Appendices

A. Model

We develop a stylized consumer choice model to capture how consumers react to delivery speed information in their purchasing and returning stages. We first model customers' ex ante purchasing decision. We assume that a customer has a budget limit M and decides on the budget c to spend on general goods and the budget g to spend on products on Collage.com, which are often time-sensitive. That is, the budget constraint is $c+g=M$. The consumer receives the following utility from making a purchase:

$$u(c,g)=\begin{cases} c+\mathbb{E}\,v(g) & \text{if } g>0,\\ c & \text{if } g=0,\end{cases}$$

where $v(g)$ is the utility obtained from buying time-sensitive products. They only bring a positive utility if their arrival time t_a is earlier than the customer's deadline t_d:

$$v(g)=\begin{cases} \log(g) & \text{if } t_a\le t_d,\\ 0 & \text{if } t_a>t_d.\end{cases}$$

For a given customer, t_d is deterministic. Because the actual delivery speed is subject to uncertainty, t_a is stochastic.

We assume that customers do not have full information about the arriving time t_a when they make the purchasing decision. They can only observe the speed information t_p promised by the retailer. When the retailer promises that the order will arrive before t_p, customers expect the actual delivery speed to be uncertain and thus add a rational adjustment ϵ to the promised time:

$$t_a=t_p+\epsilon, \tag{9}$$

where $\epsilon\sim F_\epsilon(x)$. If the retailer often delivers orders earlier than the promised date, customers would rationally expect their delivery speed to be faster, that is, $\mathbb{E}\,\epsilon<0$. Similarly, if the retailer often overpromises and delivers orders later than the promised date, customers would adjust their expected delivery speed to be slower, that is, $\mathbb{E}\,\epsilon>0$.

Given t_d and t_p, we have

$$\mathbb{E}\,v(g)=\Pr(t_p+\epsilon>t_d)\times 0+\Pr(t_p+\epsilon\le t_d)\times\log(g)=F_\epsilon(t_d-t_p)\log(g).$$

We can see that, given t_d, the expected utility of consuming g is a decreasing function of t_p. This means that a more aggressive promise, that is, a lower t_p, increases customers' expected utility.

The customer maximizes the utility function subject to the budget constraints:

$$\begin{aligned} \max_{c,g} \quad & u(c,g) = c + \mathbb{E}\, v(g) \\ \text{s.t.} \quad & c + g = M, \\ & g = 0 \text{ or } g \geq \underline{g}, \end{aligned}$$

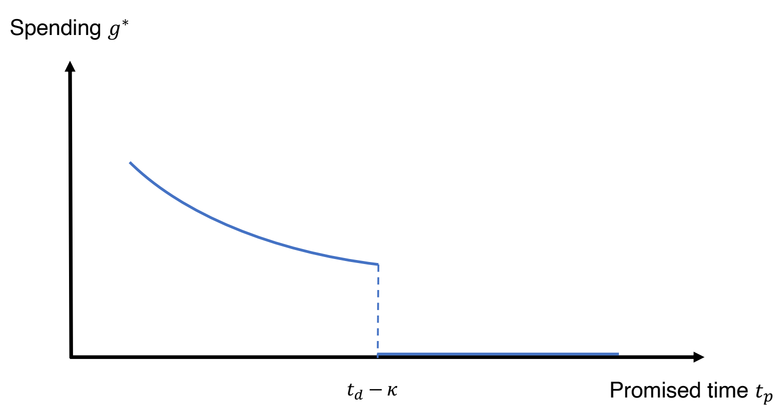
where $\underline{g}$ is the customer's minimum consumption level in relation to the retailer.

