



# Search

Tim Komarek

Department of Economics

Dragas Center for Economic Analysis and Policy

Strome College of Business





# Information Economics

- Uncertainty and economic behavior
  - Search
    - Baye's Theorem and updating beliefs
- Uncertainty and the market
  - Asymmetric information
  - Signaling and screening

# Information Economics: Nobel Prizes

- Search 2010 (Diamond, Mortensen and Pissarides)



- Asymmetric info 2001 (Akerlof, Spence and Stiglitz)







## Search – consumer goods

- Previously assumed consumers knew the price of goods with certainty
- Things get more complicated when consumers do not know the prices charged by different firms for the same product
- Consumers sometimes incur a cost,  $c$ , to obtain each price quote
- After observing each quote a consumer must weigh the expected cost and benefit from acquiring an additional quote with the additional cost  $c$



# Consumer Search: Scalping tickets for the football game



- 75% of sellers charging \$100 and 25% of sellers charge \$40
- First scalper offers to sell for **\$40**. Should you search?
  - Should stop searching and buy the tickets



# Consumer Search: Scalping tickets for the football game



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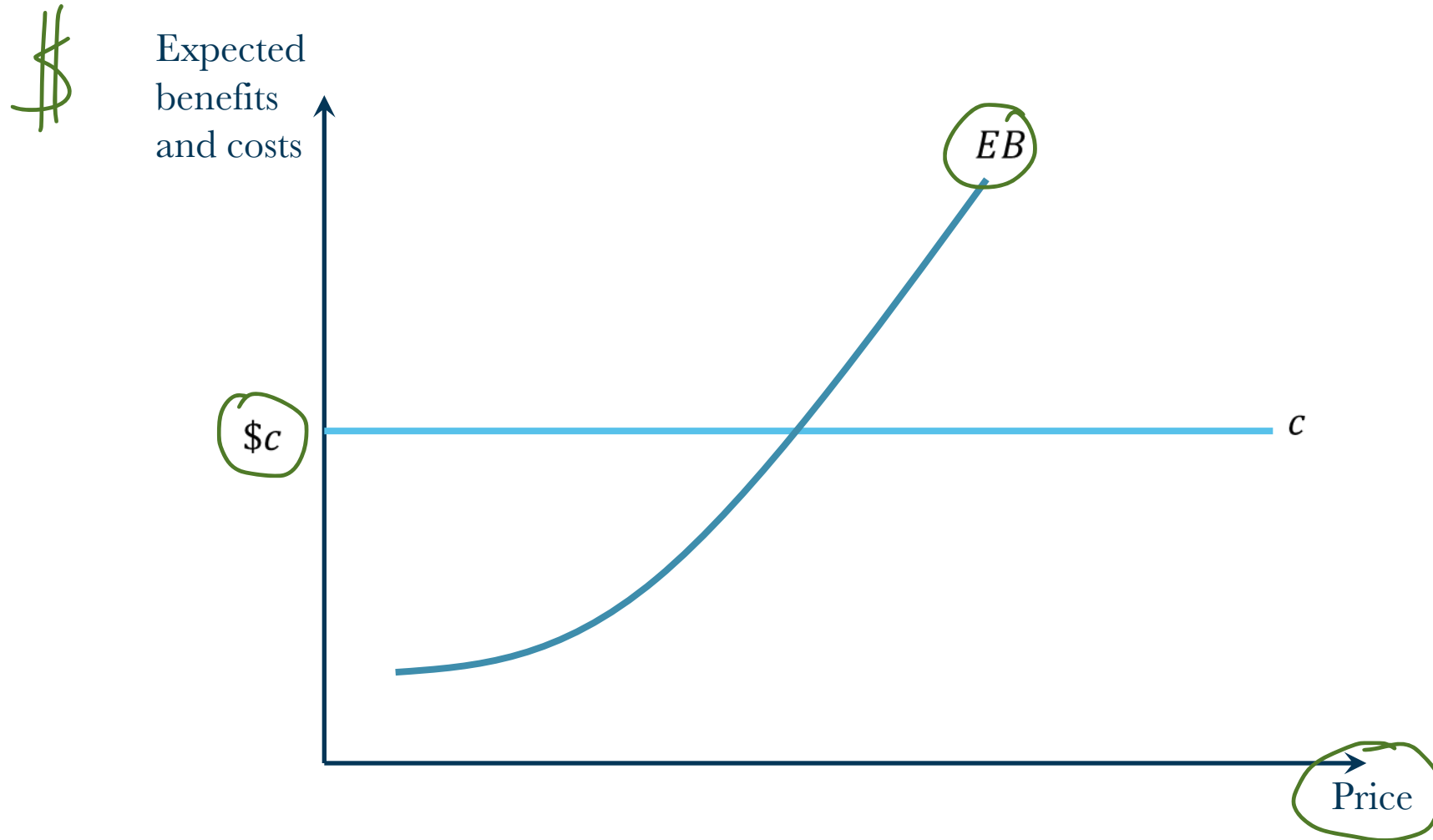
# Consumer Search: Scalping tickets for the football game



- 75% of sellers charging \$100 and 25% of sellers charge \$40
- First scalper offers to sell for **\$100**. Should you keep searching?
  - If search: 25% chance will save  $\$100 - \$40 = \$60$   
75% chance will save  $\$100 - \$100 = \$0$
  - Expected benefit from searching:  
$$= .25 * (\$100 - \$40) + .75 * (\$100 - \$100) = \$15$$
  - Expected costs from searching? C \$



