

Amazon Collider Project

Forecasting the number of vehicles required for package deliveries in an uncertain environment

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1. Introduction

An e-commerce company relies on a high-performance supply chain and needs to maintain a decent level of customer service while keeping a low cost structure to remain profitable. The part of the logistic network which delivers packages to the final customers, usually referred as « the last mile », is essential as its design and operation will determine the entire customer experience towards the company. More specifically, in this proposal, we will consider the problem of forecasting the number of vehicles required to deliver packages, given a demand distribution. Indeed, in order to decide how many vehicles are needed, there will be a tradeoff between the level of customer service and the total costs of the delivery that the company will need to adjust, depending on its objectives. In our analysis of the problem, we consider two attributes that will determine the level of customer service of the company:

- 1) The number of customers that will receive their order on time
- 2) The maximal delay that will be allowed for all customers

Furthermore, we will study how to manage effectively the booking of the vehicles, through a process that we will develop further.

Three types of vehicles will be considered:

- 1) Guaranteed vehicles: these trucks will come for sure on a given day. The number of guaranteed vehicles will be denoted X_g in the analysis
- 2) Optional vehicles: these trucks will be available on call if they are necessary to reach the level of customer service desired. The number of optional vehicles will be denoted X_o in the analysis
- 3) Spot vehicles: these trucks belong to another transportation company, and are called on very short notice, if absolutely required. The number of spot vehicles will be denoted X_s in the analysis

The decision process occurs as follows: Amazon Logistics decides how many guaranteed and optional vehicles are required on a given day before knowing the actual demand, and, depending on the policy regarding the level of customer service, uses the spot vehicles if the demand is too important relatively to the number of guaranteed and optional trucks.

a) Problem statement

Given that the daily demand distribution is normal with mean 10,000 and standard deviation 2000, we will determine how many guaranteed and optional vehicles Amazon Logistics should book per day to meet the daily demand, and how to operate the system of reservation of the vehicles.

b) Our approach

Firstly, we will consider several policies that will depend on the level of customer service that Amazon Logistics will want to satisfy, and more particularly on the 2 attributes described above. Then, we will analyze the cost structure of each type of truck. This will allow us to formulate an optimization problem that will seek, for each policy, the values of X_g and X_o that minimize the total transportation costs.

Secondly, we will describe a process that will manage the reservation of guaranteed and optional vehicles, to make sure that, on a given day, each required driver will actually show up.

2. Models

a) Notations

- C_g : cost of a guaranteed vehicle
- Co : cost of securing an optional vehicle if not called
- Co' : additional cost if the optional vehicle is called (in total we pay $Co + Co'$ if an optional vehicle is called)
- Cs : cost of a spot vehicle

We have three decisions variables:

- X_g : number of guaranteed vehicles
- X_o : number of optional vehicles
- X_s : number of spot vehicles

b) How we solve the problem

For each of our models, we approach this optimization problem by running simulations, one simulation consisting of:

- Fixing the value of X_g and X_o and generating 100,000 times a random normal demand d , with mean 10,000 and standard deviation 2000. While generating random demand, we take into account the fact that demand on the weekend differs from demand on weekdays.
- For each randomly generated demand we compute the total cost, knowing that we have X_g guaranteed vehicles and X_o optional vehicle. For each model, the total cost is computed according to the policy we choose.
- Taking the mean of all the total cost. Therefore, to one pair (X_g, X_o) corresponds one average total cost.

We ran simulations for different values of (X_g, X_o) , computed the Average Total Cost and deduced that the best policy was the pair associated with the lowest average total cost.

c) Models description

▪ Model 1:

Policy: Every customer has to be delivered, so whenever we are short on vehicles ($D > X_g + X_o$) we take spot vehicles.

