Appendix A. Bounding Output Differences with LDP

Let \mathcal{A} be a randomized mechanism, R_{θ} be the model parameter space, and ϵ denote the privacy budget associated with the noise scale δ . In δ -STEAL, we add LDP noise $Lap(0,\delta)$ to the token embeddings, which is equivalent to applying ϵ -LDP to each data sample. By the post-processing property of LDP, the adversary's model θ_{adv} is also ϵ -LDP. As a result, watermark detectors cannot determine whether θ_{adv} was trained on watermarked data and fail to verify its intellectual property, especially with small values of ϵ . The difference between θ_{adv} trained with or without watermarked data is bounded as follows: $P[\mathcal{A}(x+Lap(0,\delta),y^{wm}+Lap(0,\delta))\in R_{\theta}]\leq \exp^{\epsilon}P[\mathcal{A}(x'+Lap(0,\delta),y'^{wm}+Lap(0,\delta))=R_{\theta}].$

Appendix B. Privacy Budget Calculation

In δ -STEAL, we use a common LDP approach, which is a Laplace mechanism that adds Laplace noises into token embeddings of the model. The Laplace mechanism is defined as: $\mathcal{A}_{\mathcal{E}}(x,\mathcal{E}(x),\epsilon) = \mathcal{E}(x) + (L_1,L_2,\cdots,L_d)$, where $\mathcal{E}(x)$ is the embedding of token x,d is the embedding size, and L_i are independent and identically distributed (i.i.d.) random variables drawn from Laplace noise centered at 0, scaled by $\delta = \frac{\Delta(\mathcal{E})}{\epsilon}$. Given a noise scale δ , to compute the privacy budget ϵ , we first need to calculate the magnitude by which a single individual's data can change the function \mathcal{E} in the worst case, which is defined as: $\Delta(\mathcal{E}) = \max_{\forall x, \tilde{x} \in N^d} \|\mathcal{E}(x) - \mathcal{E}(\tilde{x})\|_1$.

For LLaMA-2, we obtain $\Delta(\mathcal{E}) = 0.3$, while for Mistral, $\Delta(\mathcal{E}) = 0.05$. With noise scales of $\delta \in 0.001, 0.05, 0.1$, the corresponding privacy budgets are:

- For LLaMA-2: $\epsilon = \frac{\Delta(\mathcal{E})}{\delta} = \{300, 30, 6, 3\}$
- For Mistral: $\epsilon = \frac{\Delta(\mathcal{E})}{\delta} = \{50, 5, 1, 0.5\}$

Appendix C. Supplemental Results

In this supplement, we include the results for the SemStamp watermark, which were not presented in the main body. SemStamp requires fine-tuning a robust sentence embedder to support the local sensitivity mechanism for sentence selection. Since we used the pre-trained embedder provided by the authors, the results are not optimal in our experiments.

 δ -STEAL against Semstamp. For Semstamp, our observations of δ -STEAL attacks in Fig. 6 are consistent with other watermarks. As noise scales increase, AttackSR rise, and PPL increases but remain comparable to the Baseline. However, a notable concern is the low Baseline watermark detection rate, which results in unexpectedly high AttackSR even without attacks, reaching 52.97% for LLaMA-2 and 59.15% for Mistral.

 δ -STEAL and Existing Attacks on Semstamp. Fig. 7 illustrates the effectiveness of our δ -STEAL attacks compared to other attacks on Semstamp. It is clear that δ -STEAL, regardless of noise scale, performs effectively, indicating high AttackSR and low PPLs.

 δ -STEAL in MMLU Downstream Task. In Table 3, we present only the KGW and EXP water-marking techniques, although we also experimented with all four techniques considered in this paper, including SIR and Semstamp. For SIR, our attempt to apply the publicly available trained model to the MMLU task resulted in poor accuracy, only 27.90% for LLaMA-2 and 20.90% for Mistral without any attacks. This poor performance is due to the fact that, due to computational complexity,

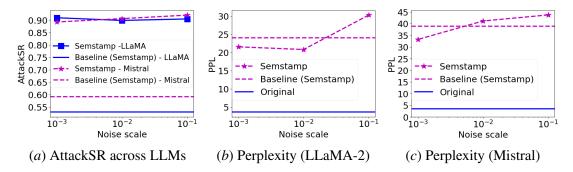


Figure 6: AttackSR and Perplexity of δ -STEAL on Semstamp.

