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Cost pass-through in the airline industry: price responses and asymmetries

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Abstract

We investigate how fuel cost shocks are passed to air travel fares. Two-staged least squares estimators are used with retail gasoline and crude oil prices employed as instruments. Our results suggest that the cost shock effect on airfare is higher for positive shocks than for negative shocks. Such effect mostly occurs approximately in the same quarter, and then it reaches to the long run equilibrium. The timing of the effect may be explained by ticket purchasing and/or carrier fuel hedging decisions. Significant differentials are found for different business models, slot capacity, service classes, and market structure.

I am grateful for helpful comments from Anderson (Nebraska), Azzam (Nebraska), Magnolfi (Wisconsin), Sorensen (Wisconsin), and from the Wisconsin IO lunch workshop. I am also thankful for comments from three anonymous referees. All errors are my own. For the online appendix, please visit https://sites.google.com/a/uwalumni.com/schuang/home/research.

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1 Introduction

How fares are set in the airline industry has been of scholarly interest for decades. Depending on ticket attributes, fares can be quite different. Pricing decisions are rather complicated, and airlines incorporate many different aspects into their dynamic pricing strategies. Operational cost is one major factor that airlines take into consideration when setting prices. With higher production costs (personnel, fuel, ground handling, etc.), prices are expected to be higher, *ceteris paribus*. When firms face cost shocks, they typically raise prices to reflect the increased cost of production. However, when firms are instead faced with cost reductions, they are more reluctant to lower prices in response to the decreased production cost.

The potential asymmetric price responses have been closely scrutinized in empirical industrial organization.[1,2] The canonical way of detecting response asymmetry is pioneered by Borenstein, Cameron, and Gilbert (1997). In that paper, they look at the speed of retail gasoline price responses to crude oil price increases and decreases. With weekly data, they confirm that there is indeed an asymmetry between the two price responses. In particular, response to crude oil price increase is faster than that of decrease. Inventory adjustment effects as well as short-run market power may be potential causes of the asymmetry. They reason two commonly cited propositions of asymmetric price adjustment: one based on consumer search, and the other based on focal price tacit collusion.

Borenstein, Cameron, and Gilbert (1997) have fostered a handful of works on cost pass-through focusing on the retail gasoline industry. Some papers find asymmetric price responses (see, for example, Balmaceda and Soruco (2008); Deltas (2008); Verlinda (2008); Lewis (2011), Remer (2015)) while some others do not (see, for example, Bachmeier and Griffin (2003); Hosken, McMillan, and Taylor (2008)). This literature also extends only to a number of other industries: online mortgage markets (Arbatskaya and Baye (2004)), supermarket chain (Peltzman (2000)), wholesale (Bonnet, Dubois, Villa-Boas, and Klapper (2013)), labor market (Aaronson (2001)), agricultural industry (Azzam (1999)), and the coffee market (Nakamura and Zerom (2010); Bettendorf and Verboven (2000)).

Given how popular cost pass-through and airline dynamic pricing are in industrial organization, it is surprising that, to the author's knowledge, these topics are rarely studied in the context of the airline industry. In this paper, we attempt to fill the gap in the literature and extend the story to the airline industry by employing fare data between 2006 and 2016. We examine price responses when carriers experience exogenous fuel cost shocks, and we test for asymmetric price responses when carriers face positive and negative shocks. Our results suggest that the cost shock effect on airfare is higher for positive shocks than for negative shocks. Such effect mostly occurs approximately in the same quarter, and it dissipates to the long-run equilibrium. The timing of the effect may be explained by ticket purchasing and/or carrier fuel hedging decisions. In addition, we find significant differentials for different business models, slot capacity, service classes, and market structure.

The paper is structured as follows. Section 2 illustrates data sources. Section 3 provides our empirical estimation strategies. Section 4 discusses our preliminary results. Section 5 concludes.

[1] With refined data frequency, this literature also closely follows the "rockets and feathers", or the price stickiness literature.

[2] In public economics, researchers have also been tackling the tax pass-through (tax incidence) question.

2 Data

Our data come from multiple sources. Fare data come from the Airline Origin and Destination Survey Databank (DB1B), maintained by the Bureau of Transportation Statistics (BTS). It represents approximately ten percent of the domestic tickets. Filters are applied to rule out outliers and other extreme itineraries.[3] We obtain data on fuel cost per gallon from the Air Carrier Financial Report Schedule P-12(a). Fleet composition comes from carriers. We combine fuel efficiency data for each type of aircraft, from the website Axlegeeks and the distance of each segment of the itinerary to calculate the final minimum fuel cost for any specific itinerary. We also need information on fleet types and sizes, which is obtained directly from each airline and/or from the website Airfleets. We obtain these variables (retail gasoline prices, and crude oil spot prices) from the Energy Information Administration (EIA).

Since the original unit of observation from DB1B is at the itinerary level, to allow for time-series operations, we transform the dataset into a panel dataset, in which the cross-sectional component is the different route/carrier/direct/service class combination, and the time-series component as quarters. Our data cover 2006 to 2016, with a total of 44 quarters. We include most carriers (legacy and low cost) and its regional feeders.[4,5] Average fare is around 461 dollars. Approximately 70% of obsverations are in economy class. Only 19% of the observations are direct flights. Flights with legacy carriers account for more than 70% of the observations.

