Black-Box Credit Scoring and Data Sharing

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Introduction

Predictive algorithms are used in economic transactions to solve asymmetric information problems.

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Loan Approvals:

- FinTechs 3-1-0 model (Ant Group, Prosper, Lending Club, Kaggle...),
- Traditional lenders (JP Morgan, Bank of America...),
- Credit bureaus (UltraFico, FICO X Data, Vantage Score...).

Introduction

Predictive algorithms are used in economic transactions to solve asymmetric information problems.

Loan Approvals:

Input Data $\longrightarrow$	Algorithm	$\longrightarrow$ Allocation
z	$a_\lambda(z)$	$\ell \in \{0, 1\}$ $x \in \mathbb{R}$

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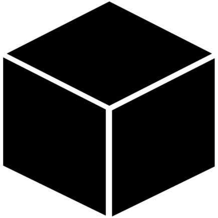

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$\ell \in \{0, 1\}$

$x \in \mathbb{R}$

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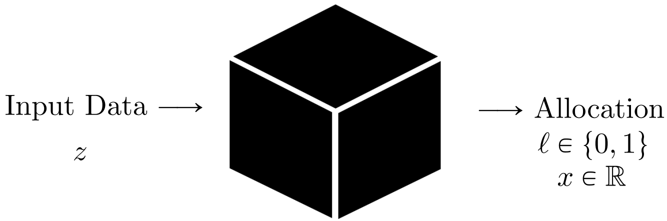

Transparency vs Opacity:

- Opacity: users hide from the system (privacy-preserving apps, not sharing cookies, paying cash, ...),
- Transparency: users game the system (YouTube tutorials to increase FICO score, ...).

This Paper

Question: Should credit scoring algorithms be transparent or opaque? (EU Artificial Intelligence Act)

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- Opacity induces *hedging* : withholding is a safe strategy against unpredictability,
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  - most conclusive evidence is disclosed when the borrower has bargaining power,

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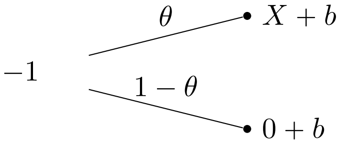
- Opacity induces *hedging* : withholding is a safe strategy against unpredictability,
  - all evidence is withheld when the lender has bargaining power,
  - most conclusive evidence is disclosed when the borrower has bargaining power,
- The lender's optimal transparency regime:
  - is driven by credit rationing motives,
  - depends on the lender's bargaining power,
  - is often socially inefficient.

Literature

Model

Sketch



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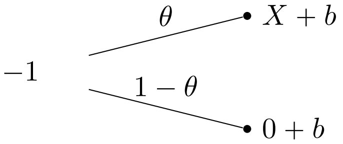

Credit Risk Estimation:

- $\theta \sim U[0,1]$ is unknown (s.t. $\mathbb{E}(\theta) > 1/X$),
- can be estimated from data $z \in [0,1]$:

DGP

$$\mu_\lambda(z) \triangleq \mathbb{E}(\theta|z) = \lambda\, z + (1-\lambda)\,\tfrac{1}{2}, \qquad \text{where}\, \lambda \in [-1,1].$$

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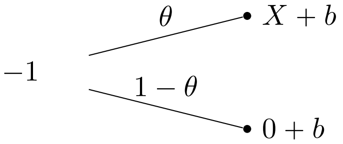

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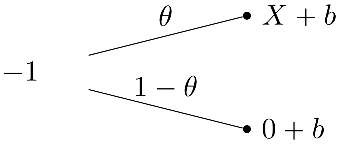
Allocation Algorithm: An algorithm is $a_\lambda(z) = \big(\ell_\lambda(z), x_\lambda(z)\big)$, where Payoffs

- $\ell \in \{0,1\}$ credit provision decision,
- $x \in \mathbb{R}$ gross interest payment.

Sketch



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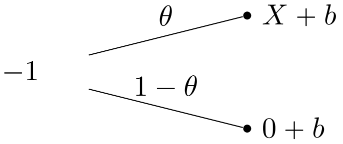
Two-Sided Private Information:

- z is the borrower's private information,
- λ is the lender's private information.

Sketch



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- $\ell \in \{0,1\}$ credit provision decision,
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Transparency/Opacity	Information	Data-Sharing	Credit Allocation	Payoffs
$(t=0)$	$(t=1)$	$(t=2)$	$(t=3)$	$(t=4)$

Optimal Credit Scoring

Optimal Credit Scoring

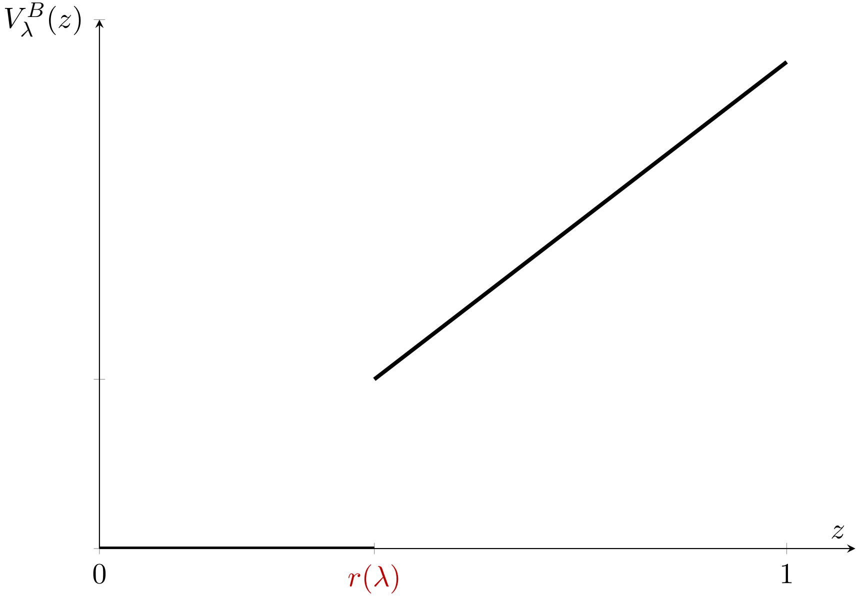
Lemma 1 (Optimal Credit Scoring)

If the lender knows the borrower's data point z, the optimal allocation algorithm is:

$$x_\lambda(z) = \frac{1}{\mu_\lambda(z)} + \phi\left(X - \frac{1}{\mu_\lambda(z)}\right),$$

$$\ell_\lambda(z) = \mathbb{1}\left\{\mu_\lambda(z) \geqslant \frac{1}{X}\right\}.$$

Borrower's Utility $V_\lambda^B(z)$



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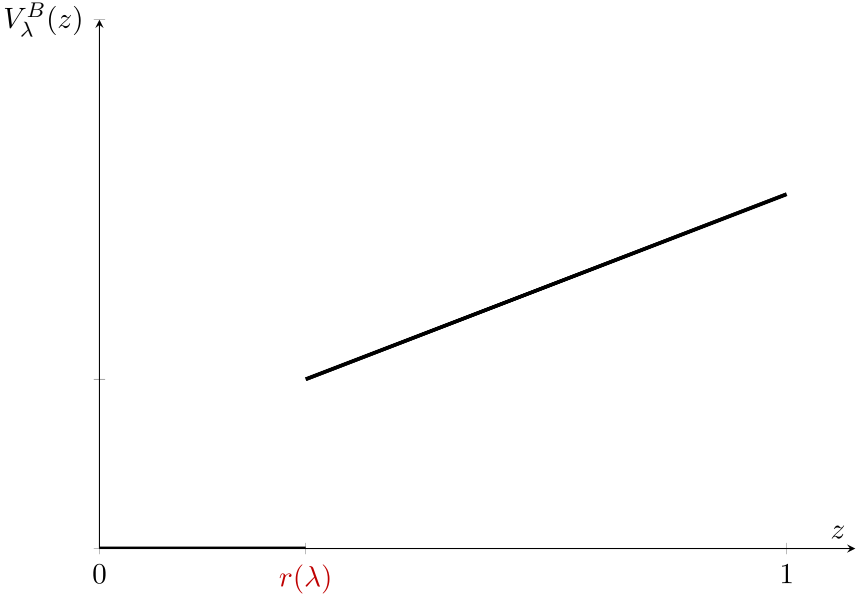

