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EFFICIENCY OF NON-COMPLIANCE CHARGEBACK MECHANISMS IN RETAIL SUPPLY CHAINS

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ABSTRACT

In practice, suppliers fill retailers' purchase orders to the fill-rate targets to avoid the non-compliance financial penalty, or chargeback, in the presence of service level agreement. Two chargeback mechanisms – flat-fee and linear – have been proven to effectively coordinate the supply chain in a single-period setting. However, the mechanisms' *efficiency*, the incurred penalty costs necessary to coordinate the supply chain, have not been studied yet. Since retailers are often accused of treating chargeback as an additional source of revenue, this study compares the expected penalties resulted from the flat-fee or linear chargeback to shed light on the retailers' choice of mechanisms. Using experimental scenarios consisting of various demand functions, demand variabilities, and fill-rate targets, the simulation results offer counter-evidence to the accusation.

1 INTRODUCTION

To retailers, any non-compliance on product availability can lead to not only operational disruptions but also revenue loss. It has been estimated that North American retailers annually lose $158.5 billion in revenue due to supplier issues, and 4.1% of that loss could be related to out-of-stock non-compliance (Chain Store Age 2016). To mitigate this issue for its merchandise suppliers, a retailer may create and maintain a service level agreement (SLA) as a reference for the inbound logistics and fulfillment requirements. Ideally, SLAs provide clear guidance as to how the purchase orders should be fulfilled. A jointly agreed-upon SLA between a supplier and a retailer can benefit both parties by enhancing the overall merchandise handling and customer service (CVS/pharmacy 2016). SLA is a widely-used contract in a variety of industries, especially in the field of retailing (Sinha and Ganesan 2011, Chen 2016). In fact, many SLAs state that, as soon as a supplier acknowledges the business relationship with the retailer and starts to process any orders, the SLA is deemed effective immediately and serves as a binding contract (Toys"*R*"Us 2013, Kroger 2015).

In the presence of an SLA, a retailer can impose a chargeback on its suppliers should they fail to meet the contractually specified expectations, such as the fill-rate target (Chen and Thomas 2016). Typically, the fill-rate target is defined as a ratio of the shipment quantity received to the shipment quantity ordered within a predetermined time horizon (Thomas 2005). From a retailer's perspective, a chargeback is a revenue, but from a supplier's perspective, it is a cost. As a result, the practitioners' perceptions on chargeback are rarely unanimous. Some think that the chargeback is a way for retailers to recoup their financial loss due to unsatisfactory service levels, while the others think that the chargeback is just a way for retailers to artificially inflate their own profits (Anderson 2010). Hence, retailers can often be accused of treating chargebacks as an additional source of revenue (Gilmore 2010, Barry 2013).

In practice, chargebacks can be characterized by the *mechanisms* and *terms*. The mechanisms indicate the structure of penalty cost to be *flat-fee* or *linear*. Under a flat-fee chargeback, the penalty cost stays constant for any non-compliance events, regardless of how much the actual fill rate fell short of the contractual fill-rate target. In contrast, under a linear chargeback, the penalty cost in any non-compliance event can linearly vary with the *shortfall quantity* which is the quantity that was ordered but not received in time. The terms of a given mechanism further specify the magnitude of the penalty cost. That is, a flat-fee chargeback would be some constant figure, whereas a linear chargeback would a multiplier to any shortfall quantity.

In terms of supply chain contracts, chargebacks are essentially a transfer payment between a supplier and a retailer in the context of supply-chain coordination. Prior studies have shown that the flat-fee or linear chargeback can *effectively* coordinate the supply chains in a single time period setting. Considering the case where replenishment lead time is zero, Liang and Atkins (2013) proved the existence of optimal base-stock levels for minimizing a supplier's expected cost of flat-fee or linear chargeback. Sieke et al. (2012) analytically established the relation between fill-rate target and chargeback that induces the optimal base-stock levels. Katok et al. (2008) viewed SLAs as coordination mechanisms and experimentally investigated the implications of SLA parameters on a supplier's optimal base-stock level. Based on the literature review, the presumption of our study is that both the flat-fee and linear chargebacks can be effective mechanisms in supply-chain coordination.

Despite its rightful purpose in coordinating the supply chain, the penalty cost assessed as chargeback concerns many suppliers as the increasingly onerous chargeback of all sorts could amount to a detrimental share of a supplier's annual sales revenue (Anderson 2010). In fact, many suppliers have gone out of business as a consequence of hefty chargebacks (Rozhon 2005). Assuming that the *efficiency* of a mechanism is inversely proportional to its resultant expected penalty cost, we believe that a chargeback mechanism should be not only effective but also efficient so that it causes the smallest possible transfer payment between a supplier and a retailer. To the best of our knowledge, little attention has been paid to the efficiency of chargeback mechanisms.

