

Differentially Private, Bounded-Loss Prediction Markets



Bo Waggoner

with Rafael Frongillo

UPenn → Microsoft

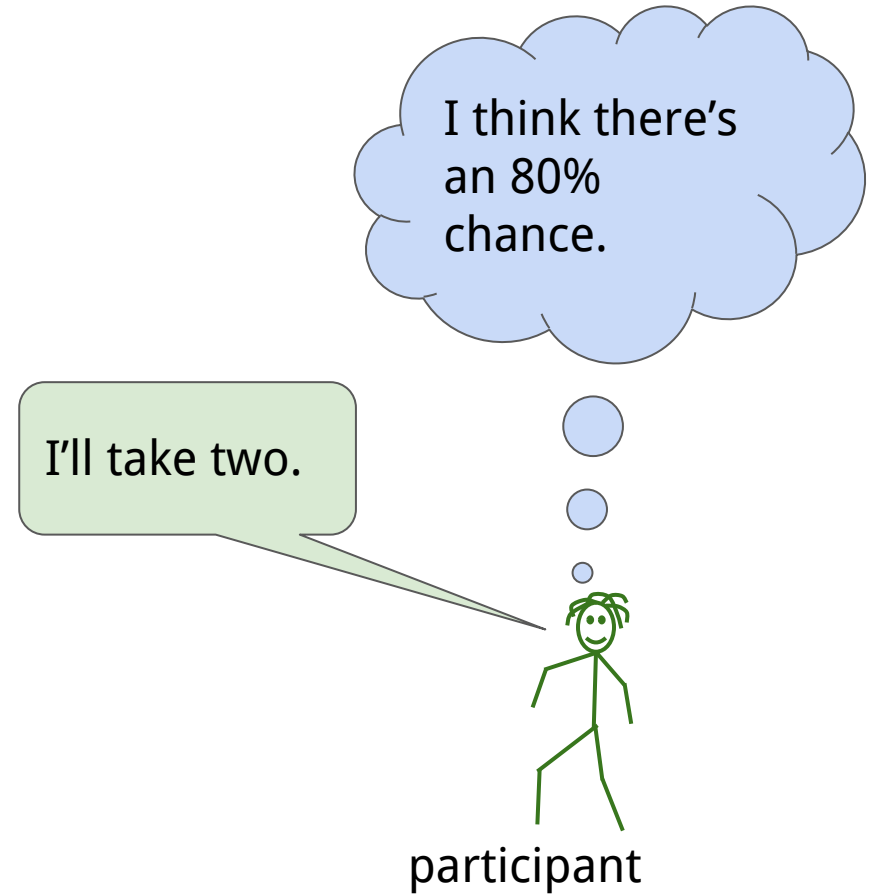
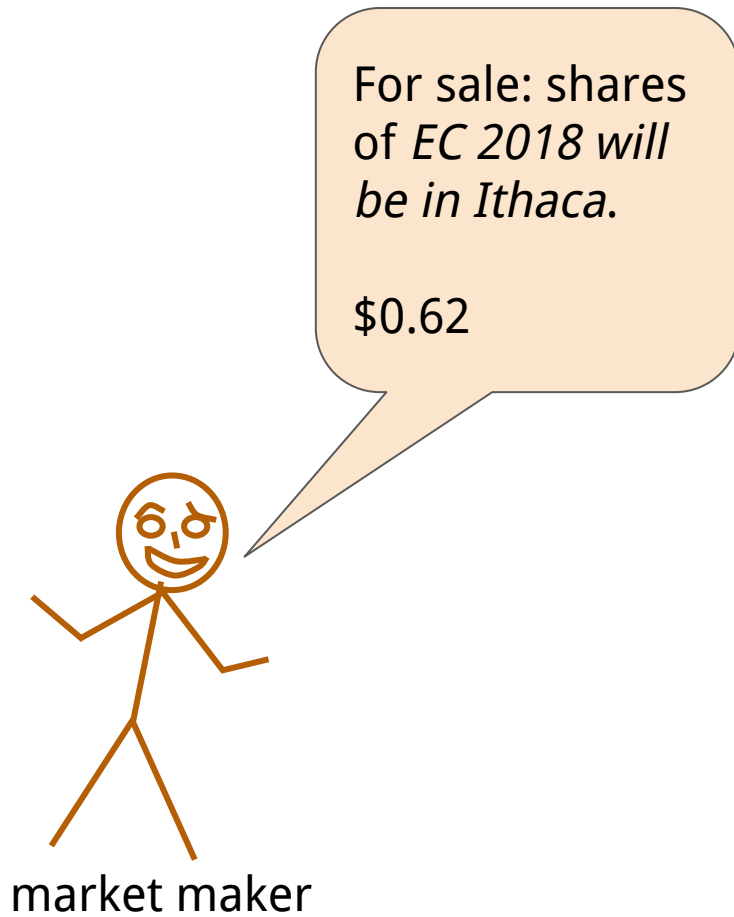
Colorado

WADE, June 2018

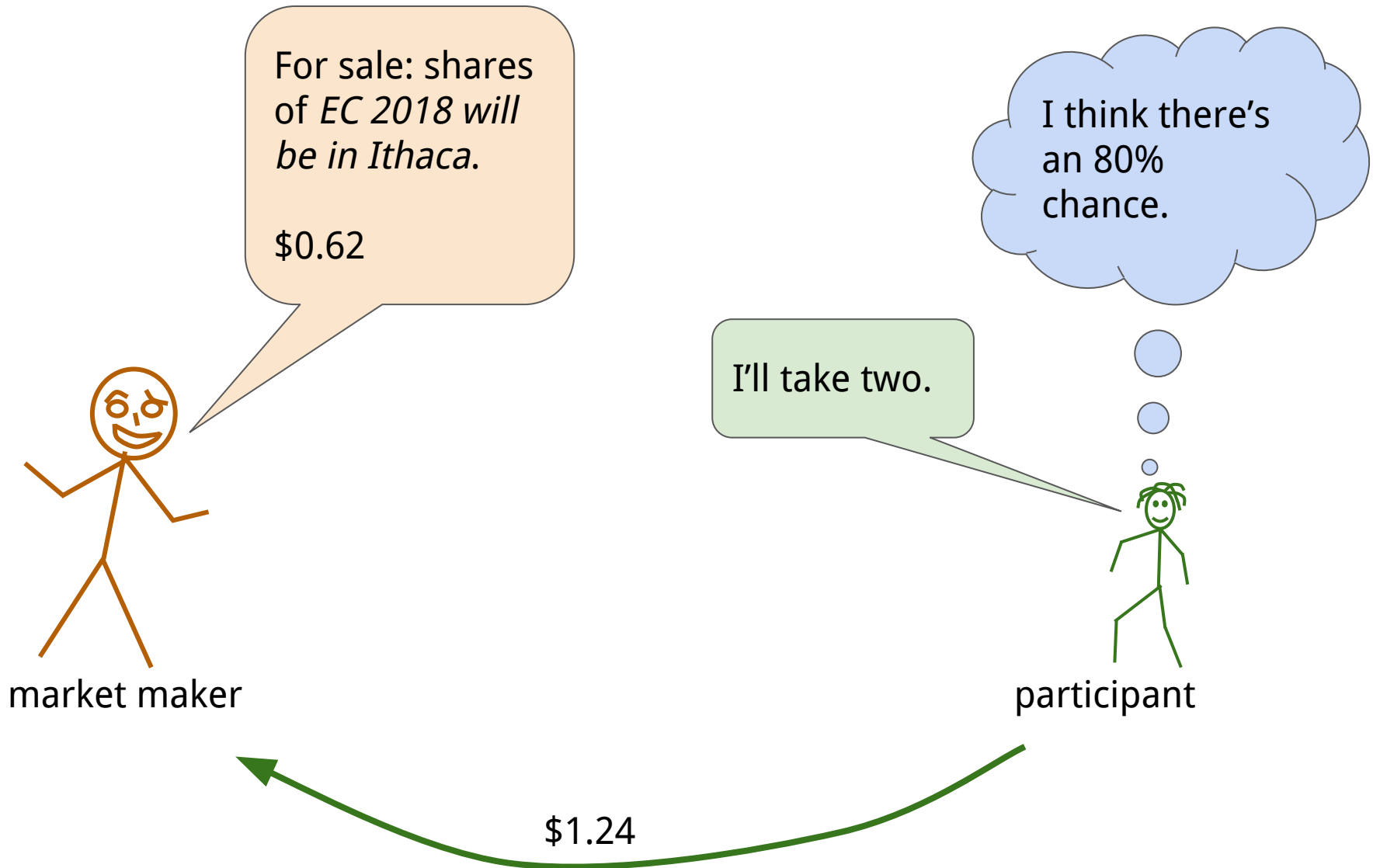
Outline

- **A. Cost function based prediction markets**
- B. Summary of results and prior work**
- C. Construction**

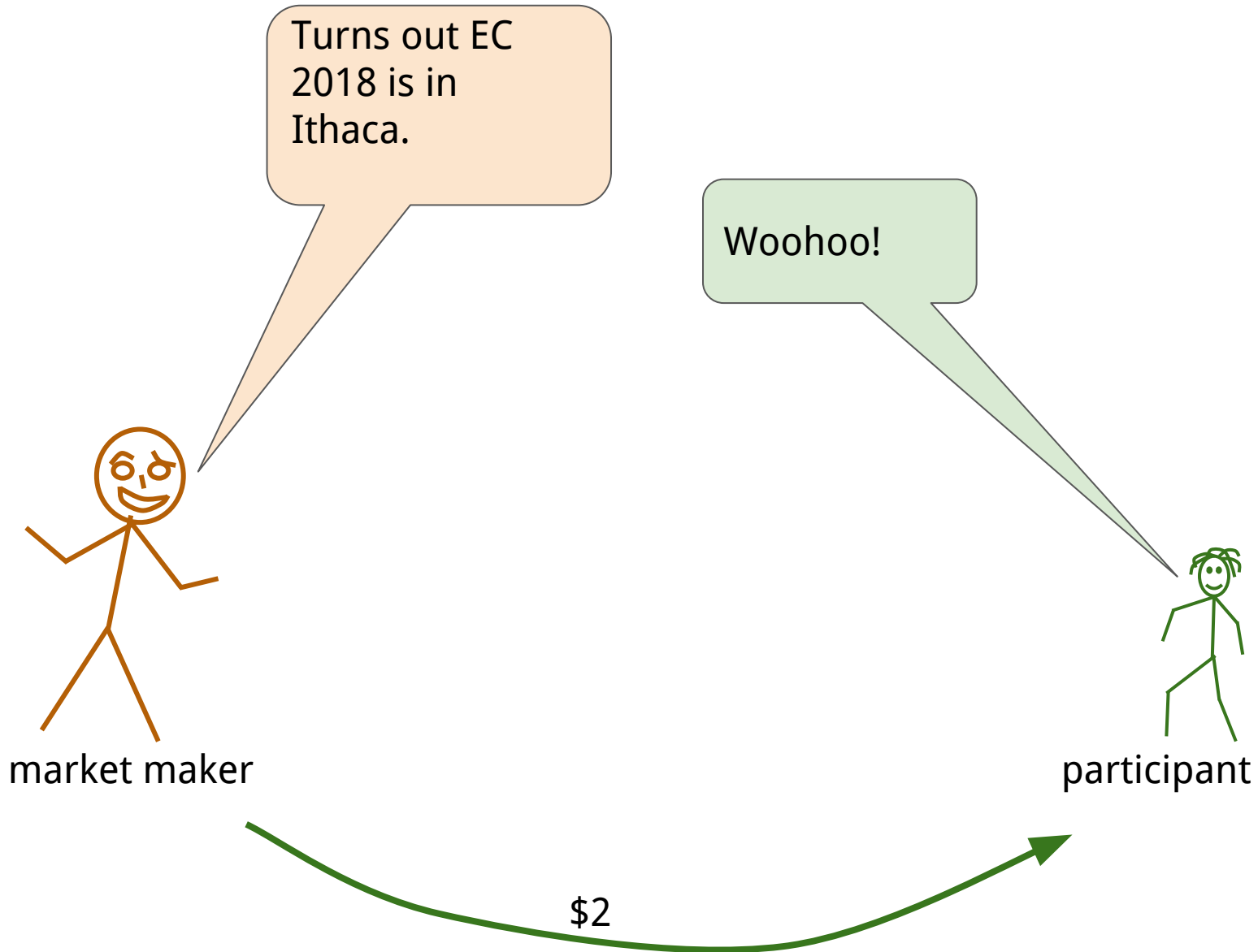
Prediction markets



Prediction markets

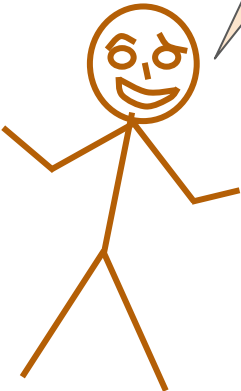


Later



(In an alternate universe)

Turns out EC 2018 is in Phoenix



market maker

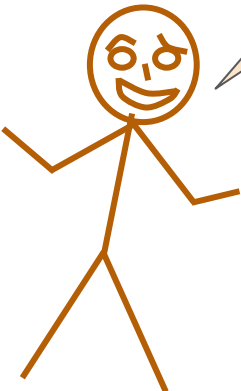
Awww!



participant

(no payoff)

Short selling

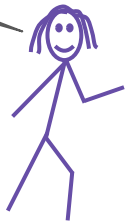


market maker

For sale: shares of *EC 2018* will be in *Ithaca*.

\$0.62

The market maker is represented by a brown stick figure with a smiling face. A large orange speech bubble points to the figure, containing the text 'For sale: shares of EC 2018 will be in Ithaca.' and '\$0.62'.



