EVALUATING THE IMPACT OF FLIGHT DELAY ON CARGO AND OVERNIGHT PACKAGE DELIVERY FIRMS

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ABSTRACT

Flight delay is a severe and widespread problem in the U.S. There have been numerous studies on the cost of delay to airlines, passengers, and society. Unfortunately, a similar concept does not exist for cargo flights. As overnight flights play an important role in the "Next Day" service provided by most main carriers, the FAA requires research into means to estimate the impact of flight delays to the cargo and package carriers. This study focuses on two pieces of analysis to fulfill this goal. First, we use logistic regression models applied to a historical dataset to understand the factors that lead to late deliveries. We have found that the flight delay (arrival time) at the destination airport and the ground distribution distance are two important factors for on-time delivery. We further conduct random effects models and airport-specific models to capture the heterogeneities among packages going to different regions. Second, based on the random effects models, we predict the percentage of package delivery delay under various levels of flight delay. Result shows that to those major market regions, flight delay can contribute as much as 22% to 38% of the total package delivery delay.

Keywords: Flight delay, Cargo, Logistic regression, Random effects

1. INTRODUCTION

The Federal Aviation Administration (FAA), like most air navigation service providers, is continuously seeking to better understand and address "customer" requirements and improve the quality of service. However, most of the previous research along these lines has narrowed the concept of "customer" to "passenger carriers", which disregarded another important player, cargo carriers.

Due to the nature of service, cargo companies such as FedEx and UPS are very sensitive to flight delays. For example, the "Next Day Air Early A.M." service from UPS promises an 8:00 a.m. to 10:30 a.m. (based on destination) delivery on the next business day after a package is shipped. And the "Priority Overnight" (PO) service from FedEx promises 10:30 a.m., 12 p.m. or 4:30 p.m. next day delivery based on destination zipcode. This leaves a delivery time window of less than 24 hours. Thus, the on-time performance of the flights involved in the delivery process may be critical to the on-time delivery of these "Next Day" packages.

However, mainly due to the inaccessibility of the package delivery data, there is little research in the open literature concerning the link between flight delay and package delivery delay. To fill this gap, we obtained a set of proprietary delivery records from a freight auditing service. A more detailed description of the data will be given in the third section. Although the data is limited to deliveries of customers of the service, and covers a limited time period, it provides a unique opportunity to examine the relationship between flight delay and package late package delivery at the individual package level.

The rest of the paper is organized as follows: Section 2 overviews the package delivery process for a representative US package operator. Section 3 uses logistic regression applied to a large sample of package delivery records to quantify the relationship between flight delay and package late delivery. Section 4 addresses some extensions to the basic logistic regression model that allow for heterogeneities in package destination cities and correlations between late deliveries across time. Section 5 presents methods and results for estimating the percentage of late deliveries as a result of flight delay and section 6 provides a summary and conclusion.

2. PACKAGE DELIVERY PRACTICE

In this section, we review the process of moving a "Next Day" package from shipment to delivery. Figure 1 shows the practice in a chain.

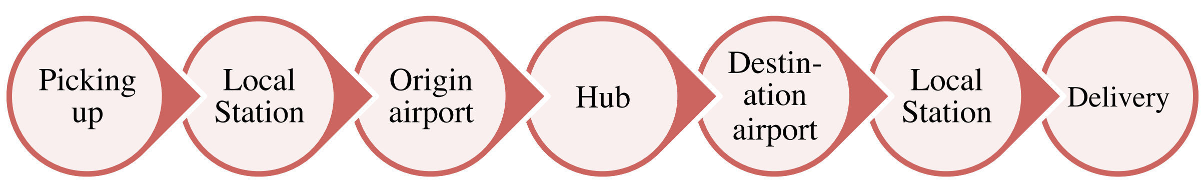

FIGURE 1 Package delivery process

2.1 Station Operations

Stations serve as intermediate connection points between the local airport and local customers. It is useful to describe the delivery process in terms of station activities. Stations differ in size and service area. A station may employ several dozen vans to make deliveries and pick up shipments for customers in its service area. For example, our subject cargo operator has 17 stations connecting with Oakland airport (OAK) and with local customers in the Bay Area. Over the course of the day, the station activities can be summarized as follows.