To model empirically grounded chargeback mechanisms and terms, we have sampled 29 SLAs of U.S. retailers that specify flat-fee or linear chargeback as shown in Table 1. Clearly, not all of the retailers

Table 1: Observation of SLA chargeback mechanisms and fill-rate target.

Frequency		Mechanisms	
		Linear chargeback	Flat-fee chargeback
Fill-rate target	$\geq 98\%$	5 (e.g., Lowe's (2015))	14 (e.g., Nordstrom (2016))
	$< 98\%$	0	10 (e.g., Burlington Stores (2016))

use the same chargeback mechanism. Moreover, we suspect that all of the retailers set the chargeback mechanism and fill rate-target as shown in Table 1 for a reason, and our conjecture is that they pair the mechanism and the target so as to artificially *inflate* penalty payments from the supplier. To this end, we herein define the relative *efficiency* of flat-fee and linear chargebacks as follows:

Definition 1 If the expected penalty cost for coordinating the supply chain is smaller under one chargeback mechanism than under the other, then the former has a higher efficiency than the latter.

To facilitate the understanding of this study, Figure 1 summarizes the SLA academic literature review and the research question of this study. The remainder of this paper is organized as follows: Section 2 of this paper presents a simple supply chain model. In Section 3, we present the Monte Carlo simulation analyses and results. In Section 4, we conclude the paper.

2 SUPPLY CHAIN MODELING

We consider a single-period newsvendor model and a simple supply chain consisting of one supplier and one retailer. The retailer places one purchase order in every period. The demand quantity D is a random variable that is independent, identically distributed, and stationary across time periods. $\phi(\cdot)$ and $\Phi(\cdot)$ denote the probability density and cumulative distribution functions of demand, respectively. The retailer

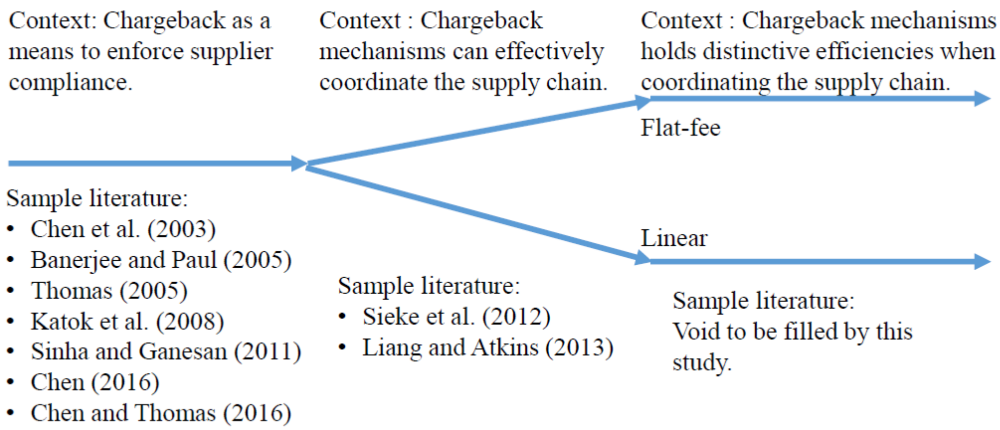

Figure 1: Diagram of the academic literature on which this paper is based.

measures the single-period fill rate against the target β. The supplier follows a periodic-review, base-stock level y inventory policy, and replenishes inventory with negligible lead time. Moreover, the supplier incurs the expected inventory holding cost H and the expected penalty cost P_m. The subscript $m \in \{f,u\}$ denote the flat-fee mechanism, f, and linear chargeback mechanism, u. We can hence write the expected penalty cost as

$$P_m(a,b) = \begin{cases} \mathbb{E}\left[a+b(D-y)^c\right] & \text{if } \beta D > y, \\ 0 & \text{if } \beta D \leq y, \end{cases}$$

where a is the flat-fee chargeback term, b is the linear chargeback term, and c is a binary variable contingent upon the retailer's chargeback mechanism choice. Particularly, $c = 0$ if $m = f$, and $c = 1$ otherwise.

