

Smarter Regulation Through Behavioral Science

Moving human services licensing from **anecdote to science**

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Learning Objectives

1. Learn how and why how people respond to regulation.
2. Understand why more enforcement doesn't always improve safety
3. Learn a smarter way to focus oversight where risk is highest
4. Understand how better measurement leads to better public safety

By the end of this presentation, participants will be able to:

1. **Learn how and why people actually respond to regulation.**
2. **Understand why more enforcement doesn't always improve safety**
3. **Learn a smarter way to focus oversight where risk is highest**
4. **Understand how better measurement leads to better public safety**



Transition slide

Before we can really address the topic of bringing in the considerations of human behavior into the regulatory environment, we first need to understand a few key components.

Why Traditional Regulation Underperforms

The Linear Fallacy

The belief that compliance behaves like a volume knob—turn it up and quality always improves.”

Drives what is called Zero-tolerance enforcement and includes exhaustive inspections & administrative overload.

The Plateau Effect

Quality increases with compliance **only up to a point (98–99% compliance)**.

When systems push beyond the plateau, inspectors are incentivized to find something — anything — to justify the inspection.

Effective systemic risk management requires mapping cognitive biases onto regulatory frameworks

We begin with why traditional regulation repeatedly underperforms—not because regulators work too little, but because the underlying behavioral model is wrong.” Traditional systems assume a **linear relationship**: more rules and more enforcement automatically produce better outcomes.

The Linear Fallacy is the belief that compliance behaves like a volume knob—turn it up and quality always improves.” This assumption drives what is called Zero-tolerance enforcement. This includes:

- Exhaustive inspections
- Administrative overload

The critical flaw: it **ignores human behavior**, cognitive bias, and diminishing returns.

Compliance improves outcomes—up to a point. After that, the curve flattens.”

Research consistently shows: Peak outcomes at **98–99% compliance and there are No additional benefit** at 100% compliance

Over-compliance can actually:

- Reduce quality
- Increase false findings

- Waste limited regulatory resources

When systems push beyond the plateau, inspectors are incentivized to find something—anything—to justify the inspection.” This creates:

- Higher false positives
- Distrust between regulators and providers
- Data pollution that undermines policy decisions

Cognitive Bias

The problem isn't enforcement — it's enforcement without a behavioral model."



Modern regulatory science moves from ‘more rules’ to ‘the right rules.’” The field evolved by introducing: **Key Indicators & Risk Assessment methodologies.**

This shift recognizes that regulation must be grounded in:

- Behavioral science
- Organizational dynamics
- Empirical outcome measurement—not anecdote

The problem isn't enforcement—it's enforcement without a behavioral model.”

Effective systemic risk management requires **mapping cognitive bias onto regulatory frameworks**, not pretending humans behave like machines.

“Once we recognize that compliance does not respond linearly to enforcement, the next question becomes: **what actually drives human behavior under regulation?**

That answer comes from Prospect Theory.”

Prospect Theory



Loss Aversion

Citations, penalties, and threats to licensure are processed psychologically as losses, not feedback.



Certainty Effect

When expectations are clear and outcomes are reliable, providers become risk-averse and compliance-oriented.



Risk Seeking

What looks like reckless or unethical behavior is predictable psychological behavior under perceived certainty of loss.

“To understand why traditional regulation breaks down, we have to understand how people actually make decisions under pressure.”

Prospect Theory, developed by **Daniel Kahneman and Amos Tversky**, explains that human decision-making is not driven by objective risk or rational calculation. Instead, people evaluate choices **relative to a reference point**, and they react very differently to **losses** than to **gains**. This matters in regulation because **citations, penalties, and threats to licensure are processed psychologically as losses—not feedback**.

Loss Aversion

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Certainty Effect

“People vastly overvalue outcomes that are guaranteed.” Providers place a premium on Predictable inspections, consistent interpretations and, stable outcomes. A predictable regulatory system anchors behavior. When expectations are clear and outcomes are reliable, providers become **risk-averse and compliance-oriented**. This is why **certainty itself becomes a regulatory resource**—it stabilizes behavior more effectively than threat.

Risk-Seeking in Loss Domains

“When individuals face a ‘sure loss,’ they gamble.” This is the most dangerous insight of Prospect Theory for regulators. When providers believe License loss is inevitable, Enforcement is arbitrary or Inspections feel punitive rather than corrective they enter a **loss frame**. And in that frame, people become **risk-seeking**. In regulatory contexts, this can lead to:

- Record hiding
 - Misrepresentation
 - Cutting corners
 - Betting that violations won’t be detected
- What looks like reckless or unethical behavior is actually **predictable psychological behavior** under perceived certainty of loss.

“Prospect Theory explains why enforcement without certainty produces resistance—not compliance.”

Heavy penalties combined with unpredictable enforcement do not improve safety. They increase volatility.

Threat-based systems unintentionally push failing providers into **high-risk psychological states**, where gambling looks better than cooperation.