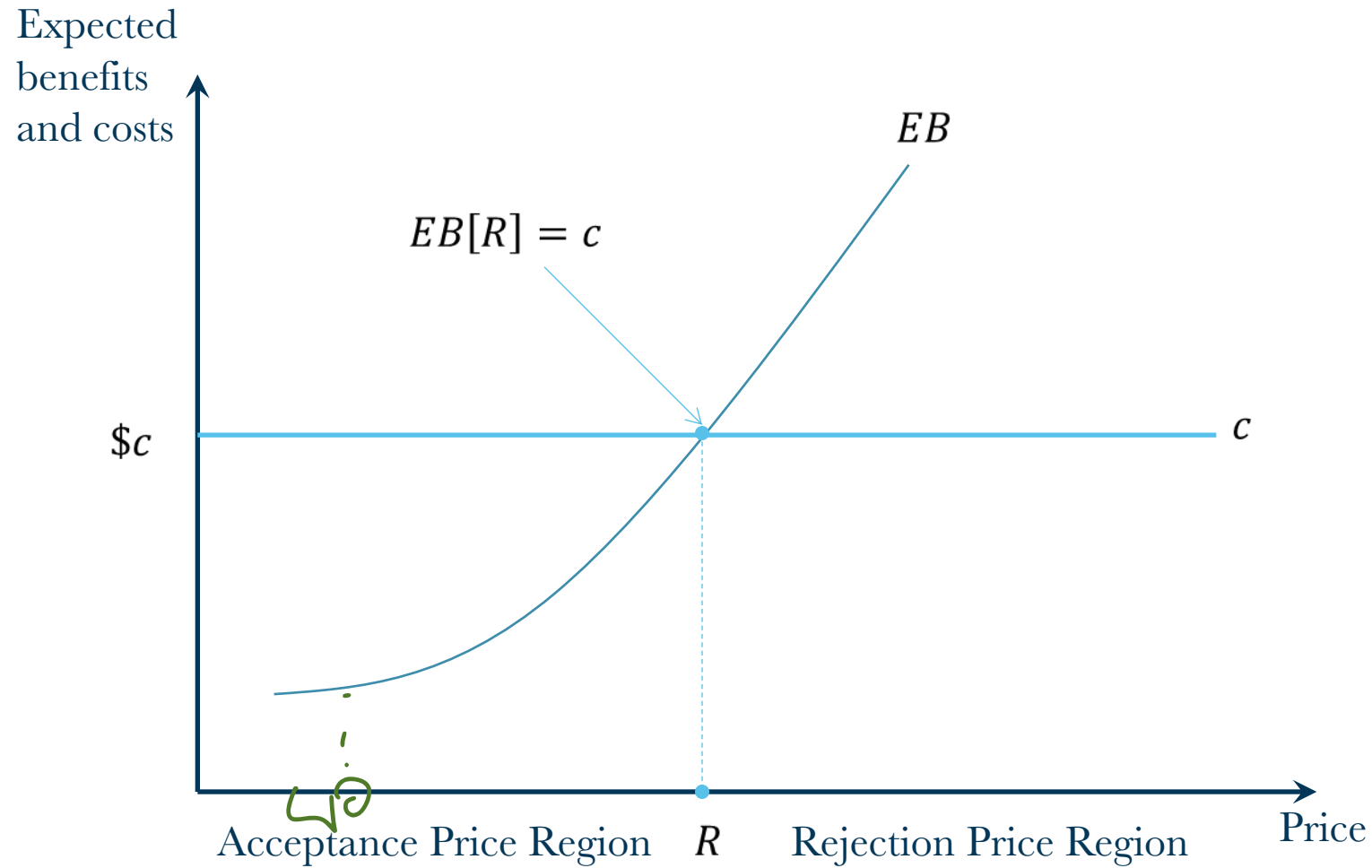
# Optimal search strategy





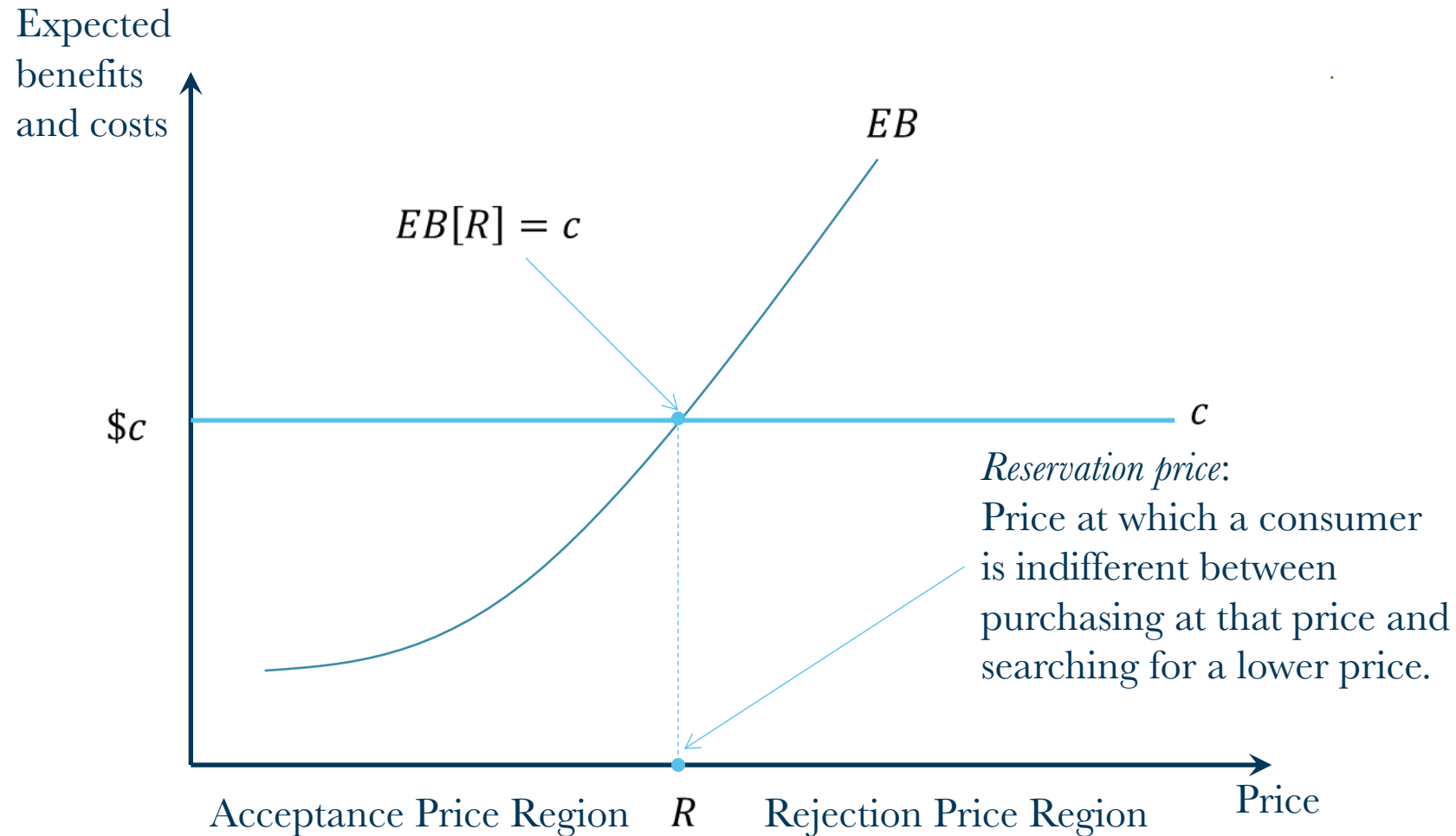


# Optimal search strategy





# Optimal search strategy



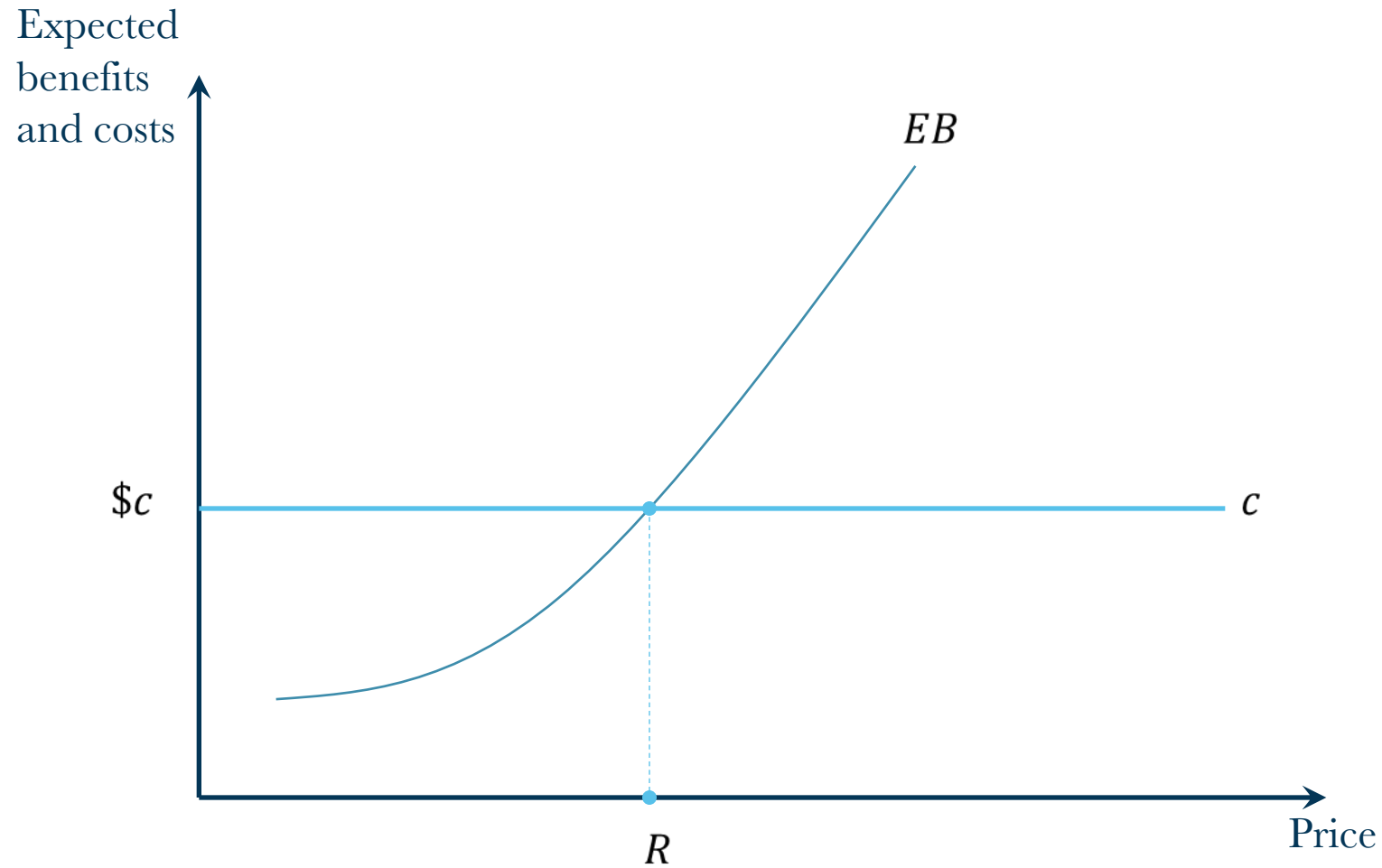


# Consumer's search rule

- Consumer rejects a price above the reservation price,  $R$ , and accepts below the reservation price
- Reservation price:
  - The price at which a consumer is indifferent between purchasing at that price and searching for a lower price
- The optimal search strategy is to keep searching if price above reservation price and stop searching when the price is below the reservation price

