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

Adam Harris (Cornell) and Maggie Yellen (FTC)

NBER Summer Institute
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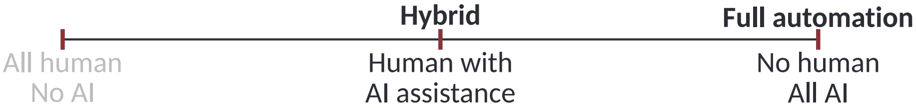
Prediction, decision-making, and artificial intelligence

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



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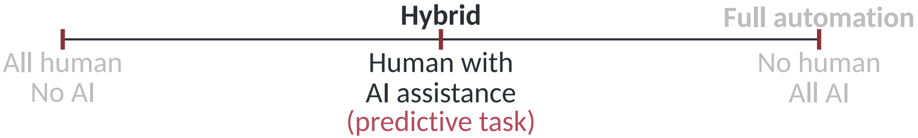

Prediction, decision-making, and artificial intelligence

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All human No AI	**Hybrid** Human with AI assistance (predictive task)	**Full automation** No human All AI

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

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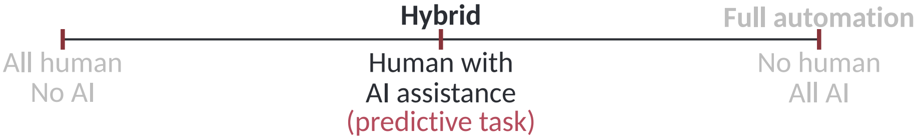

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- **Setting**: Technicians making engine repair decisions for heavy-duty trucks.
  - Trade off repair cost and breakdown risk.
  - Relevant data is abundant.
  - We observe decisions from a fleet that introduced AI to predict breakdowns.
- **Objective**: 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).

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   → Gains from AI come entirely from reduction in repair costs.

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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.

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

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Where do we go from here?

Structural approach

Observed	
Pre	**Post**
Without PredictFix Pre costs	With PredictFix Post costs

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

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Without PredictFix Pre costs	With PredictFix Post costs	With PredictFix Pre costs

Next steps:

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

Model & estimation overview

Model elements:

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Challenge 1: Separate identification. Details

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

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Counterfactuals

Overview

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

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

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Overview

	(i) **Without**	(ii) **With**	(iii) **Optimal**
Beliefs	Without PredictFix ($\rho = \rho_{\text{pre}}$)	With PredictFix ($\rho = \rho_{\text{post}}$)	True ($\rho = \pi$)
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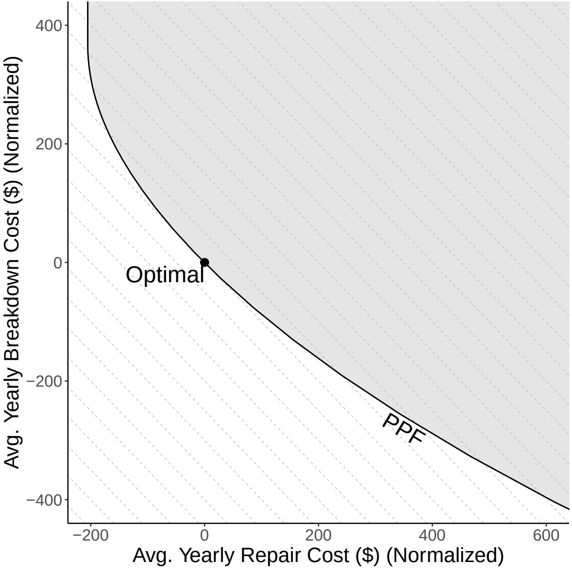
The value of PredictFix



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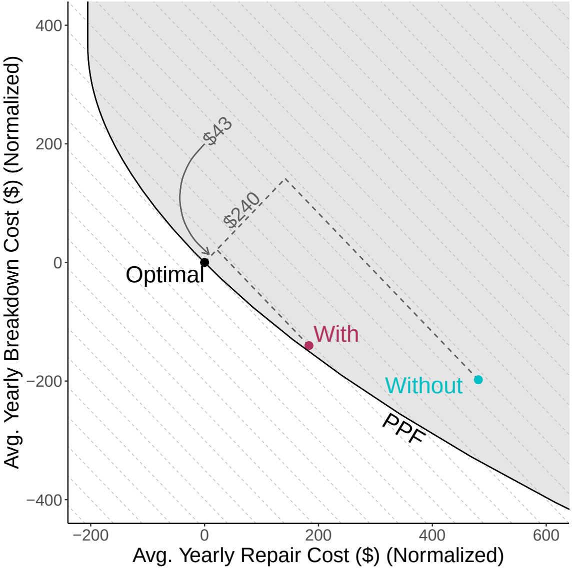

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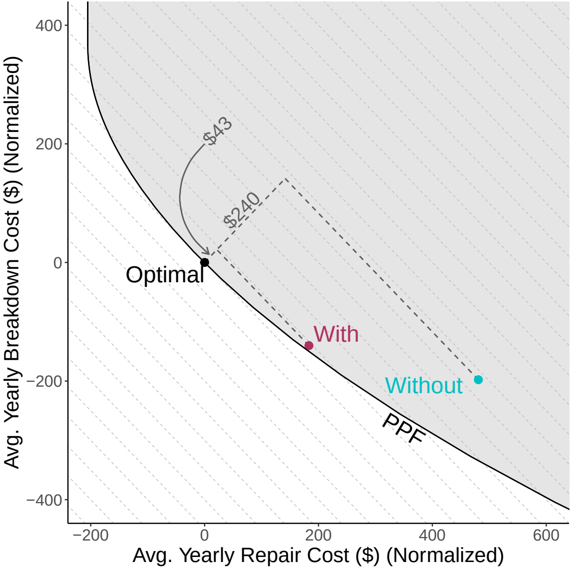

Value of PredictFix:

- Total cost reduction: **$240**.

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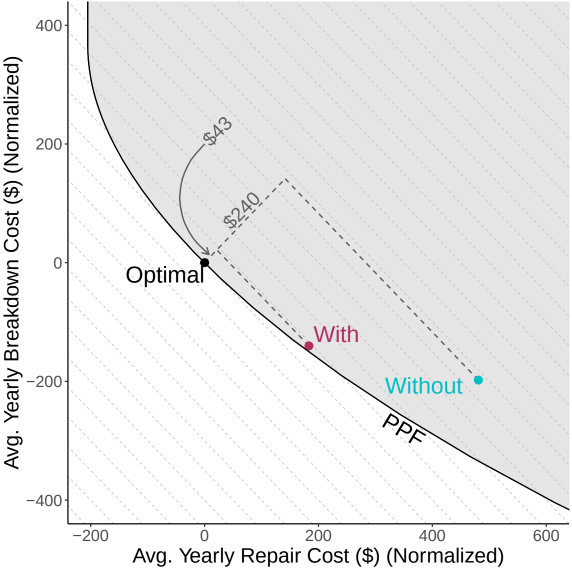
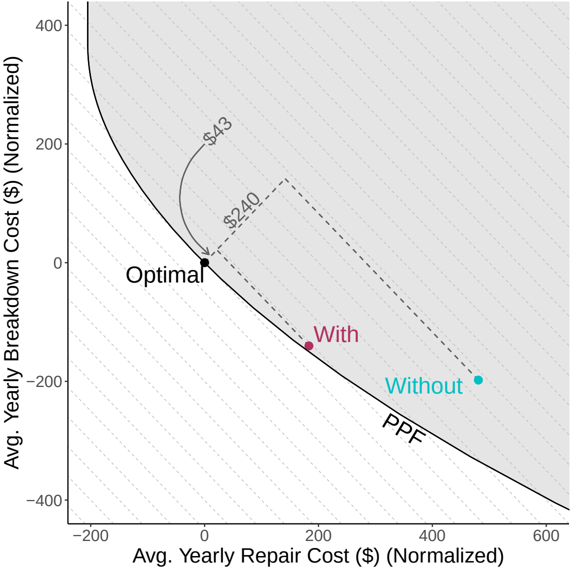


