Skewed!

Hits rule the business

- Revenue and profits are concentrated in a few movies (or records or shows)
- This raises two questions
  - Why?
  - How does this affect management

Today's class

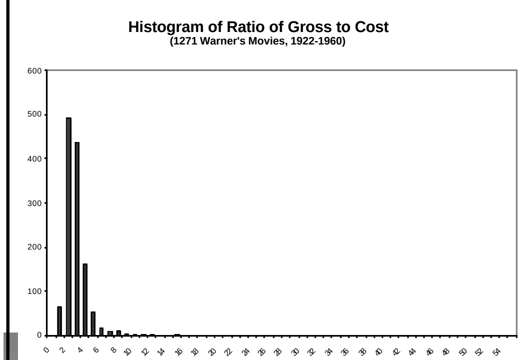
- Evidence of such concentration taken from the movie business
- Possible explanations
- Possible implications

What do we mean by skewness

- simple, this shows up in a histogram as a big right tail and a small left tail
- probability mass concentrated in low end, with a few big observations
- examples
  - income distributions
  - stock prices (not returns)

Long term evidence from Warner's

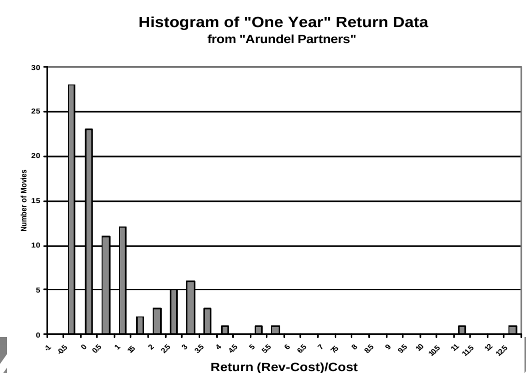
- Schaeffer ledger contains cost and foreign and domestic gross for every WB movie from 1922 - 1960
  - Schaeffer was Jack Warner's right-hand man
- Computed ratio of gross receipts to production costs
  - eliminated movies WB only distributed
  - eliminated movies WB only distributed domestic



More recent evidence from Arundel Partners Case

- The "Arundel Partners" case, which we will do later on contains information on the ratio of (revenue-cost) to cost for movies released by major studios in 1989
- The coefficient of skewness for this series is 3.2 compared to 0 for a normal distribution.
- Histogram on next slide

7 Prof. Mark Weinstein



8 Prof. Mark Weinstein

And it is getting worse

- Robbins
  - in late 1940's top 1% of films represented 2% - 3% of box office
  - by the early 1960's this is about 6%
- In 1993 the number is 13.8%

9 Prof. Mark Weinstein

Why?

- Is this skewness just an accident, or are there good reasons to expect this?
- There are two basic stories that can explain this
  - Information Cascades
    - Bikchandani, Welsh and Hirshleifer provide an overview of this idea
  - Utility comes from seeing movies (or reading books or watching TV shows, or listening to music) that other people do
    - give you something to talk about at the water cooler

10 Prof. Mark Weinstein

Information Cascade(1)

- Take a simple world. There are two movies and one is better than the other. Each individual gets a *private* signal about which movie is better. The signal is probably correct, but may be wrong. People behind you in line only observe what movie you see, not what your signal was.
- What will happen?
- The moment two people in a row see the same movie, eveyone that follows will see that movie too!

11 Prof. Mark Weinstein

Information Cascade(2)

- Why?
  - Say A gets signal that 1 is the better movie, he sees movie 1.
  - Now B gets a signal. She knows that A's signal was that 1 is the better movie. If she gets a signal for movie 1, she sees it. If she gets a signal for movie two she knows that there have been two signals, 1 or movie 1 and one for movie 2. Say she tosses a coin and ends up seeing movie 1.
  - Now C gets a signal. Work out what C will believe from seeing A and B both choose movie 1. C will ignore any signal he receives and see movie 1.

