

Quick-Start Guide to Working with the Cost-Differential Frontier

Professor Suzanne de Treville
University of Lausanne

The Cost-Differential Frontier tool

- ▶ As the time between deciding what to produce and knowing actual demand increases, decisions must be made based on increasingly noisy information
- ▶ The tool uses quantitative finance tools to price this increase in demand-volatility exposure, answering the question:
- ▶ *How much cheaper does the long-lead-time product have to be to compensate for the resulting increase in mismatch cost?*
- ▶ Once the mismatch cost is taken into consideration, short-lead-time production is often surprisingly competitive

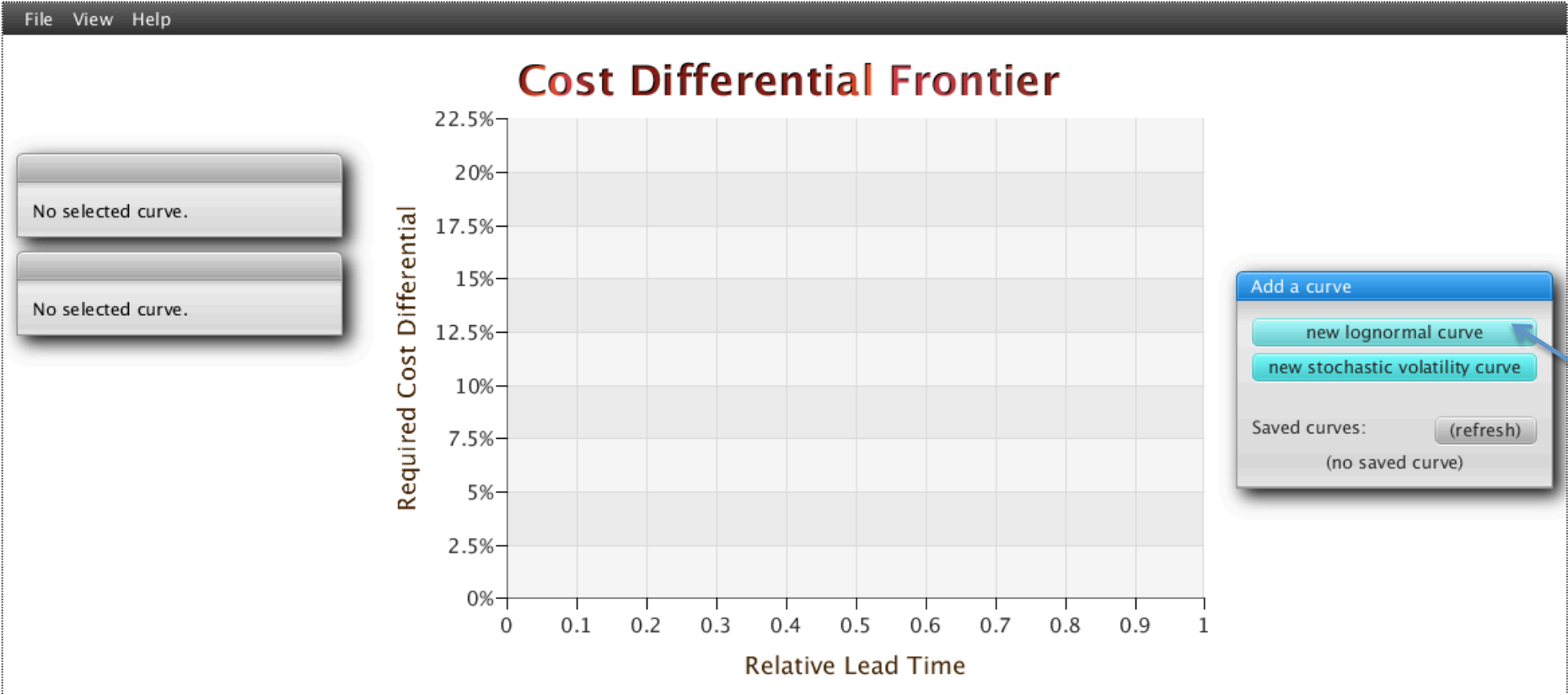
Getting started:

