

# Using Optimization to Cope with Uncertainty

Mattia Ferrini, Director, KPMG AG





### Understand uncertainty

- Identify the sources of uncertainty
- Identify risks



### Rethinking Modelling

- Rare-events and catastrophe modelling in the day to day decision making process
- More resilient business models
- Disruption as an opportunity to gain competitive advantage

### The background HOW to leverage disruption?

#### 1) Understand

• Identify what **micro and macro economic factors** drive your business

#### 2) Anticipate

- Prepare ahead of **worst case scenarios**
- Stress test your business
- Identify criticalities

#### 3) Spot opportunities

- Reason strategically
- Models as **useful representation** of a business
- Reason collaboratively

#### Example: sourcing strategies in the pharmaceutical industry

Scenario 60% Packaging Externalization Planning Fiscal Year Direct Spend and Savings	
Total Spend     1,234     Tracking (Actuals vs Butter 1,234       Total savings wrt budget     1,234       Total savings wrt previous period     1,234	adget) Planned (by Category) Scenario comparison
Finished Product Semi-Finished API Excipients	Semi-Finished Product Review assumptions for Externalized • Volume Price Volume Volume Collaboratively review business assumption and generate different scenarios based on alternative sourcing strategies.
Row Moterial A Row Moterial B	Time Reset to model Save Save as

Visu proc finis

### The background High uncertainty is everywhere





#### **Stores and Route optimization**

- Model uncertainty in
  - lead times
  - availability and cost of shipping routes



#### **Marketing optimization**

- Changes in customer habits, e.g.
  - Homework: less time on smart phones?



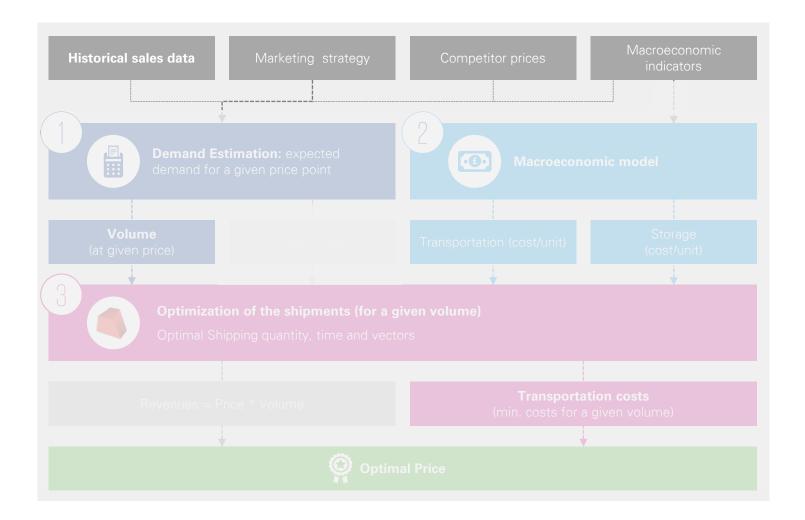
#### **Price Optimization**

- Willingness to spend
- Consumer preferences
- Demand by channel

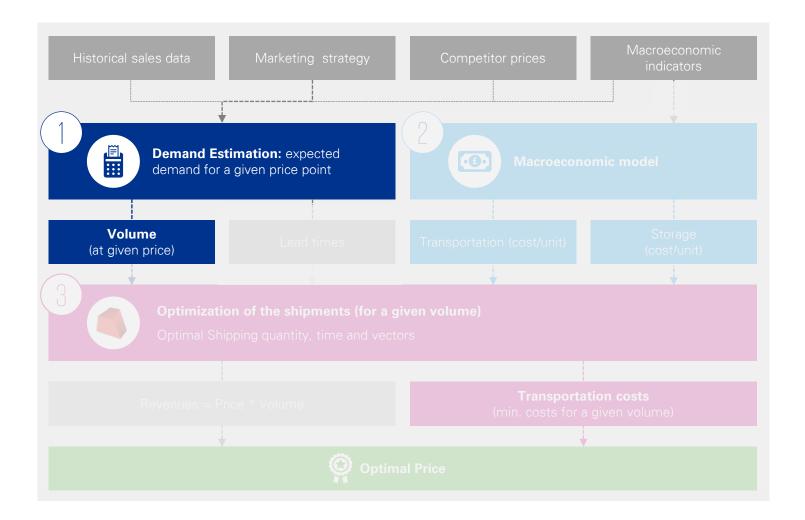
Dynamic Price Optimization 🗧	
	- Paradanex
ALCONFILMENTS.	I BETTATA
The second second	and the barriers
REALER	in the second
	to be a second s
_ or minere	Distance and
in the later of th	- EVALVERIATION
-	and a single for these to some a
Part March	Contraction and
The local billion and the second	and an arrest of the