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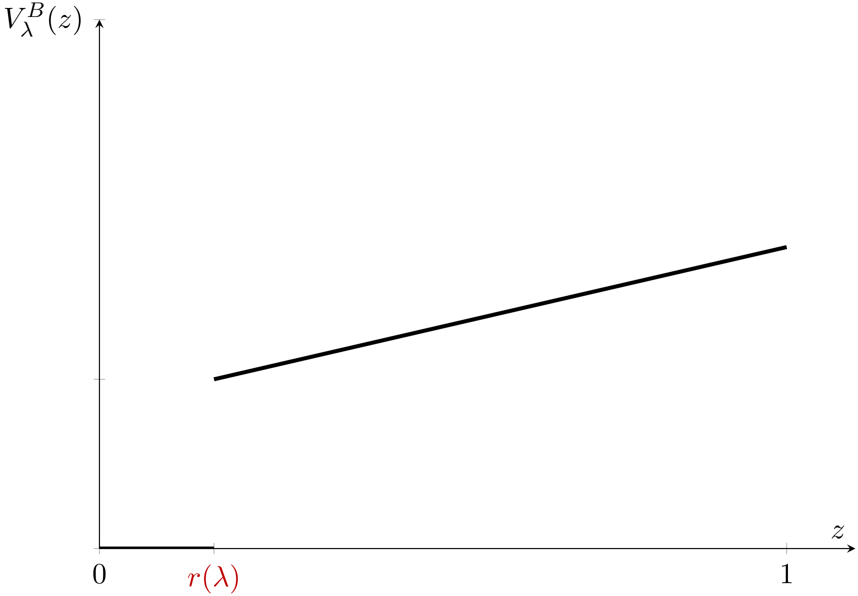

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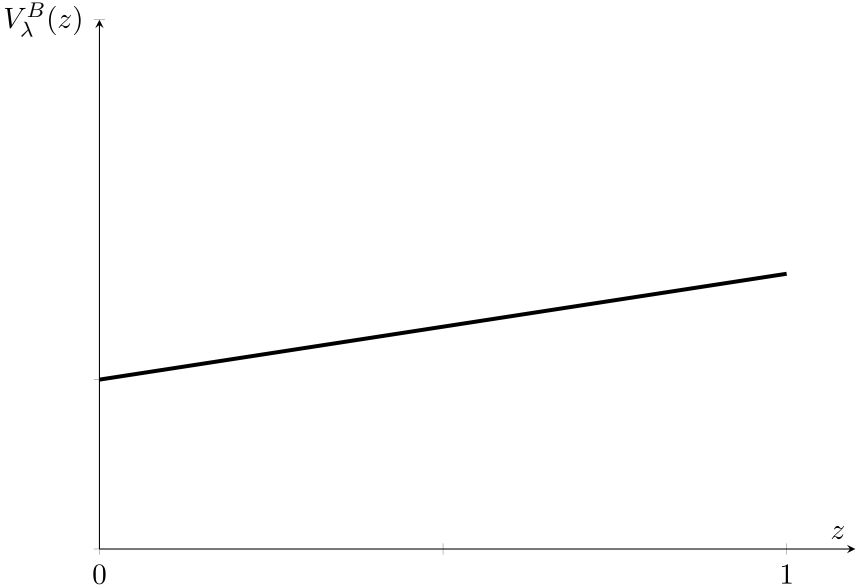

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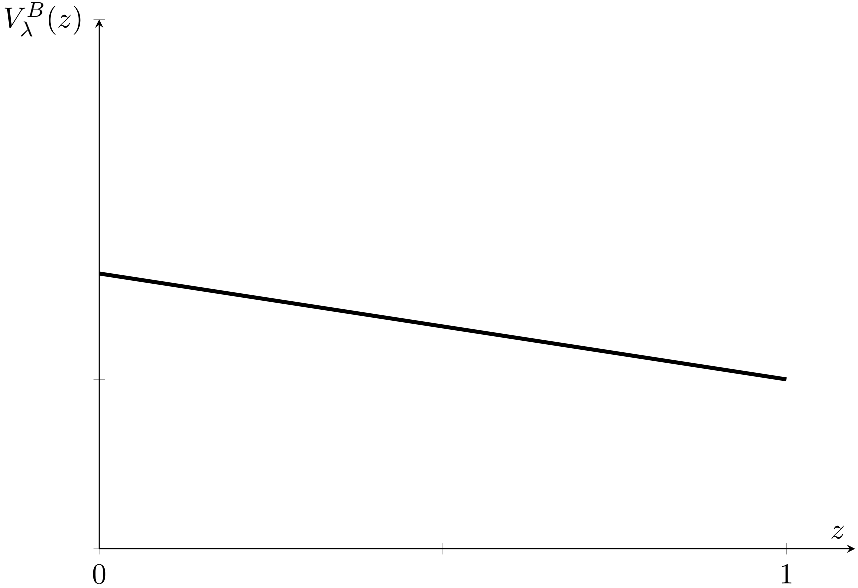
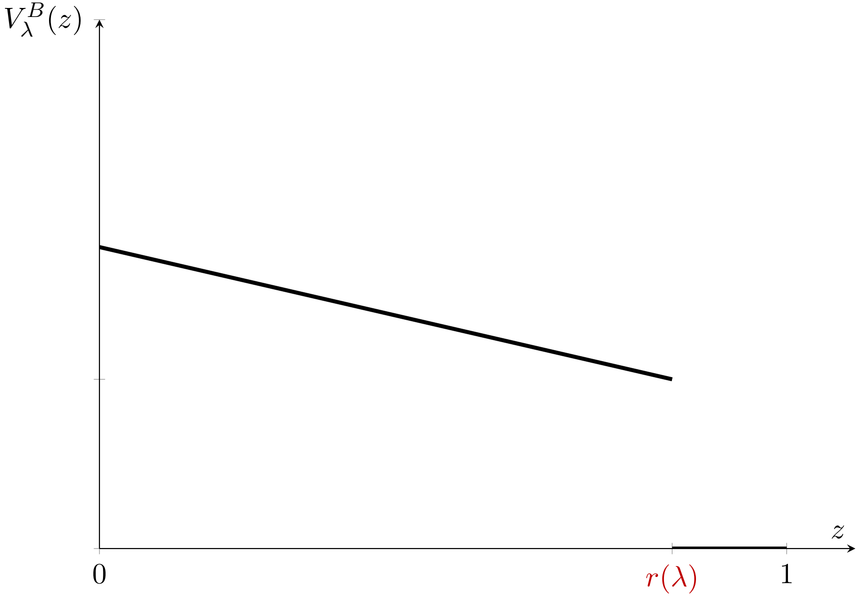


Borrower's Utility $V^B_\lambda(z)$



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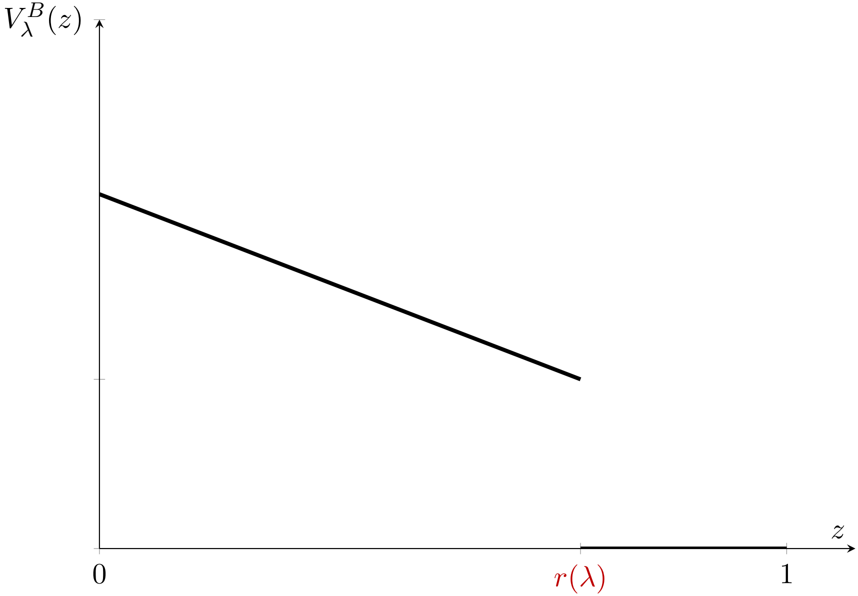

