

“Dice”-sion Making under Uncertainty: When Can a Random Decision Reduce Risk?

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Imperial College Business School

joint work with Erick Delage and Daniel Kuhn

Tilburg University, Dec 2017

Facility Location under Uncertainty



Facility Location under Uncertainty



0.45 vs. 0.59
 $\mu = 0.52$

Facility Location under Uncertainty



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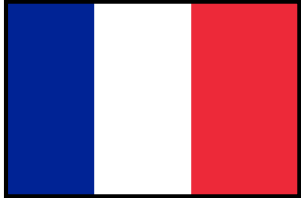
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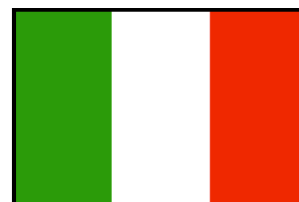
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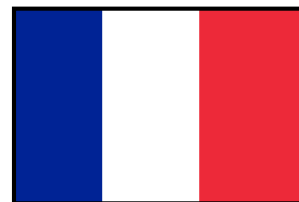
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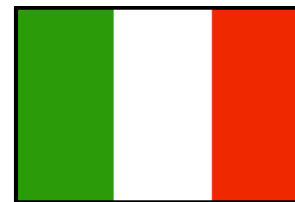
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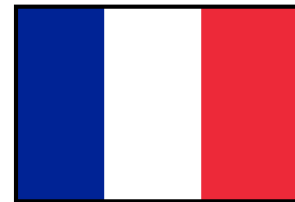
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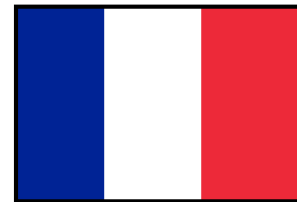
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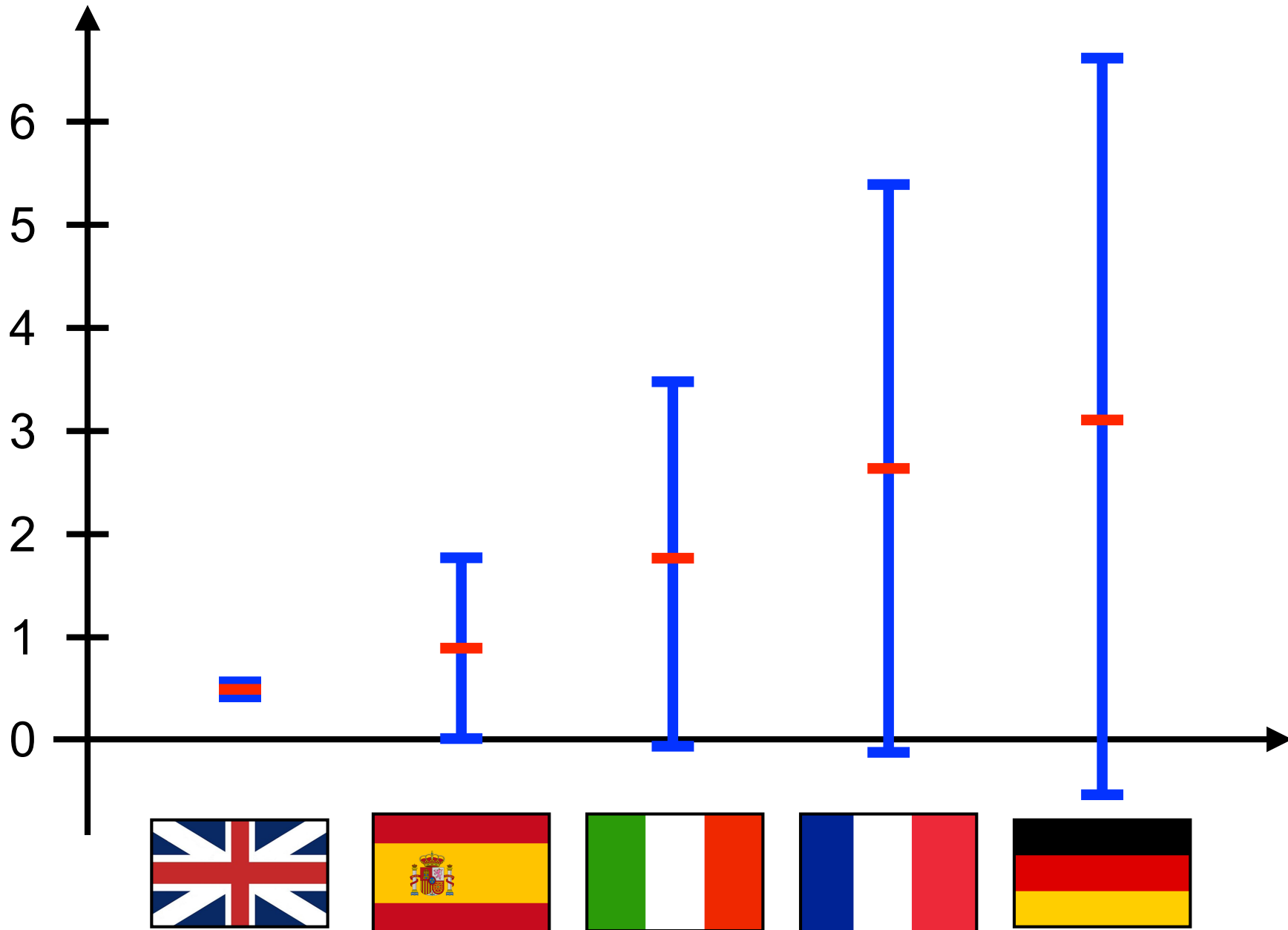


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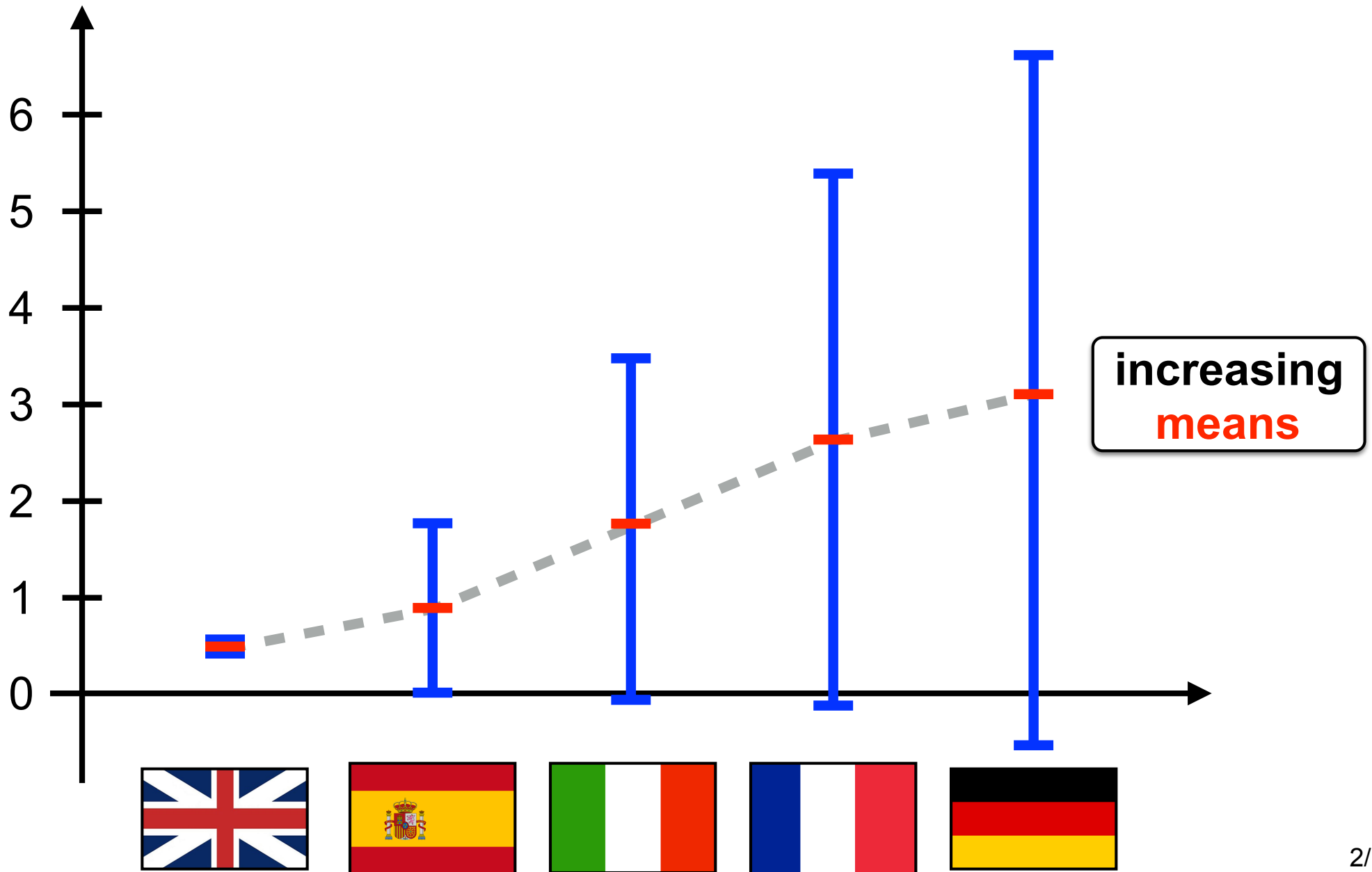


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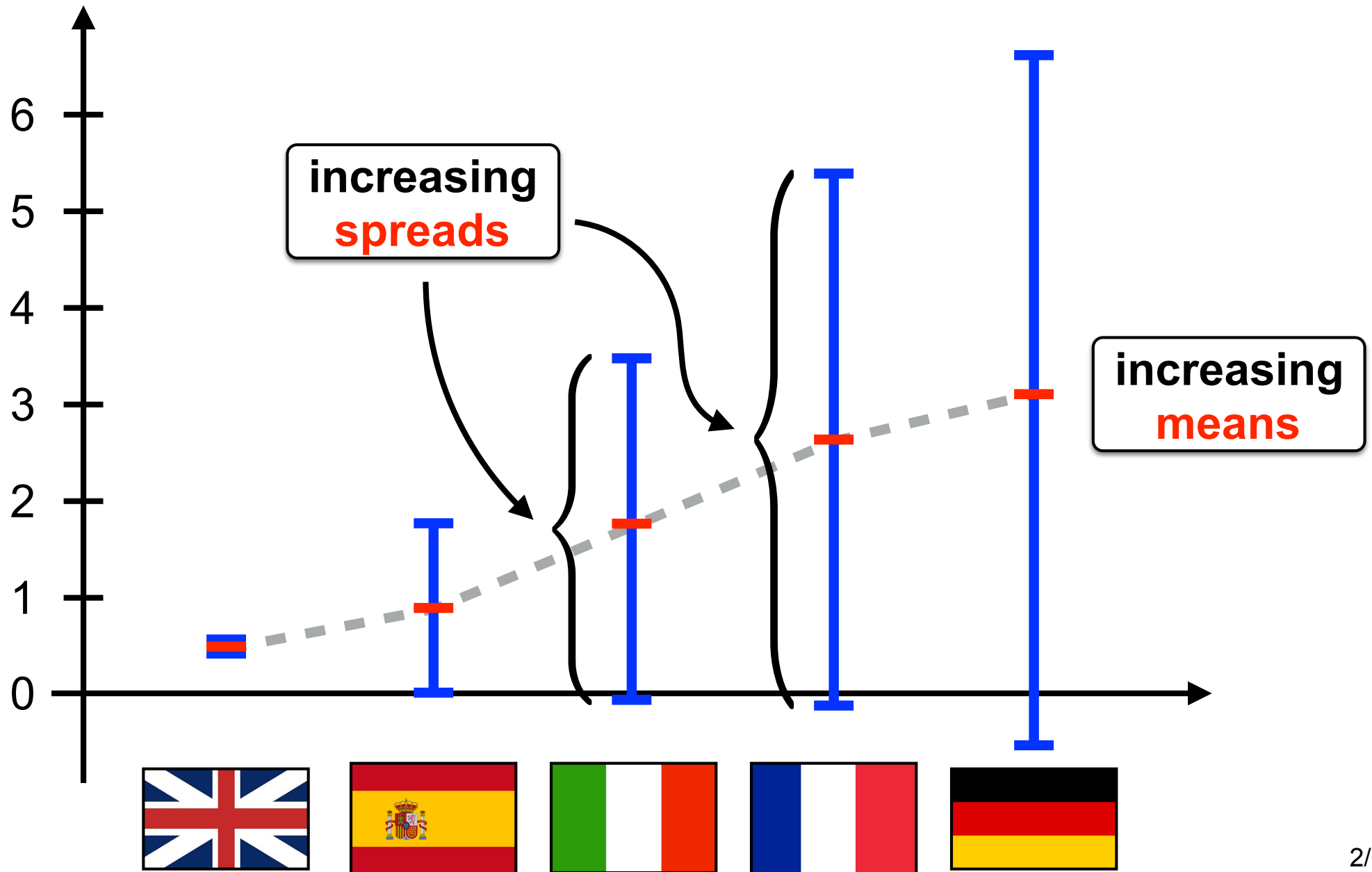
Risk Averse Decision-Making



