# Decision-Making with Machine Prediction: Evidence from Predictive Maintenance in Trucking

Adam Harris (Cornell) and Maggie Yellen (FTC)

ESIF Economics and AI+ML Meeting
August 13, 2024

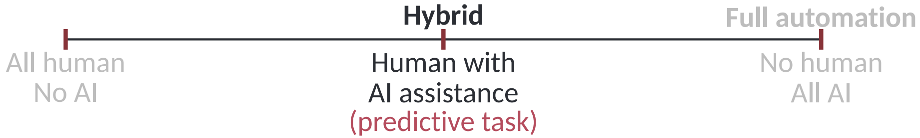
# Prediction, decision-making, and artificial intelligence

- Increasingly, **artificial intelligence plays a role in decision-making**.

| All human<br>No AI | **Hybrid**<br>Human with<br>AI assistance | **Full automation**<br>No human<br>All AI |
|---|---|---|

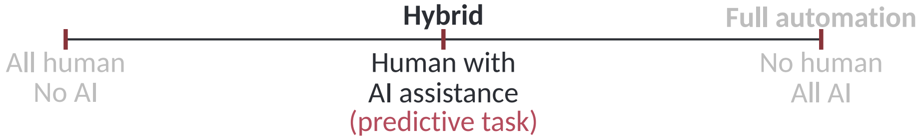
# Prediction, decision-making, and artificial intelligence

— Increasingly, **artificial intelligence plays a role in decision-making**.



# Prediction, decision-making, and artificial intelligence

— Increasingly, **artificial intelligence plays a role in decision-making**.




— Effect on decision **quality** is *a priori* unclear.

# Prediction, decision-making, and artificial intelligence

- Increasingly, **artificial intelligence plays a role in decision-making**.

| All human<br>No AI | **Hybrid**<br>Human with<br>AI assistance<br>(predictive task) | **Full automation**<br>No human<br>All AI |
|---|---|---|

- Effect on decision **quality** is *a priori* unclear.

- **Question:** What is the **quantitative** effect of predictive AI on welfare?

# This paper

- **Question:** What is the **quantitative** effect of predictive AI on welfare?
- **Setting**: Technicians making engine repair decisions for heavy-duty trucks.

# This paper

- **Question:** What is the **quantitative** effect of predictive AI on welfare?
- **Setting**: Technicians making engine repair decisions for heavy-duty trucks.
  - Trade off repair cost and breakdown risk.
  - Relevant data is abundant.

# This paper

- **Question:** What is the **quantitative** effect of predictive AI on welfare?
- **Setting**: Technicians making engine repair decisions for heavy-duty trucks.
  - Trade off repair cost and breakdown risk.
  - Relevant data is abundant.
  - We observe decisions from a fleet that introduced AI to predict breakdowns.

# This paper

- **Question:** What is the **quantitative** effect of predictive AI on welfare?
- **Setting**: Technicians making engine repair decisions for heavy-duty trucks.
  - Trade off repair cost and breakdown risk.
  - Relevant data is abundant.
  - We observe decisions from a fleet that introduced AI to predict breakdowns.
- **Objective**: Use **observational data** on decisions to value AI assistance.

# Key findings

1. **Predictive AI improves decision-making quality.**

   → *Ceteris paribus*, AI reduces costs by **$240-480** / truck / year (85% of all feasible savings).

# Key findings

1. **Predictive AI improves decision-making quality.**

    → *Ceteris paribus*, AI reduces costs by **$240-480** / truck / year (85% of all feasible savings).

2. **How** are these cost savings achieved?

    – Without AI, technicians do costly, unnecessary repairs.

# Key findings

1. **Predictive AI improves decision-making quality.**

   $\rightarrow$ *Ceteris paribus*, AI reduces costs by **$240-480** / truck / year (85% of all feasible savings).

2. **How** are these cost savings achieved?

   — Without AI, technicians do costly, unnecessary repairs.

   $\rightarrow$ Gains from AI come entirely from reduction in repair costs.

# Setting & data

## Setting

- **Technician's choice**: Do an engine repair or send the truck out for its scheduled deliveries?

# Setting & data

## Setting

- **Technician's choice**: Do an engine repair or send the truck out for its scheduled deliveries?
- **Technician's prediction problem**: Sensor measurements $\longrightarrow$ breakdown risk. What tech sees

# Setting & data

## Setting

- **Technician's choice**: Do an engine repair or send the truck out for its scheduled deliveries?
- **Technician's prediction problem**: Sensor measurements $\longrightarrow$ breakdown risk. What tech sees
- **The AI tool (PredictFix)**: Sensor measurements $\longrightarrow$ ***alerts***.

# Setting & data

## Setting

- **Technician's choice**: Do an engine repair or send the truck out for its scheduled deliveries?
- **Technician's prediction problem**: Sensor measurements $\rightarrow$ breakdown risk. What tech sees
- **The AI tool (PredictFix)**: Sensor measurements $\rightarrow$ ***alerts***.

## Data

- **Actions, outcomes**: Repairs, breakdowns at the work-order level.
- **AI output**: Alerts. More
- **State**: Everything that technicians see. Truck-generated data

# Descriptive evidence: Five facts

*Overview*

1. Breakdowns are predictable.

2. PredictFix is a good predictor of breakdowns.

3. Alerts change technician behavior.

# Descriptive evidence: Five facts

## *Overview*

1. Breakdowns are predictable.
2. PredictFix is a good predictor of breakdowns.
3. Alerts change technician behavior.

PredictFix has the *potential* to improve decision-making quality.

# Descriptive evidence: Five facts

*Overview*

1. Breakdowns are predictable.
2. PredictFix is a good predictor of breakdowns.
3. Alerts change technician behavior.

PredictFix has the *potential* to improve decision-making quality.

Does PredictFix *actually* improve decision-making quality? If so, what are the *quantitative* effects?

# Descriptive evidence: Five facts

*Overview*

1. Breakdowns are predictable.
2. PredictFix is a good predictor of breakdowns.
3. Alerts change technician behavior.

PredictFix has the *potential* to improve decision-making quality.

4. Benefits of PredictFix in aggregate data? **No.**

Does PredictFix *actually* improve decision-making quality? If so, what are the *quantitative* effects?

# Descriptive evidence: Five facts

*Overview*

1. Breakdowns are predictable.
2. PredictFix is a good predictor of breakdowns.
3. Alerts change technician behavior.

PredictFix has the *potential* to improve decision-making quality.

4. Benefits of PredictFix in aggregate data? **No.**
5. Cost conditions are different in pre and post.

Does PredictFix *actually* improve decision-making quality? If so, what are the *quantitative* effects?

# Where do we go from here?

*Structural approach*

| *Observed* | |
|---|---|
| **Pre** | **Post** |
| Without PredictFix<br>Pre costs | With PredictFix<br>Post costs |

# Where do we go from here?

*Structural approach*

| *Observed* | |
|---|---|
| **Pre** | **Post** |
| Without PredictFix<br>Pre costs | With PredictFix<br>Post costs |

**Next steps**:

1. **Identification**: Describe model of technician decision-making and conditions required for identification.

# Where do we go from here?

*Structural approach*

| *Observed* | | *Counterfactual* |
|---|---|---|
| **Pre** | Post | **Post'** |
| Without PredictFix<br>Pre costs | With PredictFix<br>Post costs | With PredictFix<br>Pre costs |

**Next steps**:

1. **Identification**: Describe model of technician decision-making and conditions required for identification.

2. **Quantification**: Estimate model, evaluate counterfactual **Post'**.

# Model & estimation overview

**Model elements**:

0. Technician's objective: Minimizing *total cost* = *repair cost* + *breakdown cost*.

# Model & estimation overview

**Model elements**:

0. Technician's objective: Minimizing *total cost* = *repair cost* + *breakdown cost*.

↰ tradeoff ↱

# Model & estimation overview

**Model elements**:

0. Technician's objective: Minimizing *total cost* = *repair cost* + *breakdown cost*.

   tradeoff

1. Costs of repair, breakdown (pre and post).

2. Beliefs about breakdown risk (with and without PredictFix)

# Model & estimation overview

**Model elements**:

0. Technician's objective: Minimizing *total cost* = *repair cost* + *breakdown cost*.
   ↰ tradeoff ↱
1. Costs of repair, breakdown (pre and post).
2. Beliefs about breakdown risk (with and without PredictFix): $\rho : \mathcal{X} \to [0, 1]$.
   $\rho(x) \stackrel{?}{=} \pi(x) =$ *objective* risk of breakdown.

# Model & estimation overview

**Model elements**:

0. Technician's objective: Minimizing *total cost* = *repair cost* + *breakdown cost*.
   ↰ tradeoff ↱

1. Costs of repair, breakdown (pre and post).

2. Beliefs about breakdown risk (with and without PredictFix): $\rho : \mathcal{X} \to [0, 1]$.
   $\rho(x) \stackrel{?}{=} \pi(x) =$ *objective* risk of breakdown.

**Objective**: Estimate costs and beliefs from data.

Results

# Model & estimation overview

**Model elements**:

0. Technician's objective: Minimizing *total cost* = *repair cost* + *breakdown cost*.
   tradeoff

1. Costs of repair, breakdown (pre and post).

2. Beliefs about breakdown risk (with and without PredictFix): $\rho : \mathcal{X} \to [0, 1]$.
   $\rho(x) \stackrel{?}{=} \pi(x) =$ *objective* risk of breakdown.

**Challenge 1**: Separate identification. Details

**Objective**: Estimate costs and beliefs from data.

Results

# Model & estimation overview

**Model elements**:

0. Technician's objective: Minimizing *total cost* = *repair cost* + *breakdown cost*.

   ↰ tradeoff ⬏

1. Costs of repair, breakdown (pre and post).

2. Beliefs about breakdown risk (with and without PredictFix): $\rho : \mathcal{X} \to [0, 1]$.

   $\rho(x) \stackrel{?}{=} \pi(x) =$ *objective* risk of breakdown.

3. Dynamic considerations.

**Challenge 1**: Separate identification. Details

**Objective**: Estimate costs and beliefs from data.

# Model & estimation overview

**Model elements**:

0. Technician's objective: Minimizing *total cost* = *repair cost* + *breakdown cost*.
   ↰ tradeoff ↱

1. Costs of repair, breakdown (pre and post).

2. Beliefs about breakdown risk (with and without PredictFix): $\rho : \mathcal{X} \to [0, 1]$.
   $\rho(x) \stackrel{?}{=} \pi(x) =$ *objective* risk of breakdown.

**Challenge 1**: Separate identification. Details

3. Dynamic considerations. **Challenge 2**: High-dimensional data. Details

**Objective**: Estimate costs and beliefs from data.

# Counterfactuals

## *Overview*

| | (i)<br>**Without** | (ii)<br>**With** |
|---|---|---|
| **Beliefs** | Without PredictFix<br>($\rho = \rho_{\text{pre}}$) | With PredictFix<br>($\rho = \rho_{\text{post}}$) |
| **Costs** | Pre costs | Pre costs |

**Comparing (i) and (ii)**: How do *total costs* = *repair costs* + *breakdown costs* compare?

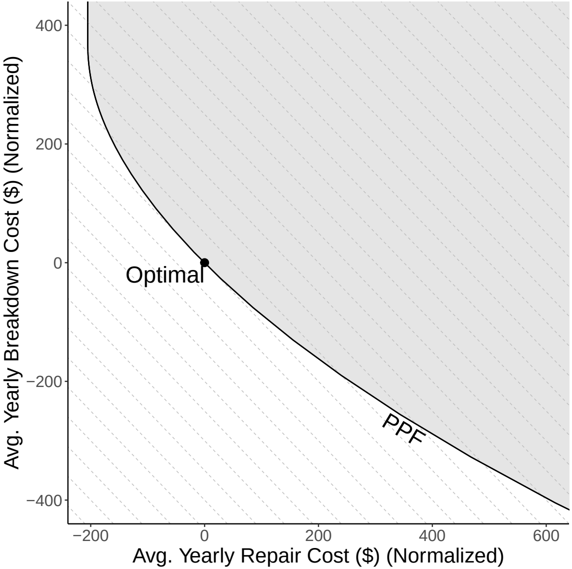
# Counterfactuals

*Overview*

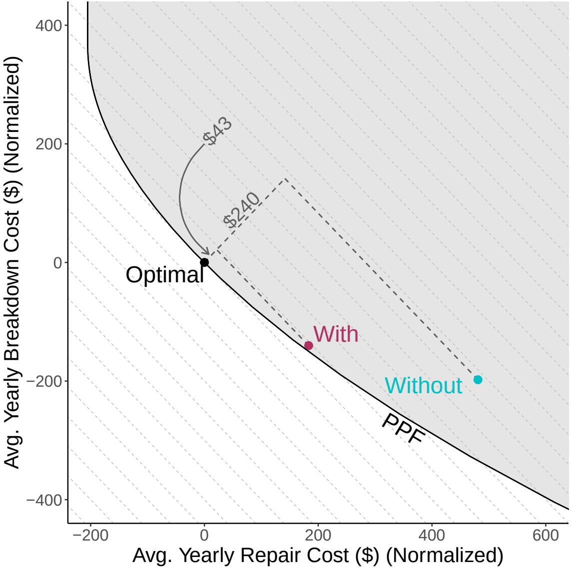
| | (i)<br>**Without** | (ii)<br>**With** | (iii)<br>**Optimal** |
|---|---|---|---|
| **Beliefs** | Without PredictFix<br>$(\rho = \rho_{\text{pre}})$ | With PredictFix<br>$(\rho = \rho_{\text{post}})$ | True<br>$(\rho = \pi)$ |
| **Costs** | Pre costs | Pre costs | Pre costs |

**Comparing (i) and (ii)**: How do *total costs* = *repair costs* + *breakdown costs* compare?

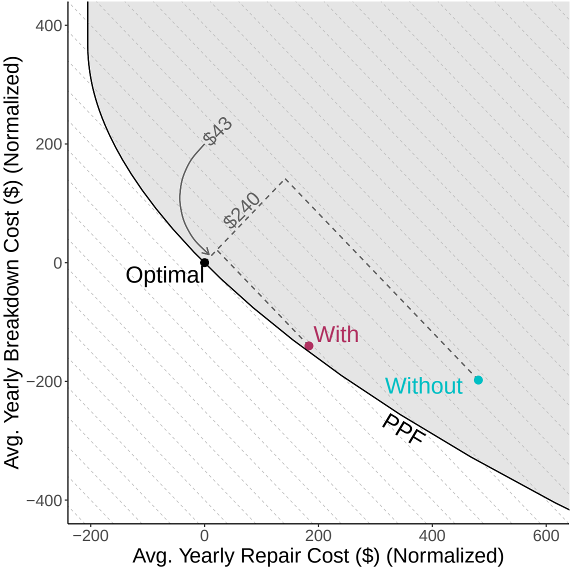
# The value of PredictFix



# The value of PredictFix



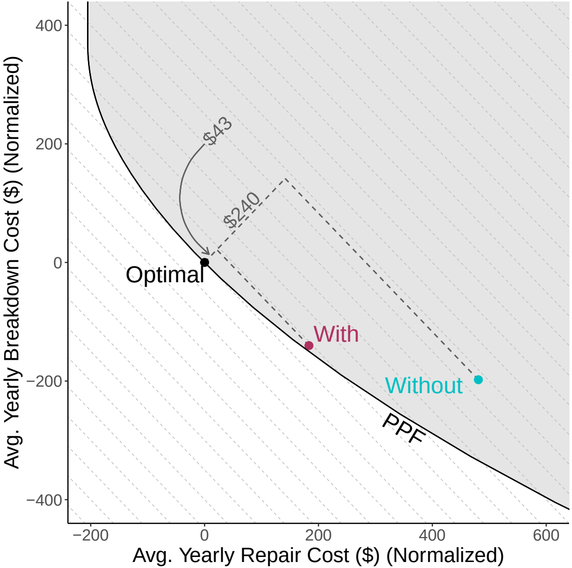
# The value of PredictFix




**Value of PredictFix:**

— Total cost reduction: **$240**.