Cargo flights have relatively stable scheduled arrival times at the local airport, usually between 4:30 a.m. to 7 a.m. After a sortation at the airport, trucks are sent out to different stations. Upon arrival at stations, packages are sorted to the van for their final destinations. Most of the vans are sent out for morning delivery at a "leaving buiding time" (LBT), usually 2 to 3 hours before 10:30 a.m. For some vans, departure time may be adjusted if they have too few packages to send. Drivers follow roughly the same routes and serve the same areas everyday. The morning duties can be roughly split into two parts. The first part is mainly for delivering urgent packages guaranteed before 10:30 a.m. Between 10:30 a.m. and 3 p.m., vans continue to fulfill other duties, for example, noon service, 3 p.m. service, as well as picking up outbound packages.

Usually around 3 p.m., vans return to stations and then depart for afternoon duty shortly afterwards. The major work in the afternoon is picking up. Drivers are equipped with an electronic pad that receives pick-up requests from customers. Sometimes, packages missed for morning delivery will also be delivered by afternoon vans. After about two hours, vans return to stations from their afternoon runs. Packages are then transloaded from the vans to the trucks, which take them to the local airport.

2.2 Hub Operations

All the "Overnight" packages of FedEx and most of the "Next Day" packages of UPS involve sortation work at hubs, such as Memphis (MEM) for FedEx and Louisville (SDF) for UPS. Figure 2 shows cumulative scheduled arrivals and departures for the MEM (FedEx) and SDF (UPS) hubs on a typical day. The figure shows clearly two banks at each hub, one over night and the other in the afternoon. Every night, around 130 domestic FedEx aircrafts and 90 domestic UPS aircrafts arrive at MEM and SDF from their origins over a three-hour period. For FedEx, this equates to a scheduled arrival every 90 seconds. Avoiding flight delay is crucial to maintaining the highest productivity levels.

Within a four-hour period, 1.3 million packages are transferred from their inbound flight to their outbound flight, with only two human touches. The speed of the sorting process can be up to 500,000 packages per hour. We refer readers to (*1*), (*2*) for more details about the hub sorting procedure and techniques.

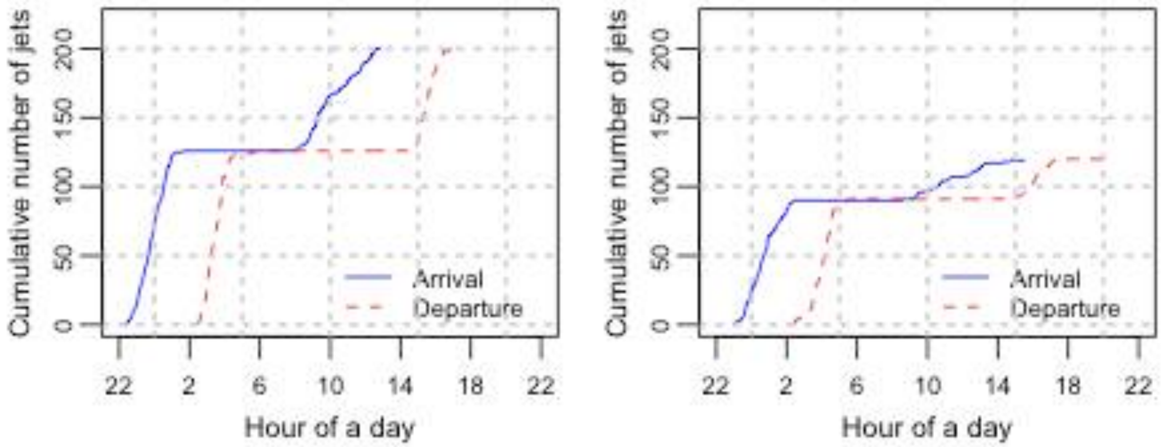

FIGURE 2 Cumulative scheduled arriving and departing flights from Memphis (left) and Louisville (right) on June 13, 2012.

