Estimating Costs of Flight Delay to Air Cargo Carriers

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***Abstract*— We consider the costs of flight delay, which has received scant attention in previous research. We present two models that are developed to estimate the costs of flight delay. First we estimate a mixed-logit model to investigate the factors that influence late deliveries, with specific emphasis on flight on-time performance. Then we build a linear regression model to monetize the loss of late deliveries, using the hedonic approach to estimate the degradation in product value resulting from less reliable on-time package delivery. Estimates of flight delay cost for four representative US airports range from $600 – $1,200 per aircraft for a five-minute flight delay and $12,000 – $25,000 for an hour.**

Keywords- Costs of flight delay, Cargo Carrier, Logit regression, Random effects, hedonic model

I. INTRODUCTION

Flight delay costs have gained increasing attention. Schumer [1] estimates the total cost of delays to the US economy in 2007 to be as much as $41 billion. Ball et al. [2] indicate that the direct costs of flight delay are more than $28 billion, of which $16 billion are direct costs to passengers in terms of time and inconvenience. Cook et al. [3] point out that among diverse components of delay cost, soft costs – those that reduce revenue through loss of brand loyalty or good will – are an important part. Cook and Tanner [4], considering passengers' soft cost of delay, find increasing marginal costs from 0.02 euros per minute per passenger given a 5-minute flight delay and 0.69 euros per minute for a 60-minute delay.

There is far less research on the cost of delay for cargo carrier flights, although the airline industry transports millions tons of cargo annually. Delays to cargo flights may result in the unpunctual deliveries, and thereby generate a "soft cost" for shippers or recipients. Unfortunately, mainly due to the inaccessibility of cargo delivery data, there is very little research in the open literature concerning either the costs of late delivery in air freight transport, or the role of flight delay in causing late deliveries. Those studies that do consider the costs of delay (or value of time) in freight transport consider road, rail or waterway shippers. For example, Kurri et al. [5] estimate the average costs of delay in Finland to be about $47 per ton per hour for road freight shippers and $0.5 for rail shippers. We refer readers to [6] and [7] for more techniques and details in freight delay cost estimation. The only literature we have found about air freight cost estimation is the work of De Jong et al. [8]. They establish several inventory models based on a SP survey dataset, which includes 18 air freight carriers, to monetize the value of time for air freight transport. The study indicates that the value of time for air freight transport is approximately 13,000 euros (in 2010) per hour per full freighted aircraft. Yin et al. [9] build regression models to quantify the impact of flight delays to package late deliveries based on a historical dataset. They find that late flight arrivals significantly increase the probability of late packages delivery, but do not consider how to monetize this effect. This paper will extend the models in [9]. Furthermore, we will consider the costs associated with late deliveries and, by combining this analysis with the models for late delivery, estimate the cost of flight delay to air cargo flights related to late package deliveries. Other costs of air cargo flight delay, such as aircraft direct operating costs or additional ground distribution costs, are not considered in this paper.

The rest of the paper is organized as follows. Section 2 reviews the general delivery process of overnight packages and establishes several logistic regression models to quantify the effect of flight delay on late package delivery. Section 3 considers the cost of late delivery and then applies the models in section 2 to estimate the flight delay costs related to later delivery. Section 4 offers conclusions.

II. ANALYSIS OF CARGO CARRIERS ON-TIME DELIVERY

Air cargo carriers including FedEx and UPS provide a variety of services ranging from one-day to one-week delivery. Among various services, "Next day" delivery is by far the most vulnerable to flight delay. Next day services include a first-class delivery (typically 8:00 am), a priority delivery (typically 10:30 am) and a standard delivery (typically 3:00 pm). In this paper, we limit our discussion to the on-time performance of the priority delivery service (10:30 am guaranteed delivery) since it is one of the most widely used next-day service types.

2.1 Next day service delivery procedure

Package handing for next day service normally follows the sequence in Fig. 1. Packages after being picked up will be first

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sent to a local station, which serves as an intermediate connecting point between origin airport and local customers, and then be transported to a local airport via ground transportation. The packages are then flown to hub airports, such as Memphis for FedEx and Louisville for UPS. After sorting at the hub, which usually takes around four hours at a processing rate as high as 500,000 packages per hour ([10] and [11]), packages are flown to their destination airports, typically arriving between 4:30 am and 7:00 am. Packages are then trucked to different local stations, where they will be sorted and loaded onto vehicles for local delivery.