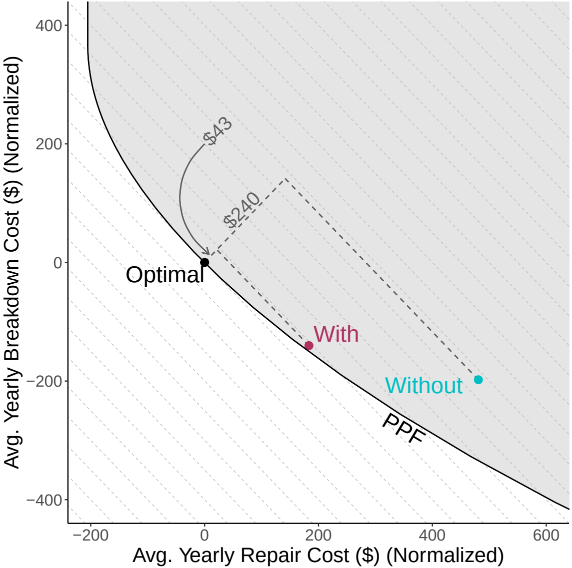
# The value of PredictFix




**Value of PredictFix:**

- Total cost reduction: **$240**.
- Achieves 240 / (240 + 43) = **85%** of all feasible cost savings.

# The value of PredictFix



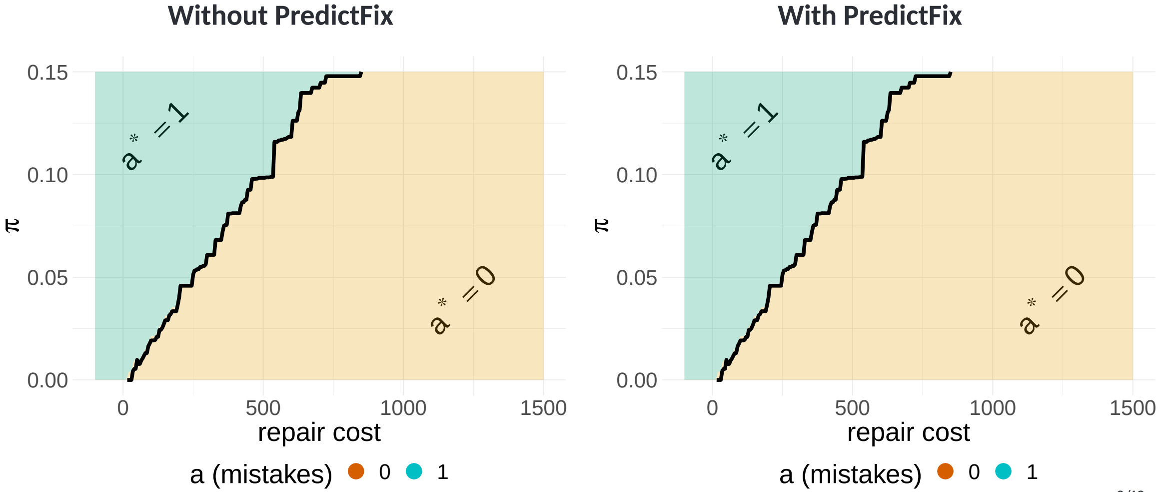

**Value of PredictFix:**

- Total cost reduction: **$240**.
- Achieves 240 / (240 + 43) = **85%** of all feasible cost savings.

**How are cost savings achieved?**

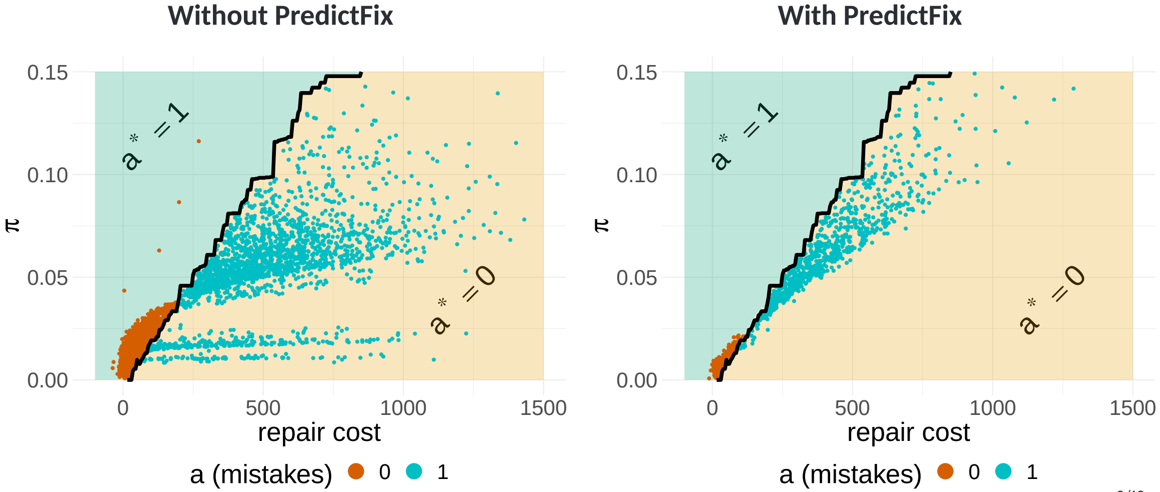
# Unpacking the value of PredictFix

*Mistakes with and without PredictFix*



# Unpacking the value of PredictFix

*Mistakes with and without PredictFix*



# Conclusion

**We study the role of AI in repair decisions made by human technicians**.

- Use **observational data** to quantify economic value of AI assistance.
  - Separately identify preferences and beliefs.
  - Account for dynamics.

$\rightarrow$ With AI, expenditures reduced by **$240-480**/truck/year (**85%** of all feasible cost savings).

# Conclusion

**We study the role of AI in repair decisions made by human technicians**.

- Use **observational data** to quantify economic value of AI assistance.
  - Separately identify preferences and beliefs.
  - Account for dynamics.

→ With AI, expenditures reduced by **$240-480**/truck/year (**85%** of all feasible cost savings).

**More broadly**, this is one small step toward quantitatively understanding AI + decision-making.

- AI prediction is stellar, but few settings where AI makes economic decisions alone.

→ As long as humans remain in the loop, **understanding how they interact with AI is critical**.

# Thank you!

adamharris@cornell.edu

www.adamharris.phd

# The technician’s decision problem

**Question**: Do you do an engine repair or send the truck out for its scheduled deliveries?

# The technician’s decision problem

**Question**: Do you do an engine repair or send the truck out for its scheduled deliveries?

# The technician's decision problem

**Question**: Do you do an engine repair or send the truck out for its scheduled deliveries?

# What technician sees

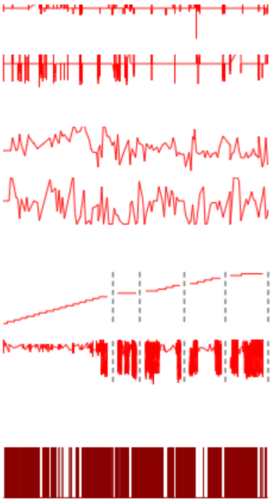
*Sensor measurements*

# What technician sees

*Sensor measurements*



| | |
|---|---|
| **Acceleration forward or braking** | -1.4...0.9G force |
| **Acceleration side to side** | -0.44...0.49G force |
| ⋮ | |
| **Engine intake manifold 1 temperature** | 68...138.2F |
| **Engine load** | 0...100% |
| ⋮ | |
| **Odometer** | 537476.5...537867.9mi |
| **Oil pressure** | 0...47.6psi |
| ⋮ | |
| **Vehicle programmed maximum road speed limit enabled (1 = enabled)** | 0...1 |



# What do you see?

*Sensor measurements*

**Oil pressure** 0...47.6psi 

| | |
|---|---|
| 2/01/23 22:05:39.427 | 25.5 psi |
| 2/01/23 22:05:40.423 | 29 psi |
| 2/01/23 22:05:43.423 | 27.3 psi |
| 2/01/23 22:05:44.423 | 38.9 psi |
| 2/01/23 22:05:46.423 | 38.3 psi |
| 2/01/23 22:05:48.423 | 44.1 psi |
| 2/01/23 22:05:49.423 | 40.6 psi |
| 2/01/23 22:05:51.423 | 43.5 psi |
| 2/01/23 22:05:52.423 | 39.5 psi |
| 2/01/23 22:05:58.417 | 38.9 psi |
| 2/01/23 22:06:00.417 | 34.8 psi |
| 2/01/23 22:06:08.413 | 37.1 psi |
| 2/01/23 22:06:14.423 | 34.2 psi |
| 2/01/23 22:06:16.417 | 25.5 psi |
| 2/01/23 22:06:19.423 | 26.1 psi |
| 2/01/23 22:06:20.423 | 34.8 psi |
| 2/01/23 22:06:23.417 | 36 psi |

Back Frequency

# The AI tool

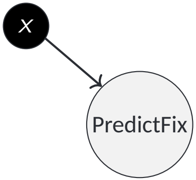
# The AI tool

- In March 2020, fleet introduces **PredictFix** (AI tool), which generates ***alerts***. Details

# The AI tool

- In March 2020, fleet introduces **PredictFix** (AI tool), which generates ***alerts***. Details

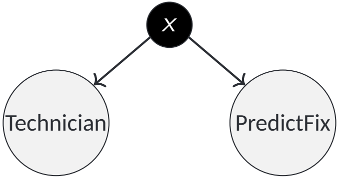
- **Function of sensor data**.



# The AI tool

- In March 2020, fleet introduces **PredictFix** (AI tool), which generates ***alerts***. Details

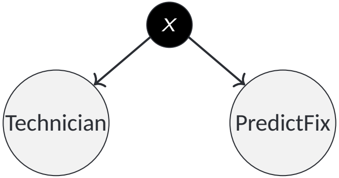
- **Function of sensor data**.



# The AI tool

- In March 2020, fleet introduces **PredictFix** (AI tool), which generates ***alerts***. Details

- **Function of sensor data** $\rightarrow$ no information that could not have been learned without PredictFix.



# Why this setting?

*Data*

# Why this setting?

## *Data*

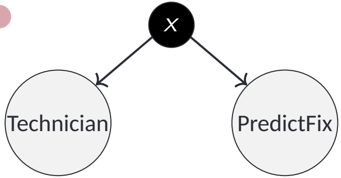
We observe:

- **Actions, outcomes**: Repairs, breakdowns at the work-order level.
- **AI output**: Alerts. More
- **State**: Everything that technicians see. Truck-generated data What techs see

# Why this setting?
*Data*

We observe:

- **Actions, outcomes**: Repairs, breakdowns at the work-order level.
- **AI output**: Alerts. More
- **State**: Everything that technicians see. Truck-generated data What techs see

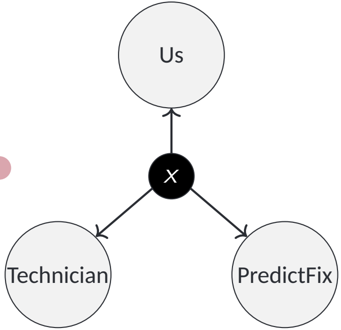


# Why this setting?

## *Data*

We observe:

- **Actions, outcomes**: Repairs, breakdowns at the work-order level.
- **AI output**: Alerts. More
- **State**: Everything that technicians see. Truck-generated data What techs see

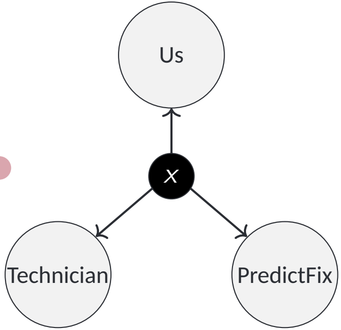


# Why this setting?

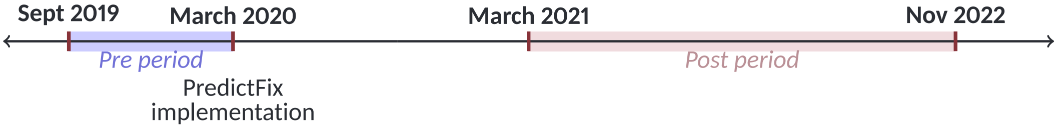
*Data*

We observe:

- **Actions, outcomes**: Repairs, breakdowns at the work-order level.
- **AI output**: Alerts. More
- **State**: Everything that technicians see. Truck-generated data What techs see




Two disjoint periods:



# The technician's problem

**Objective: cost minimization.** Costs of repairs/breakdowns include:

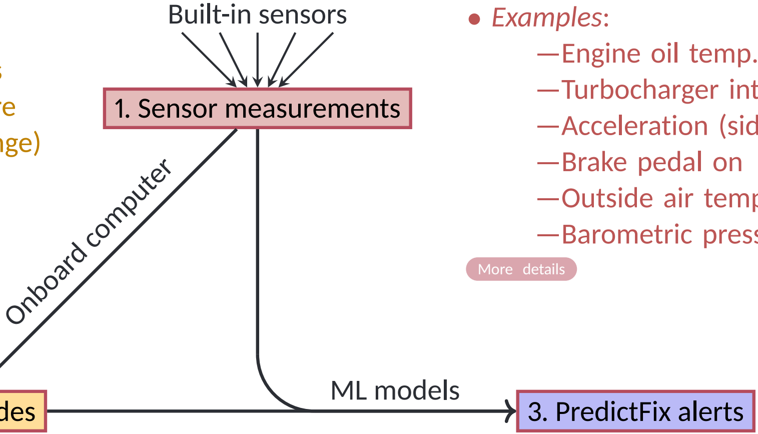
- Tangible costs: Labor, materials, towing, etc.
- Intangible costs:
  - Opportunity cost of truck not being on the road.
  - Capacity constraints (shadow costs).
  - Disruption costs of breakdowns:
    - Damage to relationships with drivers.
    - Damage to relationships with customers.

# State of the truck

*What data do technicians see?*

- *Examples*:
  - —Engine misfire for multiple cylinders
  - —Gas supply pressure (Below normal range)
- Very high rate of false positives
- Median frequency: ~ 10 per truck-day

More details

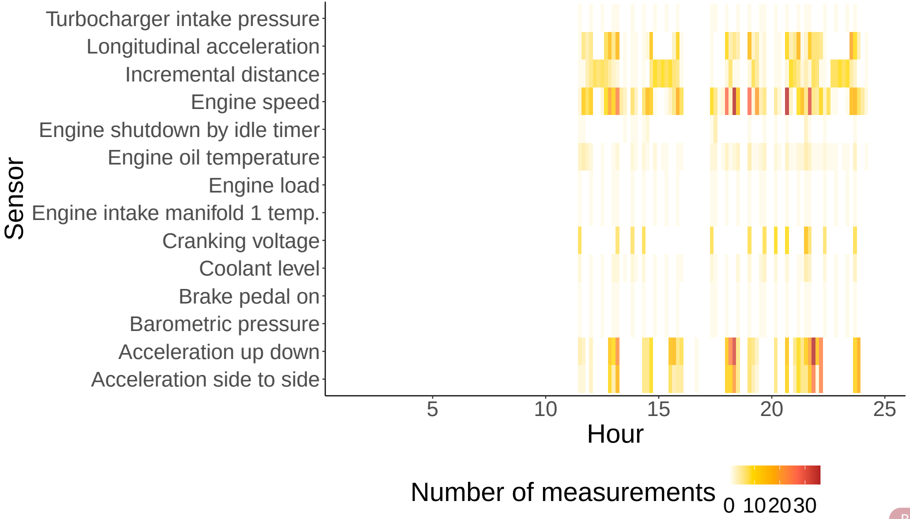



- Median frequency: ~4,000 per truck-day
- *Examples*:
  - —Engine oil temp.
  - —Turbocharger intake pressure
  - —Acceleration (side to side)
  - —Brake pedal on
  - —Outside air temp.
  - —Barometric pressure

More details

# What do you see?

*Sensor measurement frequency*




Back

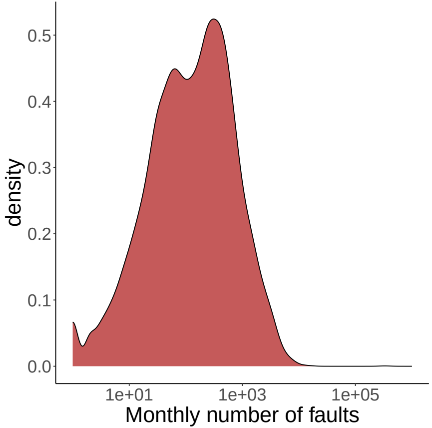
# State of the truck

*What data do technicians see?*

Back

**Fault codes.** *Examples*: “Engine misfire for multiple cylinders”,
“Gas supply pressure—Data valid but below normal operational range”.

