FinalProject

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2 Introduction and Background

Travel by plane is commonplace domestically. Whether it be for vacation, family visits, or school, many Americans fly to other parts of the country. Naturally, flights time often get delayed, especially if it's at a metropolitan hub.

As college students, many of us have experienced flight delays, so it is an interesting topic to explore. Delay has been analyzed based on destination, time of day, week, or month, and even based on flight duration. However, we are interested in analyzing the reason of delay. Maybe looking into reason of delay and how it relates to other factors can give us insights about how to travel smarter.

2.0.1 Research Question

We want to figure out what the major reason for flight delays is. Is there some relationship between the popularity of a destination and the reason of delay? How are popularity of destination, time of year, and reason for delay related to each other?

2.0.2 Hypothesis

We think that Late aircraft delay is the major reason for flight delays. Late aircraft delay is when a flight is late because another flight with the same aircraft arrives late. We also think there is a relationship between destination and delay reason. More specifically that Late aircraft delay is not a problem with unpopular destinations. We think that time of year affects popularity of destination but not reason of delay.

2.0.3 Imports

```
In [1]: %matplotlib inline
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import patsy
import statsmodels.api as sm
import scipy.stats as stats
from scipy.stats import ttest_ind, chisquare, normaltest

#countFrequencyofDelay
#findMostPopularDestinationOfMonth
#plotReasonofDelaywithDestination
```

```
/anaconda/lib/python3.6/site-packages/statsmodels/compat/pandas.py:56: FutureWarning: The panda
  from pandas.core import datetools
```

3 Data Description

We are using domestic flight data from the Bureau of Transportation Statistics. The datasets are from years 2005, 2006, 2007, and 2008. Datasets include features we are interested in like the minutes of delay, destinatinon, and the reasons for delay. There are also extraneous features we are going to ignore.

```
In [2]: df_2005 = pd.read_csv('2005.csv')
        df_2006 = pd.read_csv('2006.csv')
        df_2007 = pd.read_csv('2007.csv')
        df_2008 = pd.read_csv('2008.csv')
```

```
In [3]: frames = [df_2005,df_2006,df_2007,df_2008]
        df = pd.concat(frames)
        df.head(10)
```

```
Out[3]:    Year  Month  DayofMonth  DayOfWeek  DepTime  CRSDepTime  ArrTime  \
        0  2005      1          28          5   1603.0        1605   1741.0
        1  2005      1          29          6   1559.0        1605   1736.0
        2  2005      1          30          7   1603.0        1610   1741.0
        3  2005      1          31          1   1556.0        1605   1726.0
        4  2005      1           2          7   1934.0        1900   2235.0
        5  2005      1           3          1   2042.0        1900      9.0
        6  2005      1           4          2   2046.0        1900   2357.0
        7  2005      1           5          3      NaN        1900      NaN
        8  2005      1           6          4   2110.0        1900      8.0
        9  2005      1           7          5   1859.0        1900   2235.0

           CRSArrTime UniqueCarrier  FlightNum        ...          TaxiIn  TaxiOut  \
        0        1759            UA        541        ...             4.0     23.0
        1        1759            UA        541        ...             6.0     15.0
```

```
2        1805             UA        541          ...           9.0      18.0
3        1759             UA        541          ...          11.0      10.0
4        2232             UA        542          ...           5.0      10.0
5        2232             UA        542          ...           3.0      47.0
6        2232             UA        542          ...           5.0      26.0
7        2232             UA        542          ...           0.0       0.0
8        2223             UA        542          ...           2.0      15.0
9        2223             UA        542          ...           4.0      56.0

   Cancelled  CancellationCode  Diverted  CarrierDelay WeatherDelay NASDelay  \
0          0               NaN         0           0.0          0.0      0.0
1          0               NaN         0           0.0          0.0      0.0
2          0               NaN         0           0.0          0.0      0.0
3          0               NaN         0           0.0          0.0      0.0
4          0               NaN         0           0.0          0.0      0.0
5          0               NaN         0          23.0          0.0      0.0
6          0               NaN         0          46.0          0.0      0.0
7          1                 B         0           0.0          0.0      0.0
8          0               NaN         0          16.0          0.0      0.0
9          0               NaN         0           0.0          0.0      0.0

   SecurityDelay  LateAircraftDelay
0            0.0                0.0
1            0.0                0.0
2            0.0                0.0
3            0.0                0.0
4            0.0                0.0
5            0.0               74.0
6            0.0               39.0
7            0.0                0.0
8            0.0               89.0
9            0.0                0.0

[10 rows x 29 columns]
```

4 Data Cleaning/Pre processing

```
In [4]: df_final = df.copy()
```

We remove extraneous columns of data

```
In [5]: df_final = df_final[['Year', 'Month', 'UniqueCarrier', 'ArrDelay', 'DepDelay', 'Dest',
```

```
In [6]: df_final = df_final[df_final['Cancelled'] == 0]
```

```
In [7]: df_final['Season'] = df_final['Month']
        #df_final["Dest"].value_counts()
```

```
In [8]: def standardize_season(month):
            if month in [12, 1, 2]:
                output = "winter"
            elif month in [3, 4, 5]:
                output = "spring"
            elif month in [6, 7, 8]:
                output = "summer"
            elif month in [9, 10, 11]:
                output = "fall"
            return output
```

```
In [9]: df_final['Season'] = df_final['Season'].apply(standardize_season)
```

```
In [10]: df_final.head(100)
```

```
Out[10]:       Year  Month UniqueCarrier  ArrDelay  DepDelay Dest  Cancelled  \
         0     2005      1            UA     -18.0      -2.0  ORD          0
         1     2005      1            UA     -23.0      -6.0  ORD          0
         2     2005      1            UA     -24.0      -7.0  ORD          0
         3     2005      1            UA     -33.0      -9.0  ORD          0
         4     2005      1            UA       3.0      34.0  BOS          0
         5     2005      1            UA      97.0     102.0  BOS          0
         6     2005      1            UA      85.0     106.0  BOS          0
         8     2005      1            UA     105.0     130.0  BOS          0
         9     2005      1            UA      12.0      -1.0  BOS          0
         10    2005      1            UA     -18.0      -1.0  BOS          0
         11    2005      1            UA      17.0      17.0  BOS          0
         12    2005      1            UA      36.0      35.0  BOS          0
         13    2005      1            UA     115.0      98.0  BOS          0
         14    2005      1            UA     106.0     126.0  BOS          0
         15    2005      1            UA       5.0      19.0  BOS          0
         16    2005      1            UA       NaN      11.0  BOS          0
         17    2005      1            UA     -21.0      -1.0  BOS          0
         18    2005      1            UA       4.0      -4.0  BOS          0
         19    2005      1            UA      85.0      39.0  BOS          0
         20    2005      1            UA     138.0     148.0  BOS          0
         21    2005      1            UA       3.0      13.0  BOS          0
         24    2005      1            UA     -23.0     -11.0  BOS          0
         26    2005      1            UA      -8.0      -1.0  BOS          0
         27    2005      1            UA      -5.0      -5.0  BOS          0
         28    2005      1            UA     -11.0      -2.0  BOS          0
         29    2005      1            UA      -8.0      -2.0  BOS          0
         30    2005      1            UA       4.0     -11.0  ORD          0
         31    2005      1            UA      -4.0      -2.0  ORD          0
         32    2005      1            UA     111.0     101.0  ORD          0
         33    2005      1            UA      35.0      29.0  ORD          0
         ..     ...    ...           ...       ...       ...  ...        ...
         79    2005      1            UA       7.0       2.0  SAT          0
```

80	2005	1	UA	-4.0	-2.0	SAT	0
81	2005	1	UA	8.0	-4.0	SAT	0
82	2005	1	UA	3.0	-2.0	SAT	0
83	2005	1	UA	80.0	95.0	BOS	0
84	2005	1	UA	16.0	34.0	BOS	0
85	2005	1	UA	80.0	96.0	BOS	0
86	2005	1	UA	91.0	108.0	BOS	0
87	2005	1	UA	92.0	99.0	BOS	0
88	2005	1	UA	42.0	34.0	BOS	0
89	2005	1	UA	108.0	110.0	BOS	0
90	2005	1	UA	-5.0	0.0	BOS	0
91	2005	1	UA	70.0	75.0	BOS	0
92	2005	1	UA	-16.0	9.0	BOS	0
93	2005	1	UA	38.0	45.0	BOS	0
94	2005	1	UA	67.0	81.0	BOS	0
95	2005	1	UA	87.0	98.0	BOS	0
96	2005	1	UA	36.0	56.0	BOS	0
97	2005	1	UA	2.0	-1.0	BOS	0
98	2005	1	UA	37.0	19.0	BOS	0
99	2005	1	UA	-3.0	6.0	BOS	0
100	2005	1	UA	11.0	5.0	BOS	0
101	2005	1	UA	82.0	81.0	BOS	0
102	2005	1	UA	94.0	100.0	BOS	0
103	2005	1	UA	71.0	86.0	BOS	0
106	2005	1	UA	31.0	-1.0	BOS	0
107	2005	1	UA	-2.0	-1.0	BOS	0
108	2005	1	UA	77.0	72.0	BOS	0
109	2005	1	UA	13.0	13.0	BOS	0
110	2005	1	UA	1.0	17.0	BOS	0