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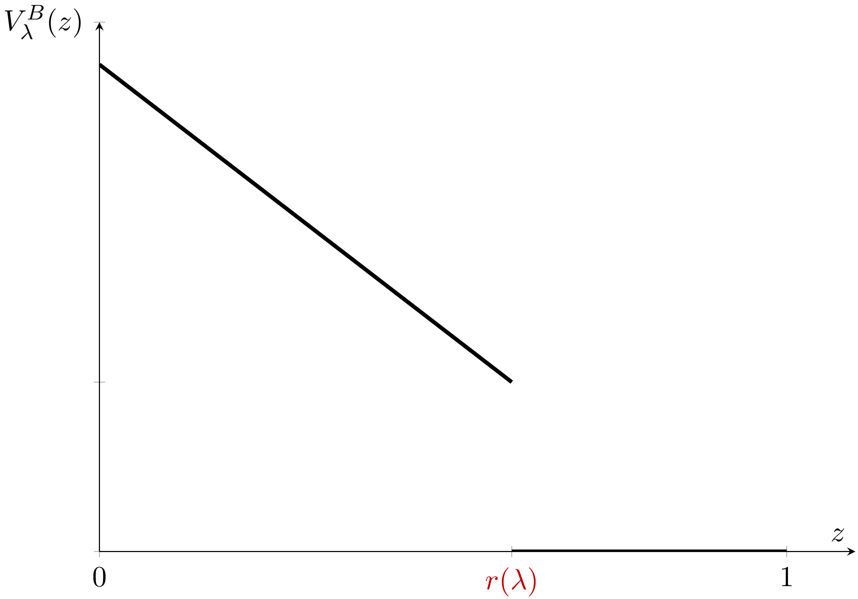

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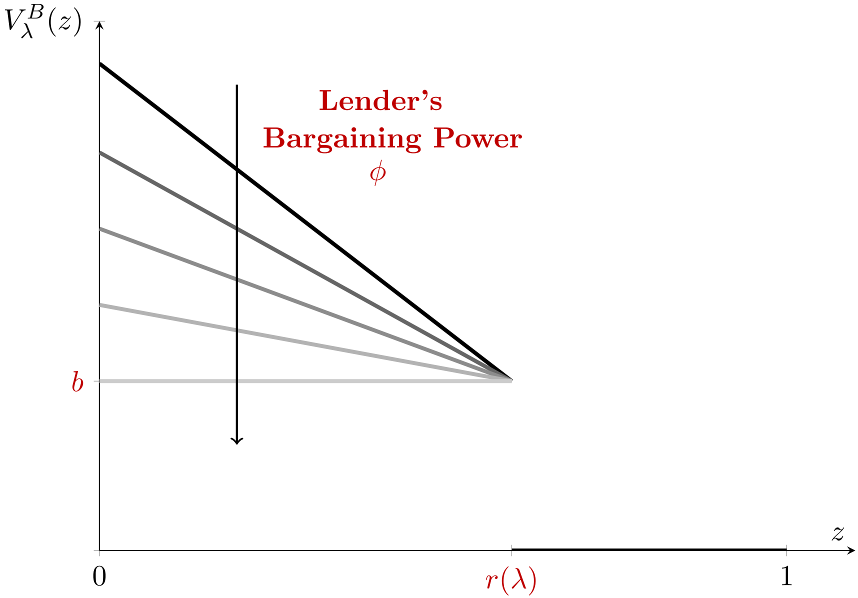
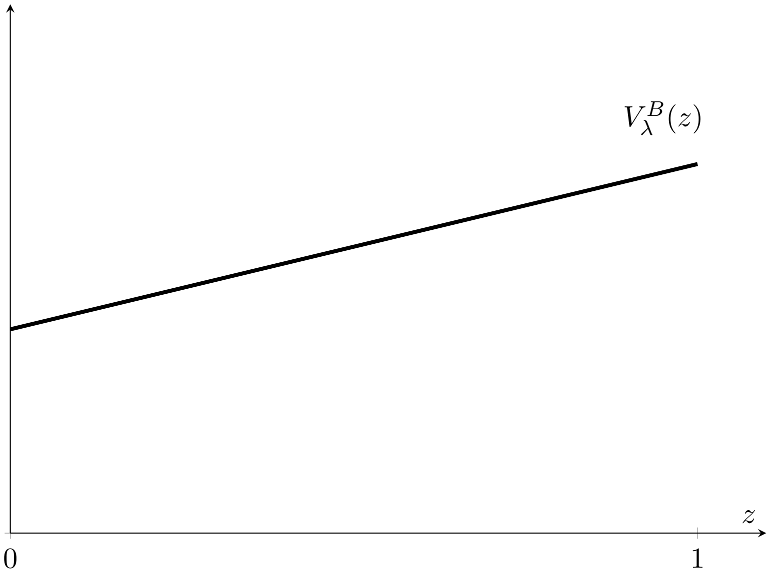


Data-Sharing to a Transparent Algorithm
(Gaming)

Transparency ⇒ Gaming



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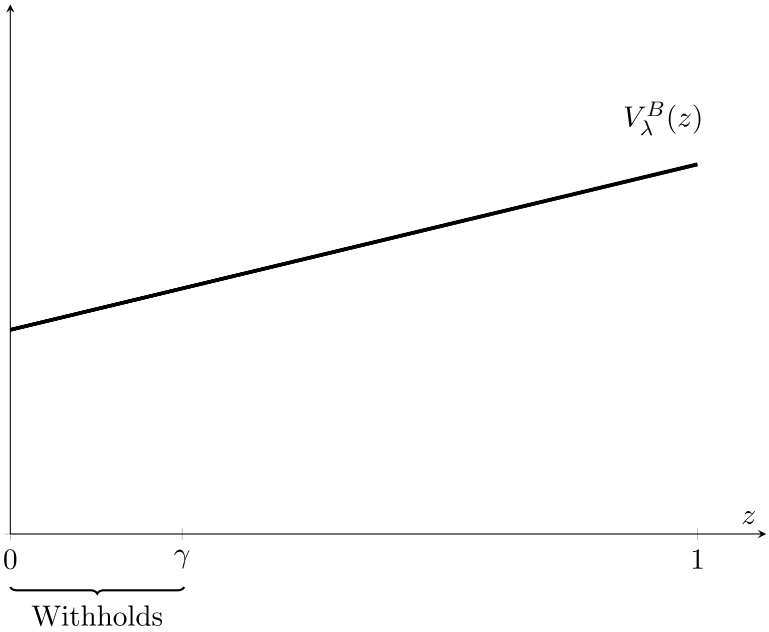

