2025

frank.computer

Playing telephone with generative models: “verification disability,” “compelled reliance,” and accessibility in data visualization

 

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(this workshop paper could have been a blog post)


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[redacted]

Sep 30, 2025, 10:38 PM (24 days ago)

my thoughts? gut reaction? lmao not your best work. probably should have been a blog post.

you're right that there's not much at this specific intersection. but maybe address this head-on? like: "Yes, we know AI hallucinates. Yes, we know accessibility matters. But here's why the combination creates a novel problem space that existing work doesn't address." does that help? o think the work is solid and important - it just needs to position itself as "applying known problems to an underexamined context" rather than "discovering unknown problems." the contribution is the framing and the specificity, not the existence of ai bias itself.

A good workshop paper stimulates discussion.

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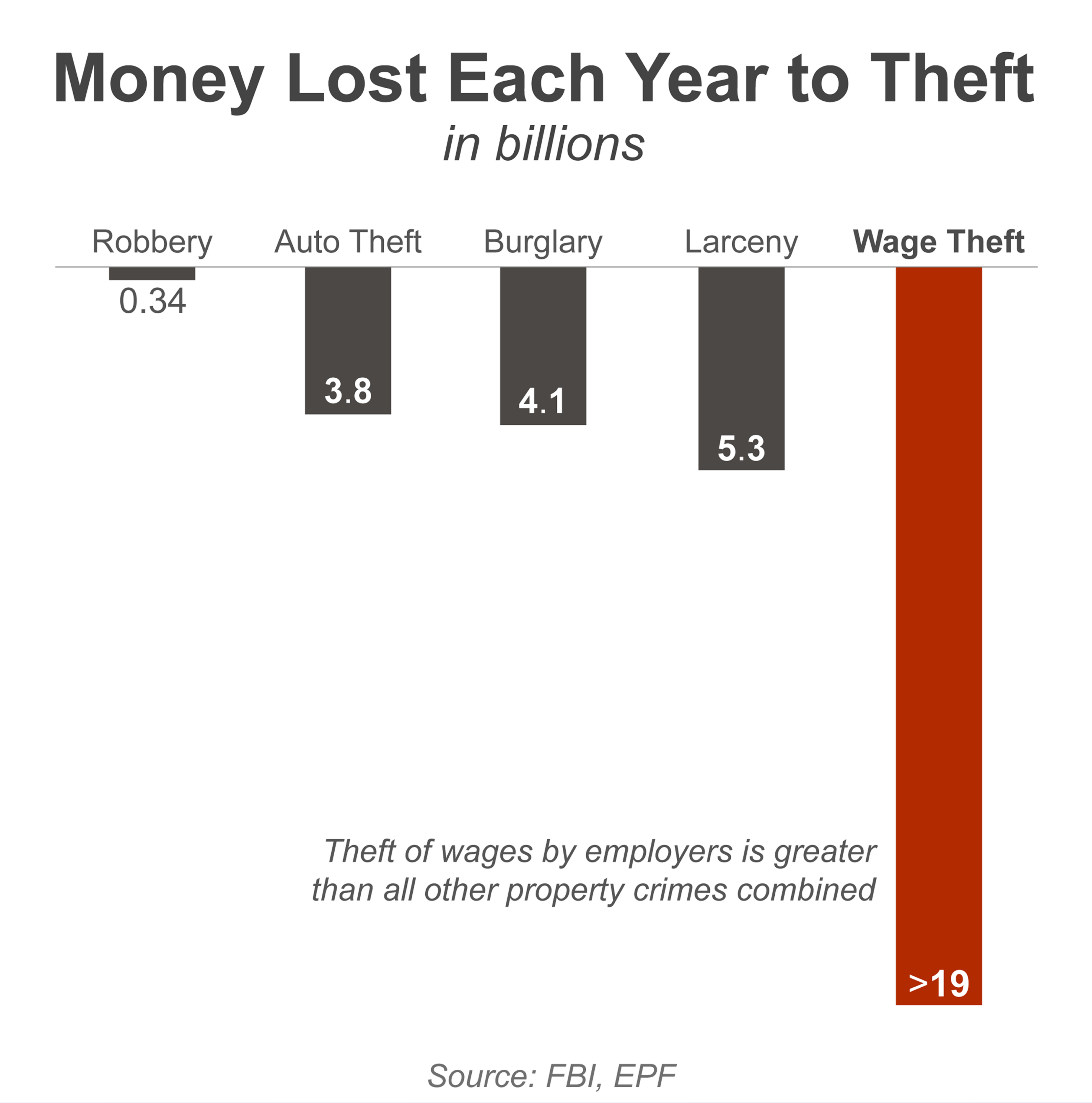
I'll try to have this talk make up for where the workshop paper falls short!

How do descriptions *bias* a person who is blind?



We decided to play a game of telephone…

Terms

“Verification disability”

Players of telephone cannot verify what they hear compared to the “ground truth” (the original statement) and must always do their best to interpret what they receive using their own sensibilities.

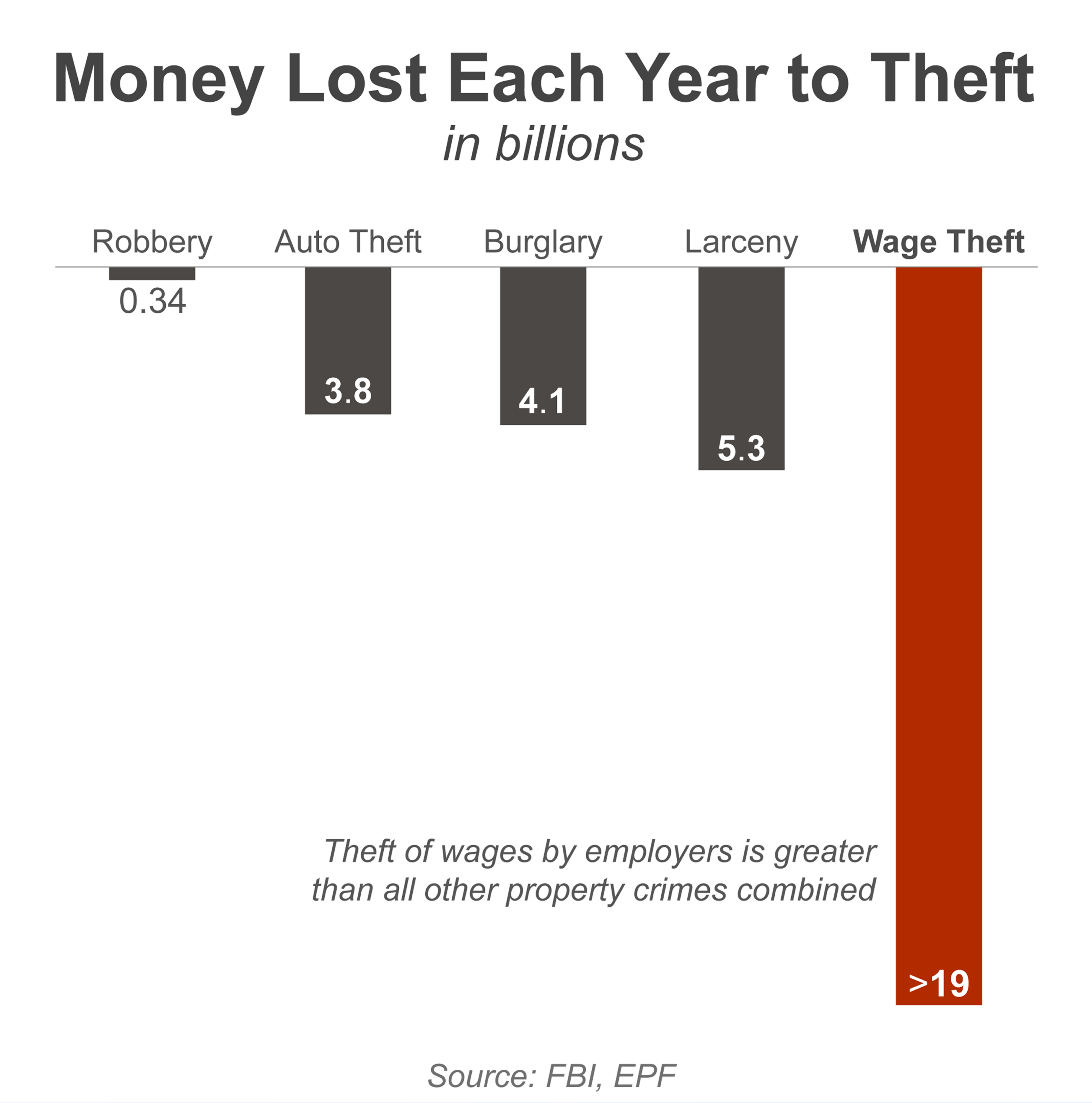
“Compelled reliance”

Because players cannot verify, it would be nonsensical to doubt the information they receive. The advantages of reliance and trust far outweigh the disadvantages of doubt.

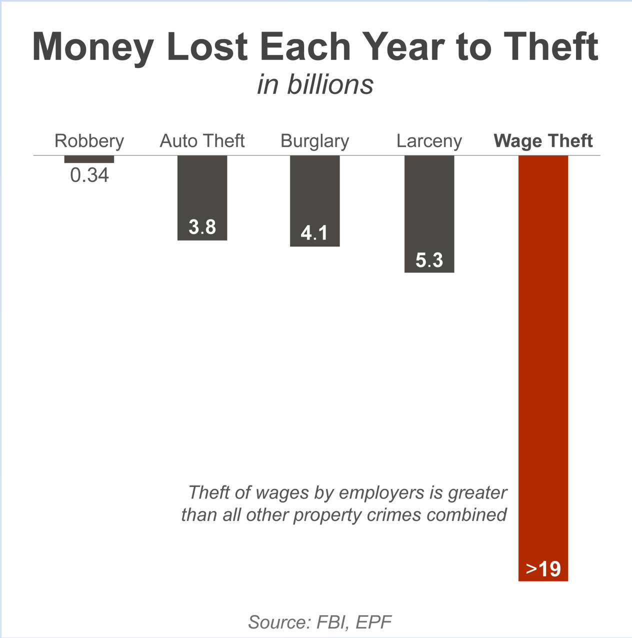
Why introduce new terms?

It stimulates discussion!

Why introduce new terms?

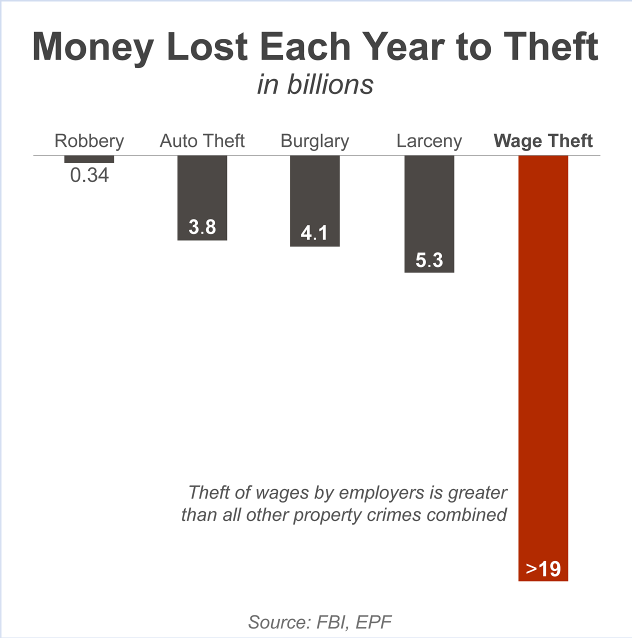

Money Lost Each Year to Theft
in billions
Robbery
Auto Theft
Burglary
Larceny
Wage Theft
0.34
3.8
4.1
5.3
>19
Theft of wages by employers is greater
than all other property crimes combined
Source: FBI, EPF

chatGPT (1st instance)



"Can you describe this?"

chatGPT (1st instance)



"Can you describe this?"

Certainly. The image is a bar chart titled "Money Lost Each Year to Theft (in billions)". It compares different types of theft based on the estimated amount of money lost annually in the United States. The data source is attributed to FBI and EPF.

Breakdown of the Chart:

- Robbery: $0.34 billion
- Auto theft: $3.8 billion
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- Wage Theft: > $19 billion (highlighted in red)

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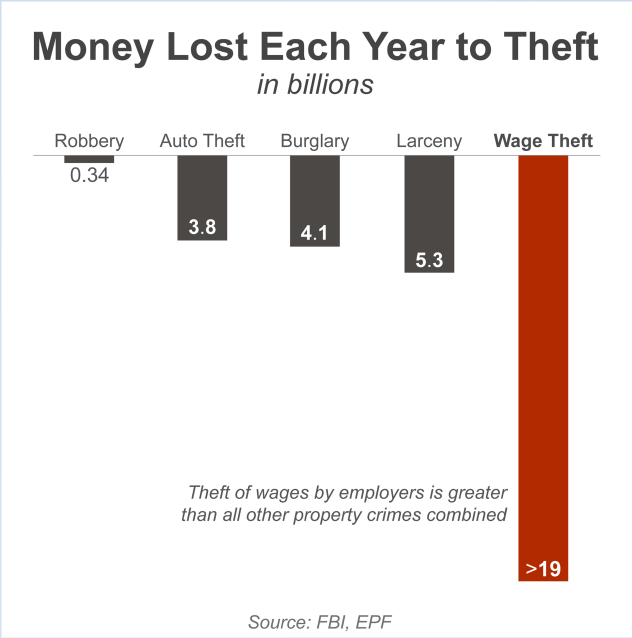

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Key Message:

At the bottom, the chart states:

“Theft of wages by employers is greater than all other property crimes combined.”

