly decrease.

4.1.1. Efficiency.

So far we have been largely ignoring the efficiency of computing the allocation in the PS mechanism. It is immediately clear that the general PS mechanism can be executed in time polynomial in n and $\log(1/\epsilon)$ to some precision ϵ using binary search and linear programming.

In fact, a purely combinatorial $O(n^2)$ time algorithm is possible. As bidders get added in step (ii), maintaining a sorted list of bidders and budgets can be done in time $O(n \log n)$. Thus it remains to show that running Find-Price-Block (and computing the reduced budget) can be done in $O(n)$ time given these sorted lists. In Find-Price-Block, computing the ratios r_ℓ can be done in linear time. Finding the allocation from Lemma 1 can also be done in linear time using the Gonzalez-Sahni algorithm [12] for scheduling related parallel machines (in fact the total time for scheduling can be made $O(n)$ since each slot is scheduled only once). Finally, computing the reduced budget is a simple calculation on each relevant ratio r_ℓ, also doable in linear time. We suspect that there is a $O(n \cdot \mathrm{polylog}(n))$ algorithm using a more elaborate data structure; we leave this open.

Theorem 4. *The price-setting mechanism (general case) is truthful.*

Proof. We split the proof into two lemmas, showing that clicks are non-decreasing in both bids and budgets. This immediately implies the theorem. First we need a small observation about Find-Price-Block:

Lemma 3. *Suppose Find-Price-Block is run on a set of budgets $B_1 \geq \cdots \geq B_n$ and produces a block $1, \ldots, \ell^*$ with price p. Then if a bidder is added to the set with budget B, and Find-Price-Block still produces price p, we must have that $B \leq B_{\ell^*}$.*

Proof. Suppose not. Then $B > B_{\ell *}$ and we have that $(B + \sum_{i=1}^{\ell^*-1} B_i)/\sum_{i=1}^{\ell^*} D_i \leq p$. This contradicts $p = \sum_{i=1}^{\ell^*} B_i/\sum_{i=1}^{\ell^*} D_i$, since $B > B_{\ell *}$. □ □

Lemma 4. *The number of clicks a bidder is allocated is non-decreasing in her declared budget.*

Proof sketch: Let bidders $\{1, \ldots, n\}$ be such that $b_1 \succ \ldots \succ b_n$, and consider a new bidder Alice with bid $b_{\ell-1} \succ b \succ b_\ell$. We will argue that the number of clicks that Alice receives is non-increasing as she reduces her declared budget B.

Suppose Alice declares $B = \infty$ and let $\hat{B}$ be the amount she would spend (Alice would always be a threshold bidder if she declared $B = \infty$). Any declared budget $B \in [\hat{B}, \infty]$ would result in the same number of clicks, because B is reduced by the mechanism in step (iii) to $\hat{B}$.

Now as B decreases from $\hat{B}$, two different events could occur: (a) Alice's price block threshold ℓ^* could change (because Find-Price-Block outputs a different ℓ^*) or (b) the lowest bidder k could change (because running Find-Price-Block on $1, \ldots, k$ gave a price less than b_{k+1}). For event (a), and between these events, the arguments from Theorem 3 imply that Alice's clicks are non-increasing.

For event (b), when the price of the Alice's block is exactly b_{k+1}, if bidder $k+1$ is added, the resulting price output by Find-Price-Block in step (ii) is still at least b_{k+1}, since adding a bidder cannot reduce the price. Also Lemmas 3 and 2 together imply that Alice is still in the price block chosen in step (iii). Thus Alice's clicks do not increase. □

Lemma 5. *The number of clicks a bidder is allocated is non-decreasing in her declared bid.*

Proof sketch: For the purposes of this proof, let bidders $\{1, \ldots, n\}$ be such that $b_1 \succ \ldots \succ b_n$, and consider a new bidder (call her Alice) with declared budget B. We will argue that the number of clicks that Alice receives in non-increasing with her declared bid b.