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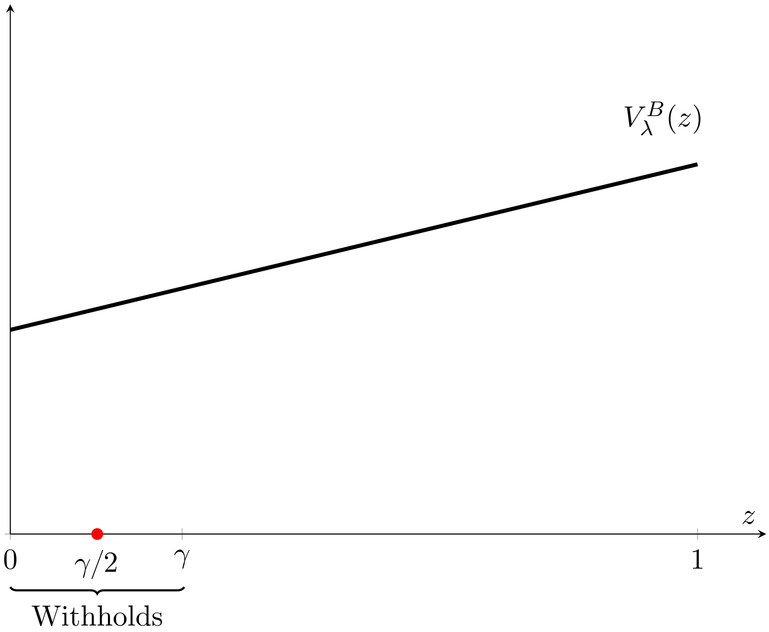

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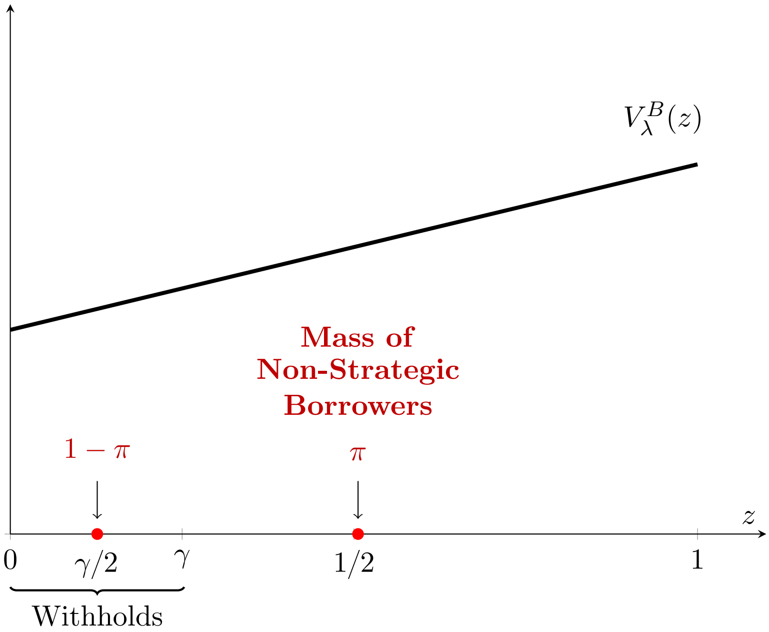

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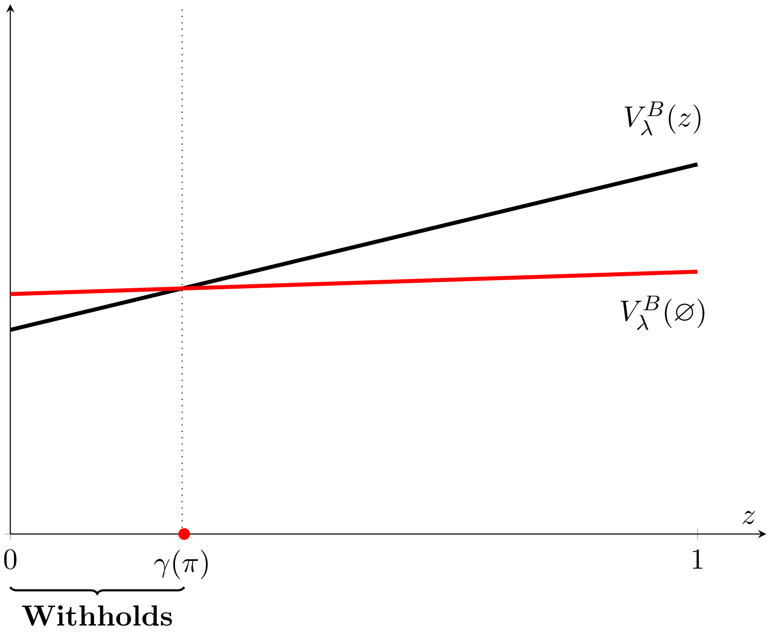

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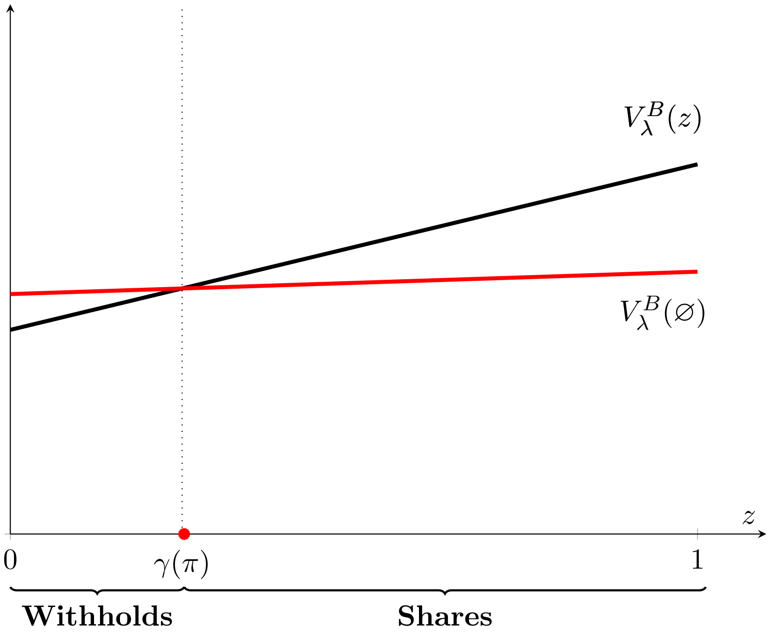

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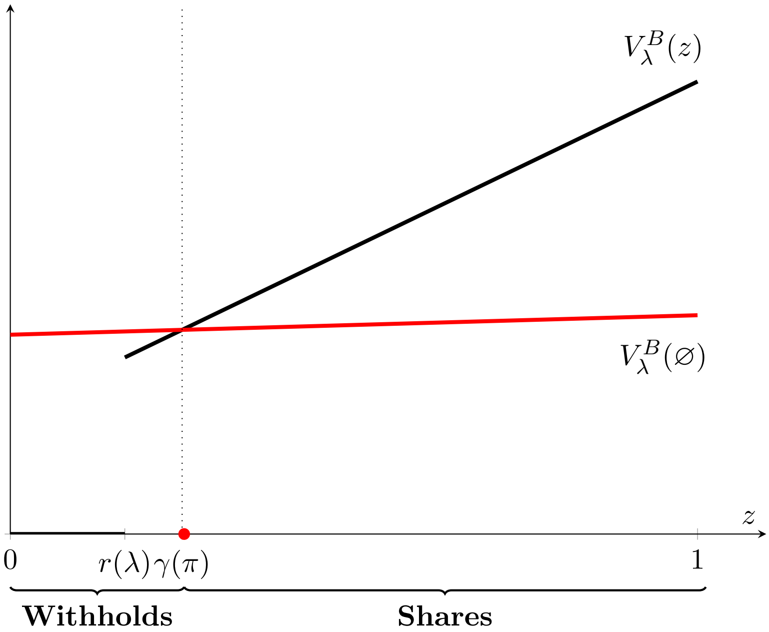