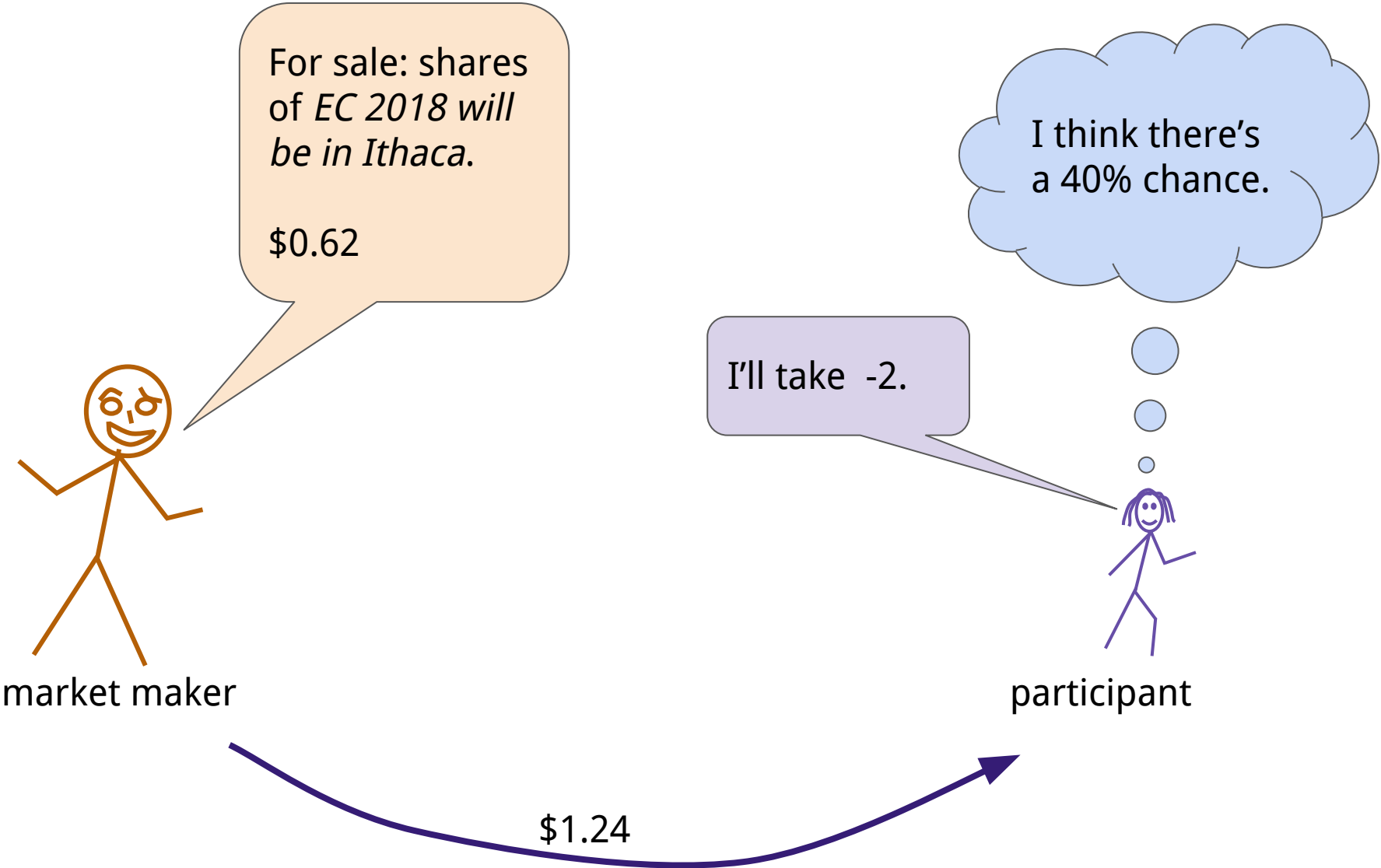
participant

I'll take -2.

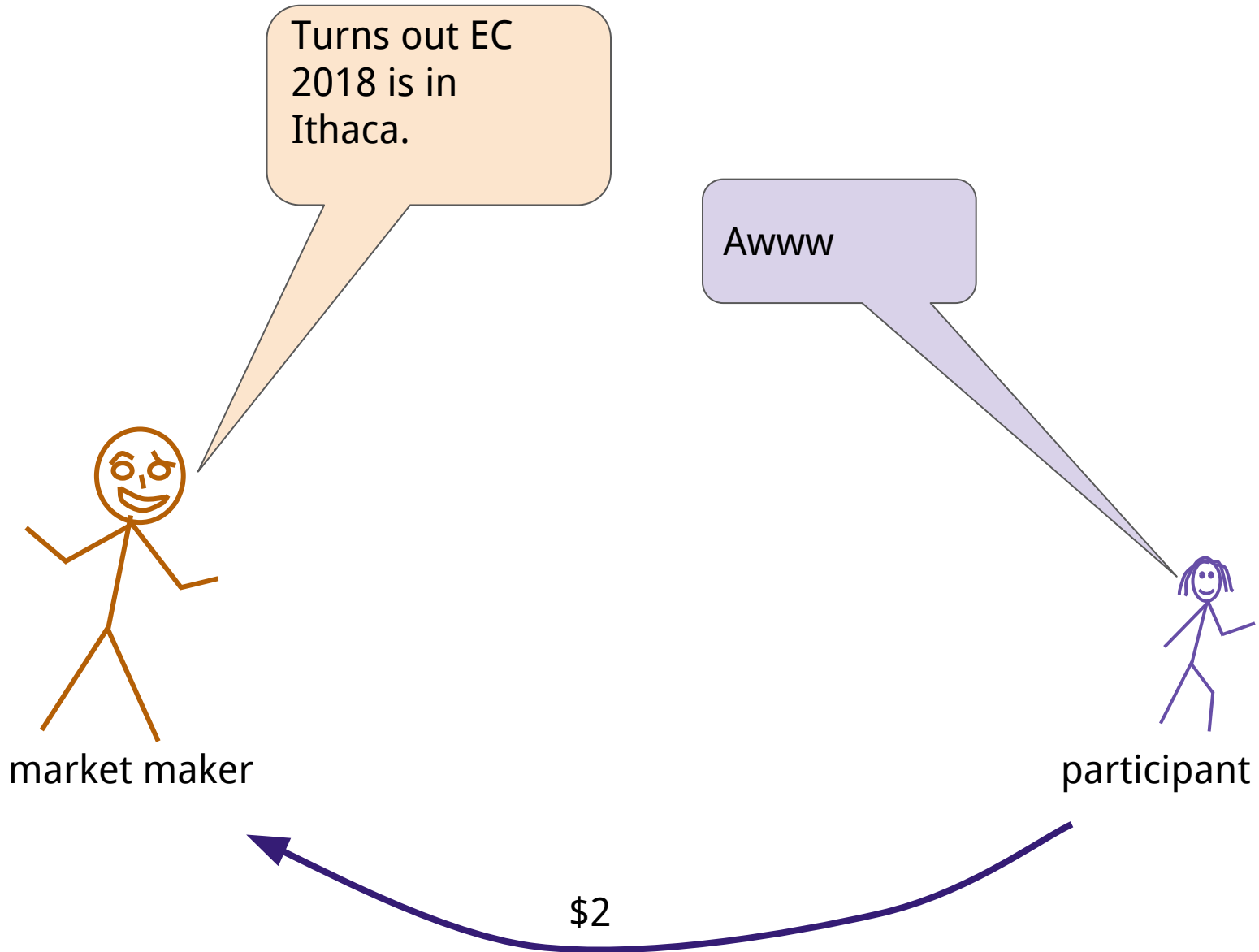
I think there's a 40% chance.

The participant is represented by a purple stick figure with a neutral face. A purple speech bubble points to the figure, containing the text 'I'll take -2.'. Above the figure is a thought bubble containing the text 'I think there's a 40% chance.', connected to the figure by three small circles.

Short selling

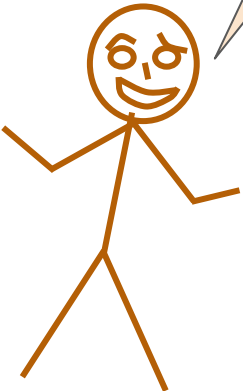


Later



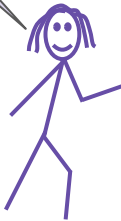
(In an alternate universe)

Turns out EC
2018 is in
Phoenix



market maker

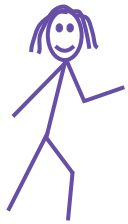
Sweet



participant

(no payoff)