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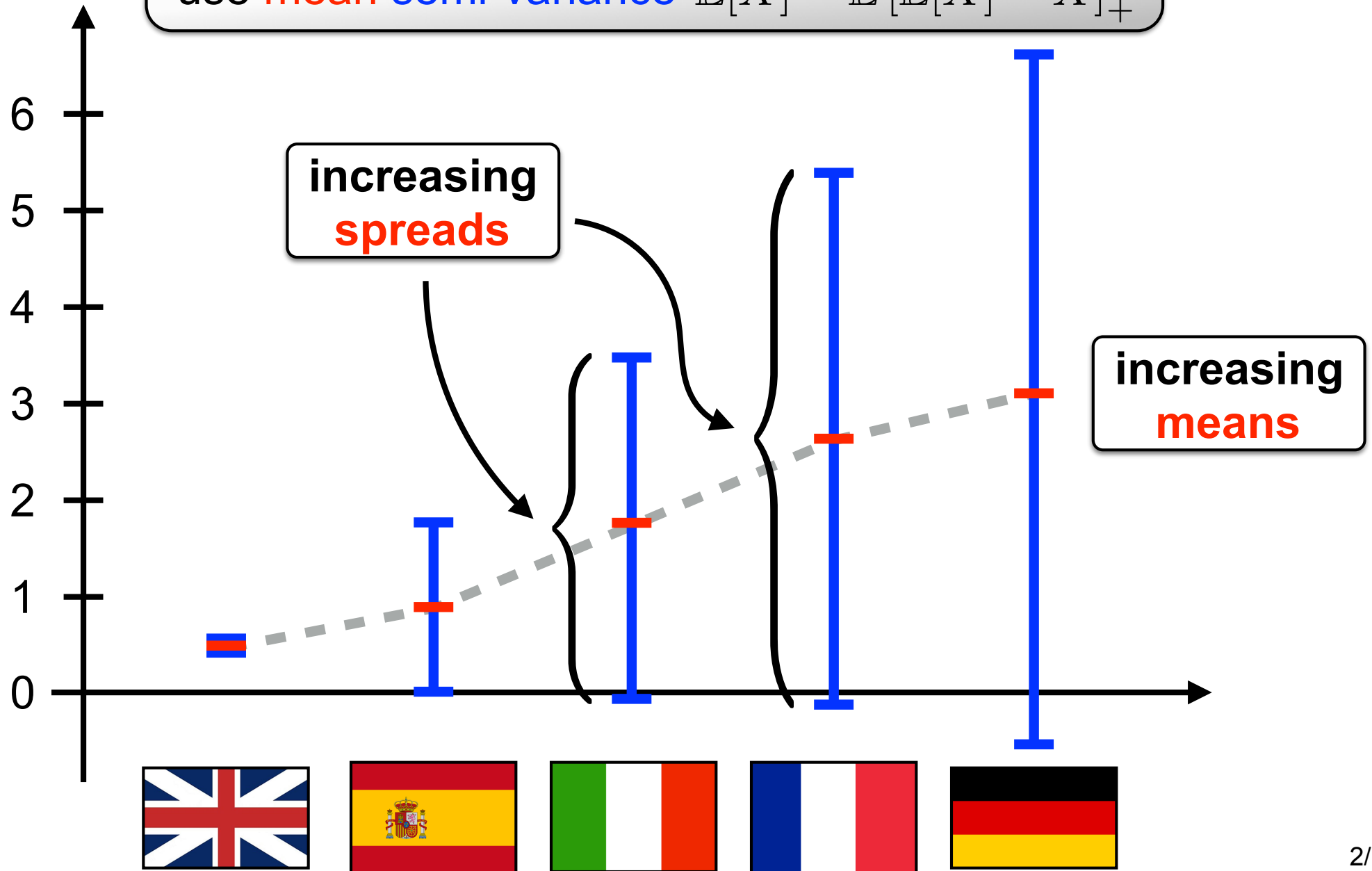
Risk Averse Decision-Making



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To account for the profit variation:

use **mean semi-variance** $\mathbb{E}[X] - \mathbb{E}[\mathbb{E}[X] - X]_+^2$



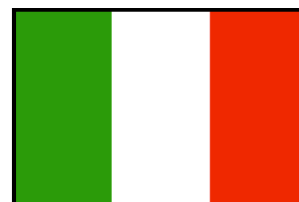
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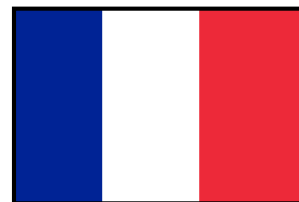
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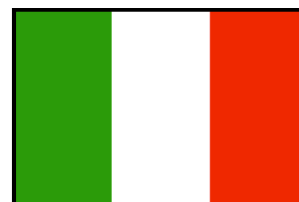
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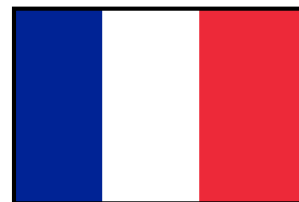
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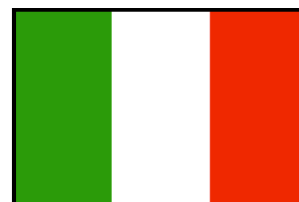
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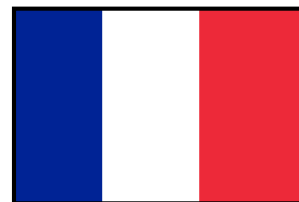
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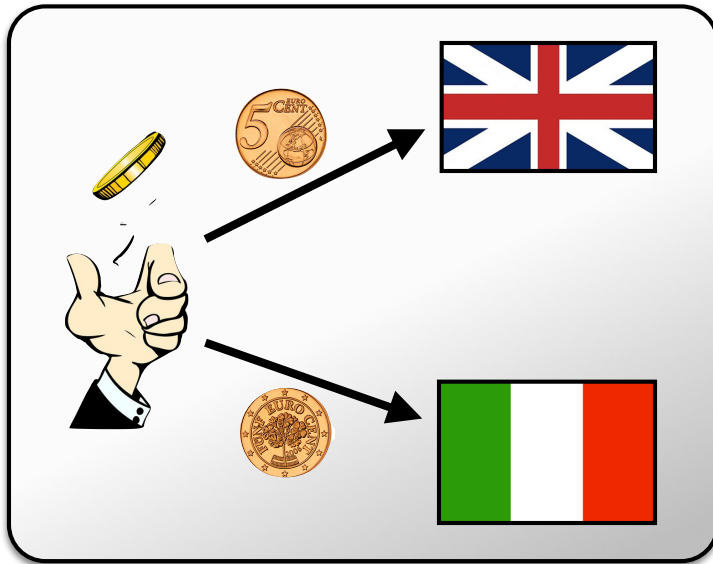
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Facility Location under Uncertainty

Randomized decisions
can reduce the risk:



$$M/SV = 0.59$$



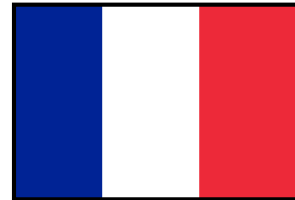
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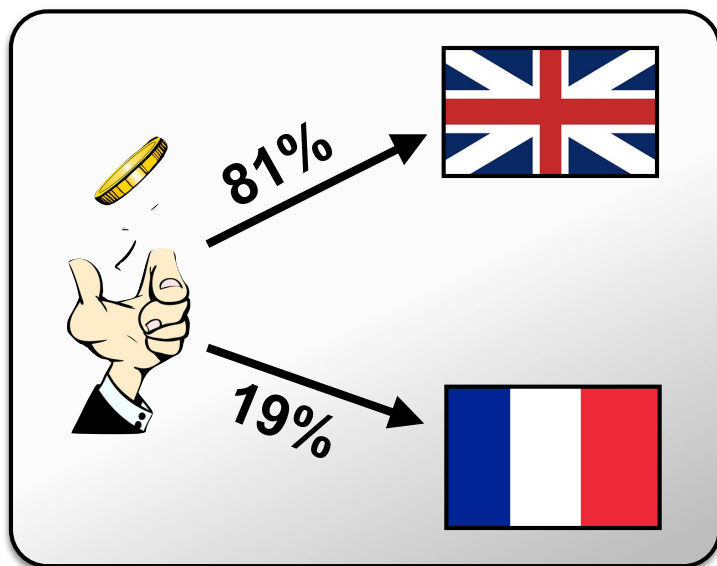
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Facility Location under Uncertainty

Randomized decisions
can reduce the risk:



$$M/SV = 0.69$$



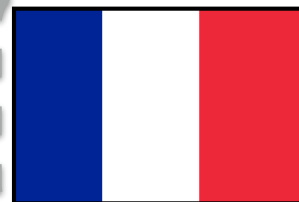
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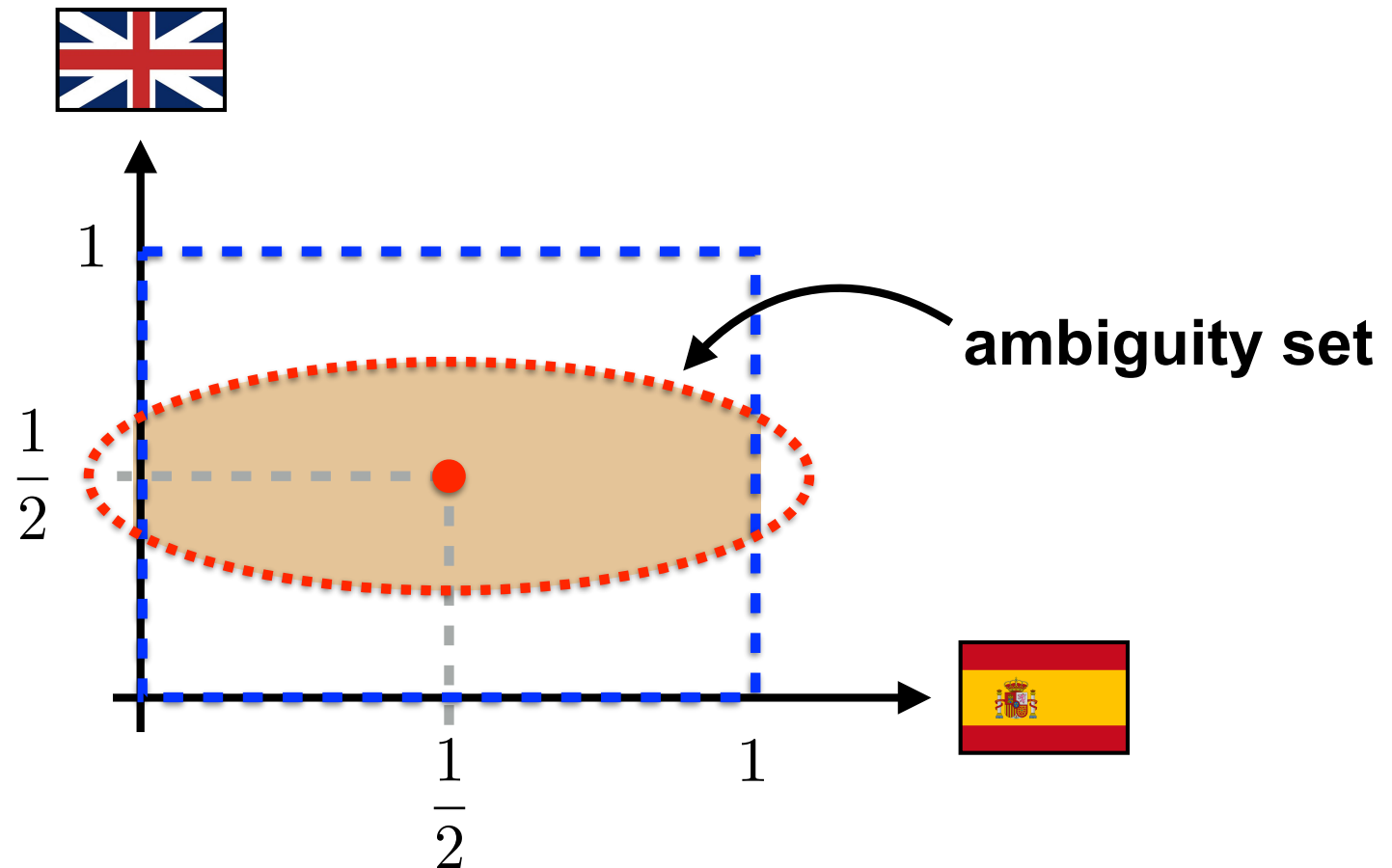
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Ambiguity Averse Decision-Making