The customer will not buy from the retailer when the cost is higher than the benefit, that is, $g = 0$ when $\underline{g} \geq \mathbb{E}\, v(\underline{g}) = F_\epsilon(t_d - t_p)\log(\underline{g})$ or equivalently $t_p \geq t_d - \kappa$, where $\kappa = F_\epsilon^{-1}\left(\frac{\underline{g}}{\log \underline{g}}\right)$. Otherwise, the second constraint is not binding. The customer's optimal spending g^* on Collage becomes a function of their time sensitivity t_d and the retailer's speed promise strategy t_p:

$$g^* = \begin{cases} F_\epsilon(t_d - t_p) & \text{if } t_p < t_d - \kappa, \\ 0 & \text{if } t_p \geq t_d - \kappa. \end{cases}$$

Figure 9 illustrates g^* as an individual customer's demand function of t_p. When the retailer promises a delivery speed that is slower than the threshold $t_d - \kappa$, the customer would believe that the probability of missing the deadline is high enough that the cost outweighs the expected gains. As a result, the customer chooses not to make a purchase on Collage. When the retailer promises a delivery speed that is faster than the threshold $t_d - \kappa$, the customer would believe that the deadline is likely to be met, and they would consider purchasing on Collage. When the promised speed is faster than the threshold, as the promised speed increases, the risk of late arrivals decreases, making the customer willing to spend more on Collage. In short, a retailer's speed promise strategy affects consumers' purchasing decisions in two ways—whether or not to buy and how much to spend.

Figure 9 Consumer Demand as a Function of the Retailer's Speed Promise Strategy



A.1. Orders and Spending

We next aggregate customers' individual demand function into an aggregate demand function within a city. Different customers may have different deadlines t_d. We assume that in a city, there is a continuum number of customers with measure 1 and with deadlines $t_d \sim F_d(t)$. Then, the number of orders from a city is given by:

$$Orders = \mathbb{E}\,\mathbb{I}_{\{g^*>0\}} = \Pr(g^* > 0) = \Pr(t_d > t_p + \kappa) = 1 - F_d(t_p + \kappa).$$

Hence, the number of orders changes with respect to the promised speed:

$$\frac{\partial\, Orders}{\partial\, t_p} = -f_d(t_p + \kappa) < 0,$$

where $f_d(\cdot)$ is the probability density function (PDF) of t_d. We can see that $Orders$ is a decreasing function of t_p. This leads to our first prediction, which is that a more aggressive shipping promise increases the number of orders.

For customers who have decided to make a purchase, their spending changes with respect to the promised speed:

$$\frac{\partial\, g^*}{\partial\, t_p} = \frac{\partial\, F_\epsilon(t_d - t_p)}{\partial\, t_p} = -f_\epsilon(t_d - t_p) < 0,$$

where $f_\epsilon(\cdot)$ is the PDF of ϵ. We can see that g^* is a decreasing function of t_p. This means that a more aggressive shipping promise increases a customer's expenditure. For the average spending across customers within a city to increase, it requires their average spending $\mathbb{E}\left[\, g^* \,|\, g^* > 0\,\right]$ to increase with respect to the promised speed, that is, $\frac{\partial \mathbb{E}\left[\, g^* \,|\, g^* > 0\right]}{\partial t_p} < 0$. While a faster speed promise t_p increases g^*, it also attracts more marginal buyers who would spend around the minimum budget level $\underline{g}$, which could drive down the average spending. We can show that the first effect dominates the latter effect for many common distribution forms of $F_d(t)$, that is, $f_d(t_p + \kappa)\left(\int_{t_p-\kappa}^{\infty} F_\epsilon(t - t_p)\, dF_d(t)\right) < (1 - F_d(t_p + \kappa))\left(\int_{t_p-\kappa}^{\infty} f_\epsilon(t - t_p)\, dF_d(t) + F_\epsilon(-\kappa) f_d(t_p - \kappa)\right)$. This leads to our second prediction, which is that a more aggressive shipping promise increases the average expenditure per order.

These two predictions together form **Hypothesis 1**.