Formulation of the expected Total Cost:

$$E(\text{Total Cost}) = C_g X_g + Co X_o + Co \int_{X_g}^{X_g + X_o} D f(D) dD + \int_{X_g + X_o}^{\infty} D f(D) dD$$

Simulation cases:

1. $D \leq X_g$: $\text{Total Cost} = X_g C_g + X_o Co$
2. $X_g \leq D \leq X_g + X_o$: $\text{Total Cost} = X_g C_g + X_o Co + (D - X_g) Co'$
3. $D \geq X_g + X_o$: $\text{Total Cost} = X_g C_g + X_o (Co + Co') + (D - X_g - X_o) Cs$

Example:

Cost	Price in \$ per vehicle
Cg	190
Co	77
Cs	2350

Truck Capacity	425
Xg	20
Xo	5

Day	Fixed Demand	Case	Total Cost
1	9219	2	4904
2	11046	3	6711
3	9092	2	4777
4	11404	3	7069
5	6697	1	4185
6	10309	2	5994

Case = 1 if $D > Xg$
Case = 2 if $Xg < D < Xg + Xo$
Case = 3 if $D > Xg + Xo$

Therefore, for this simulation and for these value of Xg and Xo (20 and 5 respectively) we have

Average Total Cost = 5607\$

In fact, instead of simulating 6 demands, we simulated 100,000 demand, for each pair (Xg, Xo)

▪ **Model 2:**

Policy: We decide that if we have not enough vehicles (both guaranteed and optional) to meet the demand, we take a number of spotted vehicle to meet a certain percentage of the demand α (for instance 95%). This percentage α can be seen as a certain level of satisfaction.

Formulation of the expected Total Cost:

$$E(\text{Total Cost}) = CgXg + CoXo + Co \int_{Xg}^{Xg+Xo} Df(D)dD + Cs \int_{Xg+Xo}^{Xg+Xo+Xs} Df(D)dD$$

Simulation cases:

- $Xg + Xo \leq \alpha D$: $\text{Total Cost} = XgCg + Xo(Co + Co') + (\alpha D - Xg - Xo)Cs$
- $\alpha D \leq Xg + Xo \leq D$: $\text{Total Cost} = XgCg + Xo(Co + Co')$
- $D \leq Xg + Xo$:
 - a. $Xg \leq D$: $\text{Total Cost} = XgCg + XoCo + (D - Xg)Co'$
 - b. $Xg \geq D$: $\text{Total Cost} = XgCg + XoCo$

▪ **Model 3:**

Policy: If the demand is not too high (threshold defined by: if $D \leq F^{-1}(\alpha)$ with $F = \text{Normal}(10000, 2000)$), we serve 100% of the demand, otherwise we serve only a certain percentage α of the demand.

Simulation cases:

We did our simulations for pairs (Xg, Xo) such that $Xg + Xo < F^{-1}(\alpha)$. We took the highest percentile $F^{-1}(\alpha) = F_{\text{weekdays}}^{-1}(\alpha)$ knowing that it will result in a better coverage of the weekend demand ($F_{\text{weekdays}}^{-1}(\alpha) > F_{\text{weekends}}^{-1}(\alpha)$).

$$D \leq F^{-1}(\alpha):$$

1. $D \leq Xg$: Total Cost = $XgCg + XoCo$
2. $Xg \leq D \leq Xg + Xo$: Total Cost = $XgCg + XoCo + (D - Xg)Co'$
3. $D \geq Xg + Xo$: Total Cost = $XgCg + Xo(Co + Co') + (D - Xg - Xo)Cs$

$$D > F^{-1}(\alpha): \text{Total Cost} = XgCg + Xo(Co + Co') + (F^{-1}(\alpha) - Xg - Xo)Cs$$

▪ **Model 4:**

Policy: We are allowed to postpone to the next day up to a certain size of the demand. This threshold that we call T is less than Xg , so that the late deliveries are sure to be delivered the next day. To take into account the postponed demand we define a new variable O, corresponding to the overflow, in other words, the demand we postpone to the next day. So, on day k we have a random demand d_k and an overflow O_k meaning that we have to meet the demand: $D_k = d_k + O_k$