This emphasizes that wage theft-when employers illegally withhold wages or underpay workers-is a signifcantly larger issue financially than traditional forms of property crime.

The chart uses color and size to underscore this disparity, with “Wage Theft” shown as a much taller red bar compared to the smaller gray bars for other crimes.

chatGPT (2nd instance)

"Can you make a chart based on this description?"

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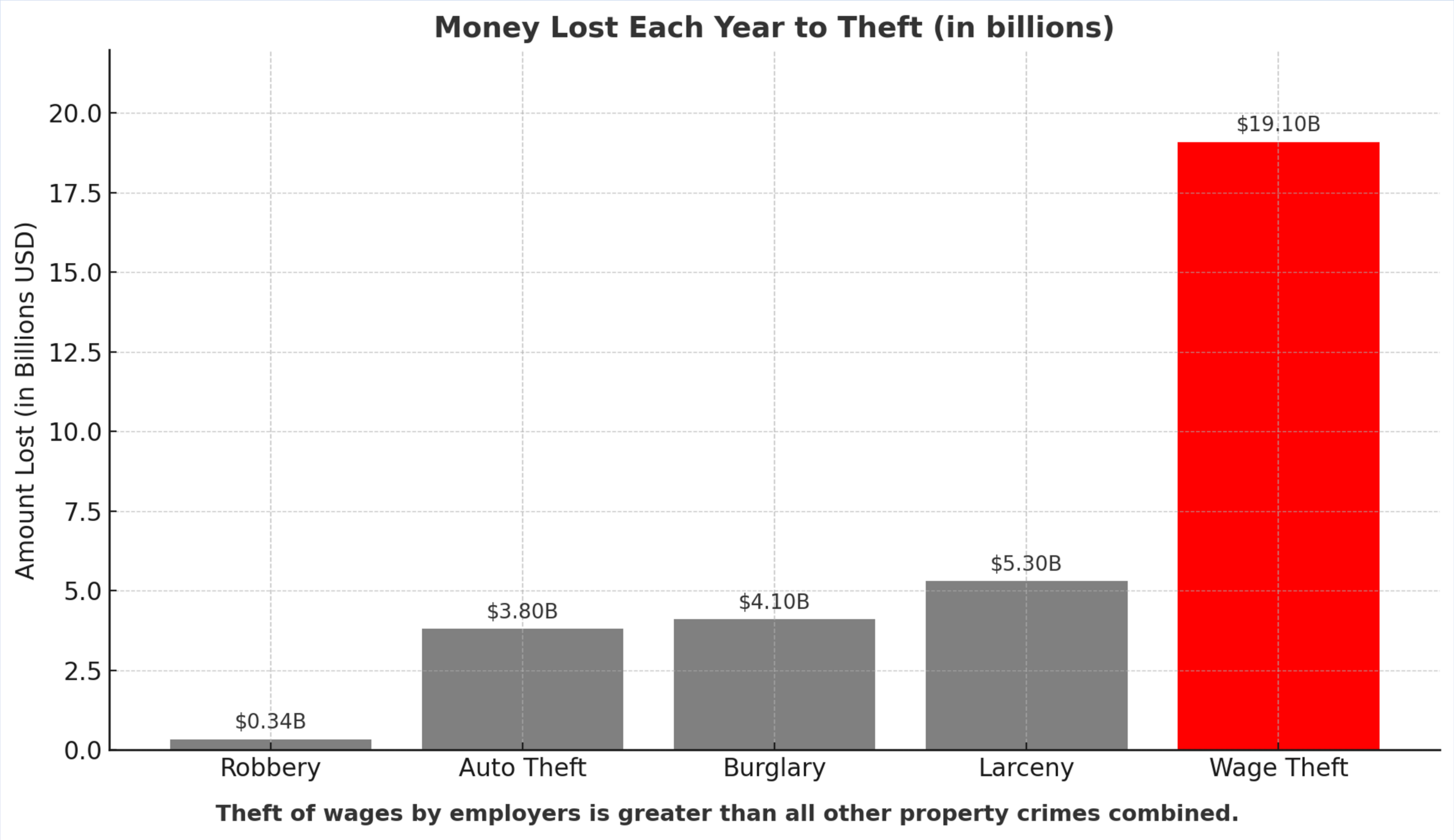
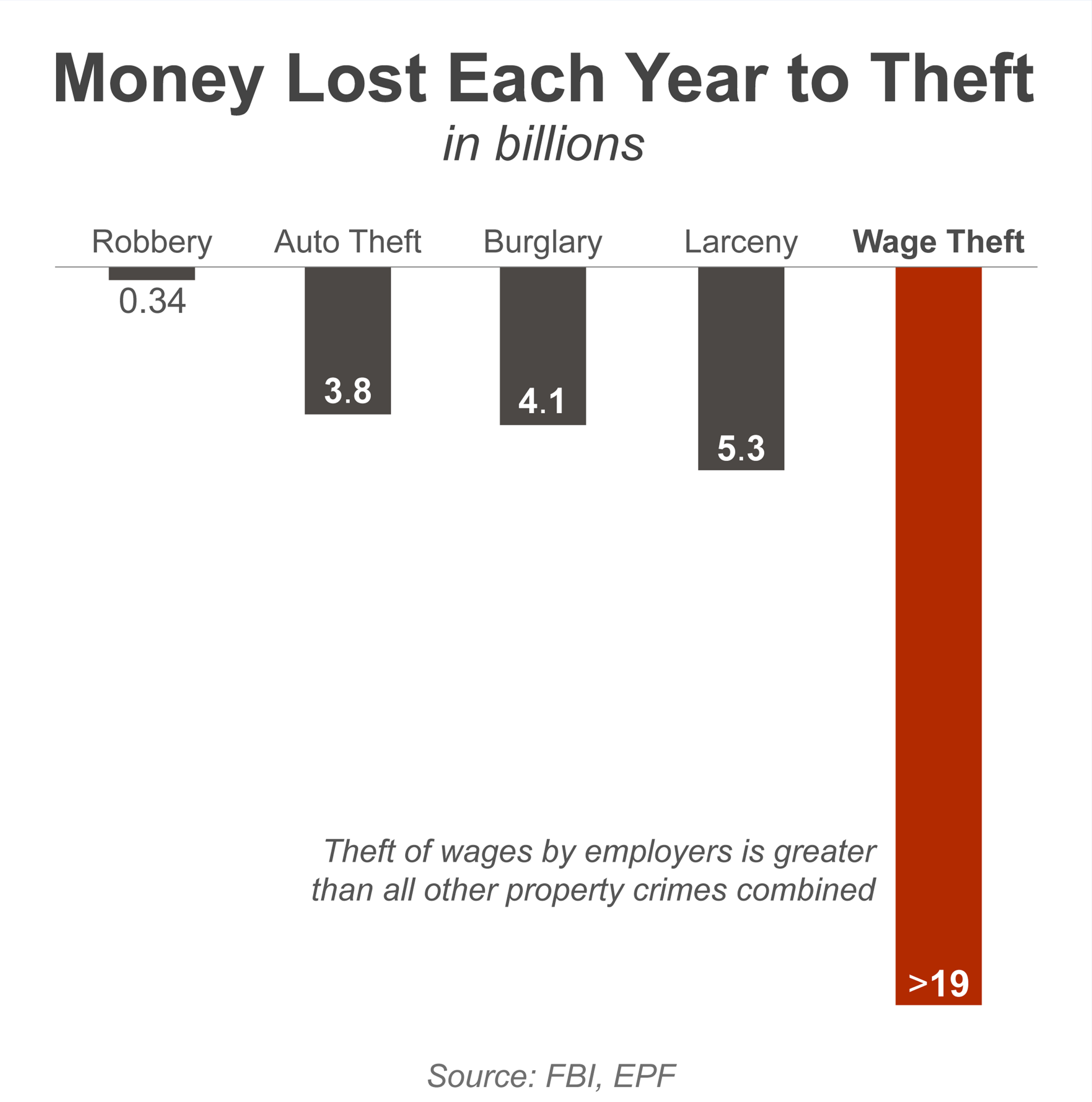
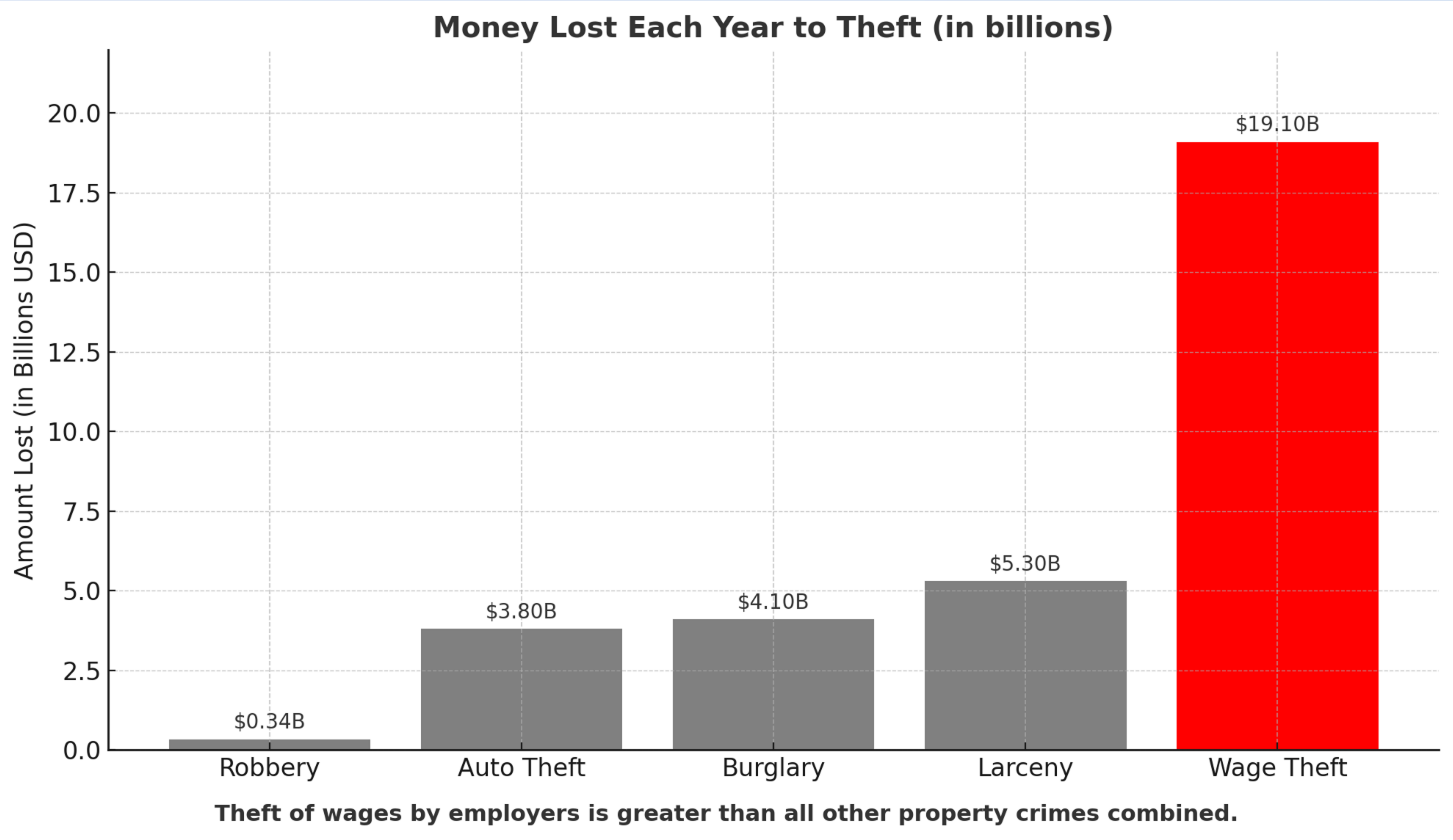