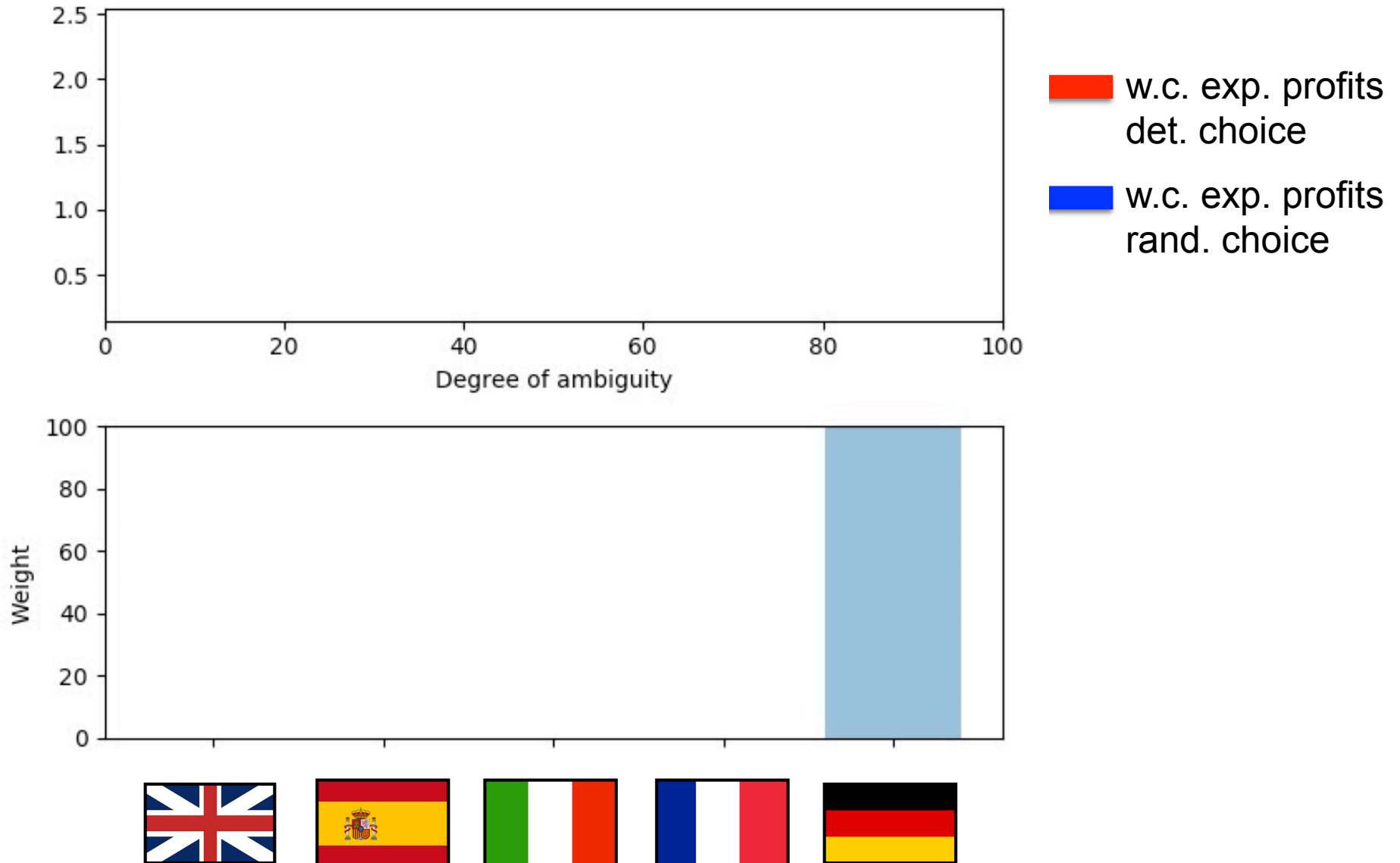
In practice, the **probabilities** for the **profit scenarios** may only be **partially known**:



Distributionally robust optimization: Optimize a **risk measure** over **worst distribution** in **ambiguity set**

Ambiguity Averse Decision-Making

Assume we want to **maximize expected profits** under the **worst probability distribution** in the **ambiguity set**.



Agenda

1 ~~Motivation~~

2 **Randomization under Distributional Ambiguity**

Background

Problem Setup

The Power of Randomization

3 Discussion

Ambiguous Probability Spaces

We model uncertainty via an *ambiguous probability space*:

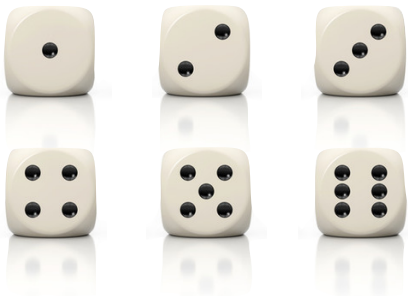
$$(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$$

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Ω_0 is the
sample space:

\mathcal{F}_0 is the
 σ -algebra of events:



\emptyset , , , ...,



($2^6 = 64$ sets)

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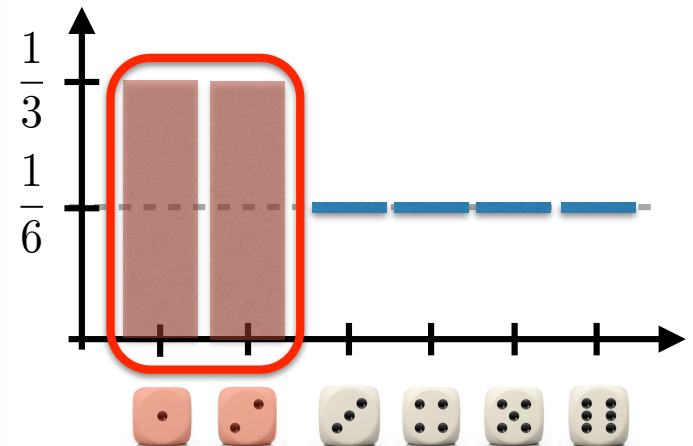


\mathcal{F}_0 is the
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$(2^6 = 64 \text{ sets})$

\mathcal{P}_0 is the
ambiguity set:



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We model uncertainty via an *ambiguous probability space*:

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We denote by $\mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$ the **real-valued random variables** that are essentially bounded w.r.t. *all* $\mathbb{P} \in \mathcal{P}_0$:

$$\mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0) = \bigcap_{\mathbb{P} \in \mathcal{P}_0} \mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathbb{P})$$







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	→ -10		→ 10	we think of X as revenues
	→ 10		→ -10	
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We denote by $F_X^\mathbb{P}$ the **distribution function** of X under $\mathbb{P} \in \mathcal{P}_0$:

$$F_X^\mathbb{P}(x) = \mathbb{P}(X \leq x) \quad \forall x \in \mathbb{R}$$

Let \mathcal{D} be the set of **all** distribution functions

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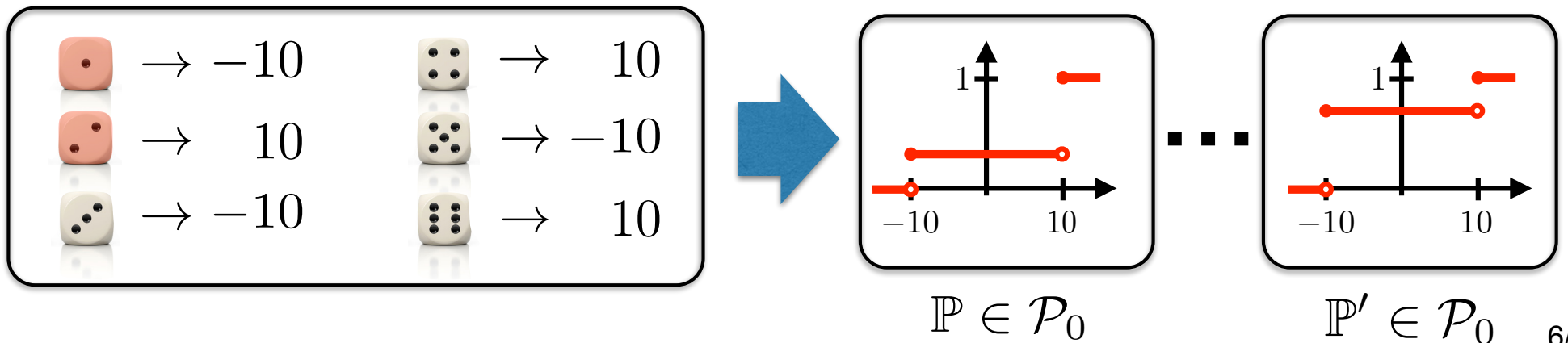
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An ambiguous probability space $(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$ is **non-atomic** if:

$\exists U_0 \in \mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$ that follows a **uniform distribution** on $[0, 1]$ under every probability measure $\mathbb{P} \in \mathcal{P}_0$.

Risk Measures

A **risk measure** assigns each random variable a risk index:

$$\rho_0 : \mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0) \rightarrow \mathbb{R}$$

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$$\rho_0 \left(\begin{array}{cc} \begin{array}{c} \text{1} \rightarrow -50 \\ \text{2} \rightarrow 10 \\ \text{3} \rightarrow -50 \end{array} & \begin{array}{c} \text{4} \rightarrow 10 \\ \text{5} \rightarrow -50 \\ \text{6} \rightarrow 10 \end{array} \end{array} \right) = 2$$