A.2. Return Rate

Recall that the previously discussed arrival time t_a is when customers believe the order will arrive. We use $\tilde{t}_a$ to denote the actual arrival time, with $F_a(t)$ as the cumulative distribution function (CDF) and $f_a(t)$ as the PDF. We assume that when an order is delayed, there is a probability of ξ that the customer would request a return. Therefore, we can express return rate *Return* as a function of the shipping promise t_p:

$$Return(t_p) = \xi \times \Pr(\tilde{t}_a > t_p) = \xi(1 - F_a(t_p)). \tag{10}$$

Thus, we have

$$\frac{\partial Return}{\partial t_p} = -\xi f_a(t_p) < 0,$$

which implies that a more aggressive shipping promise, that is, a lower t_p, increases the return rate. This prediction forms **Hypothesis 2**.

B. Additionally Robustness Check

B.1. Alternative DID Specification

We demonstrate that our main results in Table 3 are robust to alternative model specifications. The DID identification strategy takes several flexible forms in the literature. We use an alternative DID model, as specified in Fisher et al. (2019) and Cui et al. (2020):

$$Outcome_{it} = c + Fast_i + Slow_i + Week_t + \beta_1 Fast_i \times After_t + \beta_2 Slow_i \times After_t + e_{it}, \tag{11}$$

where the city-level fixed effects in Equation (1) are replaced by $Fast_i$ and $Slow_i$. The estimation results are reported in Table 15. Comparing the estimates between Tables 3 and 15, we can see that the two specifications yield highly robust results.

Table 15 Alternative DID Specification

	Log orders	Profit	Log order value	Log item price	Log shipping expense
	(1)	(2)	(3)	(4)	(5)
Fast	-0.1360^{***}	-3994.2^{***}	0.0002	0.0250^{**}	0.0023
	(0.0061)	(246.3)	(0.0083)	(0.0101)	(0.0067)
Slow	-0.0488^{***}	-1787.7^{***}	-0.0131^{***}	-0.0054	-0.0076^{**}
	(0.0040)	(172.3)	(0.0037)	(0.0047)	(0.0029)
Fast × After	0.0073^{**}	176.7^{*}	0.0426^{***}	0.0376^{***}	0.0270^{***}
	(0.0030)	(94.7)	(0.0115)	(0.0137)	(0.0099)
Slow × After	-0.0051^{***}	-245.9^{***}	-0.0367^{***}	-0.0508^{***}	-0.0357^{***}
	(0.0018)	(56.5)	(0.0051)	(0.0065)	(0.0042)
Week FE	Yes	Yes	Yes	Yes	Yes
Observations	170,160	170,160	60,748	60,748	60,748
R^2	0.151	0.063	0.046	0.017	0.046

This table reports the estimated coefficients and cluster-robust standard errors (in parentheses) in Equation (11). The coefficients for the number of orders, profit, the purchase value per order, the average price per item, and consumers' expenditure in shipping are listed in columns (1)–(5), respectively. The standard errors are clustered at the city level. FE stands for fixed effect. Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

B.2. Nonlinear Treatment Effects

In this section, we examine the nonlinear specification of the treatment effects. To study the effects on purchasing behaviors, we augment Equation (1) with the squared terms of the treatments:

$$\begin{aligned} Outcome_{it} = \alpha_i + \tau_t \; &+ \beta_1 Fast_i \times After_t + \beta_2 Fast_i^2 \times After_t \\ &+ \beta_3 Slow_i \times After_t + \beta_4 Slow_i^2 \times After_t + e_{it}. \end{aligned} \tag{12}$$

Similarly, to study the effects on returns and satisfaction, we augment Equation (2) with the squared terms of the treatments,

$$\begin{aligned} Outcome_{ijt} = \alpha_i + \tau_t\ &+ \beta_1 Fast_j \times After_t + \beta_2 Fast_j^2 \times After_t \\ &+ \beta_3 Slow_j \times After_t + \beta_4 Slow_j^2 \times After_t + \gamma \boldsymbol{X}_j + e_{ijt}. \end{aligned} \quad (13)$$

The nonlinear effects can be captured by β_2 and β_4 in Equations (12) and (13). Tables 16 and 17 report the estimation results. The nonlinear effects are quite small overall, and most of them are insignificant.

