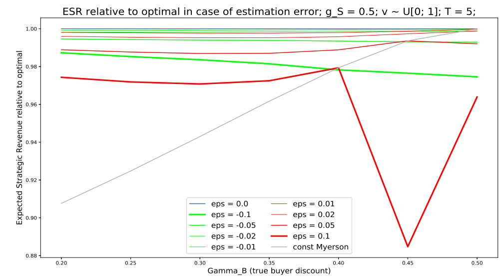

We thank the reviewers and will do our best to improve the presentation. To Reviewers #2 & #3 **on discount knowledge**. Yes, in our setup, the buyer's $\gamma_{\mathtt{B}}$ is public knowledge; we will clarify this in the text. Such scenario can arise in one of our model interpretations (Lines114-119 & Appendix F), where an RTB platform (seller $\mathtt{S}$) has more data than an advertiser (buyer $\mathtt{B}$) and may know which data are not available to $\mathtt{B}$. In this interpretation, $\gamma_{\mathtt{B}}, \gamma_{\mathtt{S}}$ are $\mathtt{B}$'s and $\mathtt{S}$'s estimates of a true discount factor γ, which is a random variable unknown to both $\mathtt{B}, \mathtt{S}$. Consider a toy example: $\gamma = \xi_1 + \xi_2$, $\mathtt{S}$ observes ξ_1 and ξ_2, while $\mathtt{B}$ observes only ξ_1. Say, $\mathtt{B}$'s estimate for γ is $\gamma_{\mathtt{B}} = \xi_1 + \mathbb{E}[\xi_2]$ (we took the simplest estimate for illustration), then the seller $\mathtt{S}$ can evaluate $\gamma_{\mathtt{B}}$.

What if the seller doesn't know buyer's $\gamma_{\mathtt{B}}$ exactly. In fact, our results can be useful in such a scenario as well. Case (1): if the seller knows only a lower bound $\hat{\gamma}_{\mathtt{B}}$ for $\gamma_{\mathtt{B}}$ s.t. $\gamma_{\mathtt{S}} < \hat{\gamma}_{\mathtt{B}}$, then she can apply "Big deal", which prices are calculated using $\hat{\gamma}_{\mathtt{B}}$: $\mathcal{A}_{\mathtt{bd}}(\mathfrak{e}) = \sum_t \hat{\gamma}^{\mathtt{B}} p^*_D$; $\mathcal{A}_{\mathtt{bd}}(1 \circ \mathfrak{n}) = 0 \; \forall \mathfrak{n}$; $\mathcal{A}_{\mathtt{bd}}(0 \circ \mathfrak{n}) = T p^*_D \; \forall \mathfrak{n}$. Buyer (whose discount $\gamma_{\mathtt{B}} \geq \hat{\gamma}_{\mathtt{B}}$) with valuation $v > p^*_D$ still accepts the first proposed price, hence, the seller gets at least $\sum_t \hat{\gamma}^{\mathtt{B}} p^*_D (1 - F(p^*_D))$. This is less than the optimal revenue (when $\gamma_{\mathtt{B}}$ is known exactly), but strictly larger than the one of static pricing. Similarly, modifications of "Big deal" can be applied when seller knows only distribution of $\gamma_{\mathtt{B}}, \gamma_{\mathtt{B}} \geq \gamma_{\mathtt{S}}$.

Case (2): Seller uses functional L to find an optimal algorithm, assumes buyer's discount is $\gamma'_{\mathtt{B}} = \gamma_{\mathtt{B}} + \varepsilon$, but faces a buyer with true discount $\gamma_{\mathtt{B}}$. We evaluate the loss in revenue by the following numerical experimentation: $T = 5$, $V \sim U[0;1]$ (uniform on $[0;1]$) and $\gamma_{\mathtt{S}} = 0.5$ (different sets of parameters give qualitatively the same results). In figure above, the expected strategic revenue (ESR) of this seller is divided by the ESR of a well-informed seller (i.e. s.t. $\varepsilon = 0$). We see: (a) if ε is small enough (for $\varepsilon = 0.02$, or $\geq 4\%$ of $\gamma_{\mathtt{B}}$), then $\mathtt{S}$ still able to extract over 99% of the optimal ESR; (b) even if ε is very large (for $\varepsilon = 0.1$, or $\geq 20\%$ of $\gamma_{\mathtt{B}}$) $\mathtt{S}$ still able to extract over 97% of the optimal ESR for most cases ($\gamma_{\mathtt{B}} \leq 0.4$); and (c) if $\mathtt{S}$ is able to just separate $\gamma_{\mathtt{B}}$ of $\gamma_{\mathtt{S}}$ with a decent margin, then she is able to gain extra revenue.

To Reviewer #2.

On time complexity. Application of pricing algorithms has no time complexity issues, since a seller just needs to track the current node in a tree to post a price in a round, however she needs to have enough memory (for $2^T - 1$ float variables). As of numerical methods to optimize our functional $L(\cdot)$, it's took few seconds to converge in all our experiments.