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Risk Measures

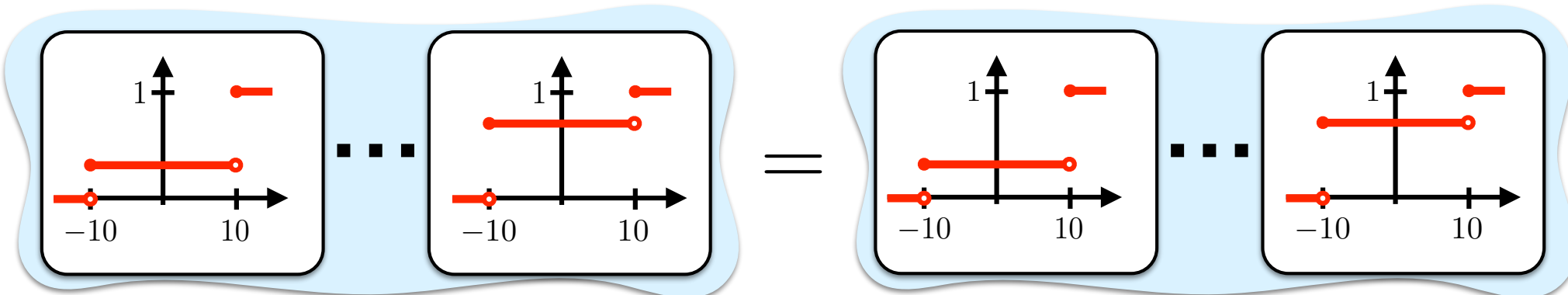
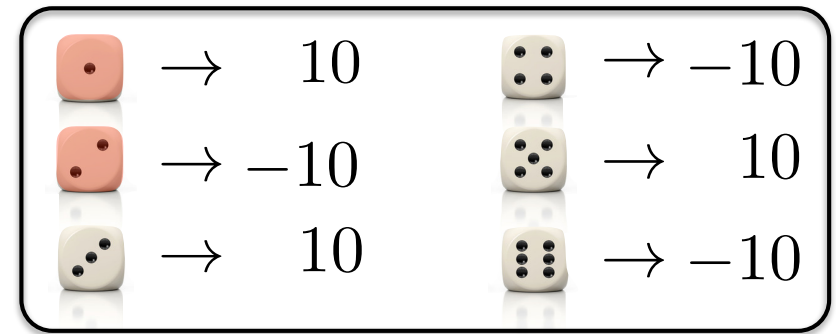
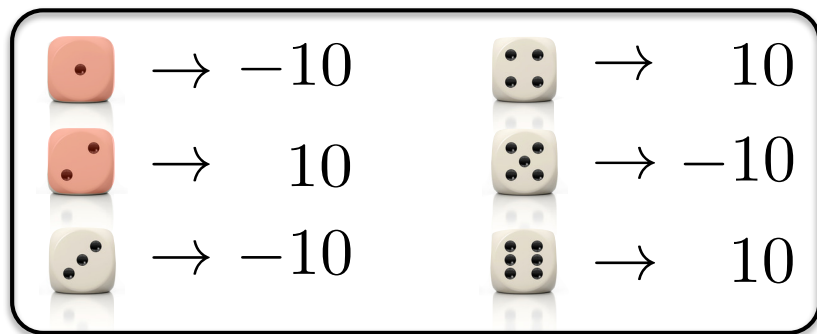
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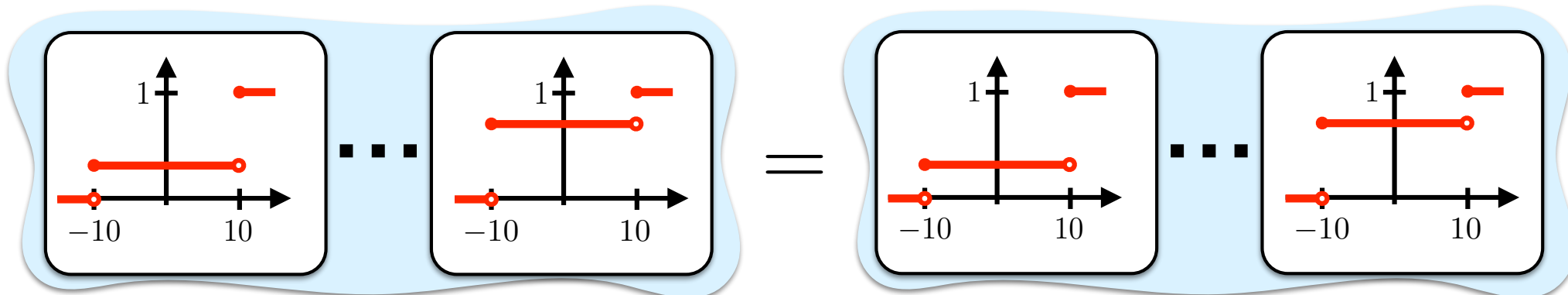
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Representation of Risk Measures

Proposition: Assume that $(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$ is **non-atomic** and that ρ_0 is **law invariant**.

☑ For all $F \in \mathcal{D}$ there is $X \in \mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$ with $F_X^{\mathbb{P}} = F$ for all $\mathbb{P} \in \mathcal{P}_0$.

☑ There exists a unique $\varrho_0 : \mathcal{D} \rightarrow \mathbb{R}$ satisfying

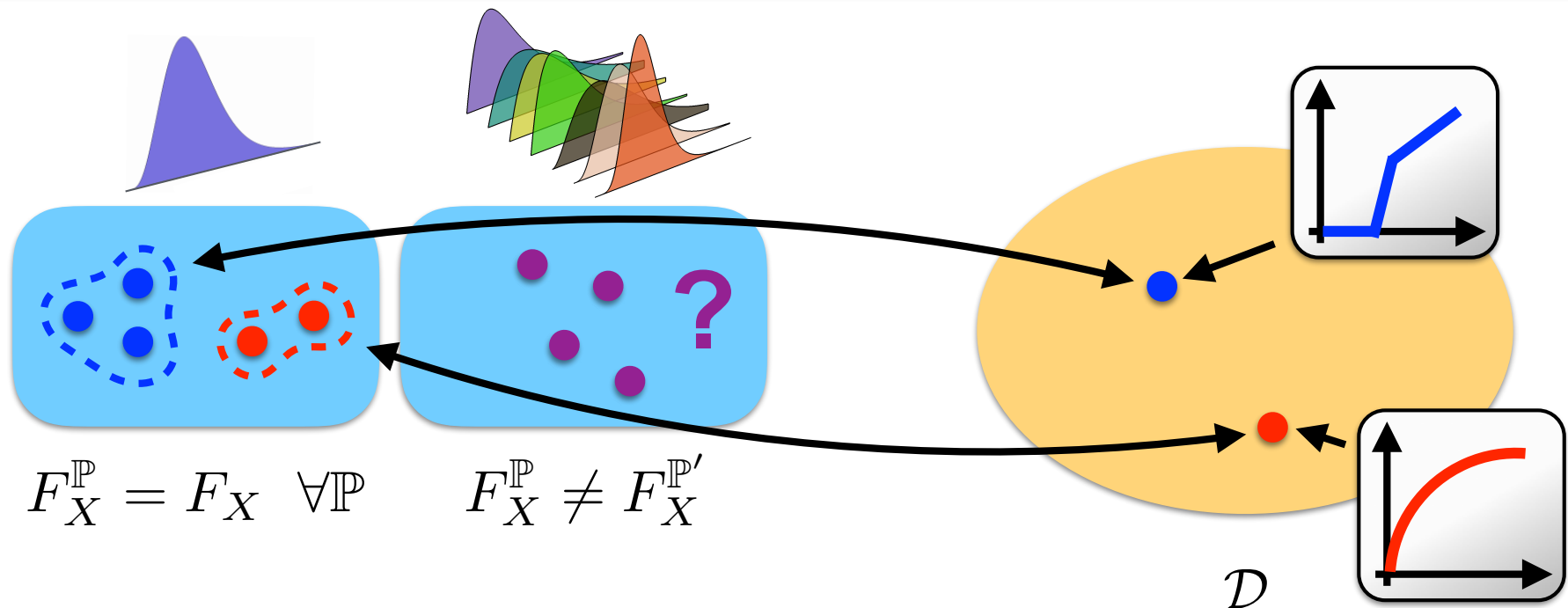
$$\rho_0(X) = \varrho_0(F_X) \quad \forall X \in \mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0) : F_X^{\mathbb{P}} = F_X \quad \forall \mathbb{P} \in \mathcal{P}_0.$$

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Ambiguity Averse Risk Measures

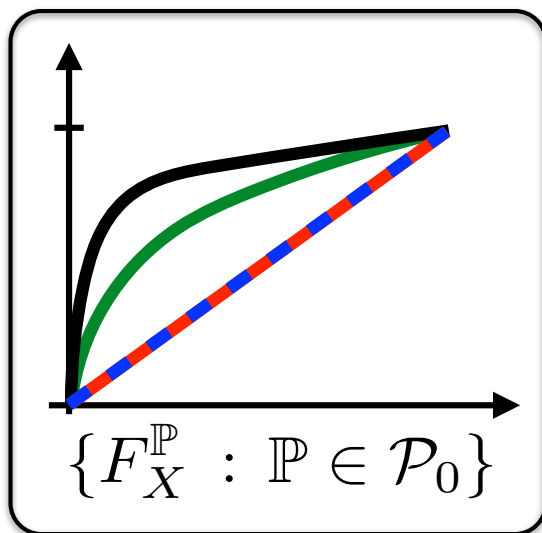
Definition: A risk measure ρ_0 is called **ambiguity averse** if it satisfies for all $X, Y \in \mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$:

- Ambiguity aversion:** If $\{F_X^{\mathbb{P}} : \mathbb{P} \in \mathcal{P}_0\} \subseteq \{F_Y^{\mathbb{P}} : \mathbb{P} \in \mathcal{P}_0\}$, then $\rho_0(X) \leq \rho_0(Y)$.
- Ambiguity monotonicity:** If $\varrho_0(F_X^{\mathbb{P}}) \leq \varrho_0(F_Y^{\mathbb{P}})$ for all $\mathbb{P} \in \mathcal{P}_0$, then $\rho_0(X) \leq \rho_0(Y)$.

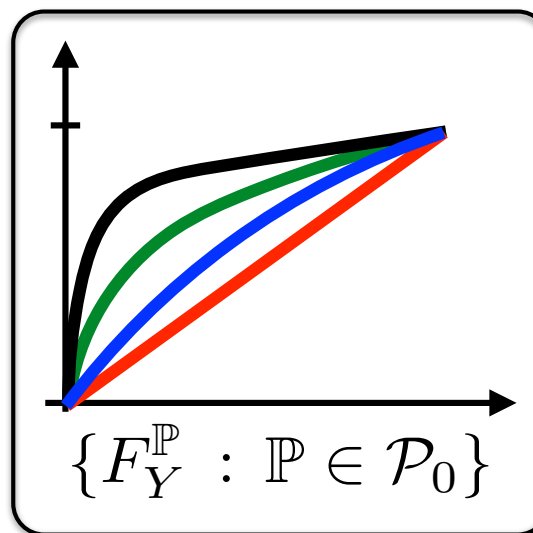
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\subseteq

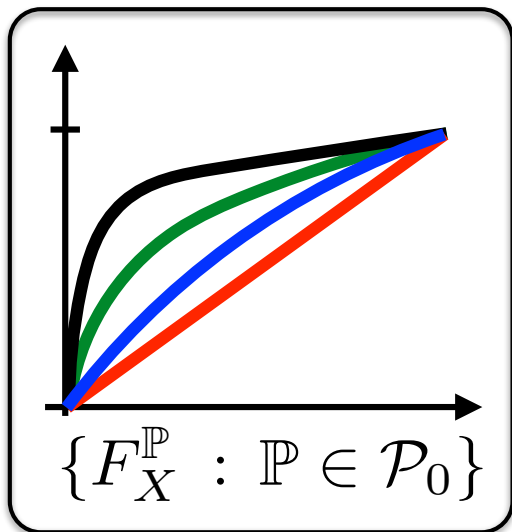


$\Rightarrow \rho_0(X) \leq \rho_0(Y)$

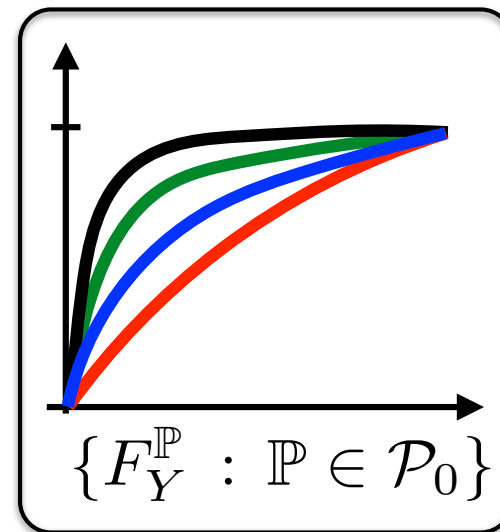
Ambiguity Averse Risk Measures

Definition: A risk measure ρ_0 is called **ambiguity averse** if it satisfies for all $X, Y \in \mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$:

- ☑ **Ambiguity aversion:** If $\{F_X^{\mathbb{P}} : \mathbb{P} \in \mathcal{P}_0\} \subseteq \{F_Y^{\mathbb{P}} : \mathbb{P} \in \mathcal{P}_0\}$, then $\rho_0(X) \leq \rho_0(Y)$.
- ☑ **Ambiguity monotonicity:** If $\varrho_0(F_X^{\mathbb{P}}) \leq \varrho_0(F_Y^{\mathbb{P}})$ for all $\mathbb{P} \in \mathcal{P}_0$, then $\rho_0(X) \leq \rho_0(Y)$.



$$\begin{aligned} \varrho_0(F_X^{\mathbb{P}_1}) &\leq \varrho_0(F_Y^{\mathbb{P}_1}) \\ \varrho_0(F_X^{\mathbb{P}_2}) &\leq \varrho_0(F_Y^{\mathbb{P}_2}) \\ \varrho_0(F_X^{\mathbb{P}_3}) &\leq \varrho_0(F_Y^{\mathbb{P}_3}) \\ \varrho_0(F_X^{\mathbb{P}_4}) &\leq \varrho_0(F_Y^{\mathbb{P}_4}) \end{aligned}$$



$$\Rightarrow \rho_0(X) \leq \rho_0(Y)$$

Representation of Risk Measures

Proposition: Assume that $(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$ is **non-atomic** and that ρ_0 is **ambiguity averse** and **translation invariant**.