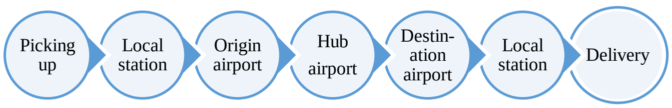

Figure 1 Package delivery process

2.2 Data description

We obtain a sample of FedEx's on-time performance data records from an anonymous freight auditing company. The dataset covers all three types of the "Next day" services from March 17th to May 21st, 2014. Each record includes actual shipping and delivery time, guaranteed delivery time, shipping cost and actual refund rate. OD information is provided at the zip code level.

We only keep records for Priority Overnight Service with 10:30am guaranteed delivery time. We further exclude those packages whose delivery was more than one day late; flight delays are unlikely to cause such long delays. We also remove deliveries to Alaska, Hawaii or Puerto Rico, or scheduled on weekends, for which FedEx has different delivery policies. We merge records having exactly the same destination zip code and actual delivery time, which we assume constitute a single delivery.

To link packages delivery performance with flight on-time performance, we firstly infer the OD airports. We assume that a package with a given origin (destination) zip code will be flown out of (into) the FedEx-served airport closest to the centroid of that zip code. This will be correct in the vast majority of cases. We then extract flight information from the FAA Aviation System Performance Metrics (ASPM) database. For each package, we find the scheduled arrival time, actual arrival time and delay of each possible inbound flight from origin airport to hub airport, and outbound flight from hub to destination airport. These flights are identified by assuming each package flew from its origin airport to the hub on the pick-up day, and from the hub to the package destination airport on a flight scheduled to arrive between 2 am and 7 am on the morning of the scheduled delivery day. Finally, we associate each destination airports with their counties as well as metropolitan statistical area (MSA) to capture regional effects.

2.3 Summary statistics

After preprocessing our data sources, our full dataset includes 12190 non-weekend delivered priority overnight package observations from 3/17/2014 to 5/21/2014. Among those packages, 1890 (15.50%) were delayed. The summary statistics are presented in Table 1.

Table 1 Summary statistics

Variable	Mean	Std.	Min	Max
Package delay (binary)	0.155	0.362	0	1
Distance (miles)	20.88	22.68	0.30	226.8
Shipping cost ($)	36.2	86.8	5.0	2842.0
Average flight actual arrival time (in hour)	5.738	0.676	3.933	7.950
Average flight delay (in hour)	0.234	0.263	-0.327	2.228
Average flight scheduled arrival time (in hour)	5.504	0.659	4.050	6.976
Multiple flight (dummy)	0.573	0.495	0	1
MSA Population density (in 1000 / mile2)	1.160	0.830	0.015	2.735
County Population density (in 1000 /mile2)	1.260	1.706	0.001	11.380

The table shows that the average distance from destination airport to the centroid of destination zip code is 20.88 miles and average package shipping cost is $36.2. Since some airports have more than one overnight flight on given days, and we cannot assign a specific flight to a package in these cases, we use the average value of scheduled arrival time, actual arrival time and flight delay. The dummy variable *Multiple flight* indicates whether there were multiple overnight flights; this was the case for 57.3% of total observations. We use destination airport county and MSA population density as an index to reflect local traffic congestion level.

2.4 On-time Delivery Model specification

In this model, the dependent variable is whether a delivery was on time – by 10:30 – at its destination. There are four categories of independent variables in our model. The first category includes variables related to on-time performance of the flights associated with the delivery--those to the destination airport associated with the delivery zip code scheduled to land between 2 am and 7 am on the morning of scheduled delivery day. Among these variables are the average actual arrival time, average scheduled arrival time, and average delay of the associated flights. The number of flights is also included in this category. We expect that, all else equal, a delivery that is associated with more than one flight will have lower probability of being late, because of the flexibility afforded by this redundancy. Yin et al. [12] emphasized the importance of time window between the flight arrival time and guaranteed delivery time, and Yin et al. [9] applied, in alternative model specifications, average actual arrival time and average delay respectively to capture the effect of late flight arrival. While highly correlated, these variables reflect somewhat different assumptions about how flight delay contributes to late delivery. Actual arrival time determines the time available to move a package from the airport to its final destination. Delay determines the degree to which the delivery process, presumably tailored to the flight schedule, is disrupted by deviations from the schedule. In reality, it is likely to that both effects matter: even if there are no delays against schedule, packages are still vulnerable to late delivery if the arrival time is later, but the effect is more severe if there is also a delay. Thus, we first follow the two specifications of flight on-time performance in the model of [9], and then include both the average delay and average scheduled arrival time in our model to reveal the joint effect of both late arrival and delay against schedule.