Is **fault code** $\rightarrow$ **repair** the optimal policy? **No**; *very* high rate of false positives.



# Descriptive evidence: Five facts

*Overview*

**Questions:**

1.
2.
3.
4.
5.

# Descriptive evidence: Five facts

*Overview*

**Questions:**

1. Are breakdowns predictable?
2. Is PredictFix a good predictor of breakdowns?
3. Do alerts change technician behavior?
4. 
5. 

# Descriptive evidence: Five facts

*Overview*

**Questions:**

1. Are breakdowns predictable?
2. Is PredictFix a good predictor of breakdowns?
3. Do alerts change technician behavior?
4.
5.

Does PredictFix have the *potential* to improve decision-making quality?

# Descriptive evidence: Five facts

*Overview*

**Questions:**

1. Are breakdowns predictable? **Yes.**
2. Is PredictFix a good predictor of breakdowns? **Yes.**
3. Do alerts change technician behavior? **Yes.**
4.
5.

Does PredictFix have the *potential* to improve decision-making quality? **Yes.**

# Fact 1: Breakdown risk is predictable.

More AUC Interpretation

# Fact 1: Breakdown risk is predictable.

More AUC Interpretation

**Constructive argument:**

1. Train ML model to predict breakdowns using sensor measurements.

2. Demonstrate its out-of-sample predictive quality using a **ROC curve**.

   $\longrightarrow$ "Receiver Operating Characteristic."

Back

# Fact 1: Breakdown risk is predictable.

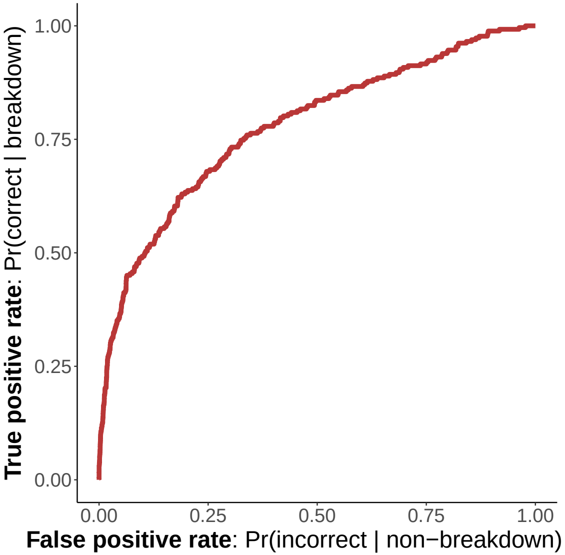
More AUC Interpretation

**Constructive argument:**

1. Train ML model to predict breakdowns using sensor measurements.

2. Demonstrate its out-of-sample predictive quality using a **ROC curve**.

   → "Receiver Operating Characteristic."




Back

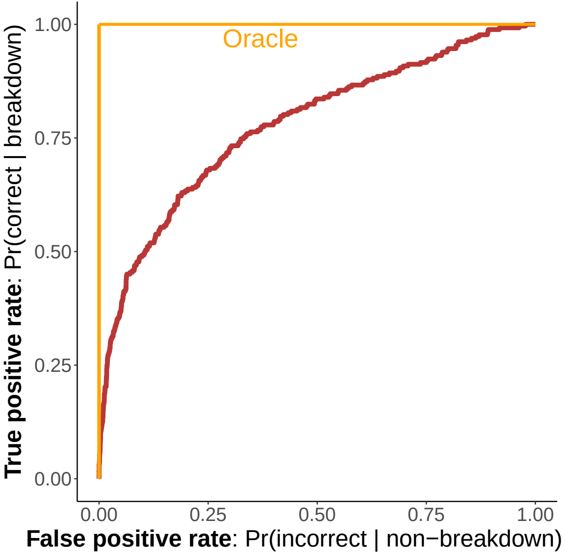
# Fact 1: Breakdown risk is predictable.

More AUC Interpretation

**Constructive argument:**

1. Train ML model to predict breakdowns using sensor measurements.
2. Demonstrate its out-of-sample predictive quality using a **ROC curve**.

   → "Receiver Operating Characteristic."




Back

# Fact 1: Breakdown risk is predictable.

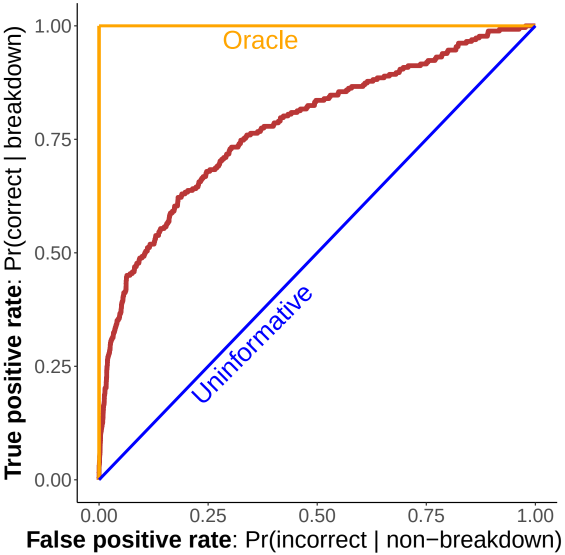
More AUC Interpretation

**Constructive argument:**

1. Train ML model to predict breakdowns using sensor measurements.

2. Demonstrate its out-of-sample predictive quality using a **ROC curve**.

   → "Receiver Operating Characteristic."




Back

# Fact 1: Breakdown risk is predictable.

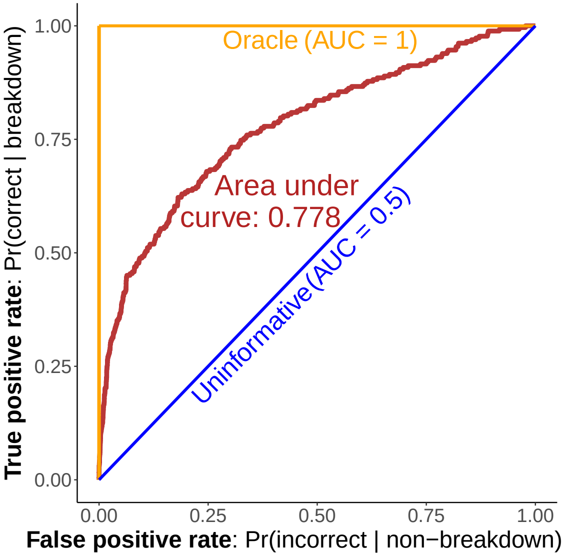
More AUC Interpretation

**Constructive argument:**

1. Train ML model to predict breakdowns using sensor measurements.

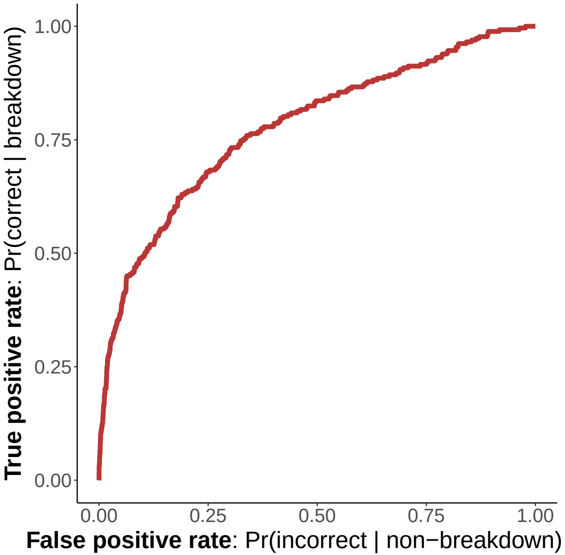
2. Demonstrate its out-of-sample predictive quality using a **ROC curve**.

   → "Receiver Operating Characteristic."



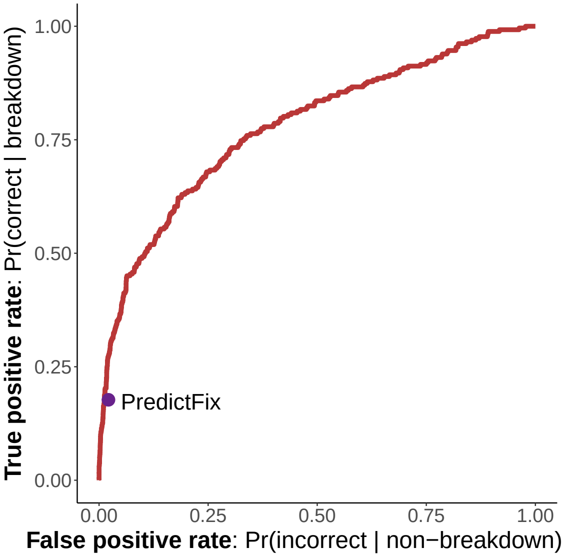

Back

# Fact 2: PredictFix is a good predictor of breakdown risk.




Combining with other signals  ◂ Back

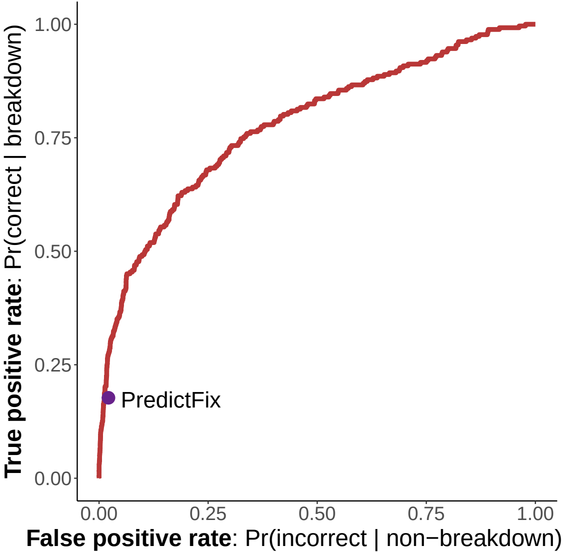
# Fact 2: PredictFix is a good predictor of breakdown risk.




Combining with other signals
Back

# Fact 2: PredictFix is a good predictor of breakdown risk.

— Among best binary predictors that can be constructed.

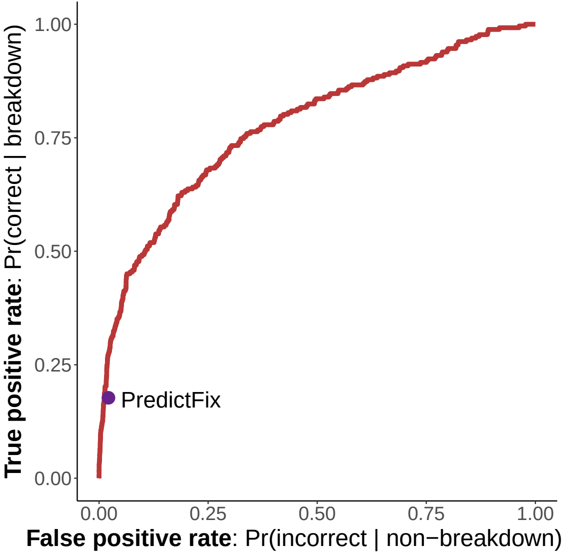



Combining with other signals | Back

# Fact 2: PredictFix is a good predictor of breakdown risk.

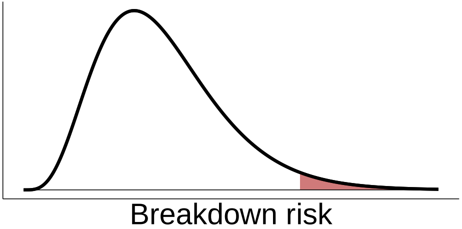
- Among best binary predictors that can be constructed.

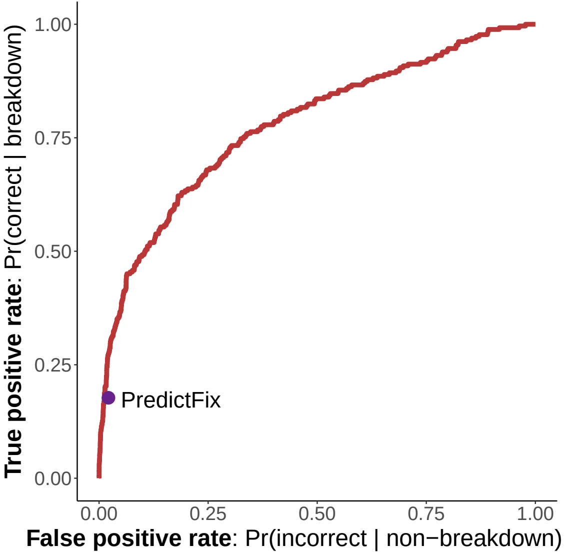
- 2.5% of truck-weeks have an alert.



# Fact 2: PredictFix is a good predictor of breakdown risk.

- Among best binary predictors that can be constructed.
- 2.5% of truck-weeks have an alert.