12 Prof. Mark Weinstein

Cascades (III)

- The simple model doesn't quite do it
  - DeVany and Lee extend the simple model to allow for more choice and more complex interaction between consumers
    - Cascades are still possible, but not as likely
    - Still possible to zero in on a bad movie
    - Better movies more likely to win out in the end
    - A patron on opening night is worth more than a patron in the middle of the run
    - Skewness can still arise

Social Aspect of Consumption

- Imagine that part of the utility from seeing a movie is that you see it with other people, or can talk to other people about it.
- Then, the more other people see the movie, the more likely you are to choose to see it. Another way to think: the more other's see a movie, the more you will pay to see it.
- This is not an information story. You don't think it is a better movie because others have seen it.

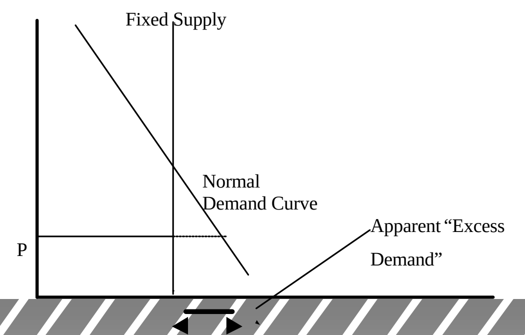
Both Stories Have Similar Implications

- A simple example, assume that a consumer i's demand for a movie, d_i depends on the price of a ticket, P, and on the aggregate market demand, D. As follows:
- Further, assume that everyone is alike

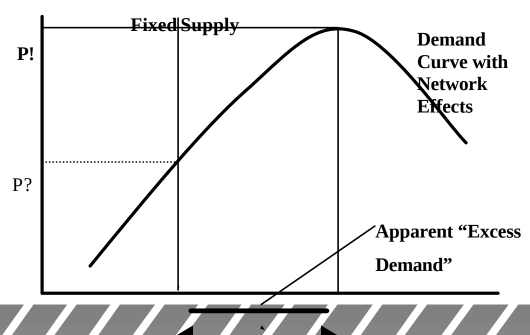
Question

- Say you are a theatre owner and you see people waiting in line.
- Should you raise the price?
- It depends

Should You Raise The Price?



What if this is the Demand Curve?



Interdependent Demand

- It turns out that the latter example is the kind of demand curve that you may get from our simple example.
- Or, consider the DeVany-Walls model

Look at DeVany & Walls' Model

All else equal, people are more likely to see movies that others have seen

maybe they enjoy talking about what movie they saw

let # of movies = S, say N_i people have seen each movie for a total of N, now, probability that the next patron will see movie i is

$$\mathbf{Pr} = \frac{\mathbf{N_i + 1}}{\mathbf{N + S}}$$

So, you start off with equal probabilities and things evolve from there. Sort of like a uniform distribution at start

Predictions:

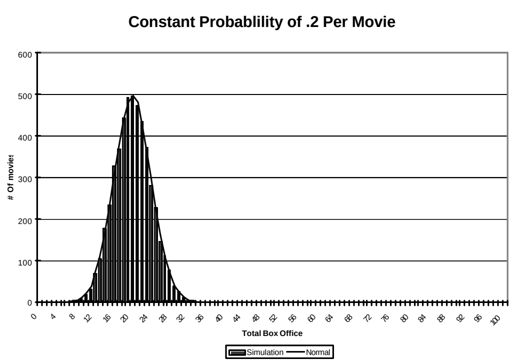
Skewness, History matters

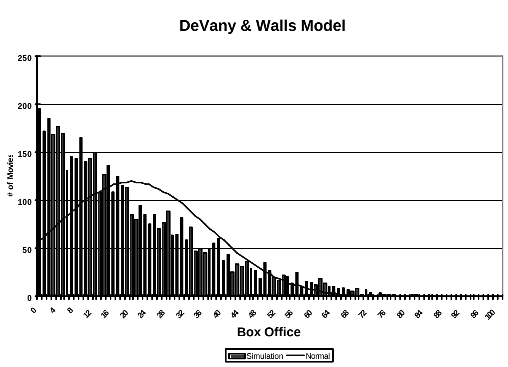
We simulated the model to see what comes out