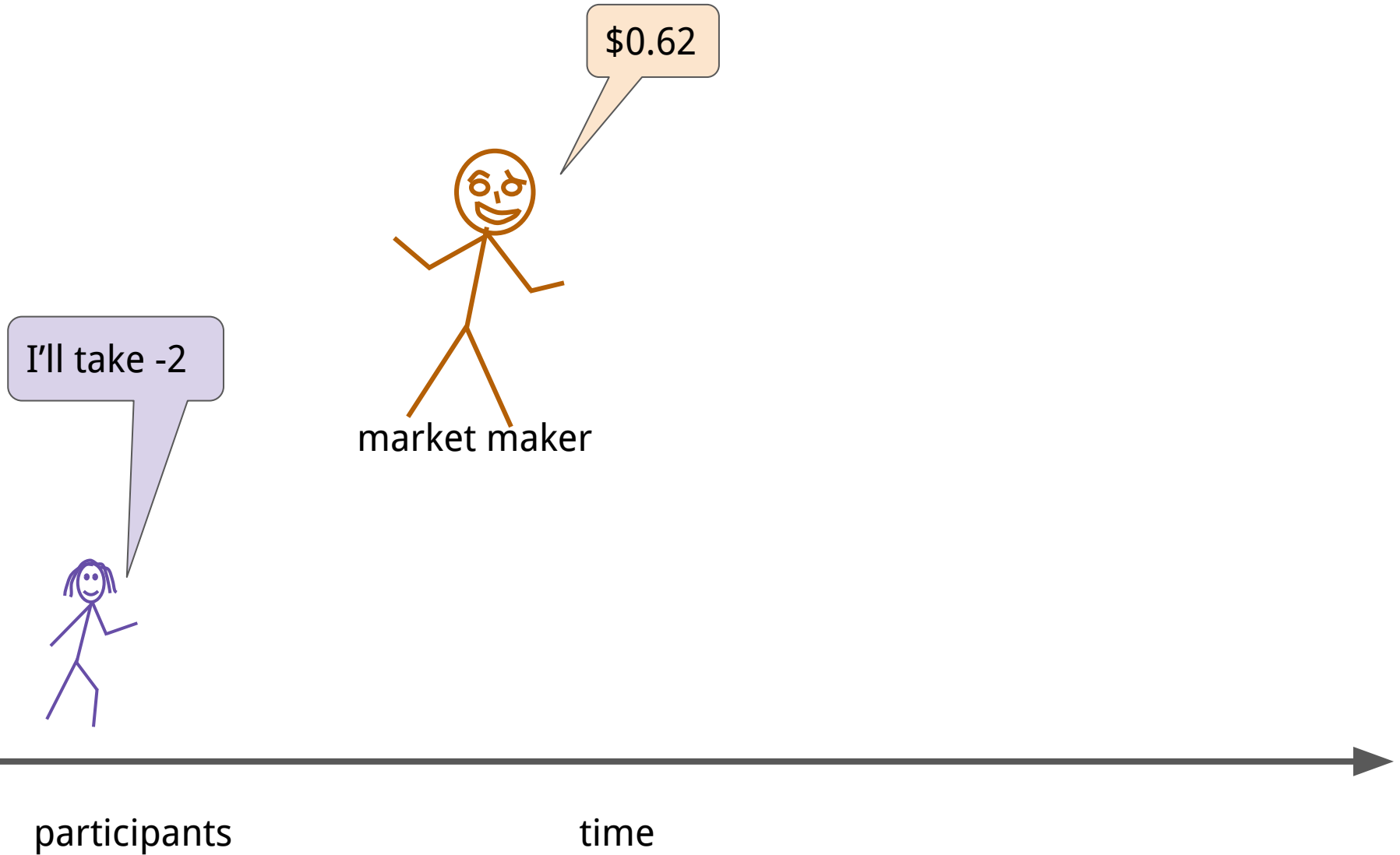
Prediction markets - dynamics



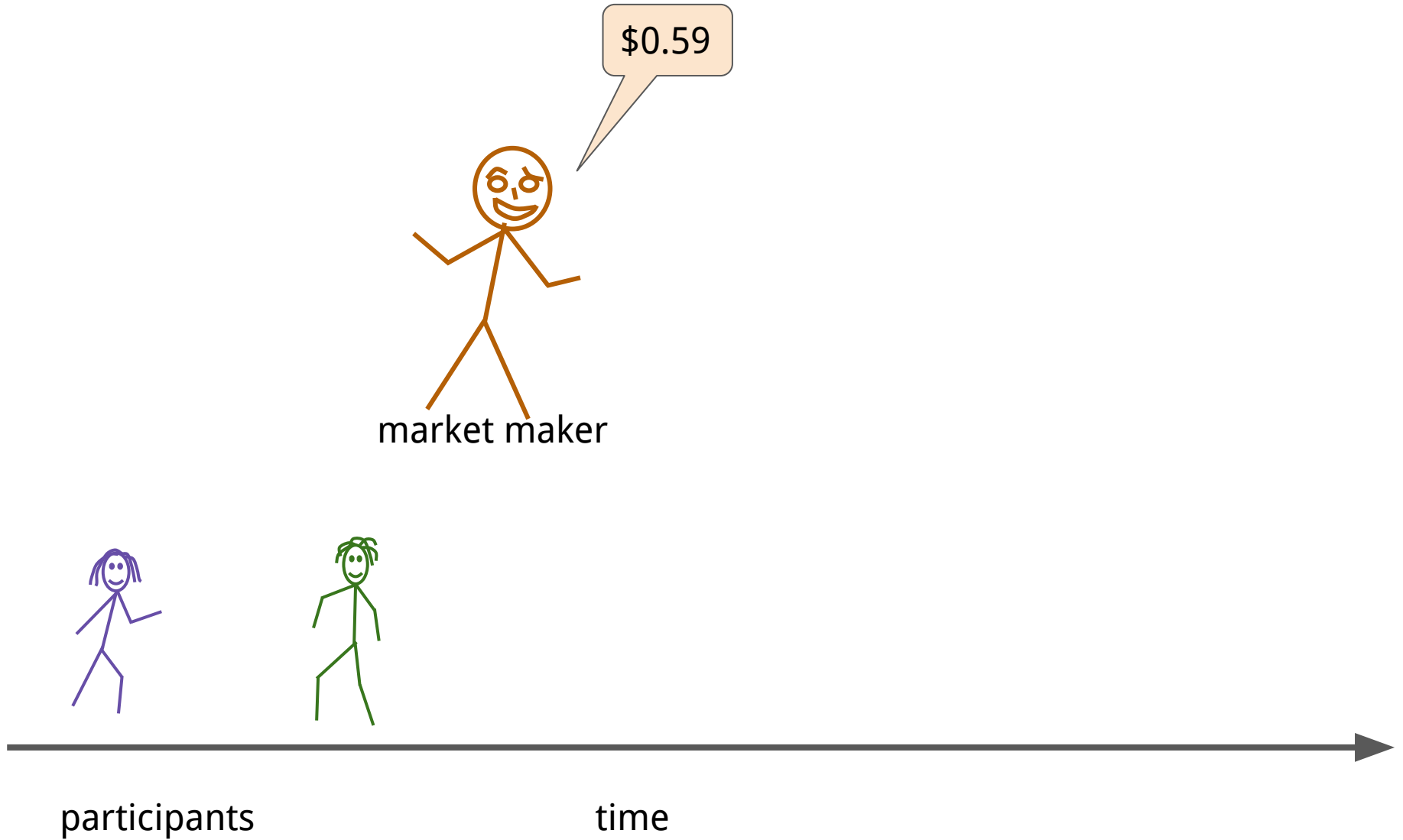
participants

time

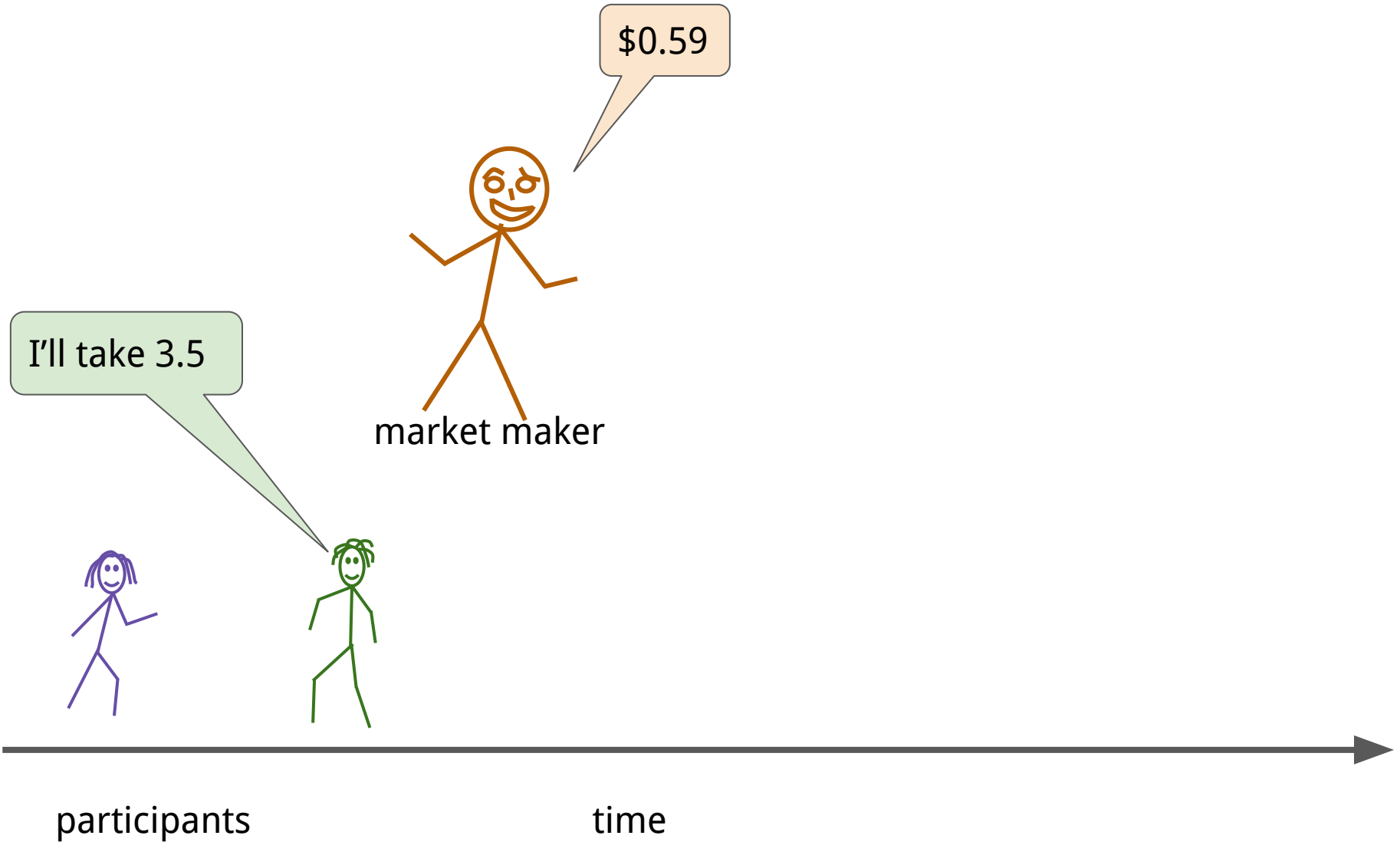
Prediction markets - dynamics



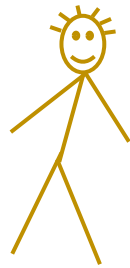
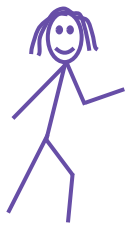
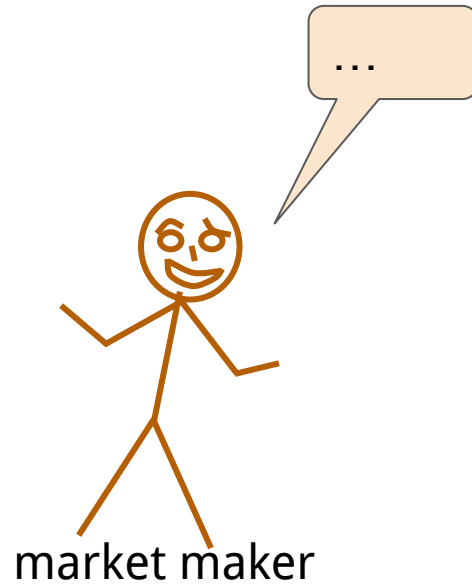
Prediction markets - dynamics



Prediction markets - dynamics



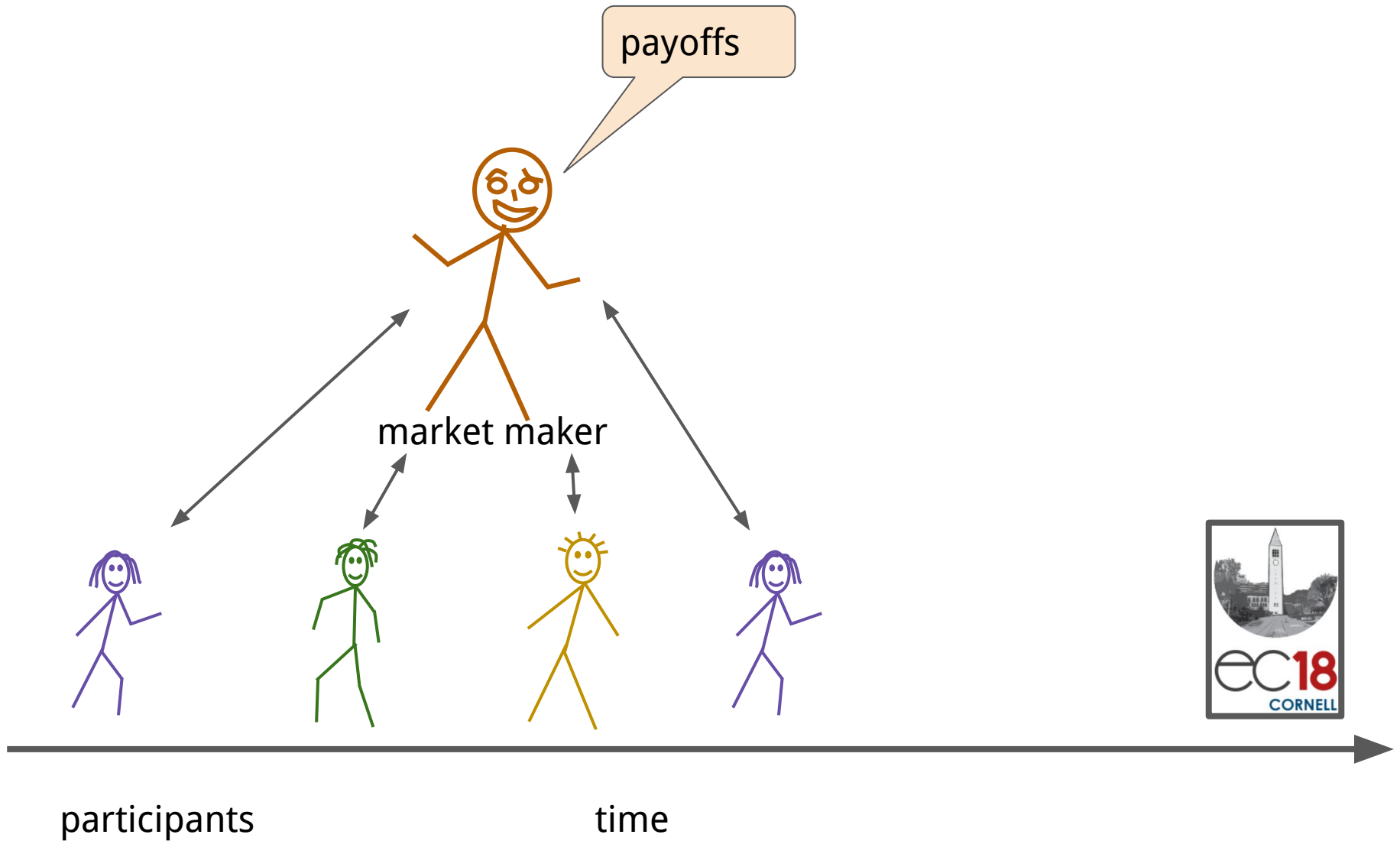
Prediction markets - dynamics



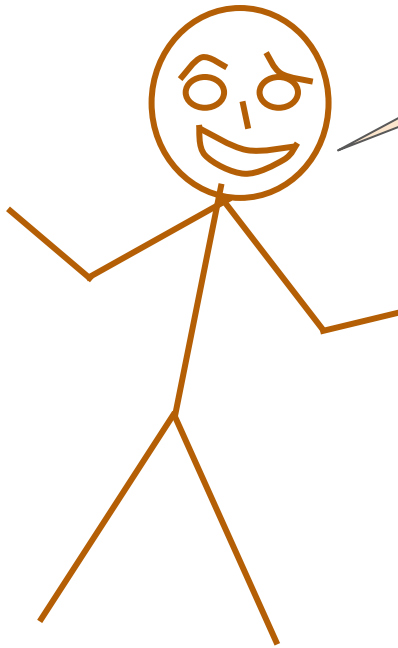
participants

time

Prediction markets - dynamics

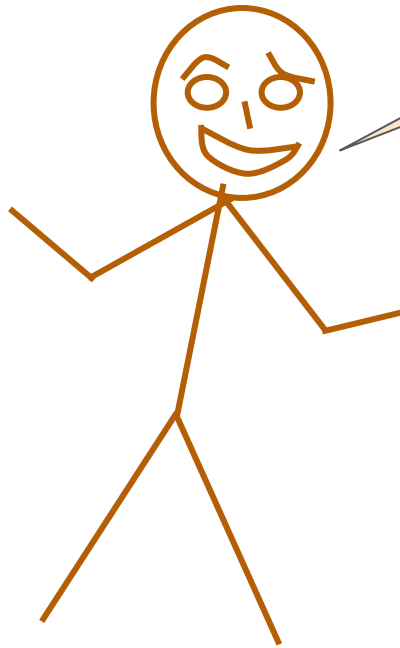


Design question



How to set the prices at each time?

Design question



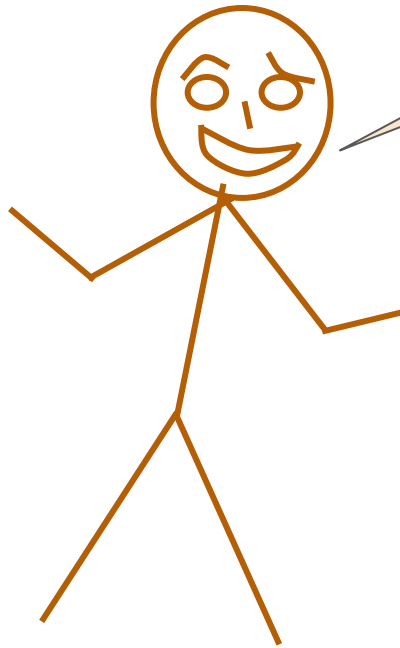
How to set the prices at each time?