	CarrierDelay	WeatherDelay	NASDelay	SecurityDelay	LateAircraftDelay \
0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0
5	23.0	0.0	0.0	0.0	74.0
6	46.0	0.0	0.0	0.0	39.0
8	16.0	0.0	0.0	0.0	89.0
9	0.0	0.0	0.0	0.0	0.0
10	0.0	0.0	0.0	0.0	0.0
11	17.0	0.0	0.0	0.0	0.0
12	0.0	0.0	1.0	0.0	35.0
13	18.0	0.0	17.0	0.0	80.0
14	13.0	0.0	0.0	0.0	93.0
15	0.0	0.0	0.0	0.0	0.0
16	0.0	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0	0.0

18	0.0	0.0	0.0	0.0	0.0
19	10.0	0.0	46.0	0.0	29.0
20	32.0	0.0	0.0	0.0	106.0
21	0.0	0.0	0.0	0.0	0.0
24	0.0	0.0	0.0	0.0	0.0
26	0.0	0.0	0.0	0.0	0.0
27	0.0	0.0	0.0	0.0	0.0
28	0.0	0.0	0.0	0.0	0.0
29	0.0	0.0	0.0	0.0	0.0
30	0.0	0.0	0.0	0.0	0.0
31	0.0	0.0	0.0	0.0	0.0
32	0.0	0.0	111.0	0.0	0.0
33	0.0	0.0	35.0	0.0	0.0
..	...	...	...	...	...
79	0.0	0.0	0.0	0.0	0.0
80	0.0	0.0	0.0	0.0	0.0
81	0.0	0.0	0.0	0.0	0.0
82	0.0	0.0	0.0	0.0	0.0
83	58.0	0.0	0.0	0.0	22.0
84	13.0	0.0	0.0	0.0	3.0
85	0.0	0.0	0.0	0.0	80.0
86	0.0	17.0	0.0	0.0	74.0
87	57.0	0.0	0.0	0.0	35.0
88	0.0	0.0	8.0	0.0	34.0
89	19.0	0.0	0.0	0.0	89.0
90	0.0	0.0	0.0	0.0	0.0
91	20.0	0.0	0.0	0.0	50.0
92	0.0	0.0	0.0	0.0	0.0
93	0.0	0.0	0.0	0.0	38.0
94	67.0	0.0	0.0	0.0	0.0
95	0.0	0.0	0.0	0.0	87.0
96	19.0	0.0	0.0	0.0	17.0
97	0.0	0.0	0.0	0.0	0.0
98	19.0	0.0	18.0	0.0	0.0
99	0.0	0.0	0.0	0.0	0.0
100	0.0	0.0	0.0	0.0	0.0
101	9.0	0.0	1.0	0.0	72.0
102	0.0	0.0	0.0	0.0	94.0
103	0.0	59.0	0.0	0.0	12.0
106	0.0	0.0	31.0	0.0	0.0
107	0.0	0.0	0.0	0.0	0.0
108	0.0	20.0	5.0	0.0	52.0
109	0.0	0.0	0.0	0.0	0.0
110	0.0	0.0	0.0	0.0	0.0

	Season
0	winter
1	winter

```
2     winter
3     winter
4     winter
5     winter
6     winter
8     winter
9     winter
10    winter
11    winter
12    winter
13    winter
14    winter
15    winter
16    winter
17    winter
18    winter
19    winter
20    winter
21    winter
24    winter
26    winter
27    winter
28    winter
29    winter
30    winter
31    winter
32    winter
33    winter
..       ...
79    winter
80    winter
81    winter
82    winter
83    winter
84    winter
85    winter
86    winter
87    winter
88    winter
89    winter
90    winter
91    winter
92    winter
93    winter
94    winter
95    winter
96    winter
97    winter
```

```
98     winter
99     winter
100    winter
101    winter
102    winter
103    winter
106    winter
107    winter
108    winter
109    winter
110    winter

[100 rows x 13 columns]
```

In [11]:
```
df_final[df_final['Season'] == 'fall']['Dest'].value_counts()
```

Out[11]:
```
ATL     404256
ORD     345478
DFW     286828
LAX     220929
DEN     220042
PHX     192160
IAH     190718
LAS     174083
DTW     143222
EWR     142862
SLC     141996
SFO     132110
MSP     128340
CVG     125594
BOS     119154
CLT     118562
LGA     117587
MCO     116319
JFK     111950
SEA     105323
BWI     105056
PHL     103861
MDW      92844
SAN      91072
DCA      89511
IAD      87449
CLE      74138
TPA      72891
OAK      68657
MEM      62895
         ...
BLI        262
```

```
HKY        260
HVN        259
LWB        247
BPT        228
SLE        224
YKM        178
ILG        168
AKN        166
CMX        164
ALO        148
RHI        141
SUX        135
PLN        115
DLG        114
SOP        112
ADK         95
ITH         90
ACK         65
INL         55
BJI         38
TTN         30
MKG         18
PVU          4
PIR          4
OGD          4
PUB          2
RCA          1
CYS          1
EAU          1
Name: Dest, Length: 313, dtype: int64
```

In [12]:
```
df_final['Dest'].value_counts()
```

Out[12]:
```
ATL    1626680
ORD    1381040
DFW    1160142
LAX     905907
DEN     883619
IAH     810097
PHX     790141
LAS     702622
DTW     591918
EWR     586503
SLC     583586
MSP     540985
SFO     529662
CVG     523859
MCO     494675
```

```
BOS      489943
CLT      476917
LGA      475414
JFK      446749
PHL      429938
SEA      427706
BWI      422842
IAD      375085
MDW      373152
SAN      369108
DCA      364916
CLE      314606
TPA      311025
OAK      279136
FLL      271605
          ...
SUX         594
CMX         575
ALO         546
OTH         504
VCT         501
LMT         499
PIE         463
VIS         417
RHI         412
MKG         391
ADK         378
GST         338
SOP         311
INL         269
BJI         189
MTH         126
ITH         125
EAU          66
OGD          16
CYS          11
PVU           9
PIR           9
PUB           9
GLH           2
FMN           2
LAR           2
LBF           1
MKC           1
RCA           1
BFF           1
Name: Dest, Length: 325, dtype: int64
```

5 Data Visualization

In [13]:
```
dfgb1 = df_final.groupby(['Dest', 'Month'])
df_mean_by_apdest = dfgb1.agg(['mean'])
df_mean_by_apdest
```

Out[13]:
```
                   Year   ArrDelay   DepDelay Cancelled CarrierDelay  \
                   mean       mean       mean      mean         mean
Dest Month
ABE  1      2006.504147  12.738295  14.816943         0     7.361777
     2      2006.431669  11.159868  13.394875         0     7.067181
     3      2006.505803   9.377370  12.581552         0     6.498523
     4      2006.535693   5.856383   8.689086         0     4.630227
     5      2006.467137   3.374796   6.782727         0     4.203504
     6      2006.524331  15.784278  16.674574         0     7.414141
     7      2006.537332  15.083436  17.042228         0     8.433770
     8      2006.515062   9.984643  12.450679         0     6.100579
     9      2006.506761   5.889032   8.502254         0     6.332543
     10     2006.626604   5.444769   8.063011         0     6.217860
     11     2006.604771   4.542931   7.000000         0     4.259984
     12     2006.548177  14.477154  17.385417         0     8.578989
ABI  1      2006.465462   7.132337   9.226355         0     5.457516
     2      2006.478652   8.487064   9.539326         0     4.375698
     3      2006.411576  10.883047  12.762058         0     6.006274
     4      2006.405022  10.156114  10.671397         0     5.325459
     5      2006.406744  11.803590  13.500527         0     5.107323
     6      2006.533409  18.040770  20.138165         0     6.467225
     7      2006.539804  18.213740  19.611778         0     8.769863
     8      2006.539130  17.136017  17.680435         0     7.018617
     9      2006.546893   6.823729   9.263277         0     5.350365
     10     2006.501661   4.447398   7.331118         0     4.305750
     11     2006.501746   4.327506   7.352736         0     4.248902
     12     2006.496018  17.175199  18.734926         0     8.505510
ABQ  1      2006.557052   6.273550   9.244254         0     3.664531
     2      2006.567108   7.635778  10.628042         0     3.778840
     3      2006.549396   6.980771  10.614239         0     4.061699
     4      2006.567833   4.300496   7.228188         0     2.830865
     5      2006.578051   5.152407   8.386975         0     3.318715
     6      2006.578600   9.437100  12.398943         0     4.417165
...                 ...        ...        ...       ...          ...
YAK  7      2006.502058  12.128099  11.090535         0     4.644670
     8      2006.500000  26.235537  25.008197         0     4.892683
     9      2006.489362  12.591489  11.714894         0     1.869110
     10     2006.479339   5.933610   5.628099         0     5.529126
     11     2006.500000  -3.195455   0.084821         0     3.632184
     12     2006.462222  10.470320  15.346667         0     1.326531
YKM  1      2008.000000  18.387097   7.032258         0    26.166667
     2      2008.000000  11.750000   2.275000         0    16.384615
```