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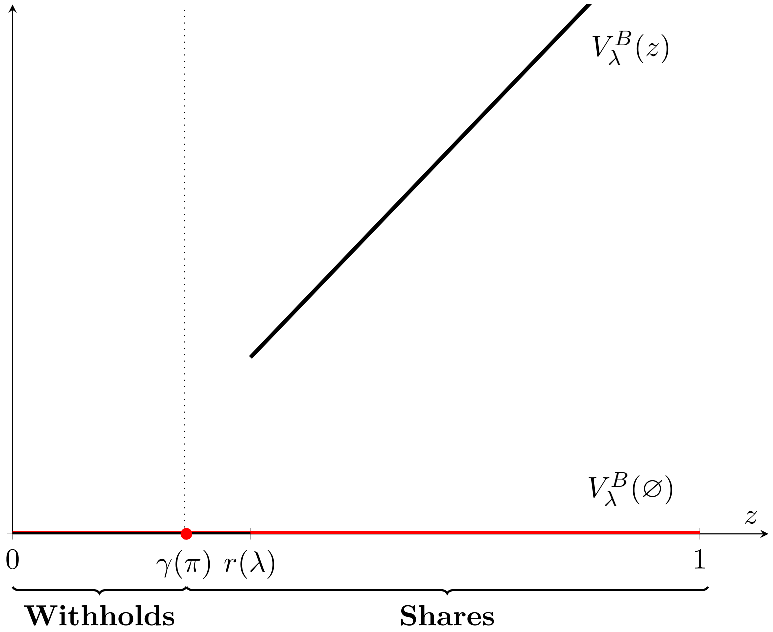

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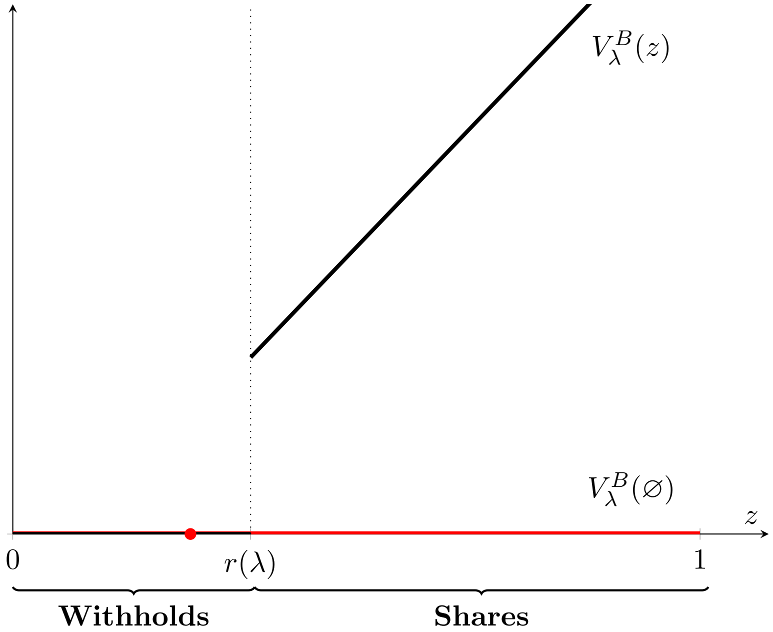


Transparency ⇒ Gaming

Proposition 1 (Data-Sharing to a Transparent Algorithm)

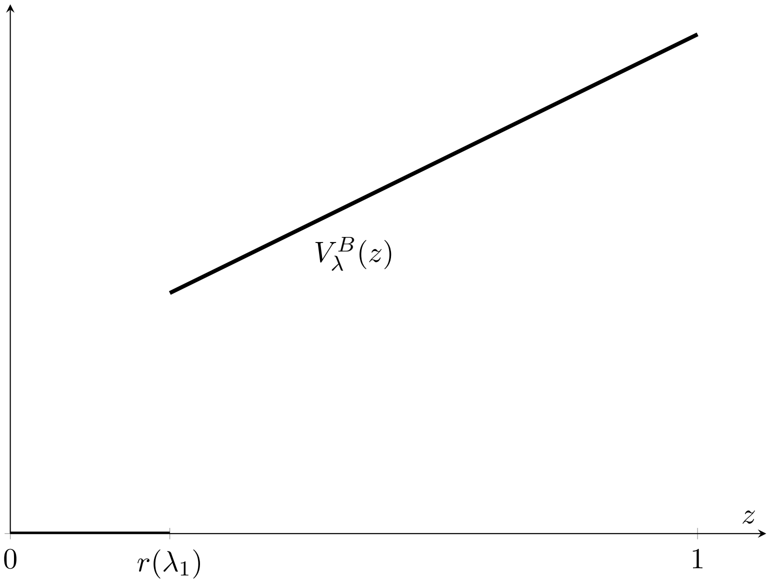
With a transparent algorithm, the set of borrowers withholding data is:

$$\mathcal{G}(\lambda, \pi) = \begin{cases} \Big[0, \max\big\{r(\lambda); \gamma(\pi)\big\}\Big] & \text{if } \lambda \in (0, 1], \\ \big[0, 1\big] & \text{if } \lambda = 0, \\ \Big[\min\big\{r(\lambda); 1 - \gamma(\pi)\big\}, 1\Big] & \text{if } \lambda \in [-1, 0), \end{cases}$$

where $\gamma(\pi)$ is increasing.

Data-Sharing to an Opaque Algorithm
(Hedging)

Opacity ⇒ Hedging



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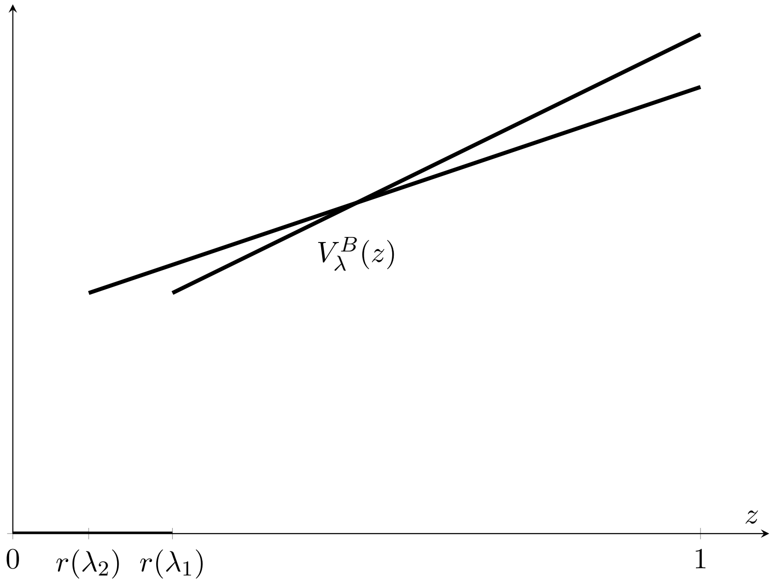

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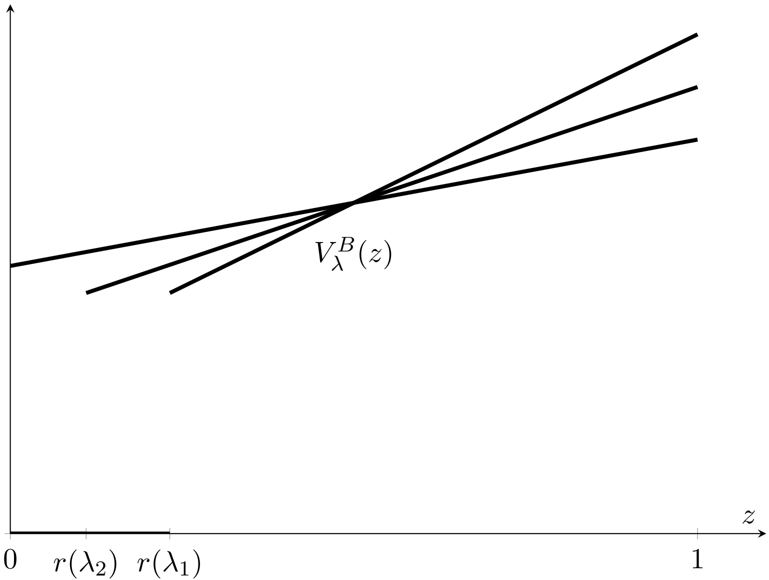