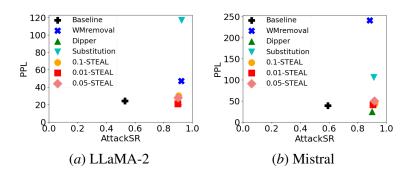


Figure 7: AttackSR and Perplexity across on Semstamp.

we do not retrain their watermark model, meaning it may not adapt well to our data and settings. For Semstamp, which generates entire sentences instead of individual tokens, it is not suitable for MMLU, which involves multiple-choice question-answering tasks.

Semantic Preservation of δ -STEAL Outputs. We present additional quantitative examples from Mistral, as shown in Table 4a), to illustrate the effects of our δ -STEAL attack. These examples highlight the subtle differences introduced while preserving the overall semantic meaning. For instance, in the first row, the attack changes "office has talked to Attorney General Jeff Sessions" to "team has talked with Jeff Sessions" and removes the adverb "now," while maintaining the key information about the Russia investigation. In the second example, "20 percent of black students and 10 percent of Latino students in Boston are attending the city's top 20 public schools" is modified to "who applied to the city's top schools were admitted," subtly shifting the focus but retaining the core message that the mentioned students were accepted into top schools. Lastly, in the third instance, δ -STEAL changes "shape of a new toy" to "shape, configuration, and appearance of a new product" and modifies the quantifiers from plural to singular, changing "patent" and "variety," while still discussing the types of patents. These examples demonstrate that our attack makes slight wording changes without altering the overall semantic content.

Table 4a): Examples of prompts and watermarked outputs with and without δ -STEAL (Mistral model). Green text highlights similarities and red text emphasizes differences.

Prompt	Watermarked (W)	Watermarked under δ -Steal (SA) (δ =	PPL	PPL
		0.01)	(W)	(SA)
There have been a	KGW: office has talked to attorney	KGW: team has talked with Attorney	8.52	8.21
number of revelations	general Jeff Sessions and that Robert	General Jeff Sessions, and that Robert		
this week related to the	Muller is now looking at sitting down	Mueller is looking to sit down for an		
Russia investigation.	with President Donald Trump. And, of	interview with President Trump. But		
Among them, that the	course, news about a deal to temporarily	with a government shutdown still		
special counsel's	end the government shutdown, but with	hanging over everyone's heads, it can be		
	no resolution [continues]	easy to lose track of [continues]		
Latino students as	EXP: percent of black students and	EXP: percent of black students and	2.87	2.03
well saw less	70-percent of Latino students in Boston	70-percent of Latino students who		
opportunity for access to	are attending schools that are considered	applied to the city's top schools were		
quality schools than	low performing. The report also found	not admitted. The report also found that		
their white and Asian	that 20-percent of black students and	20-percent of black students and		
counterparts, "O'Brien	10-percent of Latino students in Boston	10-percent of Latino students who		
said. The study found	are attending the city's top 20 public	applied to the city's top schools were		
that more than 80	schools . " The report [continues]	admitted. The report [continues]		
patent protects the	SIR: shape of a new toy. Plant patents	SIR: shape, configuration and	5.67	5.52
functional aspects of an	protect, you guessed it, new varieties of	appearance of a new product. A plant		
invention, such as a new	plants. You apply for a patent with the	patent protects inventions of natural		
machine. A design	United States Patent and trademark	organisms such as a new variety of fruit		
patent protects the	Office, but you can not put a patent	tree. Once you determine what type of		
ornamental appearance	symbol " ® " on your product until it is	intellectual property you need, you can		
of an invention, such as	[continues]	file a patent application with the U.S		
the		patent [continues]		

Table 4b) provides a comparison of our δ -STEAL with the different attack methods used in this study. While the approach of our δ -STEAL attack has been detailed previously, Dipper and the Substitution attacks present alternative solutions. As per Dipper, since it works with sentence levels, it truncates and discards all incomplete sentences within the target output to attack and always starts paraphrasing full sentences only, resulting in a disrupted reading flow from input to output and causing small loss of information. For example, in the first row, while both δ -STEAL and Substitution attacks continue to generate "JB" to complete "BJP", Dipper starts with a new sentence. Furthermore, due to Dipper's reliance on reordering sentences, the provided snippet of its output within a limited token count shown in Table 4b could not fully show relevant benchmark against other attacks. For instance, in the second example, the sentence "The company announced that it would pay \$50,000 for the silence of this alleged affair." introduces content beyond what is covered in the benchmark snippet. In contrast, the Substitution attack replaces texts by considering surrounding context, maintaining a high degree of similarity (as shown by the larger green portion) with the original watermarked text.