“Prospect Theory gives us the psychological engine behind compliance behavior.” It explains Why over-enforcement backfires, Why certainty stabilizes systems, Why risk-based monitoring works

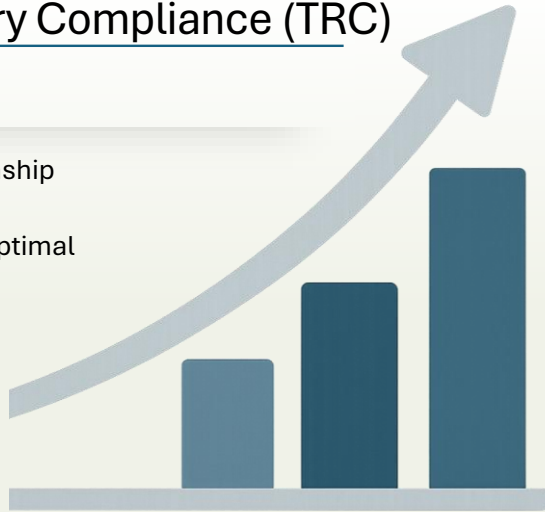
And most importantly, it tells us that **effective regulation is not about fear—it’s about managing reference points, loss perception, and certainty**.

“That insight becomes the foundation for the Theory of Regulatory Compliance.”

“Once we understand the psychology behind compliance, the next step is building a regulatory framework that optimizes it—that framework is TRC⁺.”

Theory of Regulatory Compliance (TRC)

- Compliance–quality relationship is curvilinear, not linear
- Substantial compliance is optimal
- Supports:
 - Differential monitoring
 - Targeted inspections
 - Risk-based oversight



“The Theory of Regulatory Compliance—TRC⁺—is where behavioral science becomes operational policy.” TRC⁺ starts with a key correction to traditional regulation: the relationship between compliance and quality is **not linear**—it is **curvilinear**. In other words, more compliance effort does not automatically produce better outcomes. Quality and safety improve as compliance rises, but **only up to a point**. Beyond that point, additional enforcement produces **diminishing—and sometimes negative—returns**.

The Core Insight

“Substantial compliance—not perfect compliance—is where public benefit is maximized.” The evidence shows that systems achieve their best outcomes when providers reach **high, stable levels of compliance**, not when they are pushed toward absolute perfection. Chasing the last fraction of a percent diverts resources away from actual risk and toward administrative excess. This is the principle TRC⁺ formalizes.

What TRC⁺ Changes in Practice

TRC⁺ supports a regulatory model that is:

- **Risk-based**, not one-size-fits-all

- **Targeted**, not exhaustive
- **Behaviorally aligned**, not threat-driven

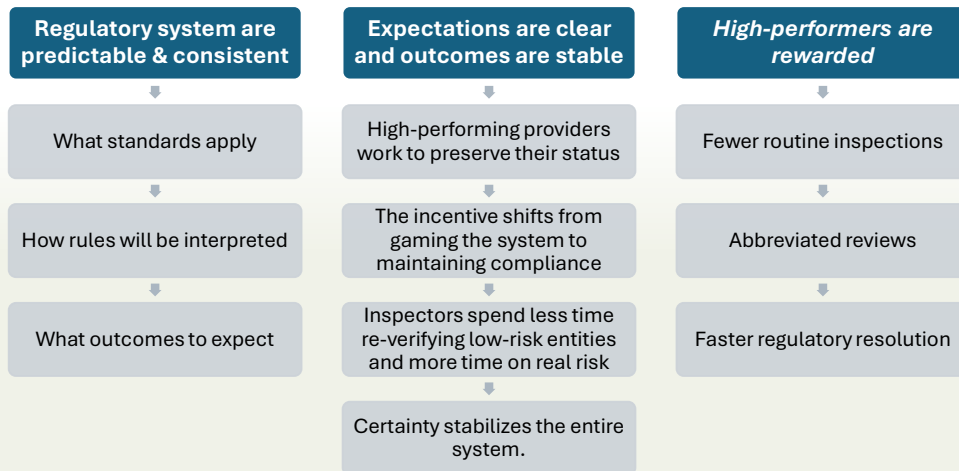
Under TRC⁺: High-performing providers receive **differential monitoring** and fewer unnecessary inspections, Regulatory attention is concentrated where risk is highest and, Enforcement resources are aligned with **actual safety outcomes**, not volume of citations

Why This Matters for Legislators

“TRC⁺ is not deregulation—it is smarter regulation.” It allows legislatures to: Improve public safety without expanding enforcement budgets, Reduce unnecessary regulatory burden while increasing detection of real risk and, Replaces anecdotal oversight with **measurable, evidence-based decision-making**. Most importantly, TRC⁺ ensures that regulatory systems **incentivize cooperation and stability**, rather than fear, resistance, or data distortion.

“If substantial compliance is the optimal target, the next question is how regulators create and sustain it—and that brings us to certainty as a regulatory resource.”

Certainty as a Regulatory Resource



“Once we accept that substantial compliance is the optimal target, the next question is how regulators sustain it over time.”

The answer is **certainty**. Providers value three things above almost everything else: **predictability, consistency, and stable outcomes**. These are not operational preferences—they are **behavioral drivers**.

