A Study on The Airline Industry:
How Ultra Low Cost Carriers Impact Quality

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1 Introduction

Ultra low-cost carriers (ULCCs) are often viewed as no-frills, with every extra add-on in the flight coming with a premium, but this structure allows them to offer typically lower base ticket prices. ULCCs began expanding more aggressively in the 2010s, reshaping the competitive landscape in the U.S. airline industry. The three main ULCCs—Spirit, Frontier, and Allegiant—offer similar stripped-down services built around low fares and unbundled products. They tend to rely on unbundling services you may see included in other airlines, things such as carry-on bags, seat assignments, and in-flight amenities, which lowers the base fare significantly and shifts more of their revenue toward ancillary fees. Their business model relies on competing primarily on price rather than service quality, which is not appealing to every traveler but has become increasingly attractive to a large share of consumers. Furthermore, LeMay, Hawkins, and Reinhardt (2025) show that "For the former, our taxonomy emphasizes how ULCCs copy the older low-cost carriers like Southwest in their approach to standardized equipment and linear routes but take these strategies to more extreme levels— pursuing minimal infrastructure investment, lean staffing, and bare-bones technology that enables their distinctive ultra-low-cost positioning."

Service quality is a key element of airline competition. Through things like arrival and departure delays, cancellation rates, and lost baggage, we are constantly seeing metrics shift, and airlines work to offer the best possible service they can. These metrics are frequent in what consumers complain about and are clear indicators of the quality of service being offered. These metrics matter even further when looking at ULCCs, as their model is built on the lowest possible price, not comfort, which could spill over to other airlines. When carriers face new competitive pressure from either mergers, new emerging airlines, or new business practices, such as what ULCCs offer, we may see changes in these metrics.

Our study is inspired by Gil and Kim (2021), who investigated whether increased competition, measured by airline mergers, led to improvements in service quality. Their work serves as inspiration for this study. That paper defines specific pre-periods and post-periods around the merger event using different service metrics. Using similar methods and logic will allow us to measure when we see more market presence by ULCCs, which we will define as a "boom" period, and whether that changes quality or if legacy airlines remain unfazed, with the business models varying too much. Most previous work focuses on either mergers or legacy carriers compared to low-cost carriers (LCC). With ULCCs differing enough from LCCs, previous studies are not fully applicable to both fields, so new research is needed on how the market is shifting further.

We initially wanted to measure across Spirit, Frontier, and Allegiant, but we quickly found this was not feasible. Leaving such a large sample across different ULCCs made it difficult to define time periods for our event study and caused major data constraints. With over 40 million observations initially, we realized this needed to be trimmed down. This led us to focus specifically on Spirit Airlines, offering a clean period where we could mark entry and a solid amount of growth to help measure before and after. Spirit makes a clear case for being the focal point of our analysis, as they are the largest ULCC within the US, making them the best option to examine market shifts.

We aim to estimate if the emergence of ULCC improves or worsens quality across incumbents, with the broader idea of understanding whether travelers benefit from better service or simply cheaper fares. This leads us to our final research question – Does the emergence and increased competition of Spirit Airlines lead to improved quality in the airline industry?

2 Related Work

The airline industry itself is one that has been extremely well studied and documented, but when you turn and look at ULCCs, and specifically how they impact quality, the work becomes very scarce, with this model only really beginning to pick up steam in the mid-2010s. One of the main things done in past work is the grouping of LCC and ULCC carriers together, but Bachwich and Wittman (2017) state that "In recent years, the emergence of the ULCC model in the U.S. airline industry has created a new competitive landscape. As part of their business model, ULCCs achieve lower costs than LCCs while collecting ancillary revenue from aggressive unbundling of fares, yet still lag LCCs and NLCs in total system unit revenue. Previous works have examined ULCCs such as Spirit and Allegiant with the underlying assumption that all major carriers fit into the NLC or LCC category." This helps push further the need for our analysis, as there is a clear gap in the previous literature regarding ULCCs specifically, and even less on their impact on quality. Furthermore, Shrago (2024) state that "the evidence and empirical results in this paper indicate that ULCCs should not be viewed as merely a subsegment of a broader LCC segment. On the contrary, the marked differences between LCCs and ULCCs in terms of both their business models and the price pressure exerted on competitors indicates ULCCs represent a distinct market segment. As such, researchers should strongly consider abandoning the legacy/LCC taxonomy in favor of a new taxonomy that distinguishes between legacy carriers, LCCs, and ULCCs whenever such a taxonomy is necessary."

One study by LeMay, Hawkins, and Reinhardt (2025) shows that "On the customer side, ULCCs did not seek to expand in our measure of underserved markets but did seek tourist markets. Interestingly, ULCCs did not respond to the same market characteristics as NLCs or LCCs, although the latter responded similarly to each other with respect to population and per capita income changes. This behavior fits their position in our resource-based taxonomy. ULCCs' minimal infrastructure and standardized fleet let them target specific markets rather than comprehensive coverage." This helps highlight the unique market behavior ULCCs exhibit, reinforcing that they differ not just in cost structure but also in how they choose where to operate.

Much of the sparse work that has been done on the ULCC market has focused on pricing aspects and how ULCCs have changed pricing structures. Shrago (2024) find that "Moving again to the fare reductions associated with ULCC presence, I find large impacts for Frontier and Spirit at the bottom end of the fare distribution, but these again diminish significantly by the 50th percentile." This helps indicate that airlines are primarily willing to adjust their lowest-tier fare classes, such as Basic Economy, when ULCCs enter a market, allowing them to better compete with ULCC fee structures. We feel this evidence helps support the idea of airlines shifting toward lower-cost models, which may in turn contribute to declines in service quality. Wang and Ma (2024)"The behavior of incumbent carriers raising prices and increasing capacity when facing entry threats from Spirit aligns with the predictions of industrial organization theory. The ULCC's business model, which is focused on offering low prices to consumers, creates price pressure on the NLC and LCC incumbents, which may lead to a reduction in profits. To counteract this, incumbents may raise prices in order to maintain their profit margins and offset the potential loss in revenue. Additionally, increasing capacity can create a barrier to entry for Spirit by making it more difficult for the new entrant to find available slots at airports and secure gate space. Incumbents therefore tend to take actions on both pricing strategies and capacity investments to protect their market position and profits when facing potential competition from a new entrant." This here also goes with the findings of the study and Gil and Kim, when there is threat of new entry in the airline industry, the incumbents will create entry deterrence, but after entry has happened they tend to ease.