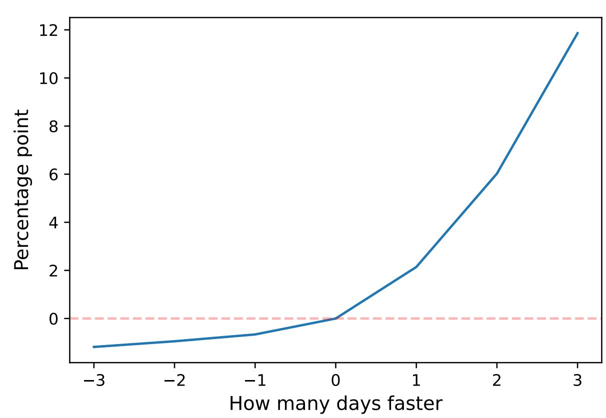
Table 16 Nonlinear Effects on Sales and Spending

	Log orders (1)	Profit (2)	Log order value (3)	Log item price (4)	Log shipping expense (5)
Fast × After	−0.0019	23.6	0.0582**	0.0801**	0.0383
	(0.0074)	(230.5)	(0.0271)	(0.0329)	(0.0236)
Slow × After	− 0.0232***	− 616.4***	−0.0229*	−0.0312*	− 0.0270***
	(0.0046)	(154.3)	(0.0124)	(0.0161)	(0.0104)
$Fast^2$ × After	0.0022	31.7	−0.0101	−0.0216	−0.0081
	(0.0022)	(64.1)	(0.0115)	(0.0138)	(0.0102)
$Slow^2$ × After	0.0053***	109.7***	−0.0025	−0.0038	−0.0013
	(0.0011)	(37.4)	(0.0040)	(0.0053)	(0.0033)
City FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Observations	170,160	170,160	60,748	60,748	60,748
R^2	0.243	0.093	0.022	0.015	0.047

This table reports the estimated coefficients and cluster-robust standard errors (in parentheses) in Equation (12). The coefficients for the number of orders, profit, the purchase value per order, the average price per item, and consumers' expenditure in shipping are presented in columns (1)–(5), respectively. The standard errors are clustered at the city level. FE stands for fixed effect. Significance at $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

C. Sensitivity Analysis of the Optimal Delivery Speed Promise

Figure 10 Change in Delivery Delay Rate



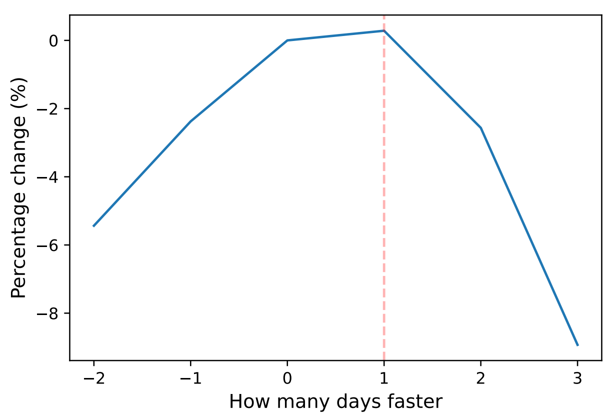
This graph shows how the delay rate changes when Collage's delivery promise becomes N days faster or slower using the order-level delivery records. The delay rate under the status quo promise is 1.8%; the delay rate under the three-day slower promise is 0.6%; the delay rate under the three-day faster promise is 13.7%.

Table 17 Nonlinear Effects on Returns and Satisfaction

	Return		Satisfied		NPS
	(1) linear	(2) logit	(3) linear	(4) logit	(5) linear
Fast × After	0.0002	0.0543	−0.0137	−0.1571	−0.0817
	(0.0007)	(0.0947)	(0.0090)	(0.1046)	(0.0640)
Slow × After	0.0002	0.0137	0.0000	−0.0484	−0.0390
	(0.0006)	(0.0917)	(0.0085)	(0.0923)	(0.0626)
Fast^2 × After	0.0001	0.0100	0.0021	0.0327*	0.0138
	(0.0001)	(0.0159)	(0.0015)	(0.0187)	(0.0107)
Slow^2 × After	−0.0001	−0.0192	0.0001	−0.0012	0.0064
	(0.0001)	(0.0167)	(0.0016)	(0.0151)	(0.0113)
Controls	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	175,647	170,554	13,719	15,635	13,719
R^2	0.012	0.055	0.059	0.077	0.077