4

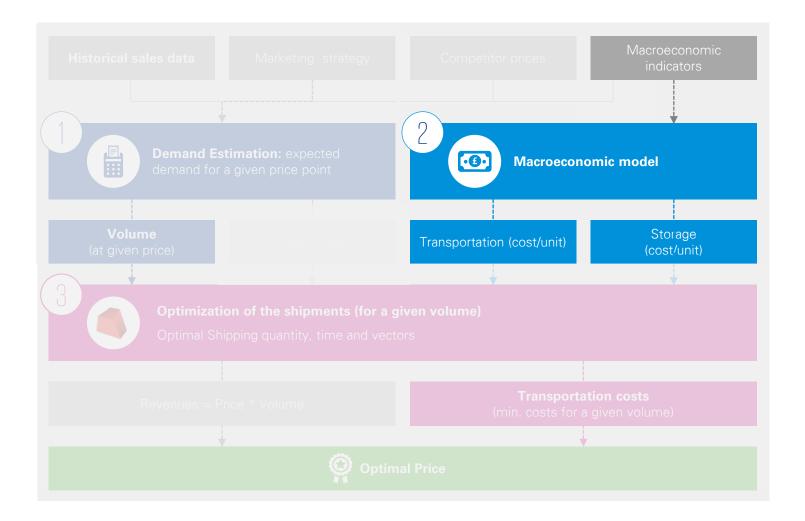
### Credential: European distributor of industrial goods primarily manufactured in Asia Price Optimization



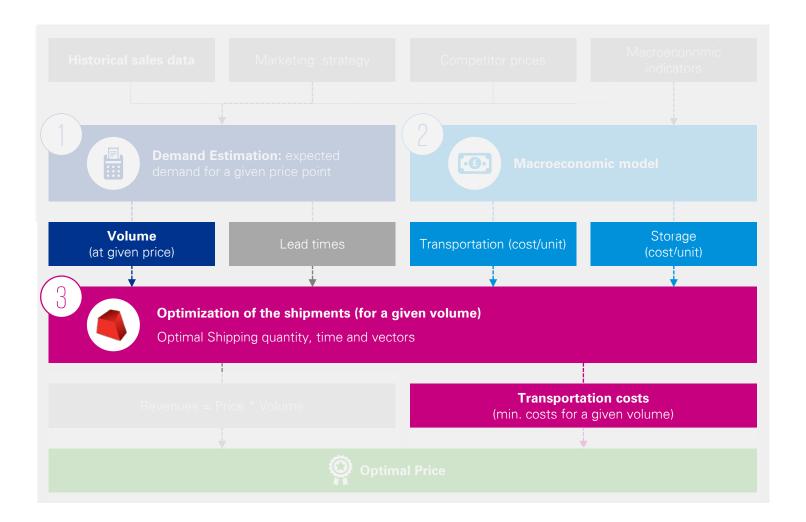
# Credential: European distributor of industrial goods primarily manufactured in Asia