Value of PredictFix:

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

The value of PredictFix



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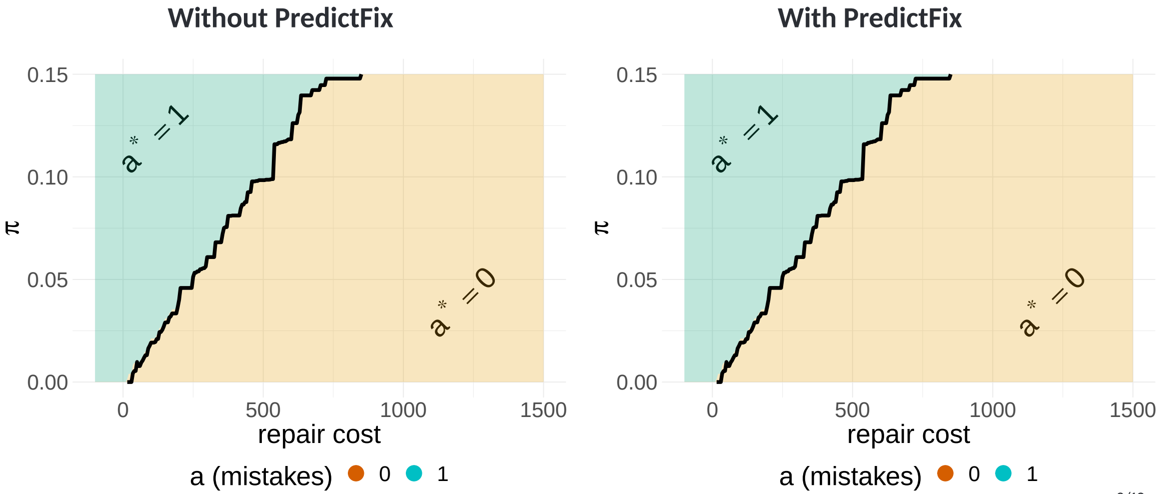
How are cost savings achieved?

Unpacking the value of PredictFix

Mistakes with and without PredictFix



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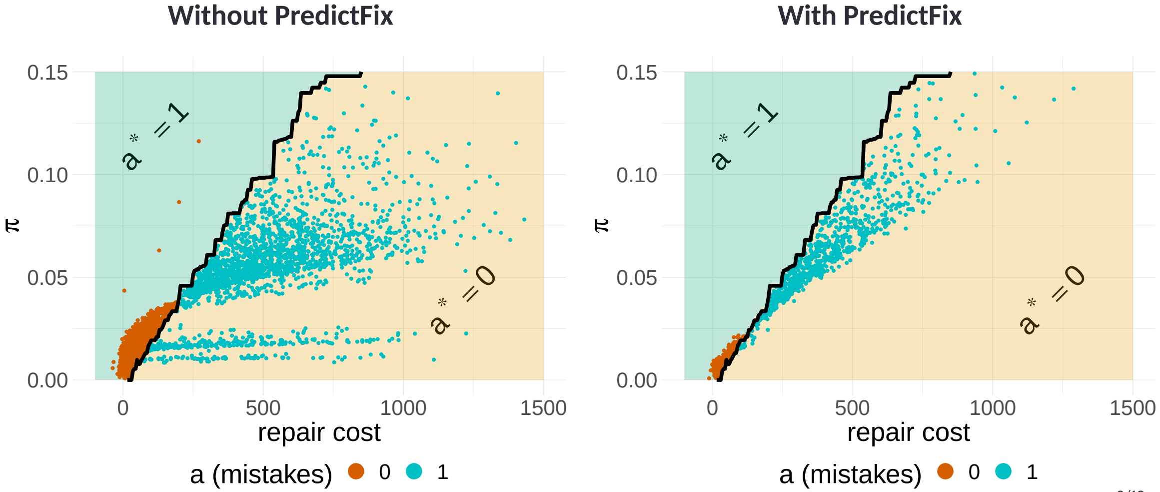

Conclusion

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).

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→ 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?

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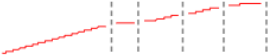
What technician sees

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

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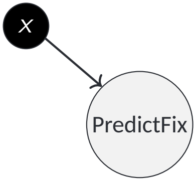

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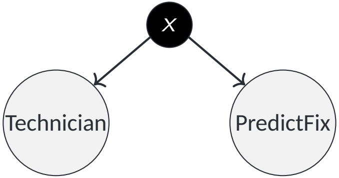
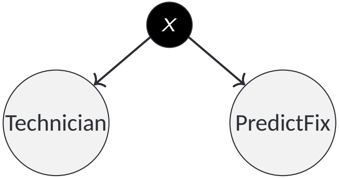


The AI tool

- 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?

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We observe:

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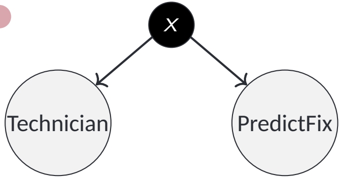

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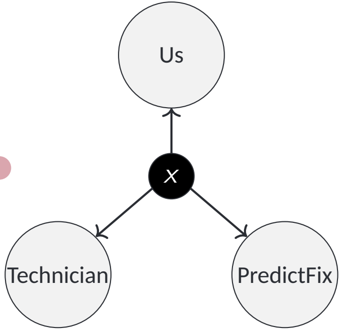

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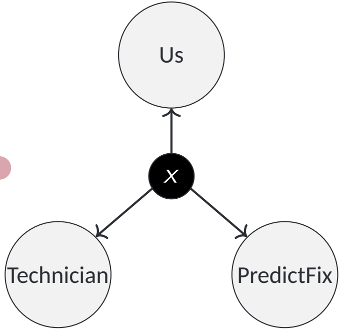
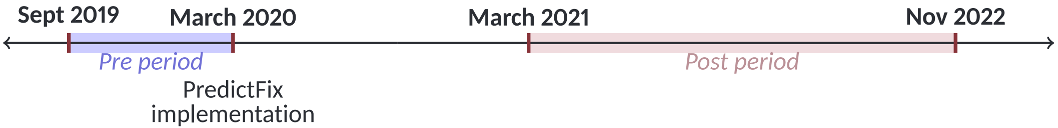


Two disjoint periods:



The technician's problem

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

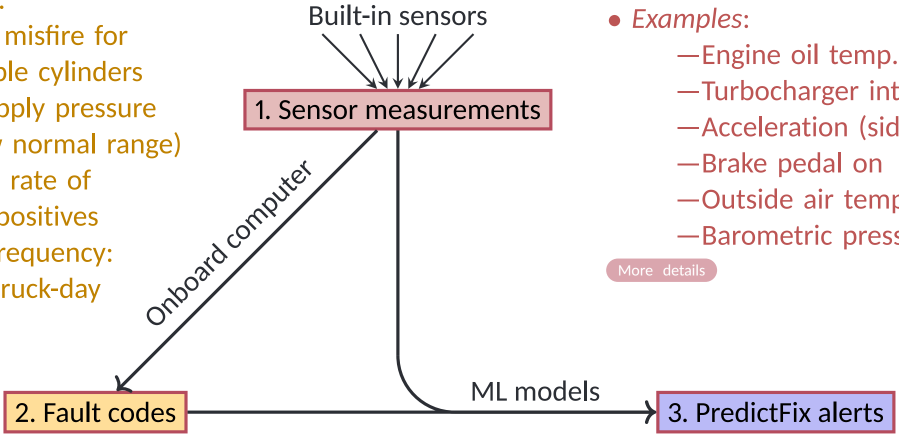
- Tangible costs: Labor, materials, towing, etc.
- Intangible costs:
  - Opportunity cost of truck not being on the road.
  - Capacity constraints (shadow costs).
  - Disruption costs of breakdowns:
    - Damage to relationships with drivers.
    - Damage to relationships with customers.