This table reports the estimated coefficients and standard errors (in parentheses) in Equation (2). Regressions are run at the transaction level. The estimates for whether the order is returned using linear and logit models are presented in columns (1)–(2); the estimates for whether the customer is satisfied using linear and logit models are presented in columns (3)–(4); the estimates for the satisfaction score are presented in column (5). For linear models, city and week fixed effects are included, and standard errors are clustered at the city level. For nonlinear models, we use state-level fixed effects instead to avoid identification issues caused by the high dimensionality of city-level fixed effects. We report adjusted R-squared for linear models and pseudo R-squared for nonlinear models. FE stands for fixed effect. Significance at $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

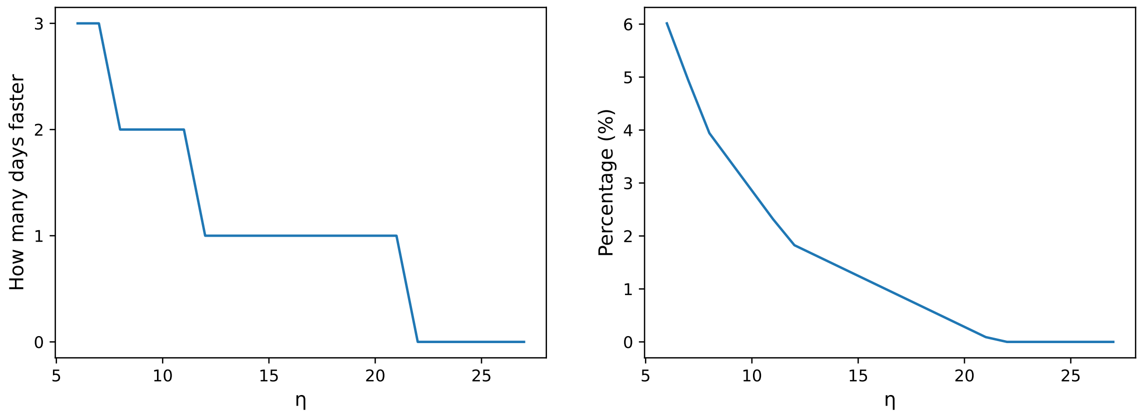
Figure 11 Optimal Delivery Speed Promise when η=20



Generally, when η becomes larger, the retailer faces less incentive to make aggressive promises because it is more costly to lose customers. The figure shows how customer lifetime value changes when the promise becomes N day(s) faster than the status quo. When $\eta = 20$, the optimal promise becomes one day faster than the status quo, and customer lifetime value increases by 0.33%. However, any further increase would lead to a lower long-term profitability. Therefore, the optimal disclosure policy should be one day faster.

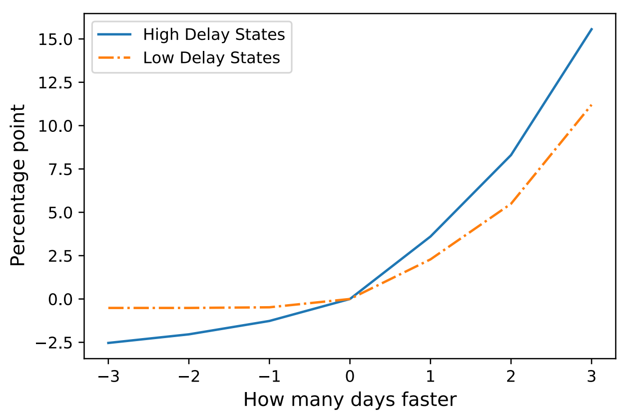
Figure 12 Sensitivity Analysis

(a) Optimal Promise (b) Increase in Customer Lifetime Value



We show the optimal promise as a function of η and compute the associated net gain. Plot (a) shows that the optimal promise is a non-increasing function of η. Plot (b) shows the change in customer lifetime value when the optimal promise is adopted. For a small η, the retailer can greatly boost sales and revenue by promising more aggressively without incurring too much future loss. The net gain can exceed 5% when η is as low as 7. However, when the long-term value of a customer becomes larger, the optimal policy also becomes less aggressive. When η is larger than 22, the status quo policy is already optimal. Any deviations would result in a long-term profitability loss.