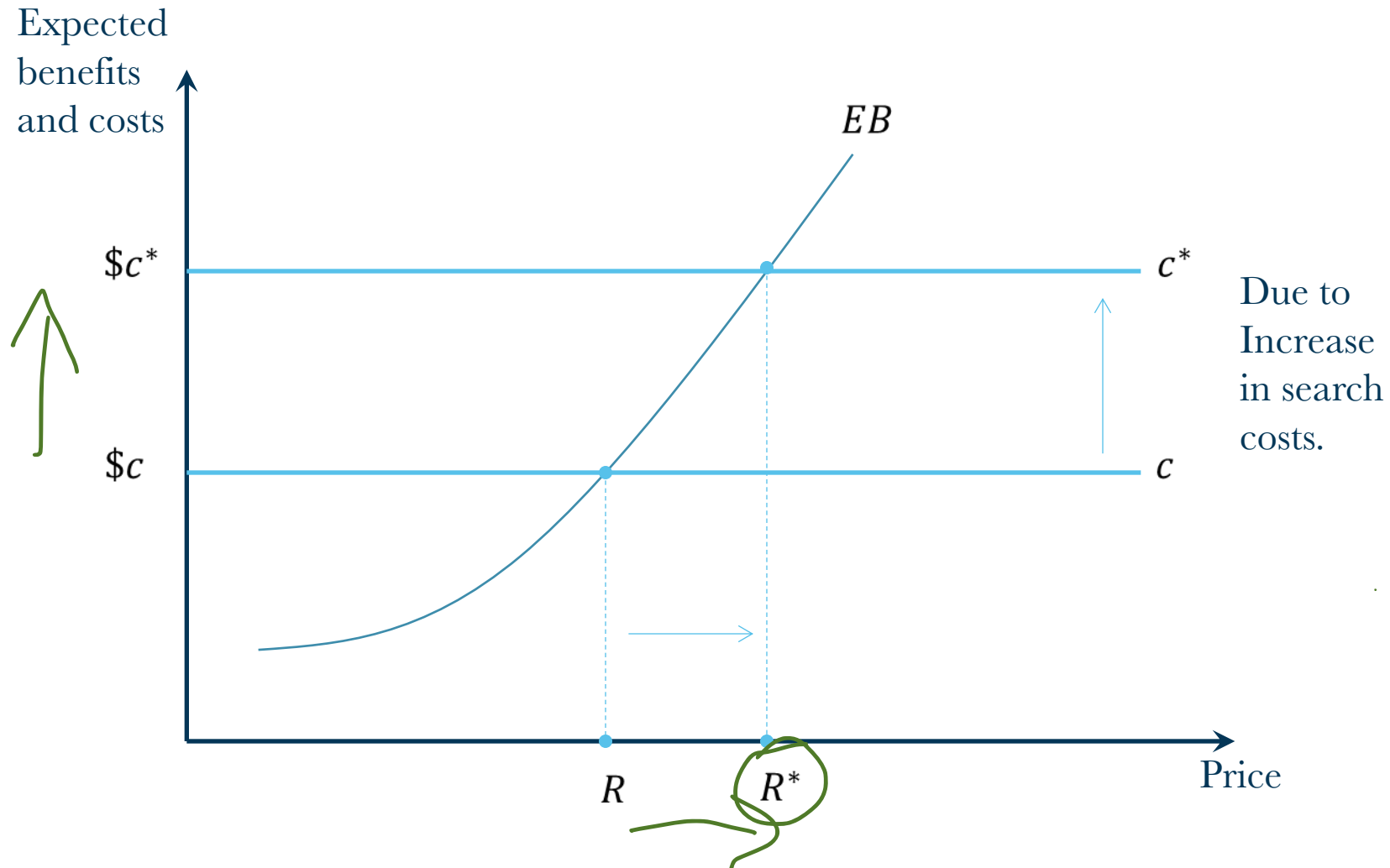


# Increasing cost of search





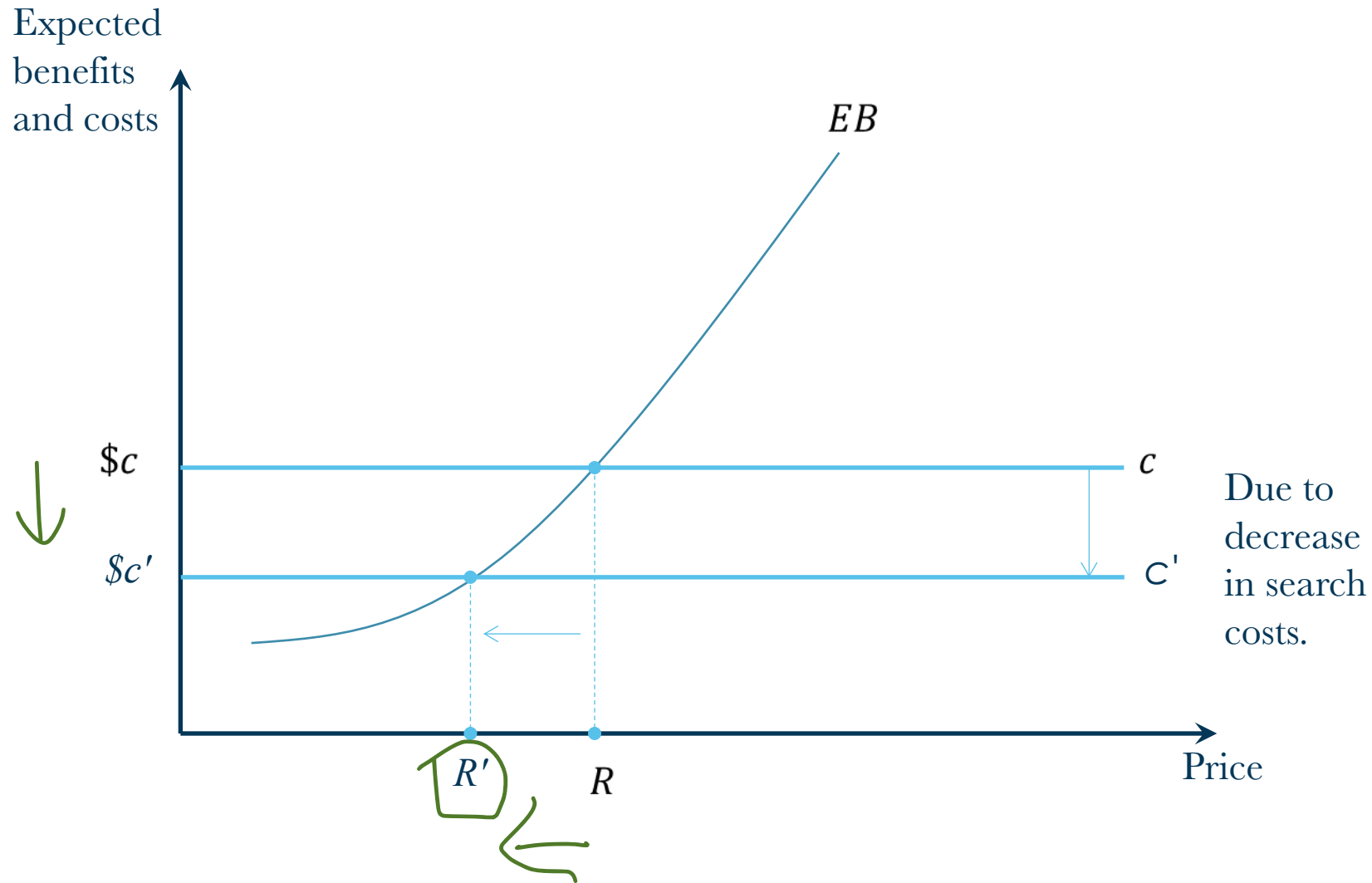
# Increasing cost of search







# Decreasing cost of search



# Search in the Labor Market

- This also comes up for the unemployed in the labor market
  - Different firms offer different opportunities
  - Workers are not fully informed about the “best” jobs
- It takes time to search, interview, etc. C
- Should you take the first job offer that comes along?







# Search in the Labor Market

- Policy questions
  - What effects unemployed workers reservation wages?
- ☞ ■ Unemployment benefits
  - Must meet certain criteria
  - Receive a portion of previous salary based on the “replacement ratio” normally for up to 26 weeks
- CARES Act in 2020
  - Offered additional benefits
  - Extended time & increase \$
- Did people remain unemployed for longer spells?
- Was there a disincentive effect?