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

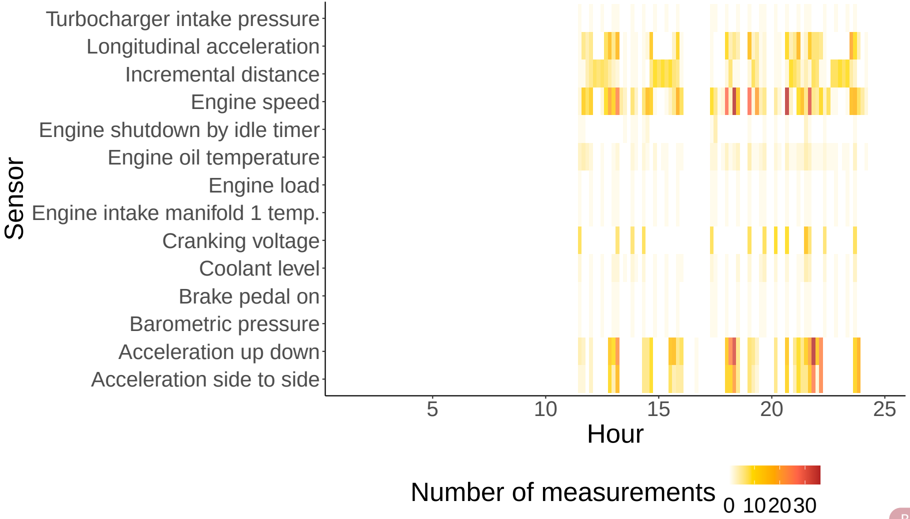


- Median frequency: ~4,000 per truck-day
- *Examples*:
  - —Engine oil temp.
  - —Turbocharger intake pressure
  - —Acceleration (side to side)
  - —Brake pedal on
  - —Outside air temp.
  - —Barometric pressure

More details

What do you see?

Sensor measurement frequency



Back

State of the truck

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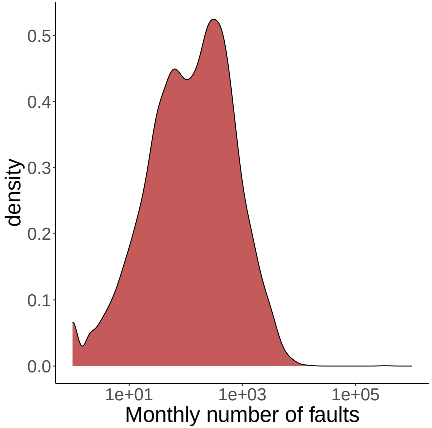
◂ Back

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.



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2.
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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."

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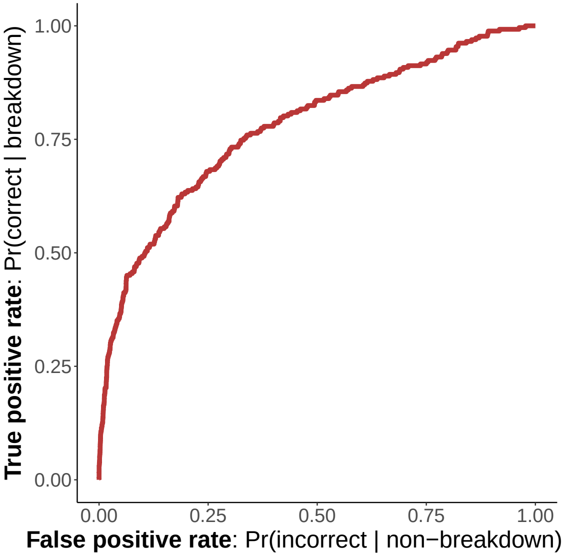

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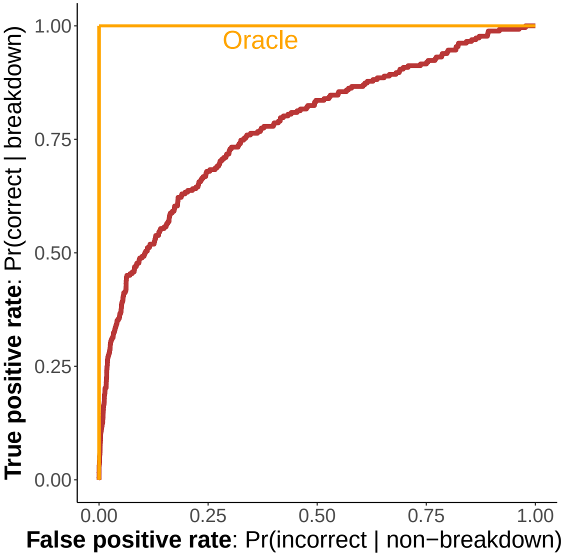

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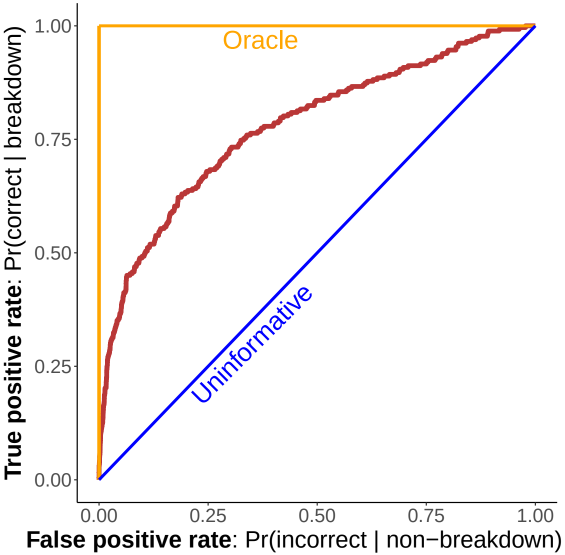

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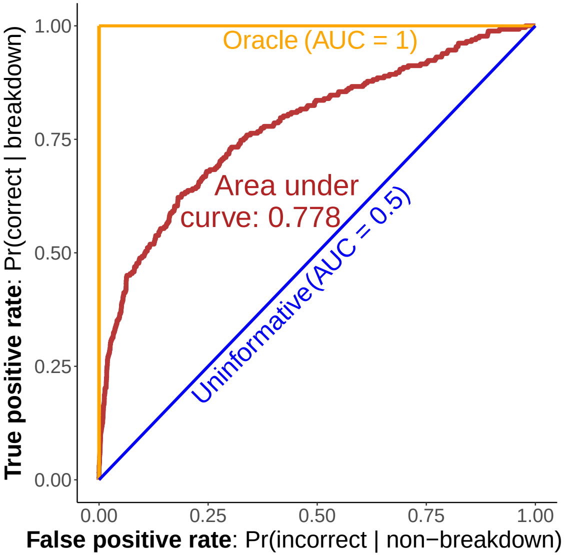

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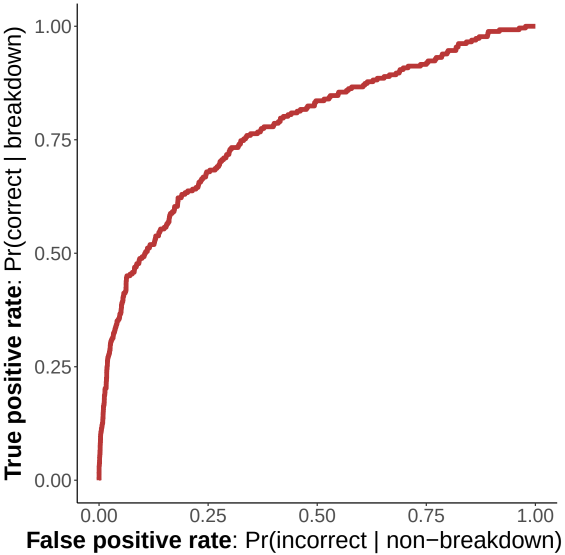