3. "NEXT DAY" LATE DILIVERY ANALYSIS

Package operators including FedEx and UPS provide a variety of services from the most urgent one-day shipping to one-week ground shipping. Among the services offered by FedEx and UPS, "Next Day" service is the most sensitive to flight delay, since there is less opportunity to recover if a flight is late. These services usually include two flight legs within less than 24 hours; thus a delay to either flight can significantly shorten the ground transport delivery time window at the destination. Here, we limit our focus to these "Next Day" services since they are the most vulnerable to disruption because of flight delay.

Several factors may cause the delay of "Next Day" package deliveries. First, if the inbound flight to hub is delayed, some packages may miss their intended outbound flights and thus will be left for the next flight. For some popular destinations (e.g., EWR, OAK), there are multiple outbound flights so that miss-sorted packages can be picked by the latter flight. Most destinations, however, have just one connecting flight from the hub, so packages will be left overnight and delayed until the daytime bank or even a full day. On the other hand, even if a package makes it to its outbound flight, the delay of the second leg may shorten the available time for ground distribution at destination. Increasing highway congestion during the early morning hours may exacerbate the flight delay and thus further imperil on-time delivery.

"Next Day" services usually include an early morning service (as early as 8:00 a.m.), a priority service (as early as 10:30 a.m.), and a standard service (as early as 3 p.m.). Here, we limit our study to the on-time performance of the priority packages. This is the most popular next-day service. It promises delivery by 10:30 a.m., 12 p.m., or 4:30 p.m. based on destination zipcode. The early morning and standard services may be considered in future research.

3.1 Description of Data

We obtained our package delivery records from a freight auditing service that requested that their identity be withheld. The data covers all the "Next Day" packages of customers of this service shipped between March 17 and May 21, 2014 by a major operator. Each record includes the shipping time and delivery time of a package. Guaranteed delivery time, net price, and whether there was a refund (usually because of late delivery) are provided as well. To assure privacy of individual customers, the origin and destination addresses are represented by zipcodes.

After extracting the priority package records, we inferred the origin and destination airport (served by that operator) based on distance to the zipcode. Although this inference may not be correct in all instances, our records from the auditor do not specify the airports through which a package travels, and we consider the closest airports to be reliable proxies. We further excluded three types of records. First, we removed the packages that were delayed for more than one day. After careful examination, we found that these severely delayed packages did not suffer from either inbound or outbound flight delays thus are likely due to exceptional cases (such as unavailability of the client when the package was delivered). As our delivering addresses were represented by zipcode, there can be multiple packages sent to a single address by the same mail carrier. These cases can be readily identified because they have the same delivery time and the same zipcode. We treated these multiple deliveries to the same address as a single observation, with their net prices added. Third, we excluded packages that are delivered on weekends because cargo companies usually have a different schedule for those packages. After applying these filters, our estimation dataset included 14227 records, covering 49 states and D.C (we excluded Alaska). Detailed statistics will be given in next subsection.

Flight informations were obtained from FAA ASPM database. For each package, we determined scheduled arrival time, actual arrival time and delay of each inbound flight from its origin to its hub and outbound flight from the hub to its destination.

3.2 Logistic Regression Model

Logistic regression model is a binary response model (*3*), which solves the limitations of linear probability model. It is used to predict the probability of a binary dependent variable—in this whether the delivery is late or not. The logistic function used in this paper can be written as:

$$P_i = \frac{e^{\sum_{j=1}^{n} \beta_j X_{i,j}}}{1 + e^{\sum_{j=1}^{n} \beta_j X_{i,j}}} \qquad (1)$$

Where P_i is the probability of late delivery for package i, $X_{i,j}$ is the observable factor j for package i, β_j is the coefficient corresponding to observable factor j . One of the $X_{i,j}$ is always set to 1 so that the associated coefficient is a constant that reflects the overall proclivity of package deliveries to be late. In this model the constant is a single deterministic value that applies to all observations. Later, we will present models in which we allow this proclivity to vary randomly among different subsets of observations.