3 Model

3.1 Fuel Cost

To examine the rate at which air travel fares react to shocks in fuel cost, we first define fuel cost in our context as follows: for each itinerary y with coupon (segment) s being ticketed by carrier c, at time t, the fuel cost $Cost$ (in dollars) is:

$$Cost_{yct} = \sum_{s}[Price_{stc} \times Eff_{ac} \times NM_s] \tag{1}$$

where $Price$ is the unit fuel cost (in dollars per gallon), Eff is the fuel efficiency for the representative aircraft type in that distance bin a (in gallons per nautical miles) for ticketing carrier c, and NM is the distance of the segment s in nautical miles. Constructing the fuel cost in this manner rather than simply using the per unit fuel cost allows us to control for different key aspects of fuel costs, which may differ by carrier, by time, and by itinerary. First, per unit fuel cost is incorporated in the calculation. Second, fuel efficiencies depends on the aircraft of choice, and different carriers use different portfolios of aircraft. To simplify

[3]See details in the appendix.

[4]Regional feeders are combined with its mainline carrier.

[5]To be specific, we include American Airlines, Alaska Airlines, JetBlue, Continental Airlines, Delta Air Lines, Frontier Airlines, AirTran, Allegiant Air, Hawaiian Airlines, Spirit Airlines, Northwest Airlines, United Airlines, US Airways, Virgin America, and Southwest Airlines.

this process, we choose a representative aircraft type for each of the three range bins.[6] Third, we control for the distance flown for the obvious reason that it takes more fuel to fly a longer route. Note that this cost measure represents the absolute minimum fuel cost needed to operate such flights in air.[7] We then aggregate this measure to the level of route/carrier/direct/service class as weighted by the number of passengers, and include it as the cost measure in our main estimation model in the next section.

3.2 Main Estimation Model

We reference our estimation strategies from Borenstein, Cameron, and Gilbert (1997), and Engle and Granger (1987). Specifically, for a grouping i of route/carrier/direct/service class combination at time t,

$$\begin{aligned}\Delta Fare_{it} =& -\gamma\alpha_0 + \sum_{j=0}^{n}(\beta_{ij}^{+}\Delta Cost_{i,t-j}^{+} + \beta_{ij}^{-}\Delta Cost_{i,t-j}^{-}) \\ &+ \sum_{j=1}^{n}(\lambda_{ij}^{+}\Delta Fare_{i,t-j}^{+} + \lambda_{ij}^{-}\Delta Fare_{i,t-j}^{-}) \\ &+ \sum_{j=2}^{4}\gamma\eta_j Q_j + \gamma Fare_{i,t-1} - \gamma\alpha_1 Cost_{i,t-1} - \gamma\alpha_2 TIME_t + \varepsilon_{it}\end{aligned} \tag{2}$$

In this equation, tax-inclusive airfare depends on contemporaneous and previous n periods of positive and negative cost shocks as well as fares from previous periods. Included in the regression is the long run error correction term in equation (4), spirited by Engle and Granger (1987), a one-period lagged residual from the long run relationship between fare and cost, as depicted in equation (3).[8]

$$Fare = \alpha_0 + \alpha_1 Cost + e \tag{3}$$

$$e_{t-1} = Fare_{t-1} - \alpha_0 - \alpha_1 Cost_{t-1} \tag{4}$$

We include quarterly fixed effects Q_j and time trends $TIME_t$ to control for seasonality and inflation.[9] Finally, ε_t is the error term.

We obtain estimates of β's, λ's, and α_1 to construct such a cumulative response function. The h-period cumulative response function after a cost increase (decrease) is given by the

[6]Details can be found in the appendix.

[7]Actual fuel consumption depends on flight time (in air), ramp time (taxi-ing between the gate and runway), additional fuel for potential diversion or circling, and the necessary fuel reserve as required by law.

[8]Modeling using differences allows us to rule out any potential problems of co-integration. See Engle and Granger (1987).

[9]A Hausman test yields a p-value of 0.000, supporting our choice of fixed effects over random effects.

recursive relationship A_h^+ (A_h^-):

$$A_h^+ = \sum_{i=1}^{h} \left(\lambda_i^+ Max[0, (A_{h-i}^+ - A_{h-i-1}^+)] + \lambda_i^- Min[0, (A_{h-i}^+ - A_{h-i-1}^+)]\right) + A_{h-1}^+ + \beta_h^+ + \gamma(A_{h-1}^+ - \alpha_1) \tag{5}$$

$$A_h^- = \sum_{i=1}^{h} \left(\lambda_i^+ Max[0, (A_{h-i}^- - A_{h-i-1}^-)] + \lambda_i^- Min[0, (A_{h-i}^- - A_{h-i-1}^-)]\right) + A_{h-1}^- + \beta_h^- + \gamma(A_{h-1}^- - \alpha_1) \tag{6}$$

In equation (2), there may be concerns of potential endogeneity between the fuel cost and the unobserved characteristics of the fare. Carriers have the ultimate knowledge of the algorithm or specification they use to set fares according to itinerary attributes. Carriers also hedge the fuel cost to prevent themselves from any unexpectedly high fuel costs. If the price setting decision is correlated with fuel hedging decisions, endogeneity arises. For example, the aircraft type used in a given route is correlated with the fuel efficiency of that aircraft type. Fuel efficiencies for different types of aircraft certainly have a non-negligible impact on the decision of fuel hedging. We then have the pricing decision and the hedging decision being simultaneously determined. We attempt to correct for this problem by utilizing prices of crude oil and retail gasoline as instruments.[10,11] All the aforementioned oil prices are highly correlated with jet fuel prices but are not affected by carriers' pricing decisions. Hence, they satisfy the necessary conditions for valid instruments.[12] We then proceed with our analysis using the estimating equation (2) with two-staged least squares (2SLS).[13]