Then the risk measure satisfies

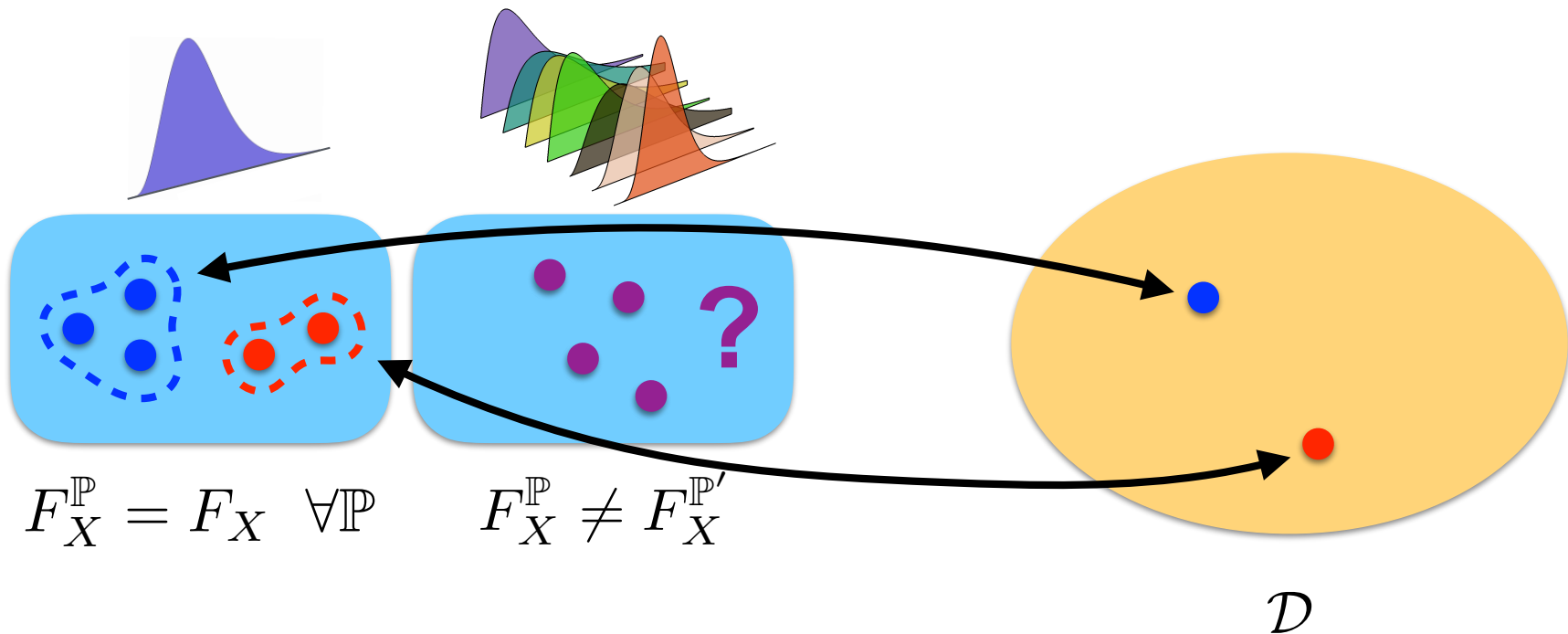
$$\rho_0(X) = \sup_{\mathbb{P} \in \mathcal{P}_0} \varrho_0(F_X^{\mathbb{P}}) \quad \forall X \in \mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0).$$

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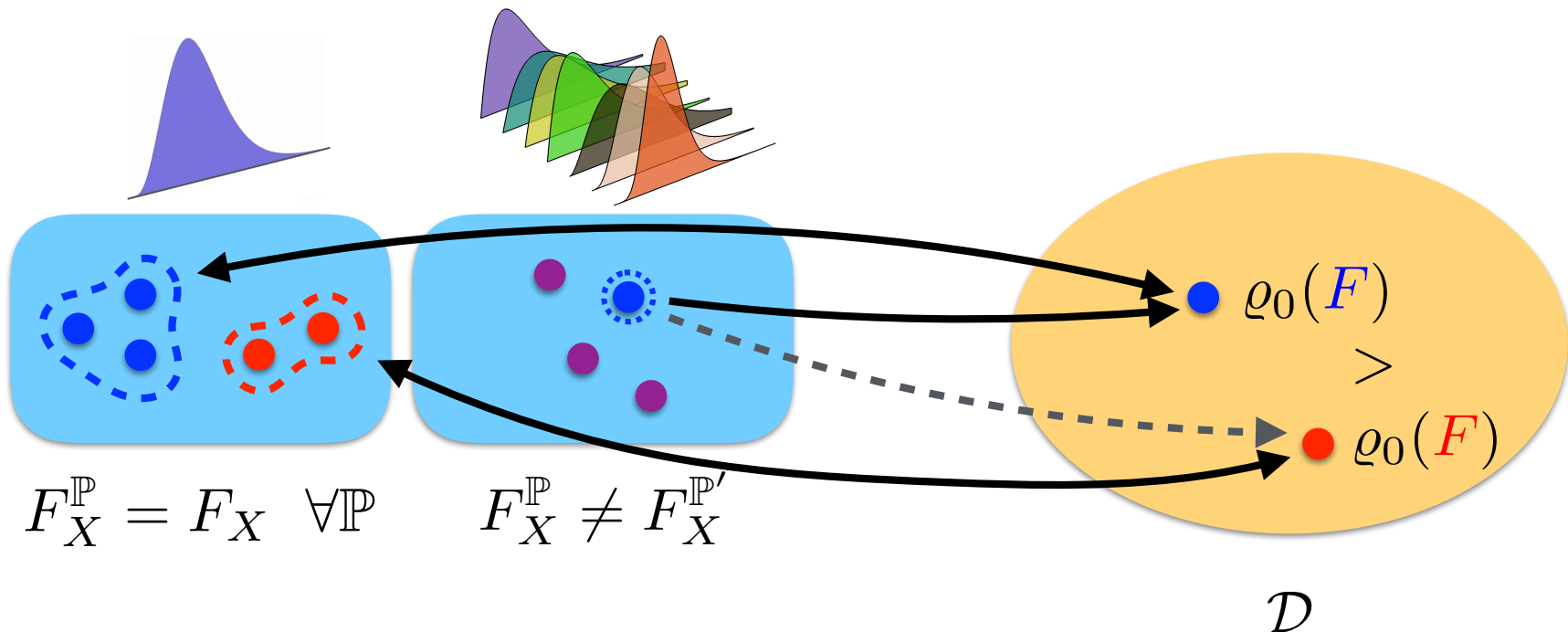


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Agenda

- 1 ~~Motivation~~
- 2 **Randomization under Distributional Ambiguity**
 - ~~Background~~
 - Problem Setup**
 - The Power of Randomization
- 3 Discussion

Pure Strategy Problem

We consider the **abstract optimization problem**

$$\underset{X \in \mathcal{X}_0}{\text{minimize}} \rho_0(X) \quad (\text{PSP})$$

where $\mathcal{X}_0 \subseteq \mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$ denotes the **feasible region**.

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Example: Facility location

$$\mathcal{X}_0 = \left\{ \begin{array}{c} \text{UK} \\ \text{Spain} \\ \text{Italy} \\ \text{France} \\ \text{Germany} \end{array} \right\}$$

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Example: Portfolio optimization

$$\mathcal{X}_0 = \{ \mathbf{r}^\top \mathbf{w} : \mathbf{w} \geq \mathbf{0}, \mathbf{e}^\top \mathbf{w} = 1 \} \quad \text{with} \quad \mathbf{r} = \begin{pmatrix} r_{\text{IBM}} \\ r_{\text{Walmart}} \\ r_{\text{pepsi}} \\ r_{\text{P\&G}} \end{pmatrix}$$

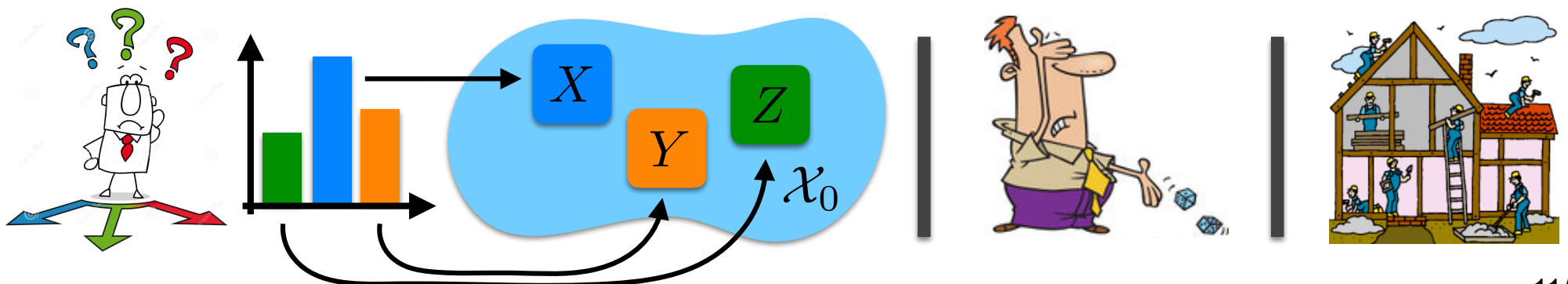
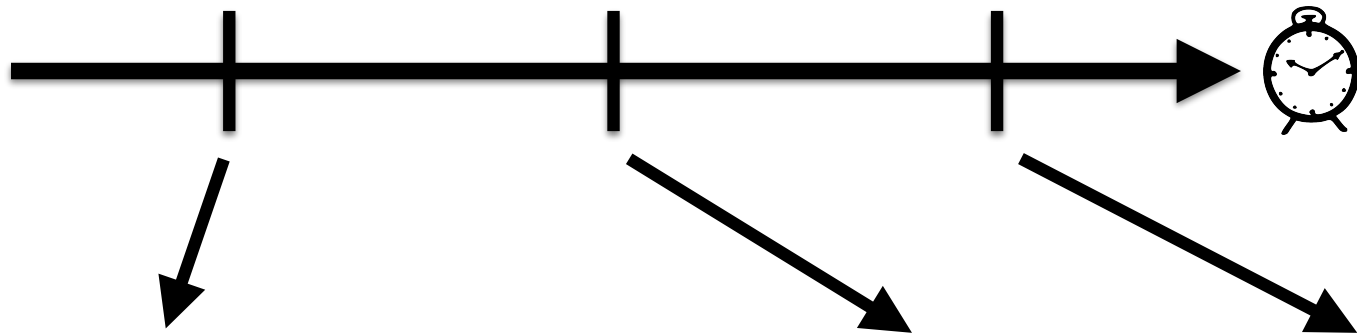
From Deterministic to Random Decisions

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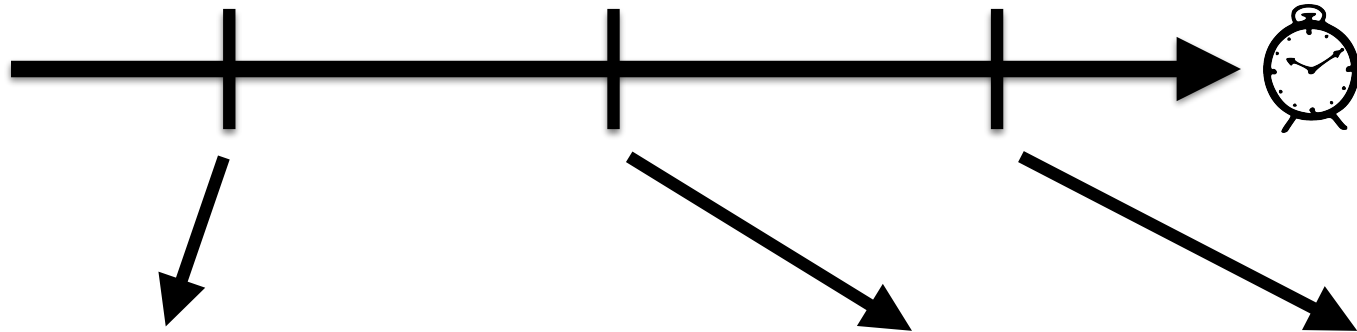
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How can we randomize over decisions?

What is the risk of randomized decisions?