Quick comparison, so far





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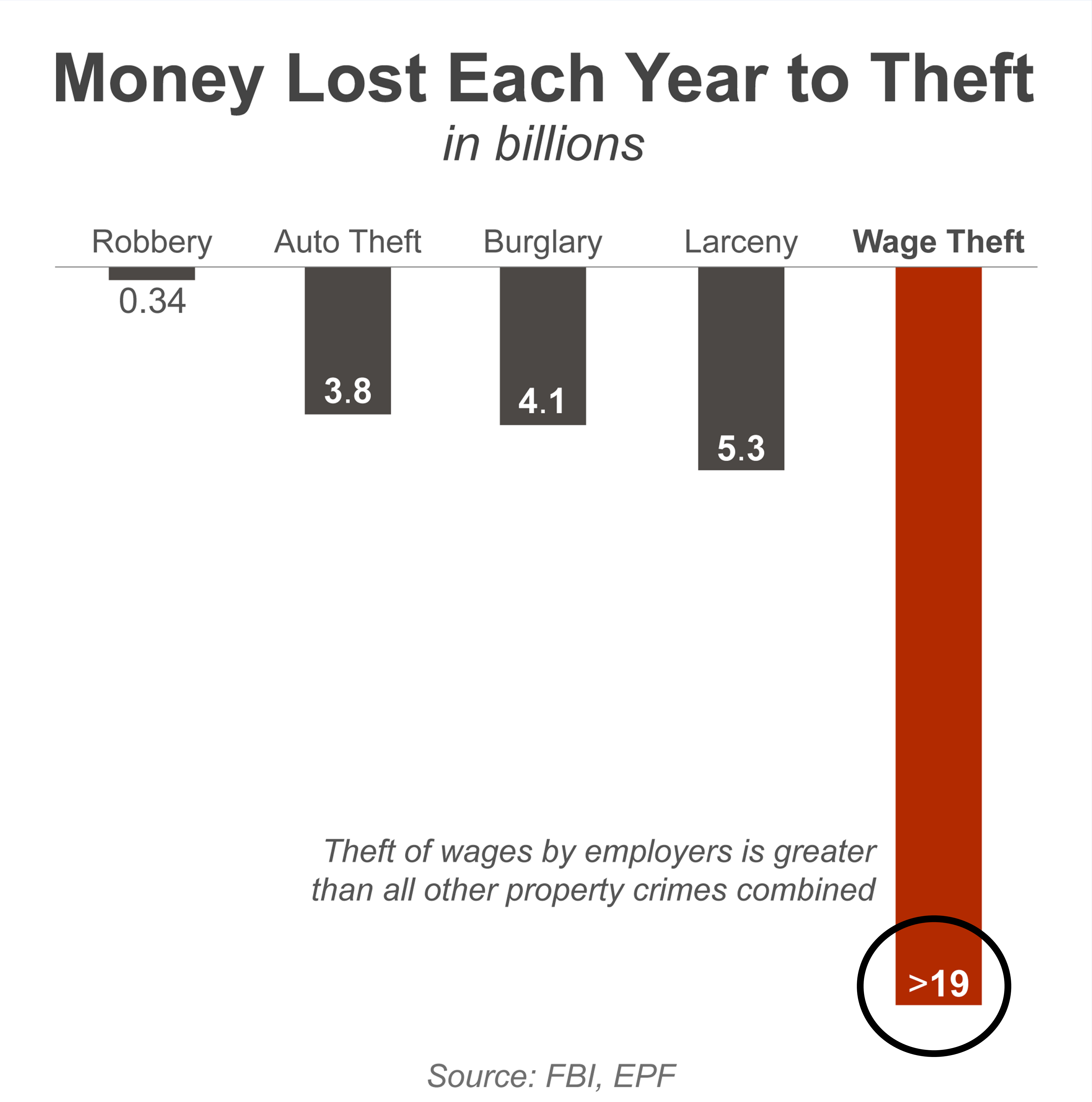

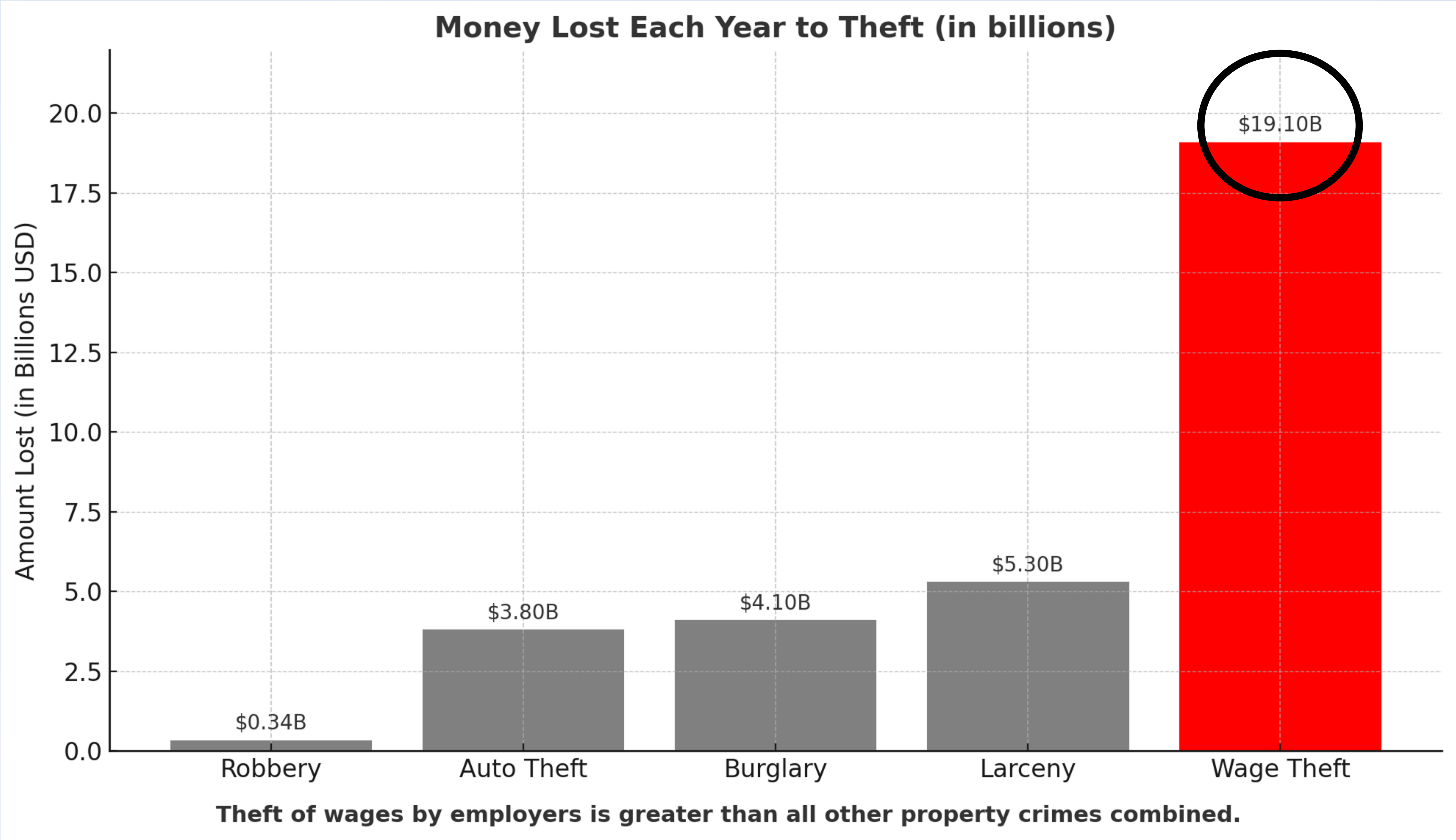

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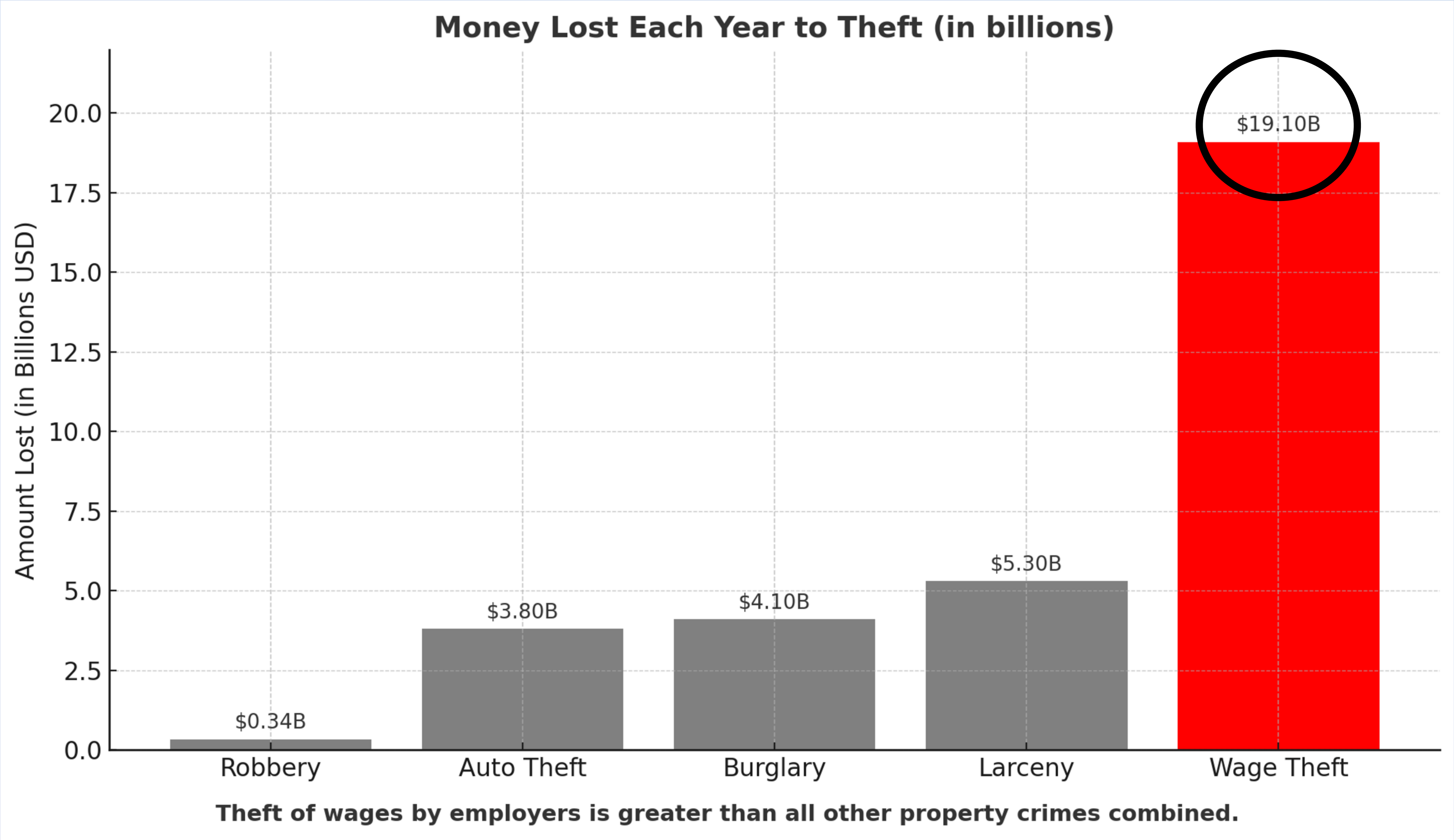
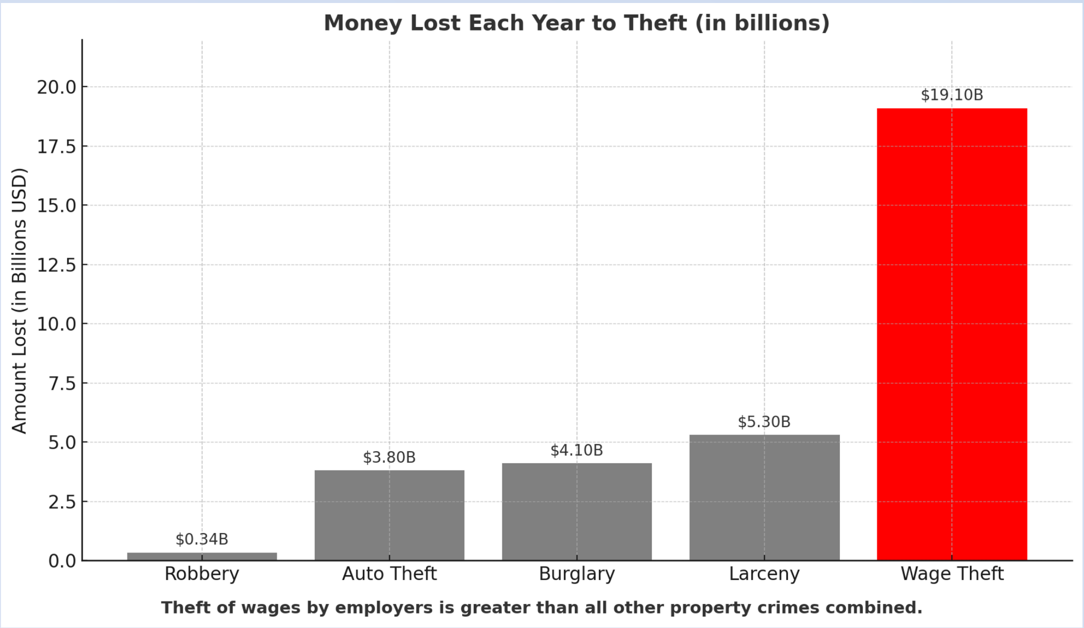


chatGPT (3rd instance)



"Can you describe this?"

This bar chart titled "Money Lost Each Year to Theft (in billions)" compares the estimated annual financial losses from different types of theft in the United States. The y-axis represents the amount lost in billions of USD, while the x-axis lists fve types of theft:

- Robbery – $0.34B
- Auto Theft – $3.80B
- Burglary – $4.10B
- Larceny – $5.30B
- Wage Theft – $19.10B (highlighted in red)

Key Observations:

Wage theft, the illegal withholding of wages or denial of benefits rightfully owed to an employee, results in far greater financial losses than any other category.