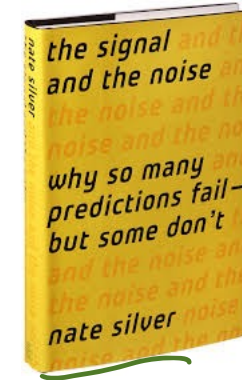
# Search in the Labor Market

- Policy questions
  - Can we reform the system to reduce the disincentive effect?
  - Illinois and Pennsylvania experiments in the 1980s
    - Experiment: randomly determined treatment and control groups
    - IL offered a cash bonus ( $\$500 = 4$  times the benefits)
    - If accepted a job within 11 week
- Results
  - Those in cash bonus group accepted jobs more quickly and for the same wage, on average, as those in the “control group”



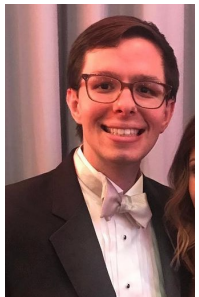
# Learning: Bayes Theorem

- Thomas Bayes
  - 1701 – 1761
  - English minister and mathematician
- Mathematical formula to update beliefs based on new info
  - Probability that some “state of the world” is true
  - Given some information or an event
  - Thinking about “signal” vs “noise”



# Learning: Bayes Theorem

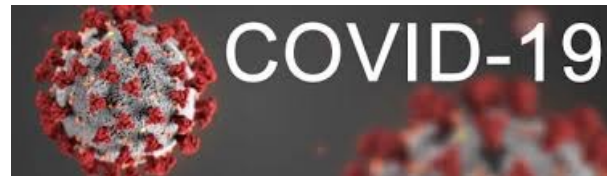
- Bayes Theorem
  - Posterior probability / final assessment =  $P(S|I)$ 
    - S - State of the world or hypothesis is true
      - Have a medical condition "sick"
    - I - Information or event takes place
      - Positive test result



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# Learning: Bayes Theorem

- Bayes Theorem
  - Posterior probability / final assessment =  $P(S|I)$ 
    - S - State of the world or hypothesis is true
      - Have a medical condition “sick”
    - I - Information or event takes place
      - Positive test result
  - To make an assessment or “update our beliefs”
    - Probability information is “true positive” or “signal”
    - Probability information could be a “false positive” or “noise”
    - Probability of S before any information “prior”



# Learning: Bayes Theorem

- Bayes Theorem
  - To make an assessment or “update our beliefs”
    - Probability information is “true positive” or “*signal*”
    - Probability information could be a “false positive” or “*noise*”
    - Probability of  $S$  before any information “prior”

$$P(S|I) = \frac{P(I|S) * P(S)}{P(I)}$$

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

THE PROBABILITY OF "B" BEING TRUE GIVEN THAT "A" IS TRUE

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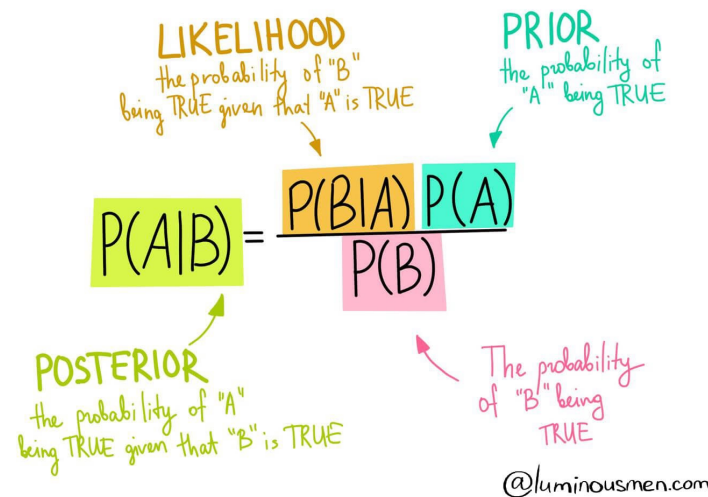
THE PROBABILITY OF "B" BEING TRUE



# Learning: Bayes Theorem

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- Bayes Theorem
  - Probability information is “true positive” or “*signal*”
  - Probability information could be a “false positive” or “*noise*”
  - Probability of  $S$  before any information “prior”

$$P(S | I) = \frac{(\text{Info is true signal}) * (\text{Prior})}{(\text{Info is true signal}) * (\text{Prior}) + (\text{Info is noise}) * (1 - \text{Prior})}$$

- Weighting the signal to the noise based on our “prior” belief



# Learning: Bayes Theorem



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Prior = chance we believe he's sick  
before getting tested

= case rate at the time (5%)

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Prior = chance we believe he's sick  
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= case rate at the time (5%)

$$P(S | I) = \frac{(\text{Info is true signal}) * (\mathbf{0.05})}{(\text{Info is true signal}) * (\mathbf{0.05}) + (\text{Info is noise}) * (\mathbf{1 - 0.05})}$$

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Info is true signal = true positive

Based on medical data = 90%

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# Learning: Bayes Theorem



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Info is noise = false positive

Based on medical data = 2%

$$P(S | I) = \frac{(0.90) * (0.05)}{(0.90) * (0.05) + (0.02) * (0.95)}$$

- Weighting the signal to the noise based on our “prior” belief

# Learning: Bayes Theorem



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Posterior probability

**70.3%**

$$0.703 = \frac{0.045}{0.045 + 0.019}$$

- Weighting the signal to the noise based on our “prior” belief



# Learning: Bayes Theorem

- Visual version of Bayes Theorem
  - Meet someone on campus and notice they are shy
    - Math major or Business major?
    - How do you tell an extroverted mathematician?