The second category of independent variables pertain to the delivery region. Two of these are proxies for congestion. Hansen and Huang [13] applies statistical analysis to show that population appears to a major determinant of vehicle miles traveled, thus we use the population density of the MSA where the airport is located to reflect congestion at the regional level, and population density of the county where the airport is located to reflect more localized congestion near the airport. We expect congestion, as captured by these densities, to increase the probability of late delivery.

The final set of variables relate to attributes of the delivery itself. First, we expect late deliveries to be more likely when they are to points further from the delivery destination airport. Accordingly, we include the great circle distance from the airport to the destination zip code centroid as an independent variable. Considering that ground distribution usually doesn't use the shortest route from airport to destinations, we use the great circle rather than road distance to capture the distance effect. In addition, we include the shipping cost in our model. Since FedEx has a full refund policy for late delivery, we expect that FedEx will give higher priority to those deliveries for which this refund would be greater.

The explanatory variables and their notations are listed in Table 2.

2.5 Binary logit model

Now let $Y_1, Y_2, \dots, Y_N$ be the dependent variable of N observations; $Y_i = 1$ represents a late delivery and $Y_i = 0$ represents a delivery that is not late. Let X_{ij} be the independent variable *j* for the *i*th package, β_j be the corresponding coefficient for explainable variable *j*, and β_0 is a constant that reflects the overall proclivity of late delivery. Then we can formulate the delay probability for the *i*th package below.

$$Pr(Y_i = 1) = F(x_{i1}, x_{i2}, \dots x_{ik}, \beta_0, \beta_1, \beta_2 \dots \beta_k) \quad (1)$$

We assume $F(\cdot)$ in equation (1) follows logistic function form:

$$Pr(Y_i = 1) = P_i = \frac{1}{1+exp(-V_i)} \quad (2)$$

$$V_i = \beta_0 + \sum_j \beta_j \cdot x_{ij} \quad (3)$$

To estimate the set of coefficients $\{\beta_j\}$, we employ maximum likelihood, forming the likelihood function from our data set of 12,190 observations for Y_i and x_{ij} and equations (2) and (3). In this model, we treat all coefficients as fixed across all observations. As a final step, we adjust the intercept to make late delivery probabilities consistent with a national estimate obtained by sending packages and recording whether they were delivered on time. The late delivery probability obtained in the study was 11.98%, while the probability in the sample was 15.51%. Accordingly, the intercept estimates presented below are adjusted by subtracting $ln(15.51/11.98)$. [14]

Table 2 Description of explanatory variables

Category	Explanatory variable notation	Variable description
Flight on-time performance	AvgActArr	Average actual arrival time (numerated as hour after midnight) of overnight flights;
	AvgDelay	Average hour of overnight flights delay at destination airport;
	AvgSchArr	Average scheduled arrival time (numerated as hour after midnight) of overnight flights;
	Multiple flight (dummy)	1 if multiple overnight flights;
Regional variables	MSA population density	Metropolitan statistical area's population density associated with each destination airport;
	County population density	County population density associated with each destination airport.
Delivery variables	Shipping cost	Shipping cost of each package;
	Distance	Great circle distance from destination airport to the centroid of destination zip code;

2.6 Estimation results

Table 3 reports the estimation results for three binary logit specifications. The first two columns present estimates for the models including actual arrival time and arrival delay individually, while the third column estimates are for the specification with both flight delay and scheduled arrival time. Model I also includes a quadratic actual arrival time term. All three models use interaction terms to capture the mutually reinforcing effects of flight delay and ground delivery distance.