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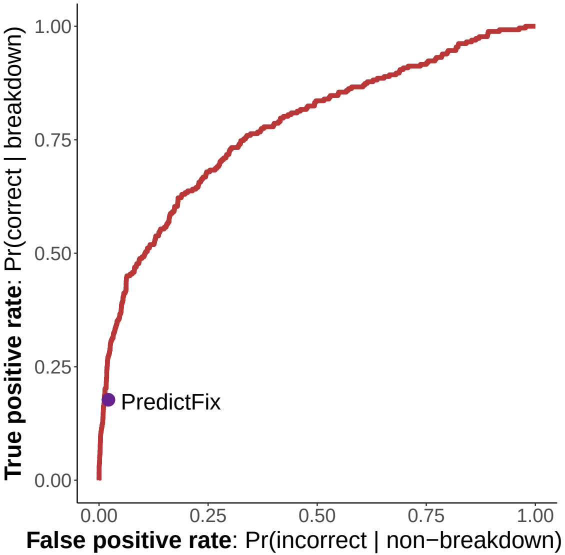

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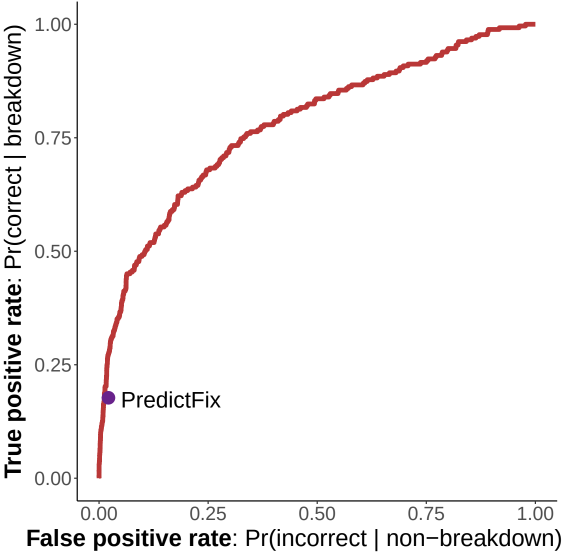
— Among best binary predictors that can be constructed.



Combining with other signals
Back

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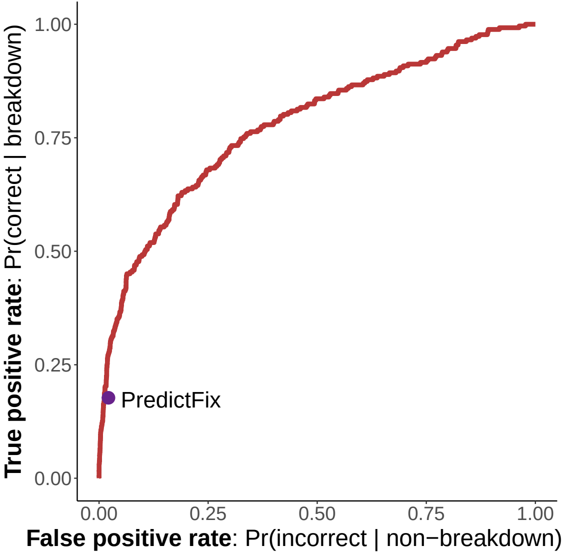

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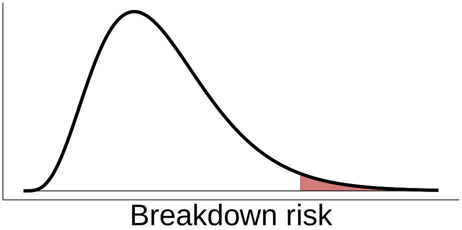

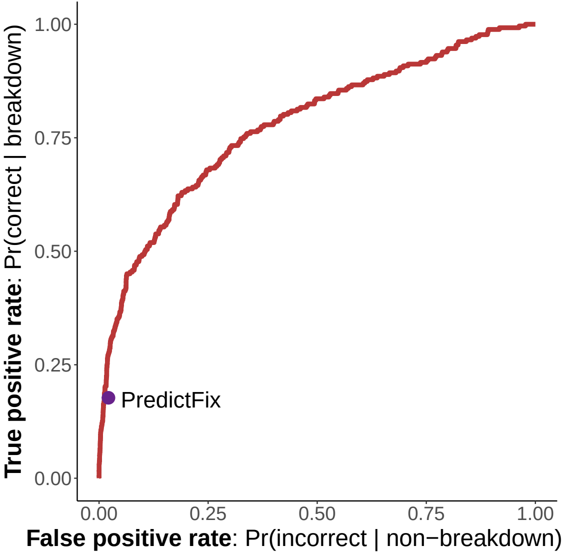

Combining with other signals
Back

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Event = PredictFix alert

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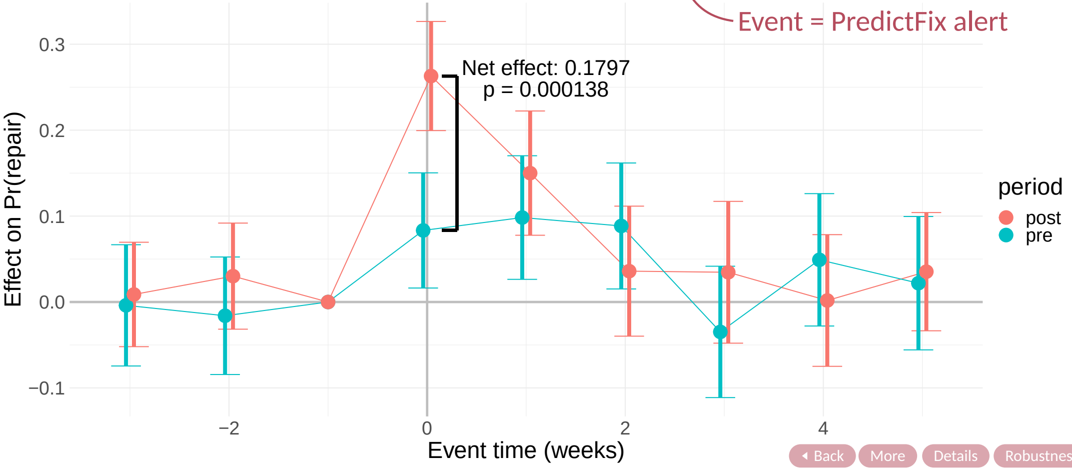

Fact 3: Technicians respond to PredictFix, but also ignore many alerts.

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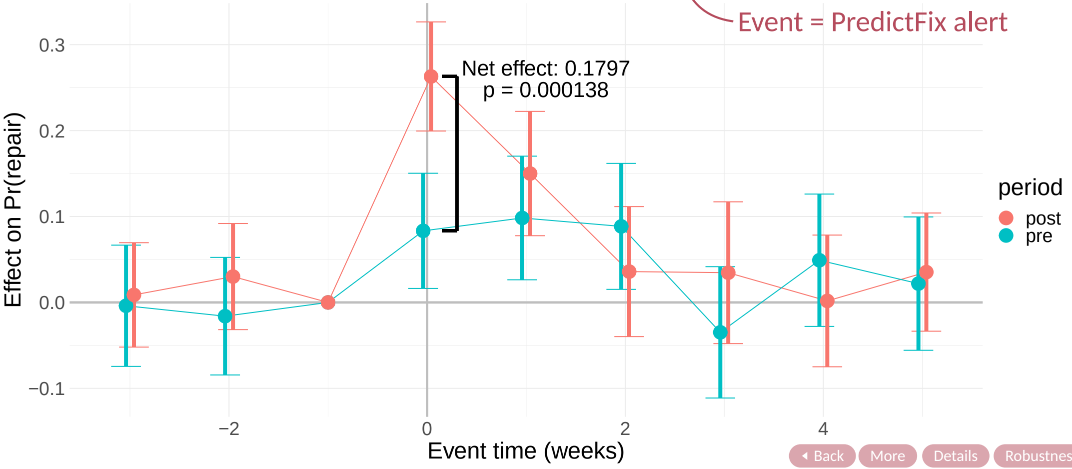

Descriptive evidence: Five facts

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

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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.
   → 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.