4 Results

We start with choosing the optimal lag length. Borenstein, Cameron and Gilbert (1997) discuss in the appendix their way to determine the number of lags. Here we repeatedly estimate equation (2) using different lag lengths. Results are shown in Table 1. A Breusch–Pagan test provides statistical evidence to reject the null of constant variance.[14] Also, a Wooldridge test for autocorrelation was also performed, which suggested serial correlation of the error term. As a result, we report robust standard errors clustered by route and carrier in the parentheses. As we include additional lags in our regressions, estimates of common variables are virtually unchanged. For brevity, from this point, we report results using the preferred

[10] Heating oil/propane prices are also used in the literature as valid instruments. It is not used because there are missing information for several months each year in the EIA data.

[11] In fact, crude oil is the source of jet fuel.

[12] We acknowledge the fact that these variables may be invariant across carriers, and therefore present lower variations, compared to fuel prices.

[13] In unreported regressions, we also instrument costs with air time, (total) ramp time, average ramp time, and ramp-to-ramp time. Definitions are in accordance with T-100. There are unmatched observations due to missing information from T-100. Overall, these 2SLS regressions generally yield larger cost pass-through for both positive and negative cost shocks. Full results are available upon request.

[14] The Chi-squared test statistic is 238,839.65 with the p-value of 0.000.

specification, four period lags, which correspond to a one-year lag.[15,16] This choice is also supported by what Morrell and Swan (2006) suggest that carriers taking reserved hedging strategies by looking forward a year.

Table 1: Regression Results: Lag Length

Dependent Variable: $\Delta(Fare)_t$	(1) OLS	(2) OLS	(3) OLS	(4) OLS
$\Delta(Cost)^+_t$	0.014*** (0.000)	0.014*** (0.000)	0.014*** (0.000)	0.014*** (0.000)
$\Delta(Cost)^+_{t-1}$	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
$\Delta(Cost)^+_{t-2}$		0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
$\Delta(Cost)^+_{t-3}$			0.001*** (0.000)	0.000*** (0.000)
$\Delta(Cost)^+_{t-4}$				-0.001*** (0.000)
$\Delta(Cost)^-_t$	0.011*** (0.000)	0.010*** (0.000)	0.010*** (0.000)	0.010*** (0.000)
$\Delta(Cost)^-_{t-1}$	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
$\Delta(Cost)^-_{t-2}$		0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
$\Delta(Cost)^-_{t-3}$			0.002*** (0.000)	0.002*** (0.000)
$\Delta(Cost)^-_{t-4}$				0.001*** (0.000)
F-Test ($Prob > F$)	0.000	0.000	0.000	0.000
R^2	0.284	0.298	0.303	0.305

$N = 1,804,129$. Other independent variables are omitted for brevity.
Time trends and quarter fixed effects are included. Full results are available upon request.
Standard errors clustered by Route × Carrier in the parentheses.
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

We report 2SLS estimates with four lags in Table 2.[17] A different instrument is used in each column as listed at the bottom of the table. Across columns, positive cost shocks appear to be passed onto consumers at a higher magnitude compared to that of negative cost shocks. The estimates suggest that, contemporaneously, a one-dollar positive cost shock leads on average to a 1.6-cent increase in the fare, while a one-dollar negative cost shock leads on average to a one-cent decrease in the fare. Note that the cost measure reflects the minimum cost needed to operate such flights. Our estimates suggest that if this cost increases by 1,000 dollars, it would translate into a more-than-ten-dollar increase in fare for each passenger. Note also that with our quarterly data, it makes sense that there is

[15] That is, $n = 4$ is Equation (2).

[16] We relax this restriction to allow for different lag lengths in unreported regressions with 2SLS. It does not generate any significant differences in estimates.

[17] Weak identification tests are performed. Even though the Stock-Yogo critical values are not avaiable, both the Cragg-Donald Wald F-test statistic and the Kleibergen-Paap Wald F-test statistic are high enough (more than 20,000) so we believe that we strongly reject the null of weak identification. In addition, both the Anderson–Rubin Wald test and the Stock–Wright LM test (both p-values smaller than 0.01) confirm the relevance of the endogenous variable. The Sanderson-Windmeijer multivariate F test of excluded instruments has a p-value of 0.0000, allowing us to reject the null that the endogenous regressor is unidentified. Detailed results are available upon request.

contemporaneous cost pass-through. For example, a cost shock in July could be reflected on fares purchased in or ticketed for September. The effect of cost shocks one period ago on airfare is still significant, although at a lower magnitude. There may be two possible rationales behind this. First, most people usually do not purchase flights until a few months in advance of the anticipated travel date. Thus, we see cost shocks reflected within one to two quarters. Secondly, the time it takes to reflect the fuel cost shock is consistent with existing literature and industry practice on how airlines look forward with their fuel hedging contract. Morrell and Swan (2006) suggest that most airlines look forward three to six months in their hedging strategies, with a few taking a more reserved view at one year, and almost none looking forward beyond two years. This also justifies our choice of the number of lags. Carriers, under the expectation that volatility in fuel prices could lead to higher operating costs, hedge against potential risks from fuel price fluctuations, in order to reduce costs.