Convex function

C: (total shares sold) \rightarrow (total price paid)

Design question

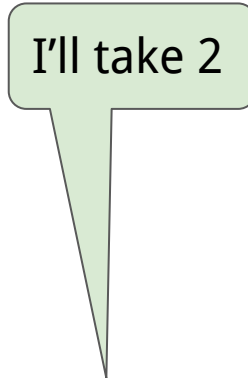
How to set the prices at each time?



Convex function

C : (total shares sold) \rightarrow (total price paid)

I'll take 2



total shares: 100

total shares: 102



Design question

How to set the prices at each time?

Convex function

C : (total shares sold) \rightarrow (total price paid)

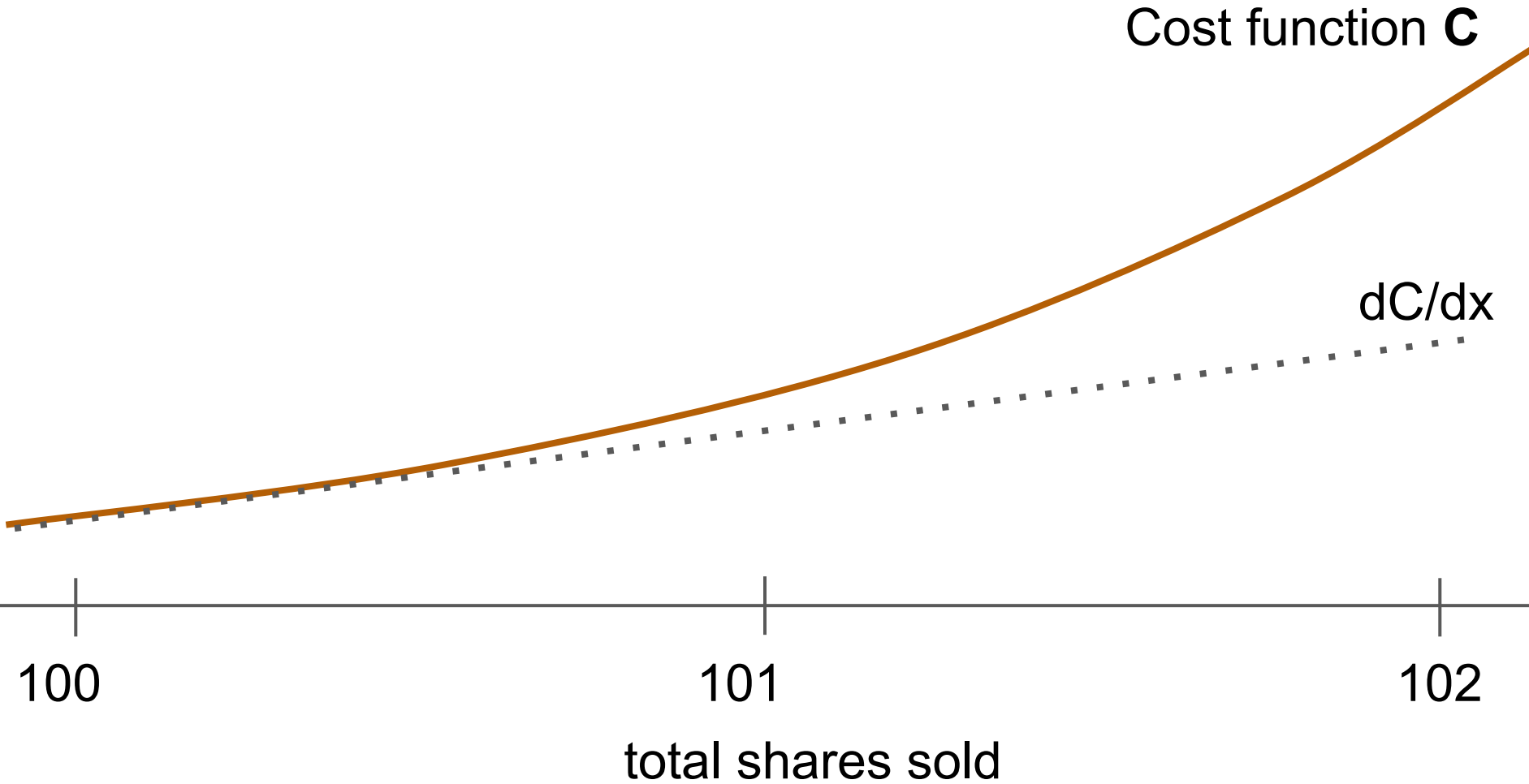
price $C(102) - C(100)$

I'll take 2

total shares: 100

total shares: 102

The cost function



The cost function

instantaneous price = dC/dx
= $\text{Pr}[\text{event}]$.

convexity \Leftrightarrow price \uparrow when you buy

Cost function **C**

dC/dx

100

101

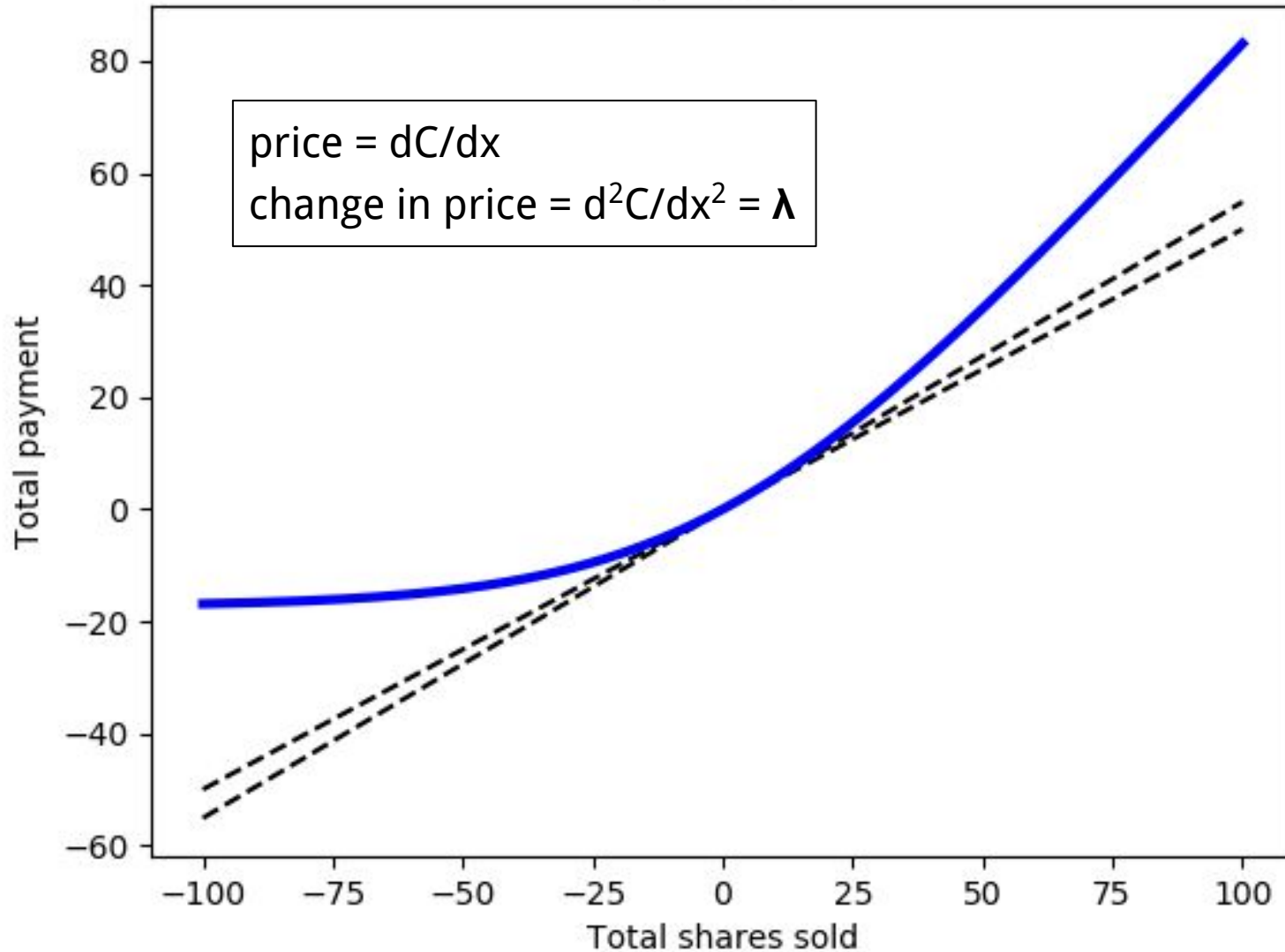
102

total shares sold

Key idea: price sensitivity λ

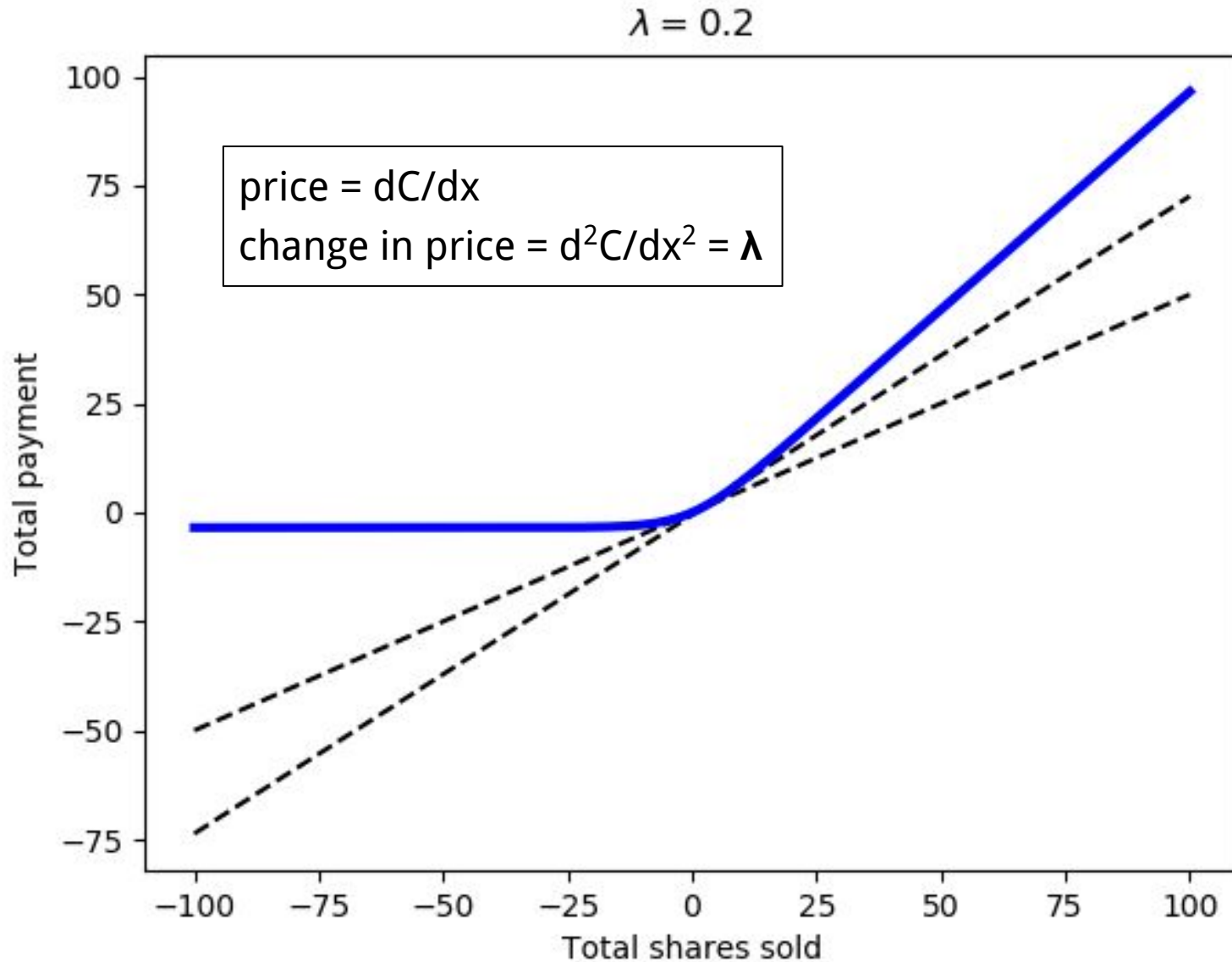
How quickly do prices respond to trades?