Randomization Devices

We assume we have a **randomization device** that generates uniform samples from $[0, 1]$:

pure strategy problem

$$(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$$

$$\mathcal{X}_0 \subseteq \mathcal{L}_\infty(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$$

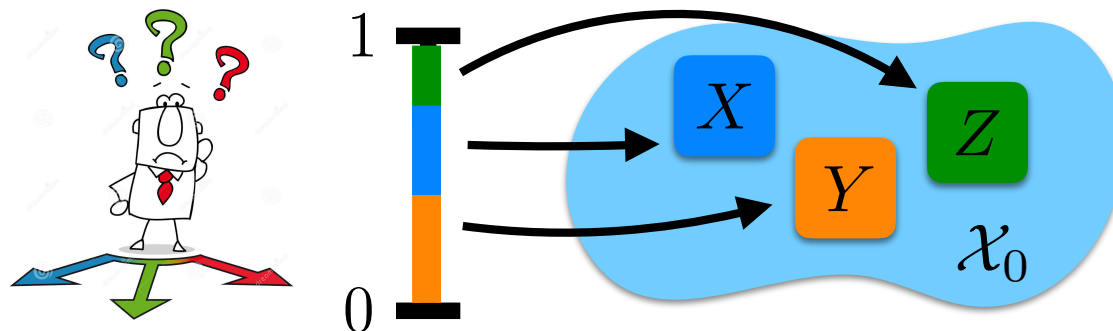
randomized strategy problem

$$(\Omega, \mathcal{F}, \mathcal{P})$$

with

- $\Omega = \Omega_0 \times [0, 1]$
- $\mathcal{F} = \mathcal{F}_0 \otimes \mathcal{B}_{[0,1]}$
- $\mathcal{P} = \{\mathbb{P} \times \mathbb{U} : \mathbb{P} \in \mathcal{P}\}$

$$\mathcal{X} = \{X \in \mathcal{L}_\infty(\Omega, \mathcal{F}, \mathcal{P}) : X(\cdot, u) \in \mathcal{X}_0 \ \forall u \in [0, 1]\}$$



Risk of Randomized Decisions

Proposition: Assume that $(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$ is **non-atomic** and that ρ_0 is **ambiguity averse** and **translation invariant**.

The **unique extension** of ρ_0 to an ambiguity averse risk measure ρ on $\mathcal{L}_\infty(\Omega, \mathcal{F}, \mathcal{P})$ is given by

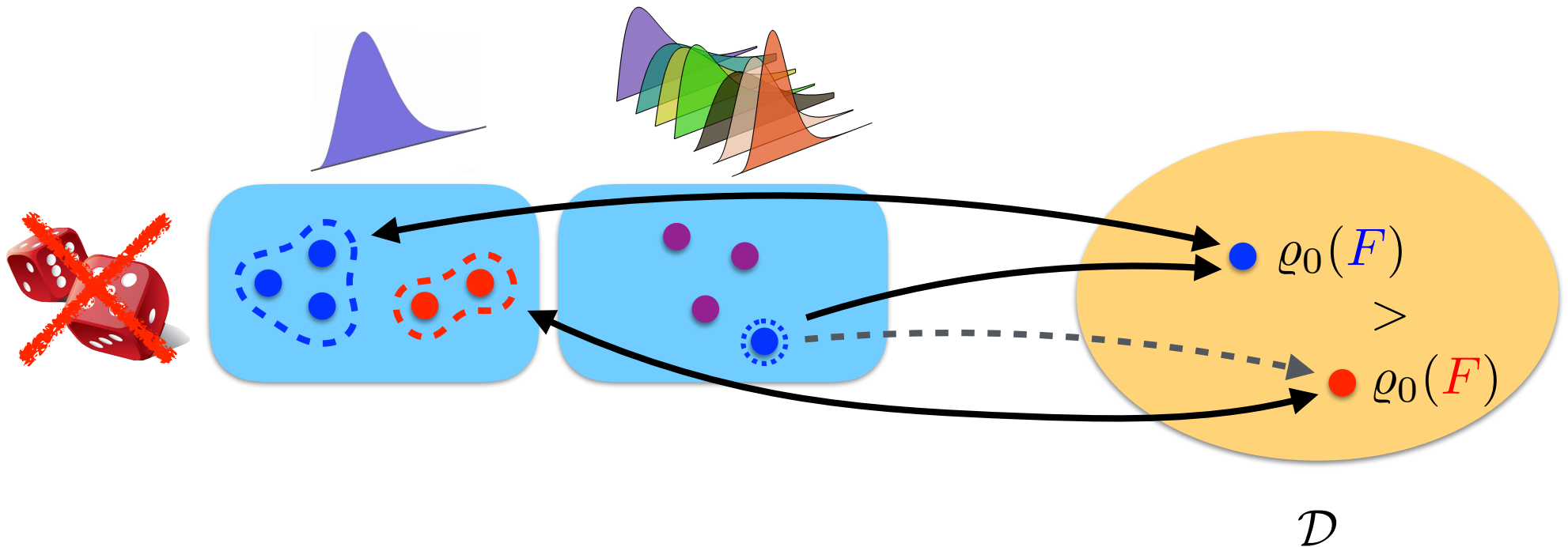
$$\rho(X) = \sup_{\mathbb{P} \in \mathcal{P}} \varrho_0(F_X^{\mathbb{P}}) \quad \forall X \in \mathcal{L}_\infty(\Omega, \mathcal{F}, \mathcal{P}).$$

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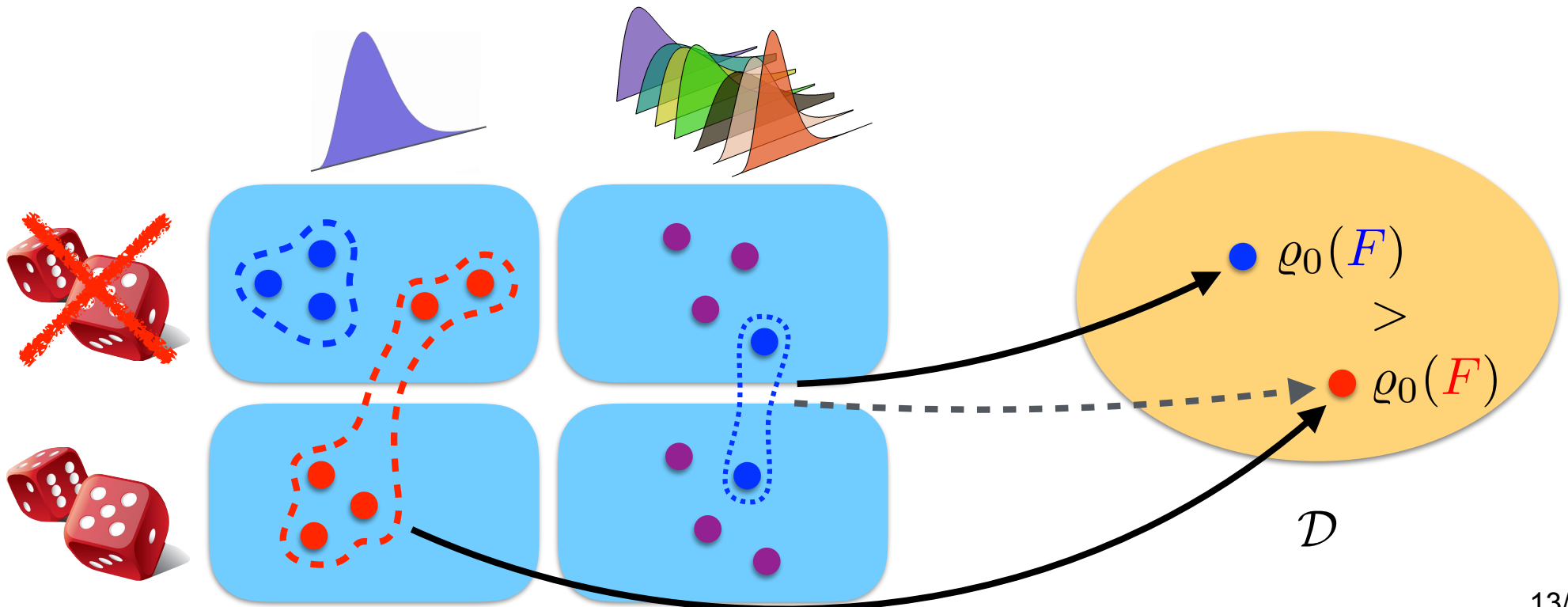


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Randomized Strategy Problem

We define the **randomized strategy problem**

$$\text{minimize}_{X \in \mathcal{X}} \rho(X) \quad (\text{RSP})$$

where the **extended risk measure** ρ is defined via

$$\rho(X) = \sup_{\mathbb{P} \in \mathcal{P}} \varrho_0(F_X^{\mathbb{P}}) \quad \forall X \in \mathcal{L}_\infty(\Omega, \mathcal{F}, \mathcal{P}).$$

and \mathcal{X} denotes the **enlarged feasible region**:

$$\mathcal{X} = \{X \in \mathcal{L}_\infty(\Omega, \mathcal{F}, \mathcal{P}) : X(\cdot, u) \in \mathcal{X}_0 \quad \forall u \in [0, 1]\}$$

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The feasible region contains all **pure strategies**:

$$X_0 \in \mathcal{L}_{\infty}(\Omega_0, \mathcal{F}_0, \mathcal{P}_0) \quad \longrightarrow \quad X \in \mathcal{L}_{\infty}(\Omega, \mathcal{F}, \mathcal{P}) \text{ with} \\ X(\omega, u) = X_0(\omega) \quad \forall u \in [0, 1]$$

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- 1 ~~Motivation~~
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The Power of Randomization

Definition: The ambiguity averse risk measure ρ_0 has the **Lebesgue property** if

$$\lim_{k \rightarrow \infty} \rho_0(F_k) = \rho_0(F) \quad \text{whenever } F_k \rightarrow F.$$

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Theorem: Assume that

- ☑ $(\Omega_0, \mathcal{F}_0, \mathcal{P}_0)$ is **non-atomic** and has a **maximally ambiguous random variable**,
- ☑ ρ_0 is **ambiguity averse** and satisfies the **Lebesgue property**.

Then there is \mathcal{X}_0 such that **(PSP) > (RSP)**.

The Rainbow Urn Game

Consider an urn with balls of K different colors where:

- ☑ the number of balls is unknown
- ☑ the proportions of colors are unknown

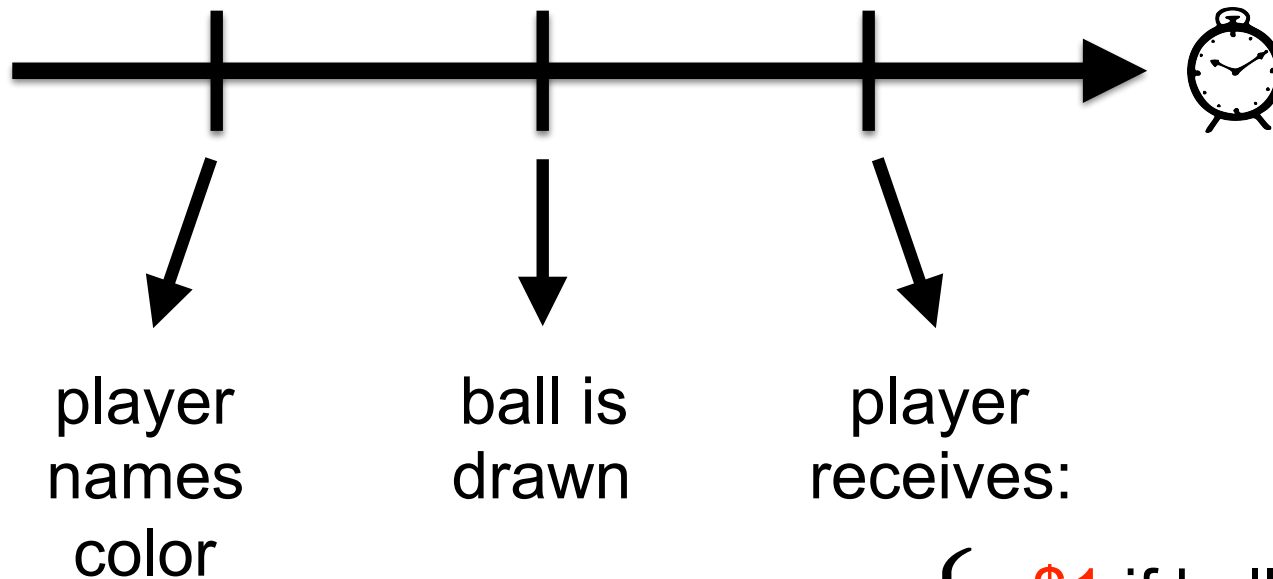


The Rainbow Urn Game

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- ☑ the number of balls is unknown
- ☑ the proportions of colors are unknown

A player is offered the following game:



{ -\$1 if ball is of stated color
+\$1 if ball is *not* of stated color


The Rainbow Urn Game

Assume the player uses an ambiguity averse risk measure ρ_0 :

The Rainbow Urn Game

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Strategy



Any *pure strategy*
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Worst-case outcome

All balls are of stated color


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The *randomized strategy* that names each color with probability $1/K$ suppresses the ambiguity

Worst-case outcome


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$\left\{ \begin{array}{l} -\$1 \text{ with probability } \frac{1}{K} \\ +\$1 \text{ with probability } \frac{K-1}{K} \end{array} \right.$


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If ρ_0 has the **Lebesgue property**, then this is as attractive as receiving +\$1 for sure as $K \rightarrow \infty$!