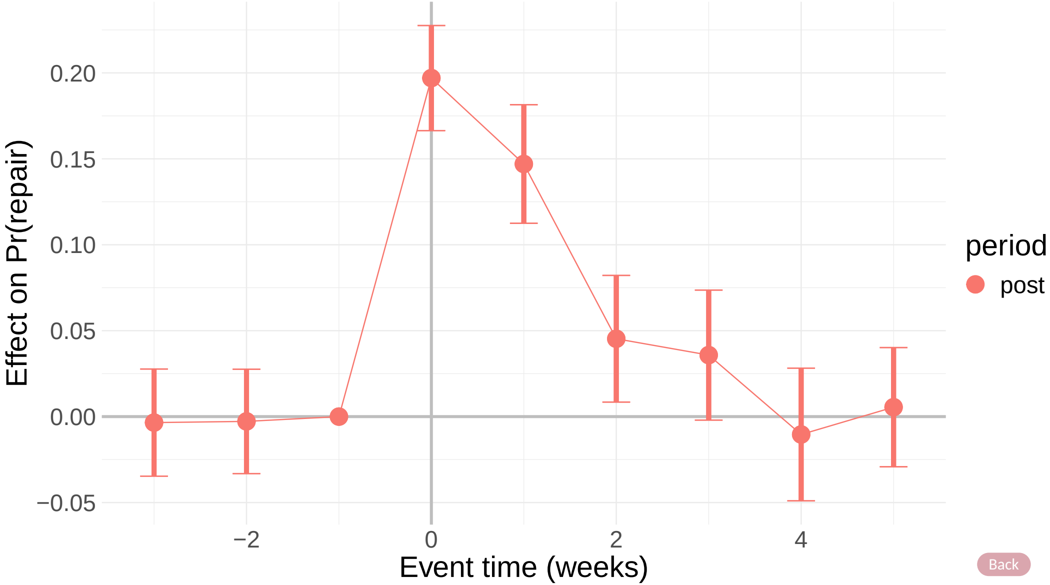
$$\text{Repair}_{i,t} = \alpha_0 + \sum_{k \in \{\text{pre,post}\}} \sum_{\tau=-3}^{5} \beta_\tau^k \mathbb{1}\{t \in \mathcal{T}_k\} \widehat{\text{PredictFix}}_{i,t-\tau} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

— 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



Fact 3 (Medium-Priority Alerts)

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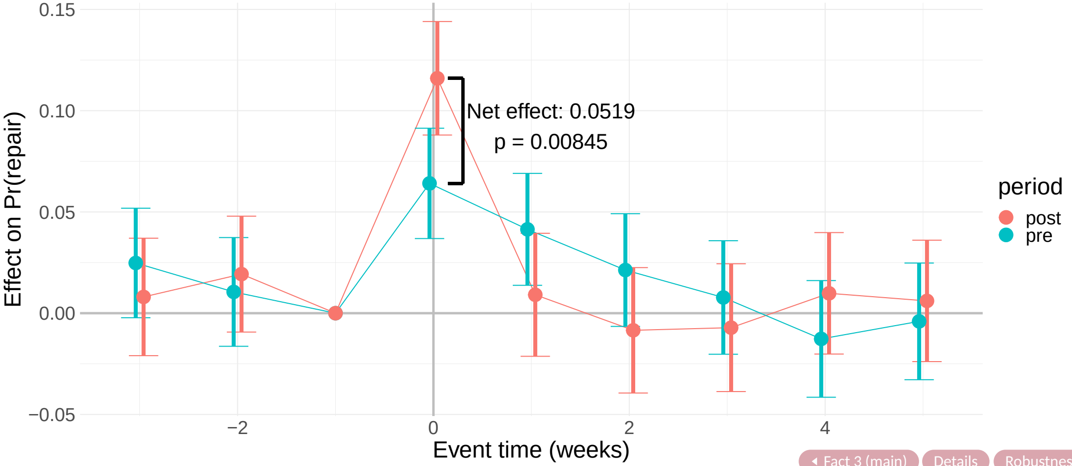
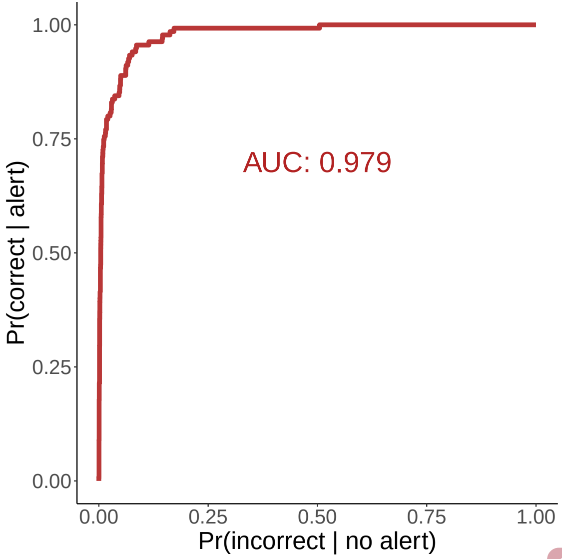


Predicting PredictFix

ROC curves



Fact 3 (details) Fact 3 (main)

Predicting PredictFix

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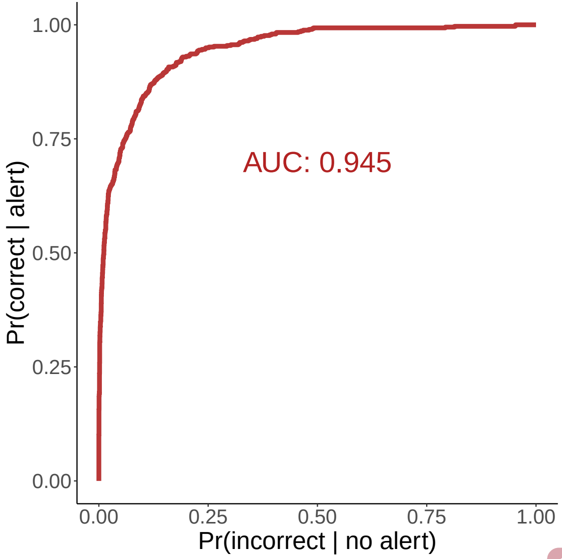
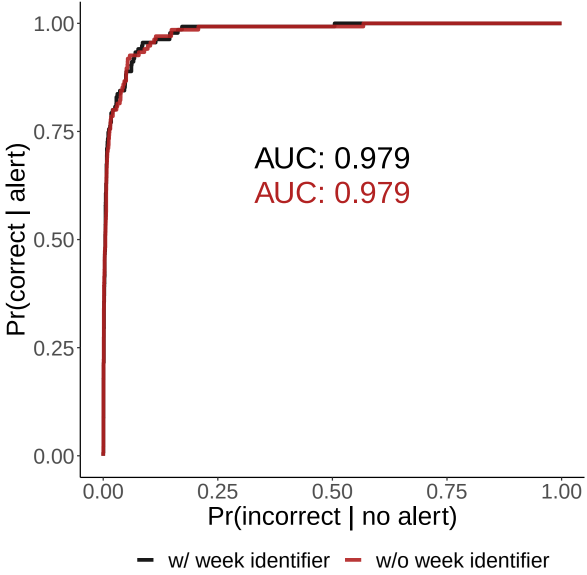
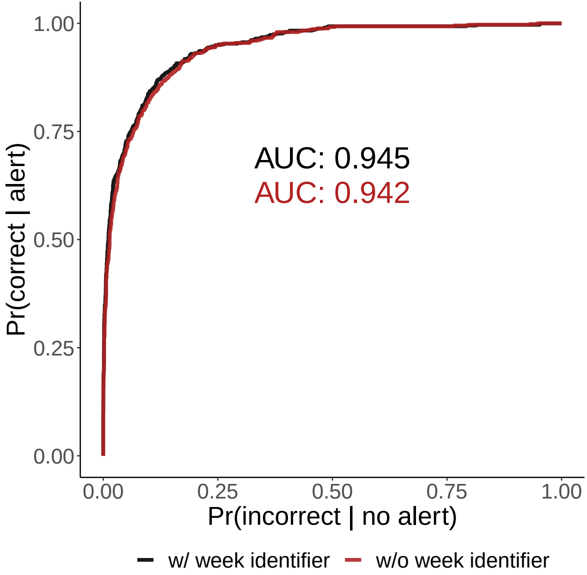