We hope to be able to contribute and provide a clear analysis that will help bridge the literature gap with our study on ULCC, specifically Spirit Airlines, and how they impact airline quality.

3 Data

3.1 Data Collection and Cleaning

Initial data were collected from four sources: DB1B coupon data and ticket data (U.S. Department of Transportation, Bureau of Transportation Statistics 2025a), T-100 data (U.S. Department of Transportation, Bureau of Transportation Statistics 2025b), and On-

Time Performance metrics (U.S. Department of Transportation, Bureau of Transportation Statistics 2025c), which were merged to form the base dataset spanning from 2000-2019. We recognize the need for immediate filtering and cleaning within these gigantic datasets, so we began with filtering only to U.S. domestic passenger flights, and then further removing any routes where there was only one carrier in a specific route, and that route had less then 10,000 flights. We also removed any routes that the route share was made up of over 90%, as this would be close to monopolistic qualities. Our initial time frame was also considerably too long, with many of the ULCC barely having any market presence during this time, so we trimmed it from 2008 to 2017, which would allow us a better time frame to create our event study. This left us with a dataset that ended with 44 million rows, over 43 unique columns. We were naive initially and thought we could form a credible analysis within this, and after much trial and error, the need for much more aggressive data cleaning was needed.

One of the major things we choose not to include are slot-controlled airports, with these being airports that the number of takeoffs and landings are managed directly by authorities, such as the FAA, to help in the prevention of delays. The most major of airports included in this exclusion is in New York, with: John F. Kennedy (JFK), LaGuardia (LGA) airports. Also within our data, we defined these routes as city-pairs, which in essence views a route of Detroit to Atlanta, the same as Atlanta to Detroit.

Within the data initially collected, it is sorted into distance groups. Once we began more aggressively cleaning we decided that only routes under distance group 2 were needed, which would represent flights under time. With this we believe that with Spirit airlines and the ancillary fee model, people would be more willing to go towards this on short-haul flights, where they don't necessarily need as many in-flight amenities. Also within this spirit itself tends to be more active with shorter haul domestic flights, so this is why we felt filtering down to these will help produce more credible results, with them not being real players in the longer haul flight market.

Within this we wanted to give more credibility to the markets where Spirit had the most presence, which we hoped to be able to represent and isolate the impact that ULCCs have on quality. With this we are left with what we see in 1 below, with these having characteristics of servicing over 5000 flights, as well as being in the second distance group or below. Within this table we can see that throughout these Spirit is ranging from having about 10% market share, all the way up to close to 30%. We hope that with this new isolation this well help clarify the impact Spirit has on the quality incumbents are offering. Secondly, within this table, we can see that many of these IATA codes, which are the unique identifier for airports, such as DTW, that these end up being Spirit hubs. The importance of hubs and how we use them will be discussed further within out empirical model setup.

Table 1: Carrier Route Data

OpCarrier	Carrier	Route	Carrier Share	HHI (10000)	Flights	Total Passengers
1331	NK	DTW_MCO	0.235887	5223.65	11769	301949
1324	NK	DFW_MCO	0.152345	7319.49	8578	301342
1300	NK	BWI_FLL	0.224423	5553.48	8556	323368
1285	NK	ATL_FLL	0.133714	5188.68	8264	595104
1336	NK	DTW_TPA	0.278182	5946.00	7421	159925
1327	NK	DFW_ORD	0.092598	5051.42	7420	528062
1316	NK	DEN_LAS	0.103732	2975.07	7054	449933
1350	NK	LAS_OAK	0.210656	6196.09	6777	229493
1284	NK	ATL_DTW	0.108787	5778.94	6744	398290
1347	NK	IAH_ORD	0.130917	5794.80	6226	365020

3.2 Data Expansion for Second Empirical Model

Within our data, we also wanted to see how the credibility of our results holds if we expand beyond the narrower, more concentrated sample. For the second model we estimate, we include a broader set of routes. Instead of limiting ourselves to the ten most populous routes for Spirit Airlines, we push the bounds further and go up to the fifty most common. This lets us explore whether our initial results still hold in a more general market setting and see how Spirit impacts quality when it operates in a less concentrated environment.

4 Methodology

4.1 Time Period

To conduct an event study, we needed to identify a treatment period that reflects a meaningful change in market conditions. In many airline competition studies, the treatment period is defined as the moment an airline enters a market. However, this approach is not suitable for Spirit Airlines, as they have operated since the early 1990s and were present on several routes long before the period of interest. Instead, we define a "boom" period that captures when Spirit's competitive presence became substantively significant. As shown in Figure 1, Spirit's market share on the selected routes rises sharply and crosses the 30% threshold in the third quarter of 2014. We therefore designate 2014 Q3 as Spirit's boom period and use it as the treatment point for the event study.

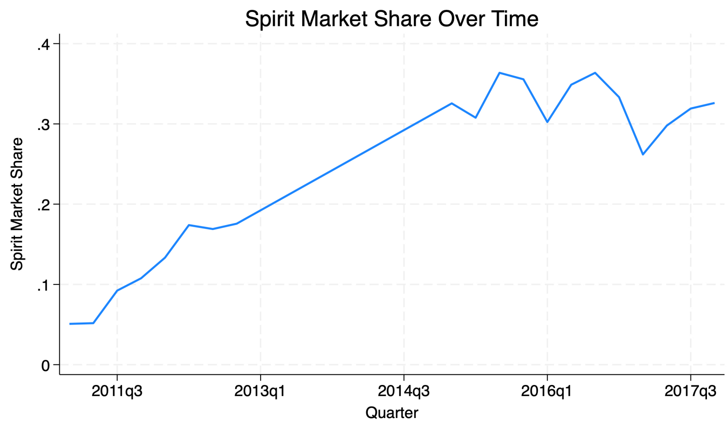

Figure 1: Defining Spirit Boom Period

5 Empirical Method I

Our empirical strategy is designed to address the effects of Spirit's increased market presence on legacy carriers and non ultra low cost carriers. In particular, its expansion around the third quarter of 2014 and how it affected service quality among incumbent non–ULCC carriers. The main hypothesis is that increased competition from an large ultra low–cost carrier (ULCC) like Spirit may cause legacy carriers and other non-ULCC carriers to adjust their performance, potentially improving quality metrics such as delays.