Combining with other signals | Back

# Fact 3: Technicians respond to PredictFix.

# Fact 3: Technicians respond to PredictFix.

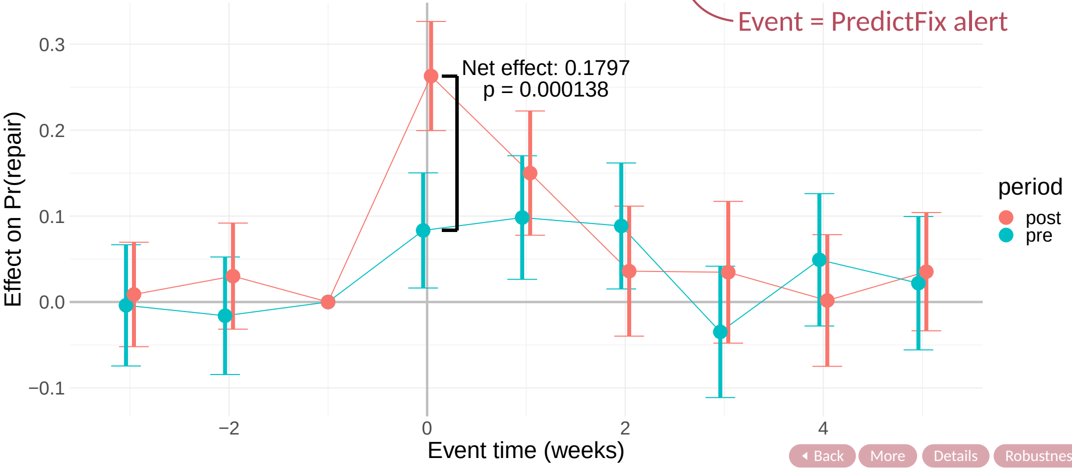
$$\text{Repair}_{i,t} = \alpha_0 + \sum_{k \in \{\text{pre,post}\}} \sum_{\tau=-3}^{5} \beta_\tau^k \mathbb{1}\{t \in \mathcal{T}_k\} \widehat{\text{PredictFix}}_{i,t-\tau} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

Event = PredictFix alert

# Fact 3: Technicians respond to PredictFix.

$$\text{Repair}_{i,t} = \alpha_0 + \sum_{k \in \{\text{pre,post}\}} \sum_{\tau=-3}^{5} \beta_\tau^k \mathbb{1}\{t \in \mathcal{T}_k\} \widehat{\text{PredictFix}}_{i,t-\tau} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

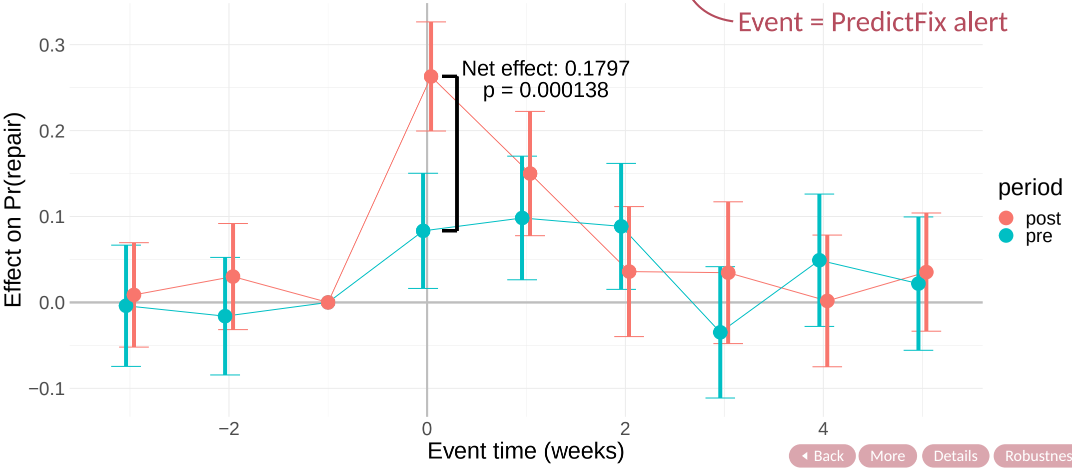
Event = PredictFix alert



# Fact 3: Technicians respond to PredictFix, but also ignore many alerts.

$$\text{Repair}_{i,t} = \alpha_0 + \sum_{k\in\{\text{pre,post}\}} \sum_{\tau=-3}^{5} \beta_\tau^k \mathbb{1}\{t \in \mathcal{T}_k\}\widehat{\text{PredictFix}}_{i,t-\tau} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

Event = PredictFix alert



# Descriptive evidence: Five facts

*Overview*

**Questions:**

1. Are breakdowns predictable? **Yes.**
2. Is PredictFix a good predictor of breakdowns? **Yes.**
3. Do alerts change technician behavior? **Yes.**
4. 
5. 

Does PredictFix have the *potential* to improve decision-making quality? **Yes.**

# Descriptive evidence: Five facts
## *Overview*

**Questions:**

1. Are breakdowns predictable? **Yes.**
2. Is PredictFix a good predictor of breakdowns? **Yes.**
3. Do alerts change technician behavior? **Yes.**

Does PredictFix have the *potential* to improve decision-making quality? **Yes.**

4.
5.

Does PredictFix *actually* improve decision-making quality? If so, what are the *quantitative* effects?

# Descriptive evidence: Five facts

*Overview*

**Questions:**

1. Are breakdowns predictable? **Yes.**
2. Is PredictFix a good predictor of breakdowns? **Yes.**
3. Do alerts change technician behavior? **Yes.**

Does PredictFix have the *potential* to improve decision-making quality? **Yes.**

4. Benefits of PredictFix in aggregate data?
5. 

Does PredictFix *actually* improve decision-making quality? If so, what are the *quantitative* effects?

# Descriptive evidence: Five facts

*Overview*

**Questions:**

1. Are breakdowns predictable? **Yes.**
2. Is PredictFix a good predictor of breakdowns? **Yes.**
3. Do alerts change technician behavior? **Yes.**

Does PredictFix have the *potential* to improve decision-making quality? **Yes.**

4. Benefits of PredictFix in aggregate data? **No.**
5. 

Does PredictFix *actually* improve decision-making quality? If so, what are the *quantitative* effects?

# Descriptive evidence: Five facts

*Overview*

**Questions:**

1. Are breakdowns predictable? **Yes.**
2. Is PredictFix a good predictor of breakdowns? **Yes.**
3. Do alerts change technician behavior? **Yes.**

Does PredictFix have the *potential* to improve decision-making quality? **Yes.**

4. Benefits of PredictFix in aggregate data? **No.**
5. Cost conditions different in pre and post?

Does PredictFix *actually* improve decision-making quality? If so, what are the *quantitative* effects?

# Descriptive evidence: Five facts

*Overview*

**Questions:**

1. Are breakdowns predictable? **Yes.**
2. Is PredictFix a good predictor of breakdowns? **Yes.**
3. Do alerts change technician behavior? **Yes.**

Does PredictFix have the *potential* to improve decision-making quality? **Yes.**

4. Benefits of PredictFix in aggregate data? **No.**
5. Cost conditions different in pre and post? **Yes.**

Does PredictFix *actually* improve decision-making quality? If so, what are the *quantitative* effects?

# Combining PredictFix with other information from $x$

If PredictFix is a good predictor of breakdown risk, why might technicians still want to look at $x$?

1. **Combining $x$ and PredictFix to form an optimal classifier.**
   — PredictFix is not *on* the ROC curve, so it's not an *optimal* binary classifier.
   $\rightarrow$ Combine PredictFix alerts with $x$ to form a binary classifier that is optimal.
2. **Variation in cost threshold.** Suppose PredictFix were an optimal binary classifier.

$$\text{PredictFix}_i \Leftrightarrow \pi(x_i) \geqslant \pi^*$$

$$a_i = 1 \Leftrightarrow \pi(x_i) > \frac{\text{Cost of repair}}{\text{Cost of breakdown}} \equiv \tau(v)$$

Table: Optimal decisions given optimal binary signal

| | $\tau(v) \leqslant \pi^*$ | $\tau(v) > \pi^*$ |
|---|---|---|
| PredictFix alert | Repair | ? |
| No PredictFix alert | ? | No repair |

Back

# Fact 3: Technicians respond to PredictFix, but also ignore many alerts.

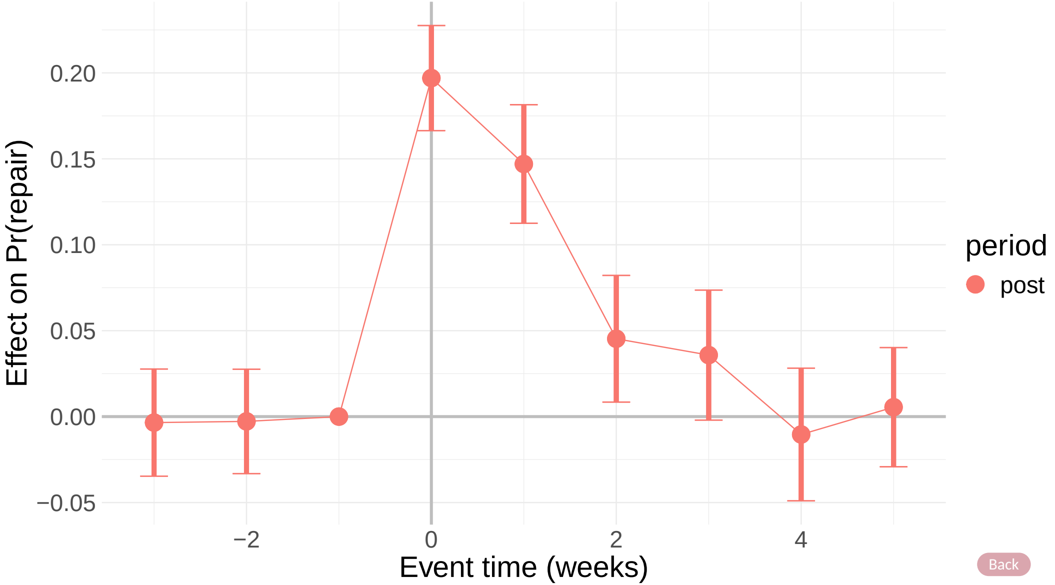
$$\text{Repair}_{i,t} = \alpha_0 + \sum_{k \in \{\text{pre,post}\}} \sum_{\tau=-3}^{5} \beta_\tau^k \mathbb{1}\{t \in \mathcal{T}_k\} \widehat{\text{PredictFix}}_{i,t-\tau} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

— What PredictFix alerts *would have happened* in pre period?

— Use ML to learn mapping: state $\rightarrow$ PredictFix alerts.

$\rightarrow$ *Very* high degree of accuracy (AUC = 0.978). Details Stability

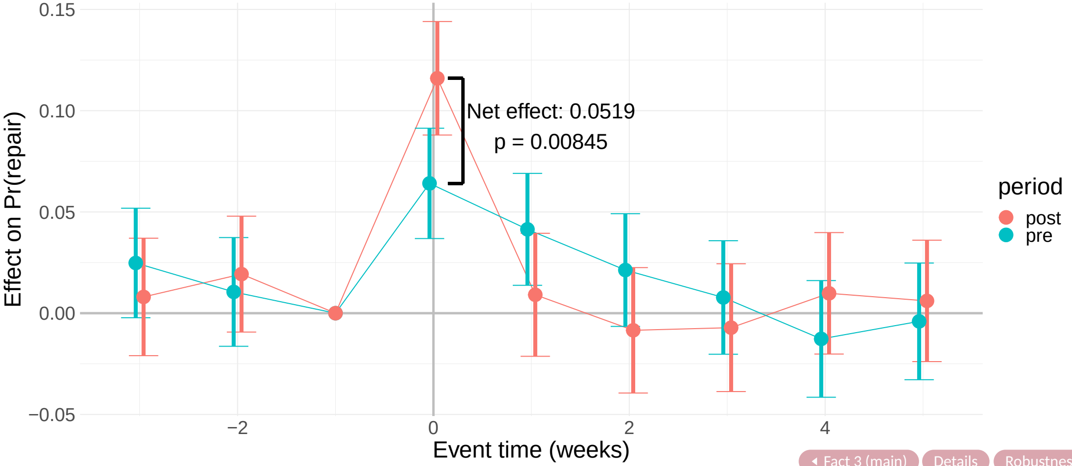
# Robustness: Actual, rather than predicted, PredictFix alerts




Back

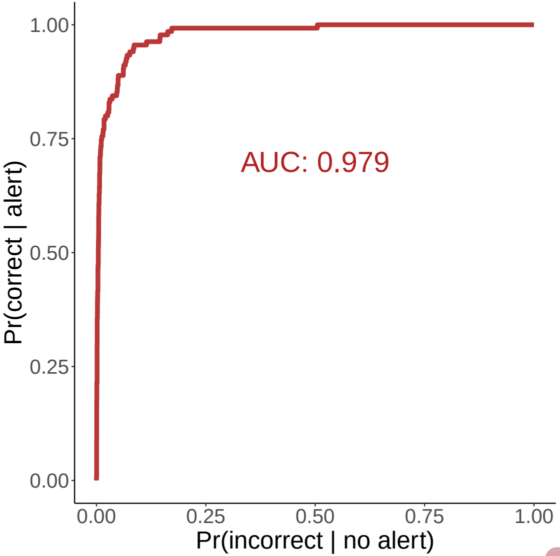
# Fact 3 (Medium-Priority Alerts)

$$\text{Repair}_{i,t} = \alpha_0 + \sum_{k \in \{\text{pre,post}\}} \sum_{\tau=-3}^{5} \beta_\tau^k \mathbb{1}\{t \in \mathcal{T}_k\} \widehat{\text{PredictFix}}_{i,t-\tau} + \alpha_i + \gamma_t + \epsilon_{i,t}$$



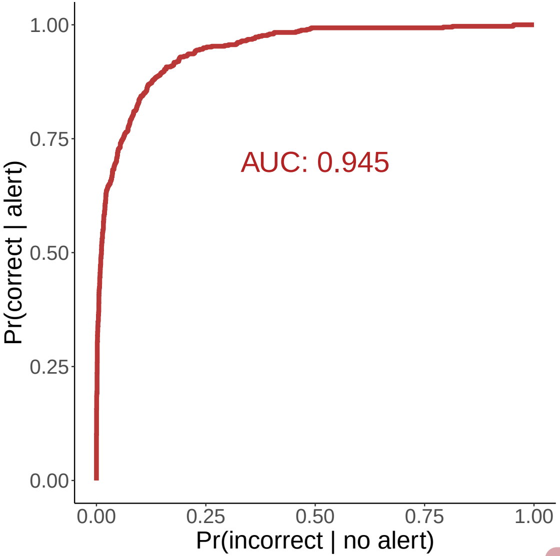
# Predicting PredictFix

*ROC curves*

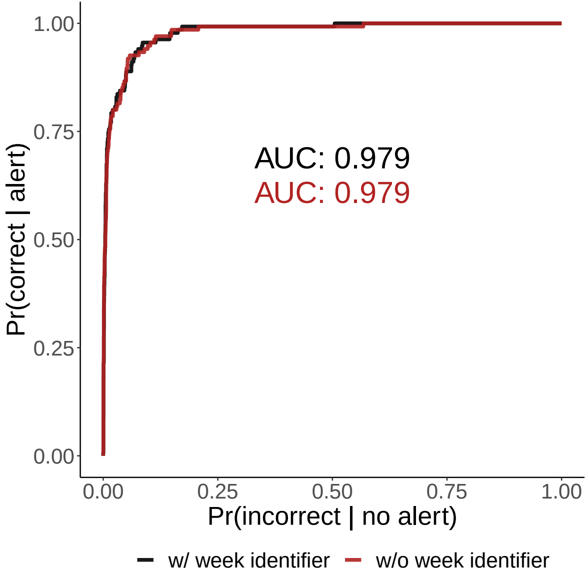


# Predicting PredictFix

*ROC curves*



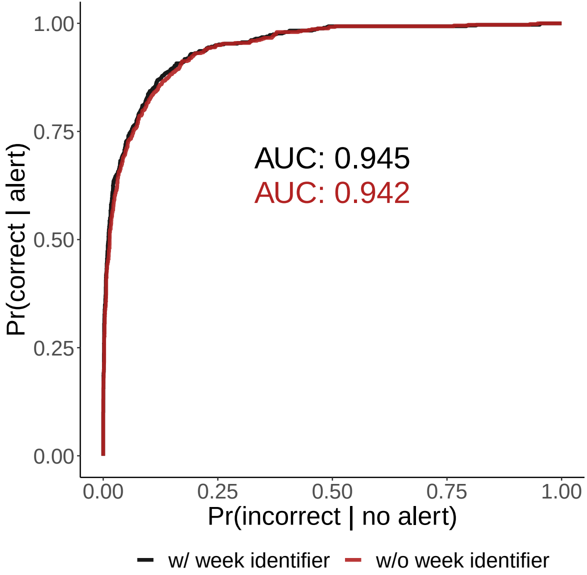
# PredictFix is stable over the post period





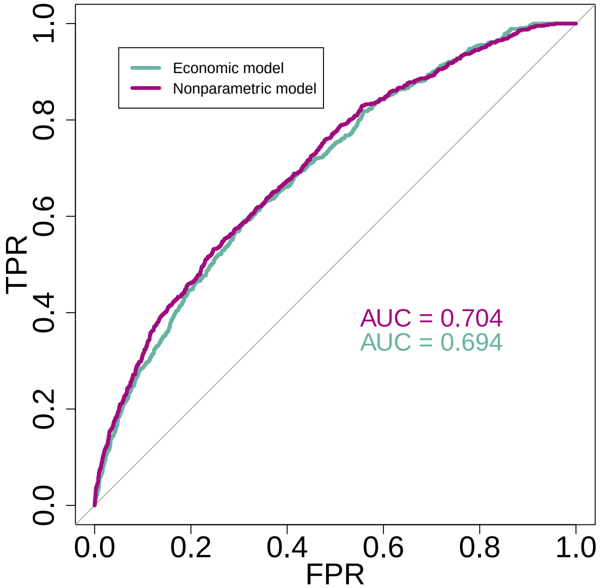
PredictFix
Data
Fact 2

# PredictFix is stable over the post period




PredictFix
Data
Fact 2

# Model fit




Back

# Dynamics

**Technician's problem is inherently dynamic**. This week's action $\to$ future weeks' states.

**Technician's beliefs about the future**

- Potentially incorrect beliefs about future breakdown risk:

$$\rho\left(x_{t+1}\right) \stackrel{?}{=} \pi\left(x_{t+1}\right)$$

- But technician knows the correct distribution of $t+1$'s state given $t$'s state and action.