The total combined losses from robbery, auto theft, burglary, and larceny amount to $13.54B, which is still less than the loss from wage theft alone.

The chart emphasizes this disparity with a bold note:

"Theft of wages by employers is greater than all other property crimes combined."

Purpose:

The visual and accompanying text clearly highlight the often-overlooked scale of wage theft, suggesting it's a more significant economic issue than conventional property crimes.

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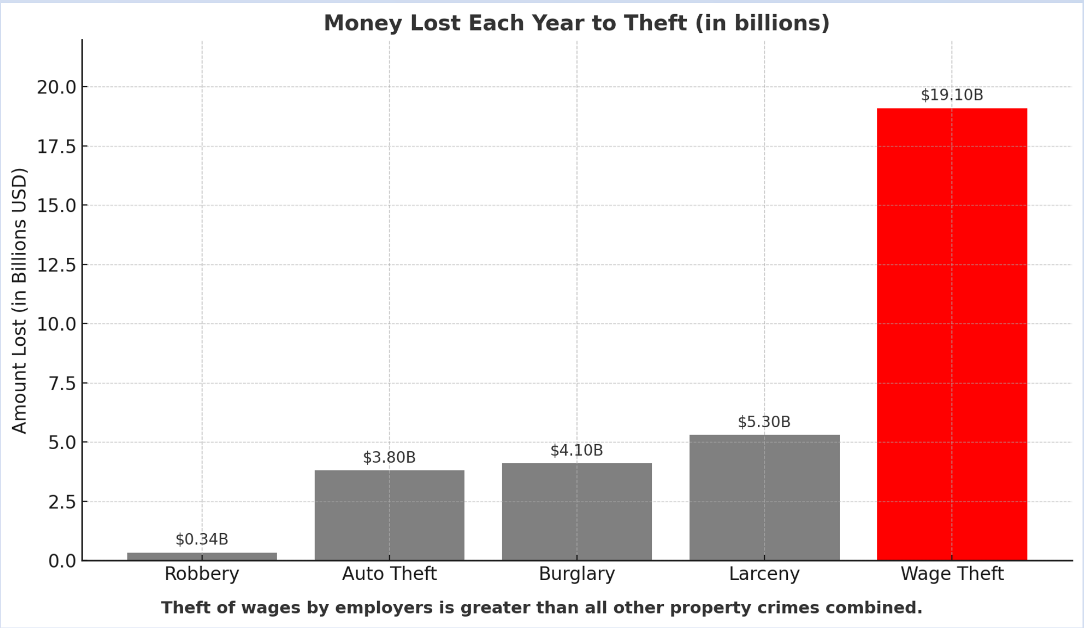

"Can you describe this?"

This bar chart titled "Money Lost Each Year to Theft (in billions)" compares the estimated annual financial losses from different types of **theft in the United States**. The y-axis represents the amount lost in billions of USD, while the x-axis lists five types of theft:

- Robbery – $0.34B
- Auto Theft – $3.80B
- Burglary – $4.10B
- Larceny – $5.30B
- Wage Theft – $19.10B (highlighted in red)

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"Can you make a chart based on this description?"

Certainly. The image is a bar chart titled "Money Lost Each Year to Theft (in billions)". It compares different types of theft based on the estimated amount of money lost annually in the United States. The data source is attributed to FBI and EPF.

Breakdown of the Chart:

- Robbery: $0.34 billion
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- Wage Theft: > $19 billion (highlighted in red)

Key Message:

At the bottom, the chart states:

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This emphasizes that wage theft-when employers illegally with-hold wages or underpay workers-is a signifcantly larger issue f-nancially than traditional forms of property crime.

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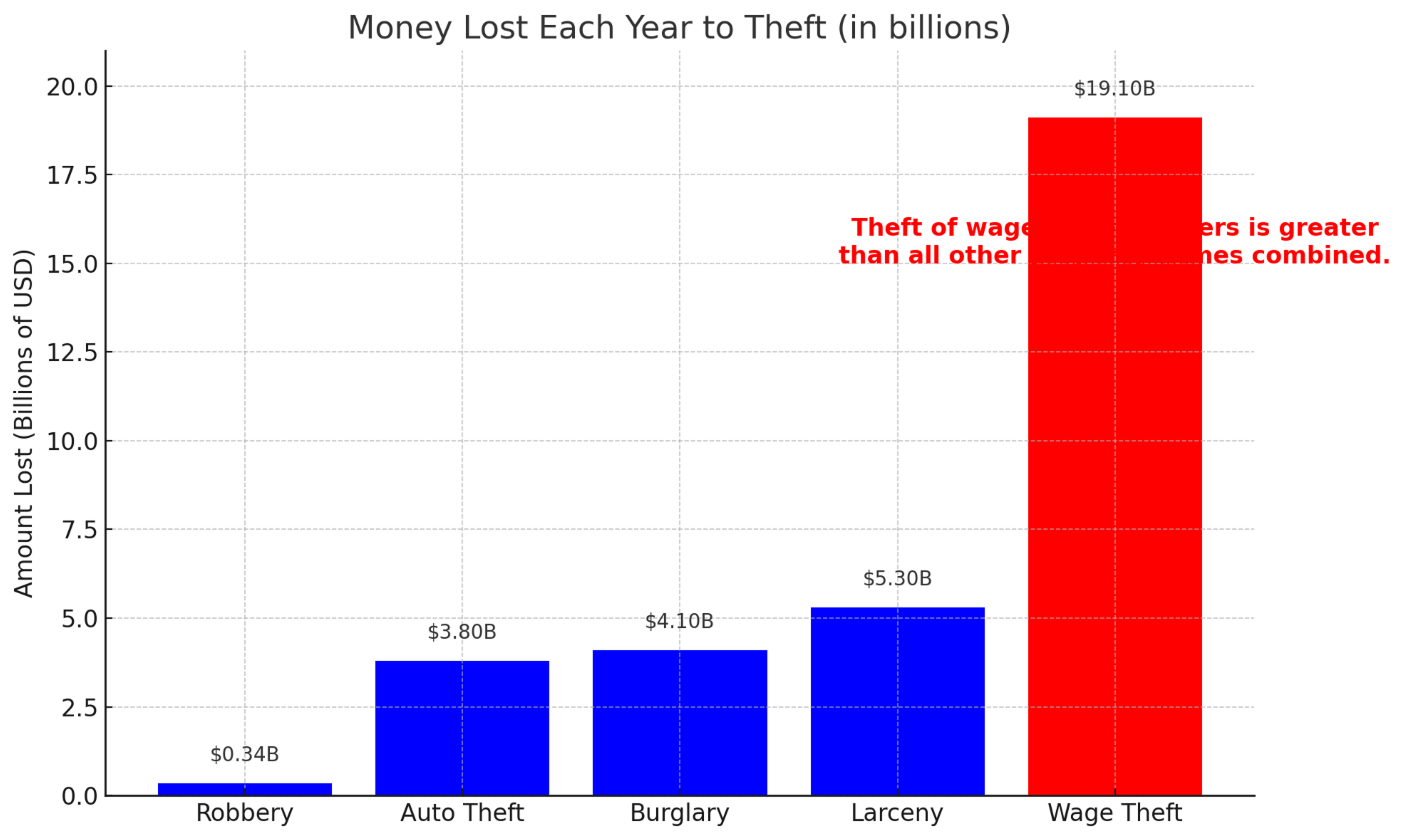
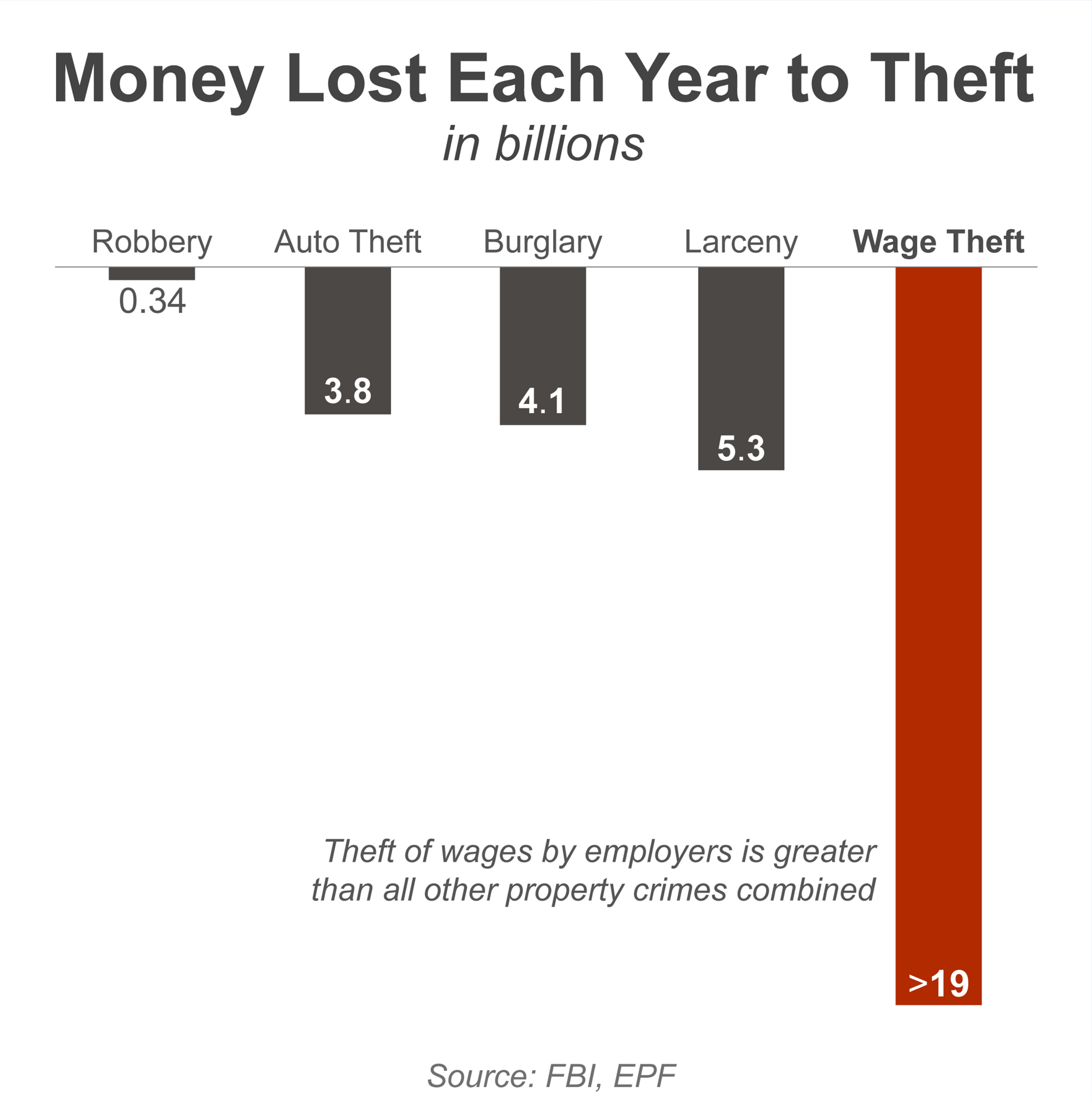
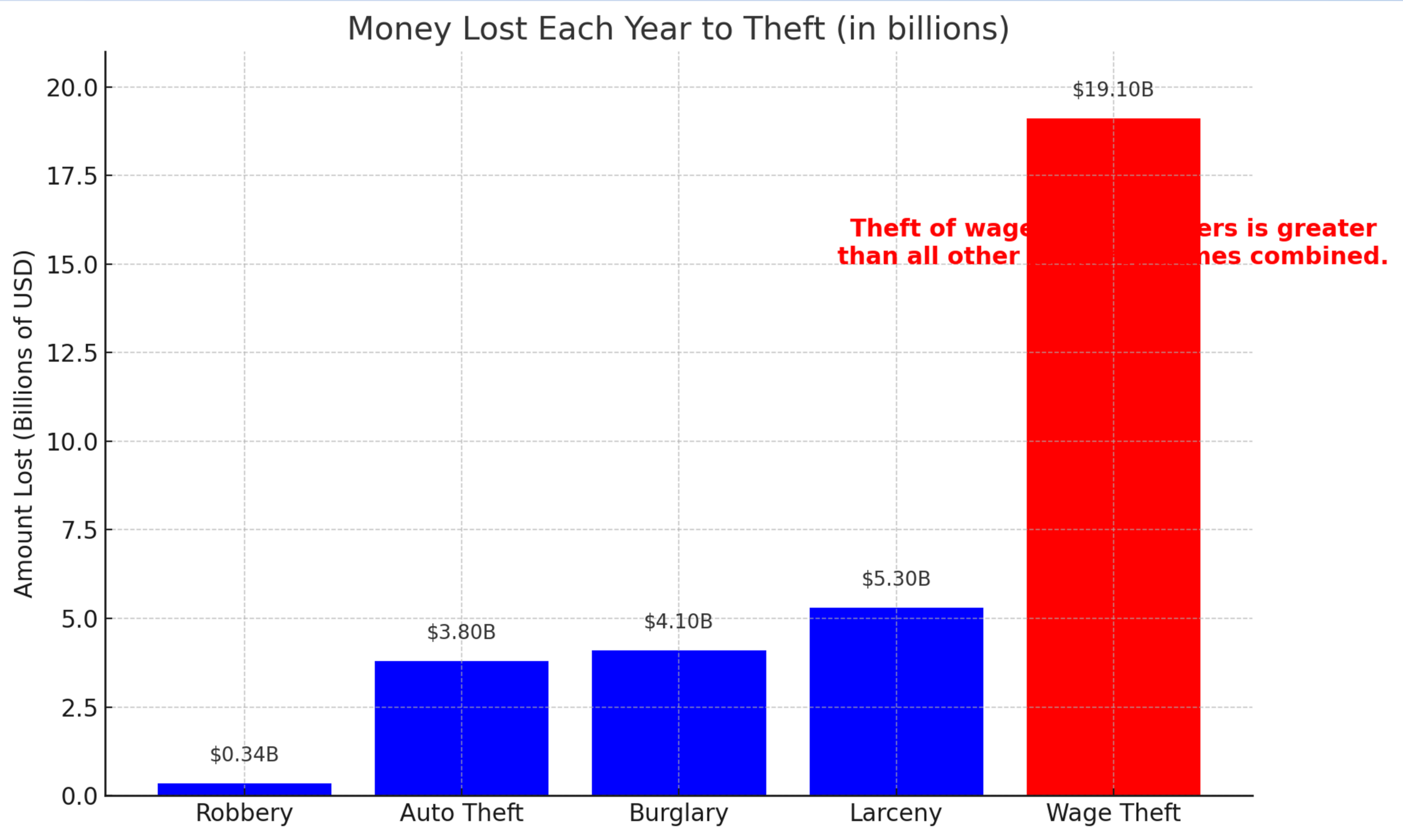
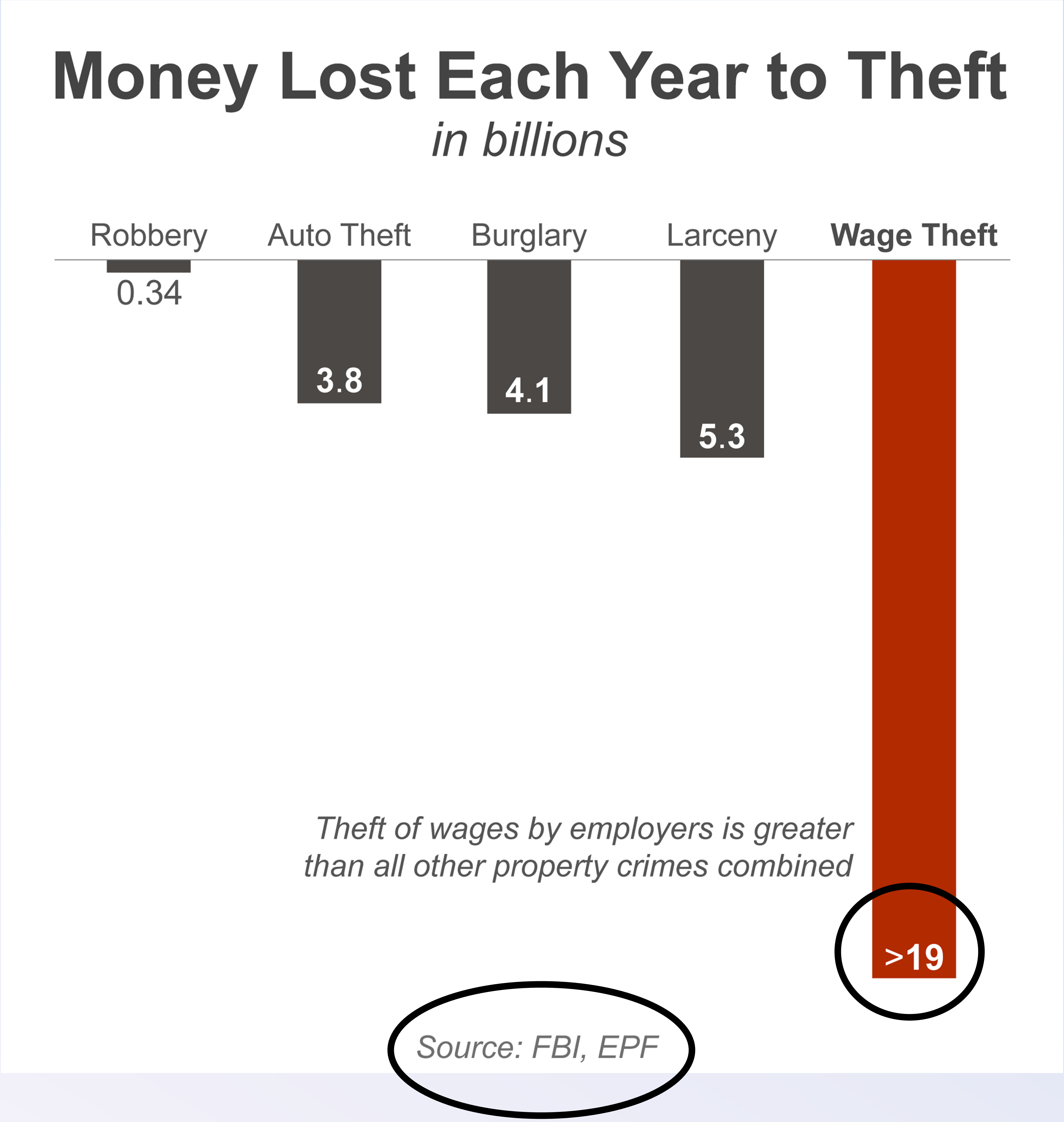


