Who CARES? Airline Quality and the Aftermath of the CARES Act

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Abstract

Questions regarding the effectiveness of different subsidies, along with the efficiency and stability they may provide, have been researched widely within the field of economics. However, the effects that result from the conclusion of subsidization have received considerably less attention. As a case study, this analysis focuses on the CARES Act subsidy and its influence on the airline industry. The CARES Act, implemented in March 2020, provided funding for airlines amidst the COVID-19 pandemic. The funding consisted of a twenty-five billion dollar allotment from the government across all airlines, which was awarded based on the preceding year's employment costs. This paper examines whether this act led to improvements in quality or productivity within the airline industry after the initial CARES Act shock subsided. Binary regression methods and on-time performance data are utilized to this end. Ultimately, I find that, by my most conservative estimates, the CARES Act's resolution led to decreased quality, with a dip in worker productivity.

1 Introduction

Questions about the effectiveness of subsidization programs have a long history in economics. Whether offered to companies to fund specific services or provided during economic downturns in the form of bailouts, economists have studied the impacts of these programs on their respective industries. However, there are still topics within the study of subsidies that require further research. One such topic is the study of what happens after a subsidy is removed. Studying these effects can help policy makers make more informed decisions when deliberating the terms of future subsidization programs.

This paper analyzes the effect of quality on airlines after the resolution of the CARES Act. This act was implemented in early 2020 after the pandemic began. The purpose of providing this support was to maintain occupations within the airline industry. As an additional benefit, regulators would help the airline industry, allowing airlines to focus on preserving other aspects of their business, such as recuperating costs by transporting cargo. This act

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ended in December 2020, with two small payment support programs following closely behind. Ignoring the other payroll support programs for simplicity, it is reasonable to suggest that the switch from government support to self-reliance (also known as switching costs) resulted in a temporary loss of product quality. To my knowledge, I am the first to test this theory.

To simplify the analysis, I use on-time performance as a proxy for product quality. On-time performance is extensively utilized within the literature as a proxy for airline quality due to its importance to consumers. Other benefits of the data include its accessibility and ease of use. Using this data, a simple binary regression model is presented. The model shows that the Act's conclusion resulted in increased quality. This may be a sign that the CARES Act was effective even after its conclusion, yet there are potential limitations to the model that necessitate discussion. As stated previously, the model ignores the other two payroll support programs, assuming their effects on the airline industry to be small and inconsequential. Furthermore, one could argue that the lack of a control variable may cause this to be a weak approximation of these effects. Although these objections remain relevant, the model nonetheless provides the first approximation of these effects, and it is a step forward in helping policymakers improve their decision-making process.

Finally, this paper proposes that the Act resulted in changes in salaries and benefits between different types of airlines and different occupational categories, thereby leading to differences in productivity. Put more simply, I propose that the CARES Act led to a redistribution of resources that benefited some groups of workers while negatively affecting others. I hypothesize that the conclusion of the CARES Act will have a short negative effect on both the quality aspect and workers' wages. This negative effect will likely increase again as the airlines readjust their funding to remain stable without external funding.

This analysis contributes to two different strands of literature within the field of economics. First, this paper adds to the literature on the industrial organization of airlines. Airlines have long been studied in economics in an attempt to understand their strategic decisions, usually through the use of game theory and structural modeling. This paper adds to this discussion by presenting an analysis of the consequences of an external shock, which itself occurred as a consequence of the U.S. government reacting to the COVID-19 shock. This paper also adds to the literature on government subsidization and its effect on businesses, especially regarding regulatory practice. In particular, this paper presents a case study that showcases the aftereffects of government subsidization. An improved understanding of the quality response to the CARES Act could have applications to other subsidies as well. Knowing whether product quality increased or decreased after the end of the CARES Act could assist policymakers in making knowledgeable decisions regarding the duration and resolution of the next subsidization program, and it could provide opportunities for policymakers to increase their understanding of the risks and opportunities inherent within future policies. Ultimately, providing this sort of context to other policies is the goal of this analysis.

The rest of this paper is structured as follows. Section 2 provides information on the background of the CARES Act and presents a summary analysis of its allocation. Section 3 then presents a review of the literature subdivided into separate categories. Section 4 provides the data and an overall explanation of its implementation. Sections 5 and 6 discuss the main econometric specification and the results, respectively. Once the model and its results are thoroughly explained, an analysis of the potential causal mechanisms is provided. This is presented in Section 8. Finally, section 9 concludes.

2 Background

In March 2020, the COVID-19 pandemic was in full effect, and the U.S. government was trying to mitigate the negative effects caused by the COVID-19 shock. During this time, the Department of the Treasury announced the CARES Act, which allocated funding to individuals and businesses negatively affected by the pandemic. One of these businesses was the airline industry. Under the CARES Act, the Department of the Treasury provided funding for the airlines through an application-based process. The announcement of this program began in March 2020, during which funding was capped at twenty-five billion dollars for the entire industry (Department of the Treasury, 2020). This funding had a few caveats, however. To begin with, all of the funding needed to be used for the employees' salaries and benefits. Furthermore, employees were not allowed to be involuntarily fired or furloughed while the firm received this funding. The program originally spanned from March 2020 through September 2020, but was later extended to December 30, 2020. The funding was based on the benefits and salary information from the airlines during the second and third quarters of 2019. Airlines could calculate and apply for their eligibility amount and expect to receive financial assistance from the government. Table 1 below explains in more detail how this process worked.

Table 1 contains information from two different datasets. The salary and benefits data are from the CARES Act Agreement Information, which is provided by the Department of the Treasury. This data is then combined with the 2019 Schedule P-1(a) dataset from the Form 41 Financial Database of the Bureau of Transportation Statistics. The Schedule P-1(a) dataset provides the aggregate employee, salary, and benefits information for any airline that earns at least $20 million in revenue. Therefore, Table 1 consists of only the top twenty-four airlines during the second and third quarters of 2019. The first column gives the name of the airline, while the second and third columns provide an estimation of the aggregate salaries and benefits paid out in the second and third quarters of 2019. The eligibility is then calculated by adding together the two previous columns, and the nominal awarded amount is provided in the fourth column. The percentage awarded is calculated in the sixth column by dividing

Table 1: CARES Act Eligibility Data Table

Participant	Salaries (Q2-Q3 2019)	Benefits (Q2-Q3 2019)	Eligible	Awarded	Percentage Awarded	Loans
AIR WISCONSIN AIRLINES LLC	$43,582,970	$20,474,410	$64,057,380	$39,438,170	61.57%	N/A
ALASKA AIRLINES INC.	$915,067,000	$390,447,000	$1,305,513,000	$1,020,911,166	78.20%	$282,060,556
ALLEGIANT AIR LLC	$145,205,550	$80,995,650	$226,201,190	$176,889,331	78.20%	$23,066,799
AMERICAN AIRLINES INC.	$5,385,698,420	$2,045,029,810	$7,430,728,280	$5,957,940,109	80.18%	$1,764,849,417
CARIBBEAN SUN AIRLINES INC.	$6,485,960	$1,576,730	$8,062,680	$6,305,017	78.20%	N/A
DELTA AIR LINES INC.	$5,391,788,130	$1,761,279,230	$7,153,067,350	$5,593,698,668	78.20%	$1,648,109,600
EASTERN AIRLINES LLC	$8,563,830	$3,619,920	$12,183,750	$9,527,690	78.20%	N/A
ELITE AIRWAYS LLC	$12,147,210	$2,690,700	$14,837,920	$11,603,248	78.20%	N/A
EXPRESSJET AIRLINES LLC	$91,626,390	$52,957,810	$144,584,190	$113,064,836	78.20%	$3,919,451
FRONTIER AIRLINES INC.	$186,365,240	$83,210,310	$269,575,560	$210,808,088	78.20%	$33,242,427
GOJET AIRLINES LLC	$31,603,350	$15,050,170	$46,653,520	$36,483,050	78.20%	N/A
HAWAIIAN AIRLINES INC.	$279,731,480	$105,084,190	$384,815,680	$300,925,853	78.20%	$60,277,756
JETBLUE AIRWAYS CORPORATION	$866,550,930	$364,705,410	$1,231,256,350	$962,842,466	78.20%	$258,852,740
MESA AIRLINES INC.	$96,220,480	$25,447,620	$121,668,080	$95,144,443	78.20%	N/A
MIAMI AIR INTERNATIONAL INC.	$12,039,650	$4,267,700	$16,307,350	$8,501,564	52.13%	N/A
OMNI AIR INTERNATIONAL LLC	$50,992,100	$37,259,700	$88,251,790	$67,427,857	76.40%	N/A
REPUBLIC AIRWAYS INC.	$179,312,870	$91,722,180	$271,035,070	$211,949,425	78.20%	$33,584,827
SKYWEST AIRLINES INC.	$369,368,730	$206,975,380	$576,344,110	$450,701,094	78.20%	$105,210,328
SOUTHWEST AIRLINES CO.	$2,827,515,000	$1,460,882,000	$4,288,397,000	$3,353,526,454	78.20%	$976,057,936
SPIRIT AIRLINES INC.	$333,969,200	$106,474,010	$440,443,200	$344,426,582	78.20%	$73,327,975
SUN COUNTRY INC.	$55,787,630	$23,895,090	$79,682,730	$62,311,885	78.20%	N/A
SWIFT AIR LLC	$11,849,520	$1,698,520	$13,548,020	$21,057,343	155.43%	N/A
TEM ENTERPRISES	$462,460	$305,390	$767,850	$600,454	78.20%	N/A
UNITED AIRLINES INC.	$4,791,103,020	$1,733,236,590	$6,524,339,600	$5,102,033,567	78.20%	$1,500,610,070
AVERAGES	**$920,543,213**	**$359,136,897**	**$1,279,680,069**	**$966,324,734**	**79.65%**	**$520,243,837**
Totals	**$22,093,037,120**	**$8,619,285,520**	**$30,712,321,650**	**$24,158,118,360**	**N/A**	**$6,763,169,882**

This table shows the eligibility and the awarded amount for the top twenty-four airlines, along with any government loan amounts taken out after funding. Of particular note is the Percentage Awarded column, which shows the percentage of the eligibility amount that was awarded. It seems that most airlines received about 78.2 % of their eligibility amount. Some exceptions have been made to airlines that had undergone a merger, or for comparable experiences.

the eligibility amount by the awarded amount, which allows us to see the airline awarded amount as a percentage of eligibility. The table shows that the airlines generally received about 78.2% of their original eligible amount. The rest of the variation in the percentage awarded is mostly due to mergers, acquisitions, or other such concerns. These situations caused the Department of the Treasury to adjust the funding provided to the airlines. Finally, CARES Act loan amounts are provided in column 7.

Based on these calculations, these twenty-four airlines took $24,158,118,360 out of the $25 billion provided by the Department of the Treasury, or about 96.6% of the funding. For a more dynamic analysis of the effects of the COVID and CARES Act shocks, graphs of the airline's aggregate salaries and benefits over time, along with graphs of the aggregate employment levels, are provided in Appendix A. In Appendix B, the normalized (salaries and benefits per person) graphs are provided. These are graphs of the Schedule P-1(a) (aggregate employment and salary levels), Schedule P-6 (aggregate salaries for five different occupational categories), and Schedule P-10 (employment information for fourteen different occupational categories) data from the Bureau of Transportation Statistics's Form 41 Financial database, which are broken up by carrier type (major, low-cost carrier, and regional) in the graphs provided.

The graphs in Appendix A illustrate the complexity of the pandemic. The COVID shock shown by the first dashed vertical line caused decreases in the aggregate payout of salaries and benefits for most airlines, though employment remained relatively unaffected for low-cost carriers and regionals. Major airlines also seem to have experienced a much sharper decline at the beginning of the pandemic than low-cost and regional carriers. This is consistent with findings by Kaffash and Kezrimotlagh, who find that low-cost carriers handled issues more efficiently during the pandemic compared to major airlines (Kaffash and Kezrimotlagh, 2022). The normalized graphs in Appendix B are created by dividing the salaries and benefits information per occupation (Schedule P-6 data) by the employment information by occupational category (Schedule P-10 data).

