INVESTOR DISTRACTION AND ABNORMAL AIR TRAFFIC

Background of Research

As March Madness arrives, distracted workers around the country will be paying more attention to their brackets than their work according to a report by outplacement firm Challenger, Gray & Christmas. The firm estimates that more than 50.5 million American workers, or 20 percent, could participate in office pools this year. The loss of productivity in the opening week of March Madness could cost employers nearly $4 billion in lost revenue and each hour of the workday wasted on building brackets or watching games will cost employers $1.3 billion. (*Paraphrased from CNBC*).

Researchers and investors have long discussed the possibility that distractions can cause the market to become less efficient. This loss of efficiency can lead to mispricing, delayed market reaction, lower trading volume, or even passive management. Events suspected of distracting investors are vast and often the same kind of events we would expect to be distracted by ourselves. From sports to religious events, we as a species tend to pay less attention to our work as the date of a desired (or undesired) event approaches.

There are a number of examples that have already been documented within the literature of events leading to investors becoming distracted and this distraction affecting their performance. One example looks at holidays and finds distraction leading up to holidays in general. Others focus on specific holidays such as Easter where Pantzalis and Ucar (2014) find that earnings announcements around Easter tend to be incorrectly incorporated into prices. Specifically, the authors find that while price response is delayed, it is more delayed for bad news. Additionally, this result appears to be stronger in areas that have a more Christian culture. Gavriilidis, Kallinterakis, Tsalavoutas (2016) find that investors tend to herd (buy in similar directions) around the Islamic religious time of Ramadan, especially in predominantly Muslim countries.

Of course distraction does not need to be related only to religious events, although a high percentage of holidays are religion-related. We can look at any number of culture specific holidays and determine whether investors in areas strongly influenced by that culture can become distracted. This can include the Shanghai Stock Exchange during Chinese New Year or the Frankfurt Stock Exchange during Octoberfest. Finally, authors such as Dellavigna and Pollet (2009) find that there is distraction and mispricing leading up to weekends.

Description of Research

In this paper we propose an alternative test to help shed light on the discussion of whether or not investors become distracted, as a result of which markets become less efficient or less accurately priced. We speculate that a great number of events that have been proposed to cause distraction can be proxied for by a single measure, *abnormal air traffic*. The logic behind this premise is that many of the previously documented events related to distraction are also events that would require a large number of individuals to travel. While many people do not travel by plane, there is likely a strong correlation between overall travel and air travel. We suggest that not all events (such as holidays) are created equal with respect to distraction for work. While we certainly think about what to present to buy our mother for Mother's Day, we are unlikely to avoid hours of work in anticipation of one Sunday in May. Alternatively, events such as major sports events do not merely distract us on the day of the game but contribute to hours, days, and weeks

of distraction leading up to the event while we "research" our favorite team or engage in water cooler conversation. We believe that a significant portion of the latter event type will be identified by times where more people are travelling than normal. Stated differently, most people do not fly across the country for Mother's Day but do so for Easter. In addition, we all have experienced the stress leading up to a travel date. It is not unrealistic to imagine that travel-related concerns could potentially lead to oversight and neglect of investors' professional responsibilities in the short term.

Data, Research Design, and Methodology

We intend to proceed with this project in three steps. The first test is to identify whether overall abnormal air traffic is correlated with investor distraction. Distraction has been measured in literature in a number of ways - decreased volume of trading, changes in bid-ask spread, delayed response to earnings announcements, and changes in mispricing to name a few. We are still in the process of determining which of these methods we will include in our tests.

For the second test, we evaluate whether only positive abnormal air traffic is related to distraction or if negative air traffic can also impact investor trading. As an extreme example, after national tragedies such as 911, or The Vegas shootings, many flights were grounded either locally or nationally. We expect that under such scenarios, events that lead to lower air traffic would also lead to investor distraction. The distraction could be a result of direct effect from the tragedy or due to time taken to follow news updates.

For the third test, we evaluate whether these events that have strong traffic to distraction relationships are predictable. Do they occur the same time every year? If so can one invest across them to make abnormal profits? We propose a two-step question. First, identify those events which appear to occur on a regular basis. Second, determine if a long short portfolio can be created that provides abnormal returns.

For the fourth test, we determine whether we can identify abnormal air traffic to/from specific states and evaluate the companies that are based in those states. An example would be Google, which is based in Palo Alto. When traffic leaving California is abnormally high it is possible Google stock will exhibit differential pricing. We may not detect different investor interest as investors are likely in Chicago, New York, London, etc. but we may find evidence of differential pricing. This finding would reinforce the legitimacy of using air traffic as a measure of investor distraction. We understand there may be some concerns about this test including - 1. Not all companies operate in the state in which they incorporate; and 2. People leaving or entering a particular state may not affect the operations of the company. However, we will conduct several robustness tests to alleviate such concerns.