5.1 Event-Study Design

A standard difference-in-difference model is not appropriate here as there are no set treatment nor control groups, only time. Owing to the fact that Spirit had a presence on many U.S. routes before the 2010s, the previously used entry design by Gil and Kim (2021) would not capture the competitive shift caused by Spirit's sustained presence in the market. Instead, we follow an event study framework centered on the period during which Spirit's market share increased to the 30% threshold and continued rising. Following visual evidence, we define a "boom period", which will be the point at which Spirit became an important competitor on the routes in our analysis. Using quarterly flight level data, Figure 1 shows Spirit's share rising sharply after 2012 and surpassing 30% during 2014Q3. We therefore define four mutually exclusive time indicators:

- **Pre-Boom**: 2013Q2–2014Q1,
- **Boom**: 2014Q2–2014Q4,
- **Post-Boom**: 2015Q1–2016Q1,

- **Post Period**: 2016Q3 and onward.

These indicators allow us to measure how service quality evolves, relative to the period prior to Spirit's 'boom'.

5.2 Empirical Specification and Variable Definitions

The primary outcomes in our models are departure delays and arrival delays. Since delays may take the value zero or be negative when flights depart on time or arrive early, we censored the data by constructing non-negative versions of each variable and setting those negative values equal to zero. To reduce skewness and allow for a percentage interpretation, the analysis uses the natural logarithm, specifically $\ln(\text{DepDelay} + 1)$ and $\ln(\text{ArrDelay} + 1)$. The scaling by adding 1 allows us to include observations of on-time performance since logs cannot take in the value of zero.

We then estimate the following log-linear model of delays

$$\begin{aligned}\ln(\text{Delay}_{crq}) &= \beta_1 \text{PreBoom}_{crq} + \beta_2 \text{Boom}_{crq} + \beta_3 \text{PostBoom}_{crq} + \beta_4 \text{PostPeriod}_{crq} \\ &\quad + \beta_5 \left(\text{HubRoute}_{cr} \times \text{CarrierShare}_{crq}\right) + \theta_Y + \theta_{cr} + \varepsilon_{crq}. \end{aligned} \tag{1}$$

The event period indicators mark each quarter's position relative to Spirit's competitive expansion (boom). The time periods as mentioned before include a pre-boom, boom, post-boom and a later post-period. These variables allow the models to compare service quality across subperiods surrounding Spirit's 2014Q3 growth threshold.

`CarrierShare` is defined as the fraction of flights in a route at a particular quarter operated by each carrier. This captures the degree of market share a carrier has on a route. A decline in `CarrierShare` corresponds to increased competition from Spirit or other carriers in that route. To capture whether a route contains airports where Spirit maintains an operational advantage, the variable `HubRoute` equals one when either endpoint of the route is one of Spirit's known hubs [1] [2]. Although Spirit itself is excluded from the estimation sample, the presence of one of its hubs could influence the competitive environment the incumbent carriers face.

1. Found well known hubs to be Atlantic City International Airport, Chicago-O'Hare International Airport, Dallas Fort Worth International Airport, Detroit Metropolitan Wayne County Airport, Fort Lauderdale-Hollywood International Airport, Harry Reid International Airport and Orlando International Airport

2. https://www.going.com/guides/spirit-airlines

The model includes carrier-route and year fixed effects to account for all time-invariant carrier-route characteristics, such as geography or static route characteristics. Carrier-quarter fixed effects are purposefully left out because they automatically remove the event-study indicators and absorb all between-carrier variation within each quarter, making it impossible to estimate the time period effects that motivate the analysis.

For robustness, we cluster standard errors at the route level to correct for random correlation in changes within routes over time. Only non-ULCC carriers (i.e., excluding Spirit, Frontier, Allegiant) are included in the estimation sample. This is done in a way that allows the coefficients to capture the incumbents' response to Spirit's expansion.

5.3 Regression Results

Table 2 illustrates the two regressions results ran on departure delays and arrival delays, estimated using year and carrier–route fixed effects. These correspond to the first two model outputs respectively and constitute our baseline model.

Table 2: Effect of Spirit Boom on Incumbent Delay Outcomes

	(1) Departure Delay ln(DepDelay)	(2) Arrival Delay ln(ArrDelay)
Pre-Boom	0.366	−0.001
	(0.189)	(0.193)
Boom	0.078	−0.294
	(0.367)	(0.333)
Post-Boom	−0.020	−0.073
	(0.210)	(0.261)
Post Period	0.296	0.252
	(0.269)	(0.256)
Carrier Share	−1.127***	−1.344***
	(0.253)	(0.279)
HubRoute × CarrierShare	0 (omitted)	0 (omitted)
Year FE	Yes	Yes
Carrier–Route FE	Yes	Yes
Clusters (routes)	17	17
Observations	1291	1291

Standard Errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4 Interpretation

The combined regression results in Table 2 show little evidence that the timing of Spirit's boom period led to significant changes in delay performance among non–ULCC incumbents. Across both departure and arrival delay specifications, none of the event-study indicators(Pre-Boom, Boom, Post-Boom, or Post Period), are statistically significant at the 10% level. This suggests that delay outcomes for legacy carriers and other non-ULCC firms did not causally shift around Spirit's rapid expansion in 2014Q3. The coefficients are generally small in magnitude, and several change sign across specifications. This adds to the conclusion that periods surrounding Spirit's growth do not have significant causal effects on the increase or decline in service quality of legacy carriers.

For departure delays, the coefficient on the pre-boom period is positive and moderately large, indicating that delays were somewhat higher in the quarters immediately preceding Spirit's expansion, although the effect is only marginally significant. Neither the boom period nor the post-boom period suggest a significant change relative to earlier quarters. This is because the estimates are close to zero with large standard errors. A similar pattern appears for arrival delays, where none of the coefficients on the event-study indicators are statistically significant. Arrival delays show a small decrease just before the boom and a modest increase several quarters after the boom, but these changes are statistically insignificant as well.