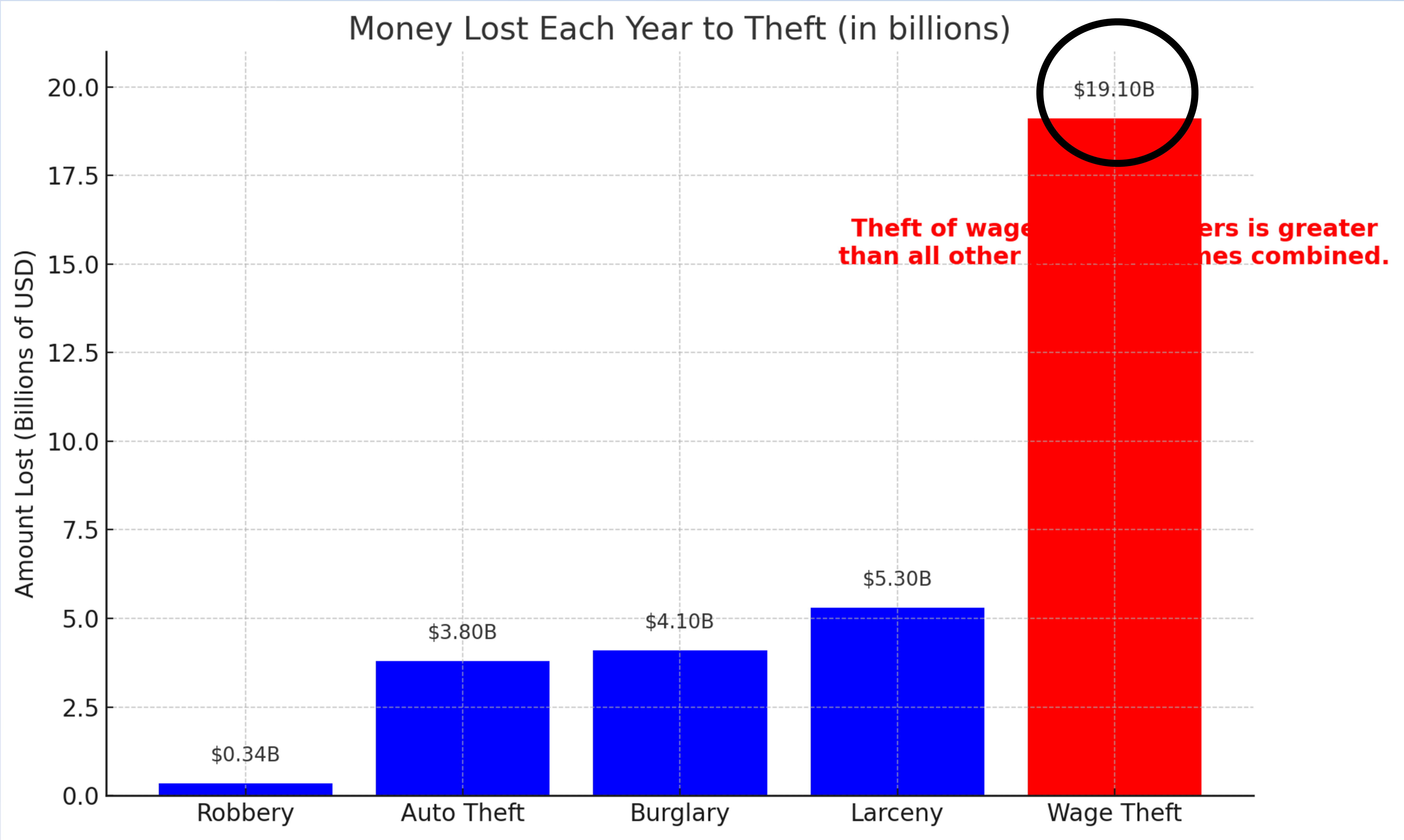
Another quick comparison





Once data is lost/manipulated, it persists





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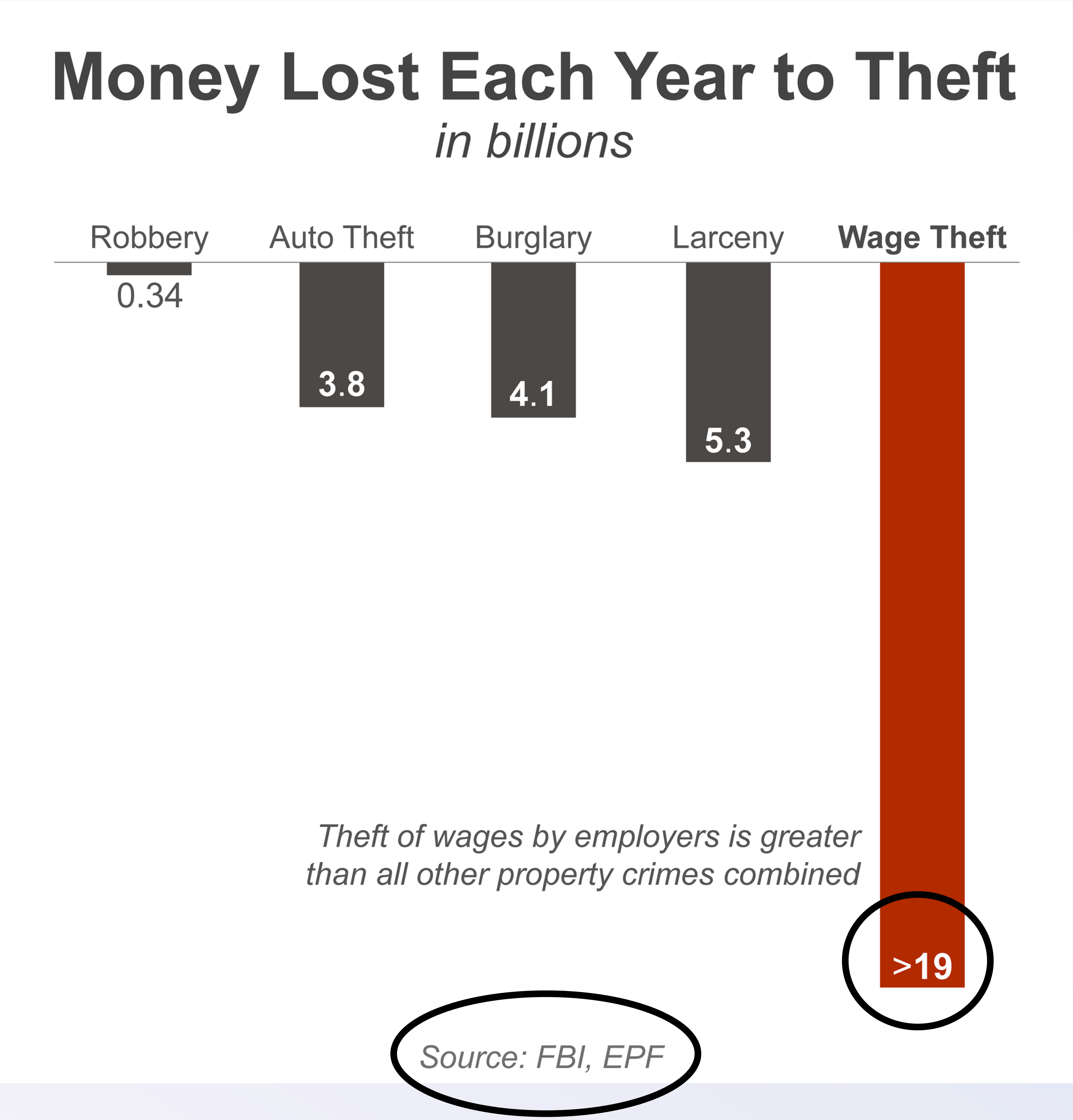
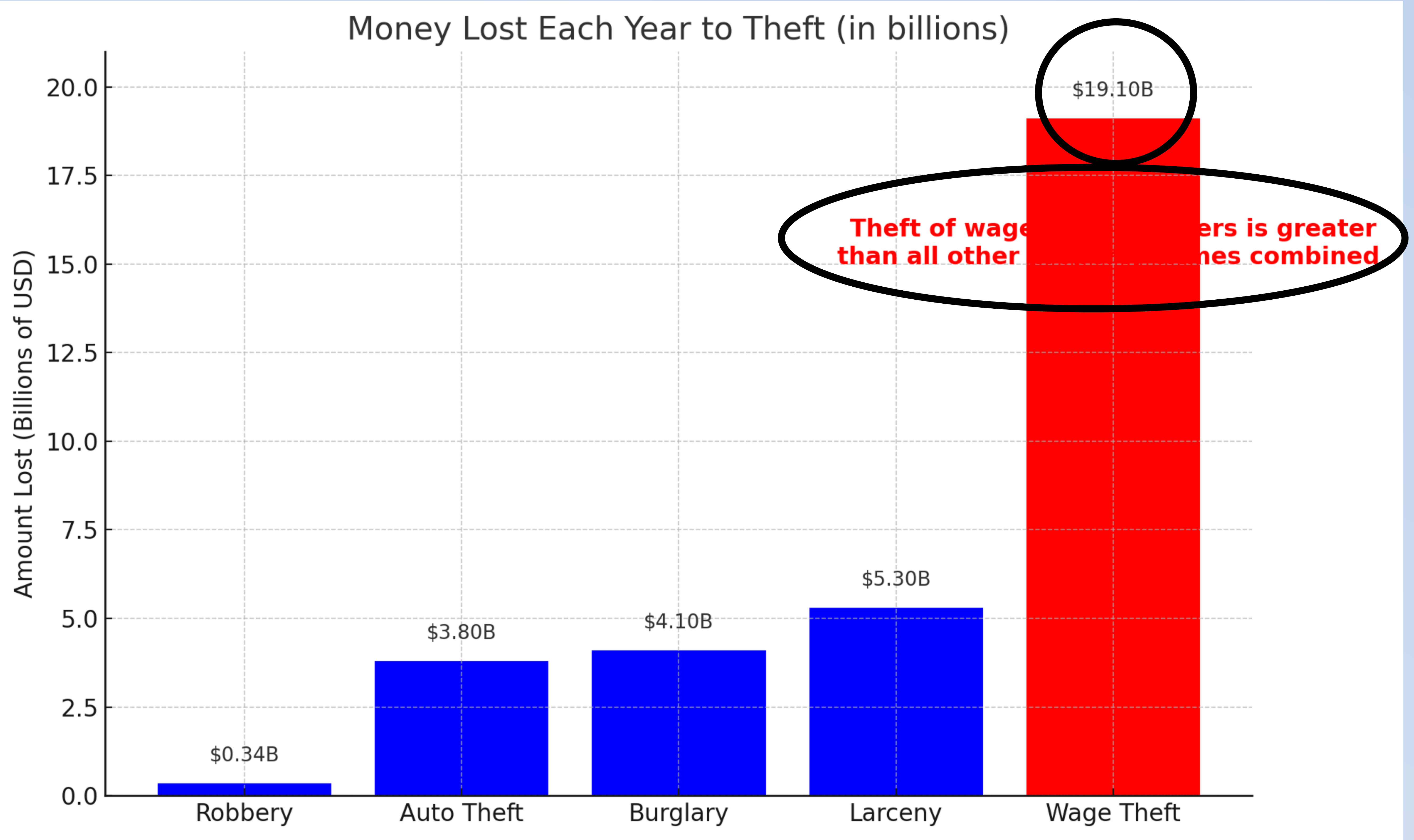
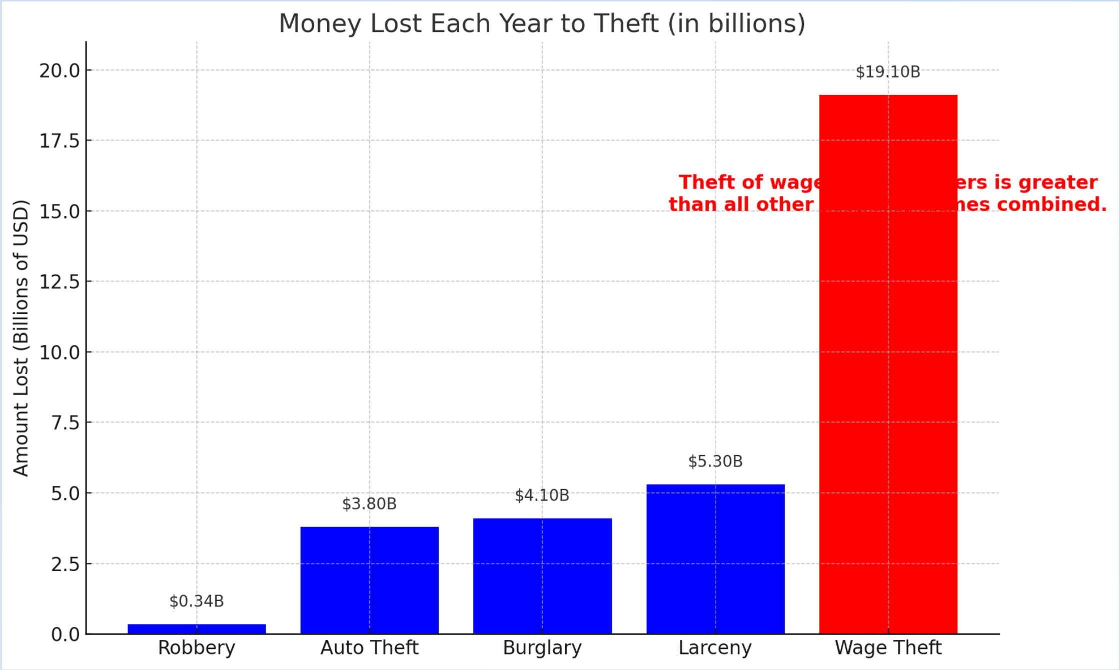




chatGPT (6th instance)



“Can you describe this?”

This bar chart titled ”Money Lost Each Year to Theft (in billions)” compares the estimated annual financial losses in the U.S. due to various types of theft. Here’s a breakdown of what it shows:

Categories & Amounts:

- Robbery: $0.34 billion
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- Larceny: $5.30 billion
- Wage Theft: $19.10 billion

Key Highlights:

The first four categories (Robbery, Auto Theft, Burglary, and Larceny) are represented in blue bars.

Wage Theft stands out in a red bar, signifying its significance and magnitude.

There is a bold red annotation stating:

”Theft of wages from workers is greater than all other forms of theft crimes combined.”

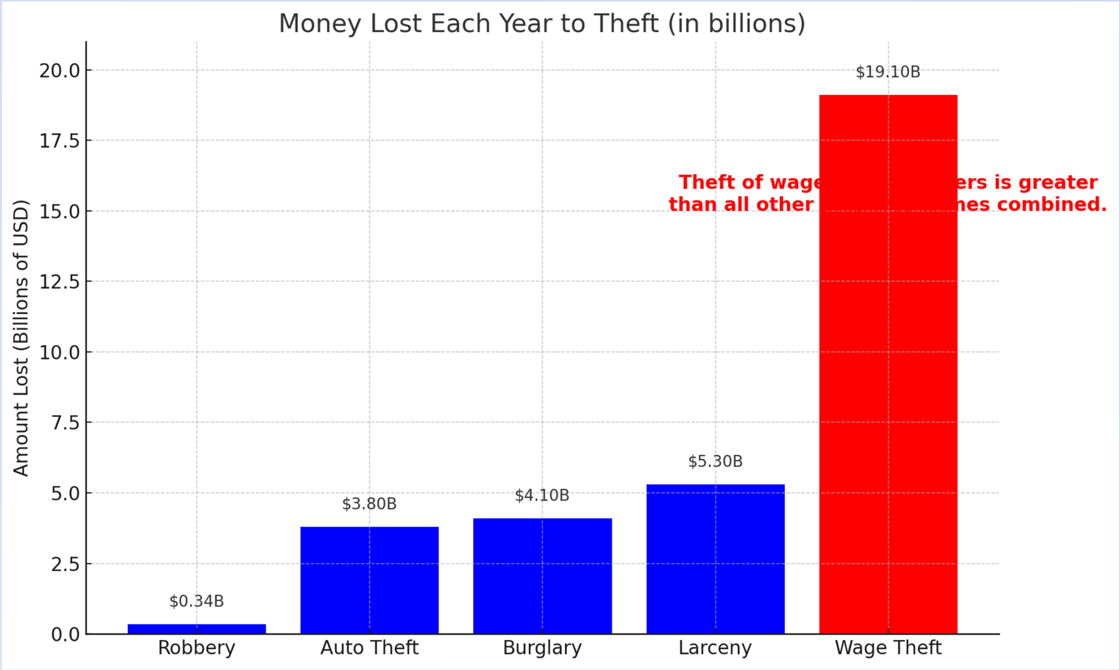
Insight:

Wage theft (employers illegally withholding earnings from workers) causes more financial loss than robbery, auto theft, burglary, and larceny combined.

This chart is making a strong point about how often-overlooked white-collar crime, like wage theft, has a far greater economic impact than more traditionally recognized forms of theft.

Let me know if you’d like help with analyzing or presenting this further.