- ▶ Open the software
 - ▶ Java must be up to date
 - ▶ Chrome does not run Java
 - ▶ Safari does not allow curves to be saved to the hard drive
 - ▶ Good results with Firefox
 - ▶ Use the webstart option if problems arise
- ▶ Beginning users should choose the “new lognormal curve” option
- ▶ Hover the mouse over data fields for additional information
- ▶ After naming a curve, hit Enter.

OpLab, Laboratory in the Operations Department at [HEC Lausanne, University of Lausanne](https://www.hec.ch), has created an innovative tool that uses concepts from quantitative finance to help businesses understand the true cost of extended supply chains. This tool uses a company's expected demand volatility, lead time, and salvage value to calculate the cost savings that offshoring would need to provide in order to compensate for the risk of stockouts or oversupply. [This video](#) further elaborates these concepts.

To learn more, you can contact [Prof. Suzanne de Treville](#), OpLab's Director.

Your Operating System or your browser may not display the application correctly. If so, please open [this app as webstart](#)



OpLab, Laboratory in the Operations Department at [HEC Lausanne, University of Lausanne](http://www.hec.ch), has created an innovative tool that uses concepts from quantitative finance to help businesses understand the true cost of extended supply chains. This tool uses a company's expected demand volatility, lead time, and salvage value to calculate the cost savings that offshoring would need to provide in order to compensate for the risk of stockouts or oversupply. [This video](#) further elaborates these concepts.

To learn more, you can contact [Prof. Suzanne de Treville](#), OpLab's Director.

Your Operating System or your browser may not display the application correctly. If so, please open [this app as webstart](#)

File View Help

Curve

Save Remove

Newsvendor

Price	p	100
Cost	c_s	44
Salvage	s	20
Critical Fractile	cf	0.7
Target Service Level	sl	0.7
Stockout penalty	sp	0

Lognormal

Coeff. of var.	c_v	0.53
Volatility	vol	0.5

Launch computation

Cost Differential Frontier

Required Cost Differential

0% 0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

0% Relative Lead Time

Add a curve

- new lognormal curve
- new stochastic volatility curve

Saved curves: (refresh)

(no saved curve)

Hit Enter after entering the curve name

File View Help

Curve

Save Remove

Newsvendor

Price	p	100
Cost	c_s	44
Salvage	s	20
Critical Fractile	cf	0.7
Target Service Level	sl	0.7
Stockout penalty	sp	0

Lognormal

Coeff. of var.	c_v	0.53
Volatility	vol	0.5

Launch computation

Cost Differential Frontier

Required Cost Differential

0% 0% 0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

Relative Lead Time

Add a curve

new lognormal curve

new stochastic volatility curve

Saved curves: (refresh)

(no saved curve)

Tool Inputs: The Product

- ▶ Price per unit sold: 100 in this example
- ▶ Cost (the per-unit cost when the product is made to order with full knowledge of demand): 44
- ▶ Salvage value (the residual value of a unit that is not sold during the demand period): 20
 - ▶ Below-cost clearance price
 - ▶ If held in inventory until the next demand period, the original production cost less inventory holding cost

Curve

Save

Remove

Newsvendor

Price	p	100
Cost	c_s	44
Salvage	s	20
Critical Fractile	cf	0.7
Target Service Level	sl	0.7
Stockout penalty	sp	0

