Salient or Not? US Air Travel Taxes

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Abstract

We exploit the abundance of tax changes in the airline industry after the Department of Transportation's full-disclosure rule in order to shed light on the thin literature on airline taxes. We analyze how passengers reacted to changes in the sum of unit taxes levied on domestic travels. A set of Hausman-type instruments and cost shifters are used to address the problems arising from endogenously determined prices. We show that passengers react more strongly to taxes than to price changes: tax elasticity of demand is 1.5 times stronger than the price elasticity of demand. We extend the literature by providing a series of possible rationales for explaining how over-optimization can arise in the airline industry.

JEL-Classification: H20, L93, L98, R41, R48
Keywords: Tax salience, Taxation, Tax incidence, Airline industry

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1 Introduction

With the advancement of the Internet, people have more ways to shop and easier access to shopping for various goods and services. This change has given rise to websites such as Google Shopping, which provides a list of different options for merchants to purchase from and details about prices, taxes, and shipping charges (if any). Travel agencies, for example, provide a complete list of available hotels and/or flights for customers to choose from, given the criteria that they input. Google Flights also allows consumers to follow a targeted itinerary and track its price over time. Moreover, there are websites that help customers search for less expensive flights by locating itineraries that are less expensive with a final destination somewhere else and a layover at the original destination. Other websites are designed to take the mileage accrued from a trip to determine the best options for customers given a specified goal (for example, a free domestic ticket or free upgrade from economy to business). All of these tools are made available to help consumers better time their purchases while seeking to identify the optimal combination of flights for them. For most people, finding the lowest price available, holding all else constant, remains the primary goal when they shop for tickets online. Clearly, price-sensitive consumers will always pay attention to the final price that they pay for goods and services, and they will optimize their behavior accordingly if there is a shock to prices.

A key factor in consumers' purchase decisions is the final cost of the good. This price includes all handling charges (if any), shipping fees (if any), and probably most important, and likely most importantly, any applicable sales tax. Sales taxes play a central role in shaping consumers' behaviors, especially when a good is expensive. For example, some people purchase expensive electronics such as computers in tax-free states such as Oregon. For such goods, the sales tax is not necessarily reflected in posted prices. Since the actual sales tax is not included, one would need to manually calculate the taxes to determine the final price. Conversely, the prices of airline tickets, which are also subject to a variety of taxes, are shown tax-inclusive. If passengers want to know what relevant taxes are being charged, they would need to examine the receipt to determine whether different taxes have been imposed and more importantly, the amount of tax due.[1] These taxes are necessary to support all types of services, security screenings, and functions provided by airports and relevant government agencies.

In the arena of public economics, an emerging topic in taxation is whether a tax is salient to consumers when they make purchases. A seminal paper by Chetty, Looney, and Kroft (2009) investigates tax salience by conducting a sales tax experiment on consumption at a California grocery store and an observation study of alcohol taxes on consumption. Their pivotal study suggests that commodity taxes included in the posted prices are more salient than those that are included at the register. In this paper, we adopt and modify their empirical strategy to investigate the salience of the taxes levied on domestic air travel. Unlike grocery items and alcohol, for which the posted price is not the final price that one pays, prices on air travel tickets are tax inclusive.

The airline industry provides a good channel for us to study questions pertaining to taxes for a number of reasons. First, since 2012, all fares shown have been tax inclusive following the full-fare disclosure rule mandated by the Department of Transportation (DOT), which provides an excellent institutional setting for research. In fact, most carriers now display both the tax-exclusive fare and the tax-inclusive fare on the checkout page, with emphasis placed on the latter. Second, studies focusing on tax structures in the airline industry have been surprisingly rare. We contribute to the literature by providing a detailed analysis of the tax structure in this industry and shedding light on the relatively thin literature on tax salience. Third, fare data are transparent in the quarterly database collected by the DOT for public use, providing abundant variation and useful information for researchers to employ.

The sample period for this study runs from 2012 to 2017. We investigate how passengers respond to the "effective" tax rate and the actual unit taxes (excluding the ad valorem tax).

[1]In some countries, online travel agencies or airlines display before-tax prices for air travel tickets. Customers must proceed with the checkout process to actually determine the final airfare, including all relevant taxes. At this point, customers find that the displayed fare is not necessarily as inexpensive as it had seemed.