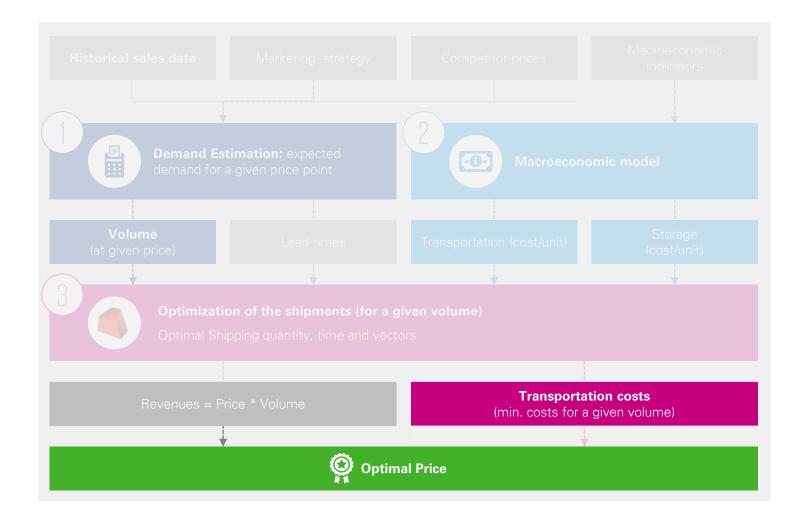
# Credential: European distributor of industrial goods primarily manufactured in Asia



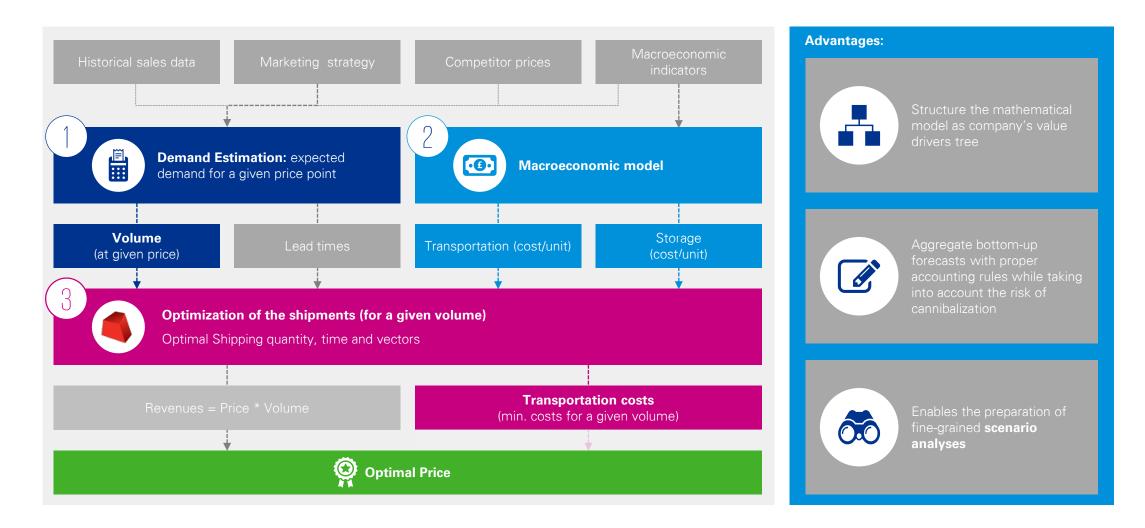
### Credential: European distributor of industrial goods primarily manufactured in Asia Price Optimization