We will use three databases for this research - air traffic data collected from the International Transportation Administration; CRSP data for stock prices, bid-ask spread, and volume; and I/B/E/S database for evaluating response to earnings announcements. The time period of our study currently covers 1990 to 2013. However we will extend the time period to end in 2017. We have approximately 6425 observations for which we have both volume and traffic. We use the following measures:

$$\text{Abnormal Traffic} = \frac{(daily\ air\ traffic - monthly\ average\ traffic)}{monthly\ average\ traffic}$$

$$\text{Abnormal Volume} = \frac{(daily\ volume - monthly\ average\ volume)}{monthly\ average\ volume}$$

Volume = Weighted average of all stocks listed on the NYSE, NASDAQ, and AMEX.

For our first test, we examine if abnormal traffic can predict abnormal trading. Model 1 includes abnormal volume as the dependent variable and abnormal air traffic as the independent variable. In Model 2, we use the absolute value of both dependent and independent variables and in Model 3 we include the squared dependent and independent variables. We include year fixed effects to control for natural increases in either traffic or trading volume (our results remain robust).

Our first set of results (*Table 1 attached separately in Appendix*) indicates a strong relationship between daily air traffic and trading volume. While the relationship changes in sign when we use either absolute value or squared values, the relationship remains highly significant, both statistically and economically. Economically, we can explain about 3-4% of changes in volume through changes in flight patterns. The negative positive relationship that we see in Model 1 implies that contrary to our initial hypothesis, volume tends to increase as air traffic increases. Model 2 and 3 tell us that deviations from average air traffic lead to increases in abnormal trading (whether it is positive or negative).

Next, we perform tests across quintiles of air traffic in order to more appropriately evaluate what appears to be a non-linear relationship we. We place each daily observation into one of five bins sorted by the amount of abnormal air traffic. The results (*Table 2 attached separately in Appendix*) show that the results found in Table 1 appear to be driven mostly by those days with very low air traffic and those days with very high air traffic. While R-squares are quite high for the highest rank (rank 5) at 6%, they are remarkably high at 17% for the lowest rank (rank 1). Next, we replace the dependent and independent variables in Model 2 with squared variables. We detect one major change with this replacement. The relationship appears to be different for those days when traffic is the lowest than when it is the highest. For low traffic days, the closer the traffic gets to the average, the more volatile the volume is. This implies that for high traffic days, a unit change in traffic will have a stronger impact on trading than for low-to-medium traffic days.

APPENDIX

Table 1

Air Traffic on Stock Market Volume

			R-Squared	3%
		Coefficient	T-Stat	
Model 1	Intercept	-2.56E-17	0	
	Abnormal Traffic	0.70295	13.51	
			R-Squared	3%
Model 2	Intercept	0.0542	3.92	
	|Abnormal Traffic|	-1.13516	-13.63	
			R-Squared	4%
Model 3	Intercept	0.02407	1.81	
	Abnormal Traffic Squared	-6.11325	-15.63	

The Table above reports the relationship between abnormal air traffic and investor distraction as measured by abnormal trading volume. Abnormal air traffic is measured as $\frac{(daily\ air\ traffic - monthly\ average\ traffic)}{monthly\ average\ traffic}$, Model 2 takes uses the absolute value of both the independent and dependent variable. Model 3 uses the squared abnormal traffic and abnormal volume. There are 6425 observations spanning 1990 through 2013.

Table 2

Relationship Broken Down By Quintile

Model 1	Rank				
			Parameter	T-Stat	R-Square
	1	Intercept	0.07535	2.44	17%
		Abnormal Traffic	1.71902	12.68	
	2	Intercept	0.00562	0.17	6%
		Abnormal Traffic	1.42679	2.34	
	3	Intercept	-0.00677	-0.2	2%
		Abnormal Traffic	0.06384	0.08	
	4	Intercept	0.10216	2.34	5%
		Abnormal Traffic	-0.53442	-0.56	
	5	Intercept	-0.03049	-0.76	6%
		Abnormal Traffic	0.79492	1.74	
Model 2	Rank				
			Parameter	T-Stat	R-Square
	1	Intercept	-0.00818	-0.29	19%
		Abnormal Traffic Squared	-6.04126	-13.54	
	2	Intercept	-0.0122	-0.4	6%
		Abnormal Traffic Squared	-22.88052	-1.86	
	3	Intercept	-0.00165	-0.05	2%

	Abnormal Traffic Squared	-22.7037	-0.58	
4	Intercept	0.09251	2.85	5%
	Abnormal Traffic Squared	-7.19086	-0.54	
5	Intercept	0.00253	0.09	6%
	Abnormal Traffic Squared	4.24192	1.61	

Table 2 breaks the tests from Table 1 into quintiles across air traffic. Rank 1 is the lowest air traffic and Rank 5 is the highest air traffic. Model 1 uses abnormal air traffic and abnormal volume while Model 2 uses abnormal traffic and volume squared. There are approximately 1285 daily observations in each rank category spanning 1990 through 2013.