PredictFix is stable over the post period



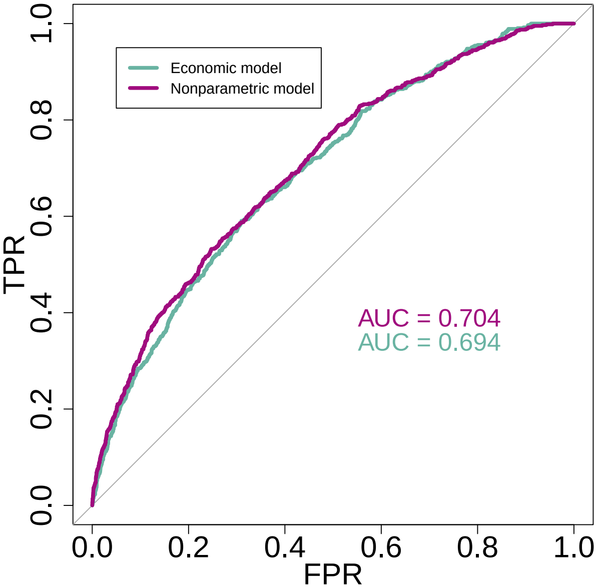
PredictFix
Data
Fact 2

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 $\rightarrow$ 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 Λ 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

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

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.

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  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

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- When (w,x) is high-dimensional, 2. is clearly infeasible.

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

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 ρ, they only affect the *interpretation* of τ.

Back

PredictFix

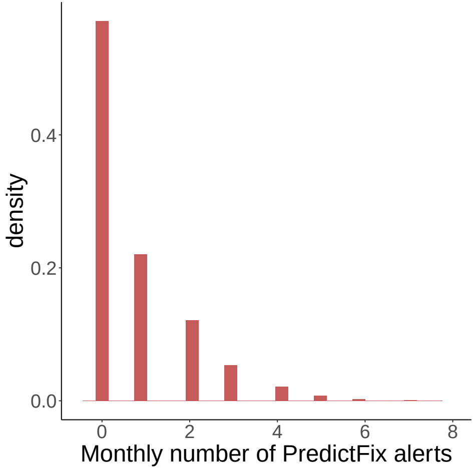
AI Tool Data

(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" $\rightarrow$ High severity
  - "Coolant leak" $\rightarrow$ Medium severity
  - "Engine knocking" $\rightarrow$ 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

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.

Results

Static model

Constant B

More on payoffs

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

Results

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  - $\rightarrow$ **Not** imposing specific model of how technicians form these beliefs.

Static model

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Threshold: Repair if and only if

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

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Key questions:

- Does PredictFix move ρ closer to π?
- If so, to what extent do better decisions result?

Results

Econometric challenge

Repair if and only if

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

Goal: Estimate preferences τ and beliefs ρ.

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

Econometric challenge

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

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Econometric challenge

Repair if and only if

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

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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 τ and beliefs ρ.

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 ρ.

Separate identification of preferences and beliefs

Two restrictions on ρ

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

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

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

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   ↳ Average over states.

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Results

Separate identification of preferences and beliefs

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- **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

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

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

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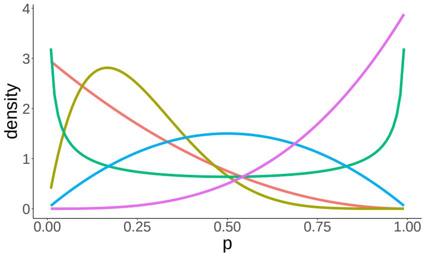
- **Challenge**: State is high-dimensional.

$\rightarrow$ **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



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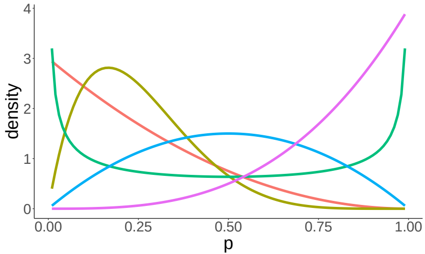
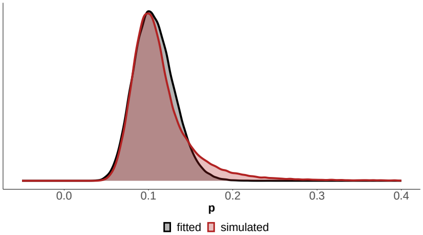
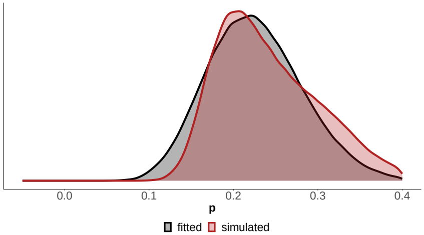


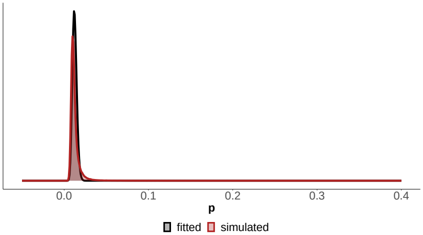
(b) Example 1



(c) Example 2



(d) Example 3



Model estimation

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

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

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

Goodness of model fit

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

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

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

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

Goodness of model fit

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.

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 ξ is observed by the technician but not by the econometrician. Then,

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

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

What this assumption buys us:

- Progress toward identification of ρ and τ.
- Identification of $\boldsymbol{\pi}(x)$.
  - $\rightarrow$ No selective labels problems.
  - $\rightarrow$ Our ML predictor of breakdown risk has the interpretation of $\boldsymbol{\pi}(x)$.

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 $\text{AUC} = \Pr\left(\hat{\pi}\left(x_{i_1}\right) > \hat{\pi}\left(x_{i_0}\right)\right)$.

Back

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 ρ:**

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

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, ρ: 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

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

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

Implies that

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

where ψ is the digamma function, and

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

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

Minimally restrictive:

- Beta is a flexible distribution.
- μ is function of (a_t, w_t, x_t).
- ν 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

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

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 $(w, x) \in \mathcal{W} \times \mathcal{X}$.

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}).

$\rightarrow$ 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**,

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

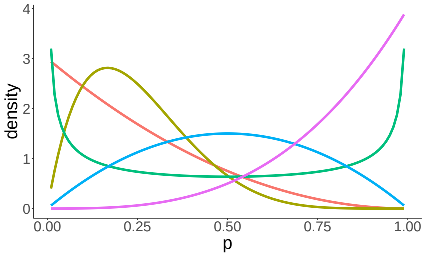
Yet identification/estimation **do not** require these assumptions.