Table 2: Regression Results: 2SLS with Full Sample

Dependent Variable: $\Delta(Fare)_t$	(1) 2SLS	(2) 2SLS	(3) 2SLS
$\Delta(Cost)^+_t$	0.015*** (0.000)	0.016*** (0.000)	0.017*** (0.000)
$\Delta(Cost)^+_{t-1}$	0.003*** (0.000)	0.003*** (0.000)	0.005*** (0.000)
$\Delta(Cost)^+_{t-2}$	-0.001*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
$\Delta(Cost)^+_{t-3}$	-0.000* (0.000)	-0.000 (0.000)	0.000*** (0.000)
$\Delta(Cost)^+_{t-4}$	-0.001*** (0.000)	-0.000*** (0.000)	-0.002*** (0.000)
$\Delta(Cost)^-_t$	0.009*** (0.000)	0.009*** (0.000)	0.011*** (0.000)
$\Delta(Cost)^-_{t-1}$	-0.000** (0.000)	-0.000 (0.000)	0.001*** (0.000)
$\Delta(Cost)^-_{t-2}$	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)
$\Delta(Cost)^-_{t-3}$	0.002*** (0.000)	0.001*** (0.000)	0.002*** (0.000)
$\Delta(Cost)^-_{t-4}$	0.000** (0.000)	0.000 (0.000)	0.001*** (0.000)
F-Test ($Prob > F$)	0.000	0.000	0.000
Instruments Used	EU Brent Crude Oil	Cushing, OK Crude Oil	Retail Gasoline
R^2	0.303	0.303	0.301

$N = 1,804,129$. Other independent variables are omitted for brevity.
Time trends and quarter fixed effects are included. Full results are available upon request.
Standard errors clustered by Route × Carrier in the parentheses.
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

At first glance, these numbers appear to be relatively small compared to what has been found in other industries. For example, when a driver purchases a gallon of fuel, the only revenue that the fuel provider receives is the selling price of that gallon of fuel. However, aviation fuel consumption is always shared by passengers. The consumption of a gallon of aviation fuel is shared by the number of passengers in an aircraft, which ranges from 40 to 500 people, depending on size. For a typical short-haul aircraft that can sit 150 people, assuming that 80% of the seats are occupied, this cost pass-through estimate can then be translated into over-shifting. We believe that despite the small magnitudes, these estimates