Using estimation strategies outlined in Chetty, Looney, and Kroft (2009) and instrumental variable strategies from the industrial organization literature, we find that passengers react more strongly to tax changes than to similar changes due to price fluctuations. Our results are also robust at the market level.[2] Our estimates are mainly in line with earlier findings for other industries. We provide several rationales from the existing literature and apply them to the airline industry to explain the sources of this over-optimization.

The remainder of this paper is structured as follows. Section 2 presents a review of the literature on tax incidence, both theoretical and empirical. Section 3 provides the source and description of the data. Section 4 illustrates the theoretical framework used to formulate the empirical strategies. Section 5 presents results and explanations of the sources of over-optimization. Section 6 acknowledges the limitations of the study and concludes with a summary and final remarks.

2 Literature Review

A central assumption in neoclassical economics posits that agents fully optimize behavior with respect to taxes. However, a strand of the economic literature has grown over the past decade and provided evidence of imperfect optimization or individuals not always perfectly responding to taxes. In some cases, the way in which an advertisement is structured can also affect behavioral responses.

Several seminal papers have documented how tax salience affects one's decision-making. Chetty, Looney, and Kroft (2009) investigate tax salience by implementing a sales tax experiment on consumption at a California grocery store, where the posted price is tax-exclusive. In the same paper, they also examine the relative tax salience of the federal excise tax and state local sales tax by conducting an observation study of alcohol consumption, in which the posted tax is federal tax inclusive but sales tax exclusive. Their pivotal study suggests that commodity taxes included in the posted prices are more salient than those included at

[2]Results at the market level are available upon request.

the register; moreover, since the federal excise tax is included in the posted price, it is more salient than the local sales tax.

Instead of investigating the relative salience of taxes, Finkelstein (2009) approaches this topic by examining the extent to which tax design can affect consumer behavior. Choosing 123 cities across the US that utilize electronic toll collection (ETC) systems, she finds that drivers are substantially less aware of tolls paid electronically (through deductions) than those paid in cash. This result even holds among regular commuters. Under ETC systems, the demand for driving becomes less elastic with respect to tolls. Essentially, driver behavior becomes less sensitive to any changes in the toll rates – a compelling result suggesting that tax salience is reduced due to the use of an ETC system. It is therefore evident that the salience of a tax changes people's perception of it. Finkelstein (2009) also reports that toll settings are also less sensitive to the electoral calendar.

Additional papers in agreement with this research include Cabral and Hoxby (2015). They focus on how property tax salience affects behavior. Tax is more salient when one is required to write separate property tax checks than when paying by escrow, in which the property tax is automatically deducted from taxpayers' bank accounts. They find that property taxes are higher in jurisdictions that allow homeowners to pay by escrow. Goldin and Homonoff (2013) extend this literature by examining the heterogeneity in these tax responses. They show that low-income consumers respond to cigarette taxes levied at the register, and the distribution of the tax burden depends on income levels. Hayashi, Nakamura and Gamage (2013) extend this result to the context of labor supply and anchoring. In another contribution on labor economics, Blumkin, Ruffle, and Ganun (2012) discover that the imposition of a labor income tax prompts a greater reduction in labor supply than an equivalent consumption tax. Rivers and Schaufele (2015) examine the salience of carbon taxes in British Columbia, Canada. The carbon tax reduces the demand for gasoline, a good for which the posted price is tax- inclusive, like air travel tickets. From a political economy perspective, Bracco, Porcelli and Redoano (2013) demonstrate that the government will replace more salient taxes with less salient taxes. This finding is confirmed using data from Italian elections. Within the airline industry, Bradley and Feldman (2018) examine the effects of tax incidence and salience on international travel in and out of the US following the full-fare-disclosure rule. They find that consumers fully optimize after the full-fare-disclosure rule. However, a potential caveat would be that there remain examples of foreign carriers, foreign travel agencies, or foreign news outlets promoting air travel tickets using tax-exclusive fares. Consumers in the US are more accustomed to purchasing tickets online. This practice, nevertheless, might not be the case in other countries since there could be country-level differences leading passengers to purchase tickets in traditional brick-and-mortar travel agencies more often than online. Such an outcome would bias the elasticity results after the full-fare advertising rule (and thus the effect of this advertising rule).[3] Instead, in the current paper, we focus on domestic travels after the full-fare disclosure rule within the US, which ideally alleviates this potential concern from the international setting. Conversely, however, carrier-imposed fees like fuel surcharges in the international setting are not viable sources of variations in the domestic setting.