chatGPT (6th instance)



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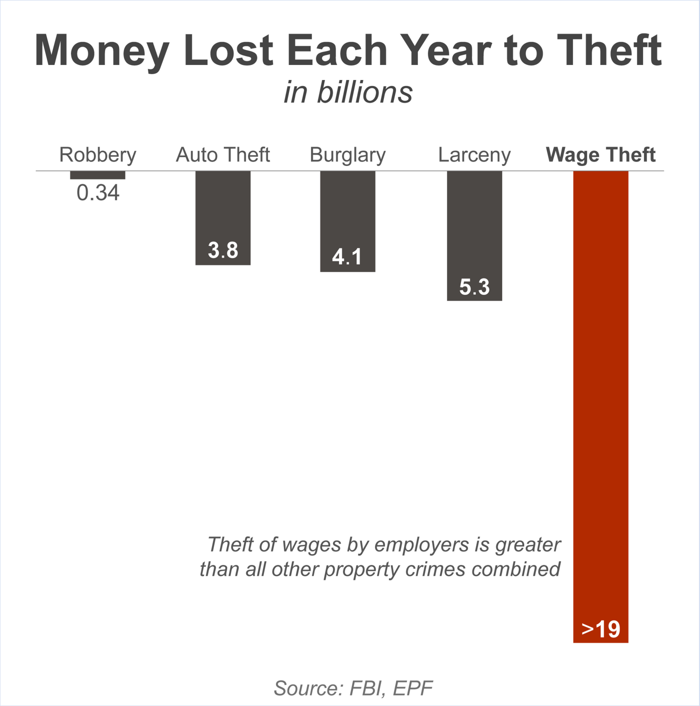


"This description does not accurately represent the original image. What is missing? Why did this happen?"

You're absolutely right to question that-thank you for pointing it out. What Was Missing from the Description:

1. Visual Layout Details:

• I didn't mention that all the bars are aligned to a horizontal baseline with bars extending downward (an inverted bar chart).

• I failed to describe that Wage Theft is the only bar in red, making it visually distinct and emphasizing its magnitude.

• I omitted the fact that the chart has exact dollar values inside the bars-this is key for quickly understanding scale.

2. Relative Comparison:

• While I stated that wage theft is greater than all other crimes combined, I didn't explicitly show that:

• All the other crimes together total approximately $13.54 billion (0.34 + 3.8 + 4.1 + 5.3),

• Wage theft alone is over $19 billion, clearly surpassing them collectively. That's a major takeaway supported visually but understated in the description.

3. Font Emphasis and Text Placement:

• I didn't describe that the subtitle "in billions" is italicized, or that the text under the chart reinforces the main message with a full-sentence callout in italics.

• The source ("FBI, EPF") is centered at the bottom in smaller italic font-this was only briefly mentioned, not described.

Why Did This Happen?