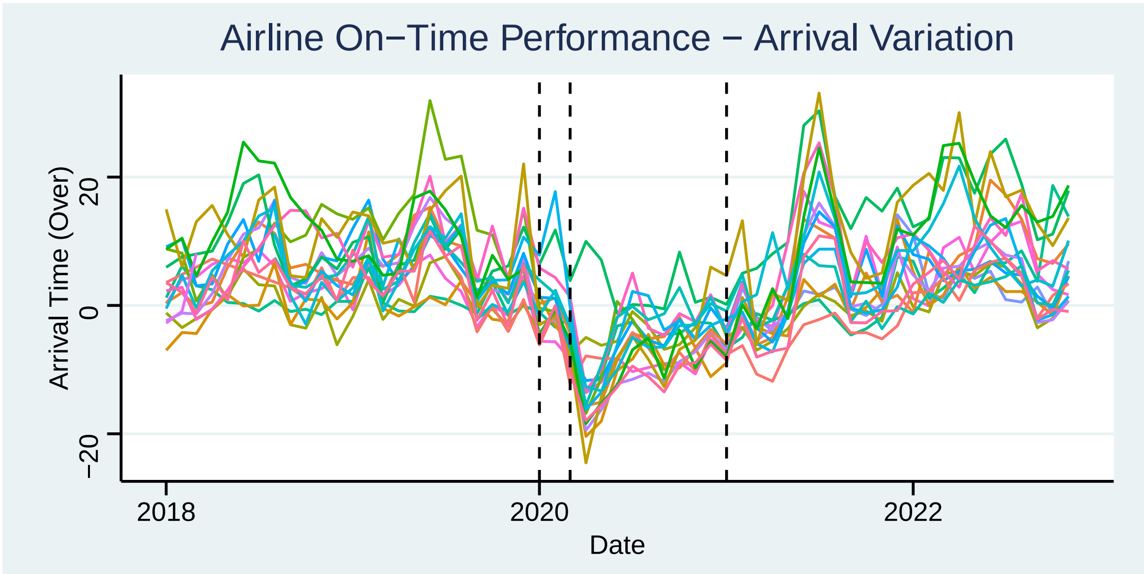

Figure 1: The above figure contains the arrival performance of all carriers within the dataset, regardless of airline type. The airlines consistently show similar patterns, with most airlines improving their on-time performance during the COVID-19 pandemic.

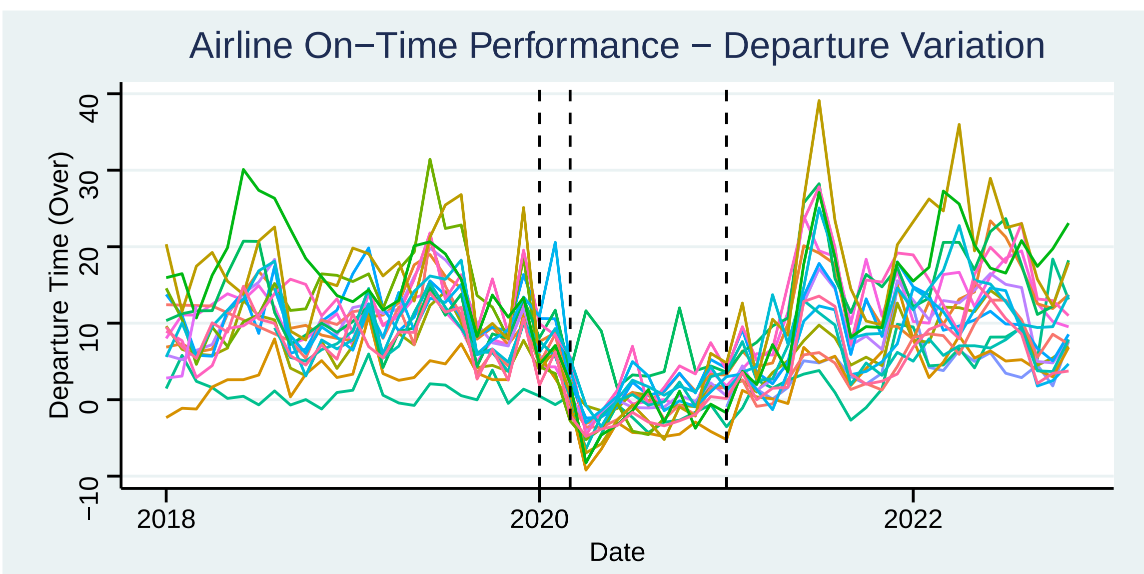

Figure 2: The above figure shows the departure variation for all of the airlines within the dataset. The results show that most airlines, regardless of carrier type, experienced similar patterns in their on-time performance before, during, and after the COVID-19 and CARES Act shocks.

As established previously, this analysis examines airline quality using on-time performance as a proxy. The graphs of on-time performance are provided in Appendix C, where on-time performance is broken into major, low-cost carrier, and regional.[1] The airlines are sorted by IATA code, and the y-axis refers to the magnitude of the delays. Using these graphs, we can see that these airlines follow a similar pattern. This is further evidenced by the "Airline On-Time Performance - Arrival Variation" and "Airline On-Time Performance - Departure Variation" graphs. These two graphs plot the arrival and departure times of all the airlines in the dataset. These graphs show exactly what we would expect. During the COVID-19 shock, the on-time performance of the airlines increased significantly. This is supported by the findings of other researchers, such as Yimga (2021), who found that airline on-time per-

[1]It is worth mentioning that owned regionals and mergers are not accounted for in these graphs, so there is some overlap in ownership.

formance increased significantly during this time. After the CARES Act ends, as exemplified by the last vertical dotted line, on-time performance appears to decrease as individuals begin flying again.

3 Literature Review

3.1 Main Review

This paper addresses two different divisions within the economics literature: the literature on the relationship between airline practices and COVID-19 and the empirical methods literature. These two divisions are discussed in the following two subsections.

3.2 Airlines COVID Literature Review

The literature is full of articles analyzing the effects of the coronavirus pandemic on the airline industry, especially now that researchers can analyze the effects of COVID-19 with a fair degree of confidence. Many papers focus on the quality effects of airlines during COVID, but, to the best of my knowledge, this paper is the first to examine the quality effects of the CARES Act on airlines. Hotle and Mumbower, for instance, analyze departures from January 2019 to May 2020, finding that the number of airline departures decreased significantly (Hotle and Mumbower, 2021). They also found that larger airports were more heavily affected by the pandemic (Hotle and Mumbower, 2021). This is an interesting finding, especially since Bauranov et al. found that smaller airports were more likely to close during the pandemic (Bauranov et al., 2021). Of course, in some ways, these two papers fit into a sort of efficiency analysis literature as well.

As stated previously, Yimga studied on-time performance during the pandemic and found that airlines increased on-time performance during COVID-19, much like the figures in Appendix A show (Yimga, 2021). Other researchers have also suggested that low-cost carriers were more efficient during the pandemic (Kaffash and Khezrimotlagh, 2022). This is likely because airlines had very different ways of approaching problems they faced during this time. Low-cost carriers, for instance, are known for following a cost-minimization style strategy, whereas majors likely follow profit maximization-related strategies. If this result holds for my analysis, low-cost carriers are likely to handle pandemic-related problems more efficiently, which suggests that their on-time performance will change the least at the conclusion of the CARES Act.

Considering that airlines may have different approaches to COVID issues, Monmousseau, Marzuoli, Feron, and Delahaye examined Twitter comments during COVID-19 (Monmousseau et. al., 2020). Their findings suggest airlines had different approaches to pandemic-related issues (Monmousseau et. al., 2020). Analyzing online comments is a popular way to study the effects of COVID within the literature, though researchers do not always examine Twitter[2] specifically. The different approaches these researchers are using suggest that different types of airlines behaved differently, though we need some analysis to show this. This, in turn, suggests that different approaches between carrier types may lead to different outcomes after the CARES Act ended. In another study, Piccinelli, Moro, and Rita study comments on an Italian website to observe consumers' travel concerns during the pandemic, finding that issues such as airline on-time performances were large concerns for consumers (Piccinelli, Moro, and Rita, 2021).

The demand-side effects of COVID-19 are not the only issues that researchers have analyzed. Rust, Stewart, and Werner provide an analysis of the COVID spillover effects on businesses tangential to the airline industry at the Duluth International Business Cluster (Rust, Stewart, and Werner, 2021). Similarly, Sobieralski studied airline employment effects across different financial shocks, finding that shocks have the strongest effects on major airlines (Sobieralski, 2020). This finding matches the employment graphs presented in Appendix A. In a study from the *Center for Economic Policy Research*, Meier and Smith analyze the amount of time it will eventually take for the airlines to pay off the CARES Act (Meier and Smither, 2021). This measure proxied efficiency by weighing government funding vs. airline repayment. Though many of these articles examine quality and efficiency in different ways, none have yet paired on-time performance data with the conclusion of the CARES Act.

3.3 Empirical Literature Review

The approach used within this paper is somewhat modern, as it has gained more repute within the literature in recent years. There are four main papers that this analysis owes recognition to. In *Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China* by Hanming Fang, Long Wang, and Yang Yang, the authors analyze the effect of the COVID-19 shutdown on migration in China (Fang, Wang, and Yang, 2020). The authors find that the shutdown drastically decreased the number of cases that would have otherwise been spread through migration to and from Wuhan (Fang, Wang, and Yang 2020). Perhaps equally as interesting, however, is that the authors use novel difference-in-difference methods to obtain their results. To examine the impact of the lockdown on migration, the authors first use the migration data for the year prior as the control (Fang, Wang, and Yang, 2020). This method is important to this article because they use the same method of exploiting previous data as a control (Fang, Wang, and Yang, 2020). Another paper of note is *Frontiers: Virus Shook the Streaming Star: Estimating the COVID-19 Impact on Music Consumption* by Jaeung Sim, Daegon Cho, Youngdeok Hwang, and Rahul Telang.

[2]During the time of Monmousseau et. al.'s writing, the site was called Twitter. It has been renamed to "X" in recent years.

This paper examines the music streaming market and finds that the consumption of music decreased during the pandemic, likely due to decreases in driving and other such events (Sim et al., 2022). As before, however, the paper uses past observations as the control group for the difference-in-difference analysis (Sim et al., 2022).

The next article that this paper draws on is *When is Parallel Trends Sensitive to Functional Form?* by Jonathan Roth and Pedro H.C. Sant'Anna. This article provides evidence that strictly monotonic transformations of an outcome variable do not change the properties of parallel trends (Roth and Sant'Anna, 2023). Finally, this paper draws much inspiration from *What's Trending in Difference-in-Differences? A Synthesis of the Recent Economics Literature* by Jonathan Roth, Pedro H.C. Sant'Anna, Alyssa Bilinski, and John Poe.

4 Data

The summary statistics are provided in Table 2. The initial data for this analysis is taken from the Department of Transportation's On-Time Performance database. This constitutes a flight-level dataset from 1987 through November 2022, which includes detailed on-time performance information for each plane. Though the Department of Transportation explains that the data is provided for the top seventeen airlines, I count nineteen distinct airlines within the dataset. The data consists of three major carriers, seven low-cost carriers (only six of which are independently owned), and nine regionals (only five of which are independently owned). The owned airlines are eliminated from the analysis to reduce potential bias. Once airline ownership is accounted for, only fourteen carriers remain. For this analysis, I use only the data from January 1, 2018, through November 31, 2022. This time range is chosen for its lack of mergers and acquisitions and because it provides a long enough time frame to run the binary regression analysis. The resulting dataset provides over 30,000,000 observations. I then aggregate this dataset to the daily level, leaving $8,686,574$ observations. There is an issue with this data, however. Each of these airlines accepted funding from the CARES Act, making it difficult to perform the binary regression specification. Drawing on the earlier literature review, I suggest a solution that would allow for the creation of a control group.

To create a control group, the data is divided into two different time ranges. The first range is from 2018 to 2019, while the second range is from 2020 to 2021. The first time range constitutes the control group, while the second time range is the treatment group. In this way, the observations for the year 2018 (control group) can be matched with the observations for the year 2020 (treatment group). Similarly, the observations for the year 2019 (control group) can be matched with the observations for the year 2021 (treatment group). By following this method, each of the airlines can be matched up with their own data during comparable points in time. This method follows (Fang, Wang, and Yang, 2020) and (Sim et al., 2022). After solving this issue, I can show the binary regressions.