Given the aforementioned evidence, a natural question is whether there is an optimal level of tax salience. Should the government choose a highly salient tax, a low-salience tax, or something between the two? What are the welfare and economic implications of these types of choices? These questions are essential for designing efficient and appropriate policies. Not only must the policy have to generate revenues for future governmental investments, but any distribution effects must also be evaluated. Goldin (2012) posits that policy makers can manipulate tax salience to better control the effects of proposed taxes, thereby achieving efficiency and other social goals. Subsequently, Goldin (2015) derives a theoretical framework to characterize the optimal policy and provide an adjustment formula if the first-best solution is not attainable. Adopting an experimental approach, Taubinsky and Rees-Jones

[3] See `https://www.transportation.gov/airconsumer/advertising` for more details on the advertising rule. From the advertising rule, it is not clear whether this rule only applies to tickets purchased within the US (on the US-based website of the carrier) and/or originated from the US.

(2018) provide a detailed welfare analysis of consumer underreactions to taxes and find that individual heterogeneities increase the efficiency cost of taxation.[4]

3 Background on Taxes in the US Airline Industry

In the US airline industry, air tickets are subject to a variety of excise taxes and fees. For domestic travels, the five most common types of taxes that are currently levied are the Ticket Tax, the Alaska/Hawaii Ticket Tax (Travel Facilities Tax), the Passenger Facility Charge, the Segment Fee, and the September 11 Security Fee.

Among these taxes, the Ticket Tax, collected by the Federal Aviation Authority (FAA), is the only ad valorem tax. The current rate is 7.5 percent and it has remained at this level for more than a decade. The Alaska/Hawaii Ticket Tax applies to certain flights between the continental US and either Alaska or Hawaii at $9.20 per segment.

The Segment Fee is collected by the FAA. It has been increasing gradually over the past few years, and the current rate is $4.20 per segment (leg). It was first introduced in the fourth quarter of 1997. It started at one dollar per segment and has gradually increased to the current level. There are no restrictions on the maximum number of times that it can apply to a ticket. Although this tax does not officially differ across carriers or routes, it can actually differ across itineraries with the same origin and destination. Consider the route of Atlanta (ATL) to Madison, WI (MSN). Delta Air Lines offer direct flights while other legacy carriers, like American or United Airlines, do not. For American or United Airlines, a roundtrip ticket from ATL to MSN will certainly involve four segments (at least), so the total segment fees will be $16.80 (at least). For an itinerary ticketed by Delta Airlines, with direct flights, the total segment fees should be $8.40. Within itineraries ticketed by Delta, it is also possible for passengers to take flights with layovers, and in such cases, the number of segments is at least three; therefore, the total segment fee is higher. As a result, this fee effectively will differ across carriers, routes, and time.

[4]For a detailed review of tax salience, see Galle (2009), Goldin (2012), and Hayashi (2014).

The September 11 Security Fee is used to support security-related activities directed by the Transportation Security Administration (TSA). It was passed to cover the increasing need for better security screening and monitoring after the September 11 terrorist attacks. It went into effect starting in 2002 at the rate of $2.5 per segment and at most $5 for one-way tickets and $10 for roundtrip tickets. It underwent a major increase in July 2014, when the rate increased to $5.6 per oneway. In December 2014, a cap was included; therefore, it is now capped at $11.2 for roundtrip tickets. Using the ATL-MSN example above, it can be shown that, before tax, the Delta direct flight itinerary has a $5 September 11 Security Fee, while tickets from other carriers have a fee of least $10. For Delta non-direct flights, this fee becomes at least $7.50. Since the tax change, for all roundtrip tickets, this tax is $11.20 regardless of the number of segments.[5]

The Passenger Facility Charge (PFC) is paid to airports. According to the FAA, airports use these funds to fund projects to "enhance safety, security, or capacity; reduce noise; or increase air carrier competition."[6] It was passed in 1990, and first started being levied in 1992. The amount of this tax varies depending on the airport of origin. Currently, the charge is capped at $4.50 for each origin airport involved in the itinerary. The cap has not been changed since its inception. Not all airports levy such a fee, although most do. Figure 1 provides an overview of the different levels of PFC charged by airports. Note that some rates are prorated since not all changes are administered at the beginning of the quarter. As the figure presents, most of the airports with a PFC charge at the cap level. Another commonly chosen PFC level is $3. There are PFC changes among these airports. During the sample timeframe, of those airports that did not undergo a change in PFC, 282 airports charge a $4.50, one charges $2, another one charges $4, and the other six charge $3. 86 of all airports included in the dataset (that charged a PFC) underwent (at least) one change in PFC levied during the sample timeframe. Consider a roundtrip ticket between Seattle

[5]In this paper, we restrict our raw data to at most four segments. Therefore, the addition of the cap in December 2014 would not impact our results at all.