Subsequently, we construct the supplier's expected total inventory cost, which is the sum of the expected holding cost and the expected penalty cost (Akcay et al. 2013):

$$\begin{aligned} G_m(y) &= H + P_m(a,b) \\ &= h\int_0^y (y-x)\phi(x)dx + \int_{y/\beta}^{\infty} \left[a+b(x-y)^c\right]\phi(x)dx, \end{aligned}$$

where h is the unit holding cost per excess inventory per time period. Next, we verify the convexity of the expected total inventory cost with respect to the base-stock level by taking the first partial derivative:

$$\frac{\partial G_m(y)}{\partial y} = h\Phi(y) - \frac{1}{\beta}\phi\left(y/\beta\right)\left[a+b\left(\frac{y}{\beta}-y\right)^c\right] - \int_{y/\beta}^{\infty} bc\left(x-y\right)^{c-1}\phi(x)dx. \quad (1)$$

Clearly, the first term of (1) increases in y, and the second and third terms of (1) would be negative given any non-negative values of a and b. That is, the higher the base-stock level, the smaller the expected penalty cost. Hence, the total expected cost is a convex function with respect to the base-stock level. As a result, one can specify ϕ and Φ before deriving the globally optimal base-stock level y^* that minimizes the expected total inventory cost by solving (1) equal to zero.

The retailer assumes that the supplier sets the base-stock level using (1). If the retailer's SLA sets a flat-fee chargeback, i.e. $m = f$, we set $b = c = 0$, and the coordinating flat-fee chargeback term is

$$a(y^*) = h\Phi(y^*)\frac{1}{(1/\beta)\phi\left(y^*/\beta\right)}. \quad (2)$$

Similarly, if the retailer's SLA sets a linear chargeback, i.e., $m = u$, we set $a = 0$ and $c = 1$, and the coordinating linear chargeback term is

$$b(y^*) = h\Phi(y^*)\frac{1}{(y^*/\beta)(1/\beta - 1)\phi(y^*/\beta) + 1 - \Phi(y^*/\beta)}. \tag{3}$$

For (2) and (3), we use $\tilde{y}$ which, on average, warrants the fill-rate target with a single-period review horizon (Chen et al. 2003, Banerjee and Paul 2005, Thomas 2005):

$$\begin{aligned} \tilde{y} = \quad & \underset{y}{\text{argmin}} \quad \left\{ \mathbb{E}\left[\frac{\text{Minimum}\{D, y\}}{D}\right] - \beta \right\} \\ & \text{subject to} \quad \mathbb{E}\left[\frac{\text{Minimum}\{D, y\}}{D}\right] > \beta. \end{aligned}$$

In a coordinated supply chain, $\tilde{y}$ can render the same minimized expected holding cost under the two chargeback mechanisms for comparison purposes. Note that we use $\tilde{y}$ instead of y^* because deriving a closed-form solution of y^* from (1) without specific functions for ϕ and Φ is not straightforward. Moreover, we believe no supplier in practice would intentionally set some base-stock level that is destined to fail the fill-rate target and disappoint its retailer.

3 MONTE CARLO SIMULATIONS

We use MATLAB codes to simulate penalty costs and holding costs of the supplier facing various demand variability or functions. Regarding demand variability, McGavin et al. (1993) investigated inventory allocation policies while setting the retailers' demand coefficient of variation (CV) to be low (0.1), medium (0.33), or high (1). Waller et al. (1999) found that a retailer's demand CV can be as high as 2 in practice, but the authors specified CV to be low (0.1), medium (0.5), or high (1.0) for simulation purposes. Similarly, Johnson et al. (1995) in the numerical experiments set CV=$\{0.1, 0.5, 1.0\}$ and Silver et al. (2009) set CV= $\{0.1, 0.3, 0.5\}$.

Regarding demand functions, we consider a number of different probability distribution functions for simulating random demand as we do not assume any specific product-life-cycle phase or nature of a product. That is, a generic product life cycle includes introduction, growth, maturity, saturation, and decline phases (Aitken et al. 2003). As a product moves from one life-cycle phase to another, the distribution function of the product demand is likely to change (Graves and Willems 2008). Additionally, product demand variability can depend on the nature of the product (e.g., functional or innovative) or on the industries (e.g., consumer product or electronic product) (Fisher 1997, Waller et al. 1999).

To generate random demands, we set aside a sample path of 10 million uniformly distributed random numbers between 0 and 1 to feed the inverse cumulative distribution functions each corresponding to the specified demand distribution, a method known as the inverse transform sampling. The distribution parameters are adjusted to yield the desired range of CV and to keep the expected demand constant.

3.1 Demand Functions

We will use three common distributions – Lognormal, Gamma, and Negative Binomial – to generate random demands. We believe these functions reasonably represent a wide variety of demand scenarios that a supplier may face. When enlisting potential demand distribution functions for this study, we consider those which have been conventionally used for modeling stochastic demands. Additionally, the functions must allow us to vary demand CV without altering the expected demand for fair comparisons. For example, Poisson function is popular for modeling slow-moving items, but it does not allow us to vary the demand CV without altering the expected demand.