# Learning: Bayes Theorem

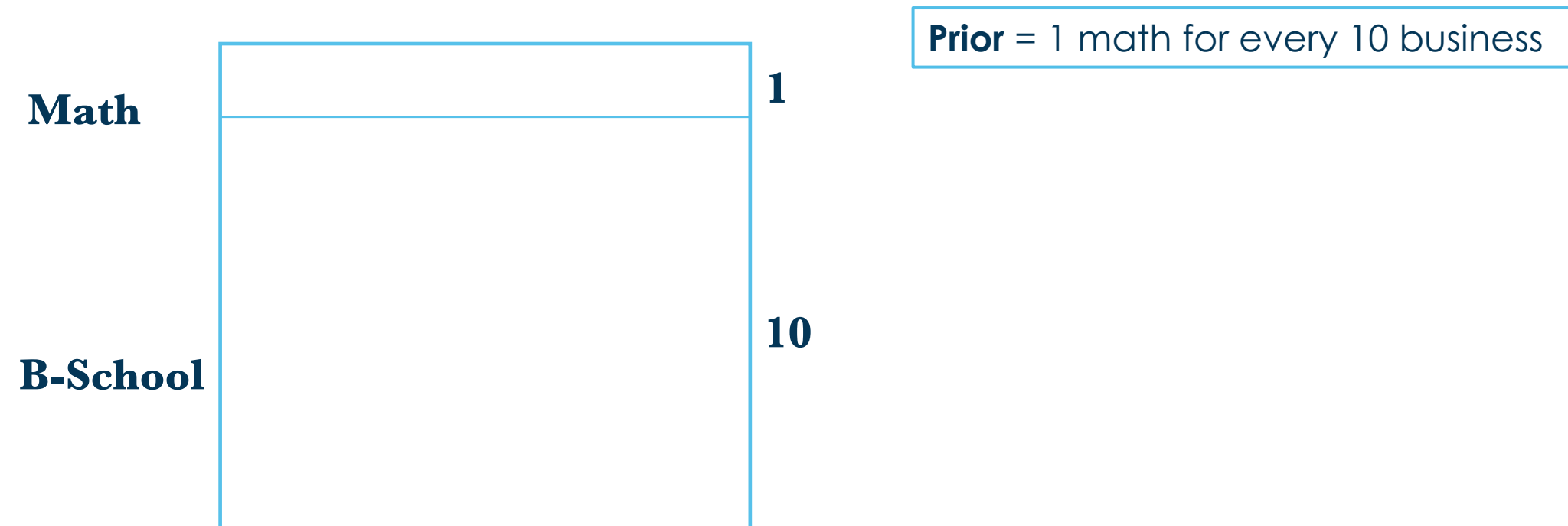
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**Prior** = 1 math for every 10 business



# Learning: Bayes Theorem

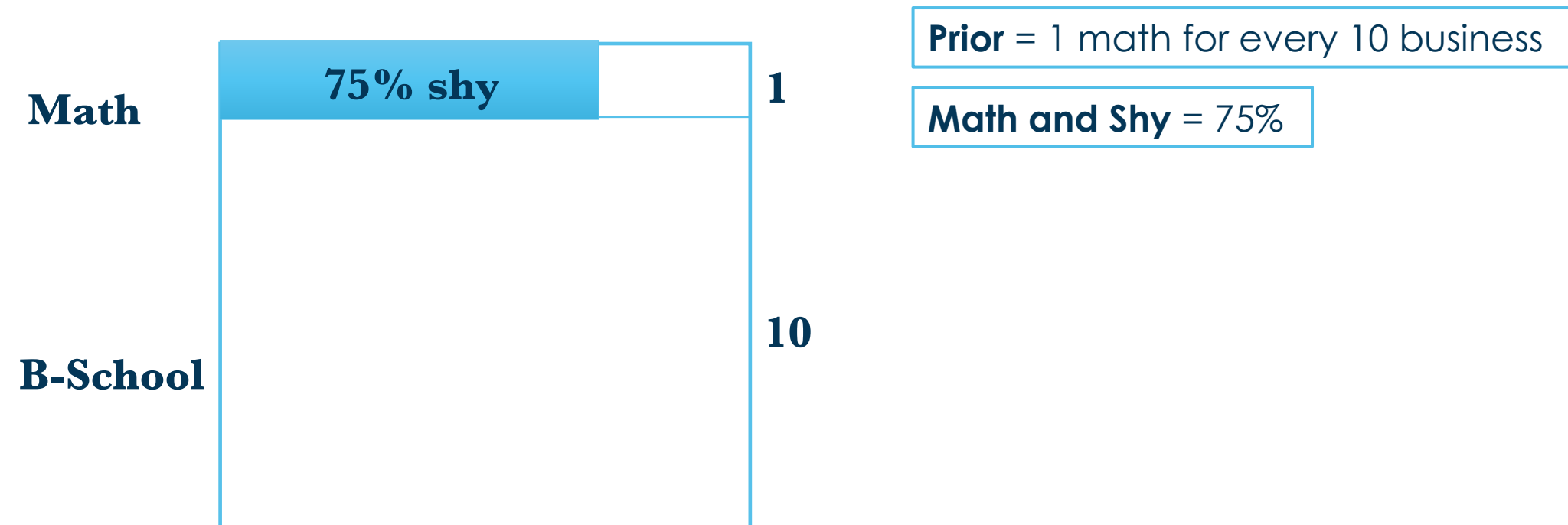
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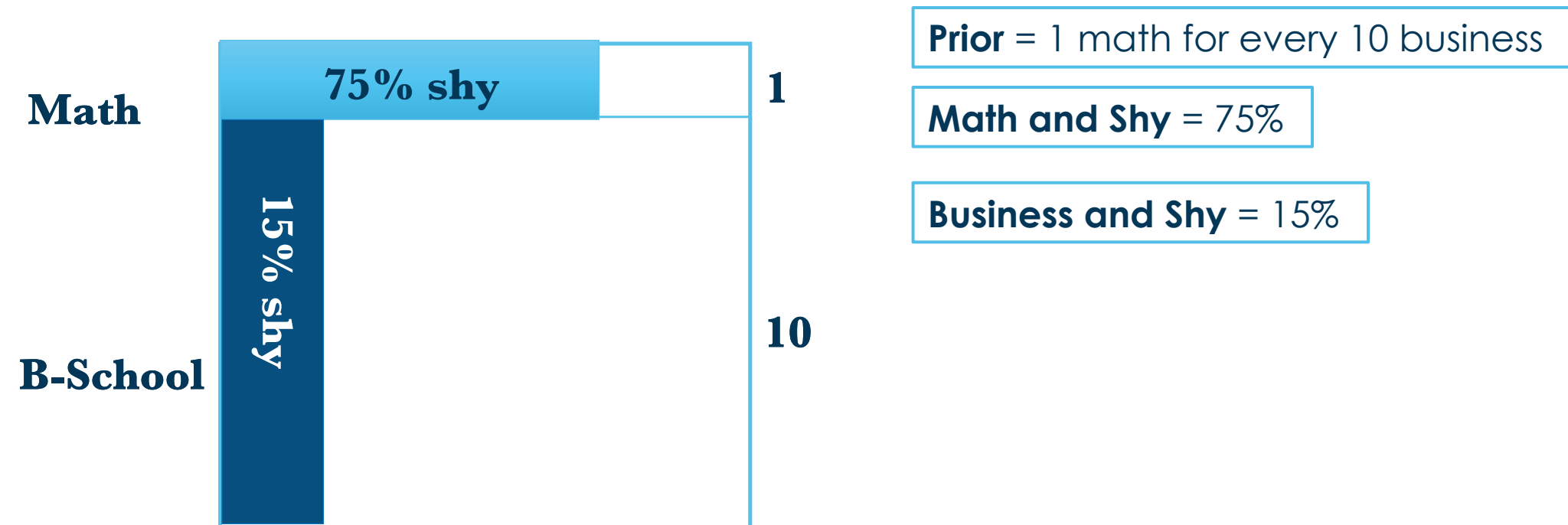
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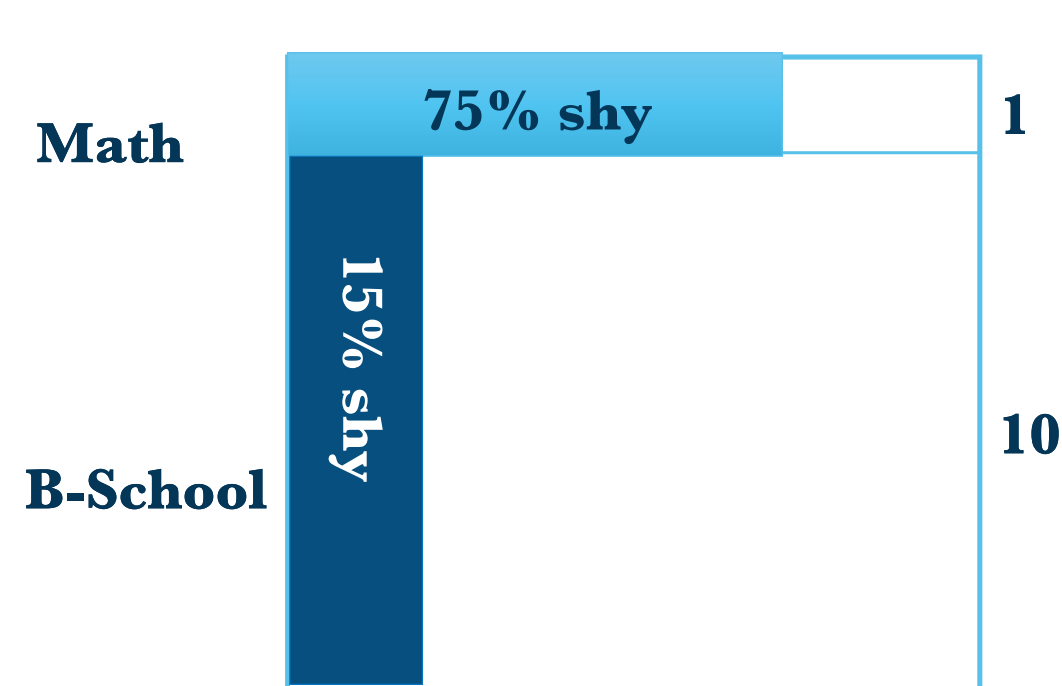