[6]See more at `https://www.faa.gov/airports/pfc/`.

(SEA) and Louisville, KY (SDF), with a layover in Houston-IAH for example. If we assume a constant base fare charged by a given carrier, the variation in taxes is generated by the variation in PFC, in segment fee, and in 911charge. Figure 2 provides an example illustrating how taxes vary, with the details broken down in Table 1. The specific routing is SEA-IAH-SDF-IAH-SEA. Note that PFCs are charged at the airport of origin (once at SEA, once at SDF, and twice at IAH). SEA charges a constant \$4.50 in PFC, while IAH and SDF charge different PFCs at different points in time.

Table 1: Tax Breakdown for Figure 2

	Segment Fee	PFC at SEA	PFC at IAH	PFC at SDF	PFC at IAH	911 Security Fee	Total
November 2012	15.20	4.50	3	4.50	3	10	40.20
November 2013	15.60	4.50	3	4.50	3	10	40.60
November 2014	16	4.50	3	4.50	3	11.20	42.20
November 2015	16	4.50	4.50	3	4.50	11.20	43.70
November 2016	16	4.50	4.50	1	4.50	11.20	41.70
November 2017	16.40	4.50	4.50	3	4.50	11.20	44.10

Table 2 provides an example of how ticket taxes are calculated based on ticket attributes. On February 29, 2016, a round-trip itinerary operated by Delta Air Lines is purchased. The routing is Madison (MSN) to Los Angeles (LAX) on July 4, 2016, and LAX to MSN on August 31, 2016. Both ways, a layover at Minneapolis (MSP) is required. The tax-inclusive airfare is \$329.20, which includes the base airfare of \$264.18 and relevant fees and taxes of \$65.02. The tax breakdown is as follows.

Table 2: Example of Domestic Ticket Taxes Calculation

Tax	**Amount**	**Remarks**
Ticket Tax	\$19.82	\$264.18 $\times$ 7.5% = \$19.82.
September 11 Security Fee	\$11.20	Round-trip ticket, 2 chargeable one-ways at \$5.60 each.
Passenger Facility Charge	\$18.00	4 take-offs. LAX, MSN, and MSP all charge \$4.50 per takeoff.
Flight Segment Tax	\$16.00	4 segments charged at \$4.00 per segment (2016 rate).
Total Tax	\$65.02	

Recall that the Ticket Tax varies in each itinerary because of variations in the base fare. It is essential for us to discuss the sources of variation in the combined unit taxes. Across