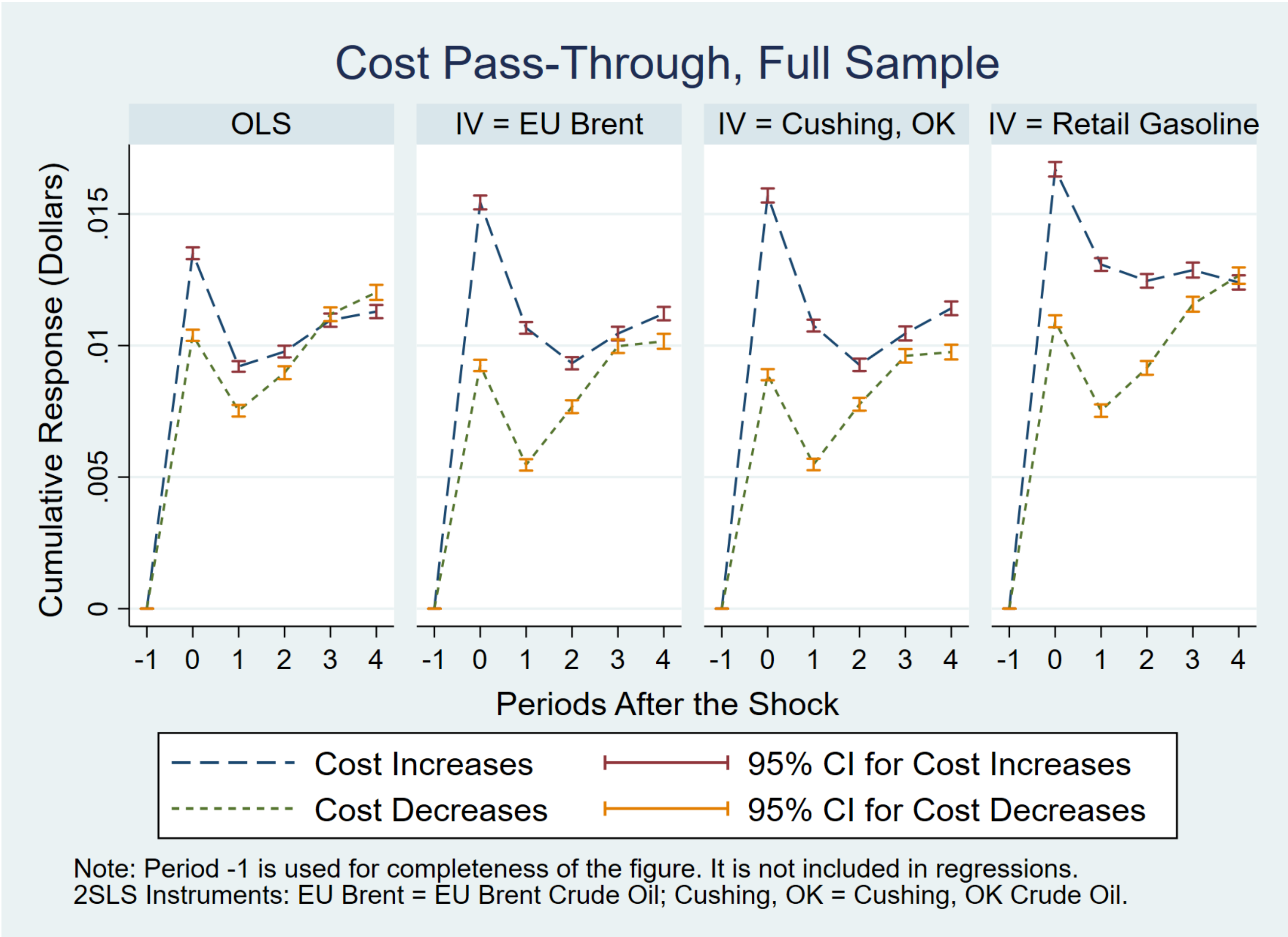

Figure 1: Cumulative Response Function: Full Sample

make intuitive and mathematical sense. In addition, although the difference in estimates between positive and negative cost shocks is small, F-tests are conducted to test for the equivalence of $\Delta(Cost)_t^+$ and $\Delta(Cost)_t^-$, or, testing for asymmetry of positive and negative cost shock pass-through in each regression, and we reject the null of symmetry in each case. In other words, we find asymmetric cost pass-through: positive fuel cost shocks are passed onto passengers at a greater magnitude than negative cost shocks are. This asymmetric pass-through is consistent with findings in other industries.

In Figure 1, we graph the cumulative response function with OLS and 2SLS estimates. As previously suggested, the cost pass-through occurs contemporaneously, then decreases, before returning to the long run pass-through at around 1.2 to 1.3 cents for both positive and negative shocks.

Next, we analyze some key differentials of cost pass-through using cumulative response functions. We use 2SLS estimates with Cushing, OK crude oil cost being the instrument. Koopmans and Lieshout (2016) outline a number of factors that may affect pass-through. In the current paper, we examine a few factors: business models, slot controls, service cabins, and market structure.

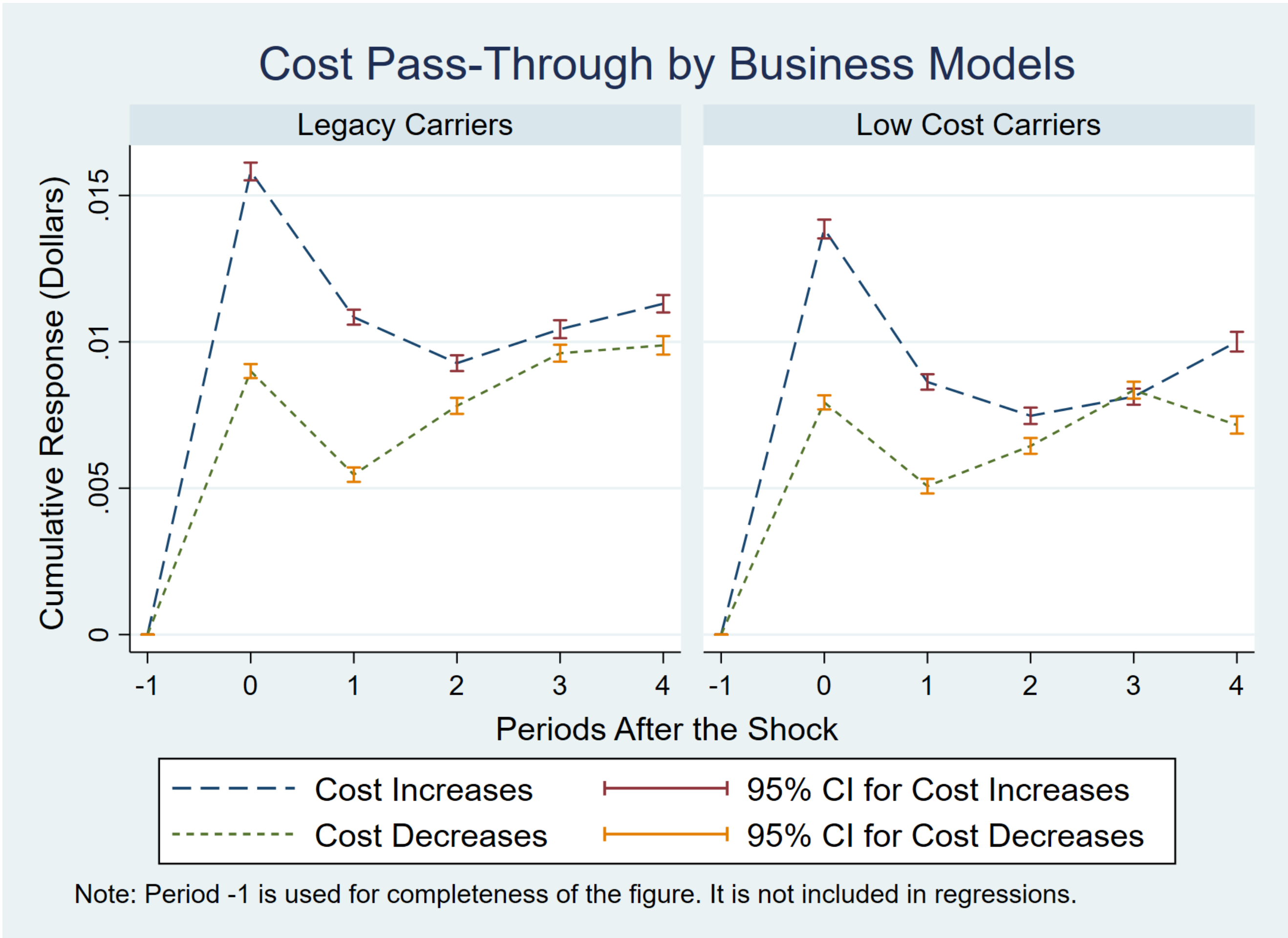

Figure 2: Cumulative Response Function: Business Models

Unlike legacy carriers, most of which operate under hub-and-spoke systems, low cost carriers (LCC) usually operate on a point-to-point basis and therefore may have multiple operating bases. As Koopmans and Lieshout (2016) suggest, they may have more flexibility to move operations around. We analyze whether such operating models have any impact on the ability to shift cost shocks. Figure 2 presents the results. As depicted from the figure, pass-through for low cost carriers are in general lower than for legacy carriers, for both positive and negative cost shocks. As low cost carriers are more likely to have the flexibility to move operations around when facing cost shocks compared to legacy counterparts, this finding should not be surprising.