	3	2008.000000	12.132075	-1.075472	0	10.533333
	4	2008.000000	7.690909	-2.109091	0	3.750000
	5	2008.000000	-1.520000	-0.520000	0	16.000000
	6	2007.384615	4.743590	2.730769	0	6.020000
	7	2007.473684	4.236842	0.824561	0	5.171875
	8	2007.436364	5.918182	2.572727	0	6.169231
	9	2007.000000	5.135593	-2.508475	0	3.661017
	10	2007.000000	5.048387	-1.209677	0	5.564516
	11	2007.000000	8.719298	-1.228070	0	2.701754
	12	2007.000000	26.683333	9.066667	0	17.633333
YUM	1	2006.896818	9.191120	8.662488	0	10.369771
	2	2006.900318	7.090138	7.296925	0	9.957576
	3	2006.880976	5.870841	7.827317	0	10.350778
	4	2006.856600	2.878443	4.205128	0	7.609890
	5	2006.857010	0.356546	1.617456	0	6.145205
	6	2006.885163	4.264228	3.863821	0	9.299566
	7	2006.861427	9.353671	8.134436	0	12.309249
	8	2006.848140	9.184917	7.857438	0	12.361272
	9	2006.777528	5.852477	4.670787	0	9.158055
	10	2006.775661	5.195122	4.158730	0	8.008547
	11	2006.756340	6.864388	6.557883	0	10.055556
	12	2006.738994	10.409853	10.643606	0	12.438411

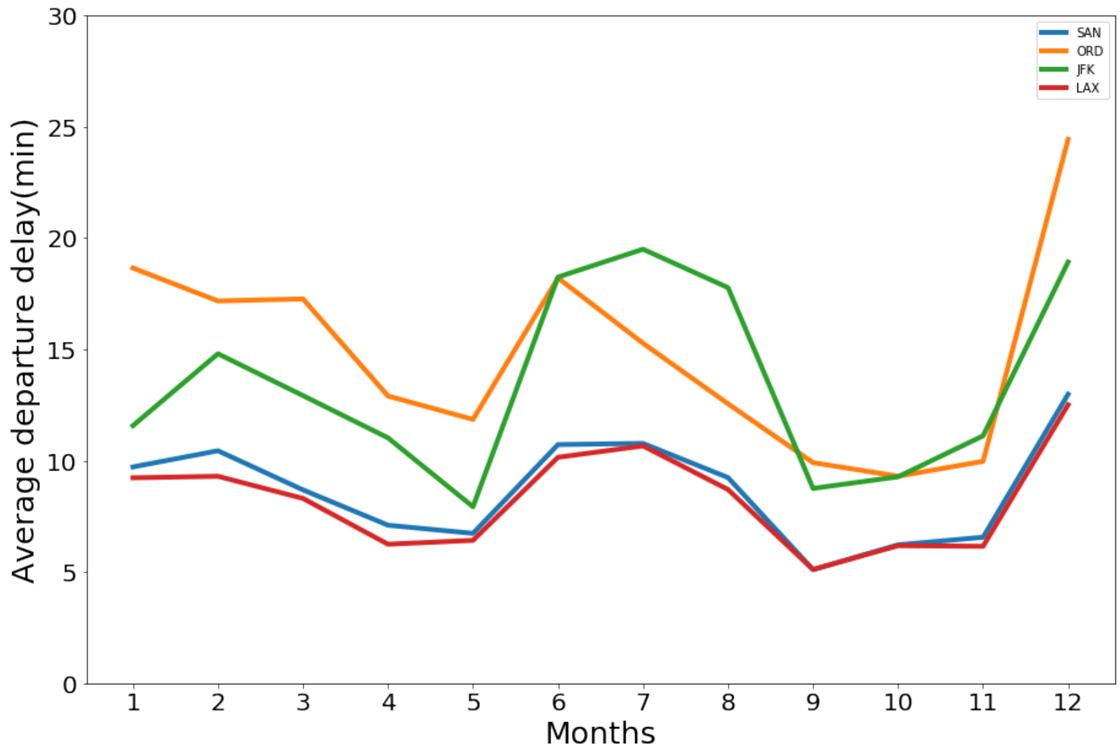
		WeatherDelay	NASDelay	SecurityDelay	LateAircraftDelay
		mean	mean	mean	mean
Dest	Month				
ABE	1	2.114245	3.352609	0.000000	6.950635
	2	1.620077	2.657915	0.094981	5.766023
	3	1.693501	2.098966	0.037666	6.141802
	4	1.176816	1.546588	0.136464	5.076302
	5	0.741240	1.799191	0.037736	4.316712
	6	2.393939	4.841991	0.020924	8.113997
	7	2.918486	4.395197	0.018195	6.427220
	8	2.565847	2.896527	0.080318	6.049204
	9	1.135861	2.146130	0.000000	3.522117
	10	1.538876	1.645112	0.000000	4.466513
	11	0.905460	2.326813	0.000000	4.415648
	12	1.785150	3.295419	0.000000	8.718799
ABI	1	2.126797	1.368627	0.000000	4.104575
	2	2.905028	2.212291	0.000000	5.248603
	3	3.643664	1.855709	0.000000	5.436637
	4	3.090551	1.944882	0.090551	4.856955
	5	2.950758	1.454545	0.000000	7.138889
	6	4.633194	1.846583	0.000000	11.857741
	7	4.604110	2.071233	0.000000	9.875342
	8	3.917553	2.722074	0.000000	9.688830
	9	2.710949	1.573723	0.000000	3.992701
	10	1.914446	1.074334	0.000000	3.103787

```
      11        1.118594   2.073206      0.000000           4.130307
      12        3.811295   2.278237      0.139118           8.965565
ABQ   1         0.603575   1.777146      0.018184           5.799979
      2         0.635147   1.942546      0.040702           6.882055
      3         0.530452   1.793939      0.047293           6.224441
      4         0.364267   1.659451      0.033351           4.553392
      5         0.417869   1.660223      0.022120           5.275630
      6         0.853187   2.109742      0.053169           7.282955
...                  ...        ...           ...                ...
YAK   7         0.000000   2.263959      0.000000          13.304569
      8         0.946341   3.365854      0.000000          23.175610
      9         0.937173   2.010471      0.026178          14.465969
      10        0.004854   1.708738      0.000000           8.699029
      11        0.419540   0.724138      0.000000           4.816092
      12        0.897959   2.719388      0.000000          13.750000
YKM   1         4.416667   0.000000      0.000000           9.416667
      2         1.769231   7.307692      0.000000           8.307692
      3         0.000000  11.266667      0.000000           7.866667
      4         0.000000  18.000000      0.000000           0.166667
      5         0.000000   5.333333      0.000000           0.000000
      6         0.000000   0.440000      0.000000           2.140000
      7         0.687500   0.531250      0.000000           2.125000
      8         0.000000   0.323077      0.000000           3.769231
      9         0.000000   0.000000      0.000000           0.932203
      10        0.000000   0.000000      0.000000           0.000000
      11        1.771930   0.000000      0.000000           1.789474
      12        2.483333   0.000000      0.000000           3.133333
YUM   1         1.461538   1.147099      0.035088           3.496626
      2         0.575758   0.953030      0.066667           2.192424
      3         1.357850   1.091938      0.000000           0.783593
      4         0.714286   0.609890      0.067308           1.204670
      5         0.235616   0.621918      0.000000           0.546575
      6         0.000000   0.562952      0.000000           1.094067
      7         0.893064   1.518786      0.043353           1.871387
      8         1.338150   1.170520      0.102601           1.040462
      9         0.056231   0.457447      0.000000           1.424012
      10        0.236467   0.737892      0.000000           1.574074
      11        0.083333   0.533626      0.147661           1.565789
      12        1.307285   1.026490      0.083444           1.892715

[3676 rows x 9 columns]
```

In [14]:
```
#DepDelays

dests = ['SAN', 'ORD', 'JFK', 'LAX']
plt.figure(figsize = (15,10))
for dest in dests:
    means = df_mean_by_apdest.loc[dest]['DepDelay']['mean'].values
```

```
    plt.errorbar(np.arange(1, 13), means, label = dest, linewidth = 4)
plt.ylabel('Average departure delay(min)', size = 25)
plt.xlabel('Months', size = 25)
plt.yticks(np.arange(0, 35, 5), size = 20)
plt.xticks(np.arange(1,13),['1','2','3','4','5','6','7','8','9','10','11','12'], size
plt.legend()
```