Some notes about the enlisted demand functions are as follow. The Negative Binomial function has been shown to fit a wide variety of empirical demand distributions, particularly at the retail level (Silver et al. 2012). Specifically, the discrete Negative Binomial distribution function typically represents stochastic demands of a slow-moving item (Silver et al. 2012). Some other studies that used Negative Binomial function are Bagchi et al. (1983), Bagchi et al. (1986), Gallego et al. (2007), Silver et al. (2012), Bijvank (2014). Demands that are highly volatile (large CV) tend to be modeled by Lognormal function (Teunter and Duncan 2009, Huang 2013). Some other studies that used Lognormal function are Das (1983), Johnson et al. (1995), Gallego et al. (2007), Hsieh and Lu (2010), Berman et al. (2011). Gamma function is highly flexible and can assume almost any shape, hence ideal for modeling slow-moving items as well as fast-moving items with appropriate scaling of the units of measure (McGavin et al. 1993, Keaton 1995, Tyworth et al. 1996, Ramamurthy et al. 2012). Some other studies that used Lognormal function are Moors and Strijbosch (2002), Berman et al. (2011). (In fact, we ran the following experiments with truncated Normal and Uniform functions as well, but the results added little value to our findings, so we decided to not report them here for the brevity of this study.)

3.2 Simulation Experiments

To align with the literature, the intended demand CV for this study is between 0.1 and 1. Constrained by the integer input for the parameter, the Negative Binomial function does not allow consistent CV increment. Thus, we will have irregular CV increments for Negative Binomial function, compared to the other functions. Moreover, only when the expected demand is 100 can we have the demand CV between 0.1 and 1 for Negative Binomial function. Therefore, for every demand distribution besides Negative Binomial, we will adjust the function parameters such that the expected demand always stays at 100. Of the three functions, only Lognormal and Gamma function permit the intended range and consistent increments of CV for the simulation purposes. Please see Appendix A for the input for the function parameters considered in the simulation and the resultant range of the flat-fee or linear chargeback terms.

First, we examine the effects of distribution function on the supplier's base-stock level $\tilde{y}$. Figure 2 shows that the functions used for modeling random demands can affect the supplier's base-stock level, especially when CV is high. For example, $\tilde{y}$ for the Lognormal demand is much larger than that for the Gamma demand, which may be attributable to the shape of the function, as discussed in Appendix B.

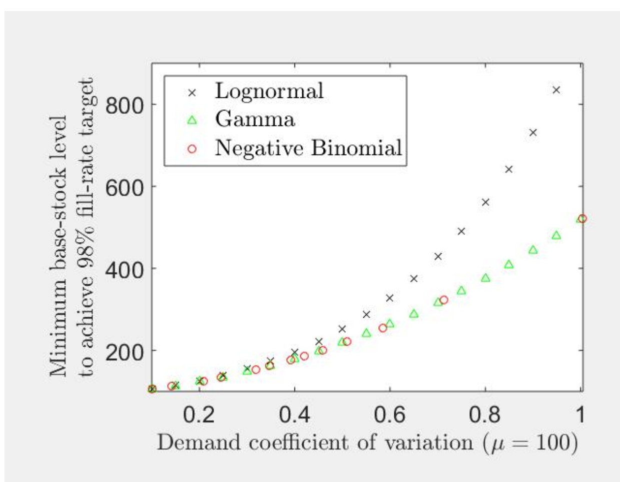

Figure 2: Different demand functions, though with the same expected demand and the same demand CV, can result in different base-stock levels for achieving a 98% fill-rate target.

Second, we consider the percentage of the expected penalty cost relative to the expected holding cost:

$$\left(\frac{P_m}{H}\right) \times 100\%.$$

The measure of the expected costs ratio allows us to focus on the expected penalty costs in contrast to the expected hold cost rather than the absolute magnitude of the individual expected costs. Without loss of generality, we set $h = 1$. Figure 3 suggests that suppliers facing different demand variabilities might not feel the burden of chargeback the same way. In general, an increase in demand variability causes the supplier to increase its base-stock level to warrant a given fill-rate target. In the experiments, the impact of increasing demand variability on the expected penalty cost tends to be increasingly outweighed by the impact of the increasing base-stock level on the expected holding cost. As a result, suppliers may feel the heaviest burden of a chargeback if demand variability is low as opposed to high. Comparing the panels between chargeback mechanisms (across columns), we may see that the supplier's perception of chargeback is less affected by the demand functions when the chargeback is flat-fee than when the chargeback is linear. Comparing the panels between fill-rate targets (across rows), we see that fill-rate target can be a significant factor that affects how a supplier may perceive the presence of a chargeback relative to holding cost.