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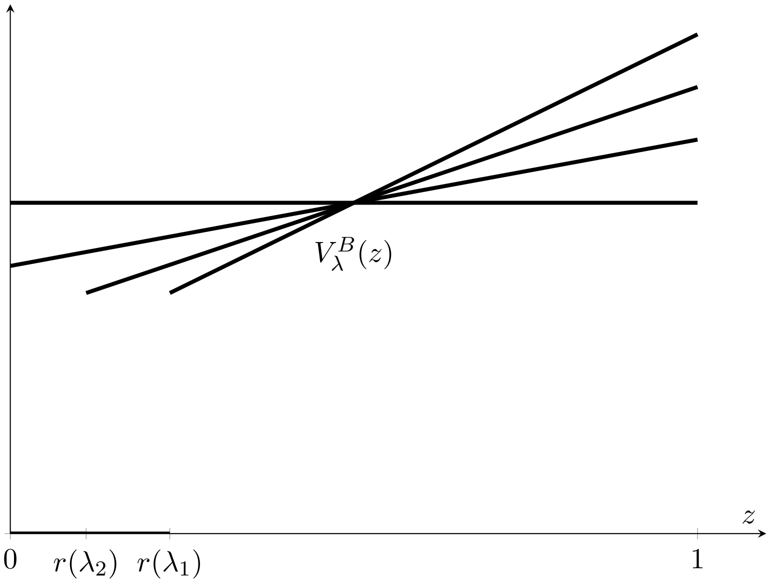

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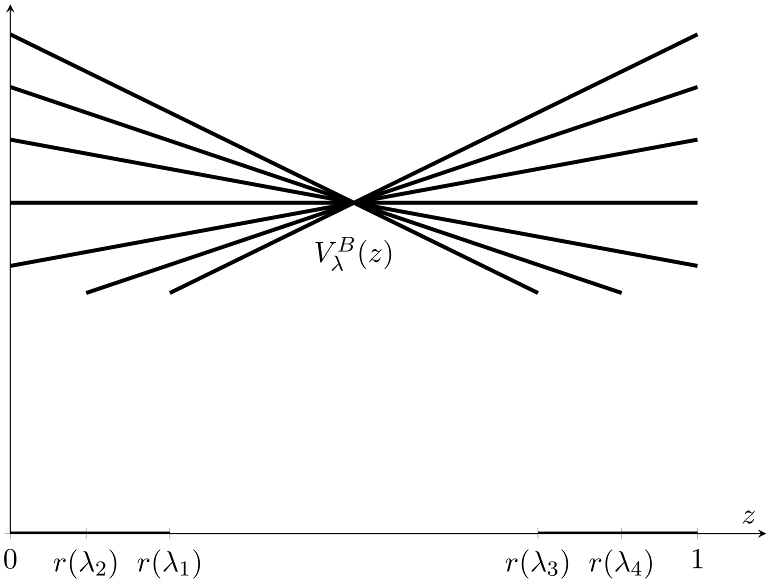
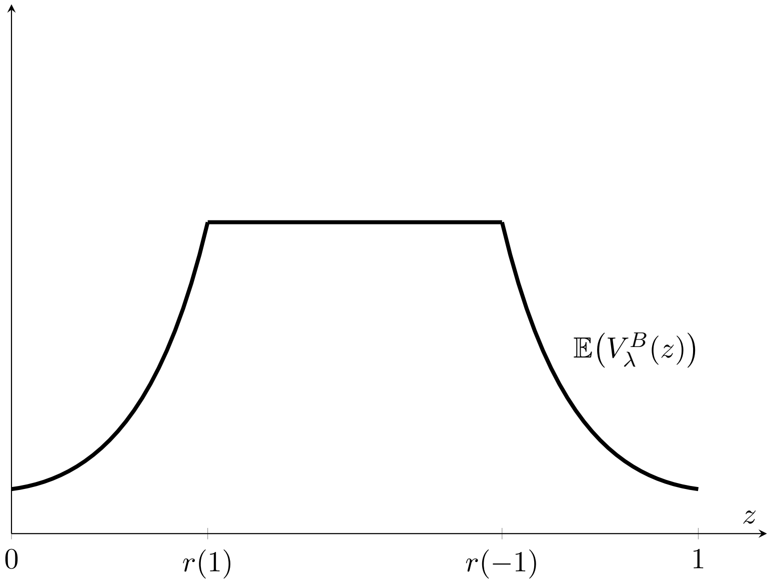


Opacity ⇒ Hedging (Case 1: Concentrated Markets)



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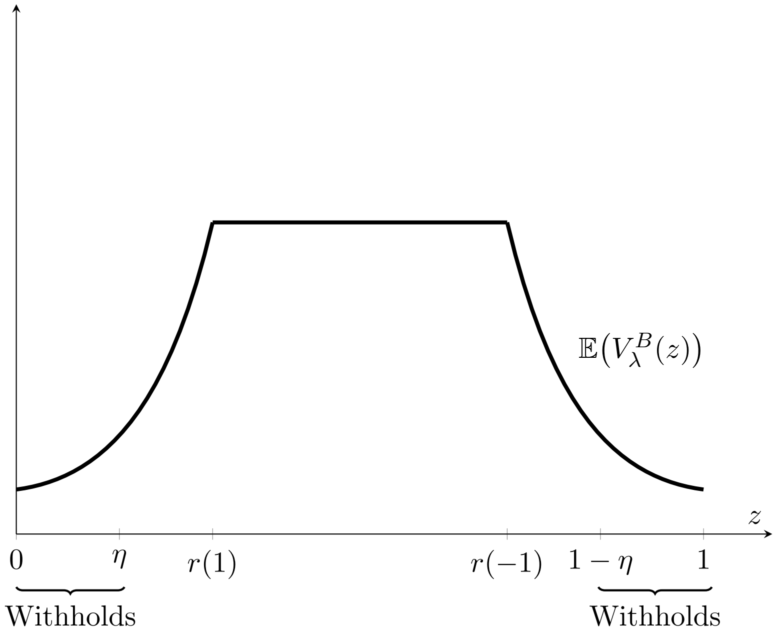

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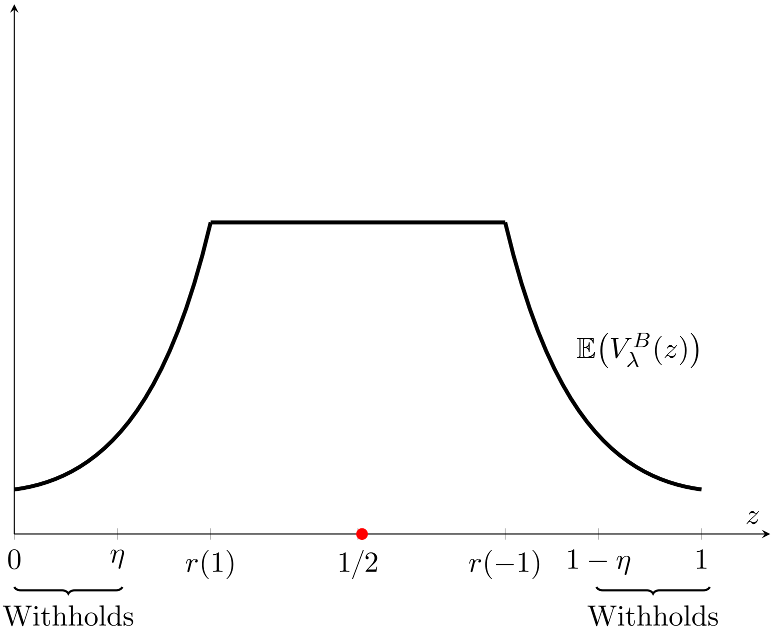