Table 4b): Examples of prompts and watermarked outputs of δ -STEAL and other attacks (LLaMA-2 model). Green text highlights similarities and red text emphasizes differences.

Prompt	Watermarked (W)	Watermarked under δ -	Dipper	Substitution
do that for the	KGW: JP achieved in the	Steal (SA) ($\delta = 0.01$)	KGW: We have to	VCW. IDti-in-t-1
		KGW: JP registered in		KGW: JP participated
MCD polls, " said	2014 Lok Sabha polls in	the 2014 Lok Sabha	study the ground	in the 2014 Lok Sabha
a senior party	Delhi, where the party	elections in the city. "	reality and political	elections in Delhi, where
leader. Another	won all seven seats. "We	We have to convince the	situation in the city.	the party won just two
reason behind not	have to take into account	people of Delhi that why	We can't ignore the	seats. "We need to take
targeting Modi in	the ground reality and the	we are the best option to	sweeping victory of the	into account the politi-
the MCD polls is	political equation in the	govern the city. We have	BJP in the 2014	cal climate and the politi-
the massive victory	city. We can not ignore	to show that the BJP 's	elections in Delhi. The	cal situation in the city.
the B	the BJP 's victory in the	victory in the 2014 Lok	party won all the seven	We cannot support the
	2014 Lok Sabha	Sabha elections was a	parliamentary seats.	BJP's performance in the
	[continues]	[continues]	[continues]	2014 Lok Sabha elec-
				tions [continues]
Daniels, who	EXP: ed affair with	EXP: ed affair with	EXP: The company	EXP: daniels spoke with
was born	Trump. Trump denies the	Trump. Cohen recently	announced that it	Trump. trump denied
Stephanie Clifford,	allegation. Cohen has	revealed that Trump	would pay \$ 50,000 for	the allegation. Cohen
was paid 130,000	admitted making the	personally reimbursed	the silence of this	later admitted to the pay-
by Cohen after she	payment to Daniels,	him for the payment to	alleged affair. Cohen	ments to Daniels, which
signed a	which he said was done to	Daniels. As a result of	admitted paying the	he said were done to
nondisclosure	protect Trump's	the payment to Cohen,	money, saying it was	protect Trump's family
agreement barring	campaign from the	the government ethics	in order to protect	from the allegations. It's
her from talking	allegations. It's possible	office sent a reminder to	Trump's campaign	possible that the cash
about her alleg	that the reimbursement	Trump that he must	from the alleged affair.	payments mentioned in
	payment revealed in the	disclose in his annual	Trump denies the	the full disclosure would
	financial disclosure may	financial disclosure	alleged affair.	[continues]
	have been [continues]	report [continues]	[continues]	
other shows,	SIR: a traditional	SIR: a major network	SIR: Furthermore,	SIR: a great wrestling
it's a GoPro on a	television platform, we	television, we would be	Foley was asked why	platform, we would be
windshield, "Foley	would be able to do more	able to do more with it. I	his daughter Nol was	happy to do something
said referring to	with it. As it stands, it 'll	think we would be able	not continuing in the	with it. as it stands, it'll
Ride Along. "I	be a while before we do	to have a bigger budget	world of professional	be a while before we
think if this was a	any new episodes of Holy	and be able to do some	wrestling, despite her	have any more fans of
show that was on	Folesy! " Foley also	cool things with it."	father's rich career. It's	holy Folesy!" Foley ##a
	addressed why his	Foley also talked about	too early for her to	explained why his daugh-
	daughter Noelle is n't	why his daughter Noelle	become a wrestler,	ter Noelle isn't pursuing
	pursuing a career in	is n't pursuing an	because the thing is	a career in WWE despite.
	WWE despite	[continues]	that it's [continues]	[continues]
	[continues]			

Appendix D. Ablation

To better understand the effect of noise injection location, we conduct a study and report results in Table 8 comparing three strategies on LLaMA-2 with KGW at $\delta = 0.01$ on (1) noisy embeddings during fine-tuning (δ -STEAL), (2) noisy pre-logits, and (3) noisy embeddings applied at inference.

Noise Location		AttackSR (%)
Noisy Embedding (training, δ -STEAL)	4.30	68.33%
Noisy Pre-logits	4.86	74.75%
Noisy Embedding (inference)	5.27	67.69%

Table 8: Ablation study comparing noise injection locations on LLaMA-2 with KGW at $\delta = 0.01$.