# Learning: Bayes Theorem

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**Prior** = 1 math for every 10 business

**Math and Shy** = 75%

**Business and Shy** = 15%

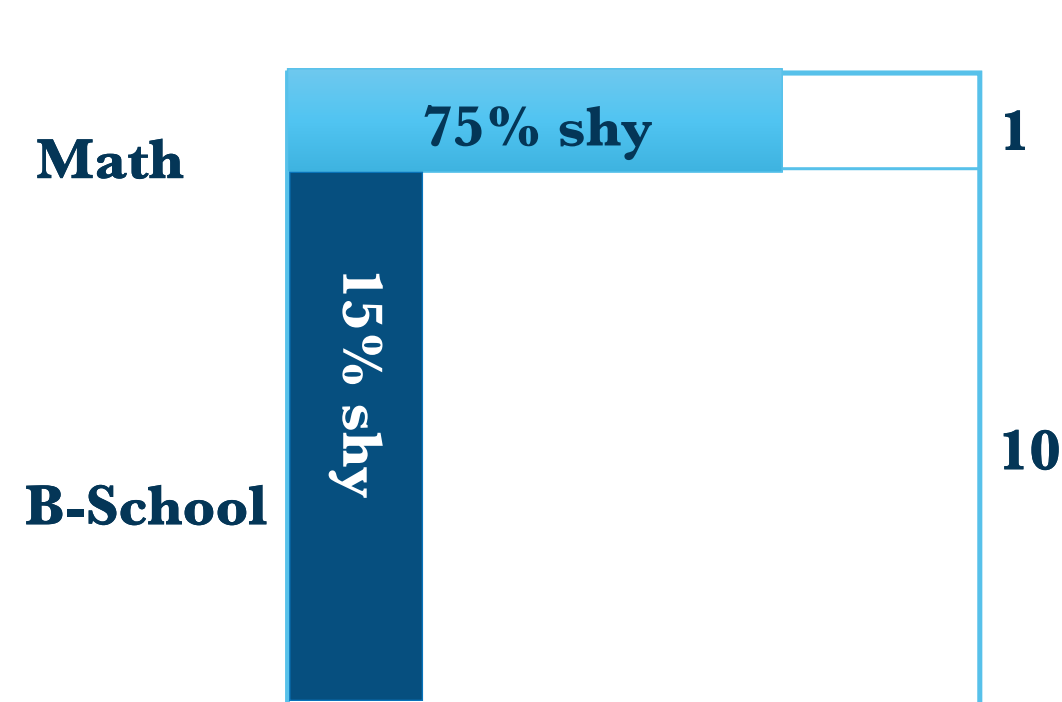
Compare relative rectangles

|            | Math | Business |
|------------|------|----------|
| Prior      | 1    | 10       |
| Likelihood | 75   | 15       |
| Posterior  | 75   | 150      |



# Learning: Bayes Theorem

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  - Meet someone on campus and notice they are **shy**
    - Math major or Business major?