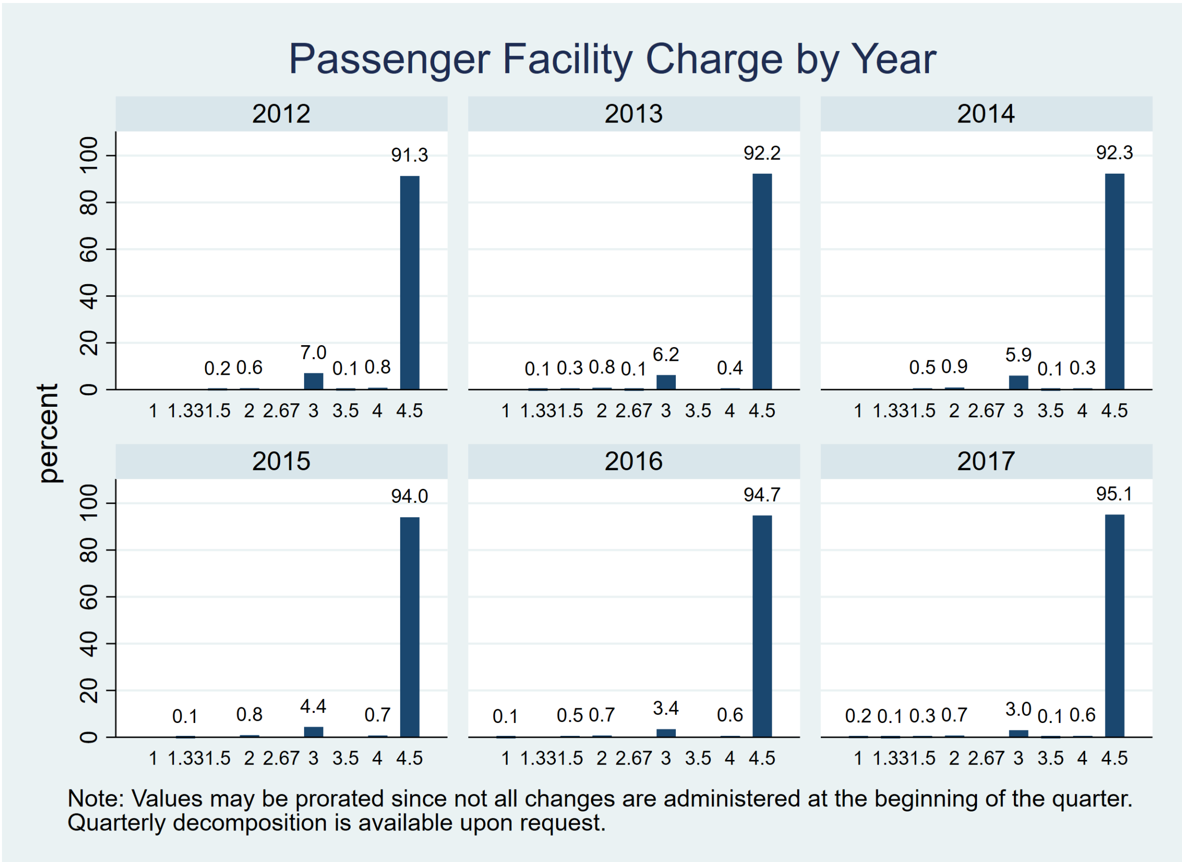


Figure 1: Passenger Facility Charge by Year

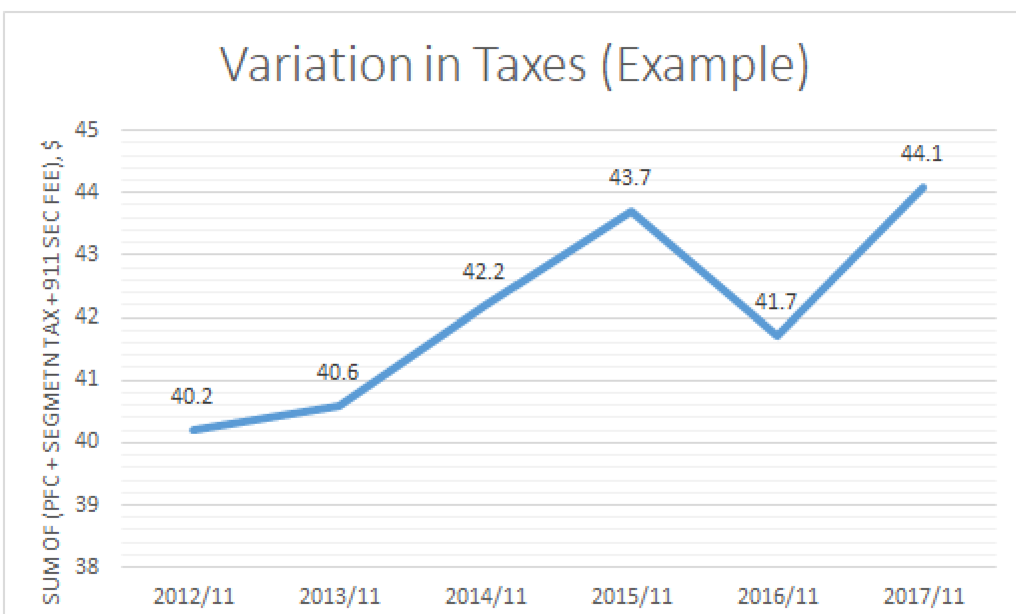


Figure 2: Example: Variation in Taxes (Seattle-Louisville)

itineraries, variations in taxes come from three sources. (1) The first source is the number of segments, which increases the tax by the amount of the Segment Fee for each additional segment in the itinerary. (2) The second source is the PFC, according to which each airport can charge at most $4.50 per take-off, but not all of the airports charge this maximum value. In fact, there are airports charging $2, $2.50, $3, $3.50, or $4, or simply not charge any at all. Moreover, this tax varies over time even within the same airport since airports can apply for an increase or a decrease in this tax before or after the current rate expires. (3) The September 11 Security Fee provides some variations across itineraries depending on the number of segments (pre-/post-September 11 Security Fee change).