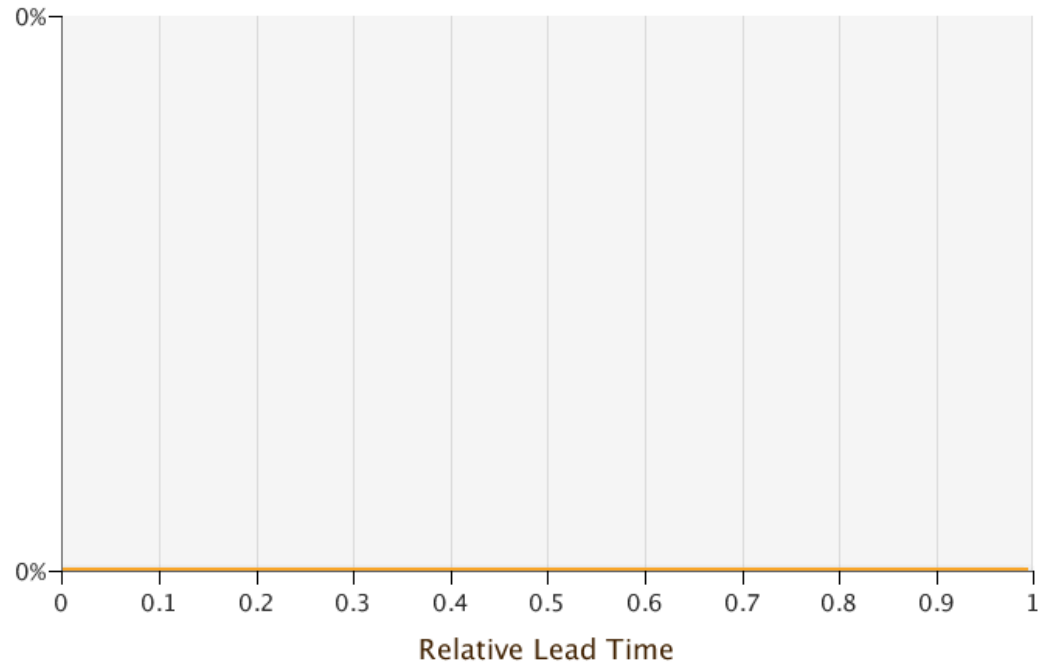
Lognormal

Coeff. of var.	c_v	0.53
Volatility	vol	0.5

Launch computation

Required Cost Differential

Cost Differential Frontier



Relative Lead Time

- ▶ Lead time t varies from 0 (order placed with full knowledge of demand) to 1 (longest lead time under consideration)
- ▶ We normalize the longest lead time to $t = 1$: If the full lead time is 100 days, represented as $t = 1$, a relative lead time of 30 days is represented as $t = 0.3$

Tool Inputs: The Demand Volatility

- ▶ The demand volatility tells us the range of demand values for a given lead time
- ▶ We calibrate volatility for the full lead time $t = 1$
- ▶ For shorter lead times— $t \in [0, 1)$ —the volatility is scaled by \sqrt{t}
- ▶ For example, a 60% volatility for the full lead time drops to $60\% \times \sqrt{.2} = 27\%$ if lead time is reduced to $t = 0.2$
- ▶ The volatility can be estimated from the coefficient of variation of demand if known, or from management intuition using the calculator provided in the tool

Calculating volatility from intuition using the tool calculator

- ▶ Consider a demand period and an order decision made with the longest lead time ($t = 1$)
- ▶ Consider median demand for that demand period (taking into consideration seasonality)
- ▶ What would be a typical demand peak relative to median demand? Here, a typical demand peak is estimated to be around twice median demand
- ▶ How frequent are such peaks? Here, we estimate that a peak occurs one demand in eight
- ▶ The tool estimates demand volatility for $t = 1$ to be 60%, thus a coefficient of variation of 66%