There are two main reasons:

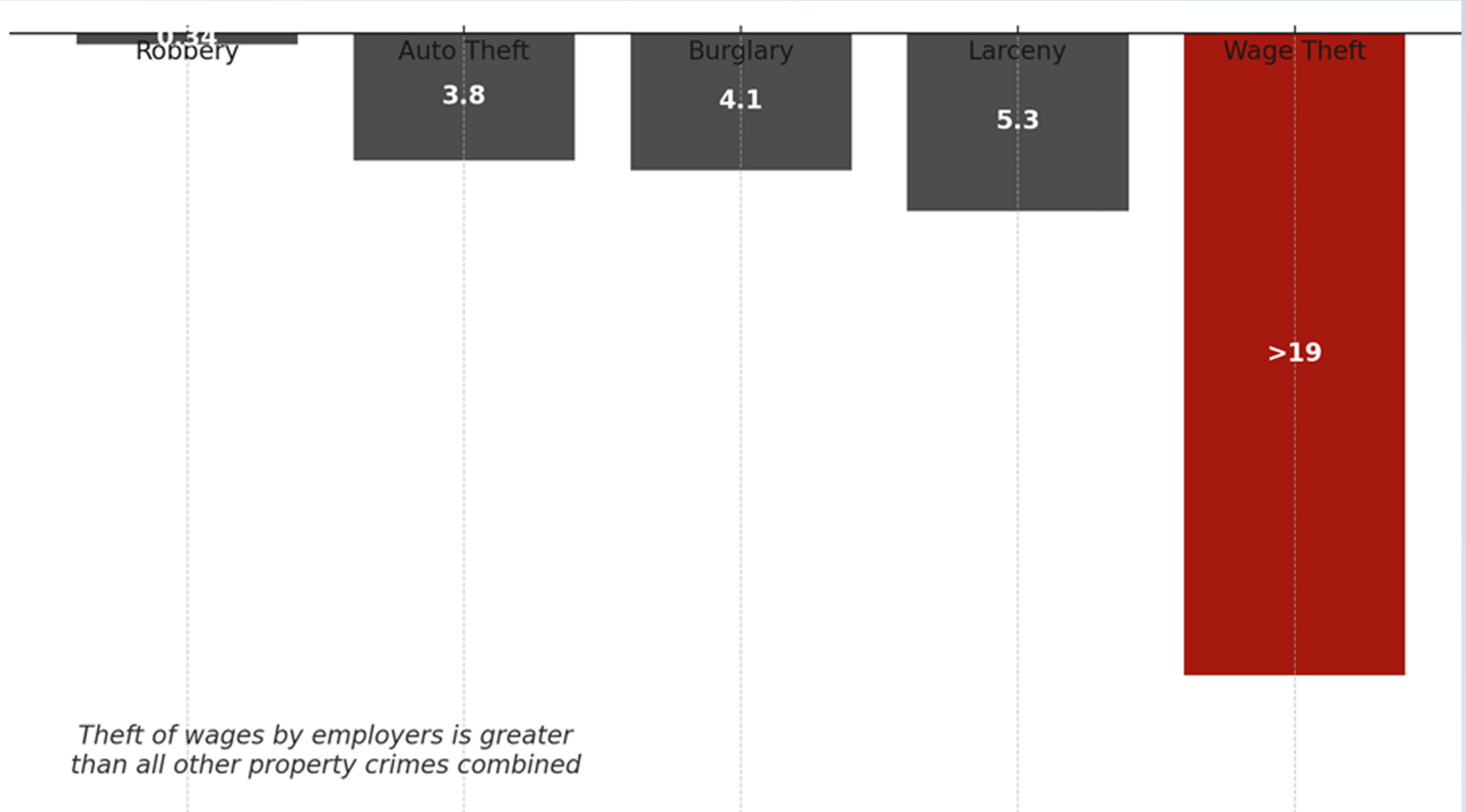
1. Under-description Bias: I focused on summarizing the data content, not the visual storytelling, which is a key part of understanding charts. The emotional/ visual impact (red bar, size difference, layout) was underrepresented.

2. Assumption of Intent Over Form: I prioritized what the chart was saying over how it said it. But in data visualization, how something is shown strongly affects what is conveyed.

Would you like a revised, more complete description of the image with all these visual and interpretive elements included?

chatGPT (6th instance)

Yes, Can you try to recreate the original, fixing our visualization using the original's design choices?



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Produce this as an **image description for a blind user** please and keep this critical information in mind, using non-visual terms

Bar chart comparing the annual U.S. financial losses from various types of theft. Robbery causes $0.34 billion in losses, auto theft $3.8 billion, burglary $4.1 billion, and larceny $5.3 billion. In contrast, wage theft by employers results in over $19 billion in losses annually-more than all other types combined. The chart emphasizes that wage theft is the largest and most financially damaging form of theft, according to data from the FBI and the Economic Policy Foundation (EPF).

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lol wat

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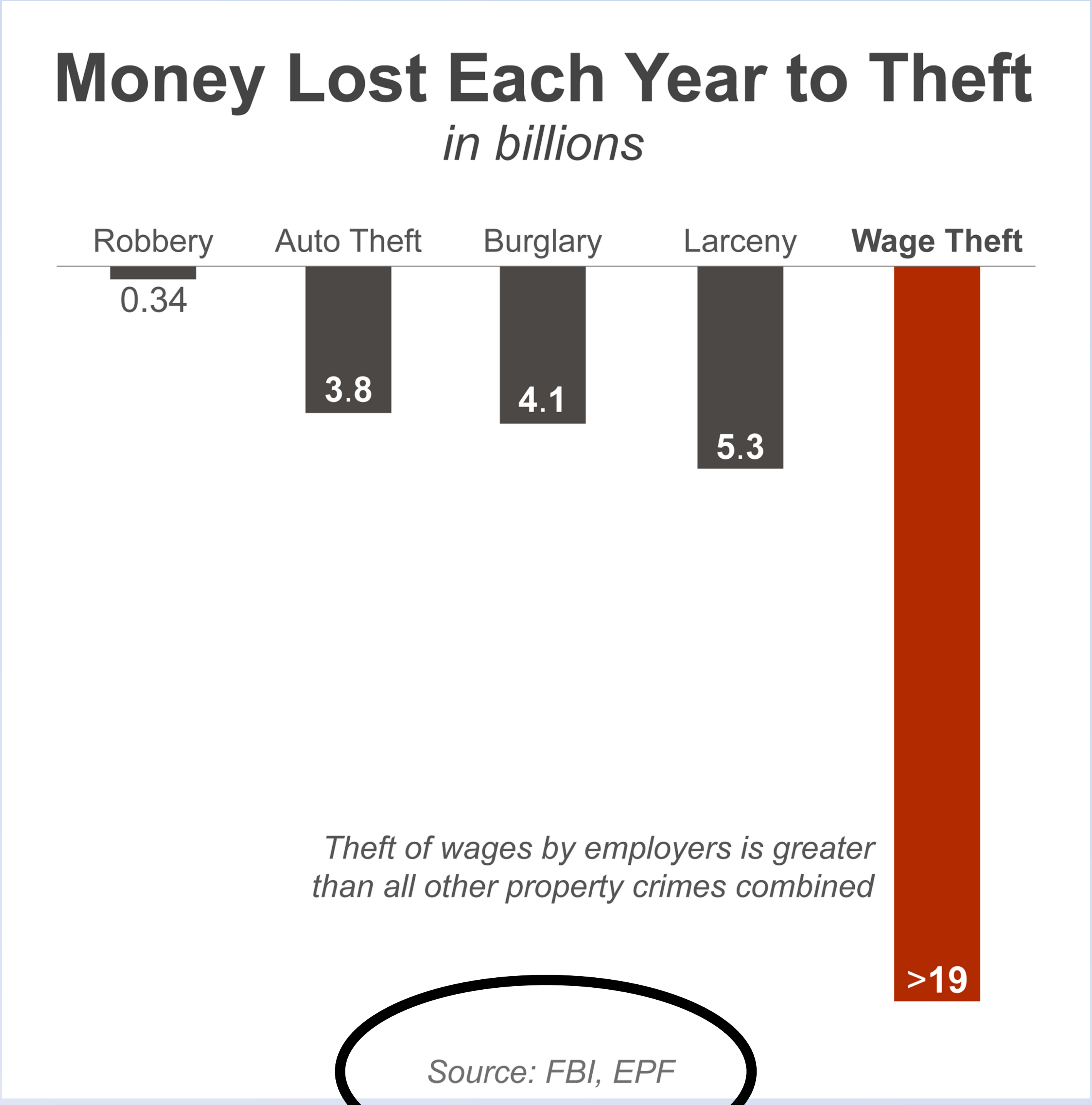
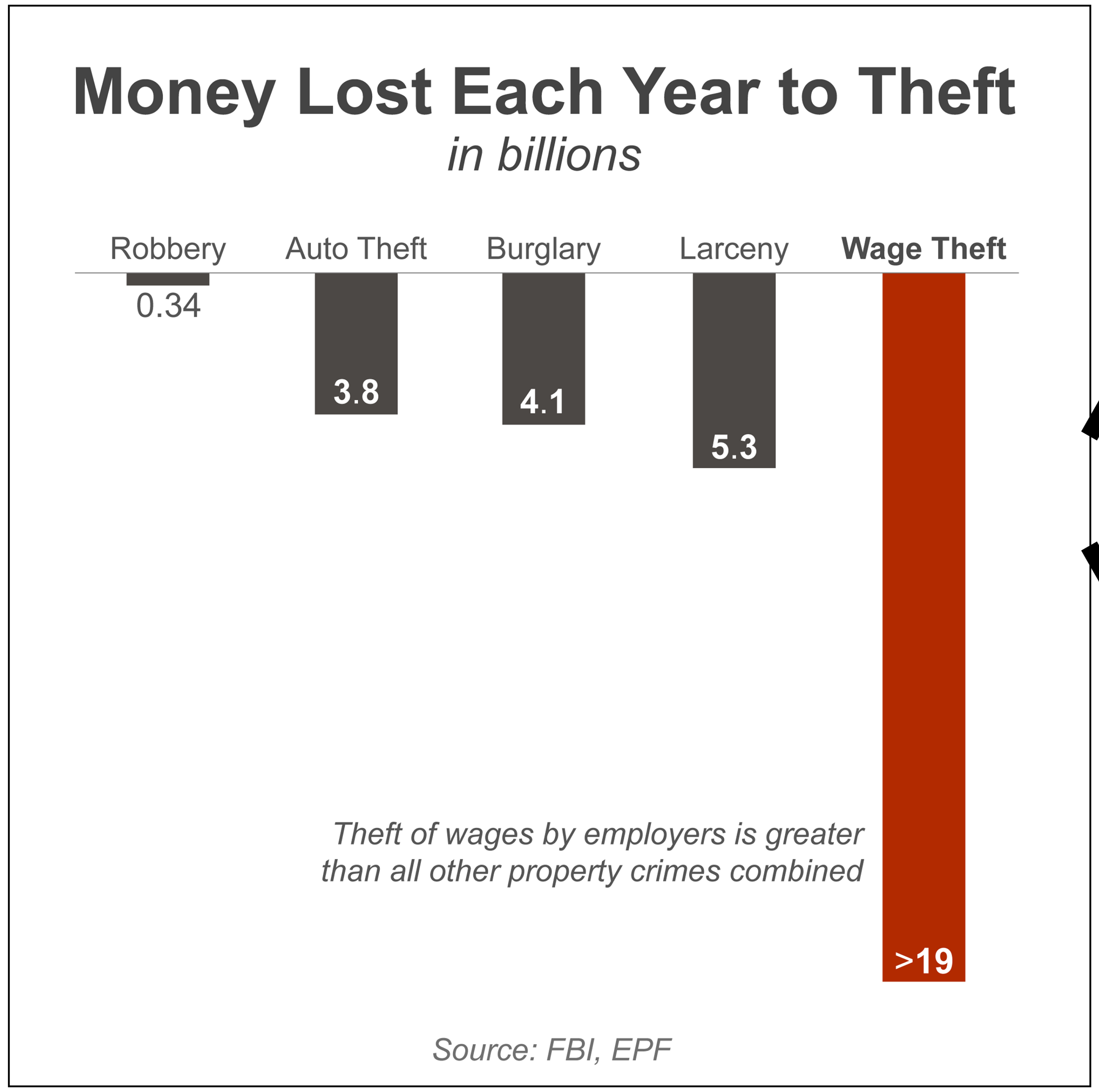
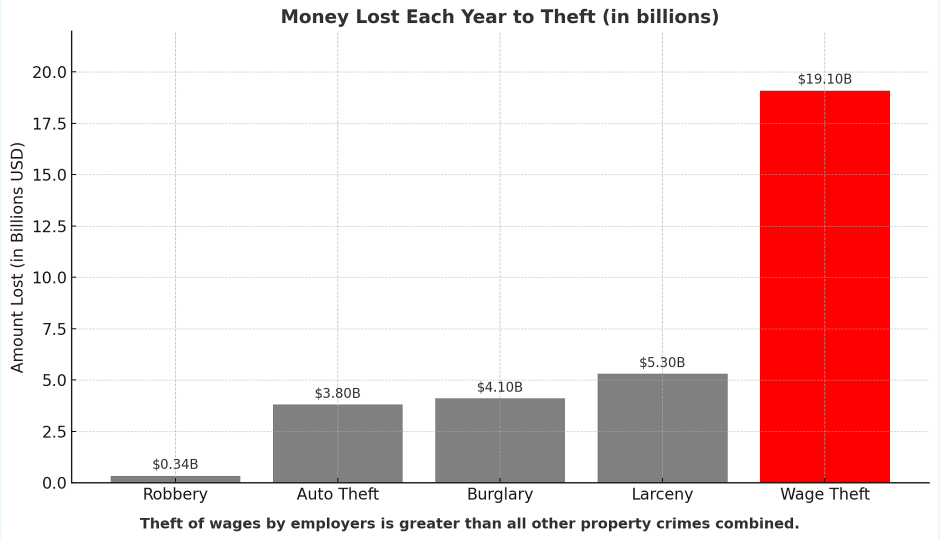