“Regulatory certainty anchors compliance.” When a regulatory system is predictable and consistent, providers know:

- What standards apply
- How rules will be interpreted
- What outcomes to expect from inspections

That clarity reduces volatility in behavior. Providers are no longer guessing how inspectors will rule or whether compliance today will be punished tomorrow. As a result, they become more **risk-averse, more cooperative and, more inclined toward self-regulation**

“Certainty is not a concession—it is a regulatory tool.” In traditional systems, certainty is often treated as something to avoid, out of concern it will reduce vigilance. Behavioral science shows the opposite. When expectations are clear

and outcomes are stable:

- High-performing providers work to **preserve their status**
- The incentive shifts from gaming the system to maintaining compliance
- Inspectors spend less time re-verifying low-risk entities and more time on real risk
- Certainty stabilizes the entire system.

“High-performing providers should be rewarded with certainty.”

Under TRC⁺, certainty becomes a **earned condition**, not a blanket entitlement.

Providers who demonstrate sustained, high compliance can safely receive:

- Fewer routine inspections
- Abbreviated reviews
- Faster regulatory resolution

This is not leniency—it is **strategic allocation of oversight**.

“By rewarding performance with certainty, regulators reinforce compliance while freeing resources to focus on true risk.” Certainty allows the system to move from constant enforcement to **institutional stability**, without sacrificing public safety.

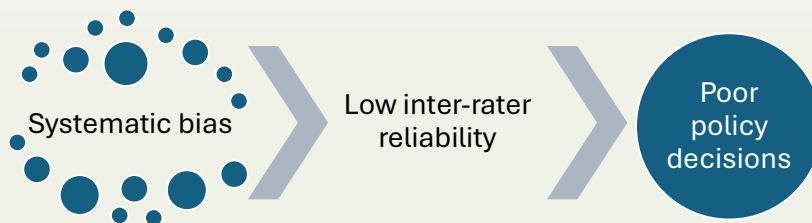
“The challenge, of course, is determining when certainty is deserved—and that requires better measurement.”

The Measurement Problem in Licensing

Binary Data Is the Core Limitation!

Binary systems:

- Collapse nuanced performance into a single outcome
- Treat minor administrative issues the same as serious safety risks
- Provide very little insight into *how certain* an inspector's decision is



“Up to this point, we’ve talked about psychology, incentives, and regulatory design. None of that works unless the system can actually measure compliance accurately.”

This slide describes **the measurement problem at the heart of human services licensing**.

Binary Data Is the Core Limitation. Licensing data is typically **binary**—a provider is either *in compliance* or *out of compliance*. That sounds simple, but it creates a serious problem.

Binary systems:

- Collapse nuanced performance into a single outcome
- Treat minor administrative issues the same as serious safety risks
- Provide very little insight into *how certain* an inspector's decision actually is

As a result, the data lacks **resolution**.

The truth is, **Inspector Reliability Is Low**. The evidence consistently shows that inspector decisions suffer from **Low inter-rater reliability and increased Systematic bias**.

In practical terms, that means two inspectors can review the same facility and reach different conclusions—not because the facility changed, but because **judgment varies**. This is not an individual failure. It is a **system design failure**.

“Garbage In, Garbage Out”

“When measurement is unreliable, policy inevitably follows bad data.” If the underlying inspection data are inconsistent or biased:

- Risk models are distorted
- Enforcement priorities are misplaced
- Legislatures receive misleading signals about system performance

This leads to Over-regulation where risk is low, Under-regulation where risk is high and, Poor policy decisions built on **noisy data rather than evidence**.

Why This Undermines Certainty

Remember from the previous slide: **certainty stabilizes compliance**. But certainty is impossible when Providers don’t know how inspections will be judged or Outcomes depend on which inspector shows up. “Compliance” today doesn’t predict results tomorrow and Unreliable measurement destroys predictability—and with it, cooperative behavior.

Key Takeaway for Policymakers

“You cannot manage risk you cannot measure reliably.” Without a better measurement framework:

- Certainty cannot be credibly earned
- Differential monitoring cannot be safely implemented
- Resources cannot be strategically allocated

“To fix the measurement problem, regulators need a way to distinguish true findings from error—and that requires a framework that explicitly accounts for certainty and uncertainty.”

That leads us directly to the Certainty Effect and the Uncertainty–Certainty Matrix.

Uncertainty-Certainty Matrix (UCM)

		Inspector Decision Regarding Compliance	
		(+) In Compliance	(-) Not in Compliance
Actual State of Compliance	(+) In Compliance	Agreement (True Positive) The decision is “in compliance” and the actual state is “in compliance”. This is a correct, certain outcome.	Disagreement (False Positive) The decision is “not in compliance” but the actual state is “in compliance”. An uncertainty to be minimized.
	(-) Not in Compliance	Disagreement (False Negative) The decision is “in compliance” but the actual state is “not in compliance”. The most dangerous uncertainty.	Agreement (True Negative) The decision is “not in compliance” and the actual state is “not in compliance”. This is also a correct, certain outcome.

*“To use certainty as a regulatory resource, it must be measured.” Here you can see the Uncertainty-Certainty Matrix. It’s a simple 2×2 diagnostic tool that compares The **inspector’s decision** to the provider’s **actual state of compliance**. There are only four possible results:*

- **True Positive** – Correctly identifying compliance
- **True Negative** – Correctly identifying non-compliance

These outcomes reinforce trust, predictability, and system stability.