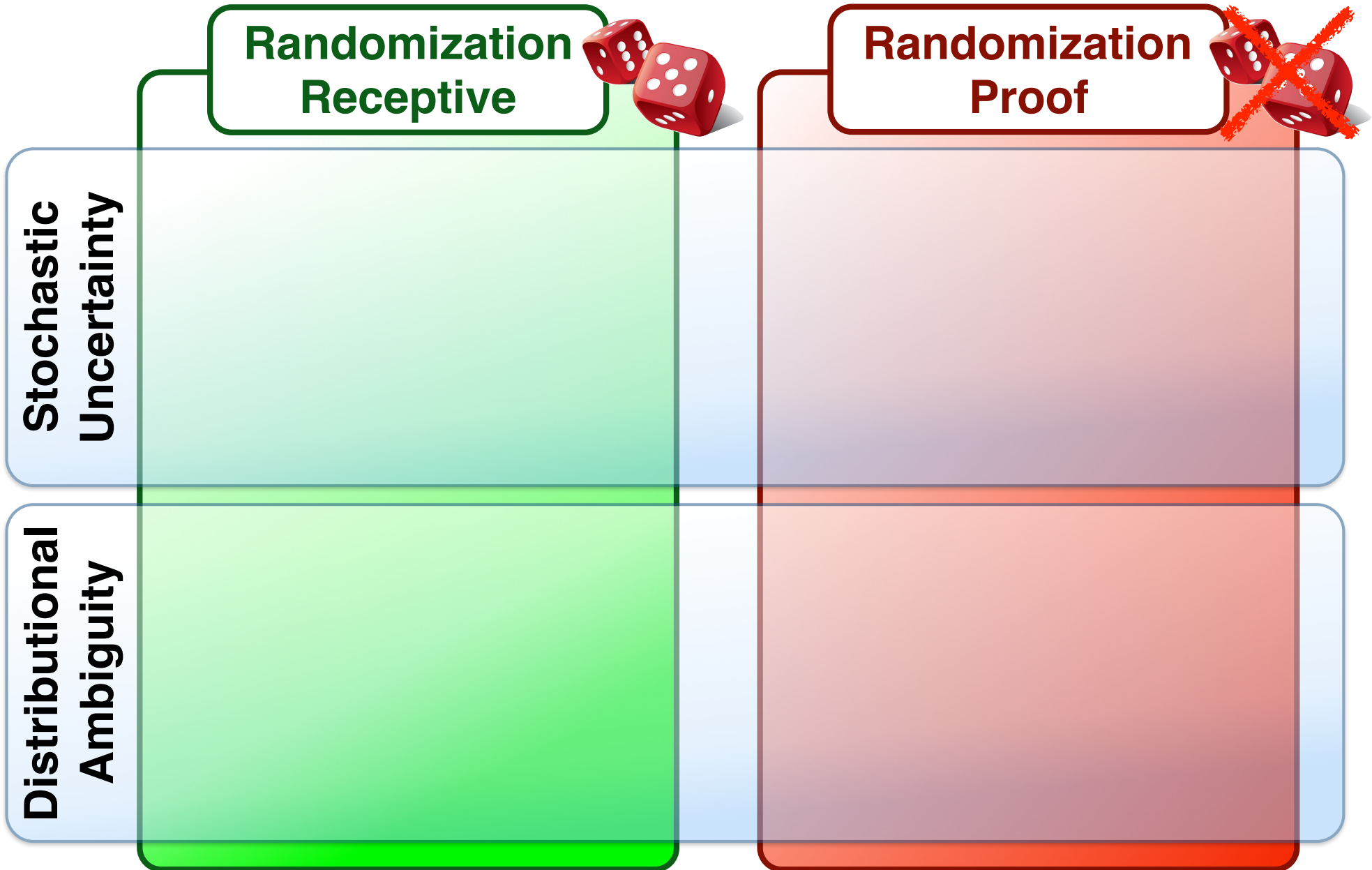


Randomization can serve as a cure for ambiguity

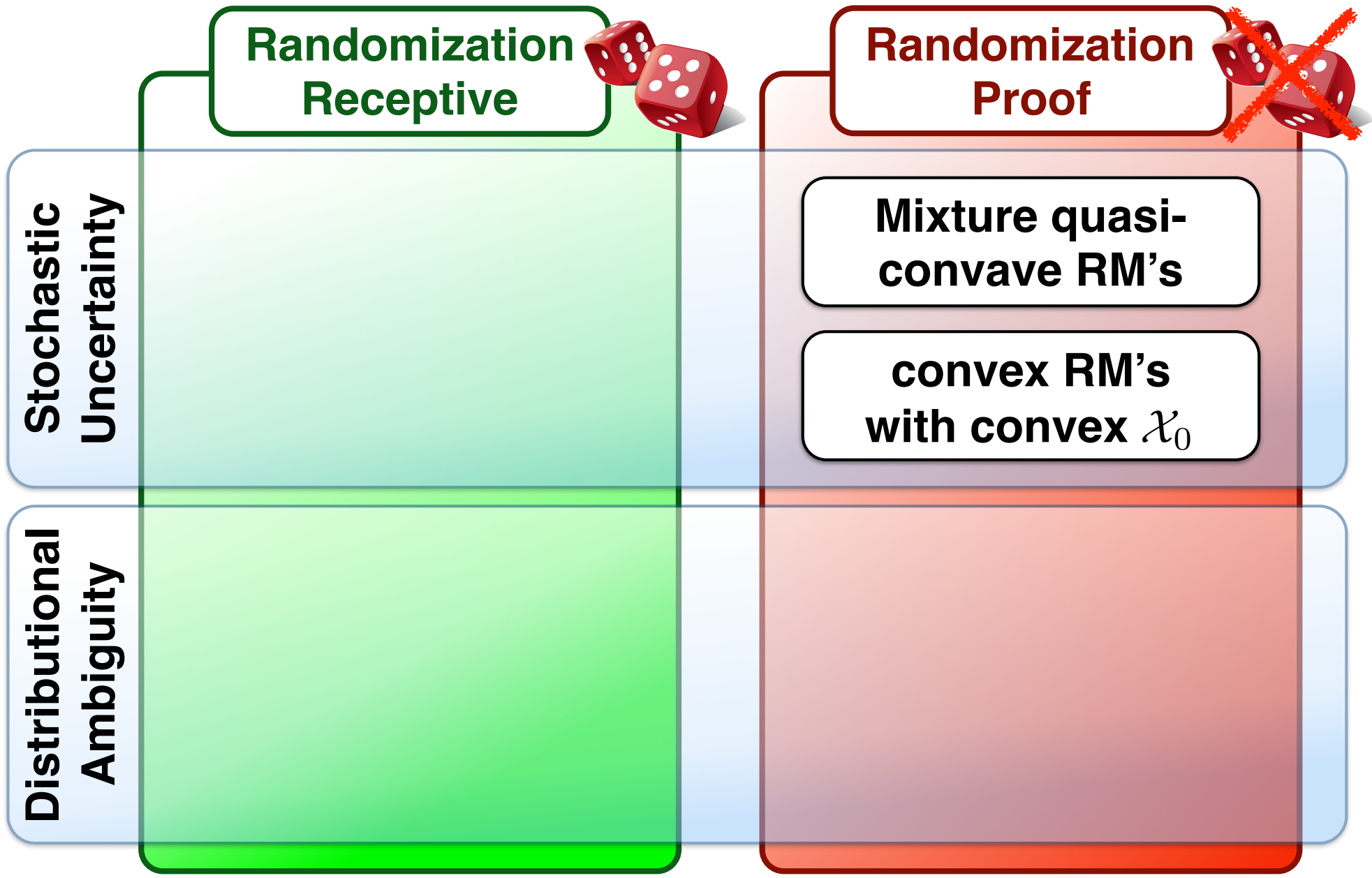
Agenda

- 1** ~~Motivation~~
- 2** ~~Randomization under Stochastic Uncertainty~~
- 3** Discussion