Table 2: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Arrival Delay	12,581,925	3.659	44.129	−121.000	3,070.000
Normalized Arrival Delay	12,581,925	13.121	40.934	0.000	3,070.000
Departure Delay	12,603,393	9.461	42.043	−102.000	3,075.000
Normalized Departure Delay	12,603,393	13.069	41.022	0.000	3,075.000
Actual Elapsed Time	12,582,040	146.192	76.044	14.000	1,604.000
CRS Elapsed Time	12,781,851	151.949	76.417	−30.000	813.000
Air Time	12,582,040	122.252	74.743	4.000	1,557.000
Taxi In	12,597,340	7.514	5.384	1.000	282.000
Taxi Out	12,601,045	16.434	7.958	1.000	218.000
Distance	12,781,907	894.492	633.112	29	5,812

After the data is cleaned and prepared, a flight-level binary regression analysis is performed. The structure of the model is as follows:

$$Y_{ijdy} = \alpha_{ij} + \delta_d + \theta(d_{ij} * d_{dy}) + X_{ijdy}\beta + \epsilon_{ijdy} \tag{1}$$

For this analysis, i, j, d, and y represent the carrier, route, day, and year, respectively. Y_{ijdy} is the on-time performance, which is measured by the elapsed time and the departure time. Elapsed time is selected as a measure of on-time performance because it controls for anticipatory airline schedule adjustment. This occurs when airlines pad their expected arrival and departure times, providing them more room in their schedules. They may report an earlier-than-anticipated arrival time or a later-than-expected departure time, making their on-time performance look better without requiring them to improve their services. The elapsed time is the difference between the scheduled time and the actual time that a plane takes from arrival to departure. Departure time is also chosen because of its direct connection to airline on-time performance. Each of these metrics are considered standard use in the literature. α_{ij} and δ_d are the route-carrier and day fixed-effects, respectively.

d_{ij} is an indicator of one if the observation falls within the treatment group, and zero if it falls within the control group. Similarly, d_{dy} is a time indicator of one if the observation falls in the treatment period (post CARES Act) and zero if it falls in the pre-treatment period (before or during the CARES Act). The equation constitutes a binary regression model. In this specification, θ is the movement of the treatment group after the CARES Act ends and the variable of interest. For the elapsed time analysis, if θ is positive, the treatment group experiences an increase in elapsed time per flight, which suggests a decrease in on-time performance at the end of the CARES Act. If negative, it shows that the treatment group experiences an increase in on-time performance at the end of the Act. The interpretation is similar in the departure delay specification. A positive θ suggests an increase in departure time, and therefore a decrease in on-time performance. A negative θ suggests an increase in on-time performance. For either specification, demand-side aspects are accounted for by a vector of controls, X_{ijdy}, which includes load factor, HHI, hub indicators, and distance. In one specification, I include indicators if they accepted money from the second or third payroll support program (PSP2 and PSP3). Finally, ϵ_{ijdy} is the error.

5 Results

The results are provided below. The regression results suggest a decrease in elapsed time and an increase in departure delays. This suggests that airlines adopted a focused scheduling approach at the conclusion of the act - hence the decrease in elapsed time - while departure delays became commonplace. Interestingly, the interaction's impact on elapsed time diminishes as PSP2 and PSP3 controls are added, while the impact of the interaction on departure delay increases. It is also interesting that load factor is negative for elapsed time and positive for departure delay, suggesting that airlines tend to decrease their scheduled time for fuller flights, which are delayed more often. Origin and destination hubs are accounted for with carrier-route fixed effects, but it is noteworthy that they may increase the elapsed time and decrease the departure time. Similar tables are provided in Appendix D, with separate regressions for major, low-cost carriers (LCCs), and regional carriers. The results appear robust to carrier type. Finally, it is important to note that PSP2 and PSP3 appear to have negative effects on both elapsed time and departure delay. This suggests that airlines decrease their schedule padding and improve on-time performance during PSP2 and PSP3. While this may seem to contradict my findings, it is important to note that the interaction of the flight and post-treatment dummies highlight the CARES Act's (PSP1's) conclusion, not the program itself. This could suggest that each payroll support program temporarily decreased departure delays, which increased at each program's conclusion. Elapsed time may have followed a similar pattern, though the COVID-19 pandemic seems to have increased the airlines' schedule padding. This is supported by the fact that airlines had increased on-time performance during the pandemic. The effects of PSP2 and PSP3 are beyond the scope of this analysis, however, though I do provide a breakdown of how money was awarded in Appendix E.

6 Causal Mechanism

For the causal mechanism of this analysis, I propose a model of the effect of productivity on on-time performance. I hypothesize that the increased quality from the end of the

Table 3: Regression Results

Dependent Variables:	Elapsed Time				Departure Delay			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Constant	5.17***	6.62***			13.7***	-4.12***		
	(0.043)	(0.152)			(0.074)	(0.220)		
Interaction	-1.60***	-1.03***	-1.25***	-0.560***	6.06***	1.93***	2.77***	5.69***
	(0.065)	(0.064)	(0.061)	(0.084)	(0.095)	(0.094)	(0.092)	(0.126)
Flight Dummy	2.07***	1.16***	1.67***	1.51***	-6.88***	-1.09***	-2.22***	-3.63***
	(0.058)	(0.057)	(0.058)	(0.065)	(0.074)	(0.082)	(0.080)	(0.086)
Post-Treatment Dummy	0.408***	0.505***	0.480***	0.477***	0.919***	0.740***	0.794***	0.798***
	(0.038)	(0.038)	(0.037)	(0.037)	(0.062)	(0.062)	(0.058)	(0.059)
Load Factor		-0.038***	-0.017***	-0.023***		0.212***	0.160***	0.113***
		(0.001)	(0.001)	(0.002)		(0.002)	(0.002)	(0.002)
HHI		-0.047	0.558***	0.556***		0.449***	0.293*	0.337**
		(0.087)	(0.094)	(0.094)		(0.151)	(0.155)	(0.155)
Origin Hub		0.361***				-0.864***		
		(0.073)				(0.136)		
Destination Hub		0.550***				-1.11***		
		(0.076)				(0.144)		
Distance		0.002***	0.004	0.004		-7.07×10^{-5}	0.010	0.008
		(5.43×10^{-5})	(0.012)	(0.013)		(8.07×10^{-5})	(0.011)	(0.011)
PSP2 Dummy				-0.977***				-5.32***
				(0.091)				(0.132)
PSP3 Dummy				-0.694***				-1.42***
				(0.061)				(0.103)
Fixed-effects								
Carrier-Route FE			Yes	Yes			Yes	Yes
Day			Yes	Yes			Yes	Yes
Fit statistics								
R^2	0.00364	0.01385	0.08510	0.08525	0.00535	0.00780	0.03356	0.03386
Adjusted R^2	0.00364	0.01385	0.08305	0.08320	0.00535	0.00780	0.03139	0.03170
F-test	23.206	33.432	4.7743	4.7576	34.164	18.708	1.7821	1.7893
Observations	8,686,574	8,686,574	8,686,574	8,686,574	8,686,574	8,686,574	8,686,574	8,686,574

Clustered (Carrier-Route FE) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

CARES Act comes through the channel of productivity. Put more simply, I expect the pandemic caused a redistribution of wages (a proxy for productivity in the literature), which then caused certain groups of workers to decrease their productivity. There are also some employment-population considerations to keep in mind. For instance, some groups of workers may receive higher wages, increasing productivity, but the majority of the workers will not receive this increase. Therefore, the decrease in the majority of workers' wages would offset the increase in wages for the minority of workers. This means that both the wages of the workers and the number of workers would need to be taken into account. The causal mechanism, then, is that the pandemic would bring about changes in wages for the majority of workers, which would then lead to changes in the on-time performance (or quality) of the airlines. For this part of the analysis, I use Schedule P-6 and Schedule P-10 data from the Bureau of Transportation Statistics's Form 41 Financial Database. The data is provided quarterly, with the wages of five different occupational categories for airlines that had revenue above $20 million. I utilize data from 2018 through 2022. Summary statistics for the dataset and each type of carrier are given in Appendix F. The data is normalized using the following equations:

1) Normalized Management Salary = Management Salaries/General Management

2) Normalized Flight Salaries = Flight Salaries/(Pilots and Copilots + Other Flight Personnel)

3) Normalized Maintenance Salaries = Maintenance Salaries/(Passenger General Service Administrator + Maintenance)

4) Normalized Traffic Salaries = Traffic Salaries/(Aircraft Traffic Handling Group 1 + General Aircraft Traffic Handling + Aircraft Control + Passenger Handling + Cargo Handling)

5) Normalized Other Salaries = Other Salaries/(Trainee Instructor + Statistical + Traffic Solicitors + Other)

6) Normalized Salaries = Salaries/Employee Total

7) Normalized Benefits Personnel = Benefits Personnel/Total Employed

8) Normalized Pensions = Number of Pensions/Total Employed

9) Normalized Payroll = Payroll Amount/Total Employed

10) Normalized Benefits = Benefits/Total Employed

11) Normalized Benefits and Salaries = Total Benefits and Salaries/Total Employed

After the data is normalized, I move on to the binary regression portion of this analysis. The equation takes the form shown below.

$$Y_{j,o,t} = \gamma_j + \gamma_o + \gamma_t + \beta_1(d_j * d_o) + \beta_2(d_j * d_t) + \beta_3(d_o * d_t) + \beta_4(d_j * d_o * d_t) + X_{j,o,t}\beta_5 + \mu_{j,o,t} \quad (2)$$

As is shown, the equation presents a binary regression equation. $Y_{j,o,t}$ is the salary per carrier per occupation type over time. γ_j, γ_o, and γ_t are the carrier type (major, low-cost, or regional), occupation type, and time-fixed effects. Likewise, d_j are the carrier type indicators, d_o are the occupational type indicators, and d_t are indicator variables, which are one if the period is after December 2020 (the end of the CARES Act) and 0 otherwise. $X_{j,o,t}$ is a vector of controls. Finally, $\mu_{j,o,t}$ is the error term. Running this binary regression should show how airline productivity affects airline quality.

The results of this equation are shown in Appendix G. Table 7 shows the results for the regression in which all airlines that are within the dataset are included. Table 8 shows the results when the airlines that were not present throughout the dataset are excluded. Finally, Table 9 shows the results when only the airlines that accepted funding from the CARES Act are included. For regression equation (1), the specification is given without fixed effects. For regression equation (2), the specification includes fixed effects.

The results of the regression specifications are interesting. For each set of regressions, only the regional variables seem to show statistical significance. This may be due to omitted variable bias, however, the results are interesting nonetheless. In each of the three specifications, the interaction between regional flights, the post-COVID period, and the managerial salary is positive, while it is negative for every other category. This may suggest that regional managerial salaries increased after the pandemic, whereas everyone else experienced a salary decrease. Similarly, it is possible that productivity followed this trend, leading to decreased on-time performance due to decreases in the productivity of the flight crew, the maintenance crew, the traffic crew, and others. If this is the case, and if it is true that the on-time performance of the airlines decreased after the end of the CARES Act, then it may be reasonable to assume that, at least for regionals, the on-time performance delay of the airlines were caused by an overall decrease in wages, and, therefore, productivity.

7 Conclusion

This paper has provided an examination of the CARES Act and how its completion has impacted the industry. My findings suggest that airline schedule padding decreased at the conclusion of the CARES Act, while departure delays increased. This may be because airlines had to adjust their revenue to cover their costs, since they could no longer rely solely on government support. Though they had access to PSP2 and PSP3 funding, these were much smaller in nature, which may have made the airlines less able to rely on government funding. Furthermore, this paper has suggested that another causal mechanism influencing the data is the change in productivity resulting from the end of the Act. Of course, this analysis has several limitations. To begin with, all units are treated simultaneously, making it difficult to pinpoint a control group. Furthermore, the COVID-19 pandemic that preceded the Act was plagued by exogenous shocks, making it difficult to find common trends. For this reason, I utilized the binary regression approach instead of the difference-in-difference approach.

One limitation that has not yet been discussed in detail is the influence of PSP2 and PSP3 on the model. The original CARES Act, which ended on December 30th, was the first of three funding packages the government provided to airlines. The initial funding, studied here, was capped at $25 billion and was called "PSP1" or "Payroll Support Program 1" (Department of the Treasury, 2020). Following this were two more packages, the first of which was capped at $15 billion and called "PSP2" (Department of the Treasury, 2021). PSP2 was in place from January to March 2021 (Department of the Treasury, 2020). After this came PSP3, which stretched from March 2021 to September 2021 and was capped at around $14 billion (Department of the Treasury, 2021). These two extensions had the same requirements as PSP1, with some additional requirements, such as using different methods to calculate the eligibility amount (Department of the Treasury, 2020; Department of the Treasury, 2021). For this analysis, I have ignored the complexities of PSP2 and PSP3, assuming they would produce small effects, since they were capped at a much lower level. The indicator variables I utilize may be insufficient to account for the effects of PSP2 and PSP3, especially since they were paid out at different times. It is also difficult to account for anticipatory and late effects, so this analysis used indicators for each quarter that the programs were in. Nevertheless, this paper has made a case that the CARES Act's conclusion created a negative impact on airline quality.