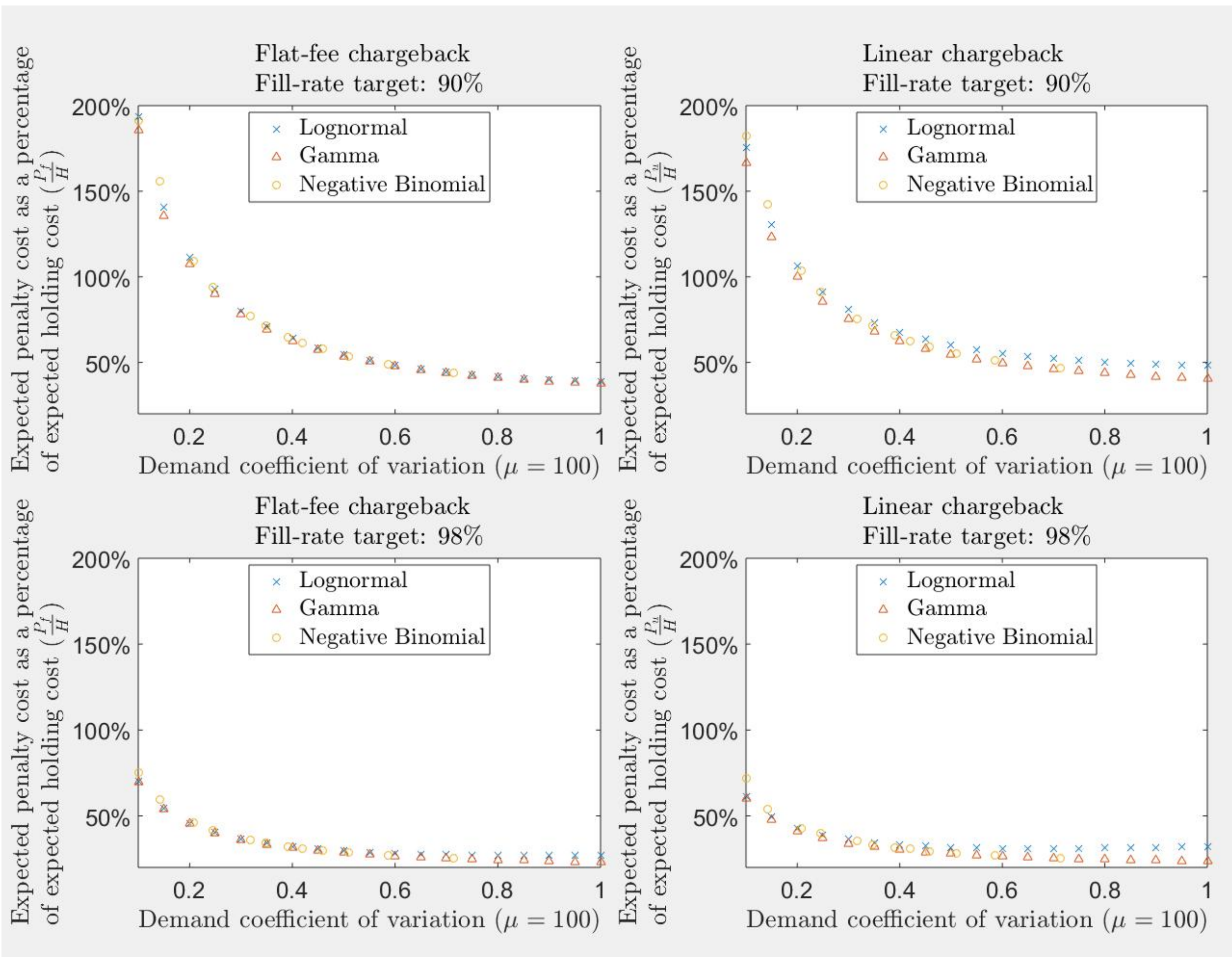

Figure 3: Given the base-stock levels attaining the specified fill-rate targets, the demand functions can affect the expected penalty costs as a percentage of the holding cost.

Third, we explicitly evaluate the relative efficiency of the chargeback mechanisms by comparing the ratios of the expected holding cost to the expected total cost:

$$\left(\frac{H}{G_f} - \frac{H}{G_u}\right) \times 100\%.$$

For example, if the difference is positive, then the flat-fee chargeback mechanism is more efficient than the linear chargeback mechanism in coordinating the supply chain. That is, the flat-fee chargeback results in a smaller expected penalty cost than does the linear chargeback, all else being equal. As mentioned, Lognormal and Gamma functions not only generate non-negative demands but enable consistent CV increment between 0.1 and 1; we, therefore, use those two functions to demonstrate the effects of demand CV or fill-rate target on the magnitude or sign of the efficiency difference. Figure 4 clearly shows that, for a given fill-rate target, the retailer facing stable demands may collect larger transfer payments by setting a flat-fee chargeback, whereas the retailer facing volatile demands may collect larger transfer payments by setting a linear chargeback. More important, this figure suggests that there could be some relationship between the chargeback mechanism and the fill-rate target, especially when the demands follow a Gamma distribution.