Simulation cases:

We note $D_k = d_k + O_k$

1. $D_k \leq Xg$: Total Cost = $XgCg + XoCo$ and $O_{k+1} = 0$
2. $Xg < D_k \leq Xg + Xo$: Total Cost = $XgCg + XoCo + (D_k - Xg)Co'$ and $O_{k+1} = 0$
3. $Xg + Xo < D_k \leq Xg + Xo + T$: Total Cost = $XgCg + Xo(Co + Co')$ and $O_{k+1} = D_k - Xg - Xo$
4. $D_k > Xg + Xo + T$: Total Cost = $XgCg + Xo(Co + Co') + (D_k - Xg - Xo - T)Cs$ and $O_{k+1} = T$

Example:

Cost	Price in \$ per vehicle
Cg	190
Co	77
Co'	184
Cs	2350

Truck Capacity	425
Xg	20
Xo	5
Threshold (T)	200

Day	Fixed Demand	Demand to cover with Spot Vehicles and Overflow	Demand + Overflow	Overflow	To cover with spot vehicles
1	9219	100	9319	100	0
2	11046	0	11046	0	0
3	9092	621	9712	200	421
4	11404	0	11404	0	0
5	10459	979	11438	200	779
6	12315	1013	13328	200	813
7	6697	2903	9599	200	2703
8	10309	0	10309	0	0

d) Relevance of the models

The first model implies no flexibility neither on the level of daily demand met nor on the delivery date. Indeed, Amazon needs to use spot vehicles whenever there are not enough available trucks, which can generate large costs when the demand is extremely high. Consequently, we came up with the second and third models designed with the purpose of satisfying a certain level of met demand, represented by the parameter α . Nevertheless, those models are not completely realistic, as the demand which is not met on a given day will never be satisfied. Therefore, in the fourth model, we introduced a dynamic approach: all the demand is met but we allow a maximum delay of one day. The demand that we cannot meet on the due date must be satisfied on the following day. This model matches more what happens in practice : all the demand should be met, as close as possible to the due date.

3. Costs and packages estimations

We tried to have realistic values for the different numbers presented below, because we think that we need to come up with values as close as in a real situation to bring value and make decent recommendations. In order to achieve this, we performed extensive research, the details of which can be found in Appendix A and will be used in the simulations.

- Estimation of the number of package per vehicle

An estimation of the number of package was calculated thanks to a three-step process:

Step 1: Estimation of the size of one package

Step 2: Estimation of the vehicle capacity

Step 3: Additional capacity assumptions and final value of packages/vehicle

The final value gave us an approximation of **425 packages/vehicle**.

- Estimation of C_g (cost of guaranteed vehicles)

Notation:

F: Fixed cost related to the delivery truck (per day per package)

W: Driver daily wage (per day)

M: Gas consumption (per mile)

$$C_g = F + W + M$$

C_g is provided per vehicle, assuming that only one driver is allocated to one vehicle, which is loaded once per day.

$$M = \$27/\text{vehicle}$$

$$F = \$21/\text{vehicle}$$

$$W = \$142/\text{vehicle}$$

$$C_g = (W + M + F) = \$ 190/\text{vehicle}$$

- Estimation of C_o (cost of optional vehicles)

As explained before, the cost of the optional vehicles is decomposed into 2 parts: C_o and C_o' .

$$C_o = 77\$/\text{vehicle} \text{ and } C_o' = \$ 184/\text{vehicle}$$

- Estimation of C_s (cost of spot vehicles)

$$C_s = \$2,350$$

4. Simulation results

a) Model simulations

After performing the simulation described in section 2, we obtained the values of X_g and X_o gathered in the following table:

Model	X_g	X_o	Total Cost (over a week)
Model 1	23	14	\$45,114 (baseline)
Model 2 ($\alpha = .95$)	23	12	\$43,921 (-2.64%)
Model 3 ($\alpha = .95$)	24	13	\$41,147 (-8.79%)
Model 4 ($T = 500$)	23	14	\$44,533 (-1.29%)

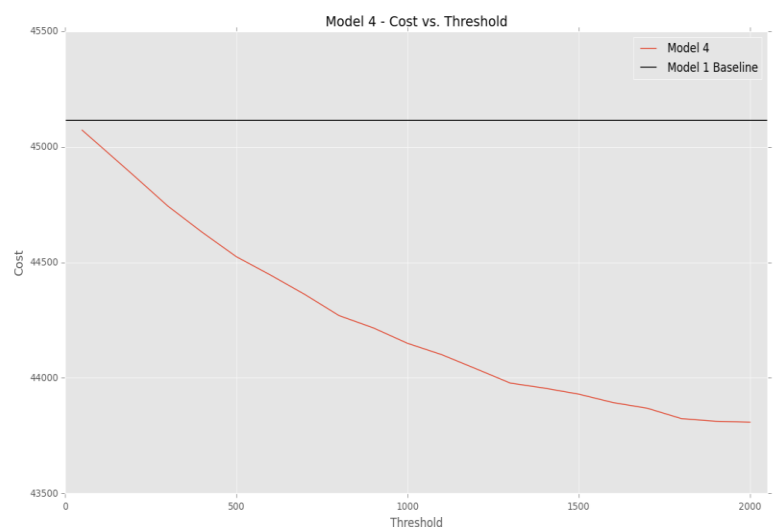
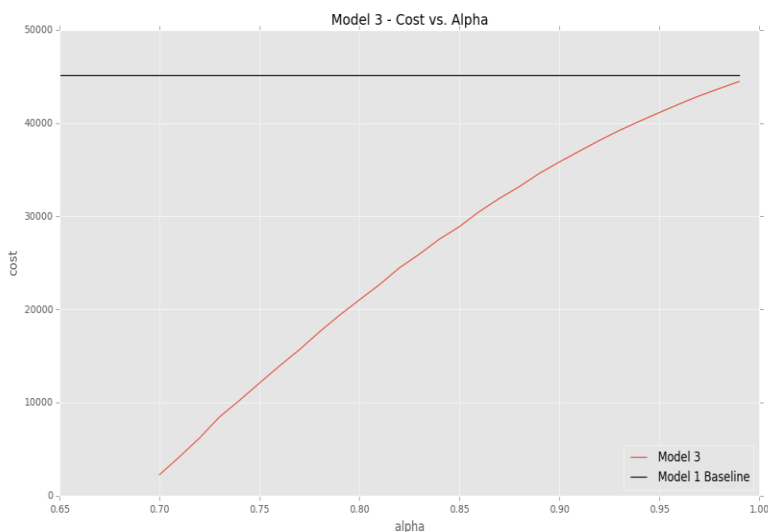
The first thing to notice is that the number of both guaranteed and optional vehicles are consistent over the different models, which means that Amazon will have the ability to choose among different policies without affecting the optimal number of vehicles. The other noticeable result is that the fourth model, implemented to authorize more leeway while still delivering every order, does not decrease the price as much as could have been expected.

We also observed during our simulations that our models were robust: even if the number of vehicles varies, the price increases by less than 1% with an X_g or X_o of 3 units away from the optimal values.

b) Analysis of parameters

We then observed the trend of the total weekly cost for different values of the model's parameters. The analysis for the 3rd model revealed that the value of α is critical for the overall cost. Therefore, while this model authorizes lost orders, which cannot be tolerated in a real situation, we reached the conclusion that ensuring the delivery of every customers, thus going through third parties for shipping, is where the biggest expenses will be made.