In the US, a few airports are capacity-constrained so that FAA imposes runway slots for congestions. These airports include Level 3 airports (JFK, LGA, and DCA) and Level 2 airports (ORD, LAX, SFO, and EWR). We investigate whether slot controls lead to differential cost pass-throughs. Figure 3 presents the results. In a given route, if either the origin or the destination is one of the airports listed above, it is considered with slot controls (right panel). Otherwise, there is no slot control (left panel). If an airport has some form of slot control (either Level 2 or Level 3), cost pass-through is higher than the airport counterparts

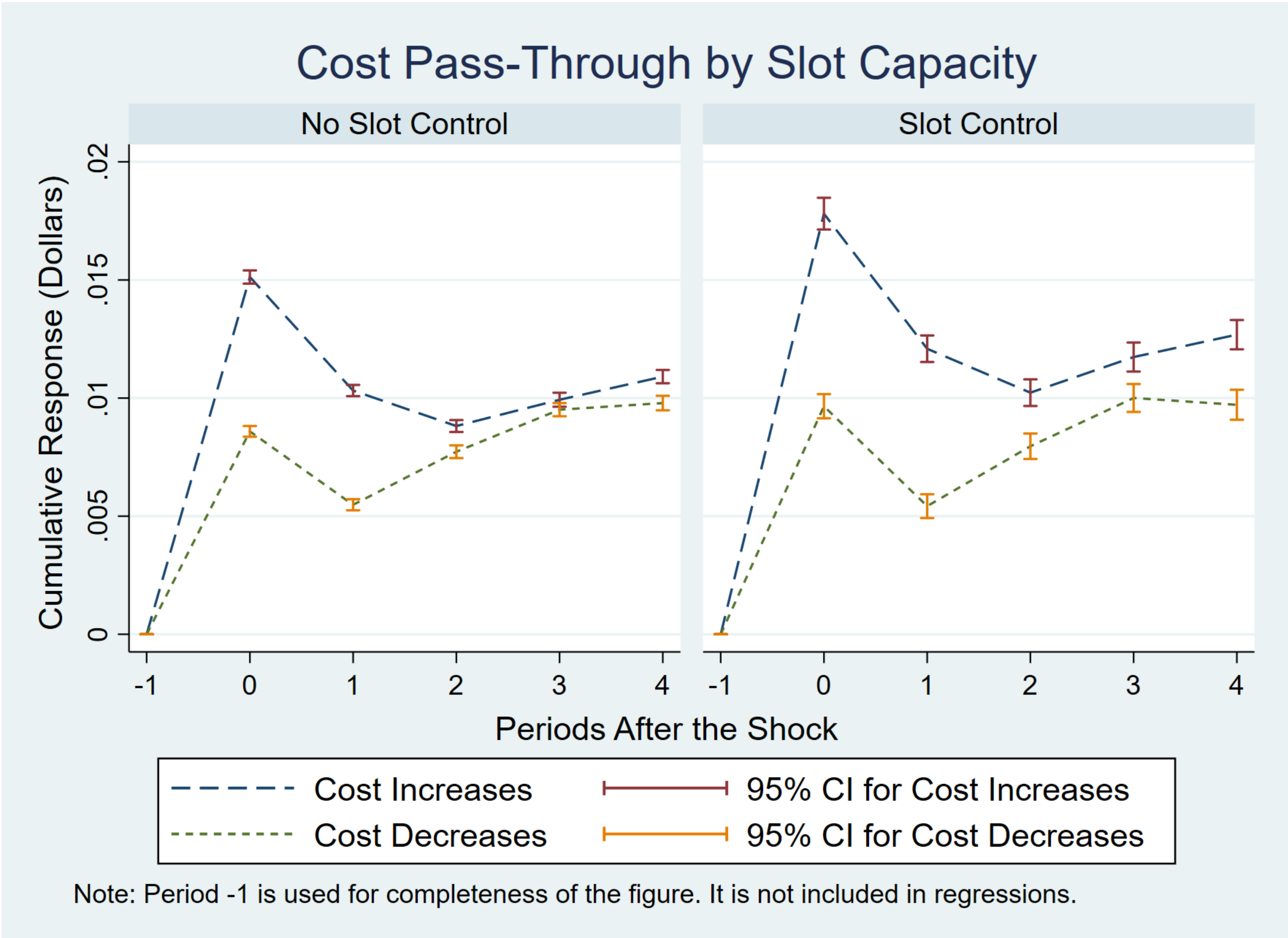

Figure 3: Cumulative Response Function: Slot Controls

without slot controls. For negative cost shocks, the pass-through are indistinguishable after reaching the long run equilibrium. For positive cost shocks, the long-run equilibrium pass-through is higher at airports with slot controls than that at airports without controls. The findings here appear to be different from Koopmans and Lieshout (2016), which states that the pass-through usually is zero at congested airports.