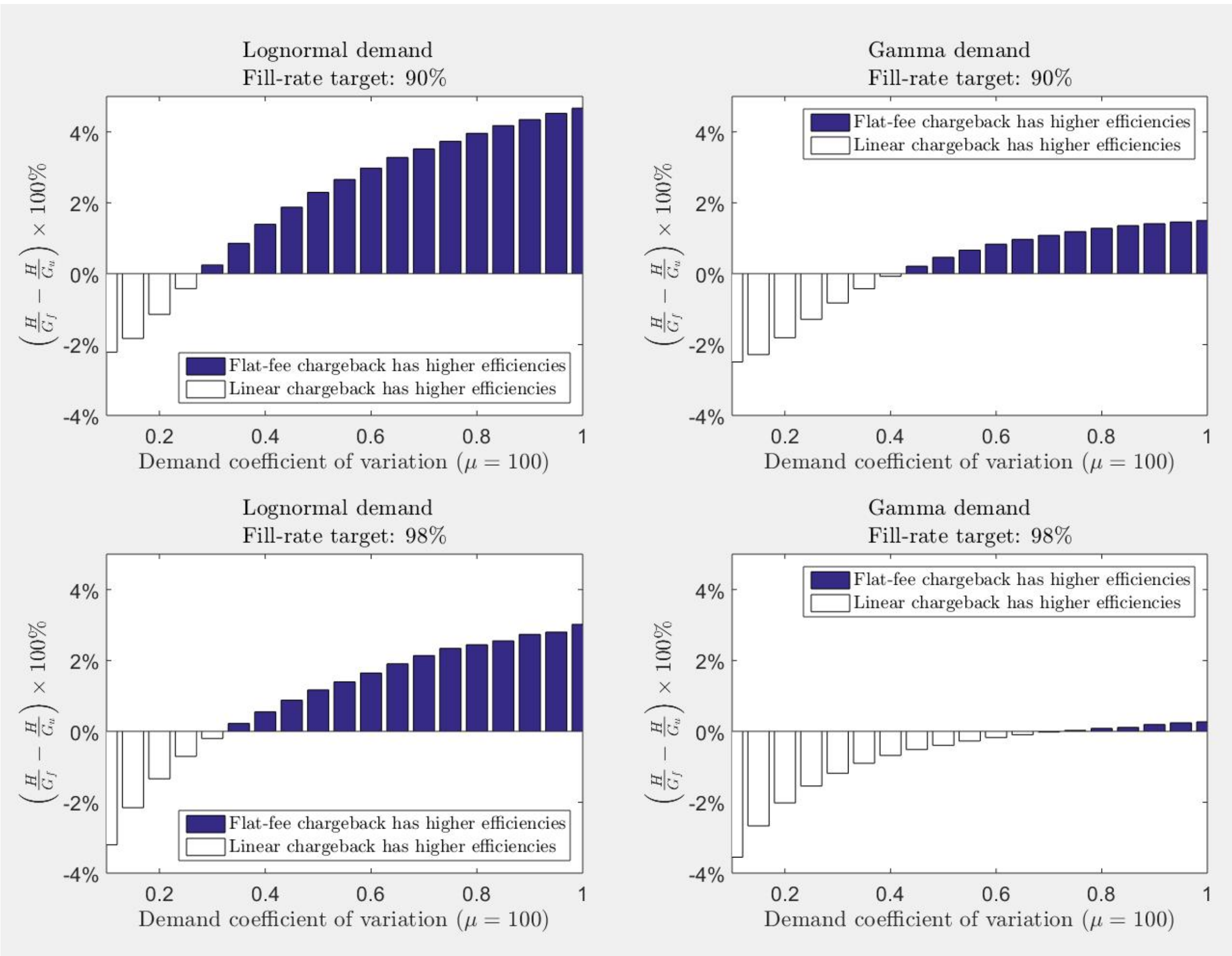

Figure 4: Demand variability, distribution, or fill-rate target can affect efficiency of chargeback mechanisms.