Stockout penalty

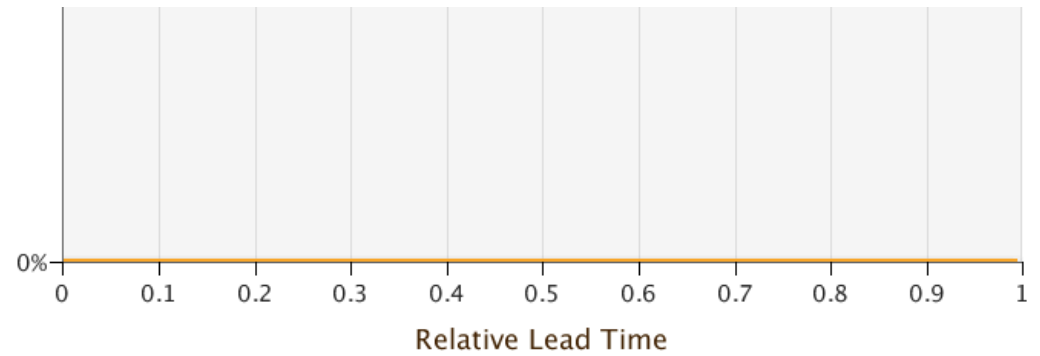
Lognormal

Coeff. of var. **c_v**

Volatility **vol**

Launch computation

Required Cc



Webstart: [click to launch this app as webstart](#)

To estimate your volatility, please click [here](#)

Peak demand as a multiple of median demand

Frequency of peak demand: times, out of periods

Estimated volatility

Calculation of the demand volatility assuming no jumps and that the forecast evolution process is smooth. If information about demand arrives in clusters, or there are sudden jumps in the forecast, then the actual cost of lead time will be higher than what is estimated using the number here calculated, and the results should be considered as a lower bound.

Corresponding coefficient of variation

Stockout penalty sp 0

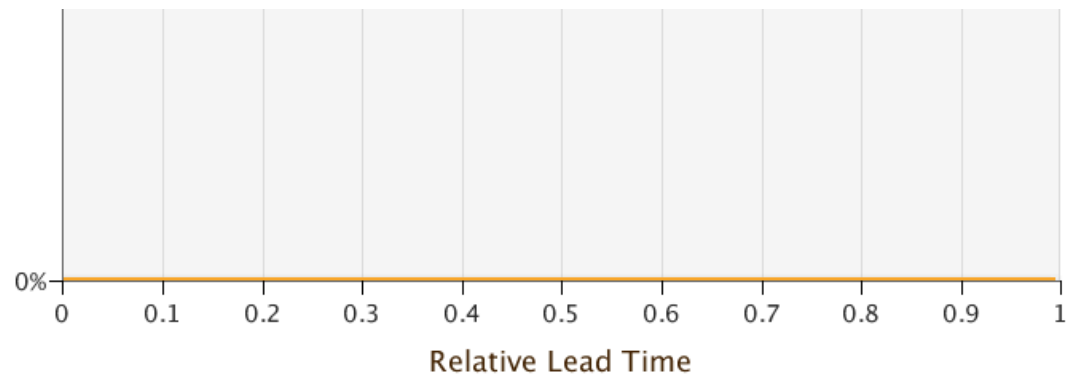
Lognormal

Coeff. of var. c_v 0.66

Volatility vol 0.6

Launch computation

Required Co



Webstart: [click to launch this app as webstart](#)

To estimate your volatility, please click [here](#)

Peak demand as a multiple of median demand

Frequency of peak demand: times, out of periods

Estimated volatility

Calculation of the demand volatility assuming no jumps and that the forecast evolution process is smooth. if information about demand arrives in clusters, or there are sudden jumps in the forecast, then the actual cost of lead time will be higher than what is estimated using the number here calculated, and the results should be considered as a lower bound.

Corresponding coefficient of variation

The Order Quantity

- ▶ The order quantity is specified as a target service level: Enough is ordered to achieve a target probability that all demand will be satisfied
- ▶ This target service level can be set to maximize profit using the well-known newsvendor model. The tool calculates this profit-maximizing value *critical fractile*
- ▶ Many companies choose to set a higher target service level because stocking out has costs that are not captured by the standard newsvendor model. This increases the mismatch cost, and pushes up the cost-differential frontier. When the target service level is higher than that which maximizes profit, the tool calculates the implied stockout penalty and incorporates it into the critical fractile calculation.