The odds ratio is the probability of success (late delivery) over the probability of failure (not late delivery) (*3*). For the logistic model, it can be expressed as:

$$Odds = \frac{P_i}{1 - P_i} = e^{\sum_{j=1}^{n} \beta_j X_{i,j}} \qquad (2)$$

3.3 Model Specification

Aside from the constant, the independent variables included in our binary logistic model could be divided into three categories. The first category is flight information, including frequency of morning service as well as flights' actual and scheduled arrival times. Two specifications are considered here. Both include a dummy variable indicating if more than one flight is scheduled to arrive at the package destination airport in the morning between 3 and 9 a.m. We expect that if there are multiple flights there is greater ability to adapt to delays without late deliveries. The first specification also includes the actual arrival time at the package destination airport, but not the arrival delay. The idea here is that, regardless of the schedule, later arrivals make late package deliveries more likely. The second specification considers arrival delay against schedule instead of just the arrival time. This presumes that the ground distribution is designed to reliably deliver packages if the flight arrives on time, even if the scheduled time is fairly late. The reality is probably somewhere in between—arrival time matters even if the flight is on schedule, but the impact on delivery delay increases when the arrival is behind schedule as well. The proper specification of this effect is a topic of future research.

We expect that package deliveries to locations more distant from the airport are more likely to be delayed. We use the great circle distance from airport to destination to reflect this effect. A longer distance should lead to a smaller buffer within the delivery time window and thus a higher probability of delay.

12 p.m. service and 4:30 p.m. services are more flexible in terms of the delivery time window. We expect that under the same flight delay and other conditions, 10:30 a.m. packages are more likely to be delayed. Thus we include two variables indicating the service type.

Lastly, we include the shipment cost in our model. Late packages are eligible for a full refund, so we expect that cargo operators will prioritize deliveries for which the potential refund is larger.

A list of explanatory variables included in our model is shown in Table 1.

TABLE 1 Description of Explanatory Variables

Category	Explanatory Variable	Variable description
Flight information	Avg. Act. Arr (hour after midnight)	Average actual arrival time of all morning flights
	Avg. Delay (hour)	Average flight delay at destination airport
	Morning flight frequency (0 or 1)	1 if more than one morning flights
Service type	12 pm service	1 if guaranteed delivered at 12 p.m.
	4:30 pm service	1 if guaranteed delivered at 4:30 p.m.
Ground traffic	Distance (30 miles)	Great circle distance from destination airport to the centroid of destination zipcode
Shipping cost	Value ($100)	Shipping cost of package (net price)

3.4 Summary Statistics

After preprocessing all our data sources, accounting for selecting those priority packages, dealing with missing data issues and so on, the full dataset includes 14,227 package observations from 3/17/2014 to 5/21/2014. Of these packages, 12195 (85%) are guranteed to be delivered by 10:30 a.m., 909 (6%) are guaranteed to be delivered by 12 p.m. and 1123 (8%) are guaranteed to be delivered by 4:30 p.m. Within this period, there were 2003 delayed packages, approximately 14.08% of all packages. The mean, standard deviation, minimal and maximal value of the independent variables is summarized in Table 2.

TABLE 2 Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Flight average arrival time	5:44 a.m.	40 minutes	3:56 a.m.	7:57 a.m.
Flight average delay (hour)	0.239	0.265	-0.327	2.228
Flight frequency	0.517	0.500	0	1
12 pm service	0.0639	0.245	0	1
4:30 pm service	0.0789	0.270	0	1
Distance (30 miles)	0.933	1.06	0.01	9.64
Shipping cost ($100)	0.349	0.811	0.05	28.42

Since some airports have more than one morning flights, we use the average value of both the flight delay and flight actual arrival time. The decision of using average value was based on the comparision with other metrics (e.g. maximum value) in the model fitting. Notice that mean values of indicator variables represent the percentage of each category. For example, around 6.4% of packages were guaranteed to be delivered by 12 p.m. the next day. Meanwhile, the average ground delivering distance is 28.0 miles and the average package value is $34.9.