For the 4th model, we studied the influence of the number of orders that we allowed to be postponed to the following day. We observed that, while the overall trend is what we were expecting, delaying



deliveries of even 20% of the mean daily demand resulted in a decrease of the total cost of only 2.89%, which represents \$67,912 over a year.

5. Platform for securing vehicles

We assume that X_g and X_o are given. The process for securing vehicles is described as follows:

- 1) At the end of each week, Amazon sends to each driver his schedule for next week, via the platform. Every day, a driver could be assigned a guaranteed or an optional vehicle. For instance, on Friday, Joe receives the following schedule:

Monday	Tuesday	Wednesday	Thursday	Friday
Guaranteed	Optional	Guaranteed	Guaranteed	Guaranteed

According to the figures we found for the optimal number of guaranteed and optional vehicles, around 25 and 15 respectively, each driver is assigned approximately 15 optional days during a shift of 40 days (25+15).

- 2) We assume that the day before, at 7pm, the demand D for the day after is known. In any case, all the guaranteed drivers come.
 - a) $X_g > D$: We notify the optional drivers that they don't need to come.
 - b) $X_g < D < X_o + X_g$: We notify all the optional drivers if they need to come or not. The $D - X_g$ optional drivers supposed to come must confirm.
 - c) $D > X_o + X_g$: All the optional driver are notified that they need to come. They must confirm. We order X_s spot vehicles(eg: we need to fulfill all the demand $X_s = d - (X_o + X_g)$)

We define a policy for choosing which optional driver will be told to come, in case b), using the following ratio: $r = \frac{\#days(optional\ and\ called)}{\#days(optional)}$. If an optional driver is needed, the driver with the lowest ratio is called. This policy ratio guarantees that in the long run each driver is called the same amount of time.

If a driver either optional or guaranteed cannot come, he must notify Amazon through the platform at least before 7pm, the day before. Depending on the demand and the type of the driver, we make small adjustments given that the demand is known for the next day (eg: if $X_g < D < X_g + X_o$ and a guaranteed driver cancels an additional optional is called).

Exceptional case (accident, a driver doesn't show up...): an optional driver is called if possible, otherwise the delivery is delayed, as we assume that we can't call a spot vehicle for the same day.

6. Conclusion

This project has enabled us to tackle this problem with different perspectives:

At first, we approached this problem analytically by formulating an optimization problem, aiming at minimizing the expected total cost (integral formulation). This led to several model, considering different attributes of the service level. Beyond a theoretical solving approach, we decided to run simulations, enabling to compute the total cost according to the randomly generated daily demand. In order to make this model consistent with reality, we performed an extensive analysis of the cost structure based on real data. Finally, we conducted a sensitivity analysis to illustrate the influence of the choice of customer service.

Appendix A: Estimation of the costs and the number of packages each vehicle can transport

a) Estimation of the number of packages per vehicle

Step 1: Size of one package

According to a web scraping study ¹, we can estimate that 58% of the products sold by amazon can fit in an $18'' \times 18'' \times 18'' = 3.375 \text{ in}^3$ box. This includes books, small electronics, digital music songs, cell phone accessories and clothing shoes and jewelries ...

We will take this type of box as the standard box for the rest of the study.

Step 2: Vehicle capacity

An average city UPS truck size is a good approximation of what the studied vehicles capacity would look like. UPS fleet guide ² is providing us some sizes. To simplify the calculations we are going to take these values for the average vehicle capacity: $L=45'$, $H=8'$ and $W=8'$.

Step 3: Capacity assumption and packages/vehicle

However another factor to take into account is that on average the vehicles are not going to be 100% full with packages. Indeed some space is required for the delivering driver to circulate in the truck. Based on some research we found that on average these vehicles are full between 50% to 65% of their full capacity. Thus assume that the truck is full in average at 50% of its full capacity when the truck leaves to deliver the daily packages.