Let p_1 be the price that Alice would pay if $b = \infty$, and suppose Alice is in the jth price block when she bids ∞. Note that for any bid $b \in (p_1, \infty]$, Alice is still in the jth price block and receives the same number of clicks (B/p_1). Let p_2 be the minimum bid required to keep Alice in the jth price block.

We claim that if $b \in [p_2, p_1]$, the price will always be exactly b: no allocation is made until Alice is considered in step (ii), and when she's considered, Find-Price-Block returns a price $p \geq p_1$, since the set of bidders considered contains all the bidders who produced price p_1. Thus Alice is a threshold bidder, and in step (iii) Alice's budget is reduced so that the price is exactly b.

Let k_b be the number of bidders with bid $b_i \succ b$. Let B_i^b be the ith largest budget among bidders with bid $b_i \succ b$. We claim that if $b \in [p_2, p_1]$, we have $\sum_{i=1}^{\ell} B_i^b / \sum_{i=1}^{\ell} D_i < b$ for all $\ell \leq k_b$, since otherwise Alice would not be in the jth block.

Let $\hat{B}_b$ be Alice's reduced budget when she bids $b \in [p_2, p_1]$, and let $c_b = \hat{B}_b / b$ denote the number of clicks she receives. To satisfy the price being at most b in step (iii), we must have that for all $\ell \leq k_b$, $\hat{B}_b \leq B_\ell^b + \Delta$, where $\Delta > 0$ satisfies $(\Delta + \sum_{i=1}^{\ell} B_i^b)/\sum_{i=1}^{\ell} D_i = b$. In addition, we must have $(B_b + \sum_{i=1}^{k_b} B_i^b)/\sum_{i=1}^{k_b+1} D_i \leq b$. Putting these constraints together we get $\hat{B}_b = \min_{\ell \leq k_b+1}\{b \sum_{i=1}^{\ell} D_i - \sum_{i=1}^{\ell-1} B_i^b\}$ and so

$$c_b = \hat{B}_b / b = \min_{\ell \leq k_b+1} \left\{ \sum_{i=1}^{\ell} D_i - \frac{1}{b} \sum_{i=1}^{\ell-1} B_i^b \right\}.$$

As b decreases, if the set of bidders with bids $\succ b$ does not change, then the B_i^bs don't change, and so this expression implies that c_b also decreases. If b decreases to the point where $b' \succ b$ for some new bidder b', then we claim that c_b also cannot increase. To see this note that for all ℓ, the expression $\sum_{i=1}^{\ell-1} B_i^b$ can only increase or stay the same if a new bidder is added. We conclude that c_b is non-increasing in the interval $b \in [p_2, p_1]$.

When b decreases to p_2, we transition from Alice being in the jth price block to the $j+1$st price block. As in Theorem 3, at the point of transition the jth price block will have the same price as the $j+1$st price block, and in both scenarios Alice spends exactly $\hat{B}_{p_2}$. Thus her clicks do not change. We can iterate these arguments for the $j+1$st price block, and so the theorem is proven. $\square$

Lemmas 4 and 5 immediately imply Theorem 4. $\square$

4.2. Greedy First-Price Mechanism for Multiple Slots.

In the general case, as in the single-slot case, there is a natural *greedy first-price* mechanism when the bidding language includes both bids and budgets: Order the bidders by bid $b_1 \succ b_2 \succ \ldots \succ b_n$. Starting from the highest bidder, for each bidder i compute the maximum possible number of clicks c_i that one could allocate to bidder i at price b_i, given the budget constraint B_i and the commitments to previous bidders $c_1, \ldots, c_{i-1}$. This reduces to the "fractional knapsack" problem in the single-slot case, and so one would hope that it maximizes revenue for the given bids and budgets, as in the single-slot case. This is not immediately clear, but does turn out to be true, as we will prove in this section.