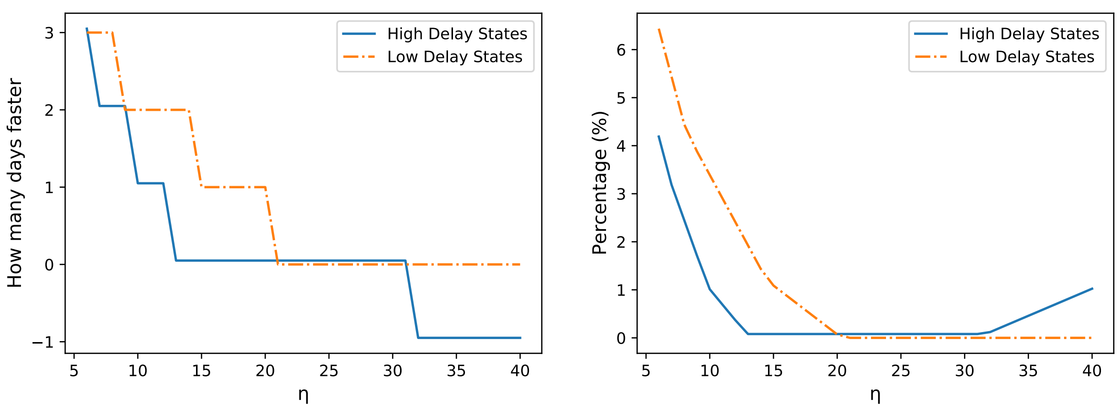
Figure 13 Change in Delivery Delay Rate (High vs Low)



This graph shows how the delay rate changes when Collage's delivery promise becomes N days faster or slower using the order-level delivery records. We select five states with the highest delay rates and five states with the lowest delay rates. We can see that because the the high delay states' status quo is more aggressive, a one-day faster promise incurs more delays for them than for the low delay states.

Figure 14 Sensitivity Analysis (High vs Low)

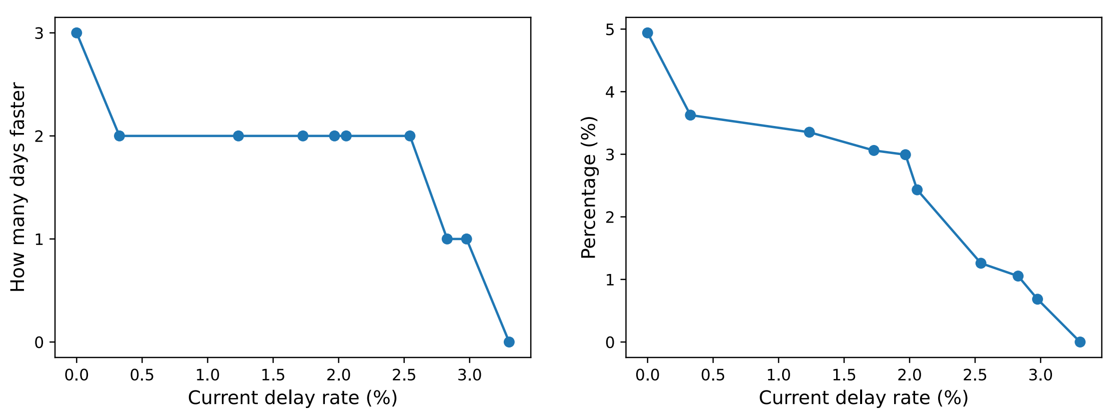
(a) Optimal Promise (b) Increase in Customer Lifetime Value



We show the optimal promise as a function of η and compute the associated net gain for high delay states and low delay states separately. We use the same set of parameters for both groups; the only difference is that their delay rates respond differently to a delivery promise change, which is shown in Figure 13. Plot (a) shows that the optimal promise is a non-increasing function of η. Plot (b) shows the change in customer lifetime value when the optimal promise is adopted. We can see that the optimal promise is more conservative for the high delay states as the solid line is below the dashed line in Plot (a). When $\eta = 10$, the national optimal promise is to become two days faster, which is also optimal for the low delay states. For the high delay states, however, it is sub-optimal.