4 Data

4.1 Data Sources

In this paper, we acquire data from multiple official sources and manually enter key control variables.[7] The airfare data come from the Airline Origin and Destination Survey Database (DB1B) maintained by the Bureau of Transportation Statistics (BTS). The DB1B database includes the final tax-inclusive fare of each itinerary. However, it does not break it down into the base fare and all relevant taxes. We obtain tax data on principle from the FAA and from the MIT Airline Tax Project. We include several demographic control variables that work as demand shifters. These variables are from the Bureau of Economic Analysis (BEA), the Bureau of Labor Statistics (BLS), and the Federal Reserve Bank of St. Louis (FRED). Carrier level cost-related measures such as unit fuel cost, operating expenses, available seat-mile, and other measures are from Air Carrier Financial Reports (Form 41 Financial Data) Schedules P-5.1, P-5.2, P-6, P-7, and P-12(a), maintained by BTS.

[7] We provide a more in-depth discussion of our data in the online appendix.

4.2 Sample Discussion and Statistics

Figure 3 shows the average fare trend at the national level. Clearly, in both nominal and real terms, there has been substantial fluctuation over the past seven years. In more recent years, fares have declined. It is thus crucial for us to consider the overall time trend of fares in our empirical analysis.

Figure 4 documents the number of domestic passengers at the national level. Clearly, as one would expect, passenger volumes exhibit seasonal trends. The number of passengers has increased over the past few years. Indeed, from the fitted line, we observe a general upward trend in the number of passengers. Therefore, it is crucial to account for time trends in our empirical analysis. As discussed in Section 5.1, we detrend by applying first differences in our estimation equations.

The sample period for the current study spans from 2012 to 2017 for a total of 24 quarters. Recall that each observation from DB1B is at the quarter level. Not all tax changes are administered at the beginning of the quarter. Segment fee changes are reflected on January 1 of the given year. PFC changes are administered at the beginning of the month. When we match PFC to itineraries, we prorate the PFCs in the given quarter. The September 11 Security Fee change went into effect in the middle of July 2014. For this particular quarter, we assume the rate after the change for all itineraries.[8]

Data obtained from the DB1B database include approximately five million observations per quarter, which generate a significant number of observations for the entire sample time-frame. To render the estimation process feasible, we apply several filters to shrink the dataset based on criteria used by Brueckner and Spiller (1994), and Berry, Carnall, and Spiller (2006). In our main analysis, we focus on economy class tickets.[9] Any itineraries with more than four coupons (enplanements) are omitted. It is rare for one to have more than four segments

[8] We acknowledge that, because of our matching strategy, it is inevitable to have itineraries with negative base fares, which we subsequently omit.

[9] We also report results using premium class tickets. However, most results reported are generated using economy class tickets.