# Toward estimation: The CCP approach

Back

**Standard notation**: The inclusive payoff from choosing $a$ is

$$v_a(w,x) = u(a,w,x) + \delta EV_a(w,x)$$

where

$$EV_a(w,x) = \mathbb{E}\left[\max\left\{\begin{array}{l} v_0\left(w_{t+1}, x_{t+1}\right), \\ v_1\left(w_{t+1}, x_{t+1}\right) + \epsilon_{t+1} \end{array}\right\} \mid w_t = w, x_t = x, a_t = a\right]$$

**Dynamic choice probability**:

$$\begin{aligned} p(w,x) &= \Lambda\left(\theta\left[v_1(w,x) - v_0(w,x)\right]\right) \\ &= \Lambda\Big(\theta\Big[-g(w) + \rho(x) \\ &\qquad + \delta\left(EV_1(w,x) - EV_0(w,x)\right)\Big]\Big) \end{aligned}$$

where $\Lambda$ is the Logistic function.

**Question**: How to bring this to the data?

1. Nested fixed-point approach: Rust (1987).
   - $\rightarrow$ For each parameter set, solve for $EV_0$, $EV_1$.
2. CCP approaches: Hotz and Miller (1993); Arcidiacono and Miller (2011).
   - $\rightarrow$ $EV_0, EV_1 = f$(choice probabilities).

# Toward estimation: The CCP approach

Back

Under this assumption

$$EV_1(w_t, x_t) - EV_0(w_t, x_t) = \Delta Eg(w_t, x_t) + \frac{1}{\theta}\Delta E \log p(w_t, x_t)$$

where

$$\begin{aligned}
\Delta Eg(w_t, x_t) &= \mathbb{E}[g(w_{t+1}) \mid w_t, x_t, a_t = 0] - \mathbb{E}[g(w_{t+1}) \mid w_t, x_t, a_t = 1] \\
\Delta E \log p(w_t, x_t) &= \mathbb{E}[\log(p(w_{t+1}, x_{t+1})) \mid w_t, x_t, a_t = 0] \\
&\quad - \mathbb{E}[\log(p(w_{t+1}, x_{t+1})) \mid w_t, x_t, a_t = 1]
\end{aligned}$$

**Choice probabilities**:

$$p(w, x) = \Lambda\left(-\theta g(w) + \theta \rho(x) + \delta\left[\theta \Delta Eg(w, x) + \Delta E \log p(w, x)\right]\right)$$

# Toward estimation: The CCP approach

Back

$$p(w,x) = \Lambda\left(-\theta g(w) + \theta \rho(x) + \delta\left[\theta \Delta E g(w,x) + \Delta E \log p(w,x)\right]\right)$$

**How to take this to the data?**

- We need not consider $\Delta E g(w_t, x_t) = \mathbb{E}[g(w_{t+1}) \mid w_t, x_t, a_t = 0] - \mathbb{E}[g(w_{t+1}) \mid w_t, x_t, a_t = 1]$.
  $\rightarrow$ $w$ evolves exogenously.

# Toward estimation: The CCP approach

Back

$$p(w,x) = \Lambda\left(-\theta g(w) + \theta\rho(x) + \delta\left[\theta\Delta Eg(w,x) + \Delta E \log p(w,x)\right]\right)$$

**How to take this to the data?**

- We need not consider $\Delta Eg(w_t, x_t) = \mathbb{E}[g(w_{t+1}) \mid w_t, x_t, a_t = 0] - \mathbb{E}[g(w_{t+1}) \mid w_t, x_t, a_t = 1]$.
  $\rightarrow$ $w$ evolves exogenously.

- $\Delta E \log p(w_t, x_t) = \mathbb{E}[\log(p(w_{t+1}, x_{t+1})) \mid w_t, x_t, a_t = 0] - \mathbb{E}[\log(p(w_{t+1}, x_{t+1})) \mid w_t, x_t, a_t = 1]$.
  A typical approach:
  1. Nonparametrically estimate CCP function $p(w,x)$.
  2. Nonparametrically estimate transition process: Dist. of $(w_{t+1}, x_{t+1})$ conditional on $(a_t, w_t, x_t)$.
  3. Integrate $\log p(w,x)$ over the transition process.

# Toward estimation: The CCP approach

Back

$$p(w,x) = \Lambda\left(-\theta g(w) + \theta \rho(x) + \delta\left[\theta \Delta E g(w,x) + \Delta E \log p(w,x)\right]\right)$$

**How to take this to the data?**

- We need not consider $\Delta E g(w_t, x_t) = \mathbb{E}[g(w_{t+1}) \mid w_t, x_t, a_t = 0] - \mathbb{E}[g(w_{t+1}) \mid w_t, x_t, a_t = 1]$.
  $\rightarrow w$ evolves exogenously.
- $\Delta E \log p(w_t, x_t) = \mathbb{E}[\log(p(w_{t+1}, x_{t+1})) \mid w_t, x_t, a_t = 0] - \mathbb{E}[\log(p(w_{t+1}, x_{t+1})) \mid w_t, x_t, a_t = 1]$.
  A typical approach:
  1. Nonparametrically estimate CCP function $p(w,x)$.
  2. Nonparametrically estimate transition process: Dist. of $(w_{t+1}, x_{t+1})$ conditional on $(a_t, w_t, x_t)$.
  3. Integrate $\log p(w,x)$ over the transition process.
- When $(w,x)$ is high-dimensional, 2. is clearly infeasible.

# Toward estimation: The CCP approach

Back

$$p(w,x) = \Lambda\left(-\theta g(w) + \theta\rho(x) + \delta\left[\theta\Delta E g(w,x) + \Delta E \log p(w,x)\right]\right)$$

**How to take this to the data?**

- We need not consider $\Delta E g(w_t, x_t) = \mathbb{E}[g(w_{t+1}) \mid w_t, x_t, a_t = 0] - \mathbb{E}[g(w_{t+1}) \mid w_t, x_t, a_t = 1]$.
  $\rightarrow w$ evolves exogenously.
- $\Delta E \log p(w_t, x_t) = \mathbb{E}[\log(p(w_{t+1}, x_{t+1})) \mid w_t, x_t, a_t = 0] - \mathbb{E}[\log(p(w_{t+1}, x_{t+1})) \mid w_t, x_t, a_t = 1]$.
  A typical approach:
  1. Nonparametrically estimate CCP function $p(w,x)$.
  2. Nonparametrically estimate transition process: Dist. of $(w_{t+1}, x_{t+1})$ conditional on $(a_t, w_t, x_t)$.
  3. Integrate $\log p(w,x)$ over the transition process.
- When $(w,x)$ is high-dimensional, 2. is clearly infeasible. Need either
  - very strong functional form assumptions on transition; or
  - a new way to compute the integral $\Delta E \log p$ without estimating the transition process.

# Taking stock of assumptions

**Most substantive assumptions:**

1. No private information.

2. Two known moments: $f_1\left(\vec{\rho}(X)\right), f_2\left(\vec{\rho}(X)\right)$.

5. $p_{t+1}\left(w_{t+1}, x_{t+1}\right) \mid a_t, w_t, x_t \sim$ Beta $\left(\mu(a_t, w_t, x_t), \nu\right)$

**What we have *not* assumed:**

- Technician's objective = the firm's objective.
  - Agency problems.
  - Technicians misunderstand firm's costs.
- Technician's risk preferences.

→ These don't affect $\rho$, they only affect the *interpretation* of $\tau$.

# PredictFix

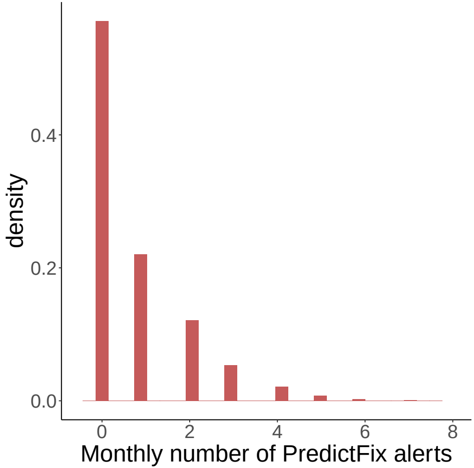
AI Tool Data

(Starting in March 2020) **PredictFix alerts.**

**The PredictFix algorithm.**

- PFC purchased PredictFix from a tech firm specializing in industrial ML prediction.
- Different models for different components. *Examples*:
  - "Cylinder issue" → High severity
  - "Coolant leak" → Medium severity
  - "Engine knocking" → Medium severity
- Each model has a PFC-assigned *severity level* (medium or high).
- *Note*: **Does not** provide new information.

Figure: Number of PredictFix alerts per truck-month



# Fact 4: No change in aggregate outcomes.

**Are positive effects of PredictFix evident in aggregate outcomes? No.**

Table: Frequency of repairs and breakdowns

| | Pre | Post |
|---|---|---|
| Engine Repairs | 462 (**10.5%**) | 1,778 (**10.5%**) |
| Engine Breakdowns | 71 (**1.43%**) | 297 (**1.73%**) |

# Fact 5: Repairs costs are higher, more variable in the post period.

- We observe (accounting estimates of) tangible repair costs.
- Comparison across periods:

| | Pre | Post |
|---|---|---|
| **Mean** | \$621 | \$721 |
| **Std. Dev** | \$1118 | \$1404 |

Back

# Static model

Constant $B$

More on payoffs

# Static model

Constant $B$

More on payoffs

| | | Potential breakdown | |
|---|---|---|---|
| | | $s=0$ | $s=1$ |
| Repair action | $a=0$ | $0$ | $-B$ |
| | $a=1$ | $-c(v,x)$ | $-c(v,x)$ |

State variables:

- $v$: cost-related variables.
- $x$: state of truck.

# Static model

Constant $B$

More on payoffs

| | | Potential breakdown $s=0$ | $s=1$ |
|---|---|---|---|
| Repair action | $a=0$ | $0$ | $-B$ |
| | $a=1$ | $-c(v,x)$ | $-c(v,x)$ |

State variables:

- $v$: cost-related variables.
- $x$: state of truck.

- **True** probability of breakdown: $\pi(x) = \Pr\left(s=1 \mid x\right)$.

# Static model

Constant $B$
More on payoffs

| | | Potential breakdown | |
|---|---|---|---|
| | | $s=0$ | $s=1$ |
| Repair action | $a=0$ | $0$ | $-B$ |
| | $a=1$ | $-c(v,x)$ | $-c(v,x)$ |

State variables:

- $v$: cost-related variables.
- $x$: state of truck.

- **True** probability of breakdown: $\pi(x) = \Pr(s=1 \mid x)$.
- **Perceived** probability of breakdowns: $\rho(x) \stackrel{?}{=} \pi(x)$.
  - → **Not** imposing specific model of how technicians form these beliefs.

# Static model

Constant $B$

More on payoffs

| | | Potential breakdown $s = 0$ | $s = 1$ |
|---|---|---|---|
| Repair action | $a = 0$ | $0$ | $-B$ |
| | $a = 1$ | $-c(v, x)$ | $-c(v, x)$ |

State variables:

- $v$: cost-related variables.
- $x$: state of truck.

- **True** probability of breakdown: $\pi(x) = \Pr(s = 1 \mid x)$.
- **Perceived** probability of breakdowns: $\rho(x) \stackrel{?}{=} \pi(x)$.
  - → **Not** imposing specific model of how technicians form these beliefs.

**Threshold**: Repair if and only if

$$\rho(x) > \frac{c(v, x)}{B} \equiv \tau(v, x)$$

Results

# Static model

Constant $B$

More on payoffs

| | | Potential breakdown $s = 0$ | $s = 1$ |
|---|---|---|---|
| Repair action | $a = 0$ | $0$ | $-B$ |
| | $a = 1$ | $-c(v, x)$ | $-c(v, x)$ |

State variables:

- $v$: cost-related variables.
- $x$: state of truck.

- **True** probability of breakdown: $\pi(x) = \Pr(s = 1 \mid x)$.
- **Perceived** probability of breakdowns: $\rho(x) \overset{?}{=} \pi(x)$.
  - → **Not** imposing specific model of how technicians form these beliefs.

**Threshold**: Repair if and only if

$$\rho(x) > \frac{c(v, x)}{B} \equiv \tau(v, x)$$

**Key questions:**

- Does PredictFix move $\rho$ closer to $\pi$?
- If so, to what extent do better decisions result?

# Econometric challenge

Repair if and only if

$$\rho(x) > \frac{c(v,x)}{B} \equiv \tau(v,x)$$

**Goal**: Estimate preferences $\tau$ and beliefs $\rho$.

**Fundamental challenge**: How to separately identify **preferences and beliefs**?

# Econometric challenge

Repair if and only if

$$\rho(x) > \frac{c(v,x)}{B} \equiv \tau(v,x)$$

**Goal**: Estimate preferences $\tau$ and beliefs $\rho$.

**Fundamental challenge**: How to separately identify **preferences and beliefs**? Identification proof

1. Restriction on private information.
2. Exclusion restriction.
3. Restriction to identify level and scale.

# Econometric challenge

Repair if and only if

$$\rho(x) > \frac{c(v,x)}{B} \equiv \tau(v,x)$$

**Goal**: Estimate preferences $\tau$ and beliefs $\rho$.

**Fundamental challenge**: How to separately identify **preferences and beliefs**? Identification proof

1. Restriction on private information. $\rightarrow$ No private information on state of truck. Details
2. Exclusion restriction.
3. Restriction to identify level and scale.

# Econometric challenge

Repair if and only if

$$\rho(x) > \frac{c(v,x)}{B} \equiv \tau(v,x) = g(w,x) + \epsilon \qquad \text{where } v = (w,\epsilon),\ \epsilon \sim \text{Logistic}(\theta)$$

**Goal**: Estimate preferences $\tau$ and beliefs $\rho$.

**Fundamental challenge**: How to separately identify **preferences and beliefs**? Identification proof

1. Restriction on private information. $\rightarrow$ No private information on state of truck. Details
2. Exclusion restriction.
3. Restriction to identify level and scale.

# Econometric challenge

Repair if and only if

$$\rho(x) > \frac{c(v,x)}{B} \equiv \tau(v,x) = g(w,x) + \epsilon \qquad \text{where } v = (w,\epsilon),\ \epsilon \sim \text{Logistic}(\theta)$$

$$\Rightarrow p(w,x) \equiv \Pr(a = 1 \mid w, x) = \Lambda\left(\theta\left[-g(w,x) + \rho(x)\right]\right)$$

**Goal**: Estimate preferences $\tau$ and beliefs $\rho$.

**Fundamental challenge**: How to separately identify **preferences and beliefs**? Identification proof

1. Restriction on private information. $\rightarrow$ No private information on state of truck. Details
2. Exclusion restriction.
3. Restriction to identify level and scale.