# Credential: European distributor of industrial goods primarily manufactured in Asia



# Credential: European distributor of industrial goods primarily manufactured in Asia



## Optimization under uncertainty





## Probabilistic Programming

## Stochastic Optimization



## Optimization under uncertainty



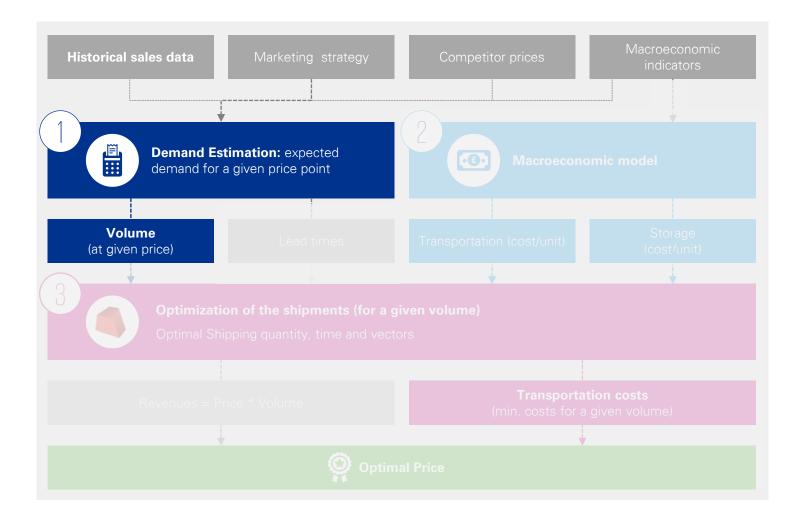


## Probabilistic Programming

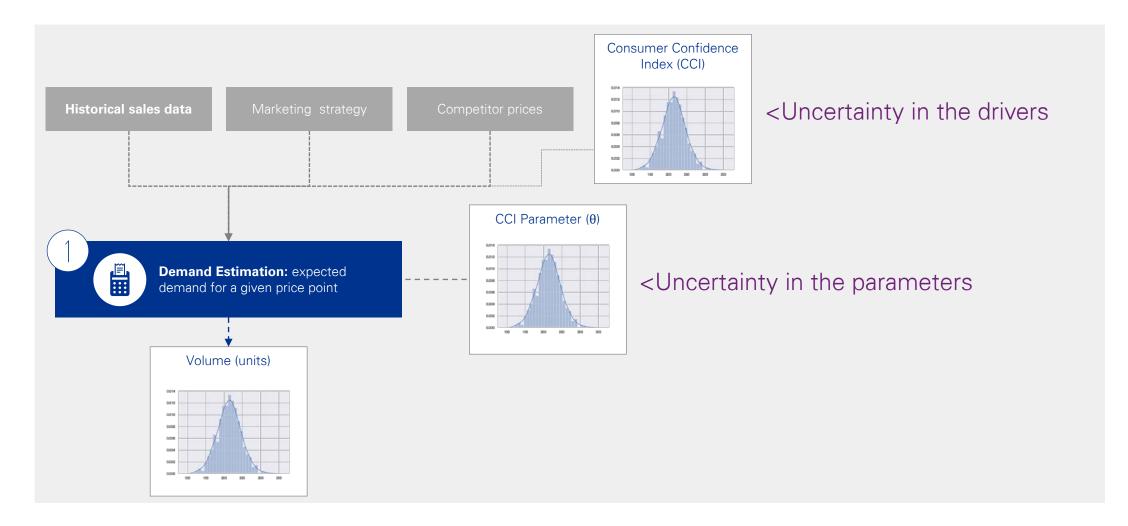
## Stochastic Optimization



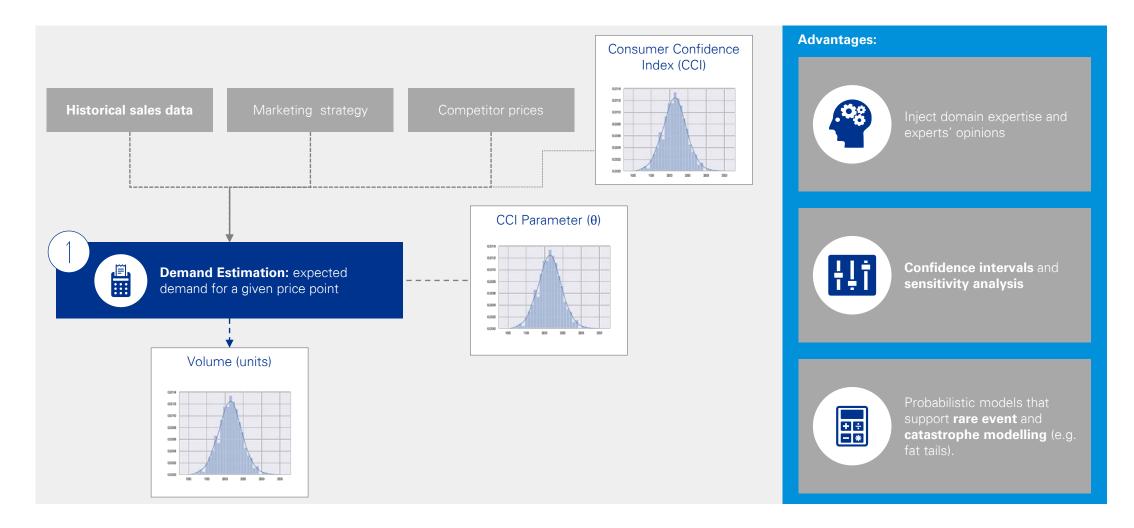
### Probabilistic Programming and Bayesian Machine Learning Price Optimization