In contrast to the weak timing effects, `CarrierShare` which measures competition intensity among legacy carriers and LCCs produces a strong and statistically significant relationship with on-time performance. Across both models, increases in `CarrierShare` are associated with large reductions in delays. The magnitudes imply that a one percentage point increase in an incumbent carrier's share of the route in a particular quarter, is associated with approximately a 1.1 percent reduction in delay minutes. This strongly negative coefficient is also stable across specifications. Despite differences in arrival and departure delays, the inclusion of fixed effects, and the exclusion of ULCC carriers, the estimated impact of competition remains unchanged. This is consistent when an increase in the market share for legacy carriers and LCCs which tend to perform better in service quality compared to ULCCs.

The interaction between hub presence and carrier share is omitted due to perfect collinearity with the carrier–route fixed effects. Spirit's hub indicator does not vary over time within a carrier-route, so once fixed effects absorb the level differences, the interacted term is dropped out due to lack of variation. This is consistent with the structure of the data where the presence of a hub on a route matters for the level of competition Spirit can impose. However, they do not vary with time in our data and are hence omitted.

Altogether, the results suggest that while the presence of significant competition is associated with increased service quality (on-time performance) by incumbents, the specific timing of Spirit's boom does not appear to influence ant significant changes in delay performance. Instead, the broader competitive environment and especially incumbents' relative market share on each route, plays a bigger role in influencing service quality. These patterns align with the idea that competition affects airline operational performance, but they do not show that Spirit's 'boom' in 2014Q3 created a shift in quality among non-ULCC carriers.

6 Empirical Method II

Building on the baseline results, this second section extends the analysis to examine whether Spirit's 'boom' affected on-time performance across a broader set of routes, rather than focusing only on the top ten largest markets. Restricting the analysis to major routes may have also introduced some selection bias, as these routes tend to have higher and more stable demand, as well as tighter scheduling constraints. As a result, changes in on-time performance following Spirit's expansion may be more limited or harder to detect on these routes. Expanding the sample allows for a more well-rounded analysis of Spirit's impact across different markets. The sample is expanded to 50 of Spirit's largest routes and further investigates whether these effects differ by route distance. This increases the number of observations from a mere 1,716 to 60,701.

The next parts of this section will deal with the the motivation behind expanding the model and segmenting routes by distance, into shorthaul and longhaul flights. We then proceed to estimate four models: a baseline similar to Section I but with added competition variables, two subsample models of the baseline into shorthaul only and longhaul only, and finally, a combined specification that includes both subsamples together to directly compare how Spirit's impact differs between shorthaul and longhaul routes.

6.1 Shorthaul and Longhaul

Route distance is an important factor that can influence Spirit's competitiveness. Shorthaul routes, which are typically less than 930 miles, differ from longhaul routes in terms of amenities and level of competition within airlines. Shorthaul markets often have more frequent flights, lower entry barriers and higher price sensitivity among passengers. This is the market where ultra low-cost carriers like Spirit tend to have the most influence over since they operate mostly in this market. In contrast, longhaul routes may have higher fixed costs, more complex scheduling and passenger preferences that prioritize amenities (meals, entertainment and added baggage), potentially dampening the competitive pressure ULCCs can impose in those markets.

We therefore categorize routes according to distance in order to capture these differences. We define shorthaul routes as shorter than 930 miles while all other routes are categorized as longhaul. This threshold is almost equal to a two-hour flight and is consistent with Anwar and Asad (2024) as the point where airlines usually switch from using narrow-body and smaller planes for short flights to wider-body and larger planes for longer flights.

6.2 Empirical Specifications and Variable Definitions II

Three model specifications are used to examine how Spirit's boom period affects incumbent carriers' on-time performance. The first specification replicates our baseline event-study model in section I on the expanded sample of 50 routes:

$$\begin{aligned}\ln(\text{Delay}_{crq}) = {} & \beta_1 \text{PreBoom}_{crq} + \beta_2 \text{Boom}_{crq} + \beta_3 \text{PostBoom}_{crq} + \beta_4 \text{PostPeriod}_{crq} \\ & + \mathbf{X}_{crq} + \theta_{\text{Year}} + \theta_{cr} + \varepsilon_{crq} \end{aligned} \tag{2}$$

where X_{crq} includes our competition controls: $\texttt{OtherULCCShare}_{crq}$, $\texttt{LCCShare}_{crq}$ as well as $\texttt{HubRoute}_{cr} \times \texttt{CarrierShare}_{crq}$.

This section retains the same boom-period definitions as Section I. However, it includes additional competition variables beyond `CarrierShare`. The other competition variables such as `OtherULCCShare` and `LCCShare` capture changes in market share for other ULCCs [3] and LCCs on each route, respectively. These were added to better account for how the competitive environment shifts when a route has a higher or lower presence of ULCCs or LCCs. As in Section I, the models also include year and carrier-route fixed effects, and standard errors are clustered at the route level as a robustness check.

To test whether boom period effects differ by route distance, we estimate Equation 2 separately on shorthaul and longhaul subsamples. These two subsample regressions (model 2 and 3) allow all coefficients,to vary freely across route distances, providing more room to observe influences of competition.

Finally, we estimate the full interacted specification that pools together all routes in the sample but allows boom period effects to differ by route distance:

$$\ln(\text{Delay}_{crq}) = \sum_{t \in T} \left[\gamma_t \text{Period}_t + \beta_t \left(\text{Shorthaul}_{cr} \times \text{Period}_t\right)\right] + \Gamma X_{crq} + \theta_{\text{Year}} + \theta_{cr} + \varepsilon_{crq} \tag{3}$$

3. All ULCCs except Spirit.

where $T = \{\text{PreBoom}, \text{Boom}, \text{PostBoom}, \text{PostPeriod}\}$. This specification includes both year and carrier-route fixed effects. The carrier-route fixed effects absorb the time-invariant Shorthaul_{cr} indicator, but the interaction terms $\text{Shorthaul}_{cr} \times \text{Period}_t$ are identified since they vary over time and carrier. The coefficients γ_t capture the boom period effects on longhaul routes (the reference category), while β_t captures the differential effect of each time period on shorthaul vs longhaul routes.

All specifications exclude ULCC carriers (Spirit, Frontier, Allegiant) from the estimation sample, ensuring that the coefficients only show incumbent responses to increased competition from ULCCs (specifically Spirit). Standard errors are clustered at the route level to account for some correlation in delays within routes over time.