# Econometric challenge

Repair if and only if

$$\rho(x) > \frac{c(v,x)}{B} \equiv \tau(v,x) = g(w,x) + \epsilon \qquad \text{where } v = (w,\epsilon),\ \epsilon \sim \text{Logistic}(\theta)$$

$$\Rightarrow p(w,x) \equiv \Pr(a = 1 \mid w, x) = \Lambda(\theta[-g(w,x) + \rho(x)])$$

**Goal**: Estimate preferences $\tau$ and beliefs $\rho$.

**Fundamental challenge**: How to separately identify **preferences and beliefs**? Identification proof

1. Restriction on private information. $\rightarrow$ No private information on state of truck. Details
2. Exclusion restriction.
3. Restriction to identify level and scale.

# Econometric challenge

Repair if and only if

$$\rho(x) > \frac{c(v,x)}{B} \equiv \tau(v,x) = g(w,x) + \epsilon \qquad \text{where } v = (w,\epsilon),\ \epsilon \sim \text{Logistic}(\theta)$$

$$\Rightarrow p(w,x) \equiv \Pr(a = 1 \mid w,x) = \Lambda\left(\theta\left[-g(w,x) + \rho(x)\right]\right)$$

**Goal**: Estimate preferences $\tau$ and beliefs $\rho$.

**Fundamental challenge**: How to separately identify **preferences and beliefs**? Identification proof

1. Restriction on private information. $\rightarrow$ No private information on state of truck. Details
2. Exclusion restriction. $\rightarrow$ $c(v,x) = c_{\text{tangible}}(v,x) + c_{\text{intangible}}(v)$.
3. Restriction to identify level and scale.

# Econometric challenge

Repair if and only if

$$\rho(x) > \frac{c(v,x)}{B} \equiv \tau(v,x) = g(w,x) + \epsilon \qquad \text{where } v = (w,\epsilon),\ \epsilon \sim \text{Logistic}(\theta)$$

$$\Rightarrow p(w,x) \equiv \Pr(a = 1 \mid w,x) = \Lambda(\theta[-g(w,x) + \rho(x)])$$

**Goal**: Estimate preferences $\tau$ and beliefs $\rho$.

**Fundamental challenge**: How to separately identify **preferences and beliefs**? Identification proof

1. Restriction on private information. $\rightarrow$ No private information on state of truck. Details
2. Exclusion restriction. $\rightarrow c(v,x) = c_{\text{tangible}}(v,x) + c_{\text{intangible}}(v)$.
3. Restriction to identify level and scale.

# Econometric challenge

Repair if and only if

$$\rho(x) > \frac{c(v,x)}{B} \equiv \tau(v,x) = g(w,x) + \epsilon \qquad \text{where } v = (w,\epsilon),\ \epsilon \sim \text{Logistic}(\theta)$$

$$\Rightarrow p(w,x) \equiv \Pr(a = 1 \mid w,x) = \Lambda(\theta[-g(w,x) + \rho(x)])$$

**Goal**: Estimate preferences $\tau$ and beliefs $\rho$.

**Fundamental challenge**: How to separately identify **preferences and beliefs**? Identification proof

1. Restriction on private information. $\rightarrow$ No private information on state of truck. Details
2. Exclusion restriction. $\rightarrow$ $c(v,x) = c_{\text{tangible}}(v,x) + c_{\text{intangible}}(v)$.
3. Restriction to identify level and scale. $\rightarrow$ Two restrictions on $\rho$.

# Separate identification of preferences and beliefs

*Two restrictions on $\rho$*

- **Technician's perceived risk of breakdown risk**:

  1. is correct on average, i.e., $\mathbb{E}_x \boldsymbol{\rho}(x) = \mathbb{E}_x \boldsymbol{\pi}(x)$; and

  2. attains the zero lower bound, i.e., $\min_x \boldsymbol{\rho}(x) = 0$.

Results

# Separate identification of preferences and beliefs

*Two restrictions on $\rho$*

- **Technician's perceived risk of breakdown risk**:

  1. is correct on average, i.e., $\mathbb{E}_x \boldsymbol{\rho}(x) = \mathbb{E}_x \boldsymbol{\pi}(x)$; and
     ↳ Average over states.
  2. attains the zero lower bound, i.e., $\min_x \rho(x) = 0$.

# Separate identification of preferences and beliefs

*Two restrictions on $\rho$*

- **Technician's perceived risk of breakdown risk**:

  1. is correct on average, i.e., $\mathbb{E}_x \boldsymbol{\rho}(x) = \mathbb{E}_x \boldsymbol{\pi}(x)$; and
     ↳ Average over states.
  2. attains the zero lower bound, i.e., $\min_x \boldsymbol{\rho}(x) = 0$.

- **Does not** restrict how technicians **order** states by risk.

# Dynamics: Toward estimation

**Technician's problem is inherently dynamic**. This week's action $\longrightarrow$ future weeks' states. Beliefs

# Dynamics: Toward estimation

**Technician's problem is inherently dynamic**. This week's action $\rightarrow$ future weeks' states. Beliefs

$$p(w_t, x_t) = \Lambda\Big(\theta\Big[\underbrace{-g(w_t, x_t) + \rho(x_t)}_{\text{static payoffs}} + \delta\,\underbrace{\left(EV_1(w_t, x_t) - EV_0(w_t, x_t)\right)}_{\text{ex-ante expected value functions}}\Big]\Big)$$

# Dynamics: Toward estimation

**Technician's problem is inherently dynamic**. This week's action $\rightarrow$ future weeks' states. Beliefs

$$p(w_t, x_t) = \Lambda\Big(\theta\Big[\underbrace{-g(w_t, x_t) + \rho(x_t)}_{\text{static payoffs}} + \delta\underbrace{\big(EV_1(w_t, x_t) - EV_0(w_t, x_t)\big)}_{\text{ex-ante expected value functions}}\Big]\Big)$$

**Question**: How to bring this to the data? More

# Dynamics: Toward estimation

**Technician's problem is inherently dynamic**. This week's action $\rightarrow$ future weeks' states. Beliefs

$$p(w_t, x_t) = \Lambda\left(\theta\left[\underbrace{-g(w_t, x_t) + \rho(x_t)}_{\text{static payoffs}} + \delta\underbrace{\left(EV_1(w_t, x_t) - EV_0(w_t, x_t)\right)}_{\text{ex-ante expected value functions}}\right]\right)$$

**Question**: How to bring this to the data? More

— Hotz and Miller (1993) + Arcidiacono and Miller (2011): Details Renewal

$$EV_0, EV_1 = \mathbb{E}\left[f\left(p(w_{t+1}, x_{t+1})\right)\right]$$

# Dynamics: Toward estimation

**Technician's problem is inherently dynamic**. This week's action $\rightarrow$ future weeks' states. Beliefs

$$p(w_t, x_t) = \Lambda\left(\theta\left[\underbrace{-g(w_t, x_t) + \rho(x_t)}_{\text{static payoffs}} + \delta\underbrace{\left(EV_1(w_t, x_t) - EV_0(w_t, x_t)\right)}_{\text{ex-ante expected value functions}}\right]\right)$$

**Question**: How to bring this to the data? More

- Hotz and Miller (1993) + Arcidiacono and Miller (2011): Details Renewal

$$EV_0, EV_1 = \mathbb{E}\left[f\left(p(w_{t+1}, x_{t+1})\right)\right]$$

- **Challenge**: State is high-dimensional.

# Dynamics: Toward estimation

**Technician's problem is inherently dynamic**. This week's action $\rightarrow$ future weeks' states. Beliefs

$$p(w_t, x_t) = \Lambda\Big(\theta\Big[\underbrace{-g(w_t, x_t) + \rho(x_t)}_{\text{static payoffs}} + \delta\underbrace{(EV_1(w_t, x_t) - EV_0(w_t, x_t))}_{\text{ex-ante expected value functions}}\Big]\Big)$$

**Question**: How to bring this to the data? More

— Hotz and Miller (1993) + Arcidiacono and Miller (2011): Details Renewal

$$EV_0, EV_1 = \mathbb{E}\left[f\left(p(w_{t+1}, x_{t+1})\right)\right]$$

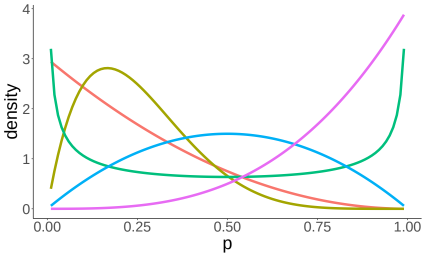
— **Challenge**: State is high-dimensional.

$\rightarrow$ **Our solution**: $p\left(w_{t+1}, x_{t+1}\right) \mid w_t, x_t, a_t \sim$ Beta $\rightarrow$ closed-form expression for $EV_0, EV_1$.

Formal statement Parameterization Details

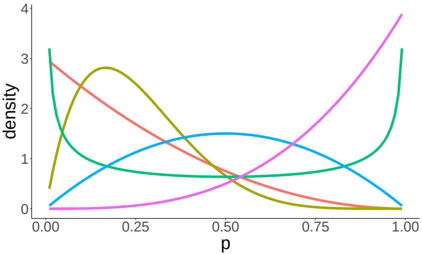
# Beta distribution

(a) Examples: Beta for various parameters

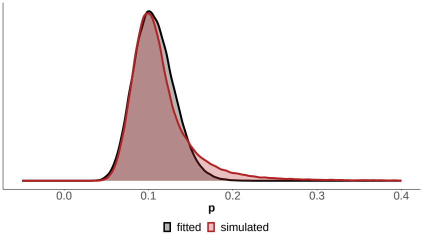


# Beta distribution

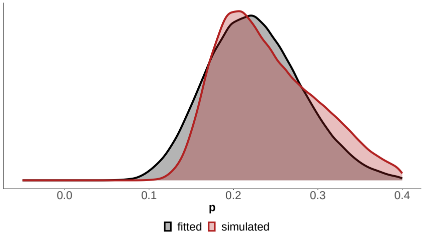
(a) Examples: Beta for various parameters



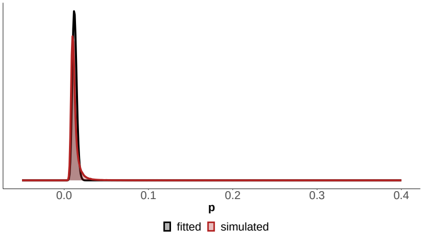

(b) Example 1




(c) Example 2




(d) Example 3



# Model estimation

- Variable selection ($x$): $\sim$ 2000-dimensional $\rightarrow$ 20-dimensional. Details
- Functional form for $\rho$: $\rho(x) = \Lambda\left(\lambda_0 + x'\lambda_1\right)$
- Functional form for $g$: $g(w, x) = \gamma_0 + w'\gamma_1 + \gamma_2 \hat{g}_2(w, x)$. Details

# Model estimation

- Variable selection ($x$): $\sim$ 2000-dimensional $\rightarrow$ 20-dimensional. Details
- Functional form for $\rho$: $\rho(x) = \Lambda\left(\lambda_0 + x'\lambda_1\right)$
- Functional form for $g$: $g(w,x) = \gamma_0 + w'\gamma_1 + \gamma_2\hat{g}_2(w,x)$. Details

Estimate $\beta = (\theta, \gamma, \lambda, \ldots)$ **separately for pre and post** using **constrained maximum likelihood**:

# Model estimation

- Variable selection ($x$): $\sim$ 2000-dimensional $\rightarrow$ 20-dimensional. Details
- Functional form for $\rho$: $\rho(x) = \Lambda\left(\lambda_0 + x'\lambda_1\right)$
- Functional form for $g$: $g(w,x) = \gamma_0 + w'\gamma_1 + \gamma_2\hat{g}_2(w,x)$. Details

Estimate $\beta = (\theta, \gamma, \lambda, \ldots)$ **separately for pre and post** using **constrained maximum likelihood**:

$$\max_{\beta} \sum_i \log \mathcal{L}\left(a_i, w_i, x_i \mid \beta\right) \qquad (\text{Likelihood of observed repair decisions})$$

$$\text{where} \quad \mathcal{L}\left(a_i, w_i, x_i \mid \beta\right) = \begin{cases} 1 - p(w_i, x_i \mid \beta) & \text{if } a_i = 0 \\ p(w_i, x_i \mid \beta) & \text{if } a_i = 1 \end{cases}$$

Goodness of model fit

Results

# Model estimation

- Variable selection ($x$): $\sim$ 2000-dimensional $\to$ 20-dimensional. Details
- Functional form for $\rho$: $\rho(x) = \Lambda(\lambda_0 + x'\lambda_1)$
- Functional form for $g$: $g(w,x) = \gamma_0 + w'\gamma_1 + \gamma_2 \hat{g}_2(w,x)$. Details

Estimate $\beta = (\theta, \gamma, \lambda, \ldots)$ **separately for pre and post** using **constrained maximum likelihood**:

$$\max_{\beta} \sum_i \log \mathcal{L}(a_i, w_i, x_i \mid \beta) \qquad \text{(Likelihood of observed repair decisions)}$$

$$\text{subject to} \quad \frac{1}{N}\sum_{i=1}^{N} \rho(x_i; \lambda) = \bar{\pi} \qquad \text{(Correct on average)}$$

$$\min_x \rho(x; \lambda) \approx 0 \qquad \text{(Zero lower bound)}$$

$$\text{where} \quad \mathcal{L}(a_i, w_i, x_i \mid \beta) = \begin{cases} 1 - p(w_i, x_i \mid \beta) & \text{if } a_i = 0 \\ p(w_i, x_i \mid \beta) & \text{if } a_i = 1 \end{cases}$$

Goodness of model fit

Results

# Constant breakdown cost

- Reflects thinking of PFC fleet management team.
- We need not know $B$.
- **Not** assuming $B_{\text{pre}} = B_{\text{post}}$.

# Finite dependence

## Assumption 3

For every component $z$ of the state variable $(w, x)$, the transition process is such that $z$ satisfies either of the following conditions:

(i) $z$ resets after a repair, i.e., the conditional distribution of $z_{t+1} \mid a_t = 1, w_t, x_t$ does not depend on $(w_t, x_t)$; or

(ii) $z$ evolves independently and exogenously, i.e., the conditional distribution of $z_{t+1} \mid a_t, w_t, x_t$ only depends on $z_t$.

$x$ satisfying (i):

- Sensor measurements
- Fault codes

$x$ satisfying (ii):

- Weather-related variables
- Odometer readings

$w$ all satisfy (ii):

- Facility's # of trucks.
- Facility's # of open work orders.
- Month FEs.

Back

# Restriction on private information

**We observe**: performance of truck components, truck use, and environmental conditions.

$\rightarrow$ Leaves little scope for private information about breakdown risk.

## Assumption 1 (No private information on state of truck)

Suppose $\xi$ is observed by the technician but not by the econometrician. Then,

$$\Pr(\text{breakdown} \mid x, \xi) = \Pr(\text{breakdown} \mid x) = \pi(x)$$

where $x$ is fully observed by the econometrician. Moreover, the technician's perceived risk of breakdown does not depend on $\xi$.

**What this assumption buys us**:

- Progress toward identification of $\rho$ and $\tau$.
- Identification of $\pi(x)$.
  - $\rightarrow$ No selective labels problems.
  - $\rightarrow$ Our ML predictor of breakdown risk has the interpretation of $\pi(x)$.

Fact 1

Fact 1 (ROC)

Econometric Challenge

# AUC

## *Probability interpretation*

- Let $\mathcal{I}_0$ and $\mathcal{I}_1$ represent the set of non-breakdown and breakdown observations, respectively.
- Randomly draw $i_0$ from $\mathcal{I}_0$ and $i_1$ from $\mathcal{I}_1$.
- Then $\text{AUC} = \Pr\left(\hat{\pi}\left(x_{i_1}\right) > \hat{\pi}\left(x_{i_0}\right)\right)$.