The new available capacity is $L'=45'$, $H'=4'$ and $W'=8$ for a corresponding volume of $1,440 \text{ in}^3$, which can contain 426.667 packages that we will round to **425 packages/vehicle**

b) Estimation of the costs

1. Guaranteed vehicle:

F: Fixed cost related to the delivery truck (per day per package)

W: Driver daily wage (per day)

M: Gas consumption (per mile)

$$C_g = F + W + M$$

C_g is provided per vehicle, assuming that only one driver is allocated to one vehicle, which is loaded once per day.

a) Estimation of M:

The volatility of the oil price pushed us to make an assumption on the diesel price, which will be at a constant price of **\$ 3.50/gallon**. According to a report evaluating the performance of UPS Diesel Hybrid Delivery vans³, the consumption per gallon for a hybrid vehicle is estimated to be **13.1 mpg**. Thus the cost per mile would be **\$0.267/mile**.

We also assume that during the 8 service hours, the vehicle will cover an average of **100 miles/day**. (5 hours of "real" driving time * average speed of 20 mph)

¹ <http://learn.scrapehero.com/chart-count-of-products-in-amazon-us-for-major-categories/>

² <http://lftl.upsfreight.com/shipping/instructions/Index.aspx?p=FINFO>.

³ <http://www.nrel.gov/docs/fy10osti/44134.pdf>

Finally we have $M = 100 \times 0.267$ which is rounded to **$M = \$27/\text{vehicle}$**

b) Estimation of F:

Table 1 is providing an estimation of the hybrid delivery truck price, which would be **\$20,000**. This low price includes the consideration that Amazon has a premium price for this purchase regarding the amount of vehicles purchased.

Table 1: Cost of a Hybrid Truck

Source: <https://www.californiahvip.org/making-the-case>

Example Fleet Cost Savings from Hybrid Truck Purchase			
	Incremental Hybrid Cost	HVIP Voucher	Net Hybrid Cost After Voucher
Package Delivery Truck	\$35,000	\$15,000	\$20,000

The car manufacturing industry is evolving toward a much cleaner consumption (Growth of electric and hybrid cars....); Amazon could rely on state subsidy programs such as California's Hybrid Truck and Bus Voucher Incentive Project to make such an investment. This is a decent assumption, which describes what the delivery truck industry will look like in the next 20 years, considering the future policy decisions related to the reduction of carbon emission. This will also save fuel cost over the current conventional delivery trucks. Indeed placed in the right application, hybrids and battery-electric vehicles can result in substantial fuel savings over vehicle life.

Assuming again that Amazon have a premium comparing to the normal customer, let us estimate the warranty cost to be \$50 per month which makes **\$1.67/day** (1 month=30 days). For the maintenance, based on the research done on UPS hybrid trucks⁴, the estimated cost is broken down into a fixed value per day, which includes for instance the parking spot cost for the truck, in addition to a variable cost per mile. The total warranty cost will be equal to: **\$0.15/mile + \$1/day**

Finally we will obtain F, considering the 100 miles/day assumption and that the truck price is going to be amortized in 20 years this will make a total cost of (Assuming that 1 year = 365 days):

$$F = \frac{20,000}{20 \times 365} + 0.15 \times 100 + 1 + 1.67 = \$20.41$$

F = \$21/vehicle

c) Estimation of W:

For the average wage (W) of the "Light Truck or Delivery Services Drivers", according to the Bureau of Labor Statistics website⁵ we can either focus on the "Local Messengers and Local Delivery" industry and take the national hourly mean wage or focus on the area we are delivering in for the general Delivery Services Drivers industry e.g the San Francisco-San Mateo-Redwood City metropolitan area for example.

The two different assumptions give two different prices (see table 2):

Table 2: Annual mean wage statistics

Industry		Employment (1)	Percent of industry employment	Hourly mean wage	Annual mean wage (2)
Local Messengers and Local Delivery		21,150	39.65	\$16.10	\$33,490
San Francisco-San Mateo-Redwood City, CA Metropolitan Division	5,500	5.06	0.86	\$19.39	\$40,340

⁴ <http://www.nrel.gov/docs/fy10osti/44134.pdf>

⁵ <http://www.bls.gov>

Taking the average of the two prices will give us a more accurate hourly mean wage = **\$ 17. 745** taking into account both the industry and the geo-localization.