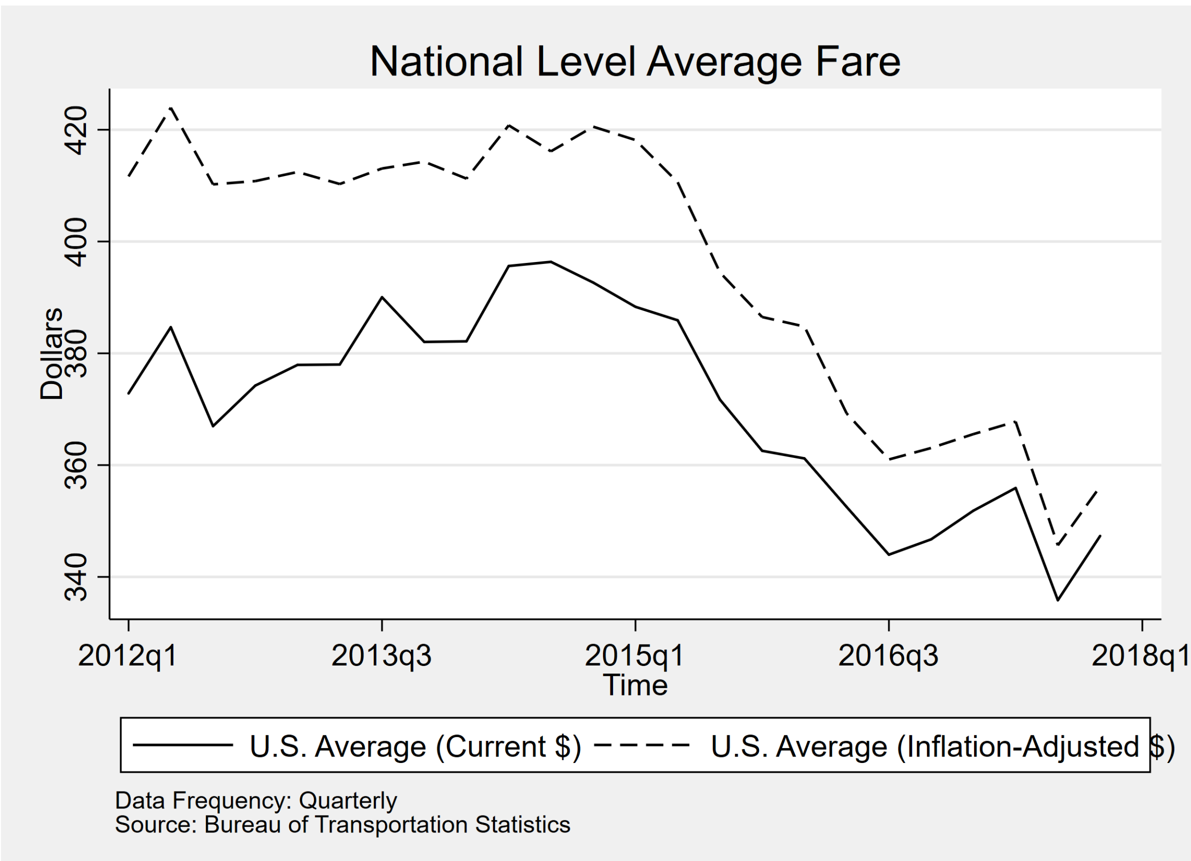


Figure 3: Average Fare at the National Level

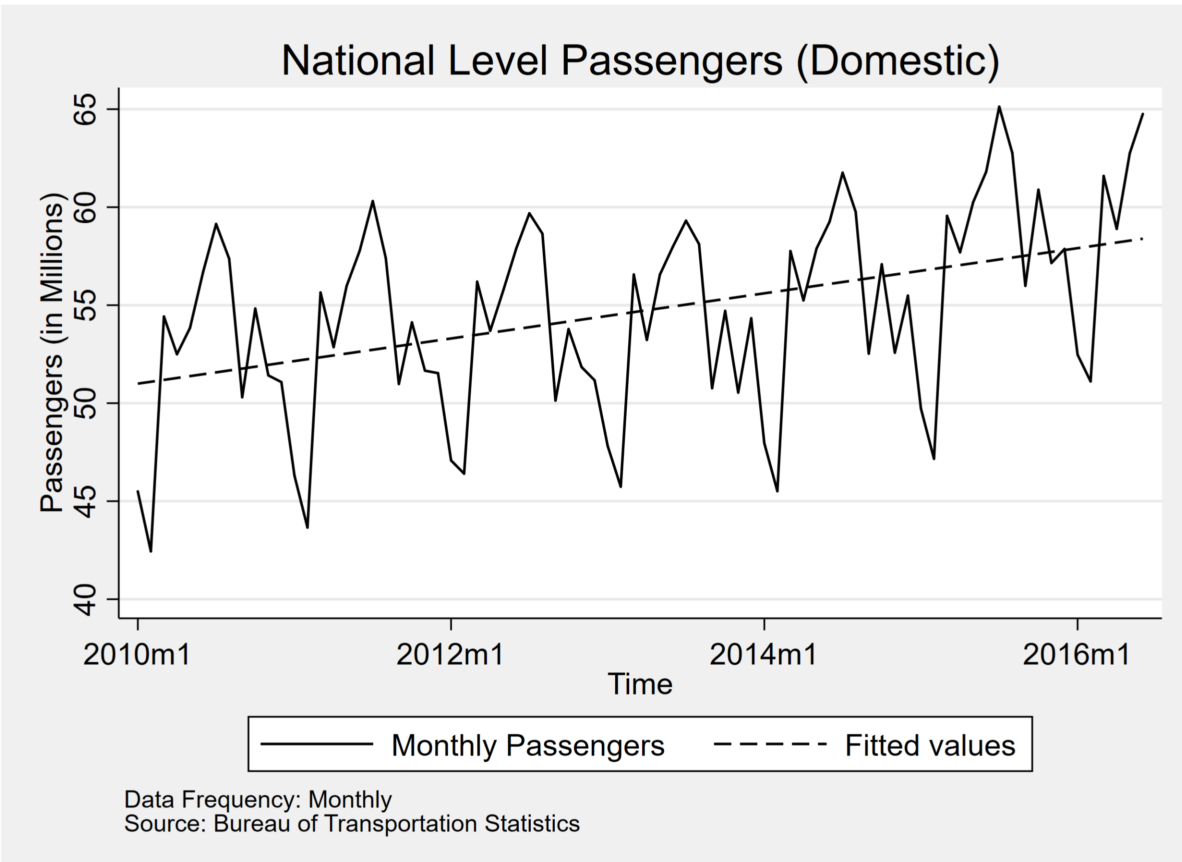


Figure 4: Total Domestic Passengers at the National Level

in an itinerary for domestic travels. Ticket fares lower than \$50 or exceeding \$2,000 are omitted. Itineraries with a negative base fare are eliminated also.[10] We consequently drop the itineraries for which the total miles flown are more than 10,000 (track) miles. Tickets purchased in bulk are disregarded. Itineraries with zero dollar credibility are omitted. We do not allow ticketing carrier or cabin class changes within any given itinerary. The included geographic areas in the study are the contiguous United States (including the District of Columbia).[11] Finally, since there could be multiple observations under the same route by the carrier at the same time, we collapse them into a single observation at the carrier-route level weighted by the number of passengers in a given itinerary, and thus forming our panel dataset.

Table 3 presents summary statistics of our sample. On average, with DB1B's 10 percent sample, a carrier has approximately 38 passengers in a given route in a given quarter. This measure, as expected, fluctuates substantially depending on passenger volume. The average (roundtrip) economy class tax-inclusive fare is approximately \$522. This appears to be relatively high average fare compared to the national statistics provided by the DOT, which might be due to our filters removing most observations with low fares. The September 11 Security Charge is averaged at \$10.50. Segment Fee and PFC average at \$15 and \$16, respectively. After accounting for the unit taxes (T), which is averaged at \$42, and the ad valorem tax rate, the base fare lies at \$447. Note that the base fare of non-competing routes is an averaged measure; therefore, the maximum would not be as high.