Next, we investigate how different products may see different cost pass-through, which may stem from how price sensitive different groups of passengers are. We focus on the two cabin products airlines typically offer: economy (coach) class and premium cabins. We present our results in Figure 4. The figure provides a convincing story for differential cost pass-through. The figure indicates that premium cabin passengers experience approximately a three-cent fare increase following a one-dollar cost hike and a two-cent fare decrease after a one-dollar cost decrease. For economy class passengers, pass-throughs are lower: 1 cent for a cost increase and less than a cent for a cost decrease. Since the demand for premium cabins flyers is typically more inelastic, it is not surprising the cost increases are being passed to these passengers at a higher rate.[18]

[18]The story is consistent when we look at the percentage change pass-through. In unreported regressions,

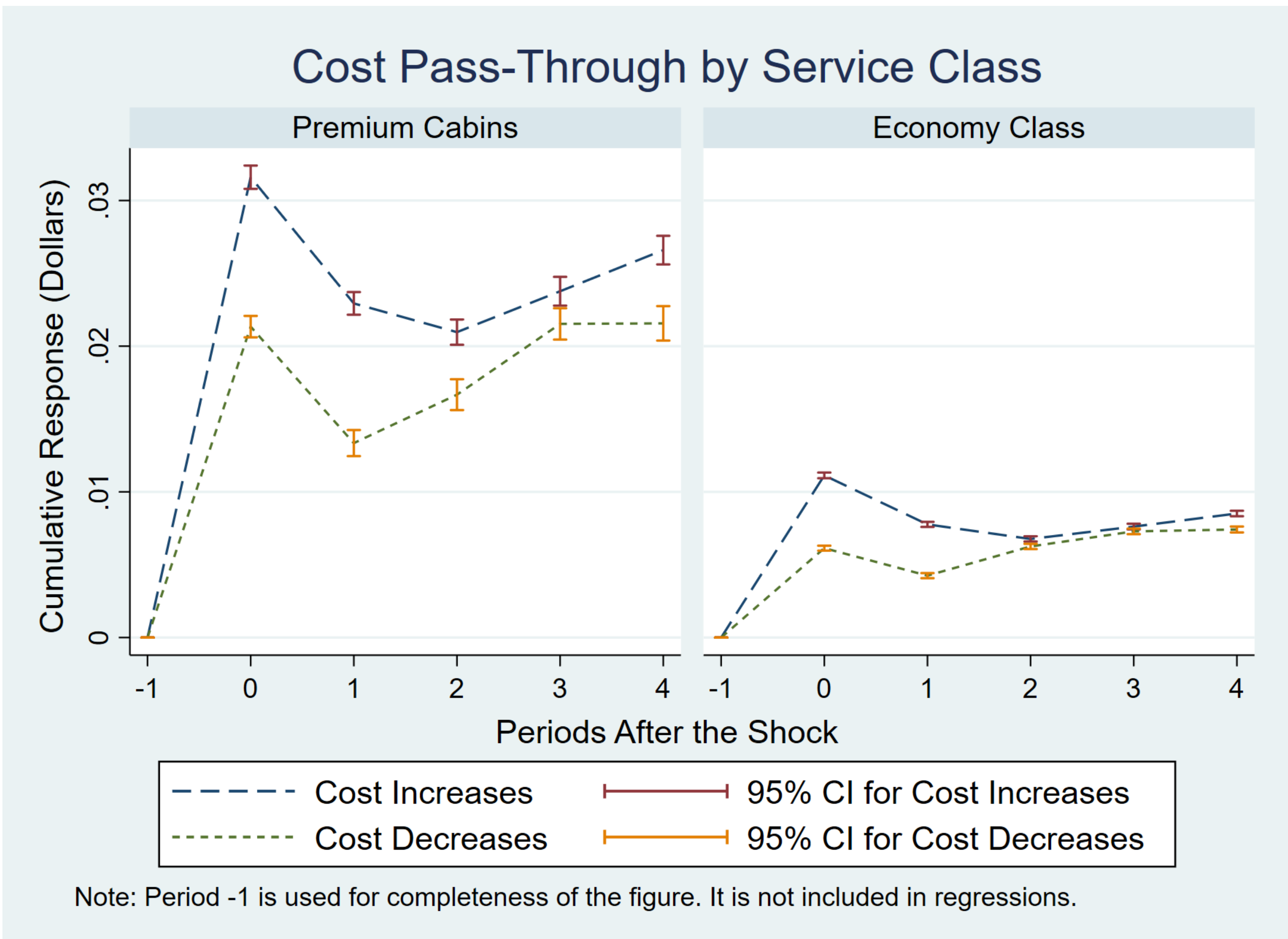

Figure 4: Cumulative Response Function: Service Class

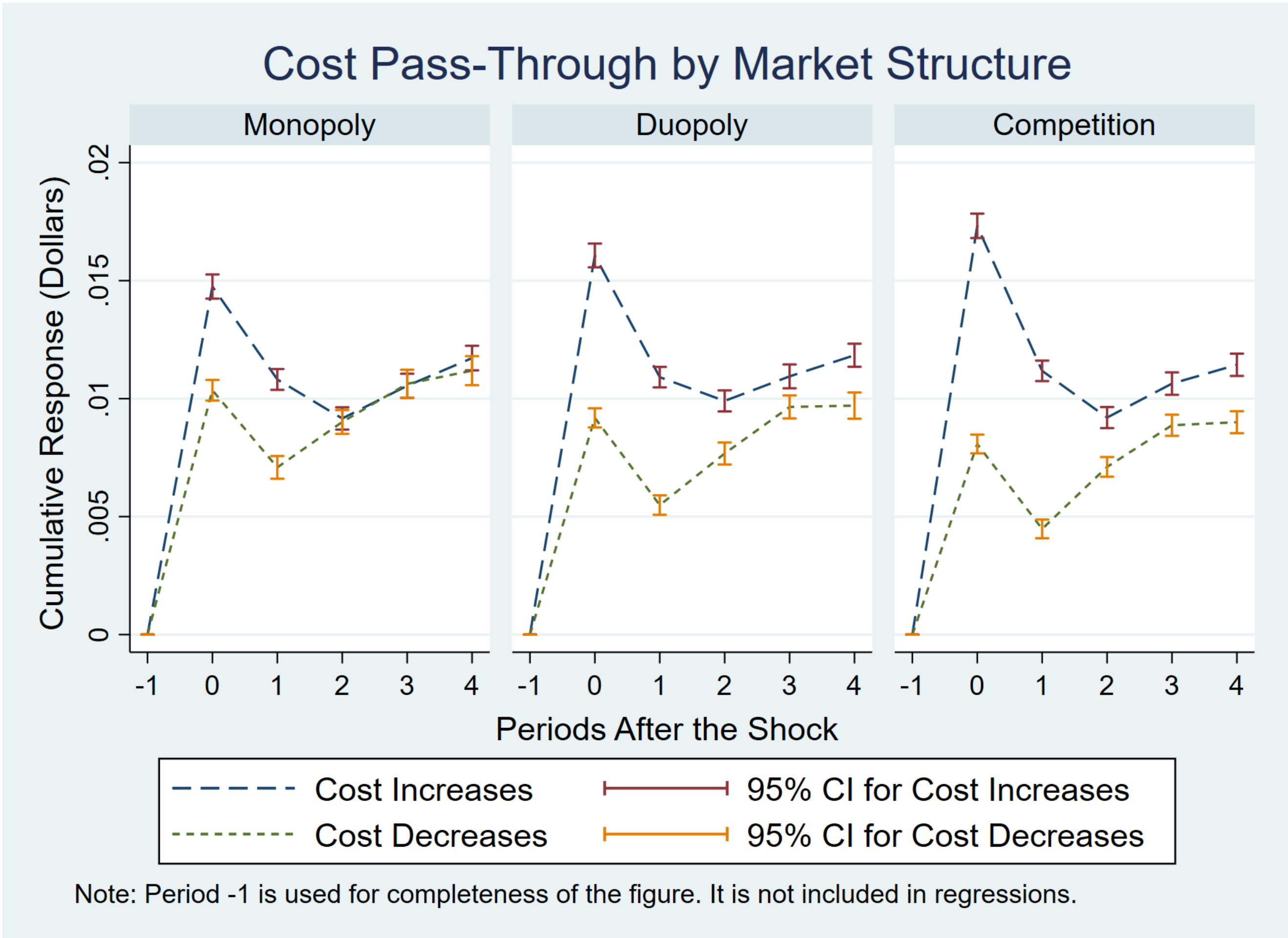

Figure 5: Cumulative Response Function: Market Structure

Figure 5 shows the cost pass-through under different market structures as defined by Dana and Orlov (2014). Similar to what has been found in the pooled sample, the long run equilibrium pass-through is around one cent. There appears to be a differential between pass-throughs for positive and negative cost shocks. This differential becomes greater as competition intensifies: pass-through of positive cost shocks increases while that of negative cost shocks decreases. Findings here are consistent with the results outlined in Bettendorf and Verboven

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we investigate how a percentage change in cost shock is reflected on the fare in terms of (contemporaneous) percentage changes. Our results suggest that for premium cabin flyers, a one-percentage change in positive cost shock is reflected on a fare change at 0.59 percent