Back

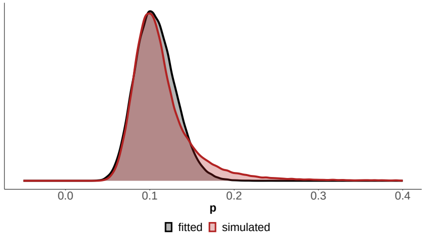
Beta distribution

Back

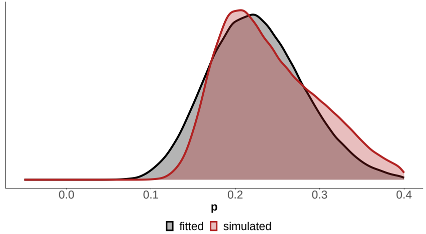
(a) Examples: Beta for various parameters



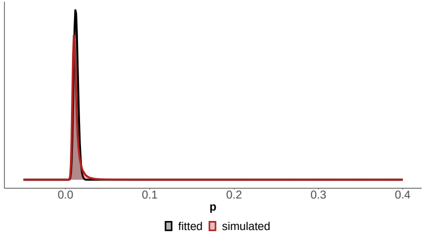
(b) Example: $a_{it} = 0, g_{it} = 0.1, \pi_{it} = 0.014$



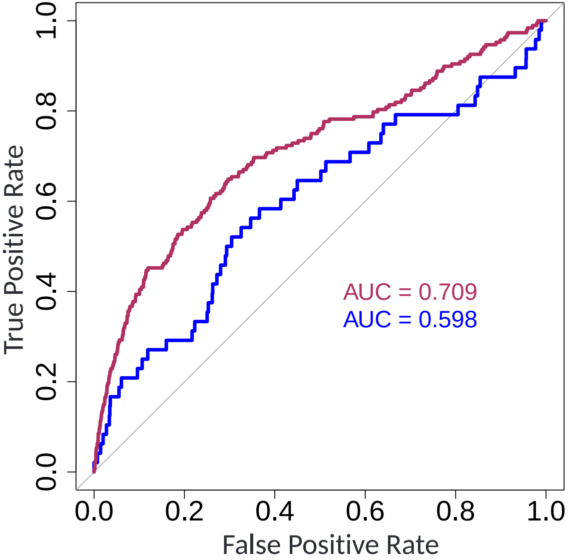
(c) Example: $a_{it} = 0, g_{it} = 0.04, \pi_{it} = 0.05$



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



The effect of PredictFix on technicians' predictions (ρ)

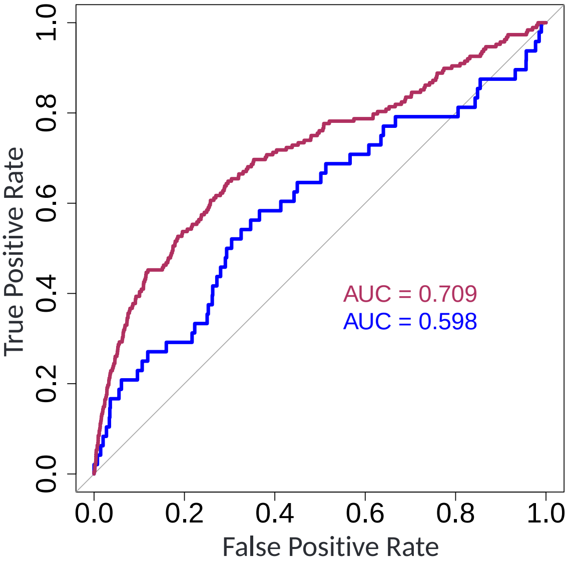


Predictor	
$\hat{\rho}_{pre}$	Beliefs w/o PredictFix
$\hat{\rho}_{post}$	Beliefs w/ PredictFix

Note:

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

The effect of PredictFix on technicians' predictions (ρ)



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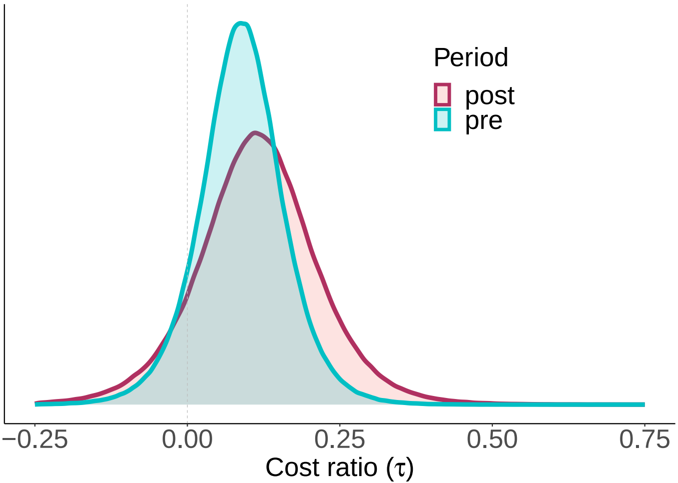
$\hat{\rho}_{post}$	Beliefs w/ PredictFix

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

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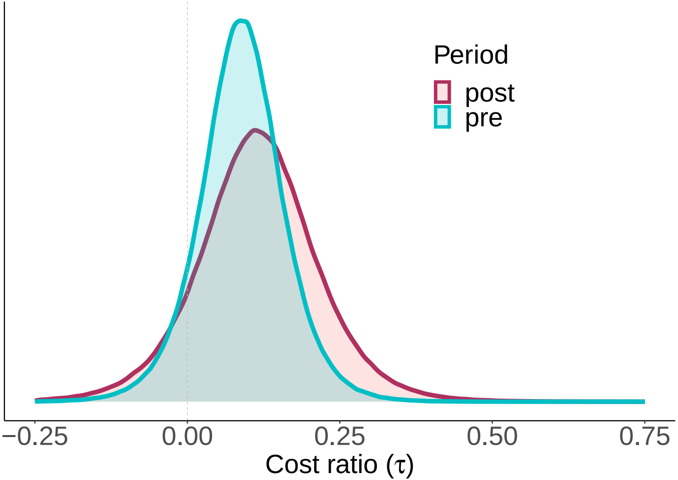

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→ Supply chain disruptions.

- Fact 5: Tangible costs ↑.
- Repair completion time ↑.

The effect of PredictFix on technicians' beliefs

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

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

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Tool: ROC curves.

Table: ROC curve specifications

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

More

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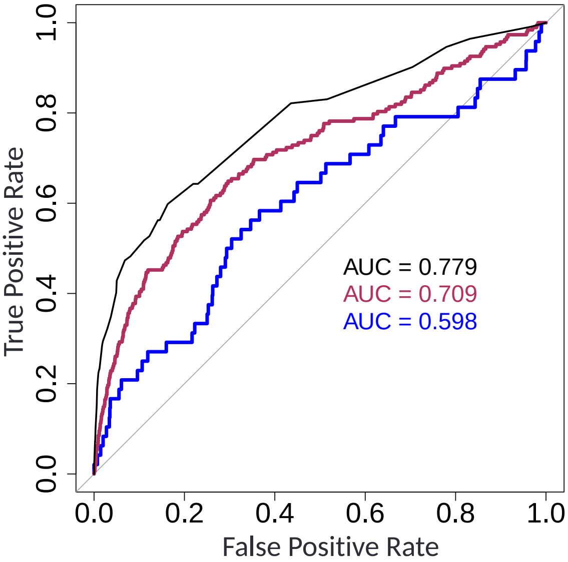
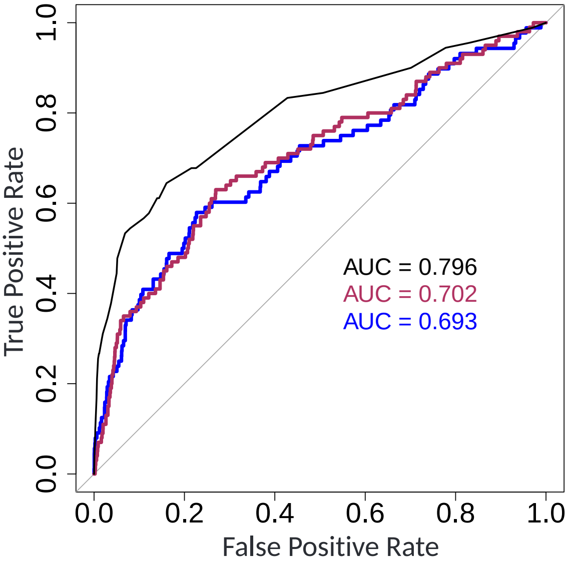