# Static identification proof (1/2)

◂ Challenge ◂ Assumption 3

1. **Identifying $\theta\alpha$:**

$$\frac{d}{dw_2}\log\frac{p(x,w)}{1-p(x,w)} = -\theta\alpha\frac{d}{dw_2}g_2(w_1,w_2,x)$$

2. **Partially identifying $g_1$:** WLOG, $g_1(w_1)=\gamma_0+\tilde{g}_1(w_1)$ where $\tilde{g}(w_1^0)=0$ for some $w_1^0$. Then

$$\frac{d}{dw_1}\log\frac{p(x,w)}{1-p(x,w)} = -\theta\nabla\tilde{g}_1(w_1)$$

3. **Partially identifying $\rho$:**

$$\log\frac{p(w,x)}{1-p(w,x)} + \theta\tilde{g}_1(w_1)+\theta\alpha g_2(w_1,w_2,x) = -\theta\gamma_0+\theta\rho(x)\equiv\tilde{\rho}(x)$$

# Static identification proof (2/2)

◂ Challenge ◂ Assumption 3

**Recall:** $\tilde{\rho}(x) \equiv -\theta\gamma_0 + \theta\rho(x)$ is identified.

4. **Point identification of $g_1$, $\rho$:** Note that the mean and minimum of $\tilde{\rho}(x)$ can be written as

$$\mathbb{E}_x \tilde{\rho}(x) = -\theta\gamma_0 + \theta\mathbb{E}_x \rho(x)$$
$$\min_x \tilde{\rho}(x) = -\theta\gamma_0 + \theta \min_x \rho(x)$$

Writing this in matrix form,

$$\underbrace{\begin{bmatrix} -1 & \mathbb{E}_x \rho(x) \\ -1 & \min_x \rho(x) \end{bmatrix}}_{A} \begin{pmatrix} \theta\gamma_0 \\ \theta \end{pmatrix} = \begin{pmatrix} \mathbb{E}_x \tilde{\rho}(x) \\ \min_x \tilde{\rho}(x) \end{pmatrix}$$

# DDC estimation with high-dimensional state

## Assumption 5

The transition process for state variables $(w, x)$ and the technician's conditional choice probability function $p(\cdot, \cdot)$ are such that

$$p(w_{t+1}, x_{t+1}) \mid a_t, w_t, x_t \sim \text{Beta}(\mu(a_t, w_t, x_t), \nu)$$

where $\mu : \{0, 1\} \times \mathcal{W} \times \mathcal{X} \to [0, 1]$ and $\nu \in \mathbb{R}^+$.

Implies that

$$\Delta E \log p(w_t, x_t) = \psi(\mu(0, w_t, x_t)\nu) - \psi(\mu(1, w_t, x_t)\nu)$$

where $\psi$ is the digamma function, and

$$\mu(a_t, w_t, x_t) = \Pr(a_{t+1} = 1 \mid a_t, w_t, x_t)$$

$\rightarrow$ Easy to estimate (offline using GBDT).

**Minimally restrictive**:

- Beta is a flexible distribution.
- $\mu$ is function of $(a_t, w_t, x_t)$.
- $\nu$ to be estimated.

# Beta parameterization

Back

- We use the “mean-precision” parameterization of the Beta distribution.
- First parameter can be arbitrary function of state and action.

$$p\left(w_{t+1}, x_{t+1}\right) \sim \mathrm{Beta}\left(\mu\left(a_t, w_t, x_t\right), \nu\right)$$

# Dynamics: Toward estimation

Under the finite dependence assumption,

$$p(w_t, x_t) = \Lambda\Big(\theta\Big[-g(w_t) + \rho(x_t) + \delta\left(EV_1(w_t, x_t) - EV_0(w_t, x_t)\right)\Big]\Big)$$

$$EV_1(w_t, x_t) - EV_0(w_t, x_t) = \frac{1}{\theta}\Big(\mathbb{E}\left[\log p(w_{t+1}, x_{t+1}) \mid a_t = 0, w_t, x_t\right] - \mathbb{E}\left[\log p(w_{t+1}, x_{t+1}) \mid a_t = 1, w_t, x_t\right]\Big)$$

**Challenge**: State $(w, x)$ is high-dimensional.

$$\mathbb{E}\left[\log p(w_{t+1}, x_{t+1}) \mid a_t, w_t, x_t\right] = \int \log p(w', x') dF(x', w' \mid a_t, w_t, x_t)$$

**Trick**: If $p\left(w_{t+1}, x_{t+1}\right) \sim \text{Beta}\left(\mu\left(a_t, w_t, x_t\right), \nu\right)$, then

$$\mathbb{E}\left[\log p(w_{t+1}, x_{t+1}) \mid a_t, w_t, x_t\right] = \psi\left(\mu(a_t, w_t, x_t)\nu\right) - \psi\left(\nu\right)$$

# Technical Condition

There exists some state $(w, x)$ such that

$$\text{sign}\left(\frac{d^2}{dw^j dx^k} f(w,x)\right) \neq \text{sign}\left(\frac{d}{dw^j} f(w,x) \frac{d}{dx^k} f(w,x)\right)$$

where

$$f(w_t, x_t) = \mathbb{E}\left[\log p(w_{t+1}, x_{t+1}) | w_t, x_t, a_t = 0\right],$$

and $x^k$ is a resetting variable and $w^j$ is an exogenously and independently-evolving variable.

**Note**: Need only hold for *one* state $(w, x) \in \mathcal{W} \times \mathcal{X}$.

Back

# Pre-estimation step

*Variable selection*

$$\underbrace{\begin{pmatrix} \text{Weekly fault code counts} \\ \text{Weekly sensor mean} \\ \text{Weekly sensor min} \\ \text{Weekly sensor max} \\ \text{Weekly sensor std. dev.} \\ \text{Weekly sensor count} \\ \text{3 lags of the above} \\ \text{Weeks since repair} \\ \widehat{\text{PredictFix}}^{\text{high}} \\ \widehat{\text{PredictFix}}^{\text{medium}} \end{pmatrix}}_{\sim\text{2000-dimensional}} \longrightarrow \underbrace{x_{\text{model}}}_{\text{20-dimensional}}$$

**Method**: Train GBDT to predict $a_{it}$ conditional on $(w_{it}, x_{it})$.

$\longrightarrow$ Take the 20 $x$ variables with the highest "gain."

Back

# Preferences and agency issues

If the technician has **risk-neutral preferences**,

$$\begin{aligned} c(v) &\rightarrow \text{repair cost to technician} \\ B &\rightarrow \text{breakdown cost to technician} \end{aligned}$$

If there are **no agency issues**,

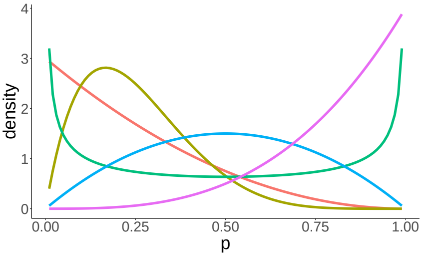
$$\begin{aligned} c(v) &\rightarrow \text{cost of repair to firm} \\ B &\rightarrow \text{cost of breakdown to firm} \end{aligned}$$

Yet identification/estimation **do not** require these assumptions.

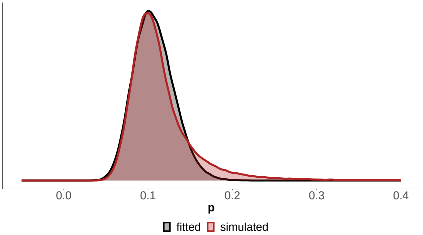
# Beta distribution

Back

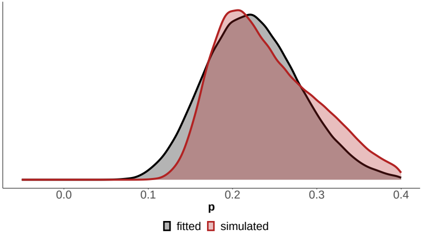
(a) Examples: Beta for various parameters



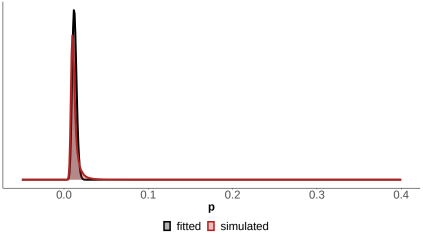

(b) Example: $a_{it} = 0, g_{it} = 0.1, \pi_{it} = 0.014$



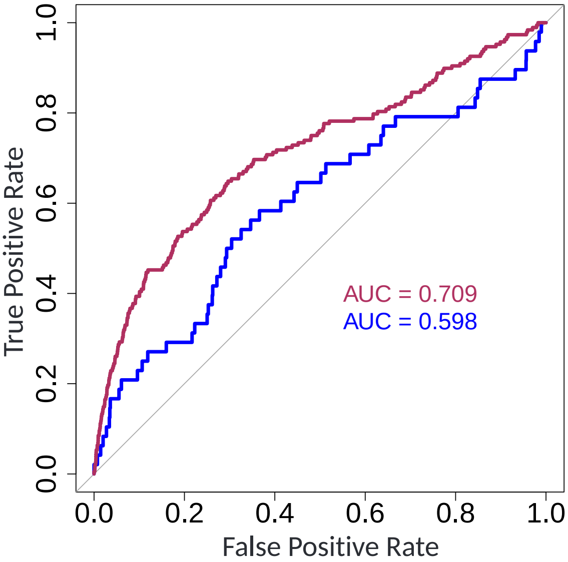

(c) Example: $a_{it} = 0, g_{it} = 0.04, \pi_{it} = 0.05$




(d) Example: $a_{it} = 0, g_{it} = 0.24, \pi_{it} = 0.004$



# The effect of PredictFix on technicians' predictions ($\rho$)

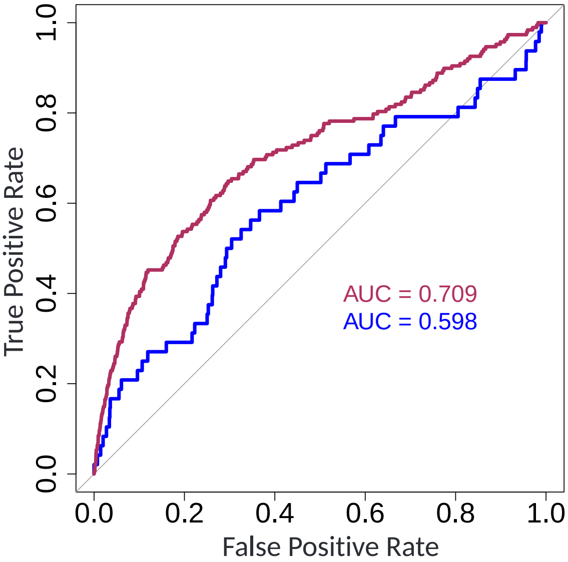



| Predictor | |
|---|---|
| $\hat{\rho}_{pre}$ | Beliefs w/o PredictFix |
| $\hat{\rho}_{post}$ | Beliefs w/ PredictFix |

**Note:**

- $\hat{\rho}_{post}$ strictly dominates $\hat{\rho}_{pre}$.

# The effect of PredictFix on technicians' predictions ($\rho$)

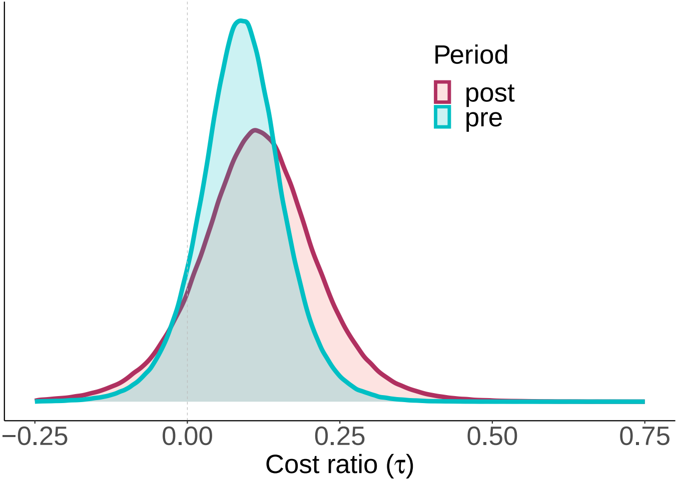



| Predictor | |
|---|---|
| $\hat{\rho}_{pre}$ | Beliefs w/o PredictFix |
| $\hat{\rho}_{post}$ | Beliefs w/ PredictFix |

**Note:**

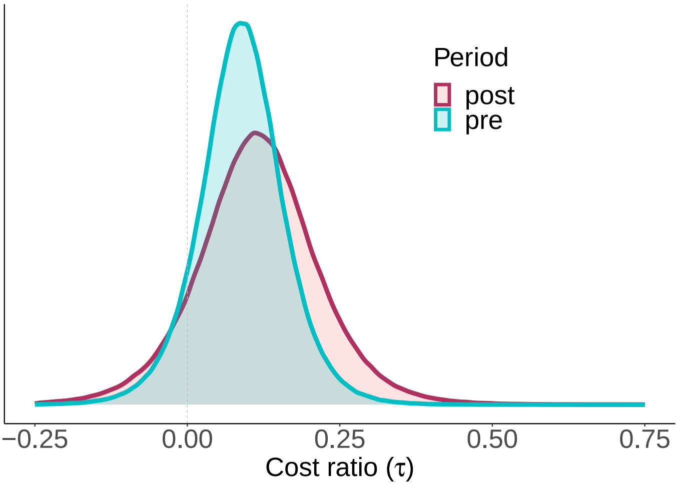
- $\hat{\rho}_{post}$ strictly dominates $\hat{\rho}_{pre}$.
- **Robust** to relaxation restrictions on beliefs: (1) correct on average and (2) zero lower bound.

# Cost ratio (τ) = repair cost / breakdown cost




| | Pre | Post |
|---|---|---|
| mean(τ) | 0.0892 | 0.115 |
| std. dev.(τ) | 0.0718 | 0.102 |

# Cost ratio ($\tau$) = repair cost / breakdown cost




| | **Pre** | **Post** |
|---|---|---|
| mean($\tau$) | 0.0892 | 0.115 |
| std. dev.($\tau$) | 0.0718 | 0.102 |

$\rightarrow$ Supply chain disruptions.

- Fact 5: Tangible costs $\uparrow$.
- Repair completion time $\uparrow$.

# The effect of PredictFix on technicians' beliefs

**A key question**: With PredictFix, do technicians exhibit a better understanding of breakdown risk?

# The effect of PredictFix on technicians' beliefs

**A key question**: With PredictFix, do technicians exhibit a better understanding of breakdown risk?

$\rightarrow$ Is $\hat{\rho}_{\text{post}}$ a better predictor of breakdowns than $\hat{\rho}_{\text{pre}}$?

More

# The effect of PredictFix on technicians' beliefs

**A key question**: With PredictFix, do technicians exhibit a better understanding of breakdown risk?

$\rightarrow$ Is $\hat{\rho}_{\text{post}}$ a better predictor of breakdowns than $\hat{\rho}_{\text{pre}}$?

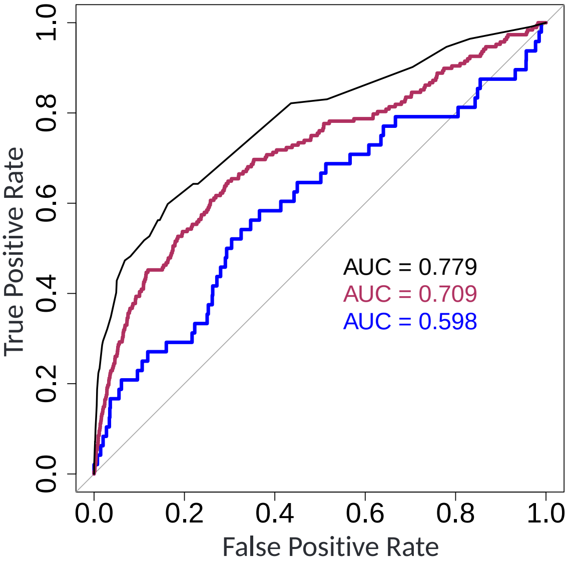
**Tool**: ROC curves.