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Appendix A: Salary and Employment Shocks

Major Carriers

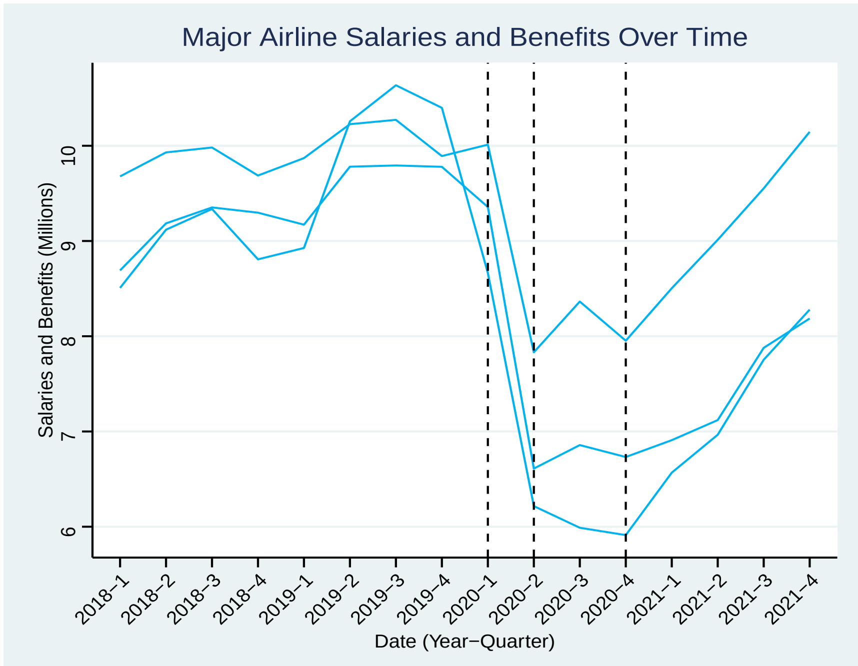

Figure 3: This figure shows the decline in salaries and benefits from the first quarter of 2020 to the fourth quarter of 2020. While a large dip occurs between the first and second quarter of 2020, it appears to temporarily stabilize before it starts to increase again after the fourth quarter of 2020.

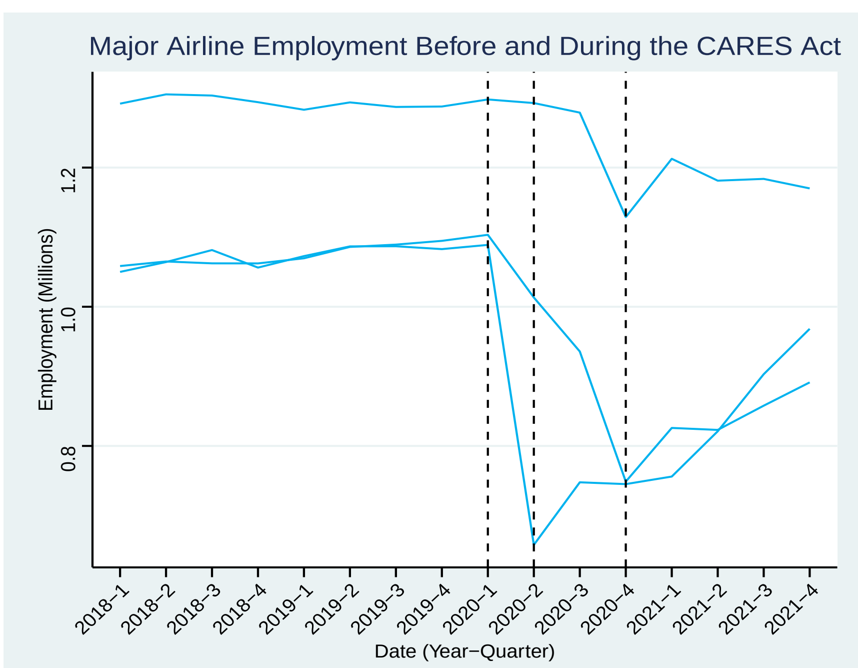

Figure 4: Here, there is a drop in employment from the first quarter of 2020 to the second quarter of 2020. After this point, some airlines seem to stabilize while others continue to struggle. Though it may seem odd that employment would drop for an airline that accepts CARES Act funding, it is important to remember that the industry was subject to large restructuring under COVID and that incentive packages (such as early retirement) were not curtailed by CARES Act acceptance.

Low-Cost Carriers

Figure 5: Consistent with the literature, the figures provided appear to show that LCCs were the most resilient during this time. Most LcC salaries and benefits appear largely unaffected by the COVID and CARES Act shocks, though this article does not explore this in depth.

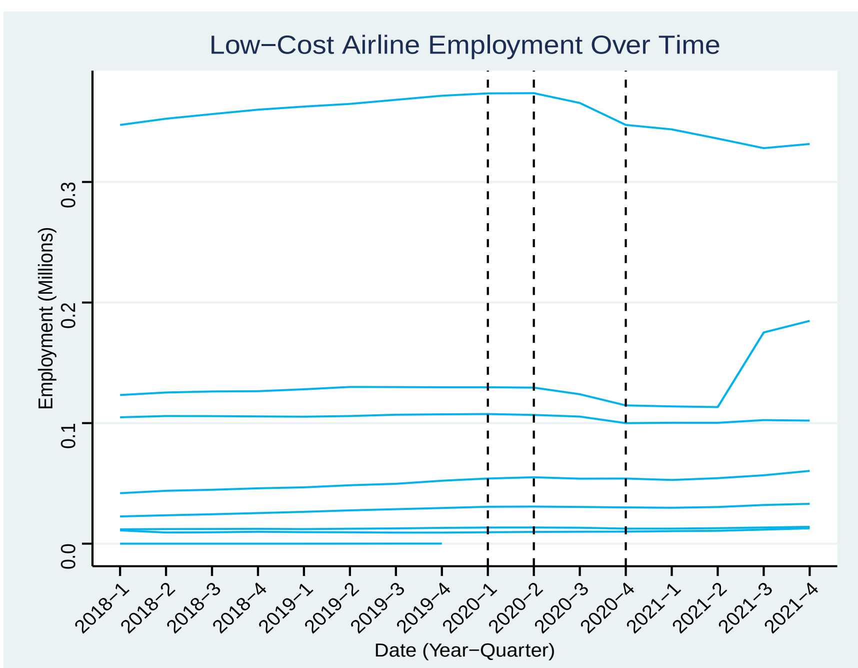

Figure 6: The employment of the low-cost carriers also seems largely unaffected by the COVID and CARES Act shocks. This speaks to the resilience of the low-cost airlines during this time period.

Regional Carriers

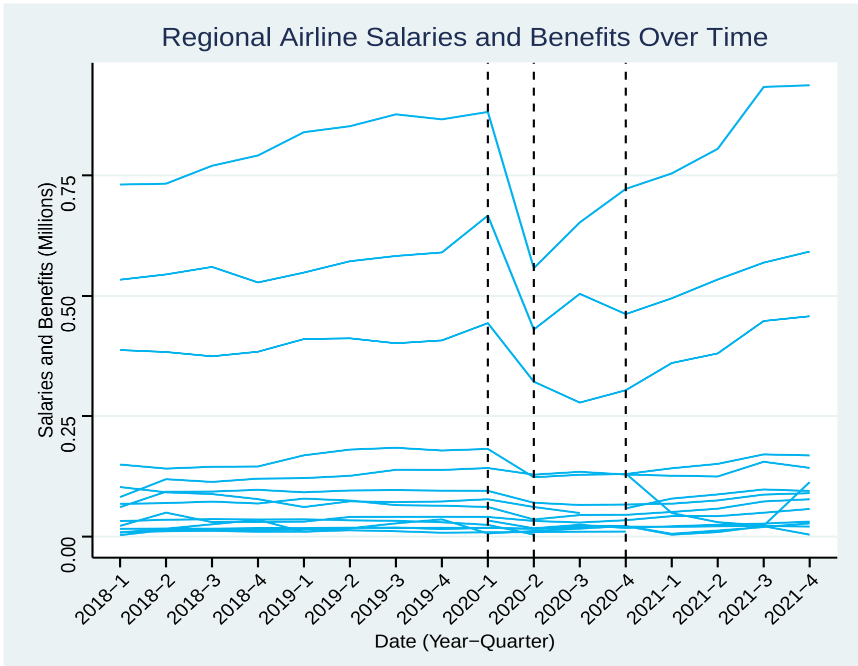

Figure 7: This figure shows the effect of the regional airline salaries and benefits during the initial COVID shock and the CARES Act shock. Initially, there is a drop in salaries and benefits, which then begins to stabilize after the CARES Act is announced. Once the CARES Act ends, the airlines appear to follow an upward trend.

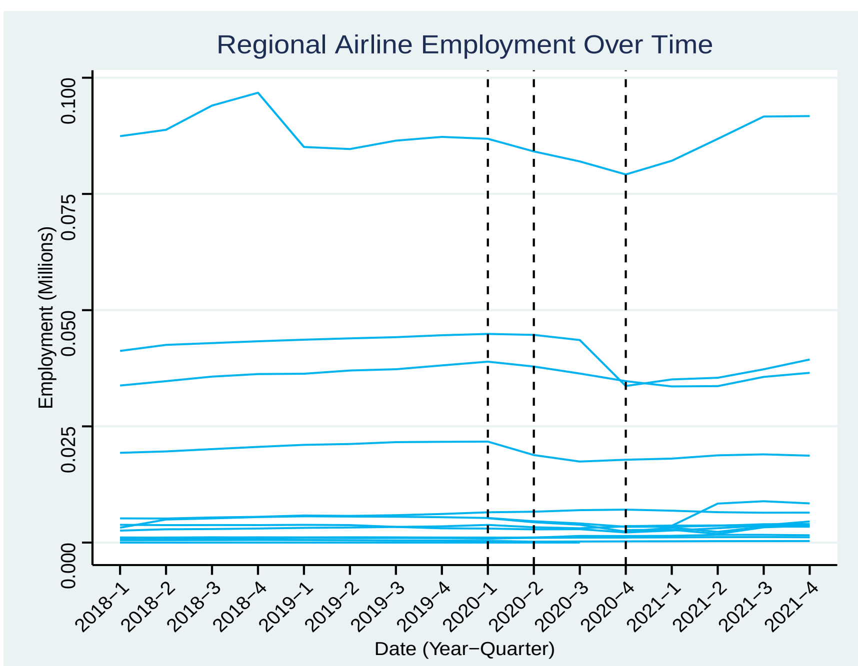

Figure 8: The above figure shows the relative stability of regional airline employment during the specified shocks. Though not quite as resilient as the LCCs, regional airlines nonetheless appear to maintain stability despite the economic shocks.

Appendix B: Normalized Salary and Employment Shocks

Major Carriers

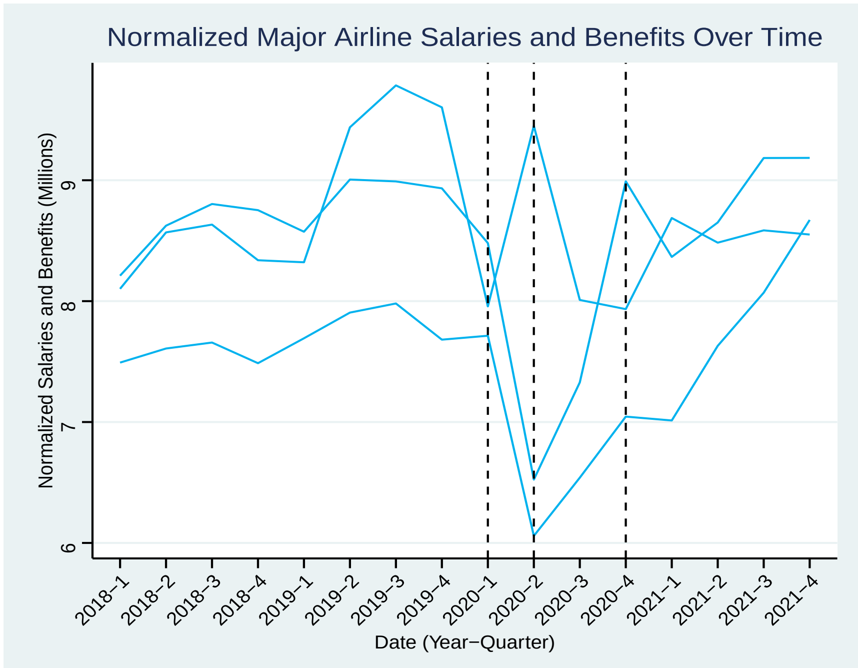

Figure 9: This figure has been normalized by taking the wage categories provided in the Form 41 financial database and dividing by the occupational categories. Though still only an estimate, we can see that major carriers tended to have a decrease in the normalized wage when the COVID shock was first introduced. This eventually went back up after the CARES Act was announced and remained on a consistent slope until the end of the dataset.