Finally, we plot a 3-D relative chargeback efficiency to further shed light on the conjecture raised earlier regarding retailers might be treating chargeback as an additional source of revenue. Figure 5 visualizes the simultaneous influence of the demand CV and the fill-rate target on the efficiencies under a given demand distribution. The circled dash lines in the panels denote the latitude where the efficiencies of the two mechanisms are equivalent. This figure reaffirms the findings that the effective mechanisms have distinctive efficiencies in coordinating the supply chains. Most important, Figure 5 shows that the linear chargeback mechanism tends to have a greater efficiency with smaller demand CV and higher fill-rate target. On the contrary, the flat-fee chargeback mechanism tends to have a greater efficiency with larger demand CV and lower fill-rate target. Therefore, the retailers using the linear (flat-fee) chargeback mechanism tend to receive *smaller* transfer payments from the supplier if the fill-rate target is higher (lower). Recall the conjecture that retailers choose the chargeback mechanism and fill-rate target to artificially inflate penalty payments from the supplier, our findings suggest otherwise because the retailers in the upper-left or lower-right quadrants of Table 1 are counterexamples.

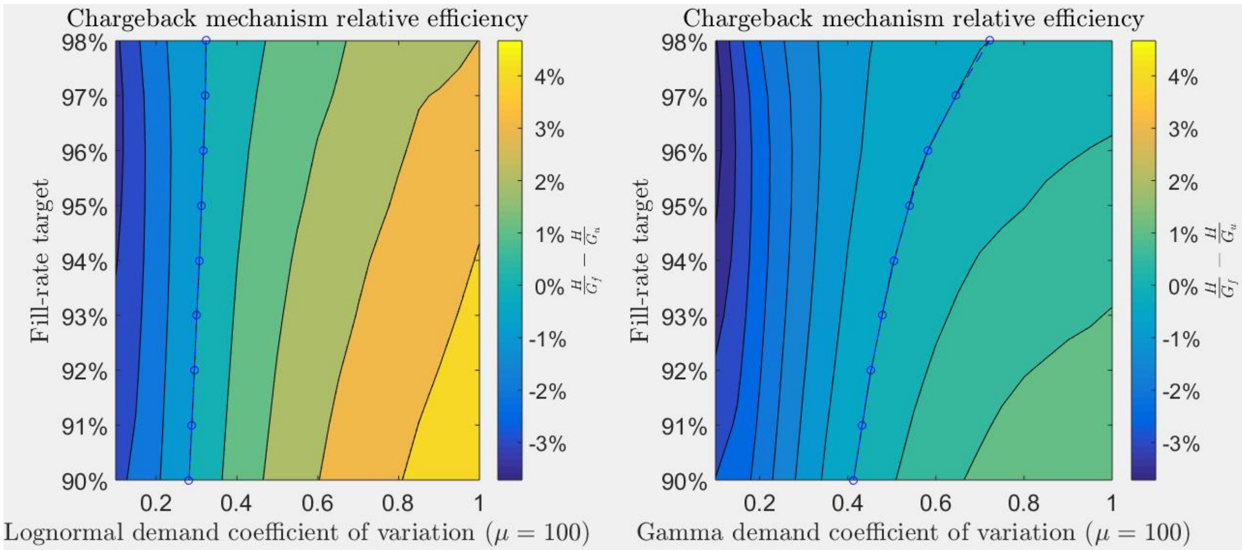

Figure 5: Lighter yellow areas are where the flat-fee chargeback have higher efficiencies as compared to the linear chargeback. High demand CV or low fill-rate target tends to render high efficiency for the flat-fee chargeback mechanism.

4 CONCLUSION

The practice of issuing non-compliance chargeback to suppliers is very common, especially in the retail industry. However, the retailers are often accused of treating the chargeback as an additional source of revenue. Prior studies have proven the effectiveness of the flat-fee and linear chargeback in coordinating the supply chains, but little research on the efficiency of the chargeback mechanisms can be found. In this study, we assume the chargeback efficiency is inversely proportional to the expected penalty cost under a single-period newsvendor model consisting of a single supplier and a single retailer. We collected a sample of SLAs to identify some pattern with respect to the chargeback mechanism and the fill-rate target. Using various demand functions, demand variabilities and fill-rate targets, we found that the chargeback mechanisms demonstrate distinctive efficiencies and hence should not be underestimated.

The key practical implications of the results are as follows. First, the SLA chargebacks tend to be a rather imminent issue to the suppliers that face low demand variability than to the suppliers that face high demand variability. While the literature suggests that suppliers generally do not like chargebacks, the suppliers that complain chargebacks the most might not necessarily be those that face volatile retailer demands. Second, the choice of chargeback mechanisms hold the opportunity of alleviating suppliers' financial burden of chargeback. Many retailers claim that they have no monetary goal regarding chargebacks for SLA non-compliances. We think the retailers that are not aware of the distinctive efficiencies of the mechanisms could unintentionally choose a mechanism that tends to result in penalty costs larger than some other mechanism does.