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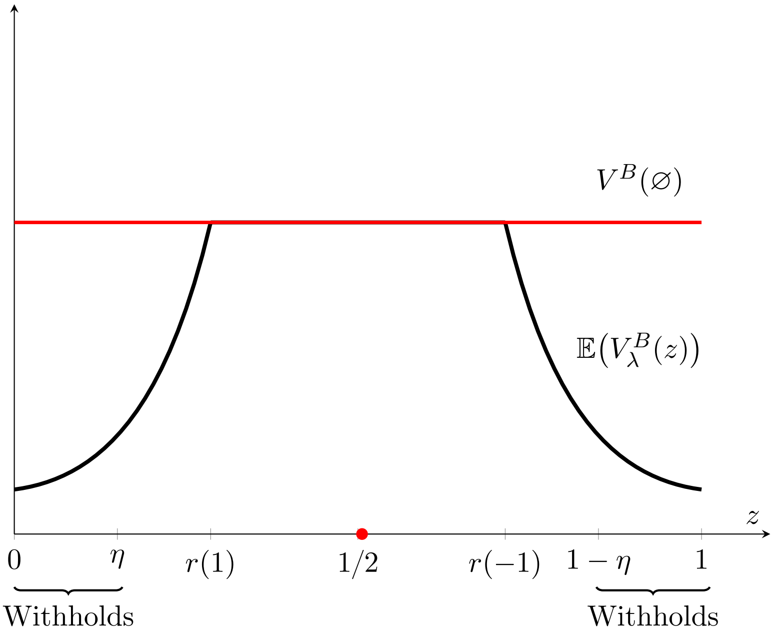

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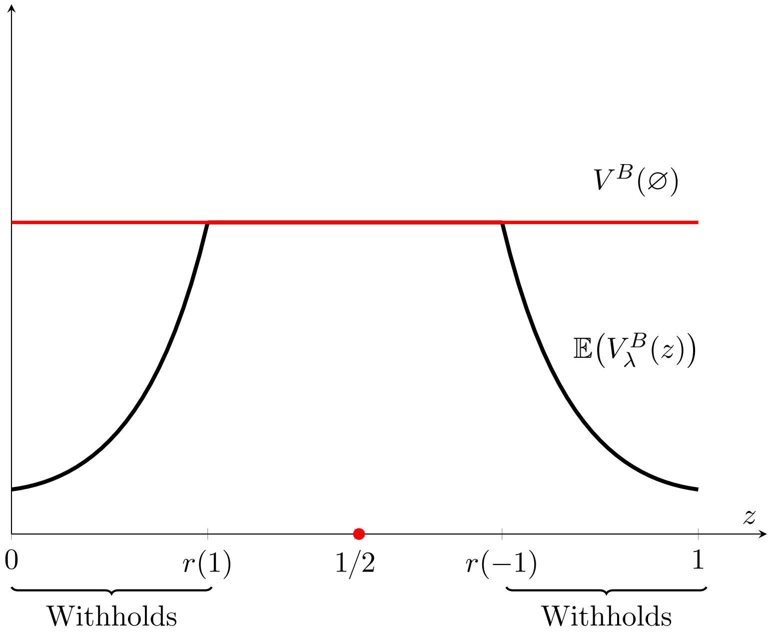

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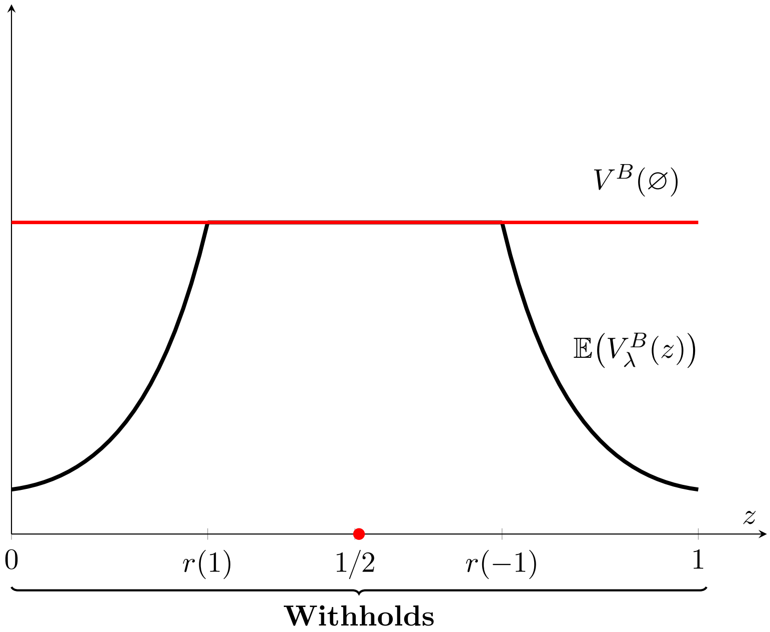
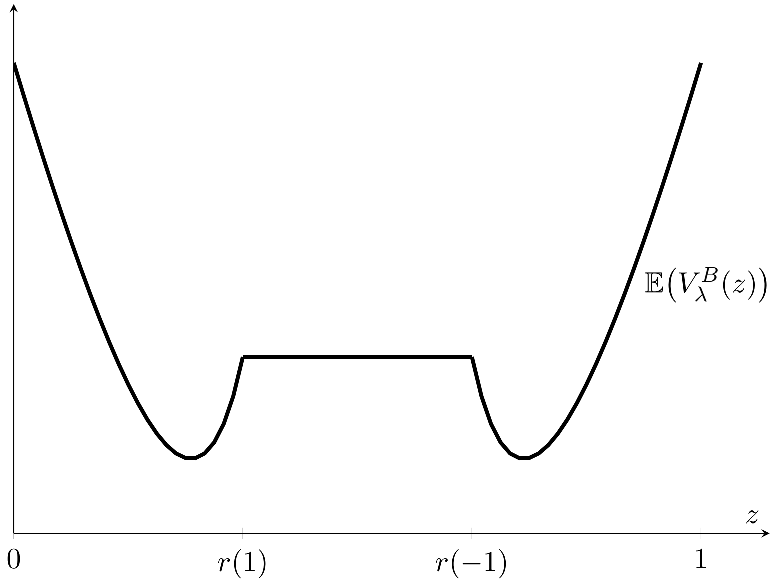


Opacity ⇒ Hedging (Case 2: Competitive Markets)



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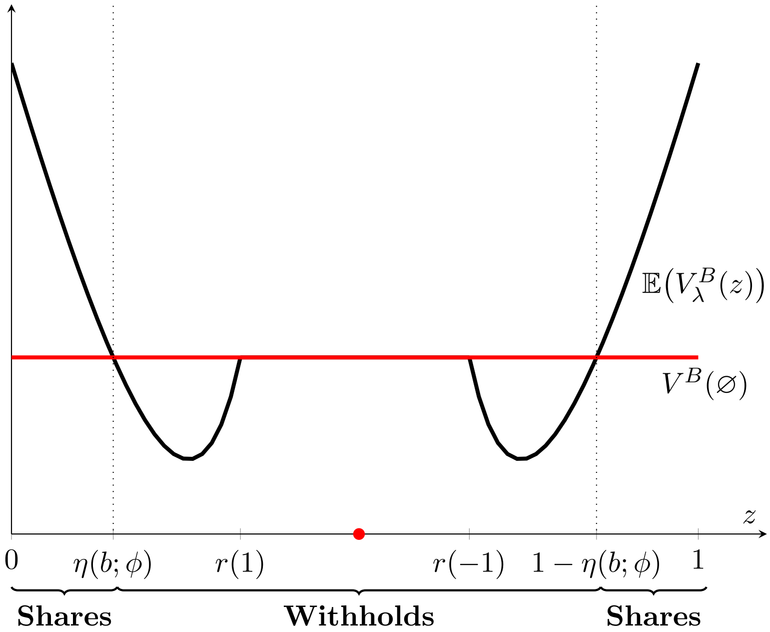


Opacity ⇒ Hedging

Proposition 2 (Data-Sharing to an Opaque Algorithm)

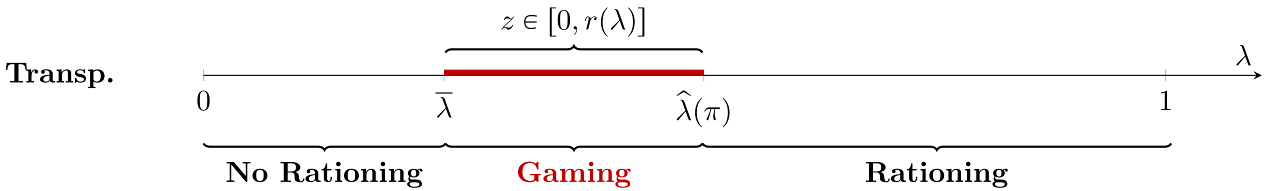
With an opaque algorithm, the set of borrowers withholding data is:

$$\mathcal{H}(b,\phi) = \begin{cases} [0,1] & \text{if } \phi \geqslant 1-2b, \\ [\eta(b,\phi), 1-\eta(b,\phi)] & \text{if } \phi < 1-2b, \end{cases}$$

where $\eta(b,\phi)$ is decreasing in ϕ and b.