Table: ROC curve specifications

| **Predictor** | **Outcome** |
| --- | --- |
| $\hat{\rho}_{\text{pre}}$ | Breakdowns |
| $\hat{\rho}_{\text{post}}$ | Breakdowns |

More

# The effect of PredictFix on technicians' predictions ($\rho$)

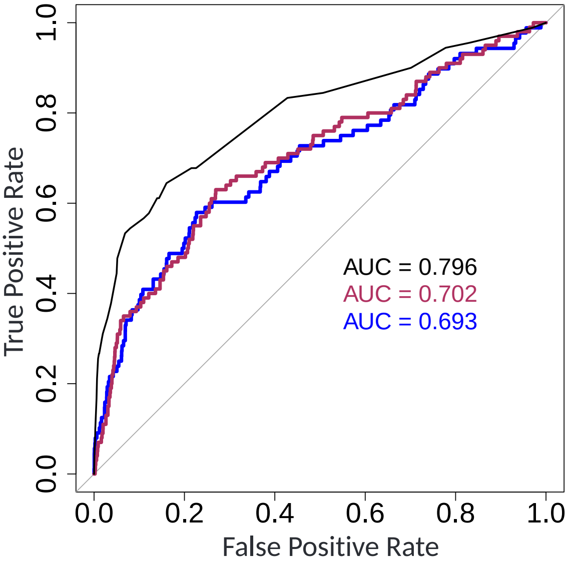



| Predictor | |
|---|---|
| $\hat{\rho}_{pre}$ | Beliefs w/o PredictFix |
| $\hat{\rho}_{post}$ | Beliefs w/ PredictFix |
| $\hat{\pi}_{ML}$ | Benchmark |

**Note**:

- $\hat{\rho}_{post}$ strictly dominates $\hat{\rho}_{pre}$.
- **Robust** to relaxations of "correct on average" and "zero lower bound" assumptions.

# Differences in ρ *within* the post period




| Predictor | |
|---|---|
| $\hat{\rho}_{\text{post (first half)}}$<br>$\hat{\rho}_{\text{post (second half)}}$ | Beliefs |
| $\hat{\pi}_{\text{ML}}$ | Benchmark |

Back to ROC curves

# Counterfactuals

Back

## What do we need to evaluate these counterfactuals?

- Need to know the transition process.

→ Express it in terms of lower-dimensional objects:

$$g_{it+1}, \rho_{it+1}, \pi_{it+1} \mid g_{it}, \rho_{it}, \pi_{it}$$ Details

rather than

$$w_{it+1}, x_{it+1} \mid w_{it}, x_{it}$$

→ Flexibly estimated (using Gaussian Mixture Regression.) Details

- To get dollar interpretation, set value for $B$. A reasonable range: \$5,000-\$10,000.

# Counterfactuals

Back

**What do we need to evaluate these counterfactuals?**

— Need to know the transition process.

→ Express it in terms of lower-dimensional objects:

$$g_{it+1}, \rho_{it+1}, \pi_{it+1} \mid g_{it}, \rho_{it}, \pi_{it}$$

Details

rather than

$$w_{it+1}, x_{it+1} \mid w_{it}, x_{it}$$

→ Flexibly estimated (using Gaussian Mixture Regression.) Details

— To get dollar interpretation, set value for $B$. A reasonable range: \$5,000-\$10,000.

# Counterfactuals

Back

**What do we need to evaluate these counterfactuals?**

— Need to know the transition process.

→ Express it in terms of lower-dimensional objects:

$$g_{it+1}, \rho_{it+1}, \pi_{it+1} \mid g_{it}, \rho_{it}, \pi_{it}$$ Details

rather than

$$w_{it+1}, x_{it+1} \mid w_{it}, x_{it}$$

→ Flexibly estimated (using Gaussian Mixture Regression.) Details

— To get dollar interpretation, set value for $B$. A reasonable range: \$5,000-\$10,000.

# Counterfactuals

Back

**What do we need to evaluate these counterfactuals?**

— Need to know the transition process.

→ Express it in terms of lower-dimensional objects:

$$g_{it+1}, \rho_{it+1}, \pi_{it+1} \mid g_{it}, \rho_{it}, \pi_{it}$$

Details

rather than

$$w_{it+1}, x_{it+1} \mid w_{it}, x_{it}$$

→ Flexibly estimated (using Gaussian Mixture Regression.) Details

— To get dollar interpretation, set value for $B$. A reasonable range: \$5,000-\$10,000.

# Counterfactuals

Back

**What do we need to evaluate these counterfactuals?**

— Need to know the transition process.

→ Express it in terms of lower-dimensional objects:

$$g_{it+1}, \rho_{it+1}, \pi_{it+1} \mid g_{it}, \rho_{it}, \pi_{it}$$ Details

rather than

$$w_{it+1}, x_{it+1} \mid w_{it}, x_{it}$$

→ Flexibly estimated (using Gaussian Mixture Regression.) Details

— To get dollar interpretation, set value for $B$. A reasonable range: **$5,000**-$10,000.

# Gaussian Mixture Regression of $y$ on $x$ (Sung (2004))

Suppose that the vector $(x, y)$ is distributed as a mixture of $M$ Gaussians, i.e., its pdf is

$$f_{X,Y}(x,y) = \sum_{m=1}^{M} \kappa_m \phi\left((x,y)'; \mu_m, \Sigma_m\right)$$

where $\{\kappa_m\}$ are weights with $\sum_{m=1}^{M} \kappa_m = 1$. We estimate $\{\kappa_m, \mu_m, \Sigma_m\}$ using the EM algorithm.

Then, the distribution of $y$ conditional on an observed value $x$ is

$$f_{Y|X}(y|x) = \sum_{m=1}^{M} \omega_m(x) \phi\left(x; \mu_{mX}, \Sigma_{mX}\right)$$

where the mixing weights $\{\omega_m\}$ are derived using Bayes' Rule:

$$\omega_m(x) = \frac{\kappa_m \phi\left(x; \mu_{mX}, \Sigma_{mX}\right)}{\sum_{m'=1}^{M} \kappa_{m'} \phi\left(x; \mu_{m'X}, \Sigma_{m'X}\right)}$$

Back

# Counterfactual details

Joint transition process for $(\pi_{it}, \rho_{it})$:

- Let $\iota_{it} = \Lambda^{-1}(\pi_{it})$.

- $\iota_{it+1} \mid \iota_{it} \sim F^{\iota}(\cdot\,;\ \iota_{it}, a_{it})$, where we estimate $F^{\iota}$ using Gaussian mixture regression.

- Relationship between $\iota$ and $\rho$: For each $j \in \{\text{pre}, \text{post}\}$,

$$\pi_{it} = \Lambda\left(\phi_0^j + \phi_1^j \Lambda^{-1}(\rho_{jit}) + \zeta_{it}\right) \quad \text{or, equivalently,} \quad \rho_{jit} = \Lambda\left(\frac{\iota_{it} - \phi_0^j - \zeta_{it}}{\phi_1^j}\right)$$

  where $\zeta_{it} \sim N(0, \sigma_j)$.

- Find $\left(\phi_0^j, \phi_1^j, \sigma_j\right)$ such that simulation matches actual AUC and logistic regression results.

# The effect of PredictFix on technicians' predictions

**A key question**: With PredictFix, do technicians exhibit better ability to predict breakdowns?

**Tool**: ROC curves.

Table: ROC curve specifications

| Predictor | Outcome | Sample restriction |
|---|---|---|
| $\hat{\rho}_{\text{pre}}$ | Breakdowns | $a_{it} = 0$ |
| $\hat{\rho}_{\text{post}}$ | Breakdowns | $a_{it} = 0$ |
| $\hat{\pi}$ | Breakdowns | Test sample and $a_{it} = 0$ |

Back: Table Back: ROC Curves

# The effect of PredictFix on technicians' predictions ($\rho$)

*What about miscalibration?*

**Logistic regression:**

$$\Pr\left(\text{Breakdown}_{it} \mid \rho_{jit}\right) = \Lambda\left(\phi_0 + \phi_1 \Lambda^{-1}\left(\rho_{jit}\right)\right)$$

# The effect of PredictFix on technicians' predictions ($\rho$)

*What about miscalibration?*

**Logistic regression:**

$$\Pr\left(\text{Breakdown}_{it} \mid \rho_{jit}\right) = \Lambda\left(\phi_0 + \phi_1 \Lambda^{-1}\left(\rho_{jit}\right)\right)$$

| | $\rho = \pi$ | $\rho_{\text{pre}}$ | $\rho_{\text{post}}$ |
|---|---|---|---|
| $\Lambda^{-1}(\rho)$ | 1 | | |
| Constant | 0 | | |

Back Simulation

# The effect of PredictFix on technicians' predictions ($\rho$)

*What about miscalibration?*

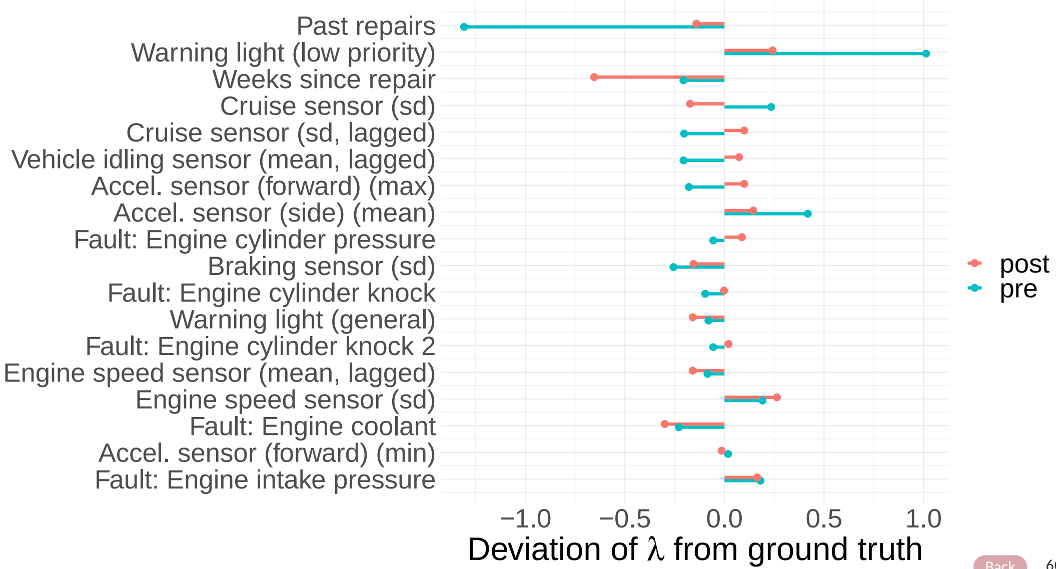
**Logistic regression:**

$$\Pr\left(\text{Breakdown}_{it} \mid \rho_{jit}\right) = \Lambda\left(\phi_0 + \phi_1 \Lambda^{-1}\left(\rho_{jit}\right)\right)$$

| | $\rho = \pi$ | $\rho_{\text{pre}}$ | $\rho_{\text{post}}$ |
|---|---|---|---|
| $\Lambda^{-1}(\rho)$ | 1 | 0.233*** | 0.814*** |
| | | (0.0435) | (0.0764) |
| Constant | 0 | -3.198*** | -0.817* |
| | | (0.218) | (0.318) |
| $N$ | | 19091 | 19091 |

Back Simulation

# Why do technicians overestimate risk?



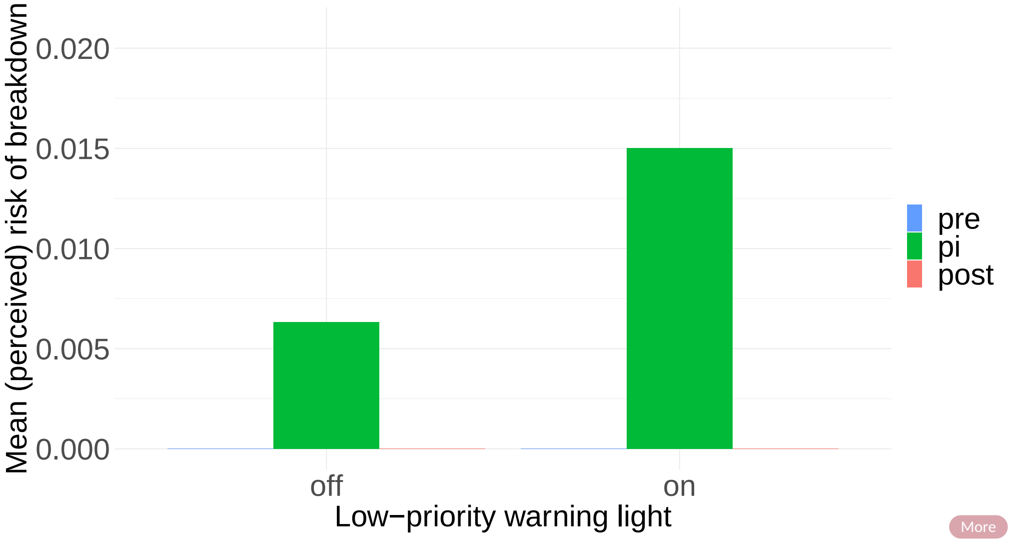

Back

# Where do technicians make mistakes?

*An illustrative example: How technicians respond to dashboard warning lights*

# Where do technicians make mistakes?

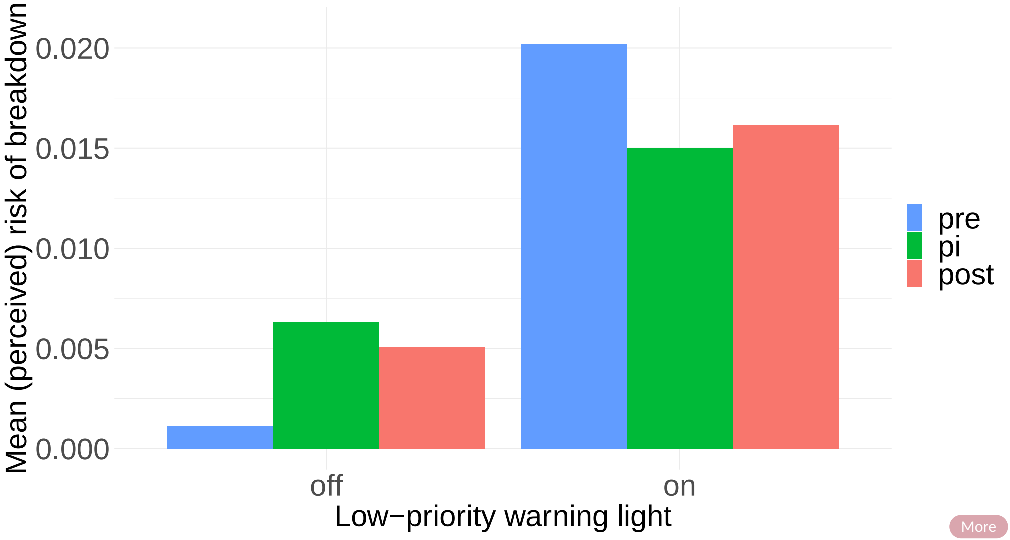
*An illustrative example: How technicians respond to dashboard warning lights*




More

# Where do technicians make mistakes?

*An illustrative example: How technicians respond to dashboard warning lights*




More

# Where do technicians make mistakes?

*An illustrative example: How technicians respond to dashboard warning lights*