99 national airports that are served by this operator are represented by destinations in our dataset. We sort out three major airports with the most amounts of package records.

TABLE 3 Summaries for Packages to Main Airports

Airport	Total packages	Total delayed packages	Percentage delay
ORD (O'Hare)	613	94	15.33%
DFW (Dallas/Fort)	893	88	9.85%
EWR (Newark)	2349	447	19.03%

3.5 Estimation Results

Estimation results for several models are shown in Table 4. Models 1 and 2 include actual arrival time in the specification while Models 3 and 4 use flight delay instead. Models 1 and 3 include only linear terms for the time/delay variable while Models 2 and 4 also include quadratic terms. The latter models also include interaction terms involving distance that are excluded from the former ones. These four models are estimated from the entire dataset, in which 99 airports represented.

TABLE 4 Logistic Estimation Results

Variable	Model 1 Est./(Z stat.)	Model 2 Est./(Z stat.)	Model 3 Est./(Z stat.)	Model 4 Est./(Z stat.)
AvgActArr	0.386***	-1.493**		
	(10.38)	(-2.70)		
AvgDelay			0.989***	0.829***
			(11.79)	(7.48)
Flight frequency	0.235***	0.220***	0.320***	0.311***
	(4.55)	(4.25)	(6.14)	(5.94)
Distance	0.167***	0.297***	0.148***	0.214**
	(6.06)	(4.47)	(5.39)	(3.06)
Value	-0.149**	-0.146**	-0.182***	-0.178**
	(-3.17)	(-3.11)	(-3.72)	(-3.66)
12 pm service	-0.826***	0.850***	-0.810***	-0.843***
	(-6.35)	(-6.54)	(-6.26)	(-6.48)
4:30 pm service	-2.069***	-2.100***	-2.063***	-2.11***
	(-10.72)	(-10.91)	(-10.71)	(-10.90)
AvgActArr Squared		0.164***		
		(3.42)		
Dist. Squared		-0.0265*		-0.027*
		(-2.10)		(-2.06)
AvgDelay×Dist.				0.196*
				(2.26)
Constant	-4.141***	1.115	-2.186***	-2.194***
	(-18.33)	(0.71)	(-37.57)	(-32.08)
Observation	14227	14227	14227	14227

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimation results are generally favourable with the vast majority of variables in all four models significant and with signs that generally match our expectations.

Examining first the simpler Models 1 and 3, both confirm that late arrivals, whether measured in absolute terms or against the schedule, increase the probability of later delivery. Distance from the airport to the final destination point also has a positive effect. Shipment cost has negative coefficient estimates. Compared to the base case of 10:30 a.m. delivery, 12 p.m. and 4:30 p.m. services are significantly less likely to be delayed under the same flight delay and other conditions, which matches our expectation. The only surprise here is the flight frenquency, which must derive from it's positive correlation with scheduled arrival time of the connecting flights—if there are more than one flights, the latter ones will tend to be scheduled later.

From Model 2, we gain some additional insights. Most importantly, the effect of arrival time appears to be quadratic. The linear coefficient is negative. Taken at face value this suggests that when arrival time is early it is negatively associated with delivery delay, but as the arrival time increases the effect flips to the expected positive one. Based on the estimated coefficients, this flip occurs at 4:33 a.m. when distance from the airport is at its average value. In the vast majority of observations, the marginal impact of arrival time on late delivery probability is positive. The apparent negative impact for very eary arrival times is probably an artifact of fitting the relationship to a quadratic function. In any case Model 2 suggests that arrival time has an increasing marginal impact on the probability of package delivery delay. The other quadratic term has significant negative coefficients. This suggests that distance has positive but diminishing marginal effect on the probability of package delay. The flip point occurs at a ground distribution distance of 170 miles. Only 1% of the packages have a longer ground distribution distance.