- **False Positive** – Over-citation
- **False Negative** – Missed violations

In a perfect world, all results would fall in the agreement cells. False negatives are the most dangerous outcome—they represent **hidden risk** that the system believes has been resolved.

Why False Negatives Matter Most

“False negatives represent hidden, invisible risk.” When serious violations are

missed:

- Risk is buried, not resolved
- Clients are exposed to harm
- Injury and mortality events become more likely
- Legal and financial liability increases

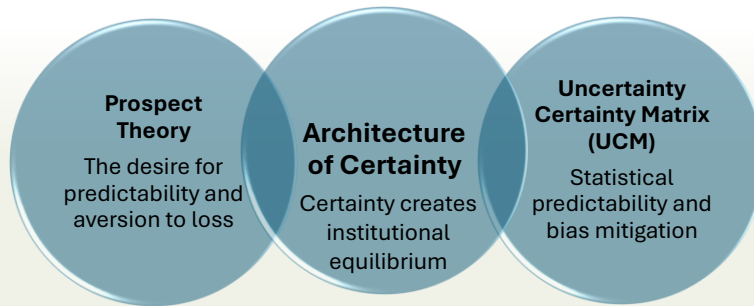
False negatives create **actuarial blind spots**—the system believes risk has been mitigated when it has not.

This is why professional regulatory frameworks adopt **zero-tolerance for false negatives**, particularly for high-risk rules. Not because regulators must be punitive—but because **missed risk is the most dangerous outcome the system can produce**.

“Once uncertainty is visible and measurable, we can finally understand why certainty—rather than threat—is what actually stabilizes regulated behavior.”

The Certainty Effect

Once a provider reaches a high-certainty state of compliance, the frequency of inspections can safely drop because the risk has already been mitigated.



“Humans inherently overvalue certain outcomes. We will pay a premium for a ‘sure thing’ over a probability.” This is known as the **Certainty Effect**, and it is one of the most robust findings in behavioral science. In regulation, this matters because **certainty—not fear—is what stabilizes behavior**.

“Certainty is the ultimate goal of a regulator—not punishment.” When a provider believes inspections are predictable; standards are applied consistently and, outcomes are stable over time they tend to perform better. They value the **sure thing of regulatory stability** more than the high-variance gamble of cutting corners. That psychological preference becomes a powerful incentive for compliance.

Under a predictable system, high-performing providers:

- Work to **preserve their status**
- Avoid behaviors that introduce uncertainty
- Choose compliance over gambling

Certainty creates what we call **institutional equilibrium**—a stable state where cooperation is rational, not forced. This is where the **Uncertainty–Certainty Matrix (UCM)** comes into play.

“To use certainty as a regulatory resource, it must be measured.”

Why This Matters for Policy

“Once a provider reaches a high-certainty state of compliance, the frequency of inspections can safely drop—because the risk has already been mitigated.” This is not assumption. It is measurement-based confidence.

The UCM allows regulators to:

- Distinguish true findings from error
- Identify where inspections add value
- Reduce unnecessary oversight without increasing risk

Key Takeaway

“Certainty is not subjective—it is measurable, and it can be managed.” When regulatory systems track certainty instead of just violations:

- High performers are stabilized
- Enforcement resources are focused where uncertainty—and risk—are highest
- Public safety improves without expanding enforcement budgets

“Understanding certainty is critical—but it becomes even more important when providers fall into the domain of losses.” That brings us to how risk preferences change when entities begin to fail.

Domain of Losses



“When a provider is failing, they enter a fundamentally different psychological state.” Prospect Theory shows that **risk preferences shift depending on whether people perceive themselves to either experience gain or loss**. Most of the time, people are risk-averse. But when outcomes are framed as a **certain loss**, behavior changes dramatically.

“Failure State”

When a provider believes that:

- License loss is likely or inevitable
- Enforcement feels arbitrary or punitive
- Recovery seems unlikely

They enter what Prospect Theory calls the **domain of losses**. In this state, **accepting the penalty feels like a sure loss**. *“In the Failure State, behavior shifts from risk-averse to risk-seeking.”* Prospect Theory predicts this shift precisely. When the loss feels certain, **following the rules no longer feels rational**.

Irrational Risks

“Prospect Theory predicts that to avoid a sure loss, people will take increasingly

irrational risks.”

In a regulatory context, that means behaviors such as:

- Falsifying records
- Hiding violations
- Cutting corners
- Gambling that violations won't be detected

This behavior often looks unethical or reckless—but it is actually **predictable human behavior** when enforcement creates certainty of loss without certainty of detection.

The Regulatory Gamble

For a failing provider, falsification becomes a **high-variance gamble**: If they comply and fail, the loss is certain - If they gamble, there is at least a small chance of avoiding the loss. From a psychological standpoint, the gamble feels preferable. This is exactly the behavior Prospect Theory predicts.

Why Threat Backfires *“Threat does not correct the Failure State—it intensifies it.”* Increasing penalties or pressure in this state does not restore compliance, nor does it increase cooperation or reduce risk. Unfortunately, it **increases the incentive to gamble**, because compliance offers no perceived upside.