We are also assuming that the average working time during a day is 8 hours. Indeed the daily mean wage will be **W = \$142/vehicle**

d) Total estimation of Cg:

Therefore the Final Cost Cg for delivery per day is **Cg= (W + M + F)= \$ 190/vehicle**

2. Optional vehicle:

As explained before, the cost of the optional vehicles is decomposed into 2 components: Co and Co'.

a) $Co = F - 0.15 \cdot 100 + W/2$, W/2 is the extra cost that Amazon will have to pay to make the driver available in case we need him. 0.15*100 is taken off from F because it is a variable cost (per mile) that we will bring back in Co' in case the driver is called.

b) $Co' = M + 0.15 \cdot 100 + W = \$184/\text{vehicle}$

Co = 77\$/vehicle and Co' = \$ 184/vehicle

3. Spot vehicle:

To approximate the cost of a spot vehicle, let us use the annual sales (2013) of Amazon and the total number of packages shipped in the same year. The shipping cost (SC) per package would be equal to:

$$SC = \frac{\text{Shipping cost for global activities}}{\text{Number of packages shipped in the United states}} * \frac{\text{North American sales activities}}{\text{Sales of global activities}}^6 * R = \$5.54$$

- Total number of packages shipped by Amazon in the US in 2013⁷: **608 Million/year**
- Total shipping cost for global activities of Amazon in 2013⁸: **\$6,636 Million**
- Since we are using the North American sales activities, we shall multiply the formula by the ratio $R^9 = \frac{\text{USA population in 2013} - \text{Canada population in 2013}}{\text{USA population in 2013}} = 35M/316M = 0.89$

SC = \$5.54/package which leave us with Cs = \$2,352.5, using the assumption 1 vehicle is loading 425 packages per day. **Cs = \$2,350**

⁶ <http://www.sec.gov/Archives/edgar/data/1018724/000119312513028520/d445434d10k.htm>

⁷ <http://www.scdigest.com/ontarget/14-04-30-1.php?cid=8012>

⁸ <http://seekingalpha.com/article/2921836-amazon-com-will-be-facing-much-higher-shipping-costs-even-with-lower-crude>

⁹ <https://en.wikipedia.org/>

APPENDIX B: Additional Results

a) Cost Stability

As we used simulation, we were aware that the main drawback is that we might obtain results that were not representative of reality. So we analyzed 1,000 expected costs obtained from 100,000 simulations. The results, presented in the table below, show that the simulation-based method is very robust as the standard deviation across 1,000 values of costs is approximately only 17, for a mean of \$40,000+. These results give us great confidence in what we presented in this report and the recommendations we made.

	Model 1	Model 2	Model 3	Model 4
Mean	45,132	43,922	41,140	44,527
Std. Dev.	16	15	25	13
Min	45,070	43,873	41,062	44,484
25%	45,121	43,911	41,122	44,518
50%	45,132	43,921	41,140	44,526
75%	45,142	43,931	41,158	44,534
Max	45,182	43,973	41,218	44,571

b) Reliance on Spot Vehicles

In Appendix A we showed that there is a large difference between the costs of in-house vehicle and third parties, which cost almost 10 times the price of an in-house vehicle. Therefore, we wanted to see how heavily our models relied on these third parties.

We performed simulations over 100,000 weeks to take into account the different demands, and we counted the number of days where spot vehicles were required for each model.

	Model 1	Model 2	Model 3	Model 4
Spot Vehicle Use	4.33%	4.58%	4.33%	6.40%

As shown in the table above, the third parties are hardly used, which is consistent with the difference in price we found.