**Prior** = 1 math for every 10 business

**Math and Shy** = 75%

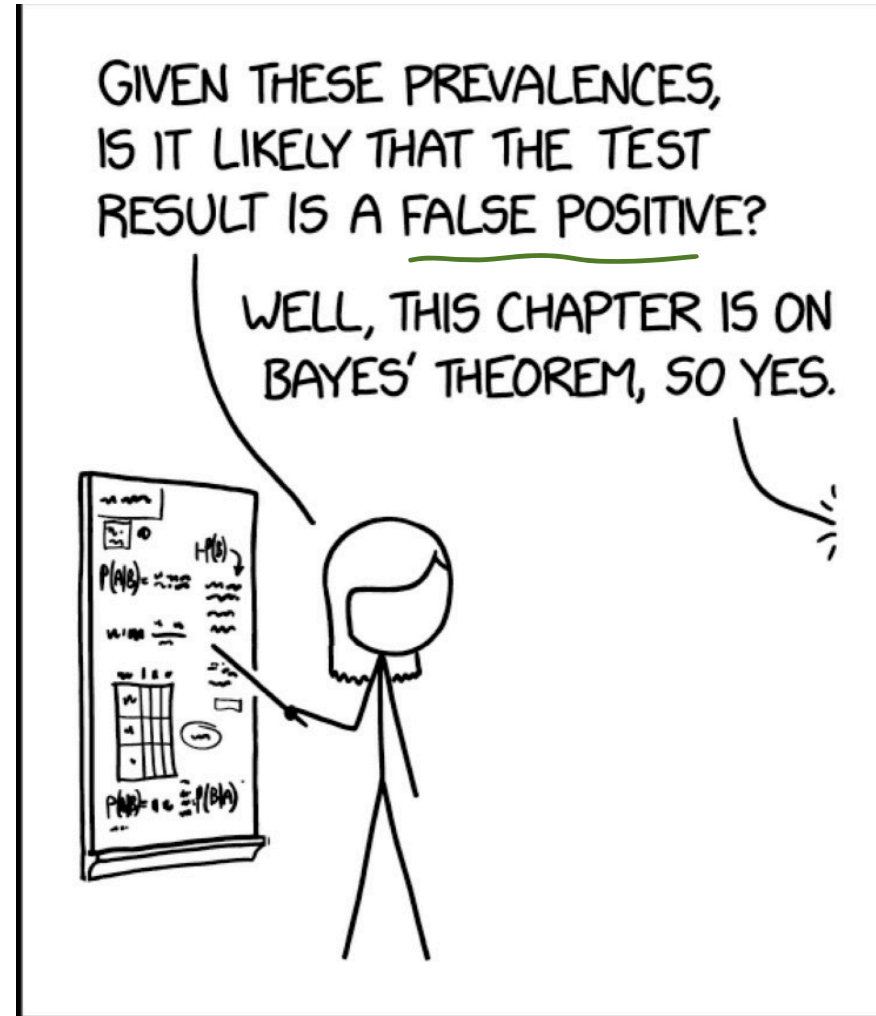
**Business and Shy** = 15%

Compare relative rectangles

|            | Math | Business |
|------------|------|----------|
| Prior      | 1    | 10       |
| Likelihood | 75   | 15       |
| Posterior  | 75   | 150      |

**P(Business | shy)** =  
66% chance business

# Learning: Bayes Theorem



SOMETIMES, IF YOU UNDERSTAND  
BAYES' THEOREM WELL ENOUGH,  
YOU DON'T NEED IT.



# Learning: Bayes Theorem

- Principals in Bayesian thinking

- 1) Remember your priors

- Don't just focus on the evidence / information
- Remember the background knowledge (prior)

- 2) How likely is a false positive?

- Imagine your theory / hypothesis is wrong. Would the world look different?

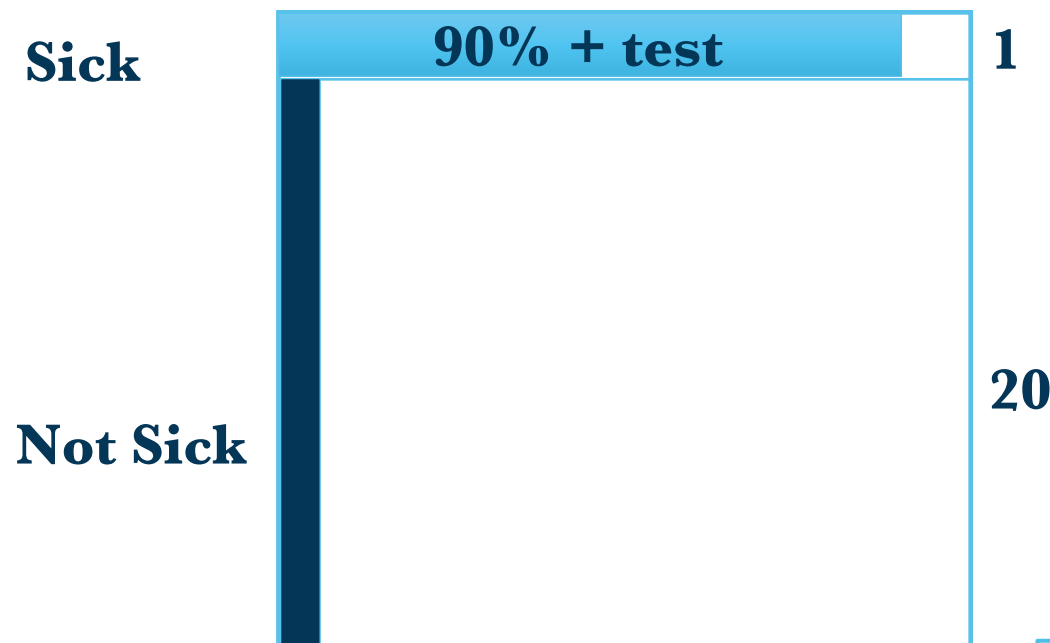
- 3) Update incrementally

- Posterior from the last piece of evidence becomes the new prior



# Learning: Bayes Theorem

- Visual version of Bayes Theorem
  - Nelson's Covid-19 test



**Prior** = 1 sick for every 20 not sick

**Sick and + Test** = 90%

**Not Sick and + Test** = 2%

**Compare relative rectangles**

|            | Sick        | Not Sick  |
|------------|-------------|-----------|
| Prior      | 1           | 20        |
| Likelihood | 90          | 2         |
| Posterior  | <b>90</b>   | <b>40</b> |
|            | <b>2.25</b> | <b>1</b>  |

**P(Sick | + Test)** = 70% chance ~~business~~