Model 4 results are similar to those of Model 2, with two major exceptions. First, the quadratic arrival delay term is insignificant, suggesting that there is no significant strengthening or weakening of the arrival delay effect as the delay increases. Second, the positive relationship between distance and late delivery attenuates as distance increases, which suggests that the ground distribution may exacerbate the chance of package late delivery when there is a flight delay.

To quantify the effects for each variable, we also compute the odds ratio for a given change in a parameter. The odds ratios are presented in Table 5.

TABLE 5 Logistic Model Odds Ratios

Variable	Unit Increase	Model 2	Model 4
		Odds Ratio	**Odds Ratio**
AvgActArr	1 hour	1.736	
AvgDelay	1 hour		2.750
Flight frequency	1	1.246	1.365
Distance (30 miles)	30 miles	1.247	1.201
12 pm service	1	0.427	0.430
4:30 pm service	1	0.122	0.121
Value ($100)	$100	0.864	0.837

The odds ratios presented above provide us a better understanding of the ceteris paribus relationship between an explanatory and dependent variable. Note that in our specifications there are quadratic and interaction terms. Accordingly we computed the odds ratio for the combined effect at the average value. The values for the (average) flight arrival time and delay against schedule are greater than 1, indicating tha the odds ratio increases (by factor 1.736 in the case of Model 2 or 2.75 in the case of Model 4) as the flight carrying the package arrives at the destination airport later.

4. PACKAGE DELAY MODEL EXTENSIONS

4.1 Random Effects model

In the previous models, random factors that influence whether a package is delivered on time are reflected implicity in the probabilistic relationship in equation (*1*). That model assumes that these factors are captured in a single logistically distributed random variable, which is identically and independently distributed across all observations. This is unlikely to be the case; in fact certain days, cities, and zip codes are likely to be particularly prone to late deliveries. We capture this in a random effects model, which we obtain by re-writing equation (2) in the form shown below:

$$\log(Odds) = \beta' X_{i,j} + \mu_{n(i)} \tag{3}$$

In this model, also termed a mixed logistics regression model, we use n to index a tuple of (airport, delivery date), such as (EWR, 4/17/2014). $n(i)$ is the tuple that package i belongs to. We assume μ_n is normally distributed with zero mean and variance σ^2 that needs to be estimated in the mixed logistic regression. We keep the model specification for all other explanatory variables identical to our basic logistic Models 2 and 4. The estimation results of these random effect models are shown in Table 6.

TABLE 6 Random Effects Model Estimation Results

Variable	**Model 5 Est./(Z stat.)**	**Model 6 Est./(Z stat.)**
AvgActArr	-1.535^{*}	
	(-2.19)	
AvgDelay		0.797^{***}
		(5.84)
Flight frequency	0.264^{***}	0.275^{***}
	(3.80)	(3.99)
Distance	0.316^{***}	0.240^{**}
	(4.50)	(3.24)
Value	-0.169^{***}	-0.178^{***}
	(-3.37)	(-3.52)
12 pm service	-0.901^{***}	-0.878^{***}
	(-6.66)	(-6.47)
4:30 pm service	-2.183^{***}	-2.187^{***}
	(-11.09)	(-11.03)
AvgActArr Squared	0.168^{**}	
	(2.76)	
Dist. Squared	-0.027^{*}	-0.0293^{*}
	(-2.02)	(-2.13)
AvgDelay×Dist.		0.220^{*}
		(2.36)
Constant	1.059	-2.369^{***}
	(0.53)	(-29.27)
Random Effect: σ	0.644^{***}	0.637^{***}
	(13.98)	(13.80)
Observation	14227	14227

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

The estimates of random effects coefficient in both models are quite large significant, which indicates that systematic variations in the probability of late delivery among airports and dates do exist. Comparing Table 6 to Table 4, we find all the coefficients are quite similar, which matches our expectations.