Predictor	
$\hat{\rho}_{pre}$	Beliefs w/o PredictFix
$\hat{\rho}_{post}$	Beliefs w/ PredictFix
$\hat{\pi}_{ML}$	Benchmark

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	
$\hat{\rho}_{\text{post (first half)}}$ $\hat{\rho}_{\text{post (second half)}}$	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.

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— 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:

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

Counterfactual details

Joint transition process for (π_{it}, ρ_{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^{ι} using Gaussian mixture regression.

- Relationship between ι and ρ: 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 (ρ)

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 (ρ)

What about miscalibration?

Logistic regression:

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

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

Back Simulation

The effect of PredictFix on technicians' predictions (ρ)

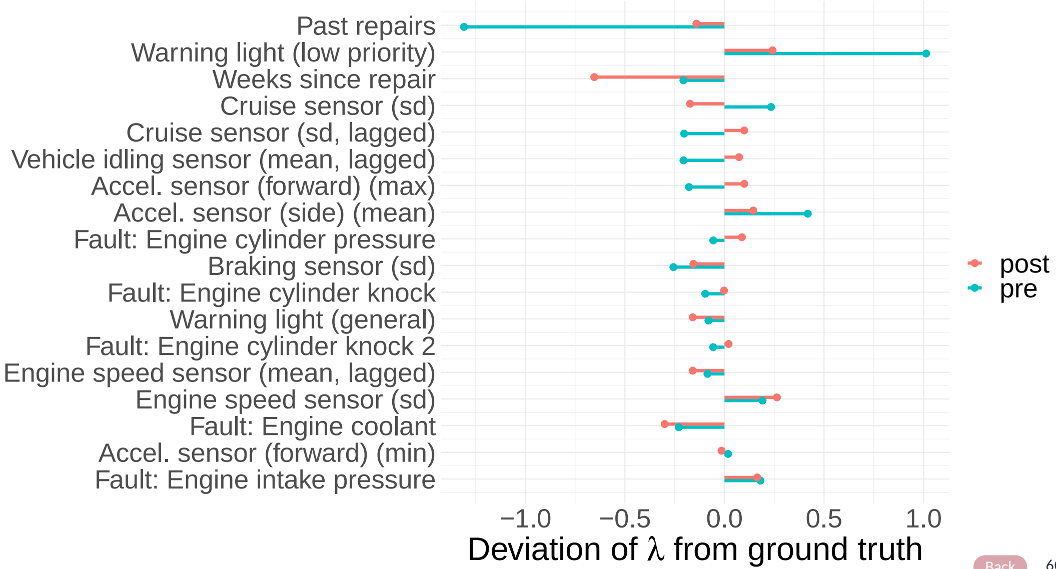
What about miscalibration?

Logistic regression:

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

	$\rho = \pi$	ρ_{pre}	ρ_{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

Why do technicians overestimate risk?



Back

Where do technicians make mistakes?

An illustrative example: How technicians respond to dashboard warning lights

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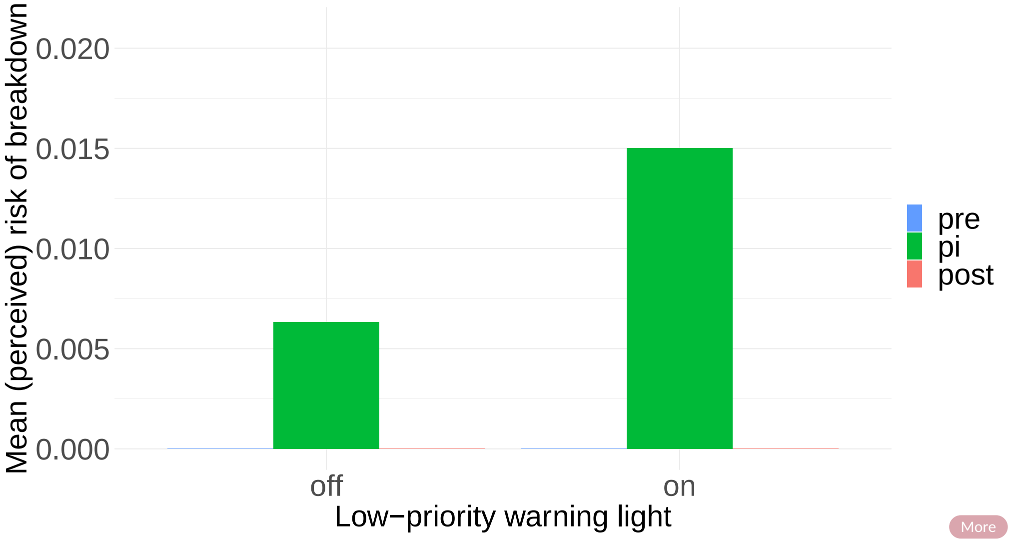
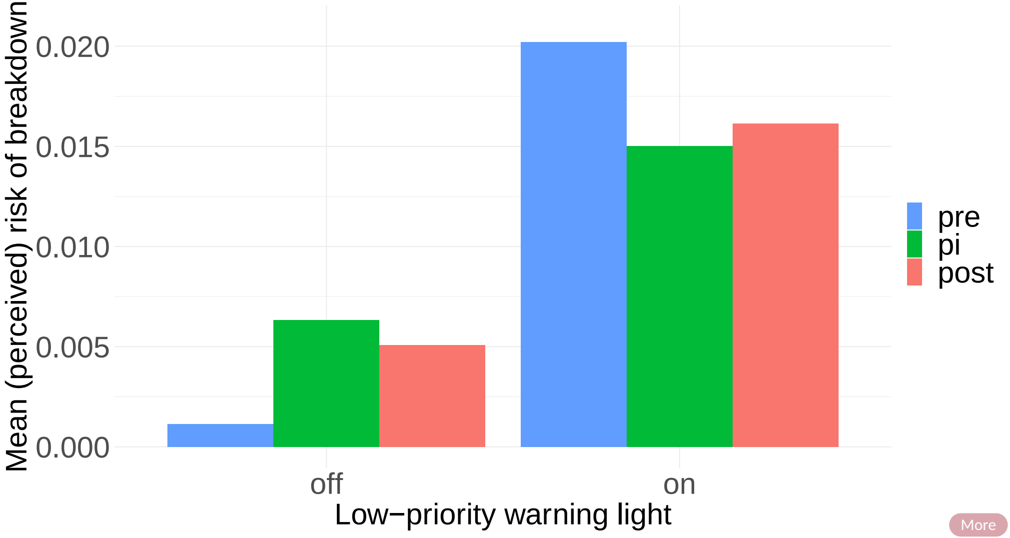
An illustrative example: How technicians respond to dashboard warning lights



More

Where do technicians make mistakes?

An illustrative example: How technicians respond to dashboard warning lights



Where do technicians make mistakes?

An illustrative example: How technicians respond to dashboard warning lights