$$\lambda = 0.04$$



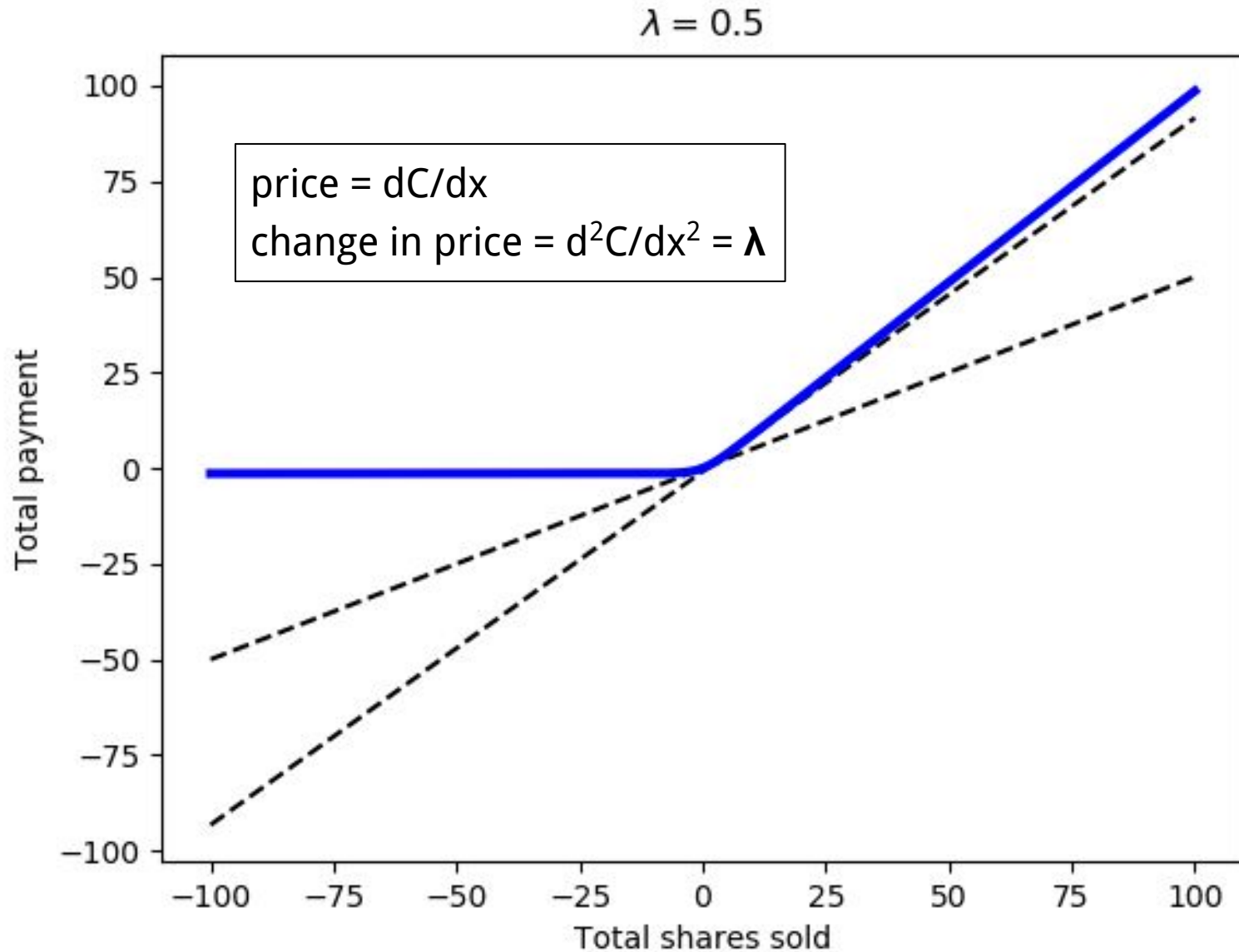
Key idea: price sensitivity λ

How quickly do prices respond to trades?

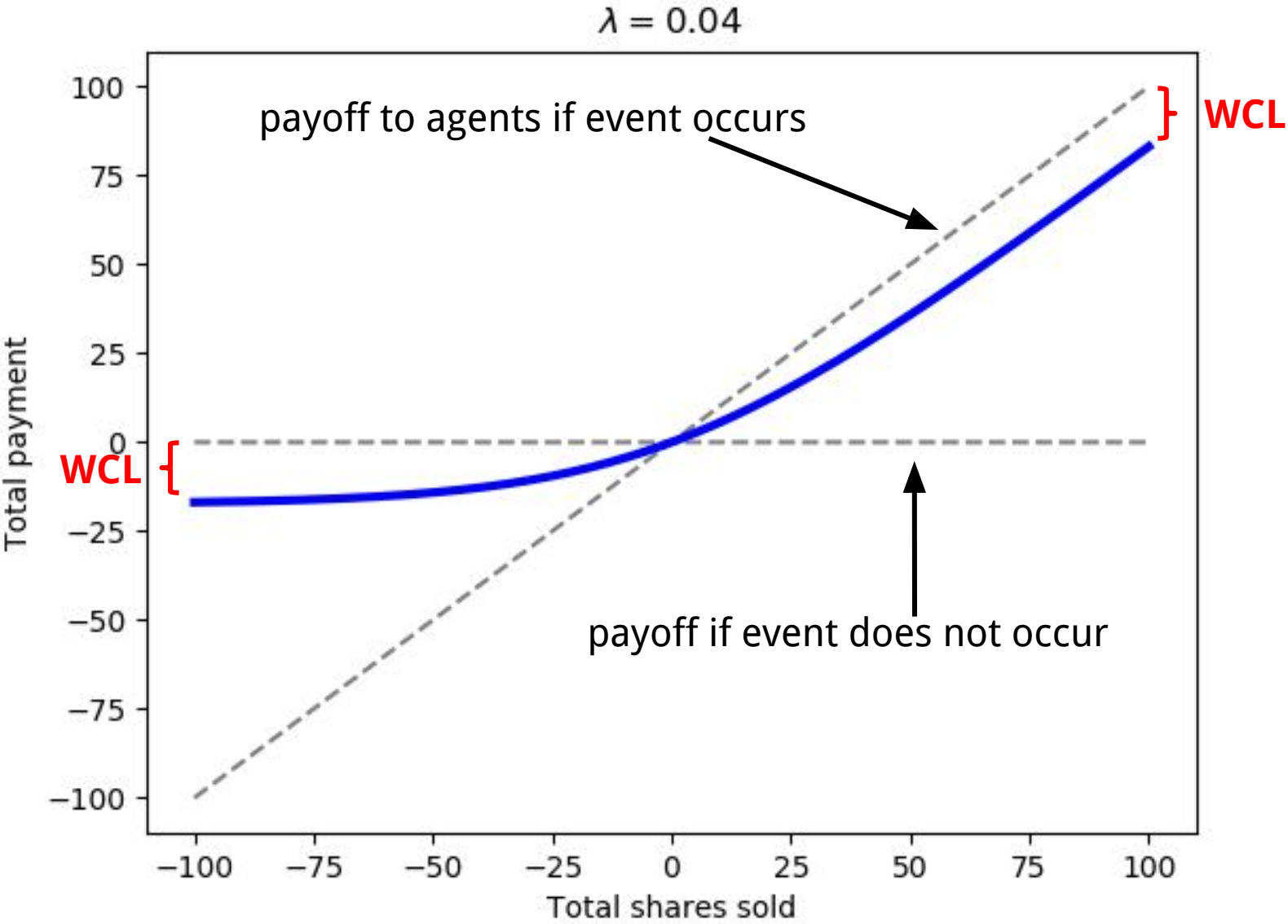


Key idea: price sensitivity λ

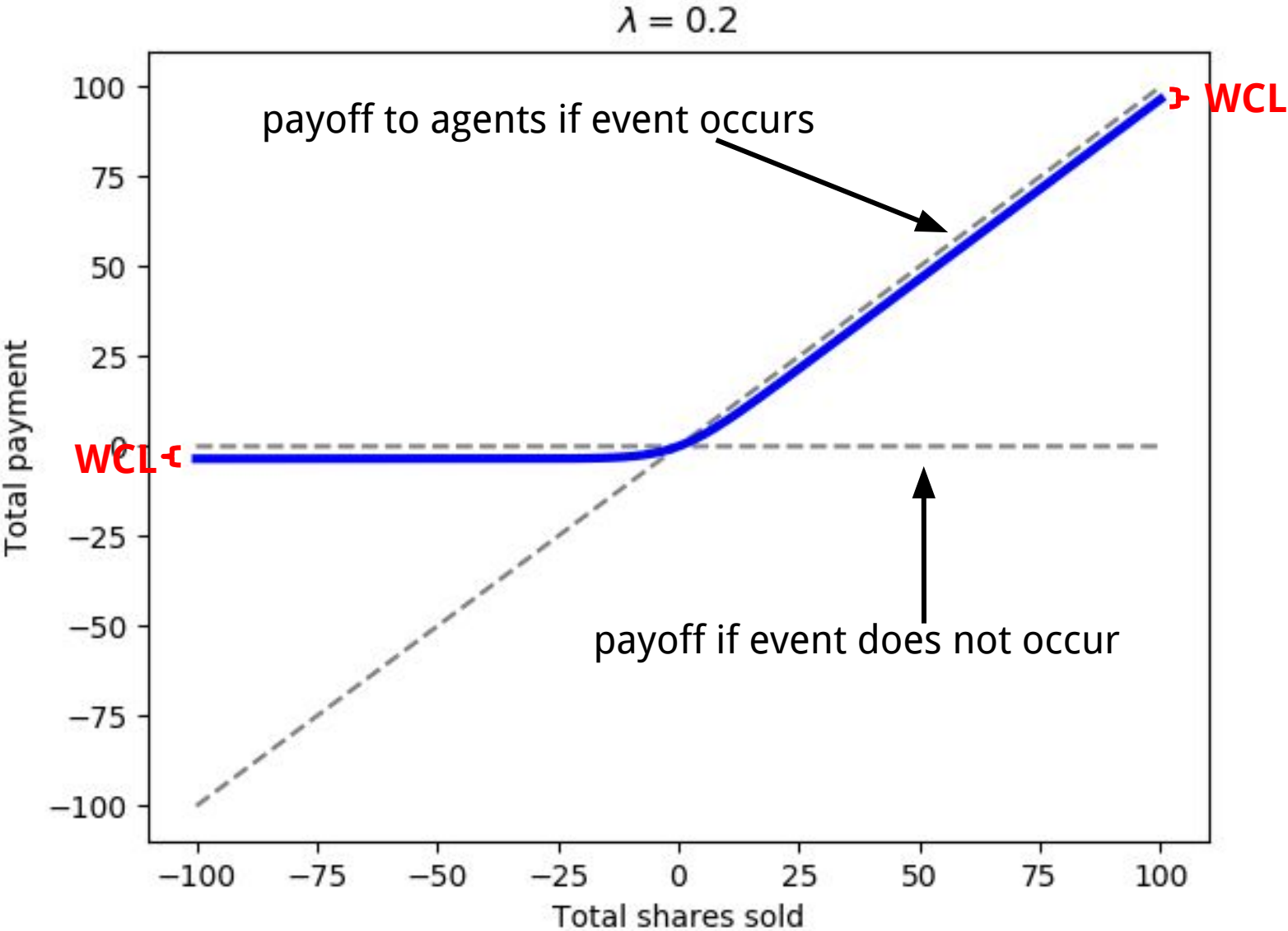
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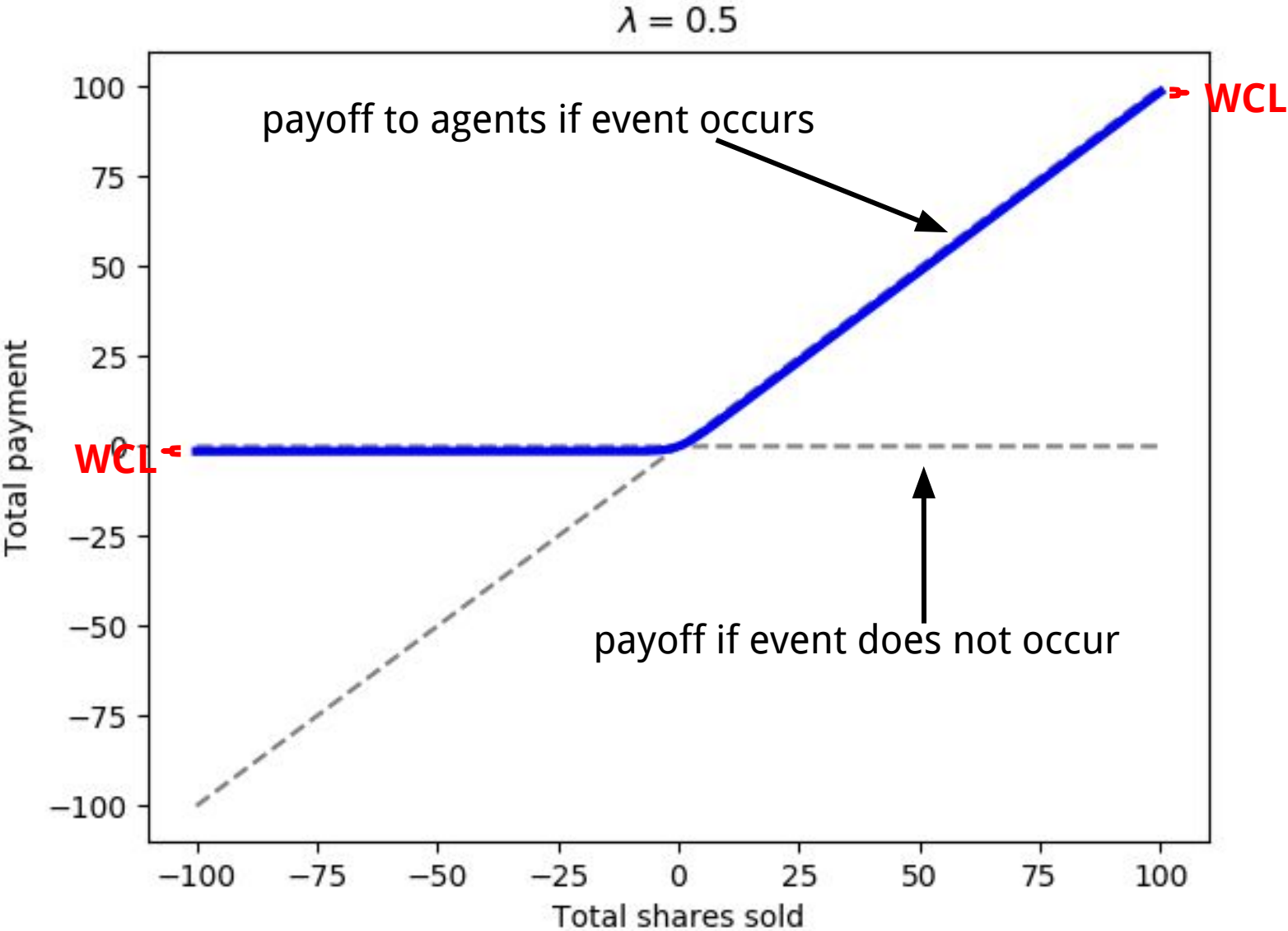
Worst Case Loss $\approx 1 / \lambda$