As in the single-slot case, the greedy mechanism is not a truthful mechanism. However, we show that it does have a pure-strategy equilibrium, and that equilibrium has prices and allocation equivalent to the price setting mechanism.

4.2.1. Greedy is Revenue-Maximizing.

Consider a revenue-maximizing schedule that respects both bids and budgets. In this allocation, we can assume wlog that each bidder i is charged exactly b_i per click, since otherwise the allocation can increase the price for bidder i, reduce c_i and remain feasible. Thus, by Lemma 1, we can find a revenue-maximizing schedule $\mathbf{c}^* = (c_1^*, \ldots, c_n^*)$ by maximizing $\sum_i b_i c_i$ subject to $c_i \leq B_i/b_i$ and $c_1 + \cdots + c_\ell \leq D_1 + \cdots + D_\ell$ for all $\ell = 1, ..., n$.

Theorem 5. *The greedy first-price auction gives a revenue-maximizing schedule.*

Proof. Note that an equivalent statement of the constraint $c_1 + \cdots + c_\ell \leq D_1 + \cdots + D_\ell$ for all

$\ell = 1, ..., n$. is:

$$\sum_{i \in S} c'_i \leq D_1 + ... + D_{|S|} \quad \text{for all subsets } S \subseteq \{1, ..., n\}. \tag{3}$$

Suppose bids are $b_1 \succ b_2 \succ ... \succ b_n$ and the corresponding clicks given to bidders in the greedy allocation are $\mathbf{c} = (c_1, ..., c_n)$. Let $\mathbf{c}^* = (c_1^*, ..., c_n^*)$ be the revenue-maximizing solution with the *closest prefix* to $\mathbf{c}$, meaning that the first i such that $c_i \neq c_i^*$ is maximized, and modulo that, $c_i - c_i^*$ is minimized.

We shall prove that the greedy $\mathbf{c}$ gives a revenue-maximizing schedule. Suppose the contrary and let i be the first index on which $\mathbf{c}$ differs from $\mathbf{c}^*$. Note that $c_i > c_i^*$ (by the definition of greedy, c_i is the maximum possible given $c_1, ..., c_{i-1}$). Let $c^*_{\max} = \max\{c^*_{i+1}, ..., c^*_n\}$. Let $J = \{j > i : c_j^* = c^*_{\max}\}$. Consider an arbitrary tight constraint on $\mathbf{c}^*$ of the form (3), defined by the set S. We claim that if $i \in S$, then all $j \in J$ are also in S.

Proof of claim: Suppose the contrary, namely that $i \in S$ and $j \notin S$ for some $j \in J$. Applying (3), we get

$$\sum_{\ell \in S} c_\ell^* = \sum_{\ell \leq |S|} D_\ell. \tag{4}$$

One of the bidders in S must have index $m > i$, otherwise (3) would be violated for c and S by $\sum_{\ell \in S \subseteq \{1,...,i\}} c_\ell > \sum_{\ell \in S \subseteq \{1,...,i\}} c_\ell^* = \sum_{\ell \leq |S|} D_\ell$. If $m \notin J$, then we would violate (3) for the set $S' = S \cup \{j\} \backslash \{m\}$: $\sum_{\ell \in S'} c_\ell^* > \sum_{\ell \in S} c_\ell^* = \sum_{\ell \leq |S| = |S'|} D_\ell$. Therefore $m \in J$.