4.2 Airport-Specific Models

The results of random effects model presented above indicate that the heterogeneities among airports should not be ignored. Therefore, we estimate individual models for three major airports listed in Table 3. These airports have the most number of records in our data. Whereas above we grouped the data by airport-day, here we do so by zip code. Packages delivered to the same zip code will tend to follow the same ground delivery routes and have similar places in the delivery sequence, suggesting that they may be systematically more or less prone to delivery delays. In this sense zip codes are analogous to panels of individuals making repeated choices over time

(*4*). We assume that this zip code effect is normally distributed with zero mean and variance to be estimated, leading to a different mixed logit model but with the same general form as equation (3). We restrict our estimation of the models with arrival delay as opposed to actual arrival time. As flight schedules into a given airport tend to be quite similar from day to day, variation in arrival time should closely correlate with variation in arrival delay.

There are two main specification differences between the full model and airport specific models. First, almost all the packages in these three major markets are guaranteed to be delivered by 10:30 a.m., thus we excluded the non-10:30 a.m. packages and the indicator of 12 pm service and 4:30 pm service in the airport specific models. Second, cargo companies have fixed number of connecting flights between the hub and each destination airports with only rare exceptionals. Thus we excluded flight frequency from the model.

The preferred models (with insignificant variables eliminated) estimated are shown in Table 7

TABLE 7 **Airport-Specific Mixed Logistic Estimates**

Variable	**Model 7 (EWR) Est./(Z stat.)**	**Model 8 (DFW) Est./(Z stat.)**	**Model 9 (ORD) Est./(Z stat.)**
AvgDelay	1.601***	1.737***	1.415***
	(4.72)	(5.71)	(3.44)
Distance	0.440*		3.274
	(2.22)		(1.73)
Dist. Squared			-2.849*
			(-2.18)
Constant	-2.055***	-2.659***	-2.814***
	(-11.71)	(-14.34)	(-4.59)
Random Effect: σ	0.893***	0.685*	0.512*
	(7.27)	(2.476)	(2.00)
Observation	2348	832	609

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As in the previous models, average delay of morning flights is significant for each airport-specific model, but the magnitudes are larger in airport specific models. The reasons will be revealed in the next section. On the other hand, the significance and nature of the distance effect varies considerably. Delivery cost is not included in any of the airport-specific models, because it was found to be insignificant in each case. Finally, the variability across zip codes is quite pronounced. Clearly, in each of these cities, some zip codes are more prone to late deliveries than others.

5. CONTRIBUTION OF FLIGHT DELAY TO PACKAGE DELAY

In this section, we estimate the percentage of package delivery delays caused by flight delays. We used the same data as in the previous sections. Again we note that the sample is for customers of a specific freight record auditing service and may not be representative of all the traffic served by the subject air cargo carrier.

To make our estimates, we change the value of average delay for each record to zero, while keeping all the other variables at the same values as in the original data. For models with arrival time rather than an arrival delay, we create a new arrival time by assuming that arrival delay is zero. Also, we have maintained the random effects of individual groups as estimated from our samples. These effects are estimated using the approach of maximizing the conditional density of the random effects given the observed responses (*5*). We then average the late delivery probability across all observations, for both the base case with flight delay and the scenario in which there is no flight delay.

Figure 3 shows the expected percentage of package delivery delay with various levels of flight delay. For the major airports, a 30 minutes' flight delay may double the probability of a late package delivery compared to the scenerio when no flight delay occurs, while a 60 minutes' flight delay may triple it.

It's noticeable that the increasing trend tends to be more dramatic in airport specific models and the effect of flight delay is more pronounced. This is due to the fact that most packages to major mackets are guaranteed to be delivered by 10:30 a.m. These packages are more vulnerable to flight delays than 12 p.m. and 4:30 p.m. packages.