Low-Cost Carriers

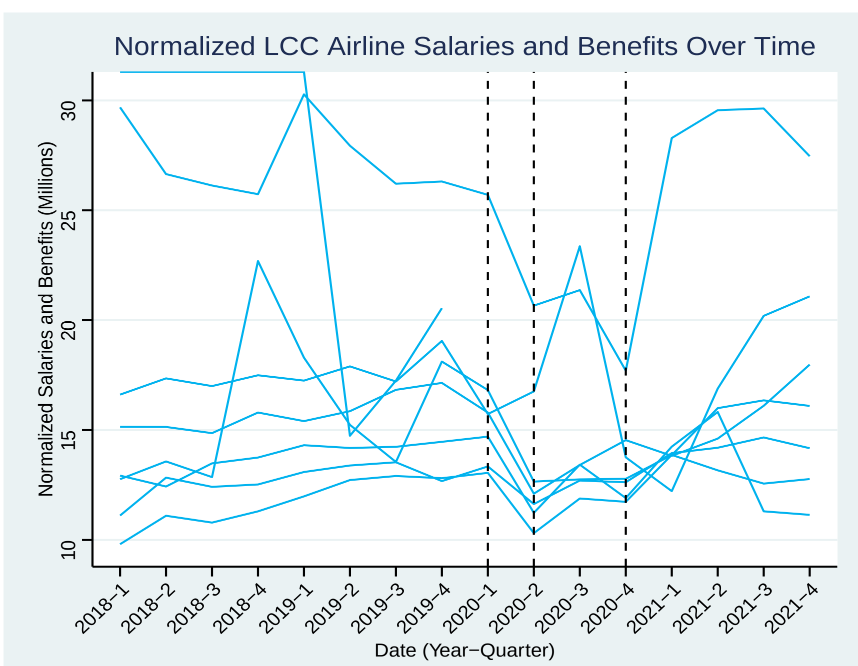

Figure 10: This graph was likewise normalized by taking the wage categories in the Form 41 financial database and dividing by the occupational categories. Here, we can see that the low-cost carriers also experienced challenges after the COVID shock was introduced (2020-1). Once the CARES Act was introduced, we observe an initial increase in the first quarter following the announcement, followed by a decrease. Once the initial CARES Act shock ends (2020-4), we see some mixed results. It is worth noting that some of the airlines within the dataset went out of business before the CARES Act was introduced.

Regional Carriers

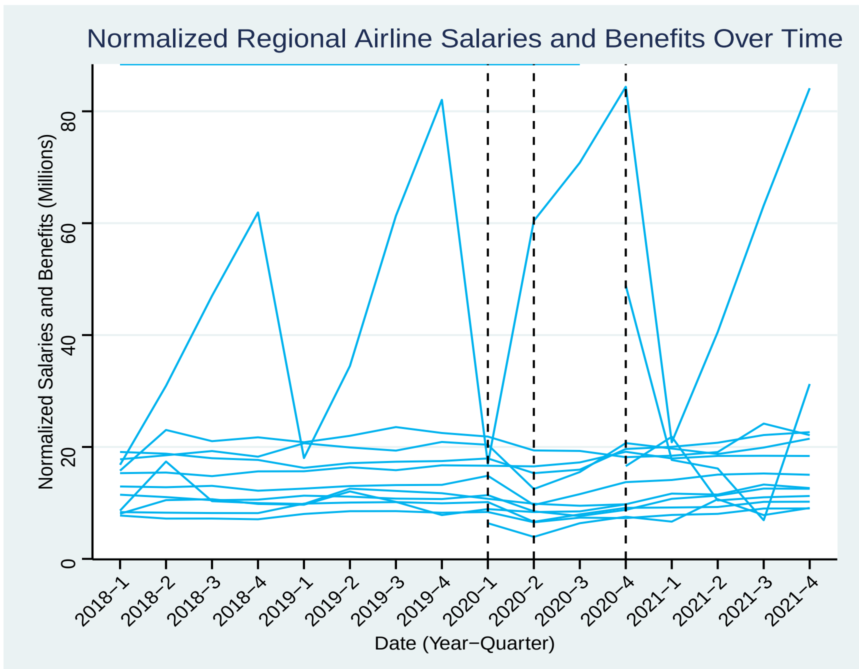

Figure 11: This final graph was normalized by taking the wage categories in the Form 41 financial database and dividing by the occupational categories. Overall, we observe the same patterns as in the low-cost carriers graph, but to a lesser extent. Admittedly, it is possible that some differences arise from differences in scale.

Appendix C: On-Time Performance Shocks

Major Carriers

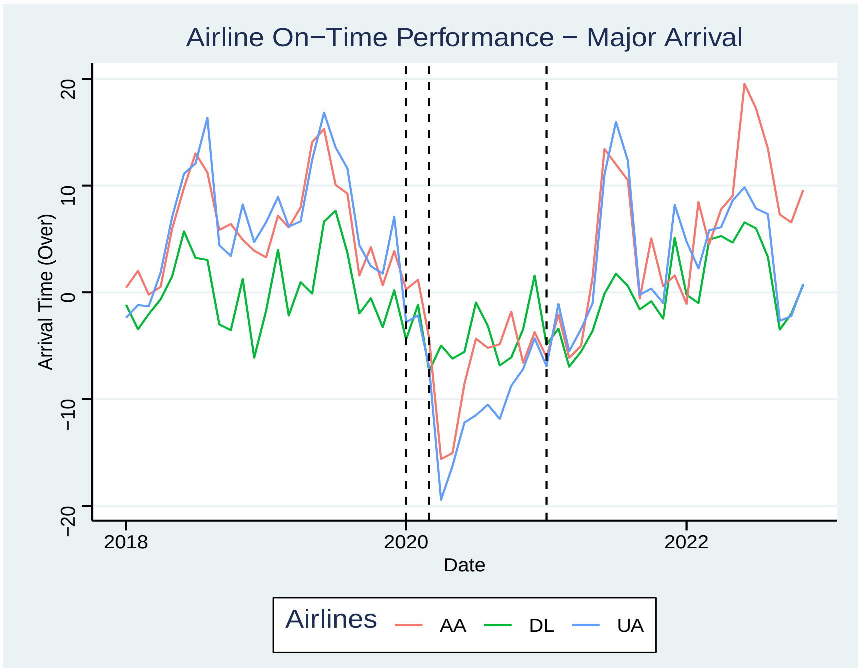

Figure 12: The above graph shows the on-time arrival performance of the three major airlines. We observe that airlines are generally more late before the COVID shock. After the COVID shock is introduced, the airlines improve their arrival time. Once the COVID shock is finished, it appears as though the arrival time gets worse once again. It is important to note that these graphs do not control for any variables, so the outcome of the paper may be different than the graphs appear to show.

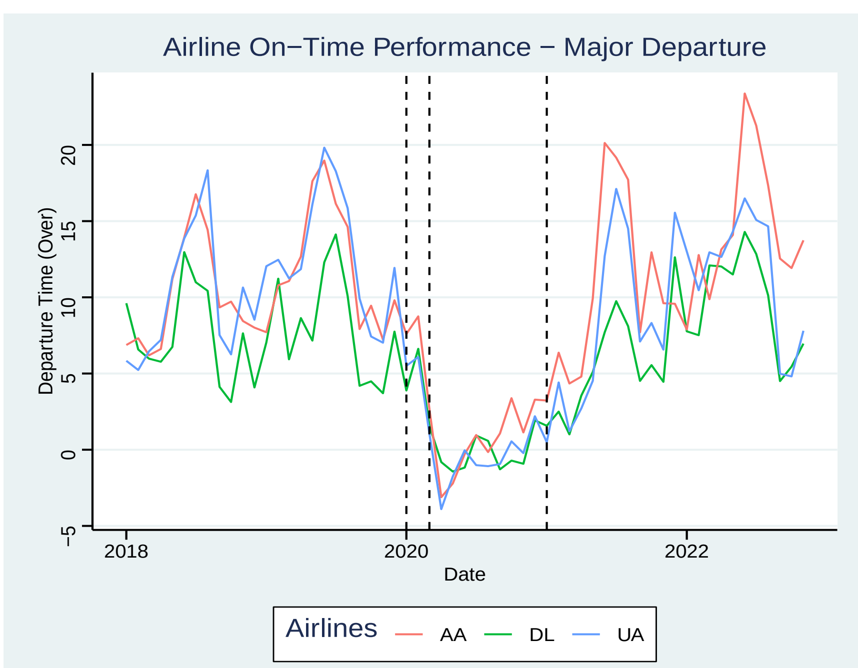

Figure 13: The above graph shows the departure on-time performance for the three majors. The results appear similar to the arrival time graph. The departure time appears worse in the quarters preceding the COVID-19 shock. Departure times then get better during COVID-19, eventually getting worse again after the initial COVID-19 shock ends.

Low-Cost Carriers

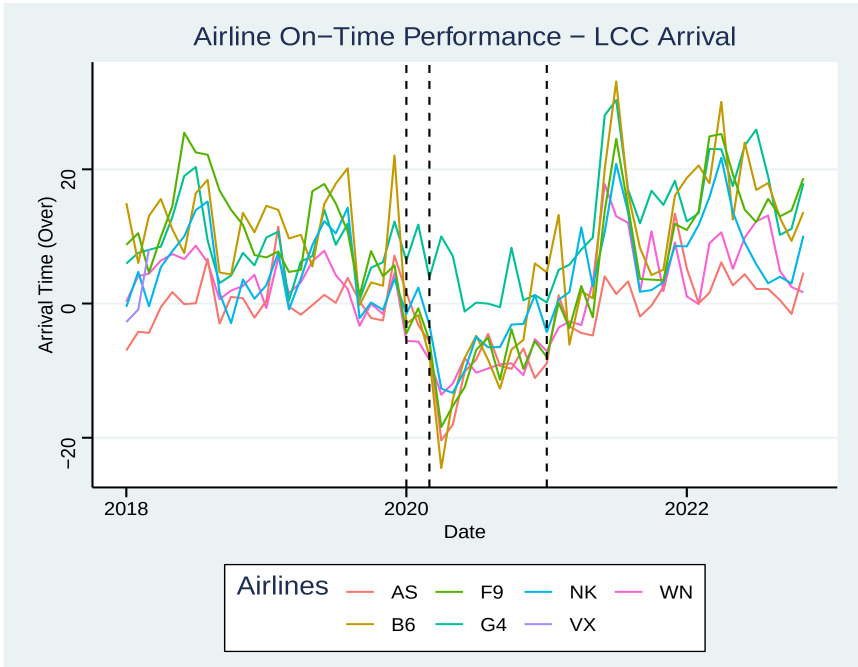

Figure 14: The figure above shows the low-cost carrier arrival time. The results remain consistent with the major carriers' on-time performance figures. The airlines temporarily improved during the COVID-19 shock, then seem to return to pre-COVID-19 levels.

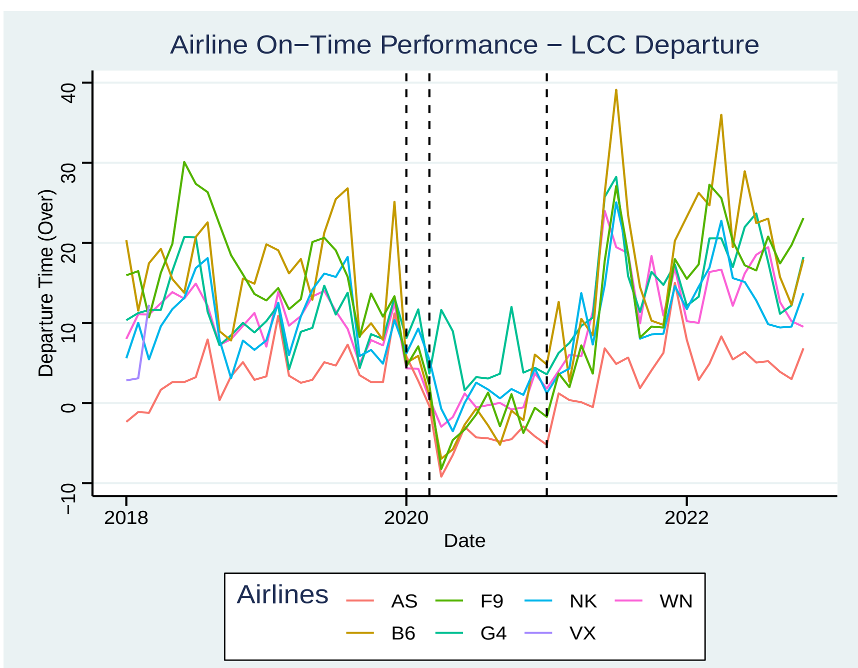

Figure 15: Consistent with the major airlines' figures, the low-cost carrier departure performance above shows that low-cost airlines had better on-time performance during the pandemic. The airlines had worse on-time performance before and after the pandemic.