Model I reveals that the flight actual arrival time has a quadratic effect on late delivery. From the estimation, when actual arrival time is earlier than 4:36 am, a later time decreases package late delivery probability, which is counter-intuitive. Very few (0.9%) observations have an actual arrival time before 4:36, however, suggesting that this is a fitting issue. The quadratic distance term in this model has a significant negative sign. Combined with the positive linear term, distance has a positive but diminishing marginal effect up to be 141 miles. Fewer than 1% of our observations lie in the region where distance is negatively related to late delivery probability. Model I confirms that both county and MSA population density have a positive and significant impact on late package delivery, and shipping cost has a negative and significant impact. The only surprise is the sign of multiple flight. This may be because, if there are multiple overnight flights, then the latter one would be scheduled later than the average, leaving a shorter delivery window.

Table 3 Fixed effect estimation results: Logit Model

Variable name	Model I	Model II	Model III
Fixed effect	Est./ Std.	Est./ Std.	Est./ Std.
AvgActArr	-1.557***		
	(0.589)		
AvgDelay		0.870***	0.893***
		(0.120)	(0.119)
AvgSchArr			0.202***
			(0.043)
Distance	0.366***	0.296***	0.301***
	(0.077)	(0.082)	(0.082)
Multiple flight	0.115*	0.071	
	(0.064)	(0.061)	
Shipping Cost	-0.156***	-0.180***	-0.170***
	(0.049)	(0.050)	(0.049)
County Population density	0.043***	0.030**	0.036***
	(0.013)	(0.013)	(0.013)
MSA Population density	0.090**	0.273***	0.232***
	(0.038)	(0.035)	(0.034)
Distance Squared	-0.039**	-0.046***	-0.047***
	(0.017)	(0.017)	(0.017)
AvgActArr Squared	0.169***		
	(0.051)		
AvgDelay × Distance		0.289***	0.293***
		(0.111)	(0.111)
Constant	1.023	-2.749***	-3.796***
	(1.678)	(0.081)	(0.240)
Observations	12,190	12,190	12,190
Note	**p<0.1; **p<0.05; ***p<0.01*		

Model II, which include average delay to reflect flight on-time performance, also indicates the positive and significant impact of late flight arrival against schedule. While the vast majority of coefficient estimations are similar to those in model I, there are generally two major differences. First, the quadratic term of delay is insignificant. Second, the interaction term between distance and flight delay is positive and significant, which suggests that ground distance becomes a more important determinant of late delivery when the flight is delayed. The positive and significant estimates for average scheduled arrival time in model III indicates the scheduling arrivals later in the morning increases the probability of late delivery, although the effect of delay against schedule is even stronger. This confirms our hypothesis that later scheduled arrival time shrink the time window and increase the chance of late delivery. Compared to models I and II, model III best captures the effect of late flight arrivals, whether as the result of schedule or of deviations from it, on late package delivery. We will therefor base subsequent models on this specification.

2.7 Mixed logit model

From section 2.4 to 2.6, we have discussed about the fixed effect binary logit models and also presented the estimates. However, those models assume that the impacts of all causal factors, as well as the intercept value, are the same across all observations, which is unlikely. Delivery locations in our dataset are scattered around the US, and associated with many different airports. The fact that different airports, regions, or zip codes might be more or less prone to late deliveries motivates us to allow for such heterogeneities in our model specification.

We first consider systematic differences across zip codes. Packages delivered to the same zip code might follow the same ground delivering routes and be nearby in delivery sequence. Thus we apply a mixed logit model, which generalizes the binary logit by allowing intercept vary across groups (Revelt and Train [15]), with a random intercept in zip code. By re-writing equation (3), we get the specification below.

$$V_{i,n} = \sum_j \beta_j \cdot x_{ij} + (\beta_0 + \xi_n) \qquad (4)$$

In equation (4), we use n to index groups of zip code, ξ_n captures the variability across zip codes. We assume ξ_n to be Gaussian distributed with zero mean and standard deviation σ, to be estimated. We keep the specification as model III in Table 3 and the estimation results are shown in the first column of Table 4.

While the vast majority of estimates are significant and have similar value to model III, the variance of random term is quite large and significant. This confirms the existence of systematic heterogeneities among zip codes. The estimates for flight on-time performance in this model is greater than those in model III.