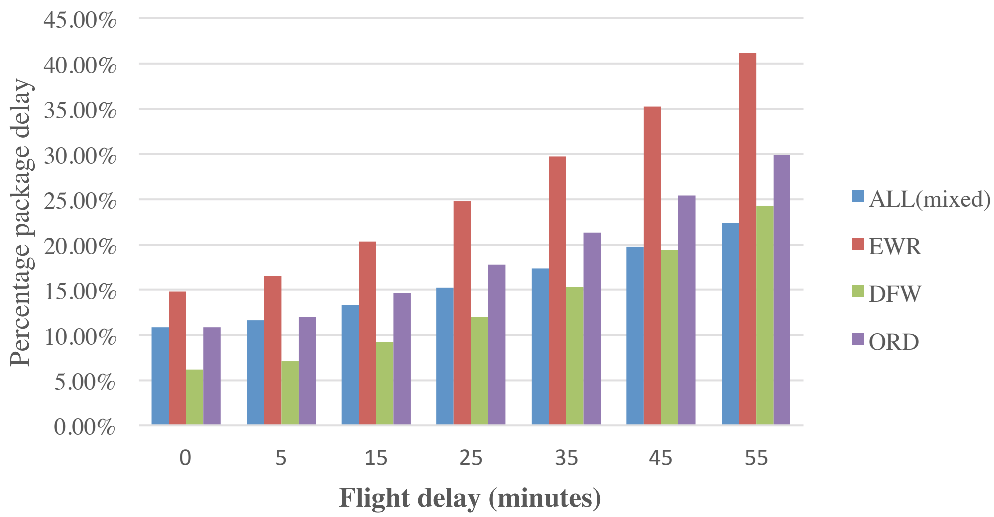

FIGURE 3 Predicted percentage package delay VS Flight delay

The contributions of flight delay appear in Table 8. According to the table, flight delay accounts for 22% (as for EWR) to as much as 38% (as for DFW) of the package delay. As above, in the all-airport model, the effect is smaller, for the reasons previously discussed.

TABLE 8 Contribution of Flight Delay to Package Delay

Airport	Percentage delay as in data	When no flight delay	Difference
All (fixed)	14.08%	11.30%	-19.74%
All (mixed)	14.08%	10.82%	-23.15%
EWR	19.04%	14.83%	-22.11%
DFW	9.96%	6.20%	-37.75%
ORD	15.44%	10.83%	-29.86%

6. CONCLUSION

In this research, we have investigated the factors influencing late deliveries of "Next Day" priority packages, with specific emphasis on the impacts of flight delay and flight arrival time. We used logistic regression model applied to a set of historical package records over two months to quantify how flight delays affect the probability of package delivery delay.

Our estimation results indicate that, as expected, flight delay (or flight arrival time) affects package delay. In addition, we discovered that gound distribution distance is important. The further the final destination is away from the airport where the package lands, the higher the probability of later delivery. We also developed a random effects model to capture correlation between unobserved variables across packages. In the full model, we grouped packages by airport-day, and in the airport specific models, we grouped packages by destination zip codes. In both models, we found strong random effects related to the grouping variables.

To further quantify the impact of flight delay on package delay, we calculate the expected percentage late package deliveries assuming several hypothetical scenarios with various levels of flight delay. If there is no flight delay, on average there is a reduction of 22% to 38% package delay in the major markets. Nationwide, however, the reduction is smaller—about 20%. It appears that most packages to larger urban areas are guaranteed to be delivered by 10:30 a.m., while packages to some rural areas are guaranteed to be delivered by 12 p.m. or even 4:30 p.m. That explains why larger urban areas are more vulnerable to flight delays.

Finally, we point out several limitations in this study. First, the data we obtained is not be perfectly representative of the population of interest. Second, to relate each package with flight, we inferred the airports and flights involved in the delivery process of each package based on the closest airport in terms of great circle distance. This inference may not be correct in some cases. Third, while there are one hundred airports served by that operator, we could estimate airport-specific model only for several major markets with sufficient data. Fourth, a model that includes the impacts of both the scheduled flight arrival time and the arrival delay should be explored, since both factors appear to be important, but their influences are probably of different magnitude. Finally, while we have explored various mixed logit specifications in this research, there are a number of other possibilities that should also be investigated. Despite these issues, our analysis clearly demonstrates the relationship between flight delay and late package delivery, an effect that, while intuitive, has not previously been studied.

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