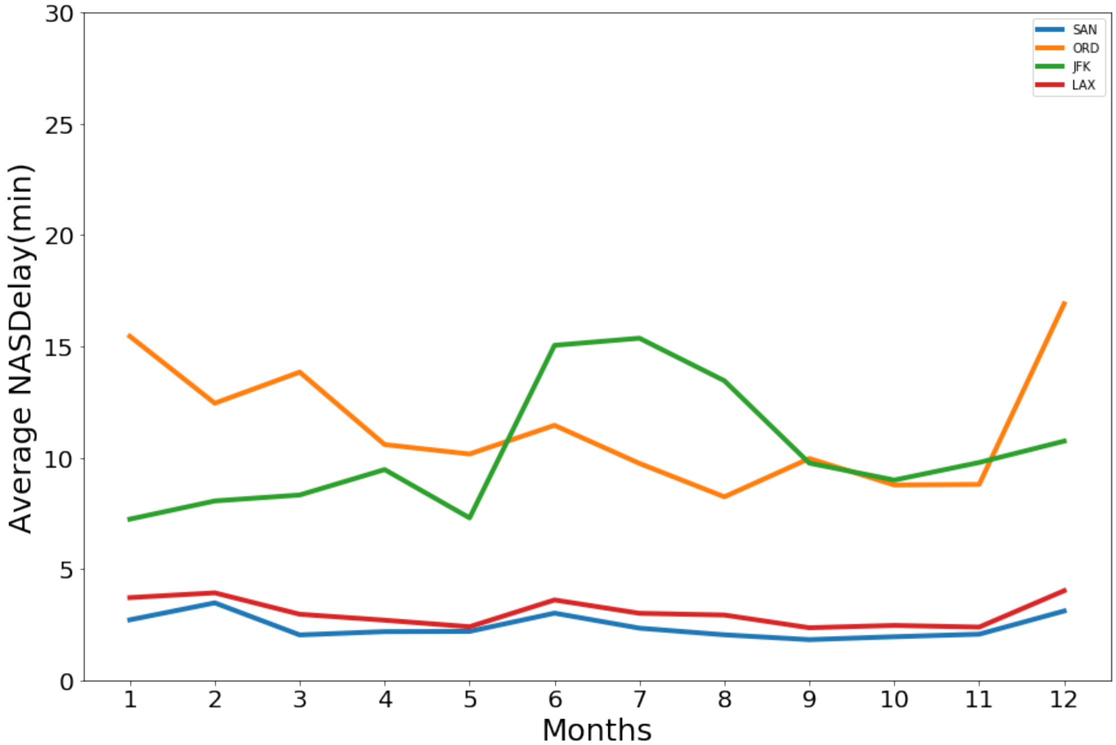
Out[14]: <matplotlib.legend.Legend at 0x10f2e8e48>



Low min of departure in months 5 and 9

In [15]:
```
#NASDelay


plt.figure(figsize = (15,10))
for dest in dests:
    means = df_mean_by_apdest.loc[dest]['NASDelay']['mean'].values
    plt.errorbar(np.arange(1, 13), means, label = dest, linewidth = 4)
plt.ylabel('Average NASDelay(min)', size = 25)
plt.xlabel('Months', size = 25)
plt.yticks(np.arange(0, 35, 5), size = 20)
plt.xticks(np.arange(1,13),['1','2','3','4','5','6','7','8','9','10','11','12'], size
plt.legend()
```

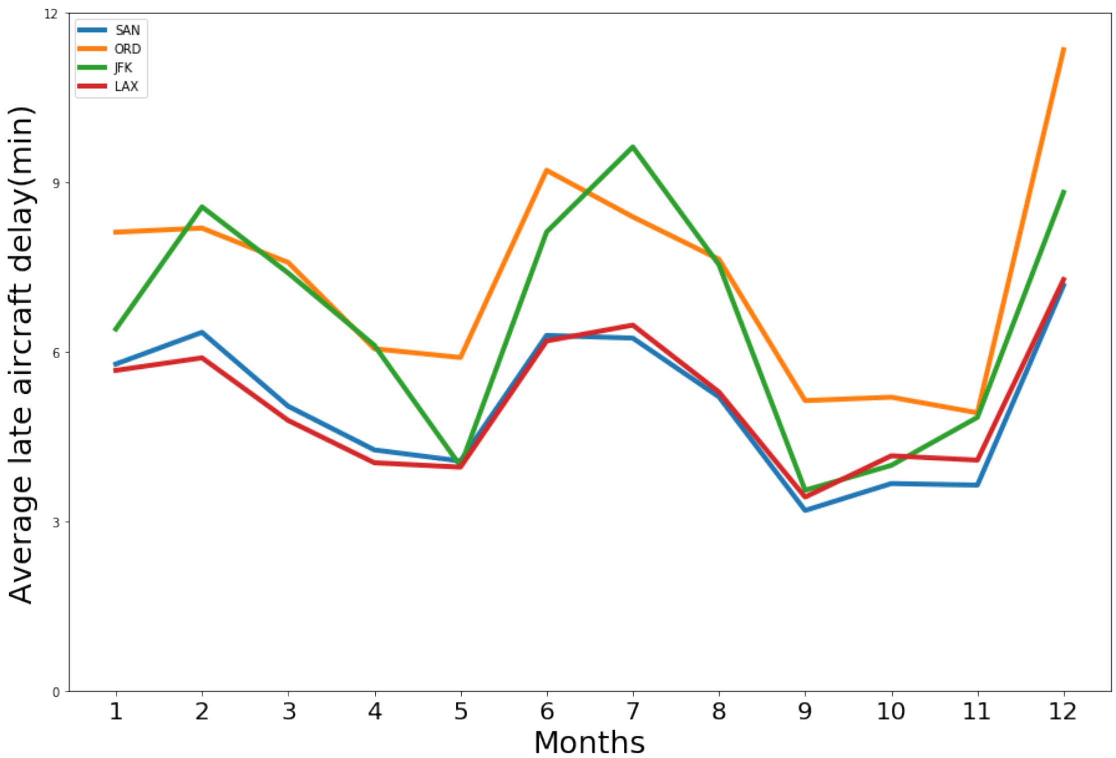
Out[15]: <matplotlib.legend.Legend at 0x117e47588>



This reason of delay does not match the overall delay very much

In [16]:
```
#LateAircraftDelays

plt.figure(figsize = (15,10))
for dest in dests:
    means = df_mean_by_apdest.loc[dest]['LateAircraftDelay']['mean'].values
    plt.errorbar(np.arange(1, 13), means, label = dest, linewidth = 4)
plt.ylabel('Average late aircraft delay(min)', size = 25)
plt.xlabel('Months', size = 25)
plt.yticks(np.arange(0, 15, 3), size = 10)
plt.xticks(np.arange(1,13),['1','2','3','4','5','6','7','8','9','10','11','12'], size
plt.legend()
```

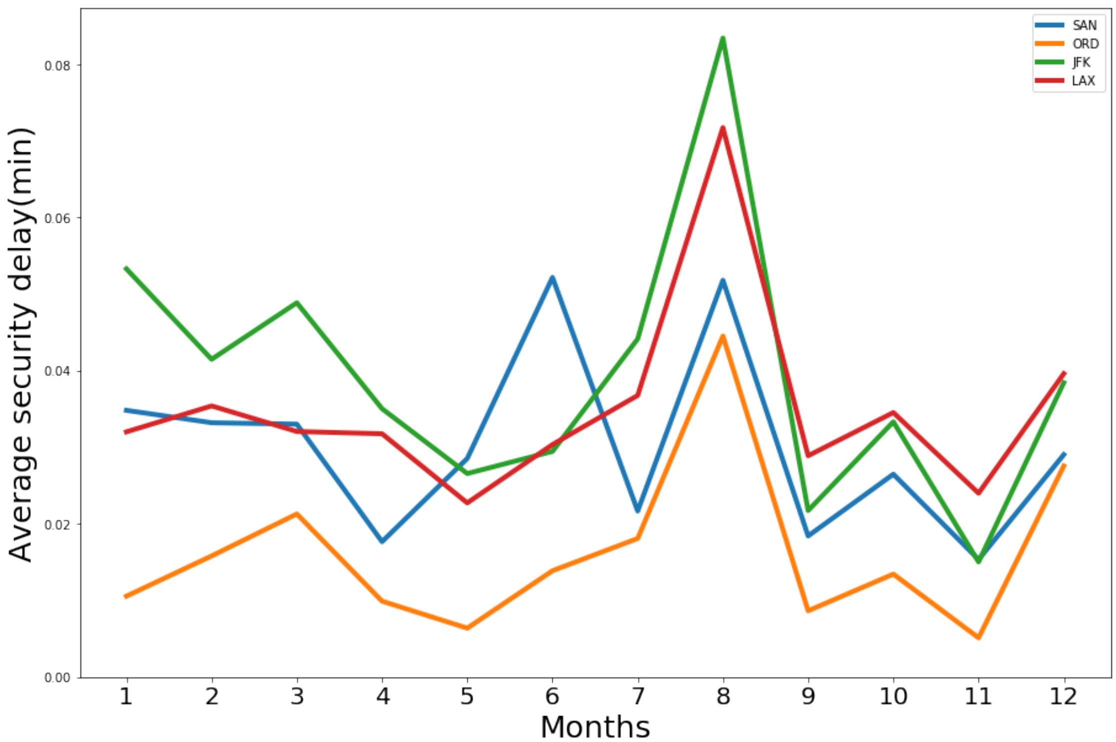
Out[16]: <matplotlib.legend.Legend at 0x117f2ecf8>