Figure 15 Optimal Promise and Current Delay Rate

(a) Optimal Promise (b) Increase in Customer Lifetime Value



We show the optimal promise as a function of the current delay rate. We divide all states into 10 groups according to their current delay rates. Their current delay rates range from nearly 0 to above 3%. We then compute the optimal promise and the associated net gain (with η=10) for each group. We use the same set of parameters for both groups; the only difference is that their delay rates respond differently to a delivery promise change. Plot (a) shows that the optimal promise as function of the current delay rates. We can see that the optimal promise is more conservative for groups whose current delay rates are high; in general, the optimal promise is a non-increasing function of the delay rate. Plot (b) shows the change in customer lifetime value when the optimal promise is adopted.

D. Shipping Policy

Figure 16 Collage's Shipping Policy

Product		Standard Shipping	Fast Shipping	Rush Shipping	International Shipping	Notes
Fleece Blankets		$15.98	$27.94	$33.94	$39.99	Extra shipping charge for each additional item: $9.99 Expedited and international shipping not available for king size blankets
Sherpa Blankets	Regular	$15.98	$27.94	$33.94	$39.99	Extra shipping charge for each additional item: $9.99
	Premium	$15.98	$27.94	$33.94	U.S. Shipping Only	Extra shipping charge for each additional item: $9.99
Woven Image Blankets		$15.98	N/A	N/A	U.S. Shipping Only	Extra shipping charge for each additional item: $9.99
Photo Books	Softcover	$5.99	$17.95	$23.95	$8.99	Extra shipping charge for each additional item: $5.99
	Small Hardcover (8"x8")	$5.99	$17.95	$23.95	$8.99	Extra shipping charge for each additional item: $5.99
	Hardcover (11½"x7½" & 11½"x8½")	$9.99	$21.95	$27.95	$12.99	Extra shipping charge for each additional item: $9.99
	Large Hardcover (12"x12" & 14"x10½")	$15.98	$27.94	$33.94	$18.98	Extra shipping charge for each additional item: $9.99
Canvas Prints / Framed Canvases / Gallery Wrapped Canvases	Small 5x7 & 6x6	$9.98	$21.94	$27.94	U.S. Shipping Only	Does not ship to P.O. boxes. Extra shipping charge for each additional item: $3.99
	Medium 8x10, 10x10, 12x12, 11x14, 10x20, 12x18, 16x16, 16x20, 16x24, 20x20, 20x24 & 24x24	$15.98	$27.94	$33.94	U.S. Shipping Only	Does not ship to P.O. boxes. Extra shipping charge for each additional item: $9.99
	Large 20x30, 24x30 & 24x36	$19.98	$31.94	$37.94	U.S. Shipping Only	Does not ship to P.O. boxes. Extra shipping charge for each additional item: $13.99
	Extra Large 12x36, 30x40, 32x48, 30x30, 36x36 & 20x60	$25.98	$37.94	$43.94	U.S. Shipping Only	Does not ship to P.O. boxes. Extra shipping charge for each additional item: $19.99

The detailed shipping policy can be found at https://www.collage.com/shippolicy.
Shipping options and shipping fees are setup at Collage in the following way. For domestic orders, there are one standard shipping option and two premium shipping options. Collage charges shipping fees across all shipping options. The shipping speed becomes faster for premium services. For the same product, the shipping fee becomes more expensive and the shipping becomes faster when the shipping option becomes more premium. Note that Collage charges extra shipping fees for each additional item and charges higher shipping fees for larger or more expensive items.