- ▶ In this example, we are setting the target service level equal to the critical fractile in order to give the long-lead-time alternative every advantage (no additional stockout penalty)
- ▶ As the lead time increases, the cost needs to decrease to compensate for the volatility exposure. This increases the per-unit profit, which increases the service level. The order quantity for each value of relative lead time is based on the service level that maximizes profit (including the stockout penalty, if any)

Curve

Save

Remove

News vendor

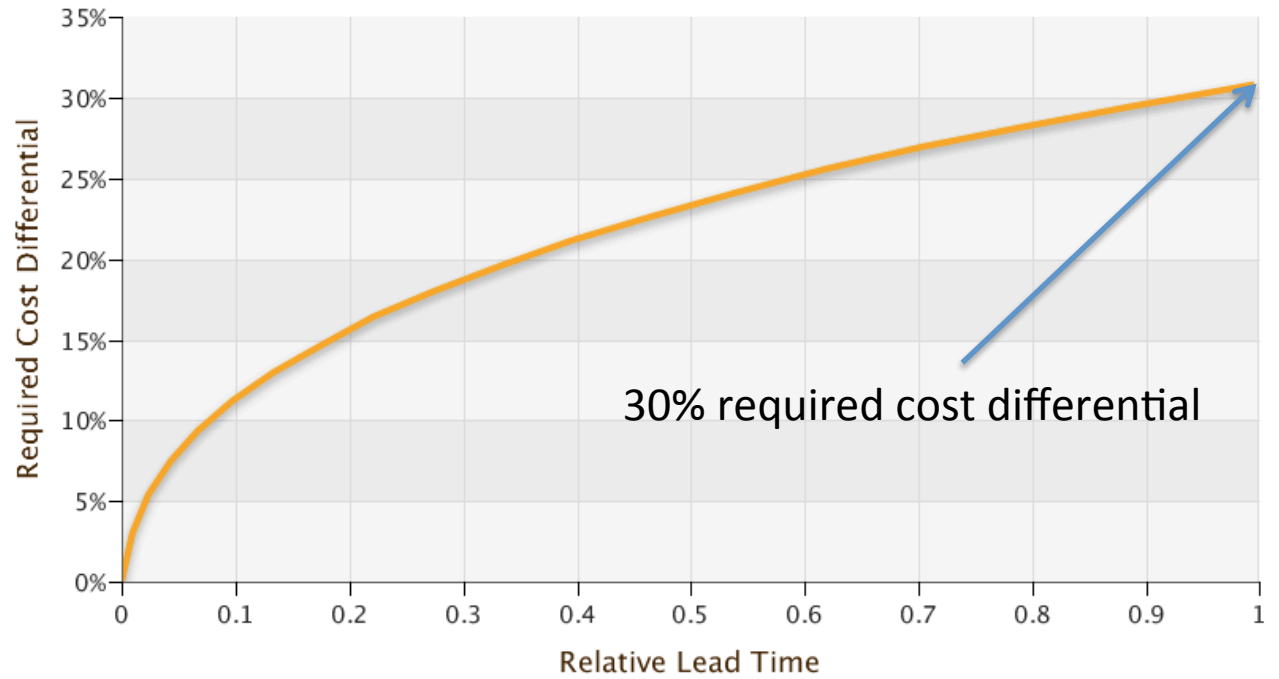
Price	p	100
Cost	c_s	44
Salvage	s	20
Critical Fractile	cf	0.7
Target Service Level	sl	0.7
Stockout penalty	sp	0