Probabilistic Programming and Bayesian Machine Learning Uncertainty is everywhere



#### Probabilistic Programming and Bayesian Machine Learning QUANTIFIED UNCERTAINTY



## Optimization under uncertainty





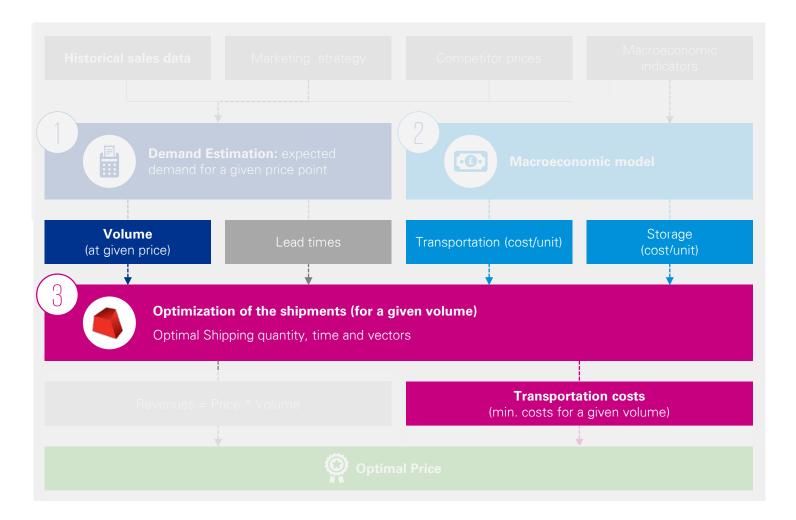
## Probabilistic Programming

## Stochastic Optimization



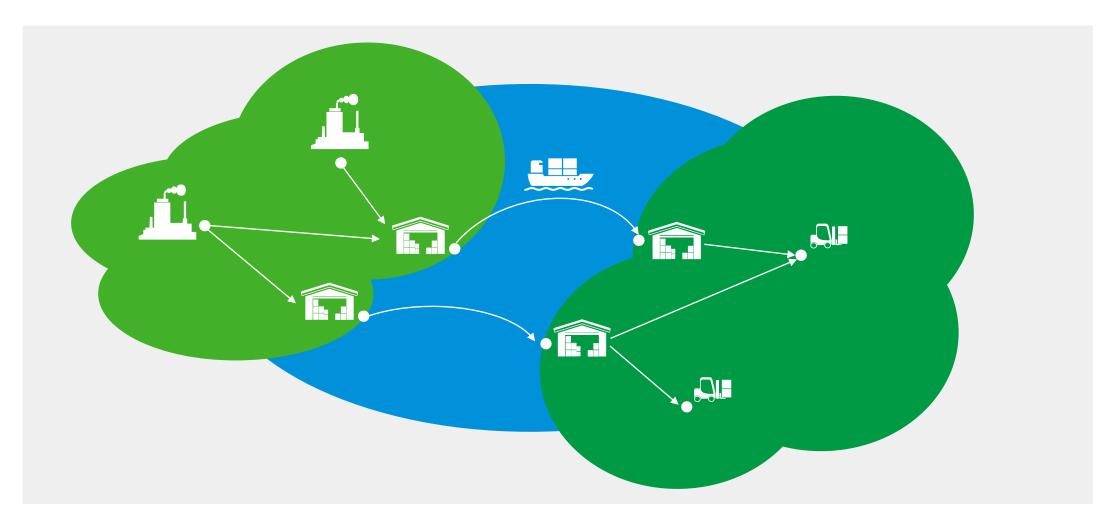
#### **Robust and Stochastic Optimization**