To Reviewer #3.

On point 4. No. Geometric discounts are considered for sake of exposition, but our results hold for non-geometric discounts as well. They are studied in Appendices A.1 & A.2, as indicated in Remarks 1 & 2 (see Lines 189, 283-284).

On point 6. No. It is written correctly: $S(\cdot)$ is piecewise *linear*, because, in a piece (an interval (v_i, v_{i+1})) $S(\cdot)$ equals to $S_{\mathbf{a}^i}(\cdot)$ for some strategy $\mathbf{a}^i$ which is a linear function of v: $S_{\mathbf{a}^i}(v) = (\sum_t \gamma^{\mathtt{B}}_t a^i_t) v - (\sum_t \gamma^{\mathtt{B}}_t a^i_t p_t)$ (see Lines 211 & 81).

On point 7. We have no hardness result for the optimization problem in Eq. (5), but, generally, it does not have a closed form solution (as we argue in Lines271-273). Numerical methods help in this case, but they are usually very sensitive to the dimensionality of the problem. This is why we address the problem of dimensionality reduction and show that our functional $L(\cdot)$ is also useful to find optimal pricing algorithms in low-dimensional spaces. Note that low-dim spaces can be obtained by different constraints (see Lines323-335), not only by τ-step algorithms (as in Lines290-322).

On point 2&5. Yes, you are right here. We will fix and make clear the text in these lines.

To Reviewer #4. **On Lines 125,158&211.** Yes, you are right here, we will improve text in these places.

On Lines 213-227 (construction of Prop.1's proof). The construction in these lines (and, thus, the proof of Prop.1) works for the case $\gamma_{\mathtt{S}} \geq \gamma_{\mathtt{B}}$ as indicated in the statement of Prop.1 (Line 228) and considered in Sec.4 as a whole. When you take an algorithm Big Deal (note that you port it from the opposite case of discounts) and consider in the case $\gamma_{\mathtt{S}} \geq \gamma_{\mathtt{B}}$, the procedure from Lines 213-227 can be applied: the only strategy that can be activated in the first step is $\mathtt{1}\mathtt{0}^{T-1}$ (see Appendix A.2.1, 3rd paragraph: we activate a strategy that has lowest last $\mathtt{1}$ position). This activation is provided via decreasing the price $\mathcal{A}(\mathfrak{e})$ and increasing all prices $\mathcal{A}(\mathtt{1}), \mathcal{A}(\mathtt{10}), \ldots, \mathcal{A}(\mathtt{1}\mathtt{0}^{T-2})$. After this step more possibilities for further "activations" arise.

On an explicit description of the algorithm. Shortly, it is as follows. Remind: for static pricing, the optimal (Myerson) price can be found from maximization of $H_D(p) = p(1 - F_D(p))$. In our dynamic case, the optimal algorithm can be found similarly: (a) construct the matrix Ξ (a code to calculate its elements is in Appendix I); (b) construct the functional $L(\cdot)$ from Eq. (4); (c) find a vector $\mathbf{v}^{\mathrm{Opt}}$ s.t. it maximizes $L(\mathbf{v})$, e.g., numerically using derivatives of $L(\cdot)$ provided in Lines 277-278; (d) convert the vector $\mathbf{v}^{\mathrm{Opt}}$ to the prices of the optimal algorithm by means of linear transformation $\mathbf{w}^{-1}_{\boldsymbol{\gamma}^{\mathtt{B}}}(\cdot)$, which is mentioned in Lines 255&249 and whose matrix is $K_T(\boldsymbol{\gamma}^{\mathtt{B}}, \boldsymbol{\gamma}^{\mathtt{B}})^{-1} J_T^{-1} Z_T(\boldsymbol{\gamma}^{\mathtt{B}})^{-1}$ (see Appendix A.2.2).

On Line 42. Yes, we will clarify: different discounts have only been studied in other setting (worst-case one [7,8,30,31]).

On Lines 75&77. Yes, we study deterministic algorithms, and, hence, a decision sequence is called a strategy (as in [7,30,31,59]). Note: it is easy to show that algorithms proposed in Sec.3 are optimal among probabilistic ones as well.

On Line 99. The word "expected" does not correspond to Eq.(1), but it is a part of the notion "expected strategic revenue" which is the reference for the expression $\mathbb{E}_{V \sim D}[\mathrm{SRev}_{\gamma^{\mathtt{S}}, \boldsymbol{\gamma}^{\mathtt{B}}}(\mathcal{A}^*, V)]$ situated at the beginning of Line 100.

On Line 171. Yes, $\gamma_{\mathtt{B}}$ is publicly known. See 1st answer for Rev.#2&#3 about the case when $\gamma_{\mathtt{B}}$ isn't known precisely.