In light of the delivery process, in which packages are first sent to a local airport from the hub, and then be distributed via ground transportation, it might be appropriate to use a hierarchical mixed logit model, to capture both the airport and zip code regional effects. In this model, zip codes are nested within destination airports and intercepts are varied across different of zip codes and airports respectively. Furthermore, we also use random parameters of flight delay and scheduled arrival time to capture the deviations of flight on-time performance among airports. This model then becomes:

$$V_{i,n,k} = \sum_j (\beta_j + \zeta_{kj}) \cdot x_{ij} + \sum_{j'} \beta_{j'} \cdot x_{ij'} + (\beta_0 + \eta_k + \xi_n) \qquad (5)$$

In this model, j' indexes coefficients that are assumed to be deterministic with values $\beta_{j'}$, and j indexes coefficients that are random, with means β_j. For the latter, ζ_{kj} are random variables that assumed to vary across delivery airports. The model also allows the intercept to vary across both the delivery airport (η_k) and delivery zip code (ξ_n). The estimates are shown in the second column of Table 4.

Table 4 Random Effects estimation results: three level models

Variable name	Model IV (Mixed Logit I)	Model V (Mixed Logit II)
Fixed effect	Est./ Std.	Est./ Std.
AvgDelay	1.006***	0.812***
	(0.135)	(0.174)
AvgSchArr	0.232***	0.191*
	(0.057)	(0.089)
Distance	0.302***	0.336***
	(0.107)	(0.109)
Shipping Cost	-0.093*	-0.105*
	(0.053)	(0.054)
County Population density	0.039**	0.055*
	(0.018)	(0.035)
MSA Population density	0.287***	0.259***
	(0.046)	(0.073)
Distance Squared	-0.047**	-0.056**
	(0.023)	(0.023)
AvgDelay × Distance	0.346***	0.416***
	(0.127)	(0.134)
Constant	-4.238***	-3.999***
	(0.323)	(0.503)
Random effect: σ (Level 2, grouped by airports. 98 groups in total)		
AvgDelay	-	0.517
AvgSchArr	-	0.311
Constant	-	1.529
Random effect: σ (Level 3, grouped by zip codes. 3465 sub-grouped in total)		
Constant	0.890	0.821
Observations	12,190	12190
*Note: *p<0.1; **p<0.05; ***p<0.01*		

The estimates of mixed logit model II reveal the significant heterogeneities across different airports. While most of the fixed effects estimates are similar with our model III, the random effects of flight delay and scheduled arrival time are quite pronounced. Obviously, some destinations are more sensitive to flight delays and thus are more prone to late deliveries.

III. COST ANALYSIS OF PACKAGE DELIVERY IN THE AIR CARGO INDUSTRY

In this section, we consider the cost of late package delivery. We first develop a model to estimate, using the hedonic method, how increased late deliveries degrades the value of overnight delivery services. Then we apply the hierarchy structured mixed logit model to relate the costs of late delivery to the quantity of flight delay.

3.1 Methodology

Costs from late deliveries can be classified into *hard costs* and *soft costs*. Hard costs in the freight industry include those due to the refund of late packages. While this cost is very real from to the company, it is not a good measure from our purposes. First, industry policies state that late deliveries resulting from flight delay are not guaranteed a refund. Second, in welfare terms the refund is really a transfer from the company to the customer. Many customers consider themselves fortunate when a late delivery, particularly when it is only slightly late, results in substantial monetary savings. Soft costs, on the other hand, manifest themselves mainly in the degraded value of overnight delivery services. The nature of soft costs makes them very hard to quantify. One indirect method, however, is to use industry service rates to infer the value on an on-time delivery guarantee and then estimate how late deliveries degrade the value of that guarantee.

We define *Reliability* as the probability of on-time delivery. *On-time Guarantee service* is a value-added service feature provided by many cargo carriers such as FedEx, UPS and USPS. With a guarantee, late deliveries are, with some exceptions related to the cause of the delay, eligible for a full refund of shipping costs. Guarantees come “bundled” with certain services and not with others. While FedEx offers an on-time guarantee on all its express services, USPS for example, offers some services with this guarantee and some without it. this offers the possibility that the *value of guarantee (VOG)* might be inferred by analyzing the rates for different services, some with a guarantee and some without. With this goal in mind, we develop a model to quantify the *VOG*.