Compliance Stabilization

“The solution is not harsher punishment—it is changing the probabilities.”

Effective response to the Failure State requires:

- **Increasing certainty of detection**, especially for high-risk rules. When the system distinguishes true findings from error, hidden risk cannot accumulate.
- Removing probabilistic enforcement. Concentrated inspection of high-risk indicators removes the option to “roll the dice” on being missed
- Eliminating the belief that gambling is the only remaining option. When violations are consistently detected, gambling no longer offers an advantage

“Failing providers do not respond to fear—they respond to certainty.” The regulatory goal in a Failure State is not leniency, and not escalation for its own sake—but **behavioral correction**.

By restoring certainty and removing the enforcement gamble, regulators:

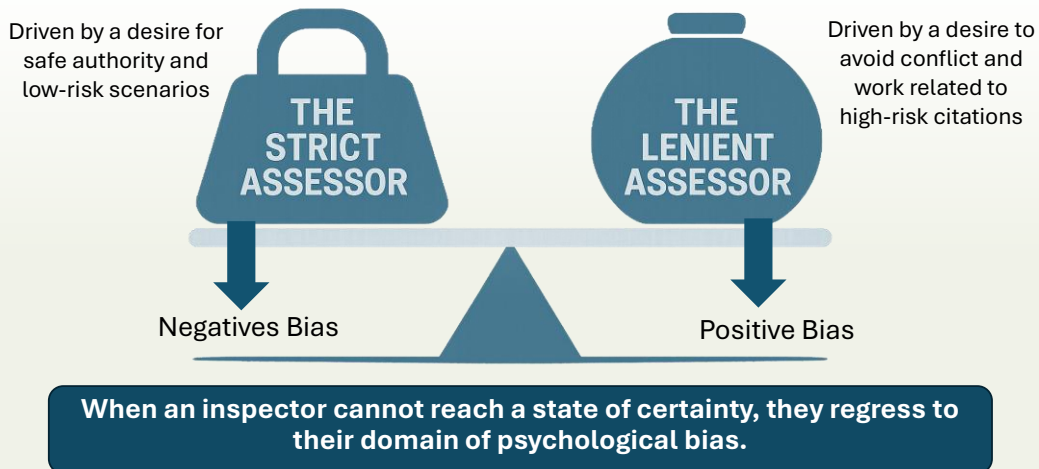
- Protect the public from hidden risk
- Reduce falsification incentives
- Re-stabilize provider behavior

“Once we understand how failure states distort behavior, the next step is identifying how measurement and inspection bias can unintentionally create

those conditions.”

That brings us to inspector bias patterns and how measurement systems shape outcomes.

Inspector Bias Patterns



“When measurement is unreliable, the problem doesn’t just create noise—it creates predictable patterns of error.” This slide shows how the **Uncertainty–Certainty Matrix** can be used to detect **systematic inspector bias**, not as a disciplinary tool, but as a **diagnostic instrument**.

Bias Is Not Random

In poorly designed measurement systems, inspection error is often treated as random variation. In reality, bias tends to show up as **consistent, directional skew**. On the matrix, this appears as a horizontal or vertical pattern—not a scatter. This tells us the issue is not individual bad actors—it is **system-induced behavior**.

Positive Bias (Over-Leniency)

A **positive bias pattern** occurs when an inspector consistently rules facilities as compliant regardless of their actual condition. This produces **False negatives**, Hidden, unresolved risk and, Client exposure to harm. From a policy standpoint, this is the most dangerous bias because the system believes risk has been mitigated when it has not.

Negative Bias (Over-Punitiveness)

A **negative bias pattern** occurs when an inspector consistently over-cites facilities, regardless of actual performance. This produces **False positives**, Inflated compliance failure rates, Erosion of provider trust and, Administrative overload and appeals. Over time, this bias undermines system credibility and drains enforcement resources away from real risk.

Why Bias Emerges

“Bias is often a rational response to a poorly aligned system.”

Inspectors operate under:

- Ambiguous standards
- Binary outcomes
- Pressure to justify inspections
- Fear of missing serious violations

Without a measurement framework that accounts for certainty and uncertainty, inspectors are pushed toward **defensive decision-making**, which manifests as bias.

Why This Matters for Policymakers

Inspector bias:

- Pollutes the data legislators rely on
- Distorts risk prioritization
- Undermines the credibility of regulatory systems
- Makes reform appear riskier than it actually is

In short, **policy gets built on distorted signals**.

The Value of the Matrix

“The Uncertainty–Certainty Matrix doesn’t punish inspectors—it protects the system.” It allows administrators to:

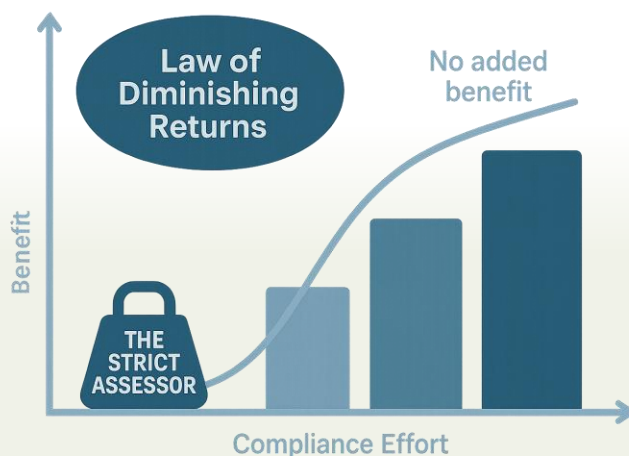
- Identify bias patterns early
- Distinguish training needs from system design flaws
- Improve reliability without increasing enforcement
- Restore confidence in licensing data

“You cannot fix regulatory performance problems without first fixing measurement.” Until bias and uncertainty are made visible, neither certainty nor risk-based oversight can function safely.