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Worst Case Loss $\approx 1 / \lambda$



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→ **B. Summary of results and prior work**

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Privacy in markets: history

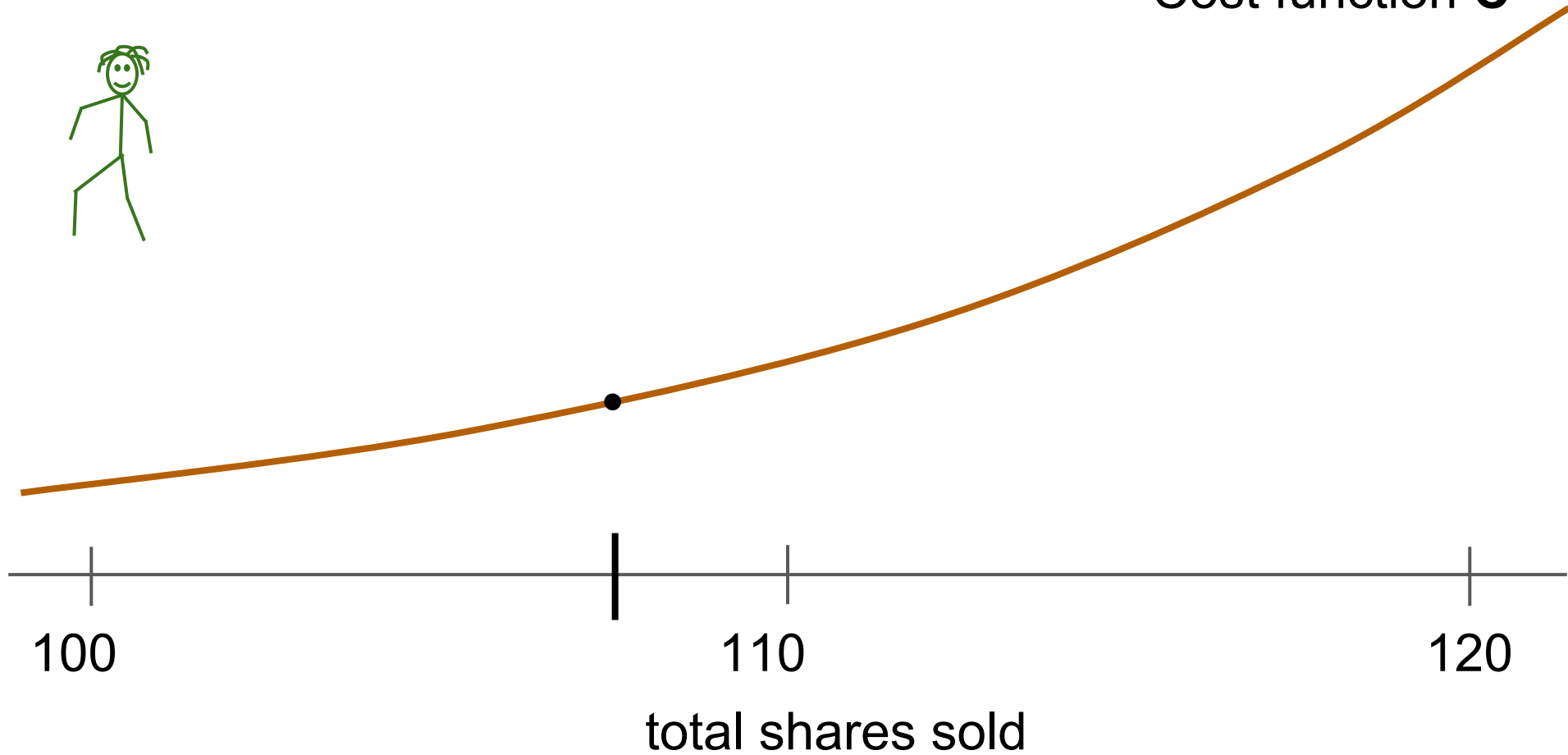
- *Waggoner, Frongillo, Abernethy. NIPS 2015*
 - includes a proposal for private prediction markets
 - focused on ML extensions; private markets not well explained
- *Cummings, Pennock, Wortman Vaughan. EC 2016*
 - every private prediction market has **unbounded financial loss**
- *Frongillo, Waggoner. 2018 (manuscript)*
 - modified market achieving **bounded** loss (with unbounded participants)
 - idea 1: transaction fee
 - idea 2: adaptive **price sensitivity** (liquidity)

Private prediction markets (with unbounded loss)

Participant arrives, makes a trade, then we add noise.

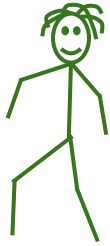


Cost function **C**



Private prediction markets (with unbounded loss)

Participant arrives, makes a trade, then we add noise.



Cost function C

payment

100

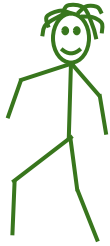
110

120

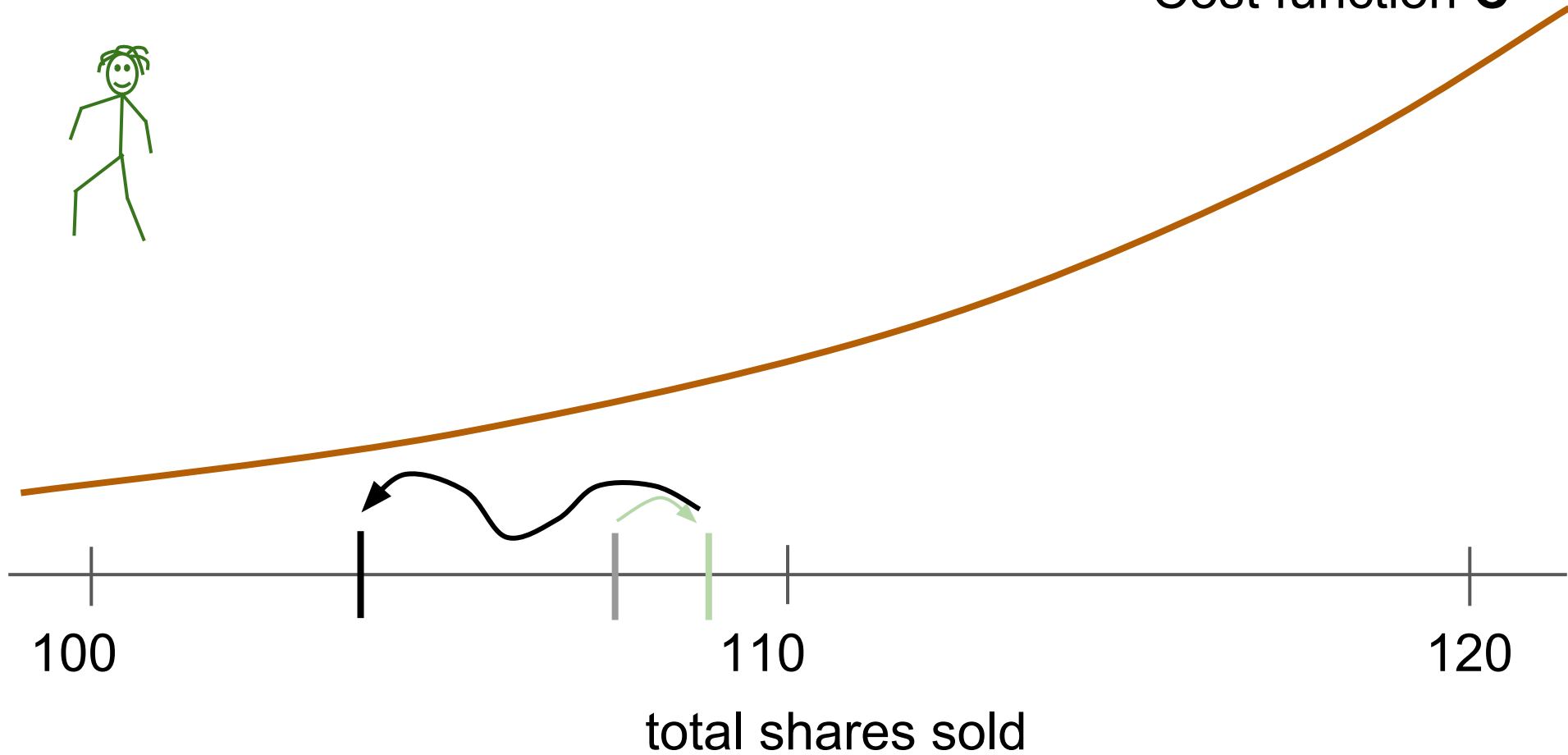
total shares sold

Private prediction markets (with unbounded loss)

Participant arrives, makes a trade, then we add noise.
Everyone else sees only the new market state.



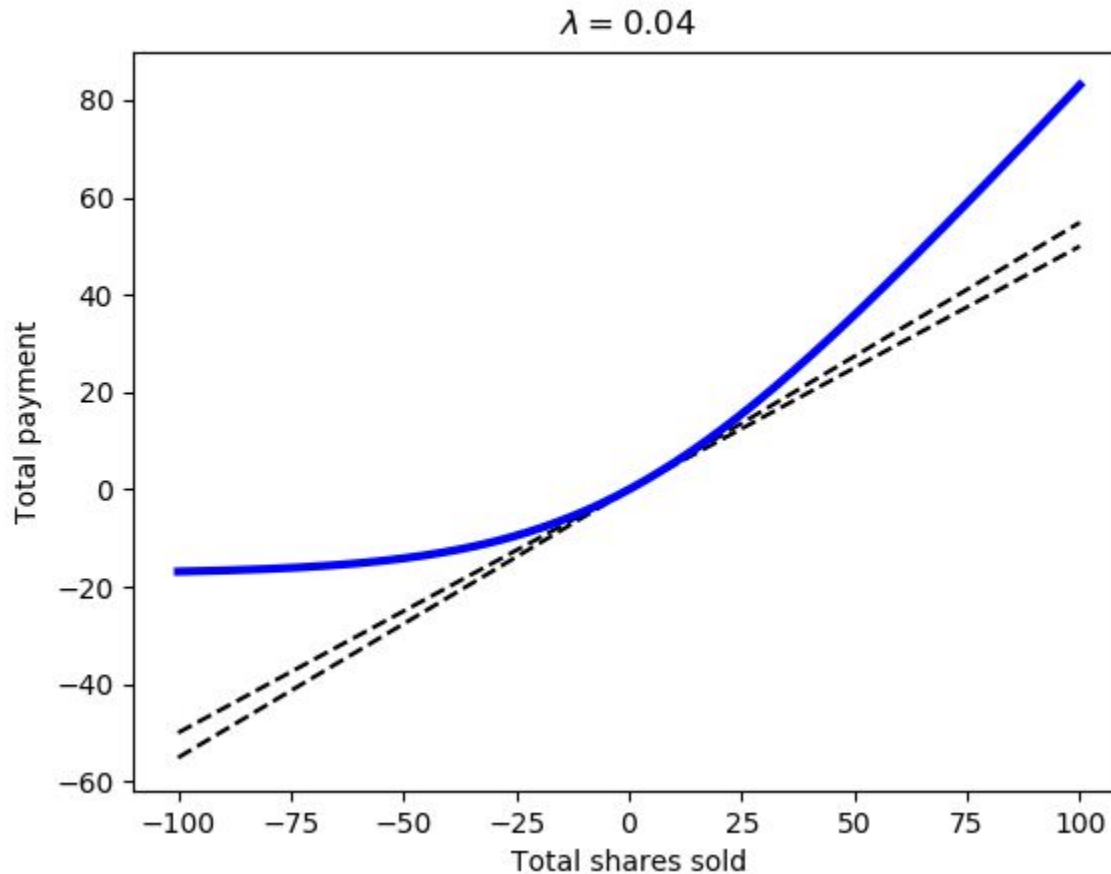
Cost function **C**



Private prediction markets (with unbounded loss)

Given privacy level ϵ , set amount of noise.

Then, given accuracy level α , set price sensitivity λ s.t. noise doesn't hurt accuracy.

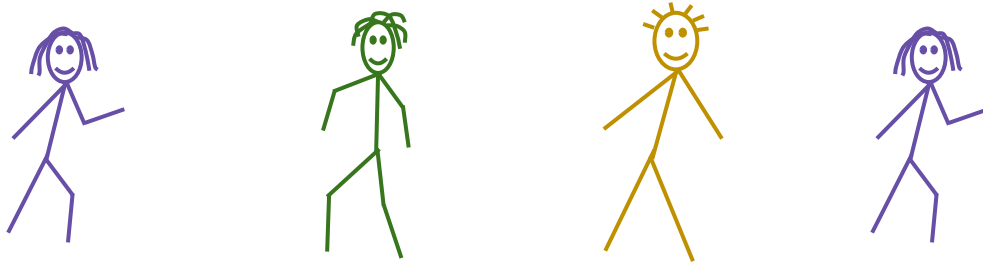


Better privacy-accuracy tradeoffs

Independent noise each step, **T total participants** \Rightarrow error $O(\sqrt{T})$.