and a one-percentage change in negative cost shock is reflected on the fare at the rate of 0.54 percent. Such a difference is statistically significant at the 10 percent significance level. For coach class passengers, a one-percent cost shock is reflected on the fare at the rate of 0.47 percent for positive shocks and 0.30 percent for negative shocks, and the two pass-through are different at the 1 percent significance level. All other tests for the significance between any two pass-throughs are statistically significant at the 1 percent significance level. However, using percentage changes, we cannot rule out the possibility of negative cost shocks being passed through to passengers as increases in fares (at most 0.28 percent) at later lags in terms of cumulative response functions.

(2000), and in Bonnet, Dubois, Villas-Boas, and Klapper (2013) that pass-through rates decrease as the market becomes less competitive if firms face the same cost shock. Tappata (2009) also finds that cost pass-through increases with the number of informed customers (search intensity), and hence with the level of competition in the market.

5 Conclusion

We fill a void in research on cost pass-through in the airline industry. Consistent with findings in other industries, we find that positive cost shocks are passed onto passengers at a greater magnitude compared to negative cost shocks. In addition, we find the effect of cost shocks on airfare to occur mainly within the same quarter. This could be due to consumer ticket purchasing timelines and/or carrier fuel hedging decisions. After the contemporaneous response, the effect returns to a long run pass-through equilibrium. Furthermore, we find significant cost pass-through differentials for different business models, slot capacity, service classes, and market structure. Although carriers practice dynamic pricing strategies, we caution against interpreting our results as price stickiness until better data frequency is available.

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