“Once bias and uncertainty are visible, the next step is understanding the economic principle that explains why enforcement intensity eventually stops paying off.”

That leads us to the Law of Diminishing Returns.

The Law of Diminishing Returns



“The Law of Diminishing Returns explains why enforcement intensity eventually stops paying off.” In regulatory systems, this law means that as **compliance effort and enforcement intensity increase beyond a certain point**, the **incremental benefit to quality or public safety shrinks—and can even turn negative**.

What the Law Means in Regulation

At low levels of compliance, increases in oversight produce large gains in safety and quality. But once providers reach **high levels of compliance**, each additional inspection, rule, or citation produces **smaller and smaller improvements**. Eventually, the system reaches a point where more inspections do not meaningfully reduce risk, more citations do not improve behavior AND more effort yields **less public benefit**. That is the point of diminishing returns.

Why Full Inspections of High Performers Don’t Pay Off

For high-performing facilities risk is already low where certainty is already high and behavior is already stable. Continuing to apply **comprehensive, resource-intensive inspections** in these settings is not an efficient use of regulatory capacity. Those resources would produce **greater public-safety**

returns if deployed where uncertainty and risk are highest.

The Policy Implication

“The Law of Diminishing Returns is the economic justification for differential monitoring.” It explains why: Treating all providers the same wastes enforcement resources, One-size-fits-all inspection models over-regulate low-risk entities and, high-risk providers receive less attention than they should. Differential monitoring is not leniency—it is **efficiency grounded in economics and behavior**.

Let’s connect this back **to TRC⁺ and Certainty**

Under TRC⁺:

- Substantial compliance is the optimal target
- Certainty stabilizes high performers
- Measurement identifies where inspections add value

The Law of Diminishing Returns tells us **when to step back** and when to **lean in**.

“Comprehensive inspections of high-performing facilities are not free—they carry opportunity costs.” Every hour spent re-inspecting low-risk providers is an hour **not spent detecting real risk elsewhere**. Smart regulation reallocates effort to where it produces the **greatest marginal benefit to public safety**.

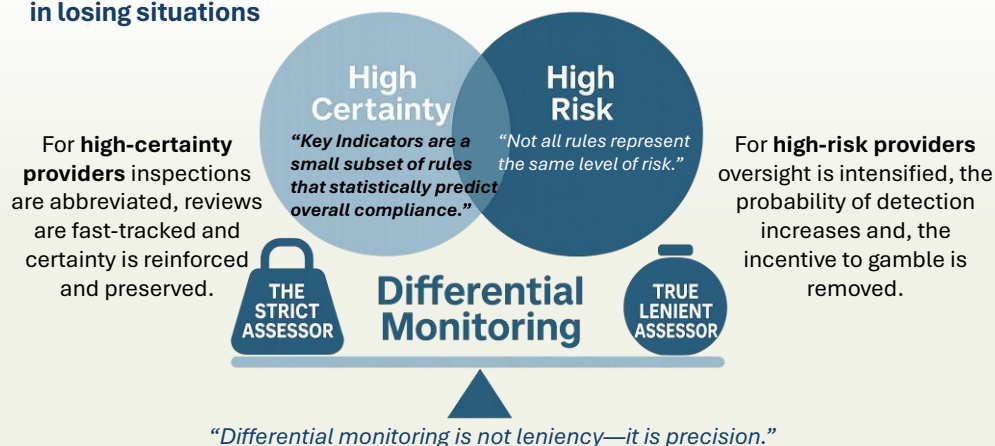


Transition Slide

When we combine behavioral science, measurement, and the Law of Diminishing Returns, the case for risk-based, differential monitoring becomes unavoidable.”

Differential Monitoring & Risk-Based Oversight

Risk-based monitoring mathematically counteracts the human instinct to gamble in losing situations



"Risk-based monitoring mathematically counteracts the human instinct to gamble in losing situations." This slide shows how the behavioral insights from Prospect Theory and TRC⁺ are translated into an **operational regulatory strategy** called **differential monitoring**.

What Differential Monitoring Is

"Differential monitoring replaces one-size-fits-all inspections with targeted oversight based on risk." Instead of treating every provider the same, this approach adjusts regulatory intensity based on:

- A provider's compliance history
- Measured certainty of compliance
- The actual risk associated with specific rules

This allows regulators to **focus resources where they produce the greatest public-safety return**.