This looks similar to the overall delay graph, with low delay in mins in months 5 and 9

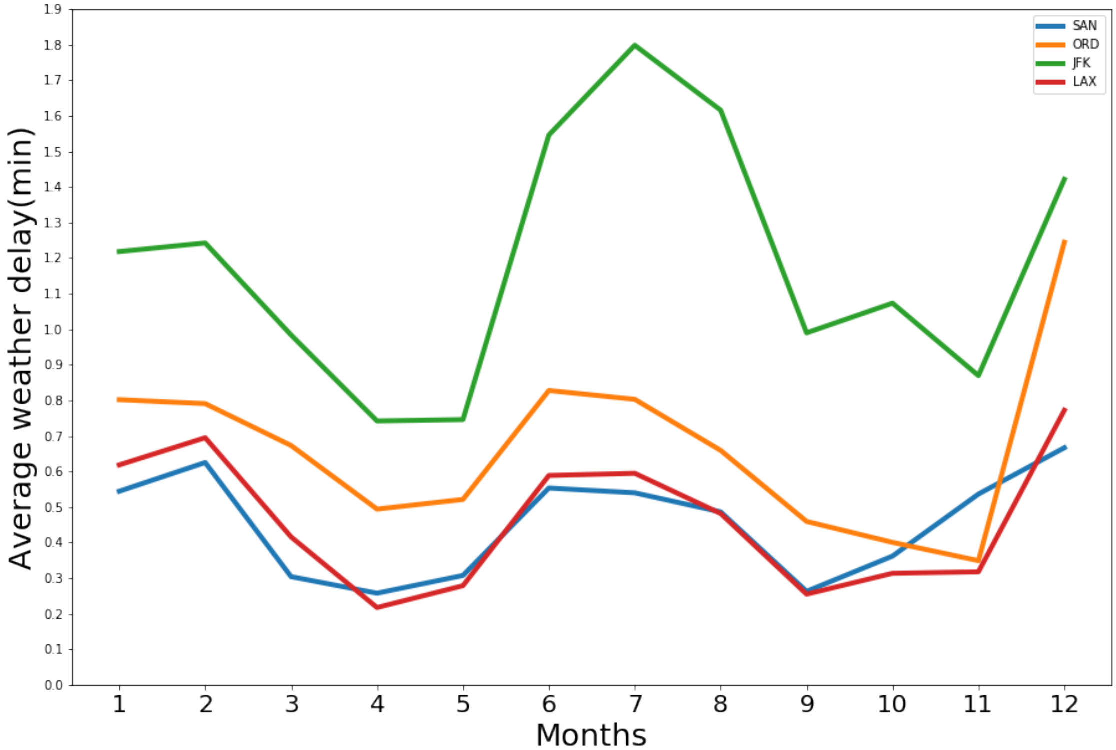
In [17]:
```
#SecurityDelays

plt.figure(figsize = (15,10))
for dest in dests:
    means = df_mean_by_apdest.loc[dest]['SecurityDelay']['mean'].values
    plt.errorbar(np.arange(1, 13), means, label = dest, linewidth = 4)
plt.ylabel('Average security delay(min)', size = 25)
plt.xlabel('Months', size = 25)
plt.yticks(np.arange(0, 0.1, 0.02), size = 10)
plt.xticks(np.arange(1,13),['1','2','3','4','5','6','7','8','9','10','11','12'], size
plt.legend()
```

Out[17]: <matplotlib.legend.Legend at 0x11a49a550>



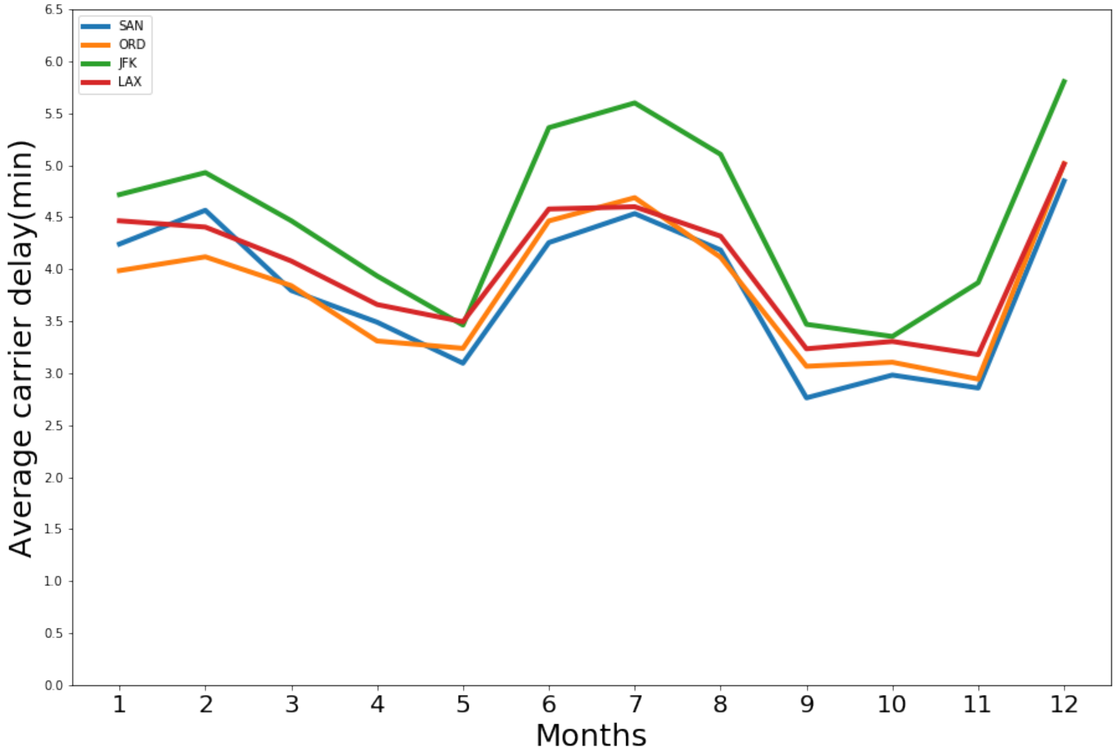
This graph does not look like the overall delay in mins graph

```
In [18]: #WeatherDelays

         plt.figure(figsize = (15,10))
         for dest in dests:
             means = df_mean_by_apdest.loc[dest]['WeatherDelay']['mean'].values
             plt.errorbar(np.arange(1, 13), means, label = dest, linewidth = 4)
         plt.ylabel('Average weather delay(min)', size = 25)
         plt.xlabel('Months', size = 25)
         plt.yticks(np.arange(0, 2, 0.1), size = 10)
         plt.xticks(np.arange(1,13),['1','2','3','4','5','6','7','8','9','10','11','12'], size
         plt.legend()

Out[18]: <matplotlib.legend.Legend at 0x11a7b6e10>
```



Looks similar to overall delay in minutes, low points at months 5 and 9

```
In [19]: #CarrierDelays

         plt.figure(figsize = (15,10))
         for dest in dests:
             means = df_mean_by_apdest.loc[dest]['CarrierDelay']['mean'].values
             plt.errorbar(np.arange(1, 13), means, label = dest, linewidth = 4)
         plt.ylabel('Average carrier delay(min)', size = 25)
         plt.xlabel('Months', size = 25)
         plt.yticks(np.arange(0, 7, 0.5), size = 10)
         plt.xticks(np.arange(1,13),['1','2','3','4','5','6','7','8','9','10','11','12'], size
         plt.legend()

Out[19]: <matplotlib.legend.Legend at 0x11a8b3860>
```



Looks similar to overall delay in minutes, with low points at months 5 and 9.

We will now try to see what the major reason of delay is in terms of minutes, all on the same graph.

To do this, first let's look at a popoular destination to look at these delay reasons with.

```
In [20]: df_final['Dest'].value_counts()[0:1]
```

```
Out[20]: ATL    1626680
         Name: Dest, dtype: int64
```

Now let's look for a less popular destination to compare to.

```
In [21]: df_final['Dest'].value_counts()[164:165]
```

```
Out[21]: RDM    13935
         Name: Dest, dtype: int64
```

So we will be looking at the mean delays in minutes for each reason, for each month. We will first look at this without a specific destination, then look at it with relation to a popular destination 'ATL' and finaly look at it with a less popular destination 'RDM'.