Now by the feasibility of $\mathbf{c}^*$ and the fact that $j \notin S$, we also have $c_j^* + \sum_{\ell \in S} c_\ell^* \leq D_{|S|+1} + \sum_{\ell \leq |S|} D_\ell$ which implies, together with (4), that $c_j^* \leq D_{|S|+1}$. Again by feasibility, we also have $\sum_{\ell \in S \backslash m} c_\ell^* \leq \sum_{\ell \leq |S|-1} D_\ell$ and this, together with (4), gives $c_m^* \geq D_{|S|}$. Putting these last two observations together yields $D_{|S|} \leq c_m = c^*_{\max} = c_j^* \leq D_{|S|+1}$. Unless $c_m = c^*_{\max} = c_j^* = 0$, this violates the distinctness of the non-zero D_j's. But if $c^*_{\max} = 0$, it means that all c_ℓ for $\ell > i$ have $c_\ell = 0$, which means that $\mathbf{c}$ gives strictly more clicks than $\mathbf{c}^*$, a contradiction. $\square$

Let j be an arbitrary member of J. By the claim, there is an $\epsilon > 0$ such that if we set $\mathbf{c}' = \mathbf{c}^*$ except $c'_i = c_i^* + \epsilon$ and $c'_j = c_j^* - \epsilon$, we get a feasible allocation $\mathbf{c}'$, since j appears in every tight constraint in which i appears. This allocation has revenue at least that of $\mathbf{c}^*$, since $b_i \geq b_j$. But, it has a closer prefix to $\mathbf{c}$ than $\mathbf{c}^*$, a contradiction. $\square$

4.2.2. Price-Setting Mechanism is a Nash Equilibrium of the Greedy First Price Mechanism.

We note that truthfully reporting one's budget is a weakly dominant strategy in GFP, since when a bidder is considered for allocation, their budget is exhausted at a fixed price, subject to a cap on the number of clicks they can get. Reporting one's bid truthfully is not a dominant strategy, but we can still show that there is an ϵ-Nash equilibrium whose outcome is arbitrarily close to the PS mechanism.

Theorem 6. *Suppose the PS mechanism is run on the truthful input, resulting in clicks $c_1, \ldots, c_n$ for each bidder. Then, for any $\epsilon > 0$ there is a pure-strategy ϵ-Nash equilibrium of the GFP mechanism where each bidder receives $c_i \pm \epsilon$ clicks.*

Proof. Theorem 6 We will abuse notation and let ϵ' denote any positive quantity that can be made arbitrarily close to zero. When the PS mechanism is run on the truthful input, let $p_1 > p_2 > \ldots$ denote the prices of each block. We will show that if in GFP each bidder i truthfully reports her budget and bids $b_i = \min\{m_i, p_j + \epsilon'\}$, where j is the price block of i in the PS mechanism, we meet the conditions of the theorem.

Suppose the first price block is determined when bidder k is considered, and ends at slot $\ell^* \leq k$. The price p_1 satisfies $m_{k+1} \leq p_1 \leq m_k$. Let $P \subseteq [k]$ denote the bidders in the first block (the ones in $[k]$ with the ℓ^* highest budgets). Also, we have that all $i \in P$ spend their entire budget in the PS mechanism, except possibly k, who may spend less than her budget if $m_k = p_1$. We now argue that GFP will produce the same allocation as the PS mechanism for this price block. For all $i \in P$ we have $b_i = \min\{m_i, p_1 + \epsilon'\} \geq \min\{m_k, p_1\} = p_1$. All bidders $i \in ([k] \setminus P)$ have $b_i \leq p_2 + \epsilon' < p_1$. All bidders $i \notin [k]$ have $m_i \prec m_k$ and so since $b_i \leq m_i$ we get $b_i \prec b_{i'}$ for all $i' \in P$. We conclude that the bidders in P are the first to be considered by the GFP mechanism. Furthermore, if $k \in P$, and B_k is reduced in the PS mechanism (because k is a threshold bidder), then we must have $b_k = m_k = p_1$, and so $b_k \prec b_i$ for all $i \in P, i \neq k$. Thus in this case bidder k is the last bidder in P to be considered by GFP. From here it is straightforward to show that GFP will assign the first ℓ^* slots to the bidders in P (almost) exactly like the PS mechanism does, with at least $c_i - \epsilon'$ clicks to each $i \in P$; the mechanism will have ϵ' clicks left over, which will be assigned to bidders not in P. Applying this same argument to subsequent price blocks, we conclude that

GFP will assign $c'_i = c_i \pm \epsilon'$ clicks to all bidders i.