## MILP optimization of shipments

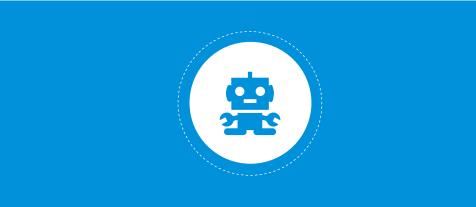


#### **Robust and Stochastic Optimization**

### Shipments optimization as a MILP problem



### Robust and Stochastic Optimization What is Stochastic Optimization?



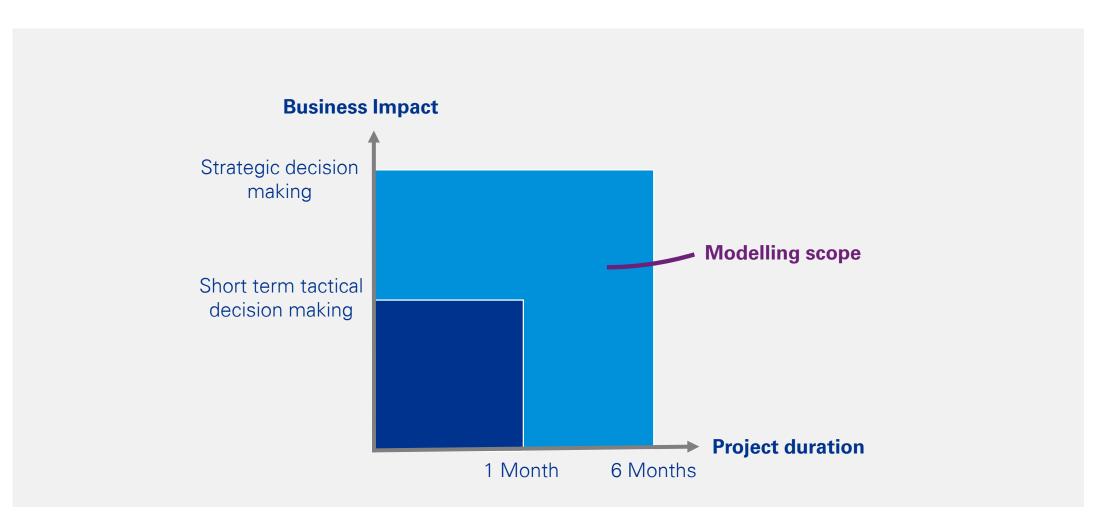
#### Robust Optimization (Implicit)

- You don't need to know how parameters are distributed
- assume parameter uncertainty sets,
  - e.g. **robust counterpart**: stochastic quantity is replaced by its expectation and a margin of safety
- Hard constraints in the uncertainty sets
- «worst case oriented»

#### Explicit Stochastic Optimization

- You make explicit use of information about the distribution of parameters
- You can define your own utility function and risk measures
- It's possible to have soft constraints (satisfy in probability)
- Can be computationally nasty
- Most of the time it is necessary to approximate solutions (e.g. Monte Carlo)

## Project Plan

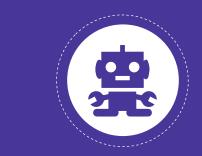


## Conclusions





- modelling in day to day decision making processes
- Quantify uncertainty



#### **Robust and Stochastic** Optimization

- Additional complexity ...
- .. Better decisions
- Can be tackled by Gurobi



### Contacts



### Mattia Ferrini

Director, Artificial Intelligence

T +41 58 249 30 51 M +41 79 57 00 430 E mattiaferrini@kpmg.com









The information contained herein is of a general nature and is not intended to address the circumstances of any particular individual or entity. Although we endeavor to provide accurate and timely information, there can be no guarantee that such information is accurate as of the date it is received or that it will continue to be accurate in the future. No one should act on such information without appropriate professional advice after a thorough examination of the particular situation.

© 2020 KPMG AG is a subsidiary of KPMG Holding AG, which is a member of the KPMG network of independent firms affiliated with KPMG International Cooperative ("KPMG International"), a Swiss legal entity. All rights reserved.

The KPMG name and logo are registered trademarks or trademarks of KPMG International.