6.3 Regression Results II

Tables 3 and 4 illustrate regression results for departure delays and arrival delays, respectively. Each table reports four models: (1) the baseline equation 2 estimation on the full expanded sample, (2) shorthaul routes only, (3) longhaul routes only and the (4) full interacted model 3.

6.3.1 Boom Period Effects

Across both departure and arrival delay specifications, the boom period itself is associated with a significant reduction in delays hence increasing service quality. In the baseline model (Model 1 of both tables), the coefficient on *boom* is negative and statistically significant, indicating that delays decreased during the quarters when Spirit's market share crossed the 30% threshold (2014Q2–2014Q4). For departure delays, the boom coefficient of -0.228 implies approximately a 20% reduction in delay minutes during the boom period relative to earlier quarters. Arrival delays show a similar pattern, with a coefficient of -0.200.

The pre-boom indicator is positive and statistically significant in most models of the departure and arrival delays, implying that delays increased in the quarters preceding Spirit's expansion. This could be taken to be that the incumbent LCCs and legacy carriers decreased service quality in order to dampen or threaten Spirit's market share following its boom, or it could simply reflect a period of industry-wide challenges. Furthermore, the post-boom and post-period coefficients tend to be small and statistically insignificant, indicating that any quality improvements realized during the boom did not persist in the subsequent quarters.

In Table 3 of departure delay results, the post-period coefficients on the shorthaul and longhaul only models are statistically significant at the 10% level. The models suggest that departure delays for shorthaul flights increased while decreasing for longhaul flights. In

Table 4 of arrival delays, post-boom and post-period are statistically significant at the 5% level only for model 4. They are both positive indicating that arrival delays for longhaul flights increased by approximately 19% during that time period.

6.3.2 Shorthaul vs Longhaul

The two subsample results in models 2 and 3 highlight the differences between shorthaul and longhaul routes. For shorthaul routes (Model 2), the boom period effect remains negative and significant for both departure delays (-0.228) and arrival delays (-0.198). The magnitudes are almost identical to the baseline specification, which is unsurprising given that shorthaul routes encompasses the vast majority (over 93%) of the sample.

In contrast, the boom period effect is statistically insignificant for longhaul routes (Model 3). The estimates remain negative but are substantially smaller in magnitude. This may be due to poor model fit, with standard errors roughly three times larger than in the shorthaul specification. This absence of a significant effect on longhaul routes is most likely a combination of a smaller sample size [4] and weaker competitive pressure from Spirit in these markets.

The full interacted specification (Model 4) should provides a more comparative estimation of these differences while maintaining the full fixed effects structure. In this specification, the main boom period coefficients (γ_t) represent effects on longhaul routes. This is because shorthaul effects were absorbed by carrier-route fixed effects. For arrival delays (Table 4), none of the main boom period effects are statistically significant, consistent with the subsample findings. The pre-boom coefficient of 0.184 suggests increased delays on longhaul routes in the quarters leading up to Spirit's expansion, but the boom period itself shows no significant effect.

The interaction terms show how shorthaul routes respond differently during the boom perods. The coefficient on `Shorthaul x post_boom` is -0.259 for arrival delays, indicating that shorthaul routes experienced significantly larger improvements in arrivals in the quarters following the boom, relative to longhaul routes. Combined with the insignificant main effect, this implies that the quality improvements documented in models 1-2 are almost driven entirely by shorthaul markets. For departure delays (Table 3), the interaction pattern is similar although weaker in magnitude.

Interestingly, the post-boom and post-period main effects (for longhaul routes) are now positive and statistically significant in the interaction specification, suggesting that

4. Approximately 3,100 observations in longhaul versus over 43,000 for shorthaul

longhaul route quality actually deteriorated in the quarters following Spirit's expansion. This contrast, with shorthaul routes improving and longhaul routes worsening, may reflect resource reallocation within incumbent carriers as they responded to Spirit's increased competition in their markets.

6.3.3 Competition Variables

`CarrierShare` is strongly negative and significant across all models in both Table 3 and 4, consistent with the interpretation that increased competitive pressure (lower market concentration) is associated with improved on-time performance or service quality. The magnitude is nearly identical across specifications whereby a one percentage point increase in an incumbent's route share corresponds to roughly a 40-42% reduction in delays. This stability across all models strengthens the robustness of the competition intensity effect.

The effects of other ULCC's share and LCC's share on a route are mostly insignificant across specifications. In the baseline model of Table 4 and the interaction specification (models 1 and 4), LCC share is negative and significant for arrival delays (-0.20), suggesting that routes with greater LCC presence experience improved service quality. This effect is even stronger in the shorthaul subsample (-0.259), where LCC competition is most direct. For longhaul routes, the LCC share coefficient switches sign but is statistically insignificant, likely reflecting both the limited LCC presence in these markets and the small subsample size.

Other ULCC competition (Frontier, Allegiant, Sun Country), is generally negative and insignificant. The lack of significance may reflect the relatively small shares of these carriers in the sample. Only in the interaction specification for departure delays (Table 3, model 4) does it have some significance. The coefficient is positive which can be interpreted as increased ULCCs in a route decrease overall service quality in that route. This is consistent with the notion that ULCCs tend to have poor service quality.

7 Conclusion

The first empirical section results seemed to suggest that while the presence of significant competitive pressure is associated with increased service quality (on-time performance) by incumbents, the specific timing of Spirit's boom did not appear to influence significant changes in delay performance. However, the second emprirical sections analysis with a broader sample size and covariates tell a slightly different story.

With the expanded sample with 50 routes, we find that Spirit's boom period is associated with significant declines in incumbent carrier delays. The boom coefficient of -0.228

for departure delays and −0.200 for arrival delays in the baseline specification (model 1 of Tables 3 and 4) indicate approximately 20% reductions in delays during 2014Q2–2014Q4. These effects stand in contrast to the insignificant findings from the small 10 route sample, suggesting that the earlier analysis may have been a victim to selection bias by capturing only the most competitive major markets where incumbents had less room to adjust service quality.

Furthermore, the subsample regressions show that quality improvements are concentrated almost entirely on shorthaul routes (under 930 miles), which constitute over 93% of the sample. Shorthaul routes show boom period coefficients of −0.228 for departures and −0.198 for arrivals (model 2), while longhaul routes exhibit no statistically significant effects (model 3). This pattern is consistent with Spirit's domain and competitive strategy, which focuses predominantly on shorthaul markets. In this market, operational characteristics such as higher frequency of flights and simpler logistics are what allow both Spirit and incumbent carriers to adjust more flexibly.