First let's look at a general case, without a specific location. We group by Month and mean to help get us variables for a graph.

```
In [22]: dfgb2 = df_final.groupby(['Month'])
         df_mean_by_apdest2 = dfgb2.agg(['mean'])
         df_mean_by_apdest2
```

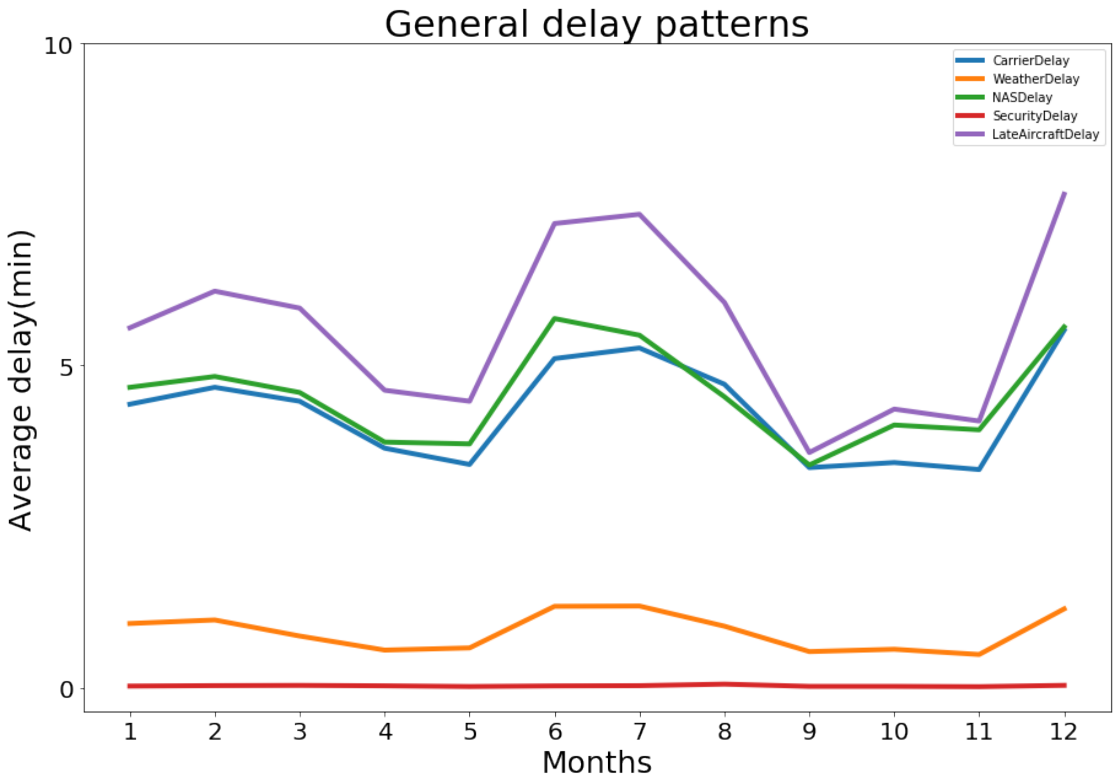
Out[22]:

```
                 Year   ArrDelay   DepDelay Cancelled CarrierDelay WeatherDelay  \
                 mean       mean       mean      mean         mean         mean
Month
1         2006.519296   8.770281  10.183391         0     4.398922     0.995643
2         2006.513668  10.079116  11.179303         0     4.661406     1.050314
3         2006.500476   9.210201  10.813852         0     4.444433     0.801404
4         2006.505769   6.101138   7.848737         0     3.716128     0.583057
5         2006.500478   5.736599   7.446081         0     3.464082     0.616716
6         2006.503999  12.846501  13.412990         0     5.106689     1.261961
7         2006.506906  12.325418  13.413387         0     5.271341     1.266751
8         2006.495365   9.335448  10.836677         0     4.708913     0.954174
9         2006.483096   3.938360   5.983095         0     3.414818     0.560286
10        2006.486113   5.667976   7.299825         0     3.493673     0.595916
11        2006.477164   4.882811   7.274100         0     3.385350     0.514717
12        2006.478560  13.775702  14.660925         0     5.546768     1.222447

       NASDelay SecurityDelay LateAircraftDelay
           mean          mean              mean
Month
1      4.660540      0.024391          5.584086
2      4.829308      0.031466          6.153434
3      4.580312      0.035115          5.890282
4      3.811203      0.028427          4.615676
5      3.782311      0.017605          4.444662
6      5.728112      0.027073          7.202234
7      5.469942      0.030764          7.346202
8      4.514669      0.055044          5.978859
9      3.455394      0.019860          3.649122
10     4.076211      0.019924          4.323167
11     4.001505      0.015538          4.137887
12     5.598102      0.035789          7.657383
```

In [23]:

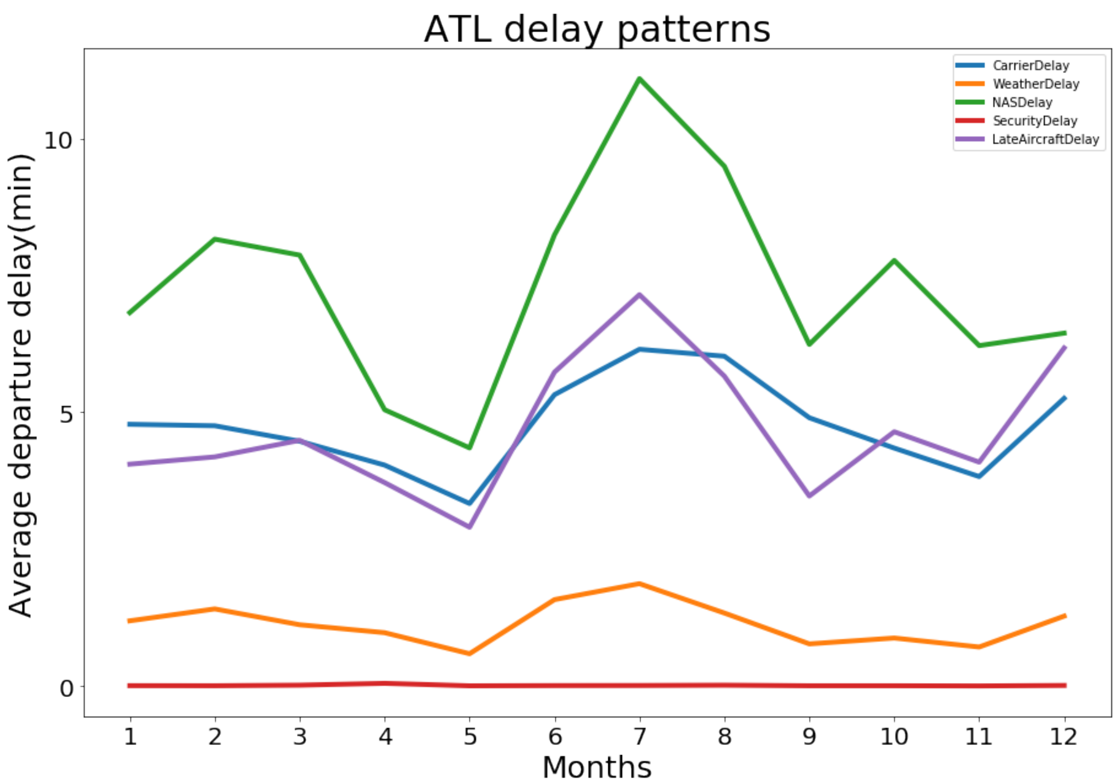
```python
DelayReason = [ 'CarrierDelay', 'WeatherDelay', 'NASDelay', 'SecurityDelay', 'LateAir
plt.figure(figsize = (15,10))
for reason in DelayReason:
    means = df_mean_by_apdest2[reason]['mean'].values
    plt.errorbar(np.arange(1, 13), means, label = reason, linewidth = 4)
plt.ylabel('Average delay(min)', size = 25)
plt.xlabel('Months', size = 25)
plt.yticks(np.arange(0, 15, 5), size = 20)
plt.xticks(np.arange(1,13),['1','2','3','4','5','6','7','8','9','10','11','12'], size
plt.title('General delay patterns', size=30)
plt.legend()
```