Table 5 Carriers and service type

Carrier and Service types	Delivery Time	Guarantee service
FedEx Priority Overnight	Next day 10:30	Yes
FedEx Standard Overnight	Next day 15:00	Yes
FedEx 2Day	Second day 16:30	Yes
USPS Priority Mail Express	Next day 15:00	Yes
USPS Priority Mail	Second day 16:30	No

We estimate a hedonic price model based on three FedEx services and two USPS domestic package delivery services. We are interested in how service attributes – specifically delivery time, on-time guarantee, and carrier – affect the price of shipments. The five services capture the variation in three service attributes of interest. Table 5 provides a descriptive summary of their service attributes.

We expect that those packages with earlier delivery time and with on-time guarantee will generally command higher prices. All independent variables and their descriptions are listed in Table 6.

Table 6 Description of independent variables

Variable	Description
Distance (miles)	Great circle distance from centroid of original zip code to destination zip code;
FedEx	1 if carrier is FedEx;
Priority	1 if priority service;
OneDay	1 if next day delivery;
Guarantee	1 if with guarantee service.

We constructed a dataset that can allow us to estimate the effects of the service attribute on service price. We first draw a random sample of 500 package delivery records from the pool of 12190 observations used in the on-time delivery model. Each record only keeps the OD zip codes and great circle distance, with other information dropped. We then randomly assigned each record to one of the five service types listed in Table 5. Using the USPS and FedEx Service Guides, we determined the rates for these services as of spring 2015. The summary statistics of all variables are listed in Table 7.

Table 7 Summary statistics

Variable	Mean	Std.	Median	Min	Max
Price ($)	27.03	15.89	23.95	5.75	59.90
Distance (miles)	679.21	588.67	601.0634	0	2562.02
FedEx	0.59	0.49	1	0	1
Priority	0.2	0.4	0	0	1
OneDay	0.6	0.49	1	0	1
Guarantee	0.8	0.4	1	0	1

Using this dataset, we estimated a log-linear regression model relating shipping rate to the various service attributes. The results are shown in Table 8. All variables are significant. We see that rates increase with distance, but that the elasticity is low. OneDay, Priority, and FedEx services all command higher rates. Most importantly for our purposes, we see that the effect of Guarantee is large, positive, and highly significant. The value of 0.716 indicates that a shipment with on-time guarantee has a rate that is roughly double an identical shipment without a guarantee (since $e^{0.716} \cong 2.05$).

While the estimation result pertains specifically to the difference between a guaranteed and non-guaranteed service, with certain assumptions this results can be used to ascribe a value to a change in reliability. Suppose that a guarantee provides a 100% of on-time delivery reliability. (While this is not actually the case—it is more like 90%--we will assume that in the eyes of the customer a guarantee means 100%.) Suppose further that without the guarantee the reliability is, say 50% -- the minimum reliability at which the advertised delivery time, even though not guaranteed, could be considered “truthful”. Then using linear interpolation, the price reduction associated with a given reliability, as compared with the price when this reliability is 100%, is:

$$\delta = P^* - P^{act} = P^* - exp(ln(P^*) - 2 \cdot VOG' \times (1 - R)) \quad (6)$$

Where δ is price reduction, P^* is the price with 100% reliability, P^{act} is the price at the actual reliability, VOG' is the estimation of variable *guarantee* in the hedonic price model, and R is the on-time delivery reliability. In the equation, $(1 - R)$ is equivalent to the late delivery probability Pr_{LD}, thus we can re-write (6) into (7).

$$\delta = P^* - exp(ln(P^*) - 0.716 \times 2 \times Pr_{LD}) \quad (7)$$

We interpret δ to be the loss in value for a given package delivery that results from the non-zero probability of late delivery. This loss is not accurately reflected in the actual price of individual deliveries, which varies discretely according to whether or not there is a guarantee, but is inferred from the price premium commanded by the guarantee. Additionally, it reflects a market-wide average: in reality, the negative impacts of late delivery vary widely from case to case. A more detailed and complete investigation of late delivery cost is left for later research.