Two Core Tools: Key Indicators and Risk Assessment

Key Indicator (KI) Methodology

"Key Indicators are a small subset of rules that statistically predict overall

compliance.” Rather than reviewing hundreds of regulations every visit, inspectors focus on a **validated set of predictive rules**. These indicators are identified using statistical testing—specifically the **Fiene Coefficient**, which measures how strongly individual rules predict overall compliance. The result include shorter inspections, higher accuracy, reduced burden on high-performing providers and, better detection of real risk

Risk Assessment and Rule Weighting

“Not all rules represent the same level of risk.” Under differential monitoring, rules are **risk-weighted**, for example:

Low risk (1) – administrative or paperwork requirements

Medium risk (4) – rules that predict broader compliance failure

High risk (8) – direct safety or mortality risks

High-risk rules are reviewed **every visit**, regardless of a provider’s status. This eliminates the possibility of gambling on undiscovered critical violations.

How Differential Monitoring Changes Behavior

For **high-certainty providers** inspections are abbreviated, reviews are fast-tracked and certainty is reinforced and preserved.

For **high-risk providers** oversight is intensified, the probability of detection increases and, the incentive to gamble is removed.

“This is how risk-based monitoring counteracts risk-seeking behavior in loss situations.”

“Differential monitoring is not leniency—it is precision.” It:

- Concentrates enforcement where harm is most likely
- Reduces unnecessary administrative burden
- Improves data quality and risk visibility
- Stabilizes both provider behavior and regulatory systems

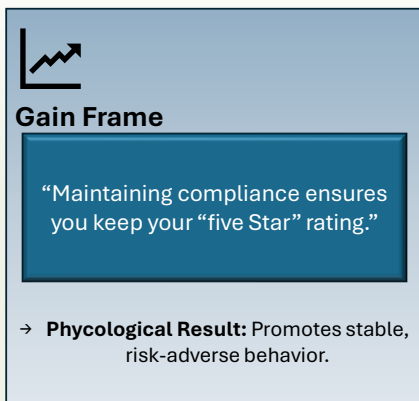
Most importantly, it **aligns regulatory design with actual human behavior**, which is what TRC⁺ demands.

“Differential monitoring operationalizes behavioral science.” It removes the enforcement gamble, protects the public from hidden risk, and ensures oversight resources are used where they matter most.

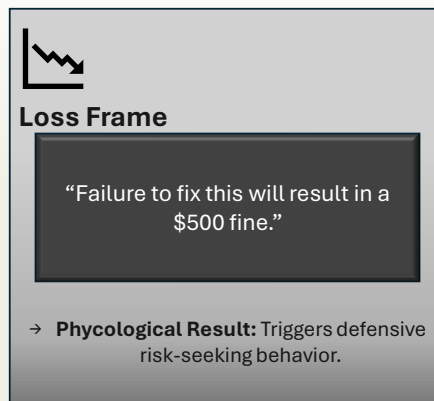
“Once oversight is risk-based, the final question becomes how enforcement is framed—and framing turns out to matter just as much as frequency.” That leads us to *behavioral framing in enforcement*.

Behavioral Framing in Enforcement

The same regulatory action can produce very different behavior depending on how it is framed. Under Prospect Theory, framing determines whether providers remain **risk-averse and cooperative** or shift into **risk-seeking behavior**.



The diagram for the Gain Frame is set against a light blue background. It features a small icon of a line graph with an upward arrow in the top left corner. Below the icon, the text "Gain Frame" is displayed. A dark blue rectangular box contains the message: "Maintaining compliance ensures you keep your 'five Star' rating." At the bottom, an arrow points to the text: "Psychological Result: Promotes stable, risk-averse behavior."



The diagram for the Loss Frame is set against a light gray background. It features a small icon of a line graph with a downward arrow in the top left corner. Below the icon, the text "Loss Frame" is displayed. A dark gray rectangular box contains the message: "Failure to fix this will result in a \$500 fine." At the bottom, an arrow points to the text: "Psychological Result: Triggers defensive risk-seeking behavior."

"Once oversight is risk-based, the final question is how enforcement is framed—because framing determines whether compliance is stable or fragile." Behavioral science shows that **the same regulatory action can produce very different behavior depending on how it is framed**. Under Prospect Theory, framing determines whether providers remain **risk-averse and cooperative**, or shift into **risk-seeking behavior**.

Gain Framing

"Maintain your high status." Gain framing emphasizes **preservation** rather than punishment. When enforcement is framed around maintaining:

- A high compliance status
- Reduced inspection frequency
- Regulatory certainty

Providers behave differently. They work to **protect what they already have**. This framing encourages cooperation, reinforces self-regulation and, promotes long-term compliance stability. Gain framing keeps providers **out of the loss domain**, where risk-seeking behavior is triggered.

Loss Framing

“Avoid penalties.” Loss framing emphasizes punishment and threat. When enforcement focuses primarily on penalties, citations or the risk of license loss. It can unintentionally push providers into a **loss frame**—especially marginal or struggling entities. As we saw earlier, once providers perceive loss as likely or inevitable:

- Risk-seeking increases
- Falsification becomes more likely
- Cooperation breaks down

Loss framing can **destabilize compliance**, even when enforcement intensity increases.