Regional Carriers

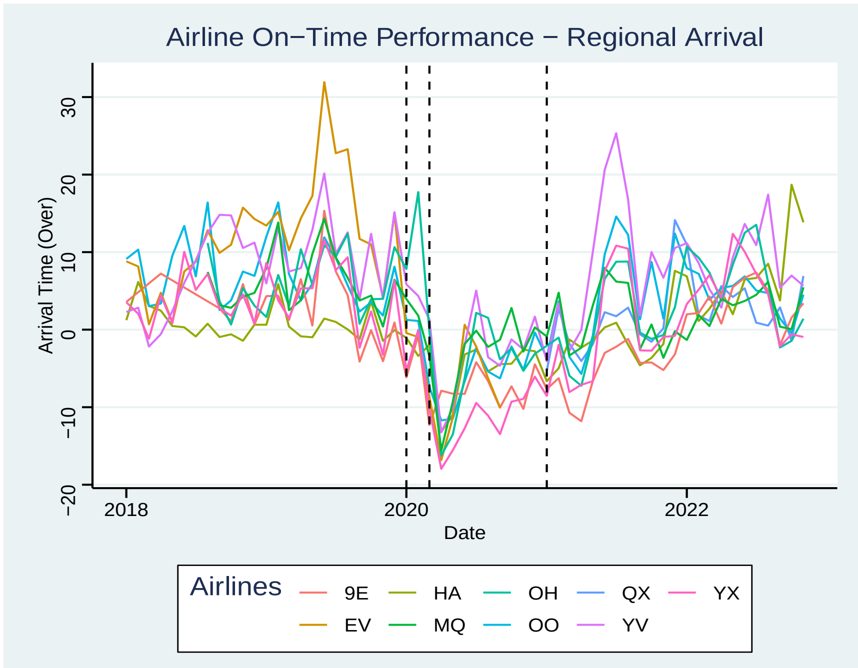

Figure 16: The figures for the airline arrival on-time performance figure remain consistent with both the majors' and the low-cost carriers' on-time performances. The regional airlines appear to have lower on-time performance both before and after the COVID shock.

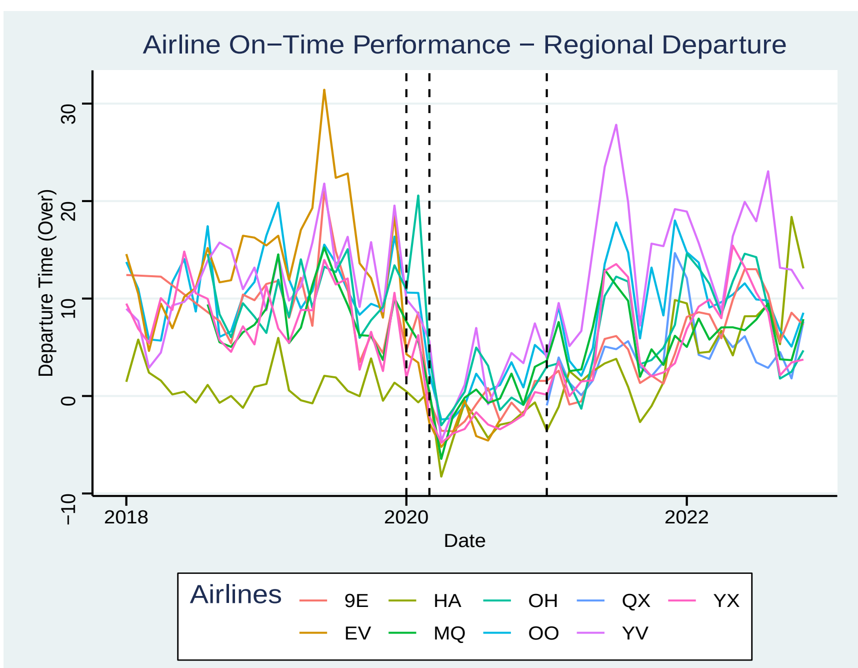

Figure 17: The above figure shows the regional departure on-time performance. The graph is consistent with each of the other on-time performance graphs. The on-time performance improves during the COVID-19 shock, but worsens before and after the shock.

Appendix D: Additional Regression Results

Table 4: Major Regression Results

Dependent Variables:	Elapsed Time				Departure Delay			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Constant	4.75***	6.82***			14.4***	-4.70***		
	(0.051)	(0.187)			(0.093)	(0.271)		
Interaction	-2.38***	-1.72***	-2.08***	-1.66***	7.02***	2.60***	3.58***	6.63***
	(0.074)	(0.076)	(0.071)	(0.098)	(0.117)	(0.115)	(0.113)	(0.156)
Flight Dummy	2.54***	1.53***	2.11***	2.09***	-7.57***	-1.36***	-2.51***	-4.22***
	(0.064)	(0.068)	(0.068)	(0.075)	(0.092)	(0.102)	(0.100)	(0.106)
Time Dummy	0.681***	0.780***	0.791***	0.786***	0.554***	0.372***	0.450***	0.453***
	(0.047)	(0.047)	(0.045)	(0.045)	(0.079)	(0.078)	(0.074)	(0.074)
Load Factor		-0.042***	-0.020***	-0.020***		0.226***	0.170***	0.115***
		(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)
HHI		-0.072	0.888***	0.886***		0.421**	-0.328*	-0.224
		(0.111)	(0.111)	(0.111)		(0.187)	(0.193)	(0.191)
Distance		0.002***	0.017***	0.017***		-0.0003**	0.007	0.006
		(7.53×10^{-5})	(0.005)	(0.005)		(0.0001)	(0.011)	(0.011)
PSP2 Dummy				-0.468***				-5.89***
				(0.105)				(0.158)
PSP3 Dummy				-0.579***				-0.974***
				(0.072)				(0.125)
Fixed-effects								
Carrier-Route FE			Yes	Yes			Yes	Yes
Day			Yes	Yes			Yes	Yes
Fit statistics								
R^2	0.00521	0.01280	0.09134	0.09141	0.00594	0.00846	0.03518	0.03556
Adjusted R^2	0.00521	0.01280	0.08917	0.08925	0.00594	0.00846	0.03288	0.03326
F-test	24.978	30.931	3.8780	3.8606	28.512	20.364	1.4065	1.4149
Observations	6,175,558	6,175,558	6,175,558	6,175,558	6,175,558	6,175,558	6,175,558	6,175,558

Clustered (Carrier-Route FE) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: LCC Regression Results

Dependent Variables:		Elapsed Time				Departure Delay		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Constant	4.78***	5.87***			13.0***	-2.93***		
	(0.059)	(0.192)			(0.095)	(0.293)		
Interaction	-0.995***	-0.471***	-0.552***	0.089	3.61***	0.159	1.14***	3.68***
	(0.093)	(0.090)	(0.087)	(0.121)	(0.120)	(0.126)	(0.125)	(0.171)
Flight Dummy	2.23***	1.27***	1.70***	1.66***	-5.82***	-0.891***	-2.00***	-3.02***
	(0.084)	(0.079)	(0.080)	(0.092)	(0.095)	(0.111)	(0.109)	(0.119)
Time Dummy	0.286***	0.455***	0.360***	0.351***	1.93***	1.72***	1.78***	1.77***
	(0.053)	(0.052)	(0.052)	(0.052)	(0.085)	(0.084)	(0.080)	(0.080)
Load Factor		-0.040***	-0.022***	-0.023***		0.186***	0.133***	0.100***
		(0.002)	(0.002)	(0.002)		(0.003)	(0.003)	(0.003)
HHI		0.586***	0.387***	0.380***		1.50***	0.554***	0.597***
		(0.103)	(0.115)	(0.115)		(0.195)	(0.202)	(0.201)
Origin Hub		0.861***				-0.593***		
		(0.081)				(0.153)		
Destination Hub		1.05***				-0.841***		
		(0.085)				(0.158)		
Distance		0.002***	0.003	0.003		-0.0003***	0.003	0.002
		(7.04×10^{-5})	(0.012)	(0.012)		(9.92×10^{-5})	(0.013)	(0.014)
PSP2 Dummy				-0.723***				-4.30***
				(0.129)				(0.192)
PSP3 Dummy				-0.883***				-1.67***
				(0.087)				(0.146)
Fixed-effects								
Carrier-Route FE			Yes	Yes			Yes	Yes
Day			Yes	Yes			Yes	Yes
Fit statistics								
R^2	0.00522	0.01759	0.08209	0.08226	0.00404	0.00584	0.02911	0.02928
Adjusted R^2	0.00522	0.01759	0.07981	0.07997	0.00404	0.00584	0.02670	0.02686
F-test	20.709	26.488	2.8527	2.8437	16.006	8.6954	0.95655	0.95704
Observations	4,913,593	4,913,593	4,913,593	4,913,593	4,913,593	4,913,593	4,913,593	4,913,593

Clustered (Carrier-Route FE) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Regional Regression Results

Dependent Variables:		Elapsed Time				Departure Delay		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Constant	5.83***	6.92***			13.5***	-4.82***		
	(0.047)	(0.182)			(0.083)	(0.250)		
Interaction	-1.39***	-0.851***	-0.997***	-0.037	7.08***	2.67***	3.21***	6.33***
	(0.074)	(0.070)	(0.068)	(0.093)	(0.104)	(0.101)	(0.099)	(0.136)
Flight Dummy	1.54***	0.739***	1.24***	0.862***	-7.08***	-0.996***	-2.09***	-3.52***
	(0.068)	(0.065)	(0.065)	(0.072)	(0.083)	(0.090)	(0.088)	(0.095)
Time Dummy	0.317***	0.340***	0.302***	0.307***	0.444***	0.288***	0.388***	0.408***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.065)	(0.065)	(0.061)	(0.061)
Load Factor		-0.032***	-0.011***	-0.024***		0.219***	0.170***	0.122***
		(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)
HHI		-0.473***	0.234**	0.222*		-0.382**	0.648***	0.624***
		(0.103)	(0.117)	(0.117)		(0.171)	(0.172)	(0.172)
Origin Hub		0.112				-0.700***		
		(0.077)				(0.138)		
Destination Hub		0.301***				-0.946***		
		(0.079)				(0.146)		
Distance		0.002***	-0.232	-0.240		0.0003***	0.168	0.138
		(5.83×10^{-5})	(0.200)	(0.209)		(8.93×10^{-5})	(0.253)	(0.226)
PSP2 Dummy				-1.63***				-5.62***
				(0.105)				(0.140)
PSP3 Dummy				-0.645***				-1.68***
				(0.069)				(0.111)
Fixed-effects								
Carrier-Route FE			Yes	Yes			Yes	Yes
Day			Yes	Yes			Yes	Yes
Fit statistics								
R^2	0.00201	0.01245	0.08149	0.08181	0.00647	0.00955	0.03755	0.03796
Adjusted R^2	0.00201	0.01245	0.07968	0.08001	0.00647	0.00955	0.03566	0.03607
F-test	8.0211	18.807	2.8541	2.8511	25.902	14.386	1.2552	1.2627
Observations	6,283,997	6,283,997	6,283,997	6,283,997	6,283,997	6,283,997	6,283,997	6,283,997

Clustered (Carrier-Route FE) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix E: Payroll Support Program Information