The interaction specification (model 4) provides additional information about the timing and persistence of these effects. While the main boom effect becomes insignificant or weaker when longhaul is the reference category, the `Shorthaul × post_boom` interaction term is negative and significant at the 1% level for arrival delays (−0.259). This suggests that the largest quality improvements on shorthaul routes emerged after Spirit's expansion phase rather than during it. This delayed response pattern may indicate that incumbent carriers required time to fully respond and adjust their operational practices: crew scheduling, aircraft use, maintenance etc. Alternatively, it could reflect a learning period over which incumbents experimented with different responses before landing on the most effective method.

Moreover, the post-boom and post-period main effects are positive and statistically significant at the 5% level in the interaction specification (capturing longhaul performance), with significant coefficients ranging from 0.178 to 0.201 for arrival delays. This indicates that service quality on longhaul routes were decreasing in quarters following Spirit's expansion. In contrast with the improvements on shorthaul routes, this divergence suggests potential resource reallocation within incumbent carriers. Incumbents may have shifted resources such as gates, aircraft and crew, toward defending their shorthaul routes, inadvertently allowing quality to fall on longhaul routes where Spirit posed a minimal competitive threat.

`CarrierShare` remains strongly negative and statistically significant across all specifications, with coefficients around −0.37 to −0.42, indicating that a one percentage point increase in an incumbent's route share corresponds to roughly a 40% reduction in delays. The stability and magnitude of this coefficient reinforces the interpretation that competition intensity is the most important factor influencing service quality.

The effects of other forms of group competition such as ULCC and LCC market shares vary across models. LCC share is negative and significant in several specifications, particularly for arrival delays (roughly 20% reduction in delays) and especially on shorthaul routes. This suggests that increased competition from carriers like Southwest and JetBlue, which maintain consistent service levels while offering lower fares, may exert continuous pressure on incumbents to maintain quality. In contrast, other ULCC share (Frontier, Allegiant, Sun Country) shows mixed and largely insignificant results, possibly reflecting that these carriers have a smaller market presence to significantly impact the market.

Overall, the expanded analysis reveals that Spirit's boom period did lead to significant quality improvements among incumbent carriers. However, the benefits are concentrated on shorthaul routes where Spirit mostly competes. These findings highlight the importance of market differentiation and sample selection in the empirical studies of airlines. This is because the aggregate effects identified in the larger sample differed from the patterns observed in the smaller restricted market.

8 Appendix

Table 3: Effect of Spirit Boom on Incumbent Departure Delay Outcomes

	(1) Baseline	(2) Shorthaul	(3) Longhaul	(4) Interaction
Boom Period Effects				
pre_boom	0.107**	0.102**	0.177	0.0868
	(0.0418)	(0.0431)	(0.168)	(0.0952)
boom	-0.228***	-0.228***	-0.239	-0.299***
	(0.0631)	(0.0659)	(0.215)	(0.0939)
post_boom	-0.00613	0.0155	-0.290	0.0578
	(0.0502)	(0.0520)	(0.190)	(0.0872)
post_period	0.0533	0.0844*	-0.362*	0.0301
	(0.0470)	(0.0483)	(0.188)	(0.0866)
Competition Variables				
other_ulcc_share	-0.176	-0.134	-0.409	0.198*
	(0.212)	(0.227)	(0.495)	(0.109)
lcc_share	-0.0947	-0.157	0.297	0.376***
	(0.0966)	(0.0997)	(0.302)	(0.0282)
carrier_share	-0.411***	-0.417***	-0.368	-0.375***
	(0.0498)	(0.0508)	(0.244)	(0.0299)
Shorthaul Interactions				
shorthaul				-0.0262
				(0.0383)
shorthaul × pre_boom				0.0104
				(0.0908)
shorthaul × boom				0.0610
				(0.0807)
shorthaul × post_boom				-0.103
				(0.0768)
shorthaul × post_period				0.0136
				(0.0769)
Observations	46755	43651	3104	47185

Standard errors clustered at route level in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of Spirit Boom on Incumbent Arrival Delay Outcomes

	(1) Baseline	(2) Shorthaul	(3) Longhaul	(4) Interaction
Boom Period Effects				
pre_boom	0.109**	0.100**	0.227	0.184*
	(0.0428)	(0.0444)	(0.161)	(0.108)
boom	-0.200***	-0.198***	-0.240	-0.128
	(0.0665)	(0.0696)	(0.212)	(0.107)
post_boom	-0.0390	-0.0235	-0.239	0.201**
	(0.0524)	(0.0543)	(0.202)	(0.0856)
post_period	0.0585	0.0765	-0.184	0.178**
	(0.0468)	(0.0483)	(0.183)	(0.0876)
Competition Variables				
other_ulcc_share	-0.222	-0.168	-0.444	-0.208
	(0.199)	(0.209)	(0.542)	(0.197)
lcc_share	-0.202**	-0.259**	0.175	-0.207**
	(0.101)	(0.103)	(0.341)	(0.0998)
carrier_share	-0.421***	-0.422***	-0.476**	-0.421***
	(0.0498)	(0.0509)	(0.234)	(0.0497)
Shorthaul Interactions				
shorthaul × pre_boom				-0.0805
				(0.104)
shorthaul × boom				-0.0771
				(0.0951)
shorthaul × post_boom				-0.259***
				(0.0771)
shorthaul × post_period				-0.128
				(0.0784)
Observations	46723	43620	3103	46723

Standard errors clustered at route level in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8.1 Annotated Python Code - Data Manipulation & Cleaning Purposes

Included in Seperate Document.