Out[23]: <matplotlib.legend.Legend at 0x11a963cc0>



Now let's look at the same type of graph, but with respect to the popular destination 'ATL'

```
In [24]: dfgbATL = df_final[df_final['Dest']=='ATL']
         dfgbATL = dfgbATL.groupby(['Month'])
         df_mean_by_apATL = dfgbATL.agg(['mean'])
         df_mean_by_apATL

         DelayReason = [ 'CarrierDelay', 'WeatherDelay', 'NASDelay', 'SecurityDelay', 'LateAir
         plt.figure(figsize = (15,10))
         for reason in DelayReason:
             means = df_mean_by_apATL[reason]['mean'].values
             plt.errorbar(np.arange(1, 13), means, label = reason, linewidth = 4)
         plt.ylabel('Average departure delay(min)', size = 25)
         plt.xlabel('Months', size = 25)
         plt.yticks(np.arange(0, 15, 5), size = 20)
         plt.xticks(np.arange(1,13),['1','2','3','4','5','6','7','8','9','10','11','12'], size
         plt.title('ATL delay patterns', size=30)
         plt.legend()

Out[24]: <matplotlib.legend.Legend at 0x11be8f0b8>
```

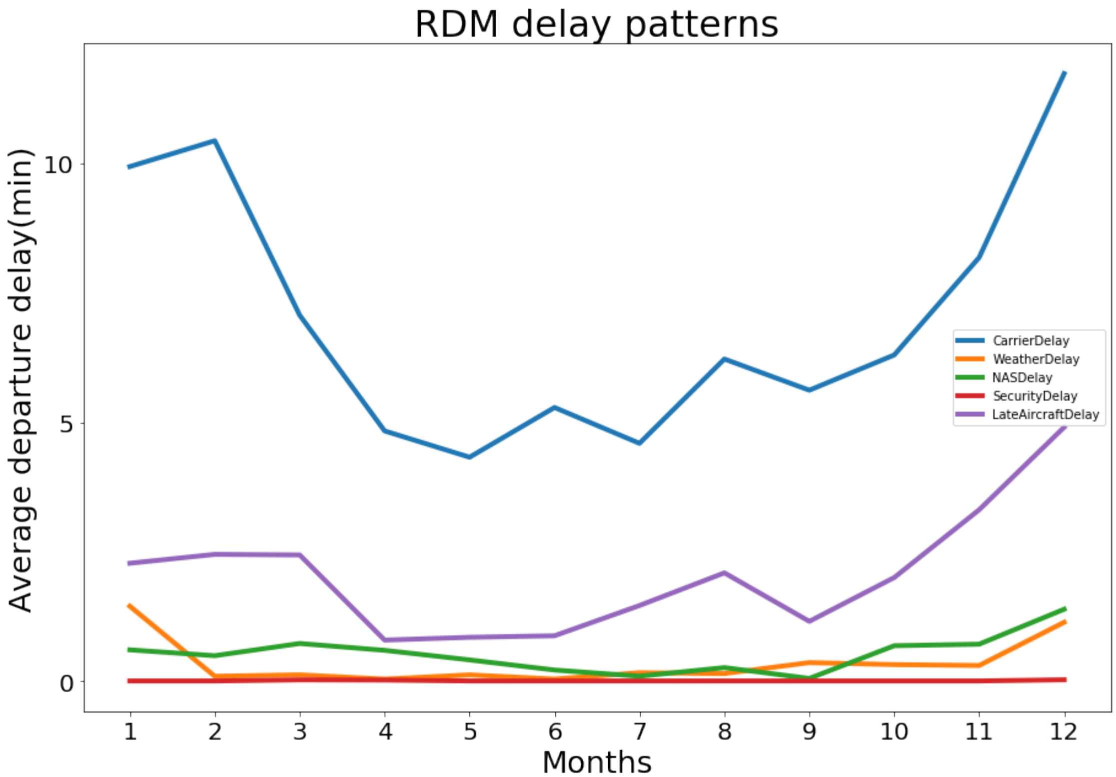


It looks like the major reason of delay in terms of minutes has changed, suggesting destination plays a role in delay reason.

Finally let's look at it with respect to an less popular destination 'RDM'

In [25]:
```
dfgbRDM = df_final[df_final['Dest']=='RDM']
dfgbRDM = dfgbRDM.groupby(['Month'])
df_mean_by_apRDM = dfgbRDM.agg(['mean'])
df_mean_by_apRDM

DelayReason = [ 'CarrierDelay', 'WeatherDelay', 'NASDelay', 'SecurityDelay', 'LateAir
plt.figure(figsize = (15,10))
for reason in DelayReason:
    means = df_mean_by_apRDM[reason]['mean'].values
    plt.errorbar(np.arange(1, 13), means, label = reason, linewidth = 4)
plt.ylabel('Average departure delay(min)', size = 25)
plt.xlabel('Months', size = 25)
plt.yticks(np.arange(0, 15, 5), size = 20)
plt.xticks(np.arange(1,13),['1','2','3','4','5','6','7','8','9','10','11','12'], size
plt.title('RDM delay patterns', size=30)
plt.legend()
```

Out[25]: <matplotlib.legend.Legend at 0x11cc06518>



6 Data Analysis/ Result

In [27]:
```
#df_final['WeatherDelay'].plot()
dfgb = df_final.groupby(['Month'])
df_mean_by_apmonth = dfgb.agg(['mean'])
df_mean_by_apmonth
```

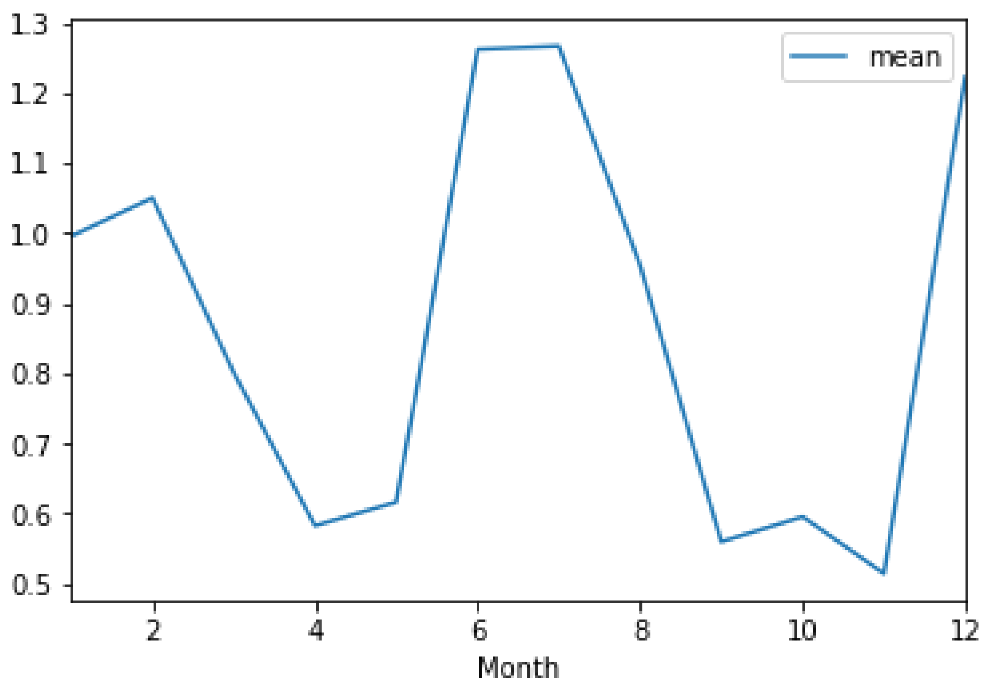
Out[27]:

	Year	ArrDelay	DepDelay	Cancelled	CarrierDelay	WeatherDelay \
	mean	mean	mean	mean	mean	mean
Month						
1	2006.519296	8.770281	10.183391	0	4.398922	0.995643
2	2006.513668	10.079116	11.179303	0	4.661406	1.050314
3	2006.500476	9.210201	10.813852	0	4.444433	0.801404
4	2006.505769	6.101138	7.848737	0	3.716128	0.583057
5	2006.500478	5.736599	7.446081	0	3.464082	0.616716
6	2006.503999	12.846501	13.412990	0	5.106689	1.261961
7	2006.506906	12.325418	13.413387	0	5.271341	1.266751
8	2006.495365	9.335448	10.836677	0	4.708913	0.954174
9	2006.483096	3.938360	5.983095	0	3.414818	0.560286
10	2006.486113	5.667976	7.299825	0	3.493673	0.595916
11	2006.477164	4.882811	7.274100	0	3.385350	0.514717
12	2006.478560	13.775702	14.660925	0	5.546768	1.222447

```
      NASDelay SecurityDelay LateAircraftDelay
          mean          mean              mean
Month
1     4.660540      0.024391          5.584086
2     4.829308      0.031466          6.153434
3     4.580312      0.035115          5.890282
4     3.811203      0.028427          4.615676
5     3.782311      0.017605          4.444662
6     5.728112      0.027073          7.202234
7     5.469942      0.030764          7.346202
8     4.514669      0.055044          5.978859
9     3.455394      0.019860          3.649122
10    4.076211      0.019924          4.323167
11    4.001505      0.015538          4.137887
12    5.598102      0.035789          7.657383
```