Transparency vs Opacity

Transparency vs Opacity: Misallocations



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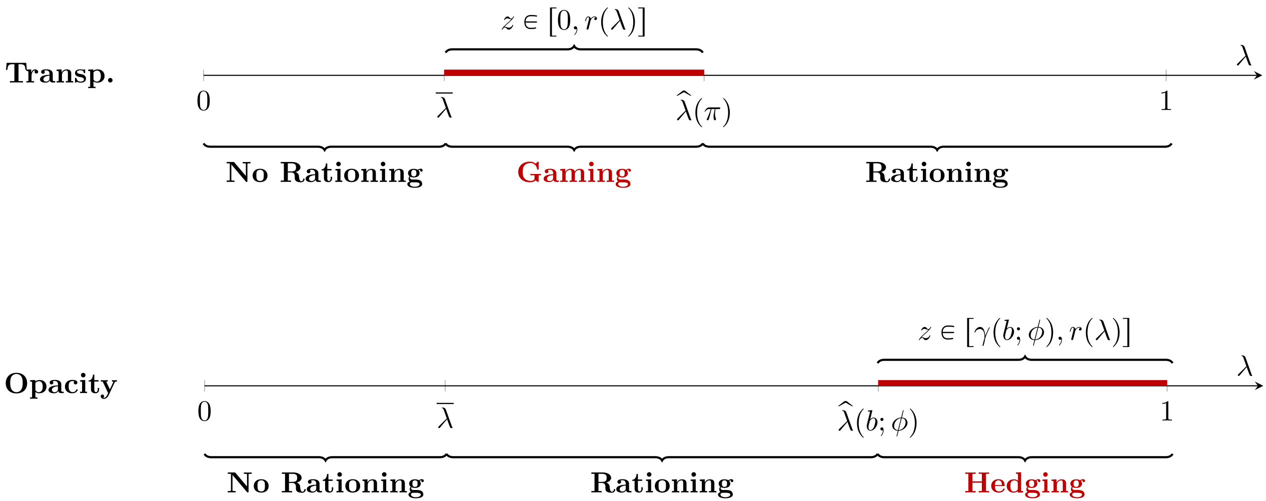
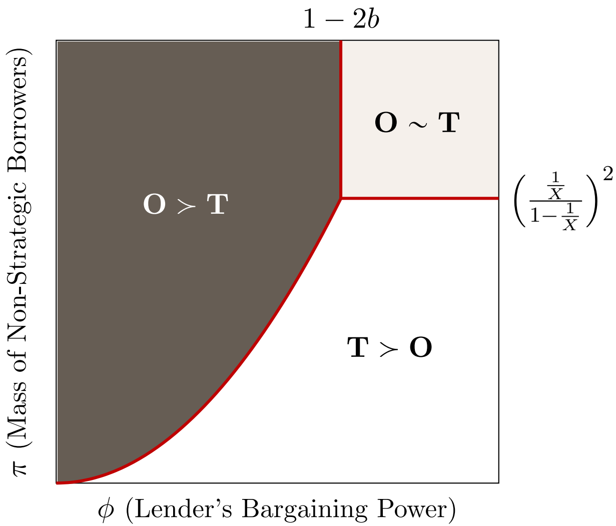


Transparency vs Opacity: Lender's Profits

Proposition 3 (Transparency vs Opacity: Lender's Profits)

The lender chooses an opaque algorithm iff $\pi > \widehat{\pi}(b, \phi)$.



Conclusion

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Findings:

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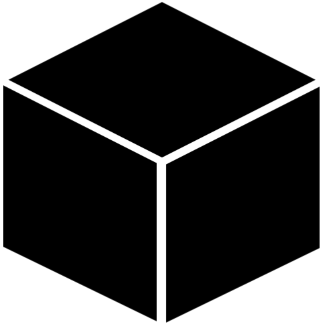
In the Paper:

- Redistributive effects,
- Welfare consequences.



Related Literature

FinTech.

Agarwal et al.(2019), Berg et al.(2020), Gambacorta et al.(2020), Fuster et al.(2022).

This Paper: Opaque statistical technologies have welfare impact.

Voluntary Disclosure / Economics of Data and Privacy.

Grossman (1981), Milgrom (1981), Dye (1985), Quigley and Walther (2022), Bond and Zeng (2022); Ali, Lewis and Vasserman (2023), He, Huang and Zhou (2023).

This Paper: No unravelling when algorithm is opaque, Comparison.

Strategic Classification.

Frankel and Kartik (2019), Frankel and Kartik (2021), Ball (2022), Perez-Richet and Skreta (2022).

This Paper: Opacity can soften gaming, but induce hedging.

Economics and Regulation of Algorithms.

Kleinberg et al. (2018), Cowgill and Tucker (2020), Cowgill and Stevenson (2020), Liang et al. (2023).

This Paper: Optimal transparency regime.

Back

Data-Generating Process

The DGP is truth-or-noise (Lewis and Sappington (1994)) allowing for negative correlation:

$$z = \begin{cases} \theta & \text{with pr. } \lambda \\ \varepsilon & \text{with pr. } 1-\lambda \end{cases} \qquad \text{if } \lambda \geqslant 0,$$

$$z = \begin{cases} 1-\theta & \text{with pr. } |\lambda| \\ \varepsilon & \text{with pr. } 1-|\lambda| \end{cases} \qquad \text{if } \lambda < 0,$$

where $\varepsilon \sim U[0,1]$ is noise independent of θ.

The conditional pdf is:

$$f_\lambda(\theta|z) = \begin{cases} \lambda\,\delta(\theta - z) + (1-\lambda)1/2 & \text{if } \lambda \geqslant 0 \\ \lambda\,\delta(1-\theta-z) + (1-\lambda)1/2 & \text{if } \lambda < 0, \end{cases}$$

where $\delta(\theta - z)$ is the Dirac's delta function.

Back

Payoffs

Transparency/Opacity	Information	Data-Sharing	Credit Allocation	**Payoffs**
(0)	(1)	(2)	(3)	**(4)**

$$V^B(\theta) = \ell\big((\theta(X - x) + b\big)$$
$$V^L(\theta) = \ell(\theta x - 1)$$
$$W(\theta) = \ell(\theta X - 1 + b)$$

Back

Equilibrium Inference

Lemma A.1 (Credit Allocation following Data Withholding)

Let $Q \triangleq \{z \in [0,1] : m(z) = \varnothing\}$ *be the set of borrowers that withhold data, the optimal credit allocation is:*

$$x_\lambda(\varnothing) = \frac{1}{\mu_\lambda(\varnothing)} + \phi\left(X - \frac{1}{\mu_\lambda(\varnothing)}\right),$$

$$\ell_\lambda(\varnothing) = \mathbb{1}\left\{\mu_\lambda(\varnothing) > \frac{1}{X}\right\}.$$

where

$$\mu_\lambda(\varnothing) = \lambda\, z(\pi, Q) + (1-\lambda)\tfrac{1}{2},$$

$$z(\pi, Q) = \omega(\pi, Q)\tfrac{1}{2} + \big(1 - \omega(\pi, Q)\big)\mathbb{E}(\theta | \theta \in Q),$$

$$\omega(\pi, Q) = \frac{\pi}{\pi + (1-\pi)\Pr(z \in Q)}.$$

Back