Lognormal

Coeff. of var.	c_v	0.66
Volatility	vol	0.6

Launch computation

Cost Differential Frontier



Tool Results

- ▶ The required cost differential for $t = 1$ in this example is around 30%
- ▶ This *only* includes mismatch cost. Other costs associated with offshore production (see acetool.commerce.gov and reshorenw.org) are not considered
- ▶ If the company moves production to an offshore producer offering a cost reduction of 30%, profit will stay the same assuming no other costs (flying engineers to work with the production line, extra packaging), no supply risk
- ▶ If the company aims for a higher service level (say, 80%), or if the salvage value was a bit optimistic (say, the true salvage value is 15 rather than 20), the required cost differential increases to 40%

Curve

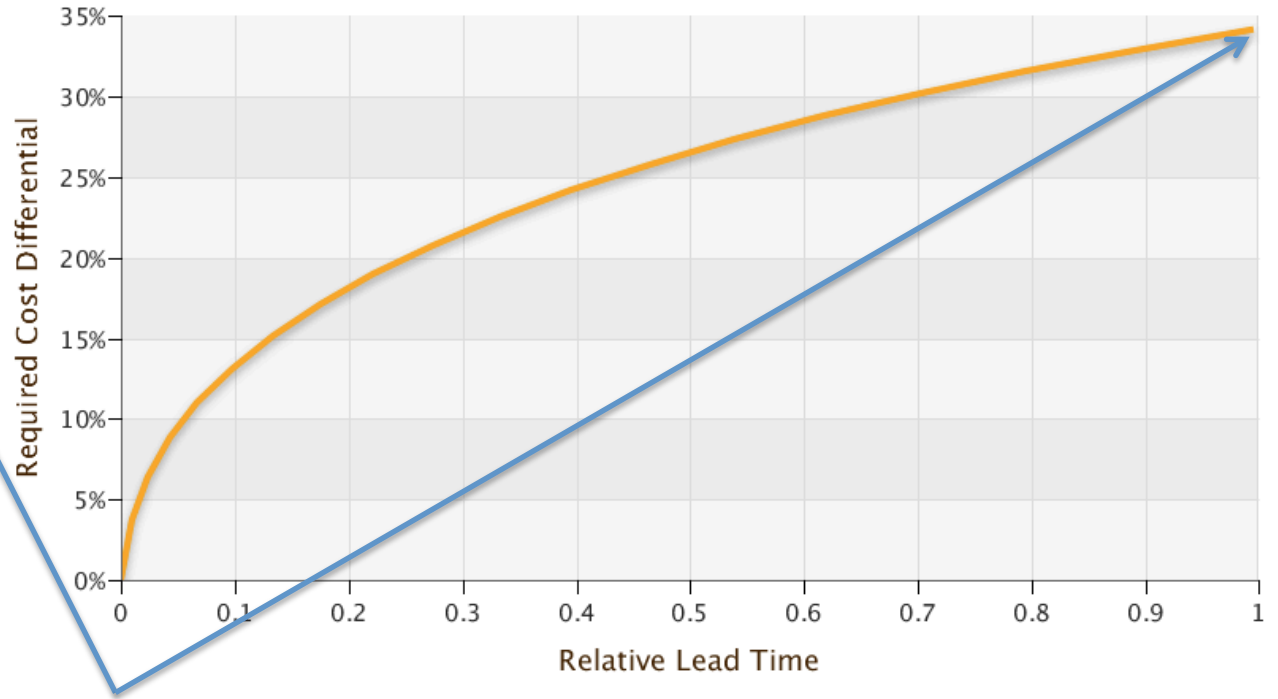
Save Remove

Newsvendor		
Price	p	100
Cost	c_s	44
Salvage	s	20
Critical Fractile	cf	0.7
Target Service Level	sl	0.8
Stockout penalty	sp	40