8.2 Annotated Stata Code - Creating Visuals & Empirical Analysis

```
/*
Smaller subset of 10 biggest Spirit routes.

This analysis creates a graph to select appropriate boom period.
Generates variables for empirical investigation using spirit hub dummy,
carrier-share, event period dummies, reghdfe and logged dependent variables
of delays and arrivals.

*/
log using "C:\Users\snk65\OneDrive - Drexel University\Kimelman,Eugene's files -
Applied Industrial Analysis\final paper work\spirit analysis\
spirit_analysis_V2.smcl", replace

clear all

use "C:\Users\snk65\OneDrive - Drexel University\Kimelman,Eugene's files -
Applied Industrial Analysis\final paper work\spirit_impact_analysis.dta"

* Year Quarter time variables
gen tq = yq(Year, Quarter)
format tq %tq


* Generate graph of Spirit's Market share over time
* To determine appropriate periods
preserve
gen spirit = (OpCarrier == "NK")

* Restricting subset to view patterns better
keep if tq >= yq(2011, 1)
```

```
gen one = 1

* Generate a number of flights variable by counting number of spirit
observations in a quarter

collapse (sum) flights = one, by(tq spirit)

reshape wide flights, i(tq) j(spirit)

rename flights0 other_flights
rename flights1 spirit_flights

gen total_flights = spirit_flights + other_flights
gen spirit_share = spirit_flights/ total_flights

* Plot graph
twoway line spirit_share tq, ///
 lwidth(medthick) ///
 ytitle("Spirit Market Share") ///
 xtitle("Quarter") ///
 title("Spirit Market Share Over Time")

restore

* Grouped time effects
* Changing boom to 2014q3 based on data/graph
gen pre_boom = inrange(tq, yq(2013,2), yq(2014,1))
gen boom = inrange(tq, yq(2014,2), yq(2014,4))
gen post_boom = inrange(tq, yq(2015,1), yq(2016,1))
gen post_period = (tq > yq(2016,2))

* Get back origin destination pairs
* Intermediate step to adding hub indicators
split route, parse("_")
rename route1 origin
rename route2 dest
```

```
* Hub indicators
gen byte hub_origin = 0
gen byte hub_dest = 0

* Spirit (NK)
* Indicate origin/destination
replace hub_origin = 1 if
    OpCarrier=="NK" & inlist(origin,"ACY","ORD","DFW","DTW","FLL","LAS","MCO")
replace hub_dest = 1 if
    OpCarrier=="NK" & inlist(dest,"ACY","ORD","DFW","DTW","FLL","LAS","MCO")

*Indicate route
gen byte hub_route = (hub_origin==1 | hub_dest==1)
label var hub_route "Route has carrier's hub airport"

* Check if double count occurs from mergers
* CO-UA, NW-DL
tab Year OpCarrier if inlist(OpCarrier, "CO", "UA", "NW", "DL"), missing

* No double counting occurrence

/*
Cleaning Delay to avoid negatives(early departures)
Can do a seperate regression for minutes
Eugene did one(depdelay mins) in spirit_log but with xtreg.
Should also do one with the change in boom
*/
gen depdelay_only = DepDelay
replace depdelay_only = 0 if depdelay_only < 0
gen ln_depdelay = log(depdelay_only + 1)

gen arrdelay_only = ArrDelay
replace arrdelay_only = 0 if arrdelay_only < 0
gen ln_arrdelay = log(arrdelay_only + 1)

* Two-way Fixed Effects
encode OpCarrier, gen(opcarrier_id)
```

```
egen cr_fe = group(opcarrier_id route)
egen cq_fe = group(opcarrier_id tq)

/*
From this small subset, the research question is more like:
"How are legacy carriers/non ulcc carriers affected by spirit's
increased presence on the route"
For this reason, keeping only non ulcc for the regressions
*/
gen ulcc = inlist(OpCarrier, "NK", "G4", "F9", "SY")

* Regressions

preserve

keep if ulcc == 0

* Departure delay without cr_fe
reghdfe ln_depdelay pre_boom boom post_boom post_period \\\
i.hub_route##c.carrier_share, absorb(Year cr_fe)  cluster(route)

/*
Hub indicator being absorbed by fe. Hub_route is only for spirit rn.
Being dropped off by model since it does not vary with time.
It appears when interacted only because carrier share varies with time

Doesn't seem like the boom period had an effect on departure delays.
Appears that the time period just before the boom is associated with
increasing delays.

However, during and after the boom,there is no statistical significance
to say whether there was a difference.

* Need to clarify what the reference time period is. For now it seems
to be earlier trends even before pre-boom.
```

```
More competition decreases delays. Seen from an increase in carrier
share. Likewise for when competition(carrier share) increases in a
route with a spirit hub.

*/

* Arrival delay without cr_fe
reghdfe ln_arrdelay pre_boom boom post_boom post_period \\\
i.hub_route##c.carrier_share, absorb(Year cr_fe)  cluster(route)

/*
Appears as though delays decrease just before the boom and in the
post period, (~7 quarters after the boom) arrival delays increase.
However, this is not statistically significant.

Similarly to departure delays, competition decreases delays

*/


* Consider taking away carrier-quarter if we have Year and carrier
route?

* They eat away at our variation. We need the time dummies to
answer our research question, not fully absorbed.

* Take the logged delay regression with Year cr and cq fe
reghdfe ln_depdelay pre_boom boom post_boom post_period \\\
i.hub_route##c.carrier_share, absorb(Year cr_fe cq_fe)  cluster(route)

restore

log close

* Starting another log file for a second empirical section,
using expanded routes
```

```
log using "/Users/nasaka/Library/CloudStorage/OneDrive-DrexelUniversity/
Kimelman,Eugene's files - Applied Industrial Analysis/
final paper work/spirit analysis/spiritanalysis_50.smcl"

clear all

use "/Users/nasaka/Library/CloudStorage/OneDrive-DrexelUniversity/
Kimelman, Eugene's files - Applied Industrial Analysis/
final paper work/spirit_impact_analysis_50.dta"

*****************************************************
* Repeating cleaning procedures
*****************************************************

* Year Quarter time variables
gen tq = yq(Year, Quarter)
format tq %tq

* Grouped time effects
* Changing boom to 2014q3 based on data/graph
gen pre_boom = inrange(tq, yq(2013,2), yq(2014,1))
gen boom = inrange(tq, yq(2014,2), yq(2014,4))
gen post_boom = inrange(tq, yq(2015,1), yq(2016,1))