Table 8 Estimation results of VOG model

Variable name	VOG model
Dependent variable	Log(price)
Fixed effect	Est./ Std.
Log(distance)	0.0989***
	(0.0036)
FedEx	0.324***
	(0.0209)
Priority	0.098***
	(0.0209)
Oneday	0.787***
	(0.0209)
Guarantee	0.716***
	(0.0295)
Constant	1.245***
	(0.0252)
R squared	0.958
Observations	500
*Note: *p<0.1; **p<0.05; ***p<0.01*	

3.2 *Monetizing the cost of flight delay in air cargo carriers*

Based on the above, we can monetize the costs of late delivery given certain minutes of flight delay in three steps. First we use the late delivery Model V in Table 4 to estimate the probability of late delivery for each record in the original dataset, assuming no flight delay. Then we change the value of average delay, while keeping other variables unchanged, and calculate how this changes the probability of late delivery. In applying model V, the random parameters and nested random intercept are estimated by maximizing the conditional density of random effects given the observed responses. We then apply equation (7) to compute the change of service value for every package in the observations. In applying (7), we assume the price P^* is the shipping price in the original data and Pr_{LD} is estimated from applying the late delivery model. Finally, we average the cost across interested groups of observations.

Table 9 Summary statistics of four major airports

Airport	Total packages	Delayed packages	Percentage of delay
ORD (O'Hare)	609	94	15.44%
OAK (Oakland)	226	38	16.81%
DFW (Dallas/Fort)	832	83	9.976%
EWR (Newark)	2348	448	19.08%

We summarize results across all observations (cover 98 airports in US) in our dataset. In order to better capture regional differences, we also summarize results for representative airports (EWR, DFW, ORD, OAK) with considerable number of observations in our sample. Summary statistics for the four major airports are in Table 9, and cost estimations are shown in Table 10. The first row in Table 10 shows the costs of late delivery when there is no flight delay; these reflect the fact that on-time delivery is not completely reliable even without flight delay. Subsequent rows reflect late delivery costs for different levels of flight delay. Nationally, these costs average $3.3 for a 15-minute of flight delay, increasing to $7.7 for a 90-minute delay. These costs differ significantly across different airports, for example, the cost of late delivery in OAK is more than twice as much as that in DFW, when there is a 60-minute flight delay. These differences reflect differences in the overall reliability of on-time delivery across regions, the sensitivity of on-time delivery to flight delay, and package delivery rates.

Table 10 Estimation of costs of late deliveries

Minute of flight delay/ min	Costs of flight delay				
	DFW	EWR	OAK	ORD	Nationwide
0	$1.113	$2.767	$3.258	$2.171	$2.580
5	$1.255	$3.013	$3.564	$2.378	$2.817
15	$1.590	$3.548	$4.244	$2.841	$3.345
30	$2.222	$4.446	$5.435	$3.664	$4.273
60	$3.953	$6.456	$8.386	$5.765	$6.498
90	$4.982	$7.471	$10.075	$6.998	$7.685

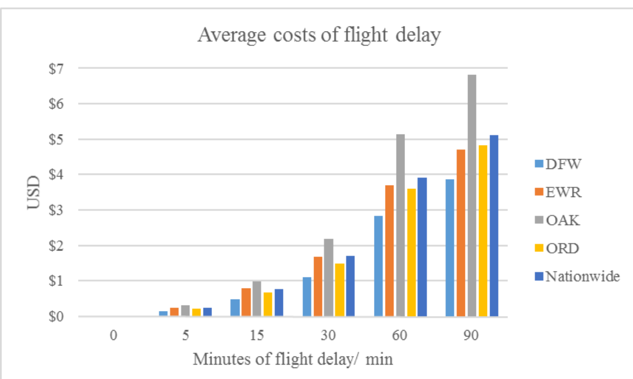

Figure 2 Independent average costs of flight delay

To estimate the cost of late delivery that is specifically attributable to flight delay, we simply subtract the values of the first row in Table 10 from the values in the subsequent rows. The results are summarized in Figure 2. Increasing marginal costs are evident through around 60 minutes, after which the effect of delay begins to diminish. This reflects the non-linear form of our late delivery model, and that as delays get very large late delivery is almost certain, at which point further delay ceases to matter.