Lognormal		
Coeff. of var.	c_v	0.66
Volatility	vol	0.6

Launch computation

Cost Differential Frontier



Curve

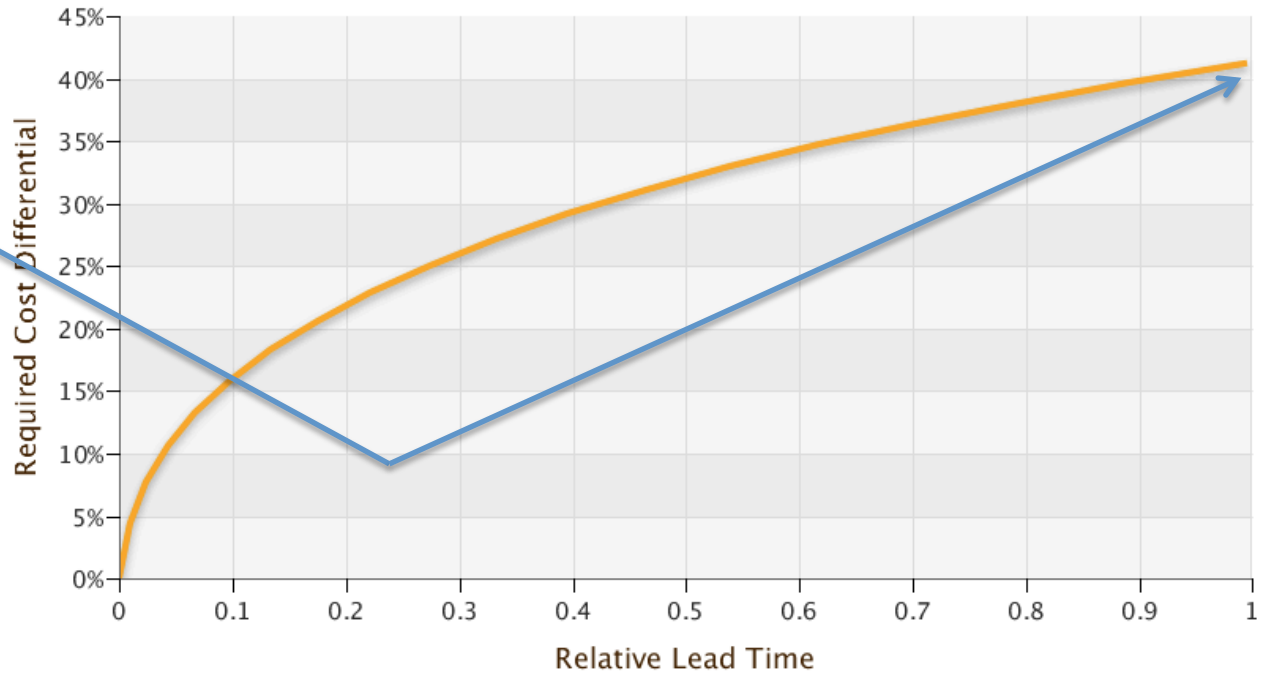
Save Remove

Newsvendor		
Price	p	100
Cost	c_s	44
Salvage	s	15
Critical Fractile	cf	0.66
Target Service Level	sl	0.8
Stockout penalty	sp	60

Lognormal		
Coeff. of var.	c_v	0.66
Volatility	vol	0.6

Launch computation

Cost Differential Frontier



Why should most users choose the lognormal curve?

This choice assumes the marginal density of demand for a given lead time is lognormally distributed, and the demand volatility increases in the square root of lead time. ($\log(\text{demand}) \sim \mathcal{N}(\mu, \sigma)$, where σ is the full-lead-time volatility and e^μ is median demand. This corresponds to Black-Scholes options-pricing assumptions.)

This describes the case in which information about demand arrives at a steady pace as the demand period approaches. If not—say information about demand arrives in clusters, such that volatility is stochastic rather than constant—then mismatch costs will be higher. The lognormal results can then be interpreted as a lower bound for lead-time cost.