Best privacy technique (“continual observation”): add $O(\log T)$ noise each step...
... coordinated across time steps s.t. total noise is always $O(\log^2 T)$.

$\Rightarrow \lambda = \Theta(1 / \log^2 T)$.



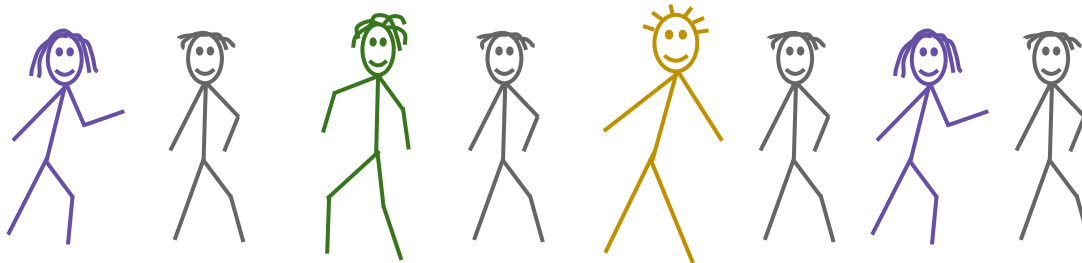
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Interpretation: “noise trader” makes random purchases after each arrival;
total loss = loss of market maker + loss of noise trader.



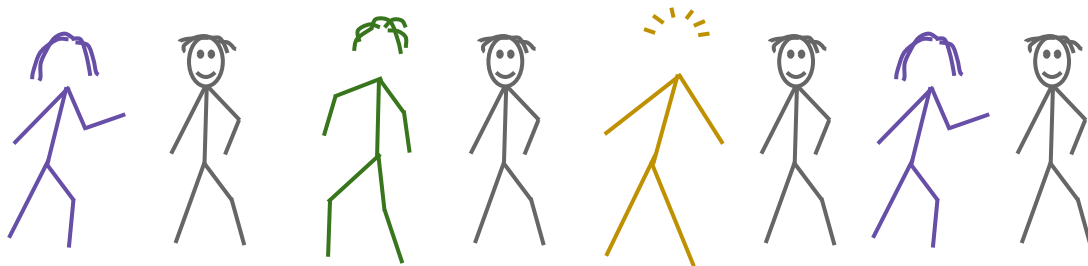
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Private prediction markets (with unbounded loss)

Theorem (based on Waggoner, Frongillo, Abernethy 2015)

The private market achieves:

- ϵ -differential privacy
- α -precision with high probability (noise affects prices by at most α)
- incentive to participate (if prices are wrong, an agent can profit by changing them)

all with

$$\lambda = \Theta(1 / \log^2 T).$$

(So about $\log^2 T$ participants coordinate a useful prediction.)

Private prediction markets (with unbounded loss)

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(So about $\log^2 T$ participants coordinate a useful prediction.)

Problem: worst case loss is at least $O(\log^2 T)$...

Private prediction markets (with unbounded loss)

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all with

$$\lambda = \Theta(1 / \log^2 T).$$

(So about $\log^2 T$ participants coordinate a useful prediction.)

Theorem (Cummings et al. 2016)

Every private cost-function based market has financial loss **unbounded in T**.

Outline

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B. Summary of results and prior work

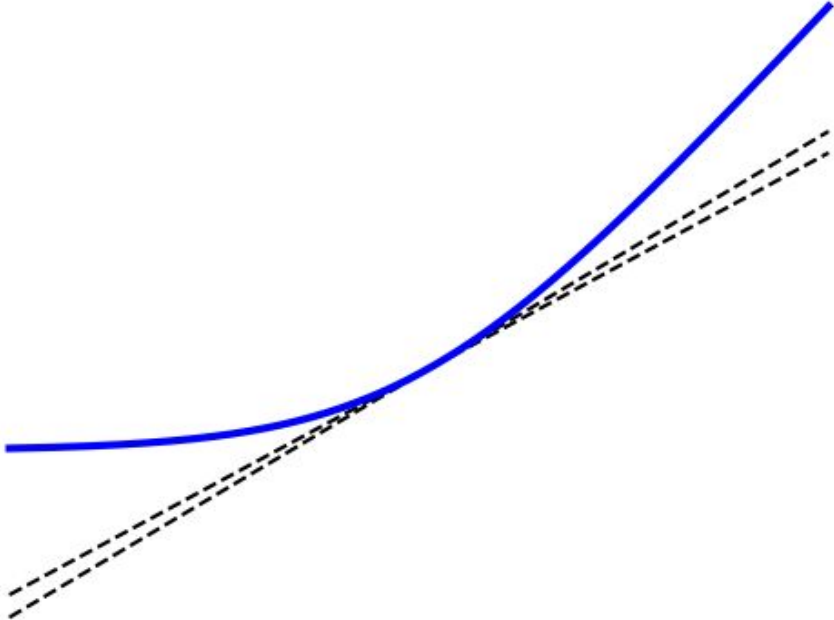
→ C. Construction

Initial approach: add a transaction fee

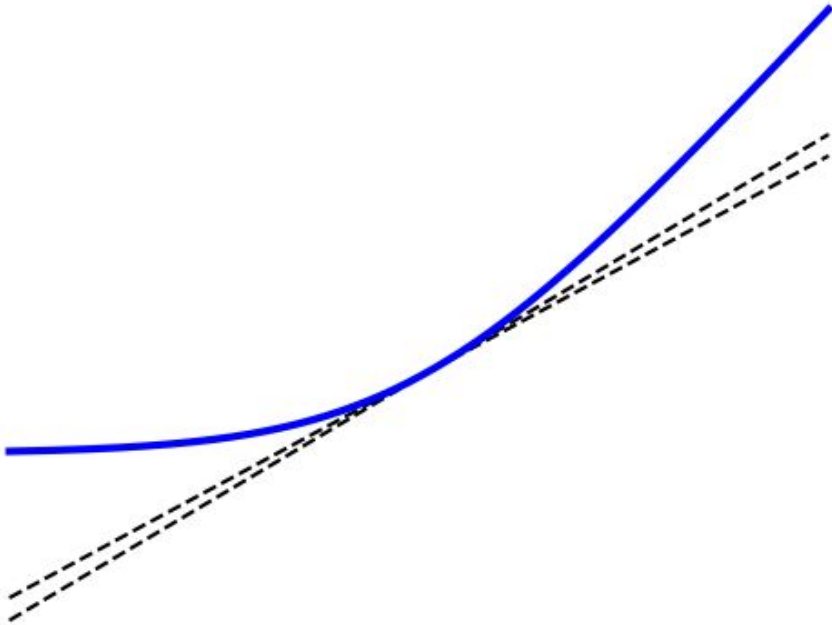
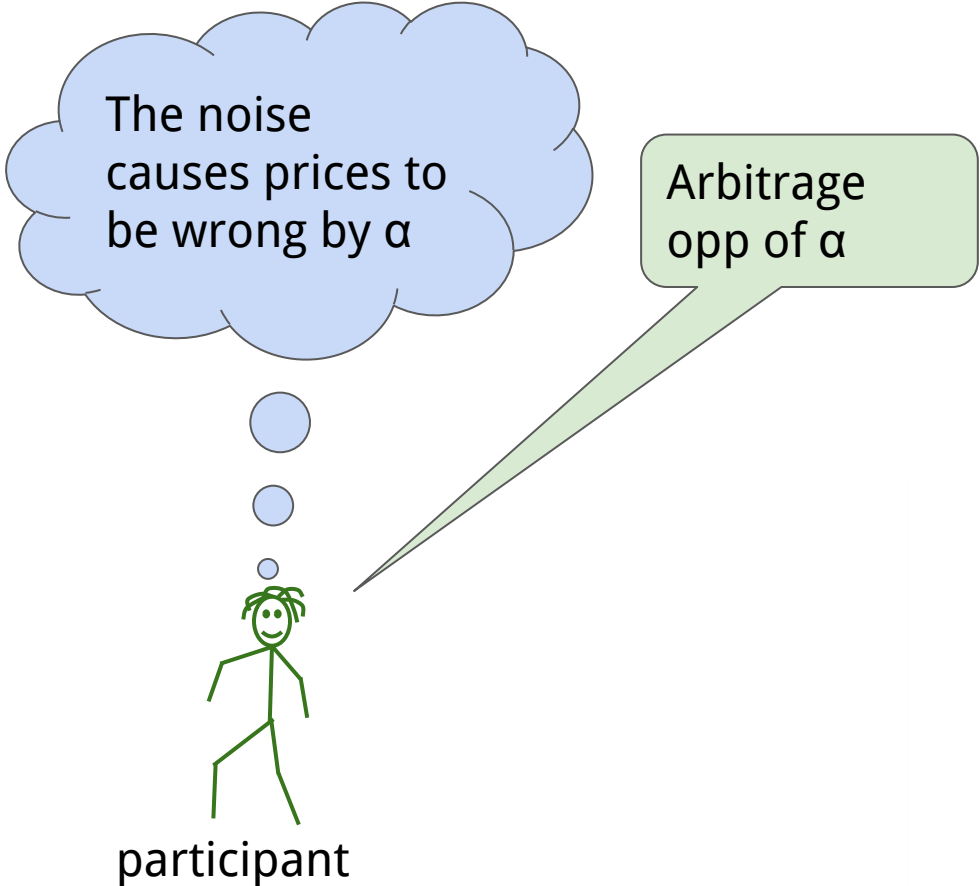
The noise causes prices to be wrong by α



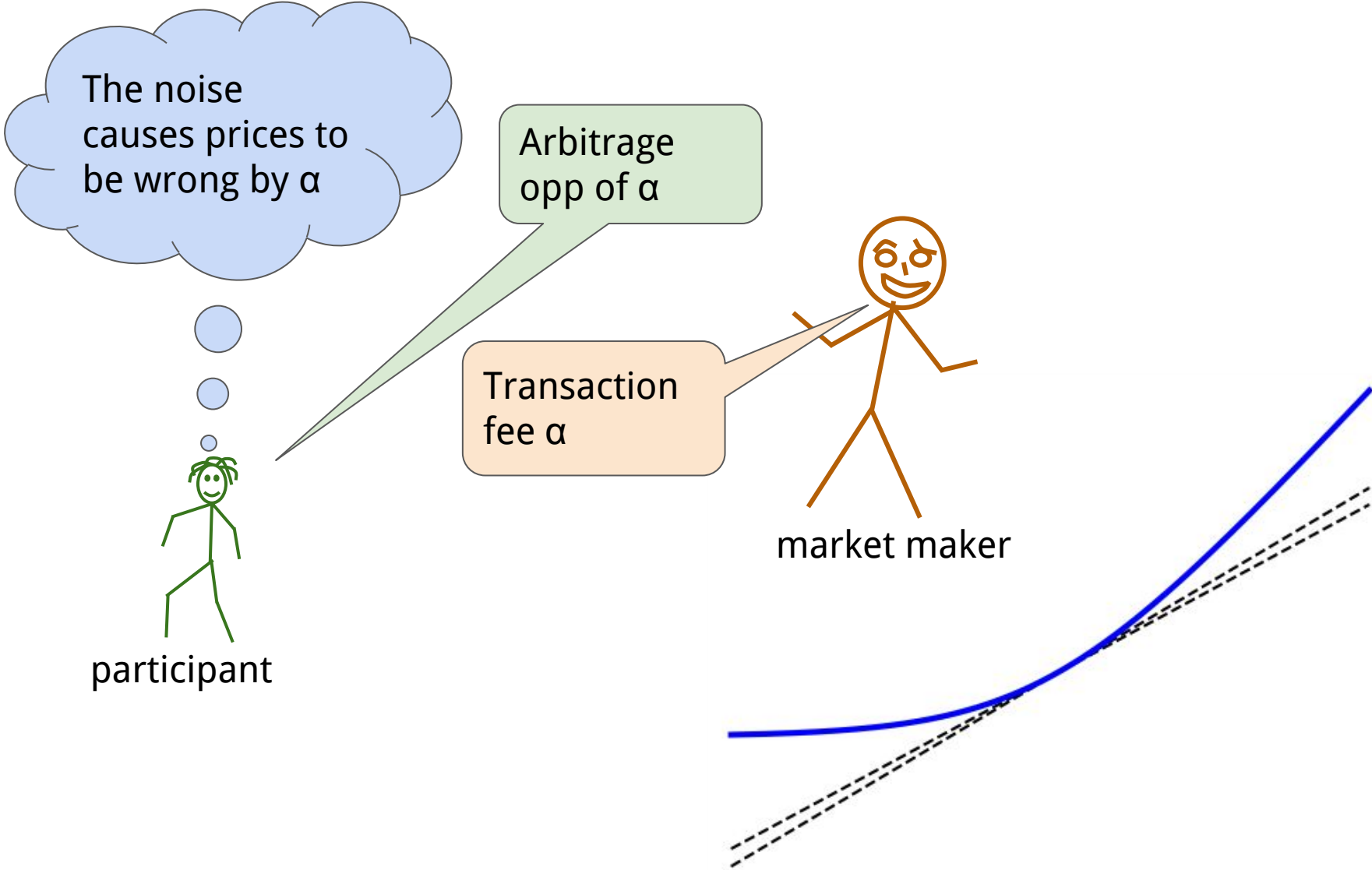
participant



Initial approach: add a transaction fee



Initial approach: add a transaction fee



Transaction fee result (stepping stone)

Theorem

The same private market, but with transaction fee α , achieves:

- ϵ -differential privacy
- α -precision with high probability
- α -incentive to participate (prices are wrong by $\alpha \Rightarrow$ profit opportunity)
- worst-case loss $O(1/\lambda) = O(\log^2 T)$.