In [28]:
```
df_mean_by_apmonth['WeatherDelay'].plot()
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x1629c6c18>



In [29]:
```
df_final = df_final.fillna(0)
wd_sp = df_final[df_final['Season'] == 'spring']['WeatherDelay'].values
wd_sm = df_final[df_final['Season'] == 'summer']['WeatherDelay'].values
wd_wi = df_final[df_final['Season'] == 'winter']['WeatherDelay'].values
wd_fa = df_final[df_final['Season'] == 'fall']['WeatherDelay'].values
```

```
In [32]: from statistics import mean
         avg_wd_sp = mean(wd_sp)
         avg_wd_sm = mean(wd_sm)
         avg_wd_wi = mean(wd_wi)
         avg_wd_fa = mean(wd_fa)
```

```
In [33]: from scipy import stats
         t_val1 = stats.ttest_ind(wd_fa, wd_wi)[0]
         p_val1 = stats.ttest_ind(wd_fa, wd_wi)[1]
         t_val2 = stats.ttest_ind(wd_sp, wd_sm)[0]
         p_val2 = stats.ttest_ind(wd_sp, wd_sm)[1]
```

```
In [34]: if p_val1 < 0.01:
             print('Data Science accomplished, there is a significant difference between weathe
         else:
             print('There is NOT a significant difference!')
         if p_val2 < 0.01:
             print('Data Science accomplished, there is a significant difference between weathe
         else:
             print('There is NOT a significant difference!')
```

```
Data Science accomplished, there is a significant difference between weather delay during fall
Data Science accomplished, there is a significant difference between weather delay during sprin
```

The first graph of this section shows departure delay in minutes throught the year of four different destinations. The next five graphs show the same thing but each of the graphs are of a differnt reason of delay. Departure delay has low delay points at month 5 and 9 of the year. The Late aircraft delay, weather delay, and carrier delay graphs all follow the same trend of Departure delay, having low delay points at month 5 and 9. This suggests that these reasons of delay are the ones that impact the delay in minutes the most, while the reasons of NAS delays and Security delays don't impact delay in minutes as much.

The next three graphs show delay in minutes throughout the months but this time for the different reasons of delay in one graph. The first is a general graph with means encompassing all of the aircraft destinations. The next graph of the three is based on only the most popular destination 'ATL' and the last of the three graphs is based on a less populular destination 'RDM.' It is important to note that this is in terms of minutes and not airport counts. These graphs suggest that there is an importance in destination in the major reason of delay, since each graph had a diffrent top reason of delay. This is in line with our hypothesis as there is a relationship between destination and reason of delay. Another important result of these graphs was that although genereally Late Aircraft delay was a major reaason of delay, when the graphs were based on the most popular destination and to a less popular destination, it wasn't the case. So our hypothesis was wrong, it is only generally true that Late aircraft delay is the major reason for delay. It isn't true when split into different destinations.

Finally, our tests have shown differences in weather delay between the seasons, which makes sense.

```
In [36]: late_aircraft_delay = df_final['LateAircraftDelay']
         arrival_delay = df_final['ArrDelay']
         departure_delay = df_final['DepDelay']
```

```
In [46]: import statsmodels.api as sm
         model = sm.OLS(arrival_delay, late_aircraft_delay)
         res = model.fit()
         res.summary()

Out[46]: <class 'statsmodels.iolib.summary.Summary'>
         """
                                     OLS Regression Results
         ==============================================================================
         Dep. Variable:               ArrDelay   R-squared:                       0.393
         Model:                            OLS   Adj. R-squared:                  0.393
         Method:                 Least Squares   F-statistic:                 1.822e+07
         Date:                Thu, 22 Mar 2018   Prob (F-statistic):               0.00
         Time:                        19:08:51   Log-Likelihood:            -1.3565e+08
         No. Observations:            28191615   AIC:                         2.713e+08
         Df Residuals:                28191614   BIC:                         2.713e+08
         Df Model:                           1
         Covariance Type:            nonrobust
         =====================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
         -------------------------------------------------------------------------------------
         LateAircraftDelay     1.1683      0.000   4268.224      0.000       1.168       1.169
         ==============================================================================
         Omnibus:                 38257720.536   Durbin-Watson:                   1.731
         Prob(Omnibus):                  0.000   Jarque-Bera (JB):      24479911858.113
         Skew:                           7.467   Prob(JB):                         0.00
         Kurtosis:                     146.587   Cond. No.                         1.00
         ==============================================================================

         Warnings:
         [1] Standard Errors assume that the covariance matrix of the errors is correctly spec
         """
```

Because the p-value is ~0, late aircraft delay is a significant predictor of a plane's arrival delay. We see the linear regression below.

```
In [53]: from sklearn import linear_model
         reg = linear_model.LinearRegression()
         late_aircraft_delay_rs = late_aircraft_delay.reshape(-1, 1)
         arrival_delay_rs = arrival_delay.reshape(-1, 1)
         reg.fit(late_aircraft_delay_rs, arrival_delay_rs) #arrival_delay = a0 + a1*late_aircr

         print("arrival_delay =", reg.intercept_[0], "+", reg.coef_[0][0], "*late_aircraft_dela

/anaconda/lib/python3.6/site-packages/ipykernel/__main__.py:3: FutureWarning: reshape is depre
  app.launch_new_instance()
/anaconda/lib/python3.6/site-packages/ipykernel/__main__.py:4: FutureWarning: reshape is depre
```

```
arrival_delay = 3.41547069303 + 1.13125260004 *late_aircraft_delay
```

```
In [47]: model1 = sm.OLS(departure_delay, late_aircraft_delay)
         res1 = model1.fit()
         res1.summary()
```

```
Out[47]: <class 'statsmodels.iolib.summary.Summary'>
         """
                                     OLS Regression Results
         ==============================================================================
         Dep. Variable:               DepDelay   R-squared:                       0.438
         Model:                            OLS   Adj. R-squared:                  0.438
         Method:                 Least Squares   F-statistic:                 2.201e+07
         Date:                Thu, 22 Mar 2018   Prob (F-statistic):               0.00
         Time:                        19:09:45   Log-Likelihood:            -1.3255e+08
         No. Observations:            28191615   AIC:                         2.651e+08
         Df Residuals:                28191614   BIC:                         2.651e+08
         Df Model:                           1
         Covariance Type:            nonrobust
         =====================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
         -------------------------------------------------------------------------------------
         LateAircraftDelay     1.1506      0.000   4691.578      0.000       1.150       1.151
         ==============================================================================
         Omnibus:                 42887008.923   Durbin-Watson:                   1.767
         Prob(Omnibus):                  0.000   Jarque-Bera (JB):      80788366658.535
         Skew:                           8.994   Prob(JB):                         0.00
         Kurtosis:                     264.635   Cond. No.                         1.00
         ==============================================================================

         Warnings:
         [1] Standard Errors assume that the covariance matrix of the errors is correctly speci
         """
```

Because the p-value is ~0, late aircraft delay is a significant predictor of a plane's departure delay. We see the linear regression below.

```
In [55]: reg1 = linear_model.LinearRegression()
         late_aircraft_delay_rs = late_aircraft_delay.reshape(-1, 1)
         departure_delay_rs = departure_delay.reshape(-1, 1)
         reg1.fit(late_aircraft_delay_rs, departure_delay_rs) #arrival_delay = a0 + a1*late_ai

         print("departure_delay =", reg1.intercept_[0], "+", reg1.coef_[0][0], "*late_aircraft_
```

```
/anaconda/lib/python3.6/site-packages/ipykernel/__main__.py:2: FutureWarning: reshape is depre
  from ipykernel import kernelapp as app
/anaconda/lib/python3.6/site-packages/ipykernel/__main__.py:3: FutureWarning: reshape is depre
  app.launch_new_instance()
```

```
departure_delay = 5.06980910098 + 1.09564372215 *late_aircraft_delay
```

7 Privacy/ethics considerations

The data we are using is public. Since they are about aircraft flights, the location based information is not a privacy concern. Nothing invades personal privacy of anybody. There are no seen biases in the data, and it allows for equitable analysis since people themselves aren't even recorded in the data. We do not see any potential issues that would affect privacy or equitable analysis.

8 Conclusions and Discussion

Our analysis and results of our tests and visualizations have given us important information about flight delays with respect to destination, reason, and time of year.

Our data have shown us that LateAircraft delay, weather delay and carrier delay are the reasons that impact minutes of delay the most. From this, we think that if we are to decrease minutes of aircraft delay, these are what should be focused on. We have also learned that destination affects which reason of delay is affecting the delay the most. Furthermore, when separated in terms of destination, the delay in minutes throughout the year is different between the destinations. So if trying to avoid the delay, we should look at different months of the year based on different destinations. This is because each destination has different volumes of traffic during the different months in the year, and some months can sufficiently prove to be better to travel during in order to avoid getting into delays. This would make sense since in some months (for eg. especially holiday season in december) the volume of traffic at airports is high since people are going back to their homes or going somewhere on the holiday.