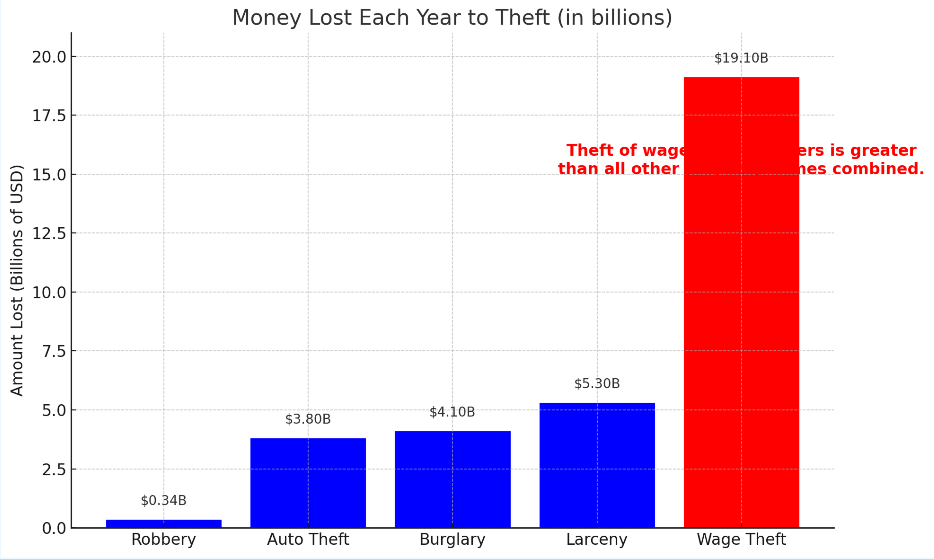
GPT-GPT, Claude-Claude, GPT-Claude, Claude-GPT

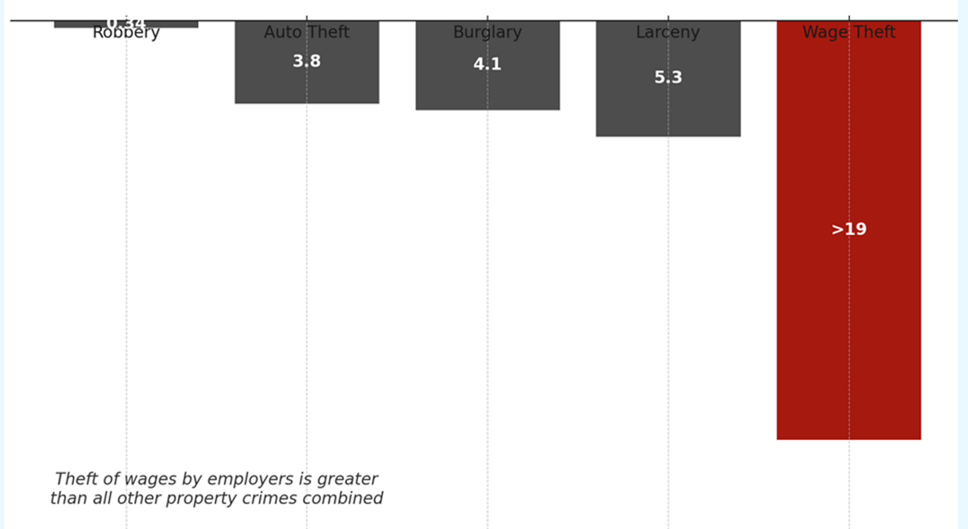
Source Image



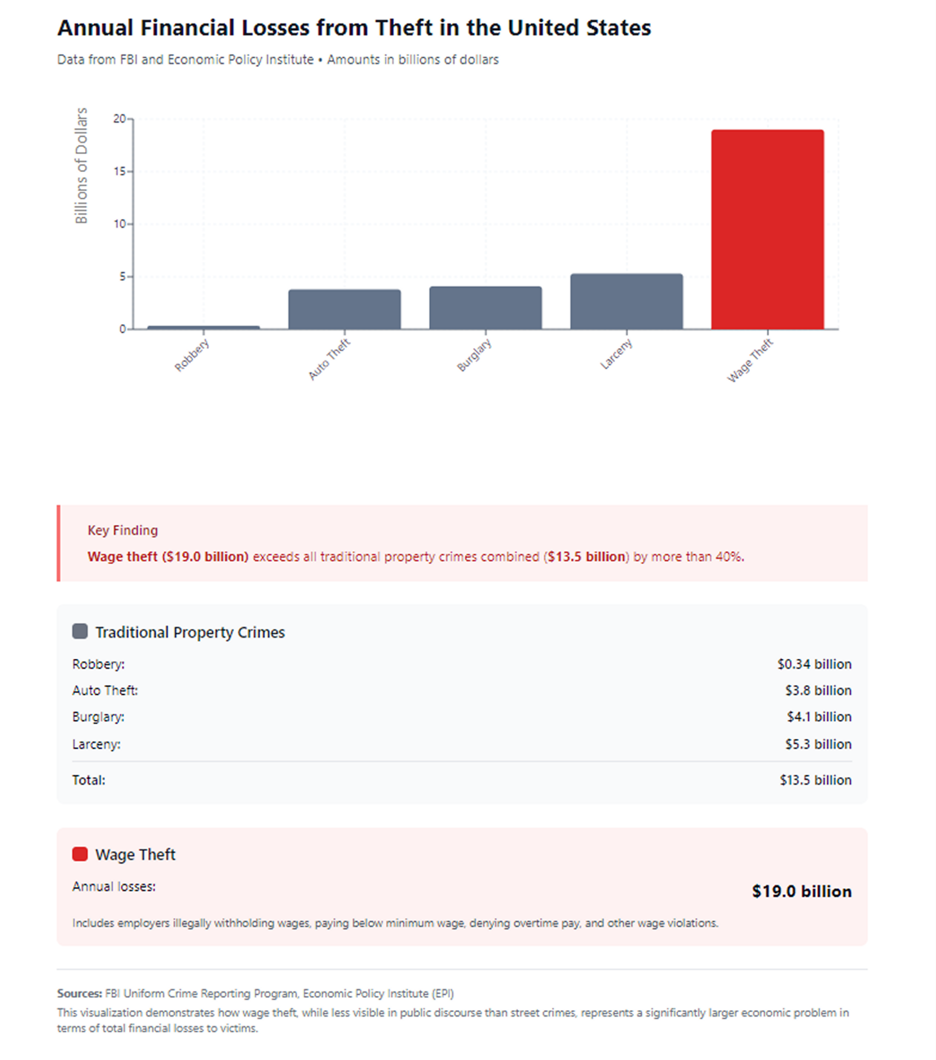
chatGPT to chatGPT

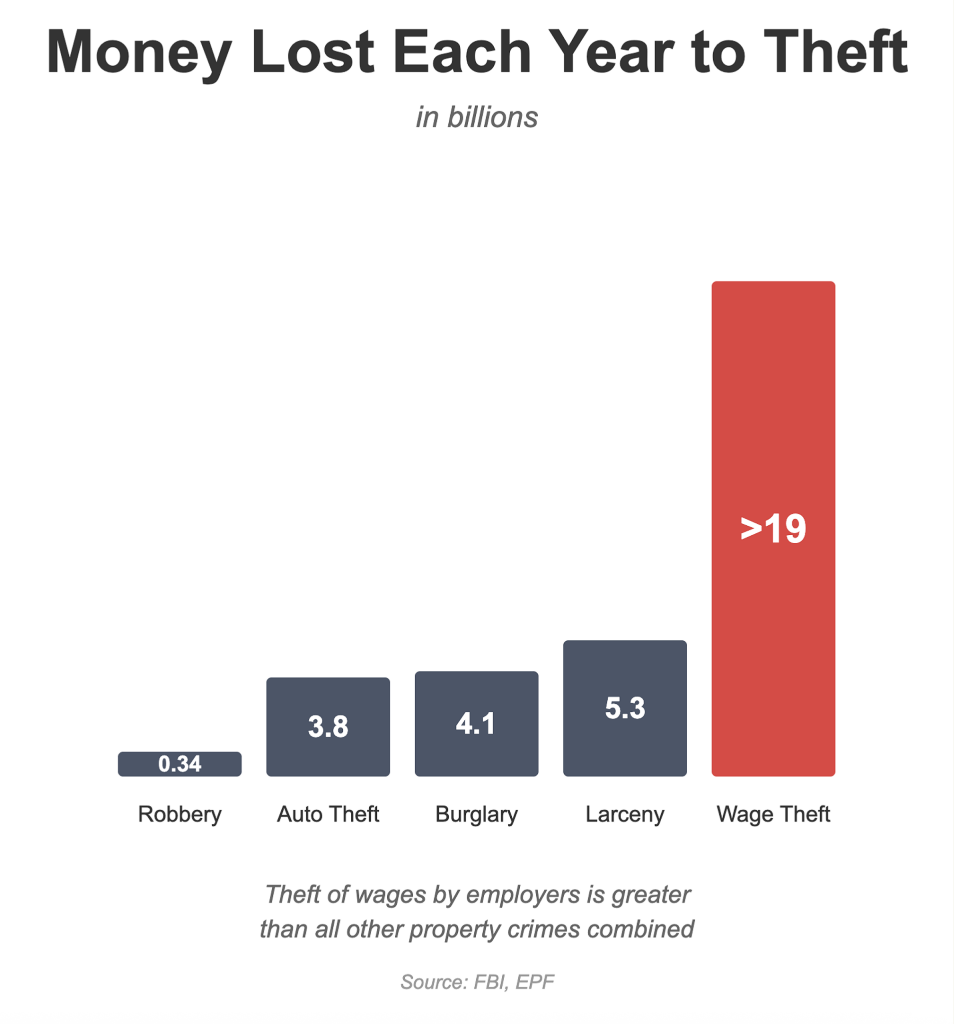






Claude to Claude





A few “observations” from this “experimentation”
(words used loosely here)

Observations

Information loss

Source: FBI, EPF

Observations

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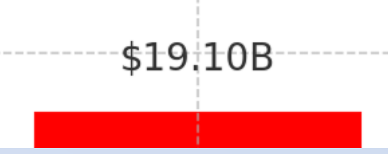
Information fabrication



“Economic Policy Foundation”

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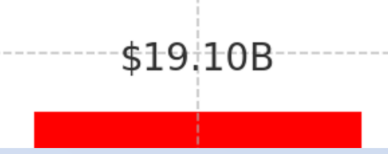

"Economic Policy Foundation"

Incorrect emphasis/interpretation

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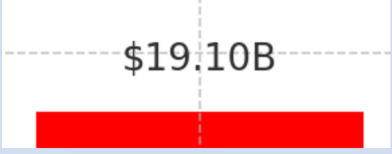

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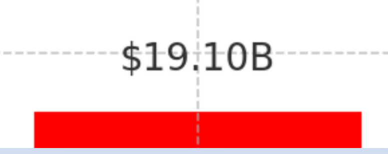

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Under-description

Mean of ~171 words for "describe this" versus mean ~80 words for "**describe this for someone blind**"

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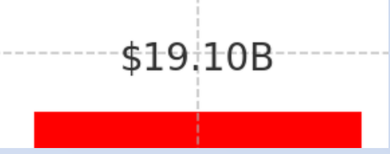

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Mean of ~171 words for "describe this" versus mean ~80 words for "**describe this for someone blind**"

Over-confidence

At no point did models acknowledge the precarity of the data and the uncertainty in the EPI's actual report. It stated the interpretation of the visualization as a fact.

A good workshop paper stimulates discussion:

[redacted]

Sep 30, 2025, 10:38 PM (24 days ago)

my thoughts? gut reaction? lmao not your best work. probably should have been a blog post.

you're right that there's not much at this specific intersection. but maybe address this head-on? like: "Yes, we know AI hallucinates. Yes, we know accessibility matters. But here's why the combination creates a novel problem space that existing work doesn't address." does that help? o think the work is solid and important - it just needs to position itself as "applying known problems to an underexamined context" rather than "discovering unknown problems." the contribution is the framing and the specificity, not the existence of ai bias itself.

My workshop paper’s conclusion: **accessibility matters + large-language models hallucinate**

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(this might not even make a good blog post 🪦)

[redacted] Aug 20th at 8:32 PM

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(I tell myself this so I can sleep at night)

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Not useful: results everyone knows Yeah, 50,000 papers every second are being written on all of this.

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(Designers, technologists, HAI researchers)

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(Visualization and/or accessibility researchers)

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(Scholars interested in critical/ethical systems)

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- **We *should* still find ways to help**: even if practitioners are “good guys” who don’t need to be reminded that LLMs are bad or PWD already know about dangers, assisting practitioners is the focus of our work anyway.

A *great* workshop paper stimulates new research ideas.

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So go now, and help engage this tricky problem space!

2025

Slides here → frank.computer

Playing telephone with generative models: “verification disability,” “compelled reliance,” and accessibility in data visualization

I’m on the job market!

Frank Elavsky, Cindy Xiong Bearfield

Human-Computer Interaction Institute

hcii.cmu.edu, axle-lab.com, dig.cmu.edu