To show this is an equilibrium, consider a bidder Alice (call her "bidder a") that was assigned to price block j^* and received $c'_a = c_a \pm \epsilon'$ clicks. If Alice spent within ϵ' of her entire budget, it means she would not want to raise her bid, since she could not possibly receive more than ϵ' additional clicks. If she did not spend her budget, then from the observations above we know that she is bidding her true max-cpc m_a, and therefore also does not want to raise her bid.

It remains to show that Alice does not want to lower her bid. Let ℓ_j denote the last slot in price block j. Let P_j denote the set of bidders in price block j. Alice's current bid b_a is at least p_j, and if she keeps her bid above p_j her clicks will remain $c_a \pm \epsilon$ from the arguments above. Let $S = \cup_{j \leq j^*} P_j$. If Alice lowers her bid to $b'_a < p_j$, then all bidders $i \in S$ besides Alice will have $b_i \succ b'_a$. Thus when Alice is considered by the greedy algorithm, her clicks will be constrained by the commitments to these bidders. Furthermore each of these bidders will still receive at least c'_i clicks. For all price blocks j, we have $\sum_{i \in P_j} c'_i \geq \sum_{i=\ell_{j-1}+1}^{\ell_j} D_i - \epsilon'$. Thus $\sum_{i \in S, i \neq a} c'_i \geq (\sum_{i=1}^{\ell_{j^*}} D_i) - \epsilon' - c'_a$. Since S has size ℓ_{j^*}, this implies that the constraint (3) restricts Alice's clicks to at most $c'_a + \epsilon'$. $\square$

5. Conclusions

In this paper we have given a truthful mechanism for assigning bidders to click-generating slots that respects budget and per-click price constraints. The mechanism also respects a scheduling constraint on the slots, using a classical result from scheduling theory to characterize (and compute) the possible allocations. We have also proved that the revenue-maximizing mechanism has an ϵ-Nash equilibrium whose outcome is arbitrarily close to our mechanism. This final result in some way suggests that our mechanism is the right one for this model. It would interesting to make this more formal; we conjecture that a general truthful mechanism cannot do better in terms of revenue.

5.1. Extensions.

There are several natural generalizations of the *Online Ad Slot Scheduling* problem where it would be interesting to extend our results or apply the knowledge gained in this paper. We mention a few here.

Click-through rates.. In sponsored search (e.g. [9]) it is common for each bidder to have a personal click-through-rate γ_i; in our model this would mean that a bidder i assigned to slot j for a time period of length α would receive $\alpha\gamma_i D_j$ clicks. All our results can be generalized to this setting by simply scaling the bids using $b'_i = b_i\gamma_i$. However, our mechanism in this case does not necessarily prefer more *efficient* solutions; i.e., ones that generate more overall clicks. It would be interesting to analyze a possible tradeoff between efficiency and revenue in this setting.

Multiple Keywords.. To model multiple keywords in our model, we could say that each query q had its own set of click totals $D_{q,1} \ldots D_{q,n}$, and each bidder is interested in a subset of queries. The greedy first-price mechanism is easily generalized to this case: maximally allocate clicks to bidders in order of their bid b_i (at price b_i) while respecting the budgets, the query preferences, and the click commitments to previous bidders. It would not be surprising if there was an equilibrium of this extension of the greedy mechanism that could be computed directly with a generalization of the PS mechanism.

Online queries, uncertain supply.. In sponsored search, allocations must be made online in response to user queries, and some of the previous literature has focused on this aspect of the problem (e.g., [21, 20]). Perhaps the ideas in this paper could be used to help make online allocation decisions using (unreliable) estimates of the supply, a setting considered by Mahdian et al. [20], with game-theoretic considerations.

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