Why Framing Determines Compliance Stability

“Framing determines whether compliance is preserved—or gambled away.” Gain framing supports certainty, anchors behavior and, reinforces high performance. Loss framing increases volatility, encourages defensive behavior and, can trigger the regulatory gamble. This is why **how enforcement is communicated matters as much as the rules themselves.**

“Effective regulation does not rely on fear—it relies on behavioral alignment.” When enforcement is risk-based, certainty-driven and, gain-framed for high performers regulatory systems achieve **higher compliance, better data, and greater public safety**, without expanding enforcement budgets.

“The greatest risk emerges when providers cross into a perceived failure state—and that requires a different regulatory response altogether.”
This leads directly to the concept of the ‘Failure State’ and how regulators should respond.

Risk Mitigation, Liability & the Behavioral Engine

Prospect Theory is essentially the engine that makes Fiene's risk-based monitoring necessary

- Aligns regulation with behavioral science
- Improves safety without expanding enforcement
- Produces more reliable data
- Reduces preventable harm and liability



“While Fiene does not always explicitly cite Kahneman and Tversky, the logic of Prospect Theory is the engine that makes risk-based monitoring necessary.”

What you see on this slide is the **closing logic of the entire framework**. The statistical tools developed by **Fiene**—risk-based monitoring, Key Indicators, and inspection reduction factors—work **not by chance**, but because they align regulation with **how human behavior actually responds to risk, loss, and certainty**.

Prospect Theory as the Behavioral Engine

Prospect Theory explains:

- Why providers value certainty
- Why over-enforcement creates resistance
- Why failing entities gamble
- Why predictable systems stabilize behavior

Fiene’s models operationalize those insights. In other words, **Prospect Theory explains the behavior**, and **risk-based monitoring neutralizes the risk that behavior creates**.

Risk Mitigation Through Error Reduction

From a policy and liability standpoint, the most important issue is **error**. **False Negatives:**

- Create actuarial blind spots
- Leave serious risk unresolved
- Increase injury and mortality claims
- Destabilize insurance and liability markets

False negatives are where the greatest harm—and the greatest downstream cost—occurs.

The Cost of False Positives

False Positives are not harmless either. They:

- Inflate failure rates
- Increase appeals and administrative burden
- Drain provider resources away from care
- Reduce system credibility

Over time, excessive false positives degrade compliance culture and produce political and legal friction.

Why Risk-Based Monitoring Stabilizes Both

“Effective regulation must manage both kinds of error simultaneously.”

Inspection Reduction Factors and risk-based monitoring do exactly that:

- They **reduce false negatives** by concentrating attention on high-risk rules
- They **reduce false positives** by limiting unnecessary inspection of high-certainty providers

This stabilizes:

- Provider behavior
- Regulatory systems
- Liability exposure
- Insurance and risk pools

Final Policy Takeaway

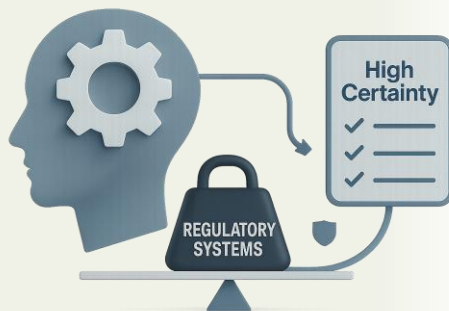
“Risk-based monitoring is not simply an inspection strategy—it is a risk-mitigation strategy.” It:

- Aligns regulation with behavioral science
- Improves safety without expanding enforcement
- Produces more reliable data
- Reduces preventable harm and liability

Most importantly, it ensures that **public safety outcomes improve while regulatory systems become more stable, predictable, and defensible.**

Summary

Smarter regulation aligns oversight with how people actually behave.



Key Takeaways

1. Compliance does not respond linearly to enforcement
2. Human behavior under regulation is driven by loss, risk, and certainty
3. Over-enforcement increases error, instability, and hidden risk
4. Certainty, not threat, stabilizes compliance behavior
5. Risk-based, differential monitoring reduces harm and liability

“In closing, this presentation makes one core point: regulatory systems fail not because enforcement is weak, but because they are built on the wrong behavioral assumptions.”

First, we showed that compliance does not behave like a volume knob. Beyond a certain point, increasing enforcement produces diminishing—and sometimes negative—returns. That’s not theory; it’s an observable system effect.

Second, behavioral science explains why. Under Prospect Theory, regulated entities respond to loss, risk, and certainty—not simply to rules or punishment. When enforcement feels unpredictable or punitive, entities gamble rather than comply.

Third, we showed why measurement matters. Binary inspection systems hide uncertainty, amplify assessor bias, and create false confidence. When regulators can’t distinguish true findings from error, risk becomes invisible.

Fourth, certainty emerges as a regulatory resource. Predictable rules, consistent interpretation, and reliable outcomes stabilize behavior far more effectively than

threat.

Finally, risk-based, differential monitoring operationalizes all of this. It concentrates attention where risk is highest, reduces false negatives that drive liability, and avoids wasting resources on over-inspection of high-performers.

“The result is not deregulation. It is smarter regulation—better data, better behavior, better safety, and lower liability.”

“With that framework in mind, I welcome your questions on how behavioral science, certainty, and risk-based oversight can improve public safety.”



Thank You

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