- 1000 replications
  - 10 "weeks" per replication
  - 10 patrons per week
  - 5 movies (so 5,000 "box office" histories)
  - Equal opening probabilities (this can vary)
    - Probabilities continuously change according to D&W model
  - Benchmark of equal probabilities all the way through
  - Also experiments with fixed first week attendance and then weeks 2 - 9 evolve according to model
    - This gets at possible use of advertising to increase opening

Random Benchmark on next slide

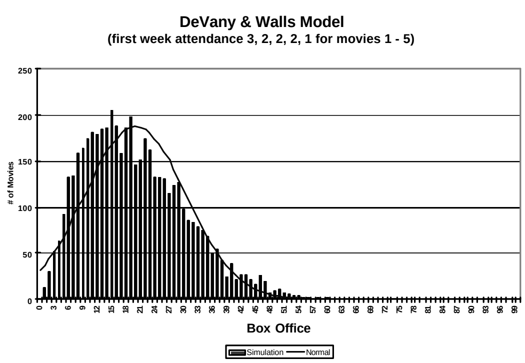
- 5,000 “movies”
- Each patron has a constant probability of .2 of seeing a movie each week
- “Normal” is # that would be expected from a normal distribution of same mean and variance as simulated distribution
- Followed by equal opening probability, but audience evolution according to D-V model

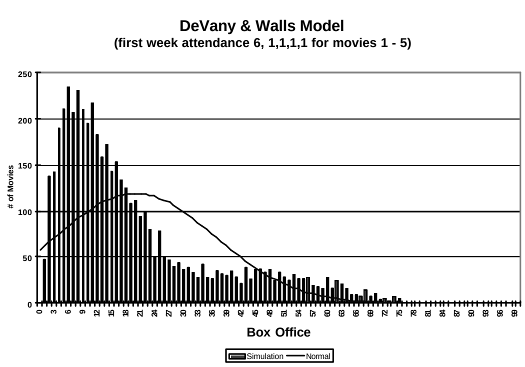


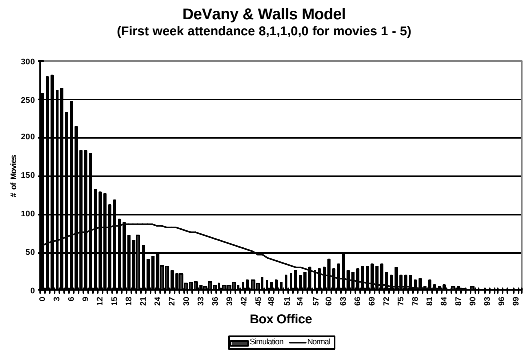


Advertising

- Now assume that you can affect the first week attendance by how you open it, with subsequent weeks evolving according to the D-V model
  - Remember, there are 10 patrons the first week and what you do is switch some to your movie







Summary of Aggregate Data from Simulation

	Mean	Std. Dev.	Skew
Benchmark	20.00	4.00	0.13
No Prior	20.00	16.63	1.04
(3,2,2,2,1)	20.00	10.61	.67
(6,1,1,1,1)	20.00	16.73	1.28
(8,1,1,0,0)	20.00	23.07	1.37

By Movie[from simulations]

each cell has mean and s-dev

Movie	1	2	3	4	5
Random	20.06 3.89	20.33 4.07	19.84 4.05	20.06 4.08	19.72 3.88
D & W model	19.58 16.56	21.22 17.26	20.44 16.30	19.27 16.51	19.48 16.45
(3,2,2,1,1)	26.91 10.39	19.71 9.88	20.28 10.13	20.06 9.66	13.04 8.07
(6,1,1,1,1)	47.95 12.42	13.14 8.23	12.87 8.04	12.68 8.09	13.36 8.38
(8,1,1,0,0)	62.56 11.88	12.81 8.25	12.59 8.26	6.00 5.93	6.04 6.29

What do we see?