Table 7: Payroll Support Program 2 Information

Participant	Salaries (Q4 2019-Q1 2020)	Benefits (Q4 2019 - Q1 2020)	Eligible	Awarded	Percentage Awarded
AMERICAN AIRLINES INC.	$4,796,885,560	$1,837,498,110	$6,634,383,670	$3,532,928,551	53%
DELTA AIR LINES INC.	$4,555,712,000	$1,798,228,000	$6,353,940,000	$3,290,410,981	52%
UNITED AIRLINES INC.	$4,610,666,070	$1,767,924,480	$6,378,590,530	$3,001,196,216	47%
SOUTHWEST AIRLINES CO.	$2,903,574,000	$1,414,852,000	$4,318,426,000	$1,986,475,960	46%
ALASKA AIRLINES INC.	$788,574,000	$390,911,000	$1,179,486,000	$612,685,500	52%
JETBLUE AIRWAYS CORPORATION	$887,738,450	$373,644,010	$1,261,382,460	$580,235,932	46%
SKYWEST AIRLINES INC.	$382,722,140	$200,038,320	$582,760,450	$268,069,807	46%
SPIRIT AIRLINES INC.	$353,788,330	$107,365,480	$461,153,810	$212,130,753	46%
HAWAIIAN AIRLINES INC.	$300,327,550	$118,494,200	$418,821,740	$192,658,000	46%
FRONTIER AIRLINES INC	$251,285,270	$98,895,460	$350,180,720	$161,083,131	46%
REPUBLIC AIRWAYS INC.	$192,499,840	$91,014,830	$283,514,670	$130,416,748	46%
ALLEGIANT AIR LLC	$151,652,130	$77,743,420	$229,395,550	$105,521,953	46%
MESA AIRLINES INC.	$94,407,280	$25,806,940	$120,214,210	$55,967,320	47%
OMNI AIR INTERNATIONAL LLC	$57,984,370	$35,538,320	$93,522,680	$43,020,433	46%
SUN COUNTRY INC. DBA SUN COUNTRY AIRLINES	$57,991,050	$22,530,300	$80,521,330	$37,039,812	46%
AIR WISCONSIN AIRLINES LLC	$43,582,970	$20,474,410	$64,057,380	$35,733,867	56%
GOJET AIRLINES LLC	$29,050,660	$12,783,860	$41,834,520	$21,460,617	51%
SWIFT AIR LLC	$23,931,640	$3,273,620	$27,205,260	$12,386,673	46%
SILVER AIRWAYS LLC	$8,629,670	$2,503,130	$11,132,800	$9,266,015	83%
MIAMI AIR INTERNATIONAL INC.	$5,870,470	$3,009,580	$8,880,050	$7,501,380	84%
ELITE AIRWAYS LLC	$11,076,170	$2,980,170	$14,056,340	$6,825,440	49%
EASTERN AIRLINES LLC	$7,596,050	$3,602,770	$11,198,820	$5,604,524	50%
CARIBBEAN SUN AIRLINES INC	$4,592,420	$1,041,190	$5,633,620	$3,708,833	66%
AVERAGES	**$892,179,917**	**$365,658,852**	**$1,697,187,395**	**$839,237,387**	**48%**
Totals	**$20,520,138,090**	**$8,410,153,600**	**$28,852,185,720**	**$14,267,035,581**	**N/A**

This table captures the payment information from the second payroll support program, or PSP2, which was capped at $15,000,000,000 for all airlines. PSP2 occurred during the first quarter of 2021. The eligibility amount was based on fourth-quarter 2019 and first-quarter 2020 salaries and benefits. As with PSP1, the airlines were not permitted to involuntarily fire or furlough workers. All awarded amounts were required to be utilized for employee wages and benefits. This table suggests that most airlines received about 46.% of their eligible amount. It is important to note, however, that PSP2 worked differently from PSP1. Awarded amounts acted like loans above $ 100,000,000. Airlines also had multiple different methods for calculating their eligibility amount (not reflected here).

Table 8: Payroll Support Program 3 Information

Participant	Eligible (Based on PSP2 Amount)	Awarded	Percentage Awarded
AMERICAN AIRLINES INC.	$3,297,399,981	$3,295,162,461	99.93%
DELTA AIR LINES INC.	$3,071,050,249	$3,068,966,322	99.93%
UNITED AIRLINES INC.	$2,801,116,468	$2,799,215,711	99.93%
SOUTHWEST AIRLINES CO.	$1,854,044,229	$1,852,786,128	99.93%
ALASKA AIRLINES INC.8	$571,839,800	$571,451,766	99.93%
JETBLUE AIRWAYS CORPORATION	$541,553,537	$541,186,053	99.93%
SKYWEST AIRLINES INC.	$250,198,487	$250,028,709	99.93%
SPIRIT AIRLINES INC.	$197,988,703	$197,854,353	99.93%
HAWAIIAN AIRLINES INC.	$179,814,133	$179,692,117	99.93%
FRONTIER AIRLINES INC	$150,344,256	$150,242,236	99.93%
REPUBLIC AIRWAYS INC.	$121,722,298	$121,639,701	99.93%
ALLEGIANT AIR LLC	$98,487,156	$98,420,326	99.93%
MESA AIRLINES INC.	$52,236,165	$52,200,719	99.93%
OMNI AIR INTERNATIONAL LLC	$40,152,404	$40,125,158	99.93%
SUN COUNTRY INC.	$34,570,491	$34,547,032	99.93%
AIR WISCONSIN AIRLINES LLC	$33,351,609	$33,328,978	99.93%
GOJET AIRLINES LLC	$20,029,909	$20,016,318	99.93%
SWIFT AIR LLC	$11,560,895	$11,553,049	99.93%
SILVER AIRWAYS LLC	$8,648,281	$8,642,413	99.93%
ELITE AIRWAYS LLC	$6,370,411	$6,366,088	99.93%
EASTERN AIRLINES LLC	$5,230,889	$5,227,339	99.93%
CARIBBEAN SUN AIRLINES INC	$3,461,577	$3,459,228	99.93%
AVERAGES	**$561,434,470**	**$561,127,677**	**100.24%**
Totals	**$13,474,427,276**	**$13,467,064,242**	**N/A**

This table captures payment information from the third payroll support program, or PSP3. This program began in the second quarter of 2021 and extended through the third quarter of 2021. As before, airlines were not permitted to involuntarily fire or furlough employees. This program, however, was based on PSP2, with eligibility calculated by $14,000,000,000 \times (PSP2AwardedAmount/15,000,000,000$.

Appendix F: Summary Statistics (Causal Analysis)

Table 9: Aggregate Airline Summary Statistics

Grouping	Statistic	N	Mean	St. Dev.	Min	Max
Aggregate Salary Statistics	Carrier Group	376	1.612	0.761	1	3
	Management Salaries	376	17,072.09	28,738.25	-10,201.98	214,354.90
	Flights Salaries	376	653,570.20	1,114,611.00	59.61	3,971,094.00
	Maintenance Salaries	376	107,221.00	229,391.90	47.35	1,189,238.00
	Traffic Salaries	376	222,893.60	442,665.40	0	1,545,181.00
	Other Salaries	376	212,311.00	442,506.20	-436.74	2,380,080.00
	Salaries	376	1,213,068.00	2,187,793.00	219.98	8,002,599.00
	Personnel Benefits	376	90,641.15	151,347.10	-253.29	661,760.70
	Pensions Benefits	376	309,509.70	561,631.60	18.25	2,042,319.00
	Payroll Benefits	376	71,651.60	135,343.90	-90,162.00	582,932.80
	Benefits	376	471,802.50	833,490.00	126.98	2,970,432.00
	Salaries and Benefits	376	1,684,870.00	3,013,789.00	346.96	10,635,129.00
	Other	376	121,860.70	379,526.00	-495,501.00	5,076,466.00
	Transport Expense	376	603,957.70	1,511,958.00	0	5,925,255.00
	Operating Expense	376	4,836,408.00	8,896,112.00	903.85	33,244,674.00
	Employee Total	376	174,408.20	355,113.30	0	1,305,204
Normalized Salary Statistics	Normalized Management Salaries	326	615.073	1,689.61	-510.099	8,963.21
	Normalized Flight Salaries	358	150.262	86.756	2.71	467.463
	Normalized Maintenance Salaries	358	20.121	20.413	1.246	151.484
	Normalized Traffic Salaries	358	39.917	38.052	0	304.835
	Normalized Other Salaries	346	67.695	61.11	-0.919	332.019
	Normalized Salaries	352	11.372	8.535	3.17	67.513
	Normalized Personnel Benefits	352	1.213	1.342	-0.089	7.959
	Normalized Pensions Benefits	352	2.082	1.712	0.136	12.329
	Normalized Payroll Benefits	352	0.774	0.683	-1.244	4.921
	Normalized Benefits	352	4.069	2.574	0.636	17.233
	Normalized Salaries and Benefits	352	15.441	10.564	3.927	84.393
Employee Statistics	General Management	358	216.011	438.691	0	1,774
	Pilots and Copilots	358	3,107.58	4,111.22	3	13,989
	Other Flight Personnel	358	10.061	25.248	0	104
	Passenger General Services Administration	358	4,618.09	6,791.13	0	25,281
	Maintenance	358	1,765.38	3,462.86	0	15,597
	Aircraft Traffic Handling Group 1	358	6.486	23.245	0	110
	General Aircraft Traffic Handling	358	1,025.13	2,829.55	0	14,084
	Aircraft Control	358	187.075	251.207	0	1,154
	Passenger Handling	358	3,194.86	6,320.54	0	25,893
	Cargo Handling	358	1,319.40	3,853.87	0	16,963
	Trainees Instructor	358	144.659	240.635	0	961
	Statistical	358	956.095	3,093.00	0	16,839
	Traffic Solicitors	358	233.338	701.486	0	5,829
	Other	358	997.453	2,559.55	0	13,450

Table 10: Major Summary Statistics

Grouping	Statistic	N	Mean	St. Dev.	Min	Max
Aggregate Salary Statistics	Carrier Group	64	3	0	3	3
	Management Salaries	64	52,973.43	48,520.97	8,580.00	214,354.90
	Flights Salaries	64	2,565,551.00	1,189,104.00	451,410.00	3,813,472.00
	Maintenance Salaries	64	473,246.60	367,148.90	64,992.00	1,189,238.00
	Traffic Salaries	64	954,563.70	506,167.50	112,179.00	1,545,181.00
	Other Salaries	64	998,389.20	565,760.20	170,097.00	2,380,080.00
	Salaries	64	5,044,724.00	2,438,266.00	926,625.00	8,002,599.00
	Personnel Benefits	64	346,382.90	189,717.00	32,766.00	661,760.70
	Pensions Benefits	64	1,244,490.00	572,558.20	269,256.00	2,042,319.00
	Payroll Benefits	64	294,382.90	175,561.60	3,327.00	582,932.80
	Benefits	64	1,885,256.00	888,055.50	366,105.00	2,970,432.00
	Salaries and Benefits	64	6,929,980.00	3,306,450.00	1,292,730.00	10,635,129.00
	Other	64	536,573.00	791,638.30	-158,499.50	5,076,466.00
	Transport Expense	64	3,519,845.00	1,787,770.00	687,693.00	5,925,255.00
	Operating Expense	64	21,011,210.00	10,319,330.00	3,259,902.00	33,244,674.00
	Employee Total	64	825,325.30	447,056.60	99,972	1,305,204
Normalized Salary Statistics	Normalized Management Salaries	64	301.071	165.996	75.975	653
	Normalized Flight Salaries	64	247.226	39.054	147.183	327.498
	Normalized Maintenance Salaries	64	18.088	8.374	9.62	41.04
	Normalized Traffic Salaries	64	38.752	8.037	24.367	66.927
	Normalized Other Salaries	64	125.539	83.793	40.749	332.019
	Normalized Salaries	64	7.174	2.15	4.426	12.368
	Normalized Personnel Benefits	64	0.544	0.311	0.124	1.233
	Normalized Pensions Benefits	64	1.854	0.698	1.006	3.889
	Normalized Payroll Benefits	64	0.426	0.183	0.004	0.93
	Normalized Benefits	64	2.824	1.114	1.429	5.83
	Normalized Salaries and Benefits	64	9.998	3.235	6.058	17.982
Employee Statistics	General Management	64	276.812	248.481	20	642
	Pilots and Copilots	64	9,896.88	4,168.57	2,871	13,989
	Other Flight Personnel	64	25	43.703	0	104
	Passenger General Services Administration	64	15,898.56	7,136.98	5,530	25,281
	Maintenance	64	7,459.06	5,072.50	855	15,597
	Aircraft Traffic Handling Group 1	64	0	0	0	0
	General Aircraft Traffic Handling	64	5,062.63	4,978.14	0	14,084
	Aircraft Control	64	607.625	280.815	222	1,154
	Passenger Handling	64	13,491.00	8,373.28	1,006	25,893
	Cargo Handling	64	4,587.56	6,755.01	392	16,963
	Trainees Instructor	64	559.562	286.255	124	961
	Statistical	64	4,655.69	6,085.07	388	16,839
	Traffic Solicitors	64	1,179.88	1,290.98	246	5,829
	Other	64	3,619.13	4,789.02	0	13,450