We suggest the following directions for future work. Researchers may adopt the framework of this study and investigate the efficiency of some other chargeback mechanisms. For example, Chen (2016) pointed out that the chargeback mechanisms can be affine (i.e., a combination of flat-fee and linear penalties) or non-linear (e.g., a convex function of inventory shortage). Another potential extension of this study is using different research methodologies to triangulate the results of this study. For example, researchers can conduct survey or interview to gain qualitative insights on the reason that different retailers adopt different chargeback mechanisms.

APPENDICES

A Function Parameters

A.1 Expected Demand

According to Graves (1985), a Negative Binomial distribution can be written as

$$\phi(j) = \binom{r+j-1}{j} p^r (1-p)^j,$$

where j denote the number of failures until the experiment is stopped, p denote the success probability, r denote the number of successes. The expected number of failures can then be written as $\mathbb{E}[D] = \mu = r(1-p)/p$. In the simulations, we want to vary demand CV while controlling the expected demand. That is, the relationship of $p = r/(\mu+r)$ must hold for a given μ. Consider the variance (σ^2) of demand following Negative Binomial distribution is $r(1-p)/p^2$. Thus, $CV = \sqrt{(\mu+r)/(\mu r)}$. Hence, we will set μ such that a range of r are able to generate the range of CV we desire for simulation purposes. For example, if $\mu = 10$, then CV has to be between

$$\left[\lim_{r\to\infty}\sqrt{\frac{10+r}{10r}}, \sqrt{\frac{11}{10}}\right] = [0.3162, 1.0488].$$

If $\mu = 100$, then CV has to be approximately between $[0.100, 1.005]$ which is the desired range of CV for this study. Thus, we will use $\mu = 100$ for the other functions as well throughout this study.

A.2 Demand Variability

Of the three demand functions under consideration, Negative Binomial function is the least flexible in terms of adjusting CV without altering the expected demand. Table 2 summarizes the numerical input for the function parameters to generate CV between 0.1 and 1.005.

B Skewness Comparison

The CV of the demands following a Lognormal distribution is $\sqrt{e^{\theta^2}-1}$, where θ denote the scale parameters. The skewness of the Lognormal demands is $\left(e^{\theta^2}+2\right)CV$. The CV of the demands following a Gamma distribution is $1/\sqrt{k}$, where k is the shape parameter. The skewness of the Gamma demands is 2CV. Therefore, for any given CV, Lognormal demand has a greater skewness than does Gamma demand.

Table 2: Paired parameter values for generating demand CV between 0.1 and 1.005 and the resultant ranges of the chargebacks.

Functions	Lognormal		Gamma		Negative Binomial	
Parameters	Log mean	Log standard deviation	Shape	Scale	Number of successes	Prob. of success event
Paired values	⋆4.60	⋆0.10	⋆100.00	⋆1.00	⋆10000.00	⋆0.99
	4.59	0.15	44.44	2.25	100.00	0.50
	4.59	0.20	25.00	4.00	30.00	0.23
	4.57	0.25	16.00	6.25	20.00	0.17
	4.56	0.29	11.11	9.00	11.00	0.10
	4.55	0.34	8.16	12.25	9.00	0.08
	4.53	0.39	6.25	16.00	7.00	0.07
	4.51	0.43	4.94	20.25	6.00	0.06
	4.49	0.47	4.00	25.00	5.00	0.05
	4.47	0.51	3.31	30.25	4.00	0.04
	4.45	0.55	2.78	36.00	3.00	0.03
	4.43	0.59	2.37	42.25	2.00	0.02
	4.41	0.63	2.04	49.00	#1.00	#0.01
	4.38	0.67	1.78	56.25	N/A	
	4.36	0.70	1.56	64.00		
	4.33	0.74	1.38	72.25		
	4.31	0.77	1.23	81.00		
	4.28	0.80	1.11	90.25		
	#4.26	#0.83	#1.00	#100.00		
Chargeback	Flat-fee		Flat-fee		Flat-fee	
Minimum	⋆4.92	($\beta = 90\%$)	⋆4.91	($\beta = 90\%$)	⋆5.54	($\beta = 90\%$)
Maximum	#279117.40	($\beta = 98\%$)	#19311.85	($\beta = 98\%$)	#19593.03	($\beta = 98\%$)
Chargeback	Linear		Linear		Linear	
Minimum	⋆0.25	($\beta = 90\%$)	⋆0.25	($\beta = 90\%$)	⋆0.29	($\beta = 90\%$)
Maximum	#1112.29	($\beta = 98\%$)	#177.86	($\beta = 98\%$)	#180.36	($\beta = 98\%$)

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