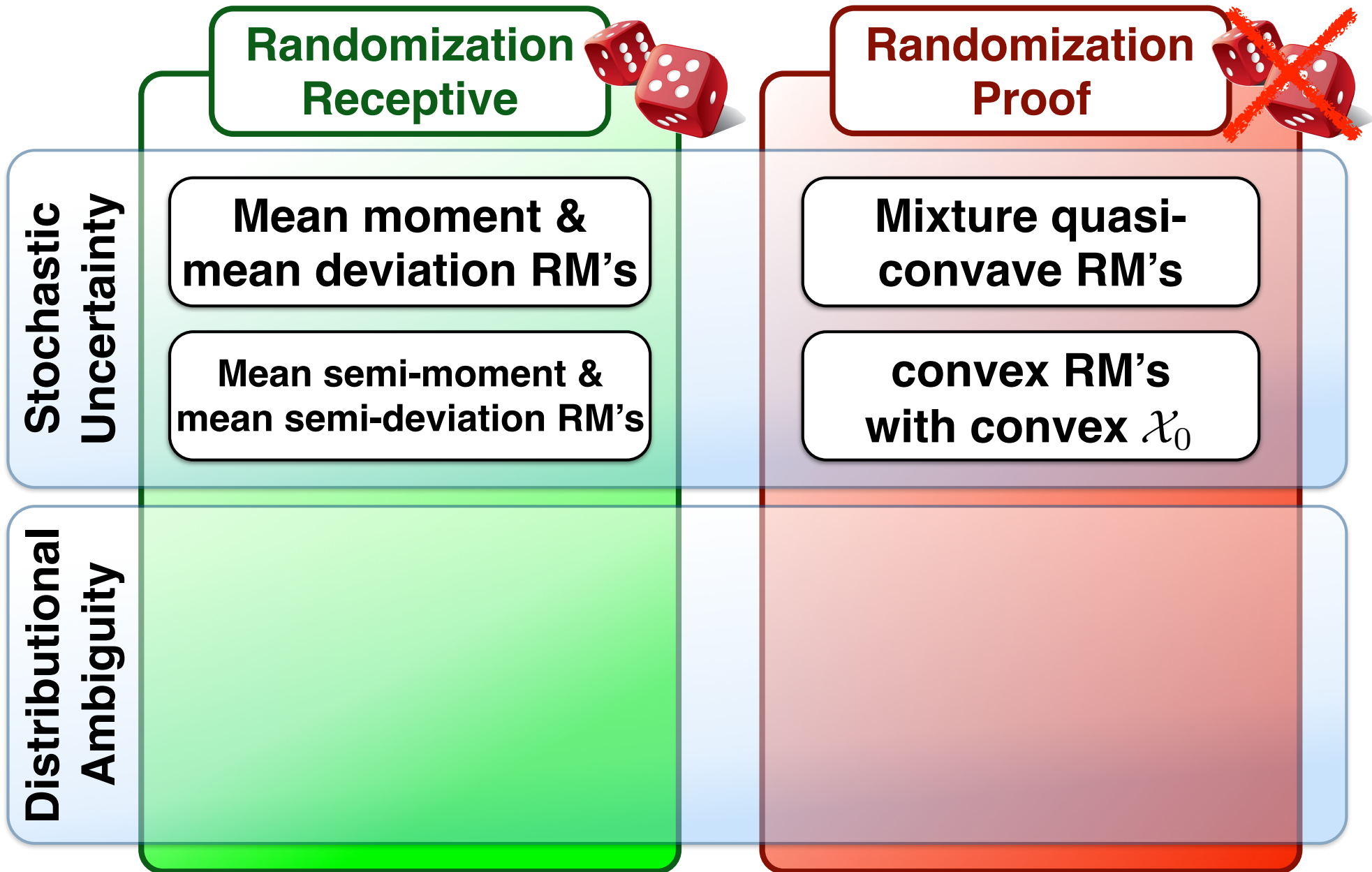
Summary



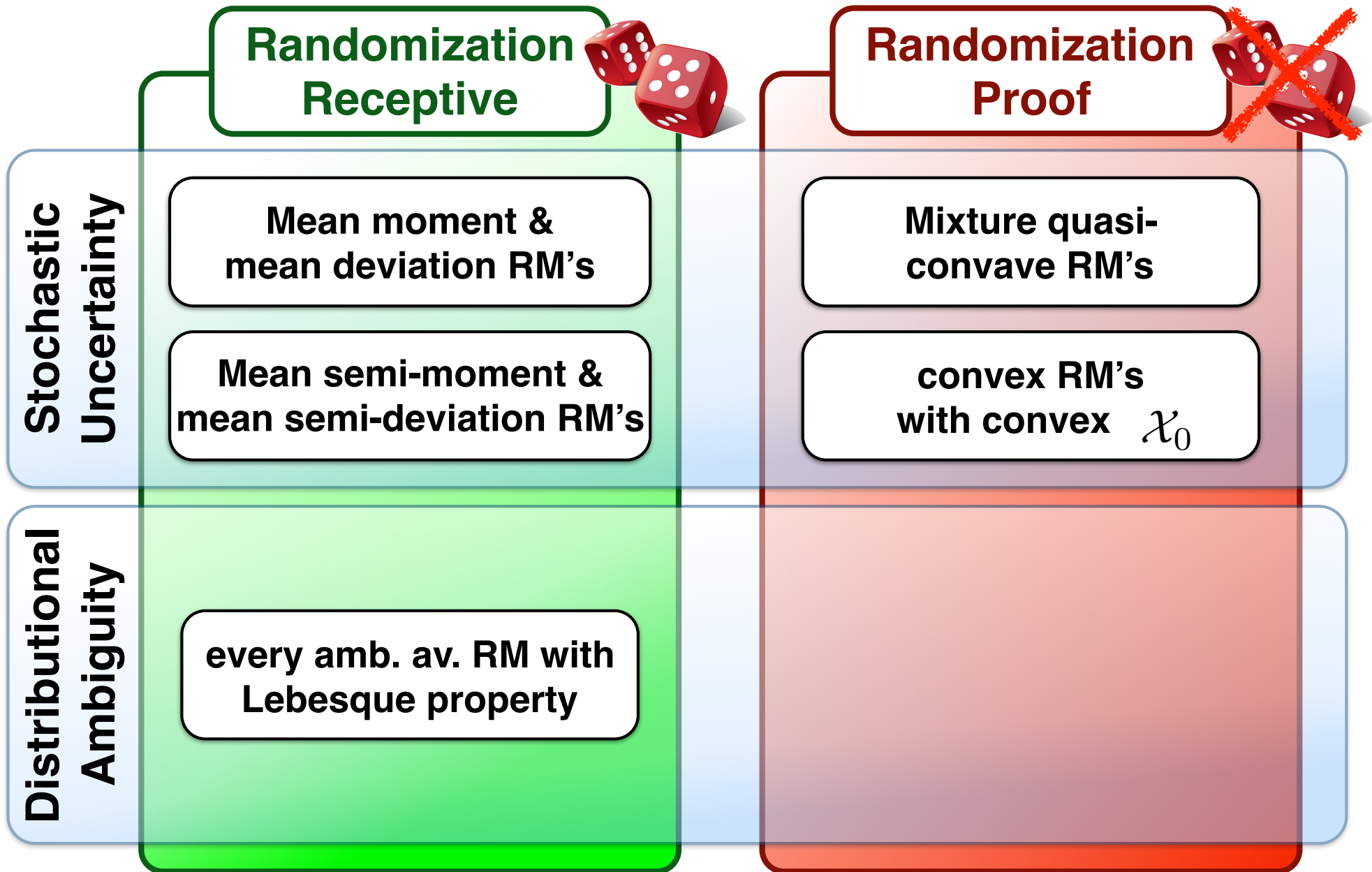
Summary



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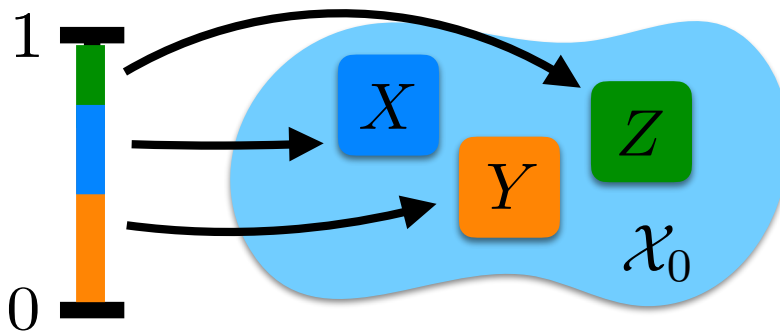
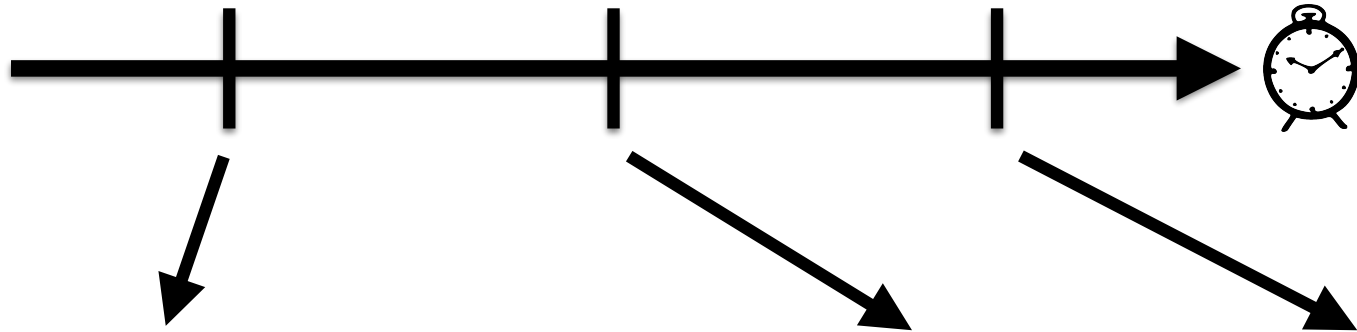
The Issue of Time Consistency

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Remember the **randomized strategy problem**:

$$\underset{X \in \mathcal{X}}{\text{minimize}} \rho(X)$$

(RSP)

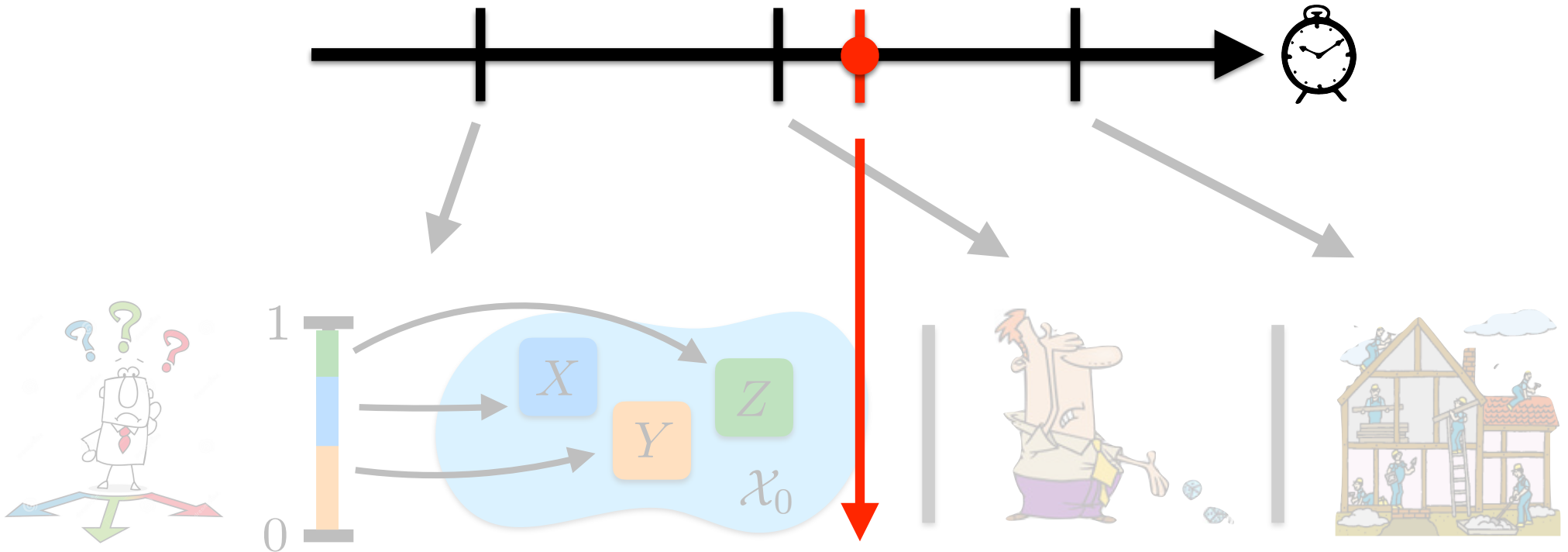


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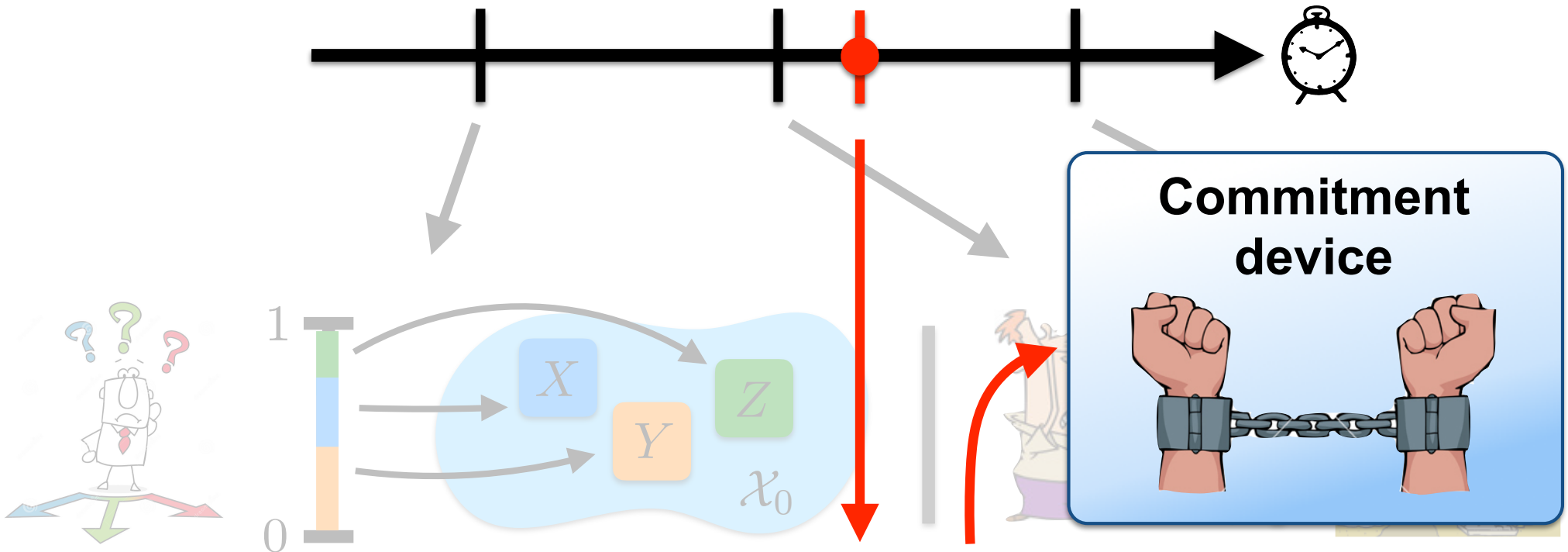
Once we observe the outcome of the randomization, we have an *incentive* to *deviate* in favour of the *optimal pure choice*!

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