Table 11: LCC Summary Statistics

Grouping	Statistic	N	Mean	St. Dev.	Min	Max
Aggregate Salary Statistics	Carrier Group	102	2	0	2	2
	Management Salaries	102	14,035.27	14,309.53	45.72	133,090.20
	Flights Salaries	102	630,559.40	842,674.60	59.61	3,971,094.00
	Maintenance Salaries	102	63,389.54	82,062.89	47.35	310,830.00
	Traffic Salaries	102	205,186.60	363,339.40	12.22	1,273,644.00
	Other Salaries	102	137,355.50	208,495.50	0	750,870.00
	Salaries	102	1,050,526.00	1,489,221.00	219.98	6,274,425.00
	Personnel Benefits	102	72,923.88	93,256.26	47.44	318,579.00
	Pensions Benefits	102	307,431.80	491,657.50	18.25	1,920,438.00
	Payroll Benefits	102	61,014.22	93,324.85	-90,162.00	349,566.00
	Benefits	102	441,369.90	668,640.80	126.98	2,522,982.00
	Salaries and Benefits	102	1,491,896.00	2,147,212.00	346.96	8,540,433.00
	Other	102	55,831.94	88,605.35	-495,501.00	300,225.00
	Transport Expense	102	14,191.53	32,272.23	0	97,383.00
	Operating Expense	102	3,687,632.00	4,448,636.00	903.85	15,193,647.00
	Employee Total	102	92,375.17	121,568.50	0	373,648
Normalized Salary Statistics	Normalized Management Salaries	102	182.991	306.058	1.039	2,464.63
	Normalized Flight Salaries	102	167.228	76.801	2.71	467.463
	Normalized Maintenance Salaries	102	12.405	5.813	1.246	40.38
	Normalized Traffic Salaries	102	51.235	61.651	1.111	304.835
	Normalized Other Salaries	98	79.24	32.197	0	167.229
	Normalized Salaries	99	11.497	3.359	6.931	21.415
	Normalized Personnel Benefits	99	1.175	0.91	0.1	7.342
	Normalized Pensions Benefits	99	2.838	1.536	0.76	8.644
	Normalized Payroll Benefits	99	0.768	0.544	-1.244	2.815
	Normalized Benefits	99	4.78	2.194	2.391	12.437
	Normalized Salaries and Benefits	99	16.278	5.248	9.808	30.278
Employee Statistics	General Management	102	511.627	698.03	9	1,774
	Pilots and Copilots	102	2,748.37	2,752.22	3	9,225
	Other Flight Personnel	102	15.392	26.89	0	89
	Passenger General Services Administration	102	4,423.73	4,727.96	0	15,882
	Maintenance	102	736.627	796.485	2	2,547
	Aircraft Traffic Handling Group 1	102	0.294	1.571	0	11
	General Aircraft Traffic Handling	102	313.608	442.562	0	1,403
	Aircraft Control	102	148.235	157.523	0	461
	Passenger Handling	102	2,368.39	3,491.28	0	9,922
	Cargo Handling	102	1,621.49	3,754.90	0	10,955
	Trainees Instructor	102	101.039	122.321	0	401
	Statistical	102	258.941	331.102	0	1,149
	Traffic Solicitors	102	53.882	67.443	0	200
	Other	102	1,075.67	1,698.58	0	4,976

Table 12: Regional Summary Statistics

Grouping	Statistic	N	Mean	St. Dev.	Min	Max
Aggregate Salary Statistics	Carrier Group	210	1	0	1	1
	Management Salaries	210	7,605.75	13,564.92	-10,201.98	74,862.30
	Flights Salaries	210	82,047.99	108,785.30	1,489.65	459,359.90
	Maintenance Salaries	210	16,959.97	19,448.94	102.96	82,245.18
	Traffic Salaries	210	8,508.91	17,244.32	0	80,239.77
	Other Salaries	210	9,151.28	20,305.43	-436.74	120,237.10
	Salaries	210	124,273.90	156,337.30	2,742.78	606,907.00
	Personnel Benefits	210	21,306.36	32,179.85	-253.29	147,274.80
	Pensions Benefits	210	25,572.56	40,346.64	377.88	138,351.00
	Payroll Benefits	210	8,938.30	13,004.24	-42,891.21	52,592.04
	Benefits	210	55,817.21	81,224.38	1,019.88	333,874.30
	Salaries and Benefits	210	180,091.10	236,094.40	4,023.84	937,234.80
	Other	210	27,543.25	44,859.28	-9,097.08	209,746.80
	Transport Expense	210	1,764.20	6,952.37	0	56,095.74
	Operating Expense	210	464,922.40	613,094.60	9,266.86	2,385,227.00
	Employee Total	210	15,878.13	24,484.13	0	96,774
Normalized Salary Statistics	Normalized Management Salaries	160	1,016.13	2,333.14	-510.099	8,963.21
	Normalized Flight Salaries	192	108.928	73.651	19.813	403.418
	Normalized Maintenance Salaries	192	24.899	26.11	3.68	151.484
	Normalized Traffic Salaries	192	34.292	23.968	0	120.54
	Normalized Other Salaries	184	41.427	46.243	-0.919	175.018
	Normalized Salaries	189	12.728	10.987	3.17	67.513
	Normalized Personnel Benefits	189	1.459	1.639	-0.089	7.959
	Normalized Pensions Benefits	189	1.762	1.913	0.136	12.329
	Normalized Payroll Benefits	189	0.896	0.806	-1.179	4.921
	Normalized Benefits	189	4.118	2.94	0.636	17.233
	Normalized Salaries and Benefits	189	16.845	13.344	3.927	84.393
Employee Statistics	General Management	192	38.698	46.686	0	132
	Pilots and Copilots	192	1,035.32	1,422.64	17	5,705
	Other Flight Personnel	192	2.25	5.276	0	19
	Passenger General Services Administration	192	961.193	1,216.28	0	4,699
	Maintenance	192	414.01	572.065	0	2,227
	Aircraft Traffic Handling Group 1	192	11.938	30.728	0	110
	General Aircraft Traffic Handling	192	57.297	113.238	0	457
	Aircraft Control	192	67.526	66.206	0	194
	Passenger Handling	192	201.87	454.443	0	1,633
	Cargo Handling	192	69.531	236.911	0	1,048
	Trainees Instructor	192	29.531	35.628	0	155
	Statistical	192	93.26	124.584	0	463
	Traffic Solicitors	192	13.161	38.552	0	156
	Other	192	82.01	76.149	0	286

Appendix G: Regression Results (Causal Analysis)

Table 13: Causal Mechanism Regression Results 1 (Whole Dataset)

	Dependent variable:	
	Normalized Salaries	
	No Fixed Effects	Fixed Effects
Majors * Post CARES * Flight Salaries	87.948	430.061
	(218.829)	(279.578)
Majors * Post CARES * Maintenance Salaries	−149.236	322.617
	(218.829)	(279.578)
Majors * Post CARES * Traffic Salaries	−126.885	323.209
	(218.829)	(279.578)
Majors * Post CARES * Other Salaries	−63.137	363.468
	(218.829)	(279.696)
LCCs * Post CARES * Manager Salaries	93.448	−8.452
	(144.114)	(238.422)
LCCs * Post CARES * Flight Salaries	−166.373	−43.228
	(297.594)	(326.473)
LCCs * Post CARES * Maintenance Salaries	−103.416	19.729
	(297.594)	(326.473)
LCCs * Post CARES * Traffic Salaries	−96.646	26.499
	(297.594)	(326.473)
LCCs * Post CARES * Other Salaries	−106.644	16.501
	(297.594)	(326.473)
Regionals * Post CARES * Manager Salaries	739.836***	480.466**
	(115.642)	(226.217)
Regionals * Post CARES * Flight Salaries	−887.251***	−756.142**
	(269.615)	(306.862)
Regionals * Post CARES * Maintenance Salaries	−729.988***	−598.879*
	(269.615)	(306.862)
Regionals * Post CARES * Traffic Salaries	−749.663***	−618.554**
	(269.615)	(306.862)
Regionals * Post CARES * Other Salaries	−810.290***	−679.181**
	(269.615)	(306.862)
Constant	171.481***	14.791
	(20.755)	(104.268)
Observations	1,746	1,746
R^2	0.029	0.256
Adjusted R^2	0.021	0.230
Residual Std. Error	754.629 (df = 1731)	669.070 (df = 1687)
F Statistic	3.655*** (df = 14; 1731)	10.002*** (df = 58; 1687)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 14: Causal Mechanism Regression Results 2 (Only Those Who Accepted)

	Dependent variable:	
	Normalized Salaries	
	No Fixed Effects	Fixed Effects
Majors * Post CARES Flight Salaries	77.659	452.155
	(225.791)	(288.582)
Majors * Post CARES * Maintenance Salaries	−159.525	353.268
	(225.791)	(288.582)
Majors * Post CARES * Traffic Salaries	−137.174	352.007
	(225.791)	(288.582)
Majors * Post CARES * Other Salaries	−73.426	390.588
	(225.791)	(288.722)
LCCs * Post CARES * Manager Salaries	83.159	−8.452
	(148.764)	(245.754)
LCCs * Post CARES * Flight Salaries	−156.084	−43.228
	(307.014)	(336.512)
LCCs * Post CARES * Maintenance Salaries	−93.127	19.729
	(307.014)	(336.512)
LCCs * Post CARES * Traffic Salaries	−86.357	26.499
	(307.014)	(336.512)
LCCs * Post CARES * Other Salaries	−96.355	16.501
	(307.014)	(336.512)
Regionals * Post CARES * Manager Salaries	811.083***	539.069**
	(125.057)	(235.907)
Regionals * Post CARES * Flight Salaries	−954.714***	−831.917***
	(282.662)	(319.435)
Regionals * Post CARES * Maintenance Salaries	−802.362***	−679.564**
	(282.662)	(319.435)
Regionals * Post CARES * TraffSal	−821.148***	−698.351**
	(282.662)	(319.435)
Regionals * Post CARES * Other Salaries	−881.229***	−758.432**
	(282.662)	(319.435)
Constant	181.770***	14.530
	(22.194)	(109.694)
Observations	1,634	1,634
R^2	0.031	0.259
Adjusted R^2	0.023	0.233
Residual Std. Error	778.374 (df = 1619)	689.645 (df = 1577)
F Statistic	3.748*** (df = 14; 1619)	9.862*** (df = 56; 1577)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 15: Causal Mechanism Regression Results 3 (Fully in the Data and Accepted Funding)

	Dependent variable:	
	Normalized Salaries	
	No Fixed Effects	Fixed Effects
Majors * Post CARES * Flight Salaries	77.981	420.011
	(231.372)	(296.395)
Majors * Post CARES * Maintenance Salaries	−159.202	329.879
	(231.372)	(296.395)
Majors * Post CARES * Traffic Salaries	−136.852	326.992
	(231.372)	(296.395)
Majors * Post CARES * Other Salaries	−73.104	360.606
	(231.372)	(296.395)
LCCs * Post CARES * Manager Salaries	83.481	−8.452
	(152.517)	(251.956)
LCCs * Post CARES * Flight Salaries	−156.406	−43.228
	(314.548)	(345.004)
LCCs * Post CARES * Maintenance Salaries	−93.449	19.729
	(314.548)	(345.004)
LCCs * Post CARES * Traffic Salaries	−86.679	26.499
	(314.548)	(345.004)
LCCs * Post CARES * Other Salaries	−96.677	16.501
	(314.548)	(345.004)
Regionals * Post CARES * Manager Salaries	992.921***	712.200***
	(152.517)	(251.896)
Regionals * Post CARES * Flight Salaries	−1,132.305***	−1,003.916***
	(310.004)	(341.956)
Regionals * Post CARES * Maintenance Salaries	−988.473***	−860.084**
	(310.004)	(341.956)
Regionals * Post CARES * Traffic Salaries	−1,001.490***	−873.101**
	(310.004)	(341.956)
Regionals * Post CARES * Other Salaries	−1,055.305***	−926.916***
	(310.004)	(341.956)
Constant	181.448***	15.884
	(23.614)	(114.655)
Observations	1,484	1,484
R^2	0.033	0.259
Adjusted R^2	0.024	0.233
Residual Std. Error	797.310 (df = 1469)	707.049 (df = 1432)
F Statistic	3.615*** (df = 14; 1469)	9.811*** (df = 51; 1432)
Note:		*p<0.1; **p<0.05; ***p<0.01