So far we have discussed about the cost of flight delay of one individual package. We now turn to quantifying the costs of flight delay per aircraft that arise from late package delivery. This requires us to estimate the average number of overnight packages per aircraft. The United States Department of Transportation publishes data (BTS – T100 [16]) that summarizes the aggregated monthly freight and mails transported by carriers. The dataset also includes the aggregated monthly departures by aircraft type, origin, and destination airport. By combining the BTS and ASPM datasets, we estimate the total monthly overnight departures and further the aggregated monthly overnight freight for four representative airports in the year of 2014. We further divide the total freight by 10.6 lbs., which is the average pounds of domestic packages provided in the annual report of FedEx. Finally, we use the records in our delivery data set to determine the fraction of packages with the 10:30 delivery deadline, on the assumption that deliveries scheduled for later are unlikely to be affected by flight delay. The resulting estimates of the number 10:30 deliveries per flight for the period from March to May 2014 are presented in Table 11.

Table 11 Aggregated monthly freight/ mail and overnight departures

Airport	Metrics	Month			Packages per aircraft
		Mar	Apr	May	
DFW	Packages	163612	181389	168509	4279
	Overnight Departures	38	42	40	
EWR	Packages	197522	218921	201364	5148
	Overnight Departures	37	42	40	
OAK	Packages	208740	215480	216653	4747
	Overnight Departures	43	46	46	
ORD	Packages	168715	182411	178310	4202
	Overnight Departures	46	42	39	

We then estimate the costs of flight delay per aircraft simply by multiplying the values in Table 11 by the average costs shown in Table 10. Table 12 presents the costs of late delivery per aircraft that attributes to flight delay. The costs of flight delay related to late delivery are extremely high. Because of the large amount of packages an aircraft carries, even a minor flight delay has a high cost. Taking OAK as an example, a 5-minute flight delay costs as high as $1500. For an hour of delay, this value increases to over $25 thousand, almost 15 times higher. As a further comparison, the FAA, using DOT data, estimates the direct operating cost for a large narrow-body cargo aircraft at $7,000 per block hour (GRA [17]).

Table 12 Estimation of independent costs of flight delay per aircraft

Minute of flight delay/ min	Costs of flight delay			
	DFW	EWR	OAK	ORD
0	$0.00	$0.00	$0.00	$0.00
5	$620.86	$1,262.63	$1,493.37	$946.90
15	$2,072.16	$4,004.30	$4,808.70	$3,063.64
30	$4,819.97	$8,602.49	$10,618.29	$6,825.62
60	$12,340.14	$18,899.27	$25,011.12	$16,431.37
90	$16,810.54	$24,098.89	$33,248.84	$22,068.64

IV. CONCLUSION

In this paper, we have estimated the cost of flight delay for door-to-door air cargo carriers that arises specifically from late delivery of packages. We first estimate logit regression models to investigate the factors that influence the on-time delivery performance of overnight packages, with specific emphasis on the impacts of flight on-time performance. We then establish a hedonic price model to quantify the costs of late deliveries in terms of the degradation of service value. Finally, we apply those two models to monetize the costs of flight delay for the air cargo carriers.

The logit model estimates show that flight delay has a significant impact on late delivery. In addition, ground distribution also makes a considerable difference. Longer distance between the package destination and the airport increases probability of late delivery. In the mixed logit model, we discover that the regional random effects of different airports and nested random effects of zip code both play important roles in predicting the probabilities of late packages.

The hedonic price model allows us to estimate the overall value of guarantee service. We find that an on-time guarantee adds increases the shipping rate by about 72%. Using this estimate and some necessary assumptions, we further construct an equation that links late delivery probability and the cost of degraded service quality.

Combining the estimates from the two models, we estimate the costs of late delivery that results from a given quantity of flight delay. If there is a 15-minute flight delay, then as a national average, the resulting late delivery cost per package is around $0.77; if flight delay is 90 minutes, this cost increases to $5.11. The costs vary among airports. For example, the per package cost of a 60-minute flight delay for OAK is more than twice that for DFW. We further convert this to a cost of flight delay per aircraft for four selected airports, based on estimates of the number of packages the planes carry. Our estimates suggest that the costs of flight delay that result from late deliveries are very high, ranging from $12 to $25 thousand for a one-hour flight delay. The values exceed the direct operating cost per block-hour for air cargo flights by roughly 2-4 times. Thus, if a proposed project is expected to reduce delay for air cargo operators, its benefits may be greatly understated if based on the official economic values published in [17].

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