We thank the reviewers for their thoughtful feedback. We will make sure to incorporate all minor editorial recommendations in the next revision of our paper. Below we explain our results at a high level and answer the reviewers' questions. We consider two fundamental problems in statistical hypothesis testing: testing independence of a bivariate discrete distribution, and testing closeness (also known as equivalence or two-sample testing) of two unknown discrete distributions given access to unequal sized sample sets from each. We designed minimax sample optimal algorithms (up to a logarithmic factor) for these two problems that satisfy differential privacy. Our main technical contribution is a methodology to privatize the "closeness tester" of [25] that relies on the idea of *flattening* the underlying distributions. (Please see Preliminaries Line 147-173 for a detailed description of this tester).

Testing closeness via the flattening technique has played a central role in testing properties of discrete distributions in the non-private setting. Several other distribution properties can be tested via a reduction or direct use of this closeness tester. Examples include identity testing (goodness-of-fit), closeness testing between two unknown distributions with unequal sample sizes, independence testing (in two or higher dimensions), closeness testing for collections of distributions, and testing histograms. For most of these properties, the only known methodology to obtain minimax sample-optimal testers is via a reduction or direct use of the flattening-based closeness tester. This is due in part on the fact that the flattening-based testers naturally allows us exploit the potential structure of the underlying distributions.

Despite the importance of the flattening technique in the non-private setting, prior to our work there were no differentially private tester that could make the flattening step private. The main barrier for designing differentially private testers using this method is the unstable nature of the statistic when we use flattening: even changing one sample in the flattening step can drastically change the behavior of the statistic and the tester — whereas a differentially private tester must be stable if a single sample is changed.

We give the first differentially private tester that achieves privatizing the flattening-based closeness tester. In particular, we design a general differentially private closeness tester that allows specific reductions for the flattening of the underlying distributions. (See Definition 3.2 for the properties of these specific reductions.) As a corollary, we obtain *the first* minimax sample-optimal and differentially private testers for closeness testing with unequal sized sample sets and independence testing. We circumvent the issue of the unstable statistic by an appropriate *derandomization* of the non-private flattening-based tester: We compute the average statistic over all possible permutations of the samples and carefully analyze its worse-case sensitivity. Furthermore, for independence testing, we provide a novel technique for mapping samples sets with high sensitivity to sample sets with low sensitivity. This technique helps us significantly reduce the sensitivity even further when the worst-case sensitivity is high.

Detecting if $\|p\|_2$ and $\|q\|_2$ are small: The ℓ_2-norm of a discrete distribution over $[n]$ is always at least $1/\sqrt{n}$, and we can efficiently estimate the ℓ_2-norm of any distribution up to a constant factor [8]. In our paper, we do not need to detect whether $\|p\|_2 = \Theta(\|q\|_2)$, as is needed in [25]. We circumvent this detection step entirely by a careful analysis of the statistic and achieve a tester with sample complexity $O\left((n/\epsilon^2)\min(\|p\|_2, \|q\|_2)\right)$. Hence, as long as one of the two distributions has small ℓ_2-norm (a property guaranteed by flattening), our tester is sample-efficient.

Advantages of statistic $\overline{Z}$: The main advantage of the statistic $\overline{Z}$ is that it has a low sensitivity. The exact improvement in the sensitivity depends on the flattening procedure and the property being tested. We precisely bound the sensitivity for independence testing and closeness testing with unequal sized sample sets in the respective sections in the Appendix. Please see Section B.2 and Section C.2, where we analyze the sensitivity of $\overline{Z}$.

Dependency on the privacy parameter: We emphasize that our algorithm is always differentially private regardless of the number of samples. The privacy guarantee follows from the properties of the Laplace mechanism. The sample complexities we obtain are necessary to obtain an accurate tester in a differentially private setting. Moreover, our algorithms have the optimal dependencies on the privacy parameter. Please see the table below for a comparison.

	Independence Testing	Closeness Testing (with unequal sized sample sets)
Our Results	$\Omega\left(\frac{n^{2/3}m^{1/3}}{\epsilon^{4/3}} + \frac{\sqrt{m\,n}}{\epsilon^2} + \frac{\sqrt{m\,n\,\log n}}{\epsilon\sqrt{\xi}} + \frac{1}{\epsilon^2\xi}\right)$	$k_1 = \Omega\left(\frac{n^{2/3}}{\epsilon^{4/3}} + \frac{\sqrt{n}}{\epsilon^2} + \frac{\sqrt{n}}{\epsilon\sqrt{\xi}}\right)$ $s = \Theta\left(\frac{n}{\epsilon^2\sqrt{\min(n,k_1)}} + \frac{\sqrt{n}}{\epsilon^2} + \frac{\sqrt{n}}{\epsilon\sqrt{\xi}} + \frac{1}{\epsilon^2\xi}\right)$
Lower Bounds [4, 25]	$\Omega\left(\frac{n^{2/3}m^{1/3}}{\epsilon^{4/3}} + \frac{\sqrt{m\,n}}{\epsilon^2} + \frac{\sqrt{m\,n}}{\epsilon\sqrt{\xi}} + \frac{1}{\epsilon\,\xi}\right)$	$s = \Omega\left(\frac{n}{\sqrt{k_1}\epsilon^2} + \frac{\sqrt{n}}{\epsilon^2} + \frac{\sqrt{n}}{\epsilon\sqrt{\xi}} + \frac{1}{\epsilon\,\xi}\right)$