Transaction fee result (stepping stone)

Theorem

The same private market, but with transaction fee α , achieves:

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- α -precision with high probability
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- worst-case loss $O(1/\lambda) = O(\log^2 T)$.

Proof idea:

$$\text{Loss} = \underbrace{(\text{Market maker loss})}_{O(1/\lambda)} + \underbrace{(\text{noise trader loss})}_{???} - \underbrace{(\text{transaction fees})}_{\alpha T}$$

Noise trader loss $\leq \alpha T$

Slightly intricate, depends on the details of the privacy scheme!

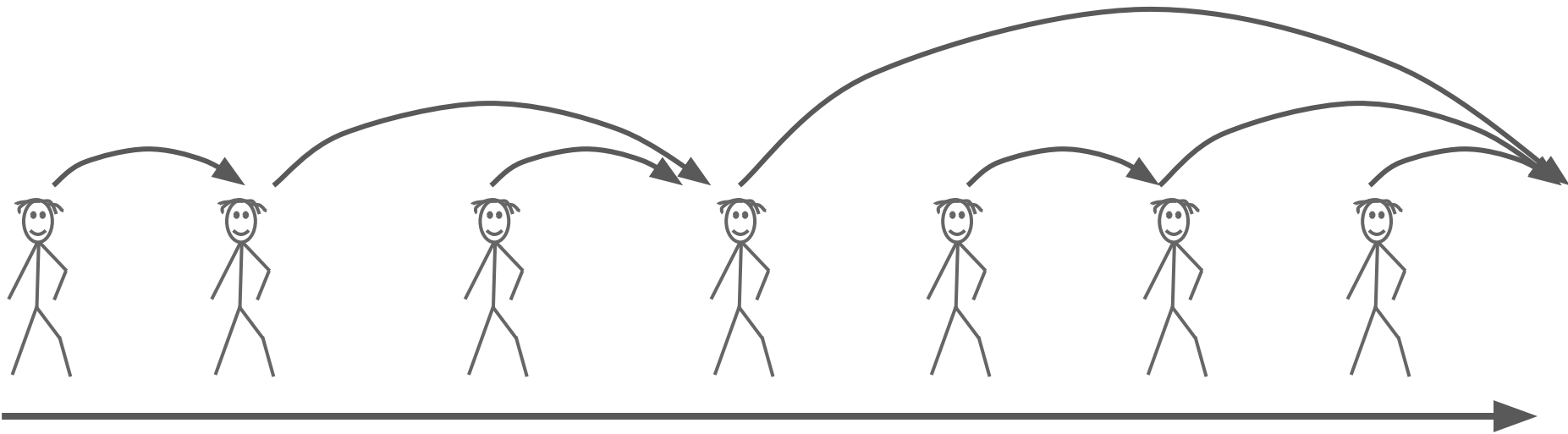
α is a convenient transaction fee that works, but not fundamental in the analysis.

Bounding noise trader loss

Each step, sell some number of previous bundle and buy a new bundle.

Bundle held for t steps \Rightarrow price changes at most $\lambda t \Rightarrow$ loss at most λt (size).

Sum over all bundles.



Wait a minute!

Let's try transaction fee 2α .

$$\text{Loss} = \underbrace{(\text{Market maker loss})}_{\log^2 T} + \underbrace{(\text{noise trader loss})}_{\alpha T} - \underbrace{(\text{transaction fees})}_{2\alpha T}$$

$$= \text{Profit } \Omega(T)!$$

Is this market guaranteed to make a profit??

Wait a minute!

Let's try transaction fee 2α .

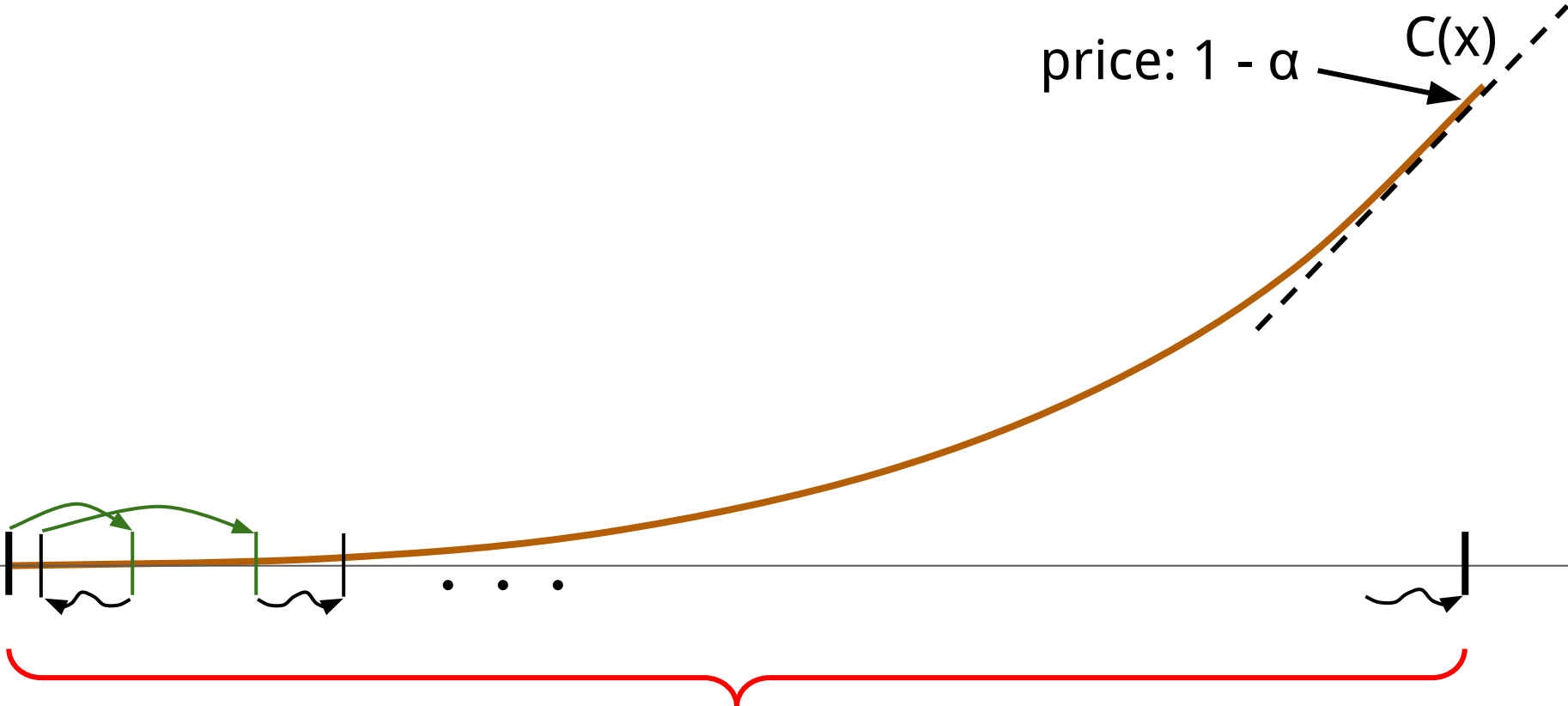
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No ... not if only $\log^2 T$ participants show up.

Wait a minute!



$1/\lambda$ informed, coordinated participants

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So worst-case loss is still $\log^2 T$.

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$$\text{Loss} = \underbrace{(\text{Market maker loss})}_{\log^2 T} + \underbrace{(\text{noise trader loss})}_{\alpha T} - \underbrace{(\text{transaction fees})}_{2\alpha T}$$

= Profit $\Omega(T)$!

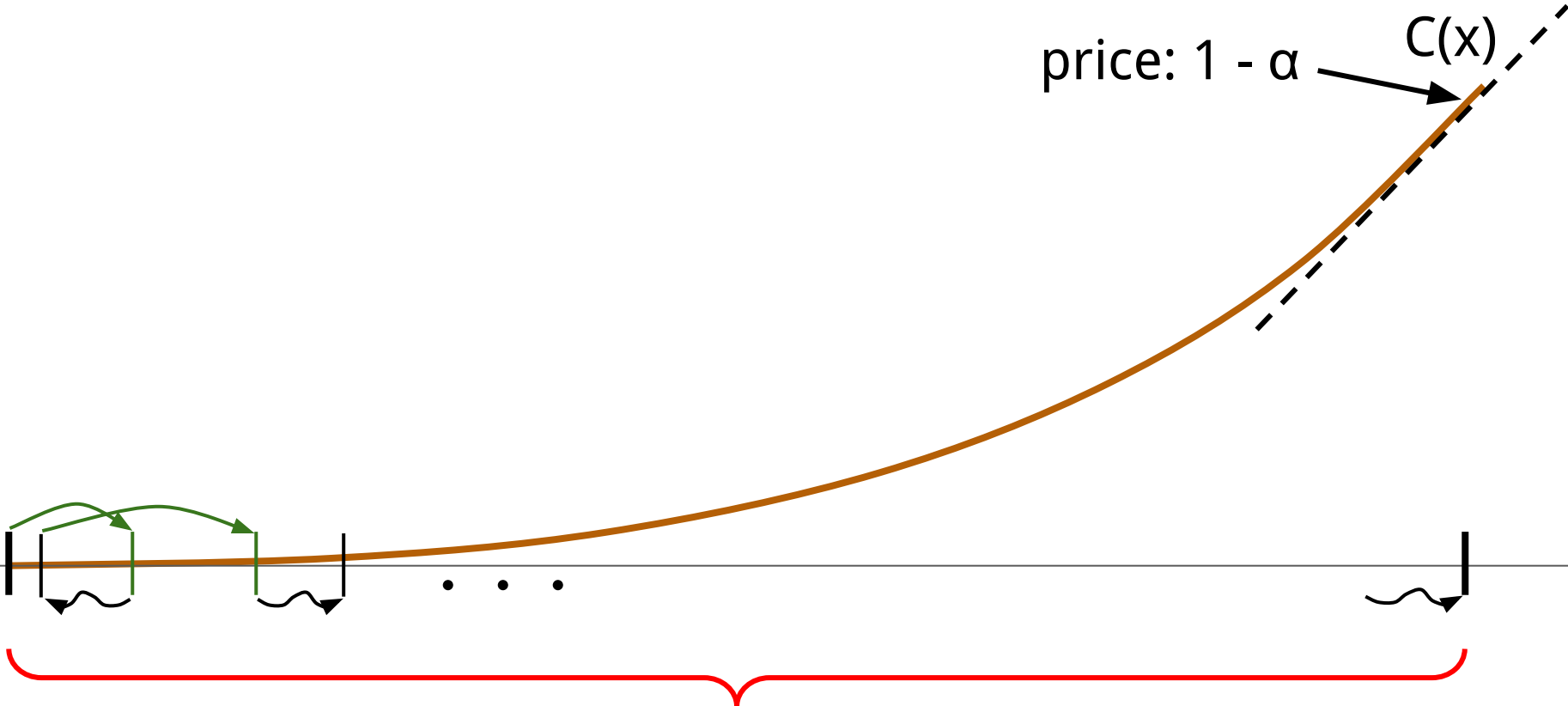
Is this market guaranteed to make a profit??

No ... not if only $\log^2 T$ participants show up.

So worst-case loss is still $\log^2 T$.

But if all T participants arrive ... then yes!

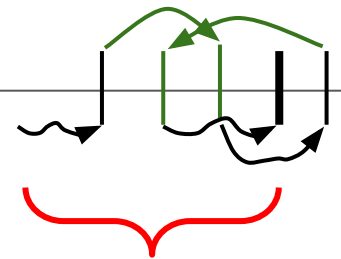
Why?



$1/\lambda$ informed, coordinated participants

Why?

price: $1 - \alpha$ $C(x)$



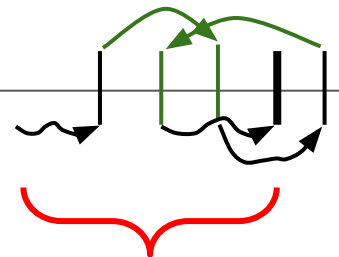
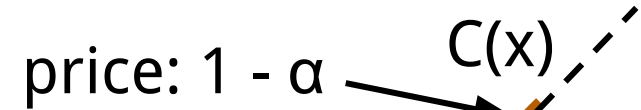
... mixed with lots of **disagreement!**

Why?

Disagreement is pure profit (transaction fees) for the market maker.

At most $1 / \lambda$ arrivals can agree!

price: $1 - \alpha$ $C(x)$



... mixed with lots of **disagreement!**

Iterative market construction

1. Set $T^1 = O(1)$ depending on privacy, accuracy parameters.
Set $\lambda^1 = \Theta(1 / \log^2 T^1)$ and run this private market.
2. If not all participants arrive, done.
3. Set initial price = final price of above market.
Set $T^2 = 4T^1$.
Halve the accuracy parameters.
Set $\lambda^2 = \Theta(1 / \log^2 T^2)$.
Run this private market.
4. If not all participants arrive, done. Else, set $T^3 = 4T^2$ and continue....

Iterative market construction

Theorem

The iterative market satisfies all the above privacy, precision, incentive constraints as well as **worst case loss bounded by $O(1)$** regardless of number of arrivals.

Iterative market construction

Theorem

The iterative market satisfies all the above privacy, precision, incentive constraints as well as **worst case loss bounded by $O(1)$** regardless of number of arrivals.

Proof idea.

Each market either completes, or stops early.

Each market that completes makes enough profit to subsidize the $O(1/\lambda)$ loss of the next market.

Only the last market stops early; it is either already subsidized (net profit), or the first market (constant-size loss).

Future directions

- Other (more elegant) constructions?
- Any helpful light shed on adaptive-volume (liquidity) markets?
- Interactions between privacy and information aggregation seem to be opposed...
- More broadly: **value of information**, purchasing information

Thanks!