- Note how skewness behaves across models
  - This is not a "normal" world
- Note that in the (8,1,1,0,0) model looks like it has two peaks
  - Suggests you can separate your movie from the pack
- Fixed first week reduces variance
  - Is this what a "star" does?
- Note that effect of fixed first week on aggregate attendance is greater than would at first appear (e.G., Fixing first week for movie 1 at 8 -- 6 more than the average -- increases average overall box office for movie 1 to 62 from 19)
  - Maybe this is what a "star" does

The trail of the opening

- The next group of slides presents the results of regressing overall box office and 10th week box office on first week box office. We are looking for evidence that the opening matters all the way through.

Regressions for Random Benchmark and DW model

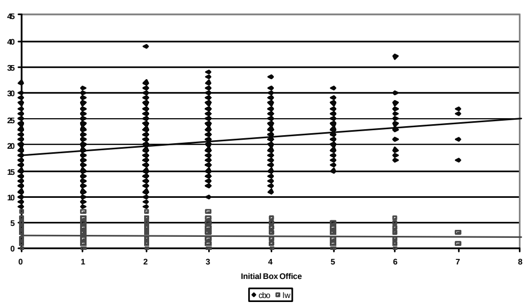
Dependent Variable is Total Box Office

Model		Constant	Opening Week Box Office
Random Benchmark	Value	18.05	0.97
	t-statistic	178.61	22.78
DW Model	Value	6.22	6.89
	t-statistic	34.14	107.50

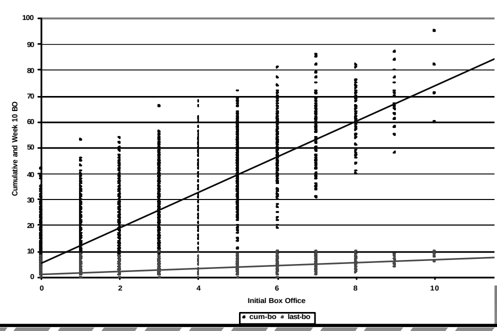
Regressions for Random Benchmark and DW model

Dependent Variable is 10th Week Box Office			
Model		Constant	Opening Week Box Office
Random Benchmark	Value	2.00	-.00
	t-statistic	60.25	-.07
DW Model	Value	.69	.65
	t-statistic	22.80	61.72

Effect of Initial Box Office on Cumulative and Last Week's Box Office Random Benchmark



Effect of Initial Box Office on Cumulative and Last Week's Box Office DW Model



Consistency with Real World

- In the real world we see similar behavior
- D-V present evidence consistent with the importance of the opening to determining the length of the run and thus total attendance that goes beyond simple 1 for 1 relation
- Clearly studios are very concerned with the opening box-office for many (though not all) movies.

Is that all there is?

- Importance of information feedback
  - Simple model does not include dynamic scheduling of movies which occurs as the box office history of the movie evolves (see NYTimes reading for day we discuss exhibition).
    - This suggests that break of distribution from exhibition required by anti-trust decisions of the late 1940's may be inefficient.
  - Simple model does not allow for negative information cascade if early viewers report the movie is bad
  - Simple model does not allow for slow building of audience.

Closing

- Two edged sword due to information cascades
  - Do you open big or small?
    - Opening big can help (that is what stars and network TV advertising are for, but-
    - If the movie is no good it dies more quickly as more people tell their friends it reeks
- Massive uncertainty in chaotic systems
- Final note, the fact that this business is driven by "winners" is not surprising, but rather is what we would expect.