gen post_period = (tq > yq(2016,2))

* Get back origin destination pairs
* Intermediate step to adding hub indicators
split route, parse("_")
rename route1 origin
rename route2 dest

* Hub indicators
gen byte hub_origin = 0
gen byte hub_dest = 0

* Spirit (NK)
* Indicate origin/destination
```

```
replace hub_origin = 1

if OpCarrier=="NK" &
inlist(origin, "ACY","ORD","DFW","DTW","FLL","LAS","MCO")

replace hub_dest = 1 \\\

if OpCarrier=="NK" &
inlist(dest, "ACY","ORD","DFW", "DTW","FLL","LAS","MCO")

*Indicate route
gen byte hub_route = (hub_origin==1 | hub_dest==1)
label var hub_route "Route has carrier's hub airport"

* Check if double count occurs from mergers
* CO-UA, NW-DL
tab Year OpCarrier if inlist(OpCarrier, "CO", "UA", "NW", "DL"), missing

* No double counting occurrence

/*
Cleaning Delay to avoid negatives(early departures)
Can do a seperate regression for minutes
Eugene did one(depdelay mins) in spirit_log but with xtreg.
Should also do one with the change in boom
*/
gen depdelay_only = DepDelay
replace depdelay_only = 0 if depdelay_only < 0
gen ln_depdelay = log(depdelay_only + 1)

gen arrdelay_only = ArrDelay
replace arrdelay_only = 0 if arrdelay_only < 0
gen ln_arrdelay = log(arrdelay_only + 1)

* Two-way Fixed Effects
encode OpCarrier, gen(opcarrier_id)
```

```
egen cr_fe = group(opcarrier_id route)
egen cq_fe = group(opcarrier_id tq)

*****************************************************
* End of repeating procedures
*****************************************************

/*
Splitting ulccs and lccs to generate marketshare variables
This is meant to observe how an increase in either ulccs/lccs in
market can also affect incumbent's response
*/
gen ulcc = inlist(OpCarrier, "NK", "G4", "F9", "SY")
gen other_ulcc = inlist(OpCarrier, "F9","G4","SY")
gen lcc = inlist(OpCarrier, "WN","B6","VX")

* Other ULCC share
gen share_ulcc_other_tmp = carrier_share if ulcc_other==1
bys route tq: egen other_ulcc_share = total(share_ulcc_other_tmp)
drop share_ulcc_other_tmp

* LCC share
gen share_lcc_tmp = carrier_share if lcc==1
bys route tq: egen lcc_share = total(share_lcc_tmp)
drop share_lcc_tmp




* Regressions

*****************************************************
* Delays
*****************************************************

* Baseline model (effect of Spirit boom + shares)
preserve
```

```
keep if ulcc == 0

reghdfe ln_depdelay ///
        pre_boom boom post_boom post_period ///
        other_ulcc_share lcc_share ///
        i.hub_route##c.carrier_share, ///
        absorb(Year cr_fe) cluster(route)

estimates store dep_base

restore

* Shorthaul vs longhaul models

* SHORTHAUL only
preserve

keep if ulcc == 0

keep if shorthaul == 1

reghdfe ln_depdelay ///
        pre_boom boom post_boom post_period ///
        other_ulcc_share lcc_share ///
        i.hub_route##c.carrier_share, ///
        absorb(Year cr_fe) cluster(route)
estimates store dep_shorthaul

restore

* LONGHAUL only
preserve
keep if ulcc == 0
keep if shorthaul == 0
reghdfe ln_depdelay ///
        pre_boom boom post_boom post_period ///
```

```
        other_ulcc_share lcc_share ///
        i.hub_route##c.carrier_share, ///
        absorb(Year cr_fe) cluster(route)
estimates store dep_longhaul
restore


* Full interaction: Spirit boom × shorthaul and shares

preserve
keep if ulcc == 0
reghdfe ln_depdelay ///
        i.shorthaul##(pre_boom boom post_boom post_period) ///
        other_ulcc_share lcc_share ///
        i.hub_route##c.carrier_share, ///
        absorb(Year cr_fe) cluster(route)

restore

estimates store dep_interacted

* Exporting regression results to tex for formatting

esttab dep_base dep_shorthaul dep_longhaul dep_interacted ///
       using "service_quality_results_dep.tex", ///
       replace ///
       label se star(* 0.10 ** 0.05 *** 0.01) ///
       compress ///
       mtitles("Baseline" "Shorthaul" "Longhaul" "Interaction" ///
               "Baseline" "Shorthaul" "Longhaul" "Interaction") ///
       mgroups("Departure Delays", pattern(1 1 1 1  1 1 1 1))



*****************************************************
* Arrivals
*****************************************************
```

```
* Baseline model (effect of Spirit boom + shares)
preserve

keep if ulcc == 0

reghdfe ln_arrdelay ///
        pre_boom boom post_boom post_period ///
        other_ulcc_share lcc_share ///
        i.hub_route##c.carrier_share, ///
        absorb(Year cr_fe) cluster(route)

estimates store arr_base

restore

* Shorthaul vs longhaul models

* SHORTHAUL only
preserve

keep if ulcc == 0

keep if shorthaul == 1

reghdfe ln_arrdelay ///
        pre_boom boom post_boom post_period ///
        other_ulcc_share lcc_share ///
        i.hub_route##c.carrier_share, ///
        absorb(Year cr_fe) cluster(route)
estimates store arr_shorthaul

restore

* LONGHAUL only
preserve
keep if ulcc == 0
```

```
keep if shorthaul == 0
reghdfe ln_arrdelay ///
        pre_boom boom post_boom post_period ///
        other_ulcc_share lcc_share ///
        i.hub_route##c.carrier_share, ///
        absorb(Year cr_fe) cluster(route)
estimates store arr_longhaul
restore


* Full interaction: Spirit boom × shorthaul and shares

preserve
keep if ulcc == 0
reghdfe ln_arrdelay ///
        i.shorthaul##(pre_boom boom post_boom post_period) ///
        other_ulcc_share lcc_share ///
        i.hub_route##c.carrier_share, ///
        absorb(Year cr_fe) cluster(route)

restore

estimates store arr_interacted

restore

* Exporting regression results to tex for formatting

esttab arr_base arr_shorthaul arr_longhaul arr_interacted //////
       using "service_quality_results_arrival.tex", ///
       replace ///
       label se star(* 0.10 ** 0.05 *** 0.01) ///
       compress ///
       mtitles("Baseline" "Shorthaul" "Longhaul" "Interaction" ///
               "Baseline" "Shorthaul" "Longhaul" "Interaction") ///
       mgroups("Arrival Delays", pattern(1 1 1 1  1 1 1 1))
```

```
log close
```

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