Note that the numbered citations refer to references in the submitted paper. The remaining citations are listed at the end of the page.

Reviewer 1. We thank you for your detailed commentary. We respond to your questions in order:

1. Within the literature on SOCO, both movement costs that are “squared” and “linear” have been studied. We have focused on the “squared” case here due to its applications to control, e.g., LQR control, which was first shown in [28] and later extended in [22]. The squared case also applies to online regression problems and economic dispatch in power systems. The ideas in the submitted paper also apply to the “linear” case. We have new results showing that G-OBD provides an order optimal competitive ratio among a class of memoryless algorithms in the “linear” case, as defined in [18], but we have yet to succeed in analyzing R-OBD in the “linear” setting. Understanding the “linear” case in more detail is a topic of our ongoing research.
2. Theorem 6 in our submission does not make additional assumptions on the scale of L. However, we have not obtained a lower bound on dynamic regret in the same problem setting thus far. In [28] a lower bound was obtained for a different notion of dynamic regret defined by the path length of minimizers. Unfortunately, the two definitions are not comparable.
3. The point of Theorem 2 is to show that OBD has suboptimal competitive ratio for any choice of the balance parameter γ. In particular, without some new insight, we cannot create an optimal version of OBD simply by adjusting γ. This observation shows the need to extend OBD, which we do in the remainder of the paper.
4. While we have not investigated ℓ-Lipshitz functions, the setting of well-conditioned cost functions is of particular interest and we have some additional results in that case. Specifically, when the condition number of the hitting cost functions is k the competitive ratio of R-OBD is bounded above by $1 + k$. However, the lower bound in the same setting is still a topic of our ongoing research.
5. Some stochastic models have been considered in related work [17], but we have not analyzed R-OBD in those situations. This is a topic of ongoing research.

Reviewer 2. We thank you for your detailed commentary. You have suggested that the problem we consider is "highly specialized." We feel strongly that SOCO is an important problem in the online learning space, and one with stunningly broad range of applications including data center capacity provisioning, demand response, speech animation, video streaming, network function virtualization, and more [24, 26, 27, 29][SLJ19]. In many of these applications, approaches based on SOCO algorithms have been deployed in production systems, e.g., within HP, Disney, Microsoft, Akaimai, Southern California Edison, and Google (among others). An example of a particularly exciting recent connection is that SOCO was used to analyze and derive policies for LQR control problems [22], which is a core problem in the community. Another important connection is to the problem of Online Body Chasing, which has led to considerable interest in the algorithms community [Sel19, AGGT19]. Because of these applications, this classical problem has received a surge of interest across the networking, theoretical computer science, machine learning, and energy communities, with multiple papers in conferences such as Sigmetrics, FOCS/STOC, e-Energy, and COLT appearing each year.

Reviewer 3. We thank you for your detailed commentary, and for pointing out some typos and redundancies which we will correct in the final version of our paper. You mentioned a slight concern with the significance of the problem setting. We hope that our response to reviewer 2 eases this concern.

References

[AGGT19] CJ Argue, Anupam Gupta, Guru Guruganesh, and Ziye Tang. Chasing convex bodies with linear competitive ratio. *arXiv preprint arXiv:1905.11877*, 2019.

[Sel19] Mark Sellke. Chasing convex bodies optimally. *arXiv preprint arXiv:1905.11968*, 2019.

[SLJ19] Ming Shi, Xiaojun Lin, and Lei Jiao. On the value of look-ahead in competitive online convex optimization. *Proceedings of the ACM on Measurement and Analysis of Computing Systems*, 3(2):22, 2019.