Figure 5, which depicts the probability distribution of unit taxes, clarifies that, although overall unit taxes are concentrated at approximately \$40 to \$45, there is a significant variation across carriers. The distributions for legacy carriers are similar in that most are in the \$40 to \$45 range, which is typical for a four-segment roundtrip itinerary.[12] Smaller legacy carriers,

[10] With our algorithm, this usually happens when the itinerary is redeemed with mileages (award travels).

[11] We exclude Alaska, Guam, Hawaii, and Puerto Rico. This exclusion is made because of the availability of our control variables in these places. We also omit observations ticketed by Hawaiian Airlines. We, however, keep observations with Alaska Airlines (or Horizon Air, a subsidiary of Alaska Airlines) since the carrier also operates flights out of Seattle to the lower 48 states.

[12] For example, in 2016, the unit tax was \$16 + \$11.2 + \$18 = \$45.2, reflecting the sum of segment fees,

Table 3: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Passengers	37.623	134.259	1	4,000	1,716,040
Tax-inclusive fare	522.632	169.62	53	1,997	1,716,040
September 11 Security Fee	10.494	1.198	5	11.2	1,716,040
Segment Fee	15.131	2.171	7.6	16.4	1,716,040
PFC	16.263	2.835	0	18	1,716,040
Base Fare	447.204	156.605	30.047	1,817.488	1,716,040
Unit Taxes (T)	41.888	5.445	12.6	45.6	1,716,040
CASM	0.653	0.356	0	2.474	1,716,040
Competitors	1.786	1.544	0	9	1,701,289
Base Fare of Non-Competing Routes	445.812	70.993	16	861.189	1,715,982
Unit Fuel Cost	2.391	0.742	1.006	3.626	1,631,676

like Alaska and Virgin America, have fewer destinations and therefore fewer possible routes, which also make transfers less likely. As a result, more distinct peaks are observed at lower levels of unit taxes. Similar situations also apply to low cost carriers, such as Frontier, AirTran, Allegiant, and Spirit Airlines.

the September 11 Security Fee, and PFCs. Refer to Table 2.

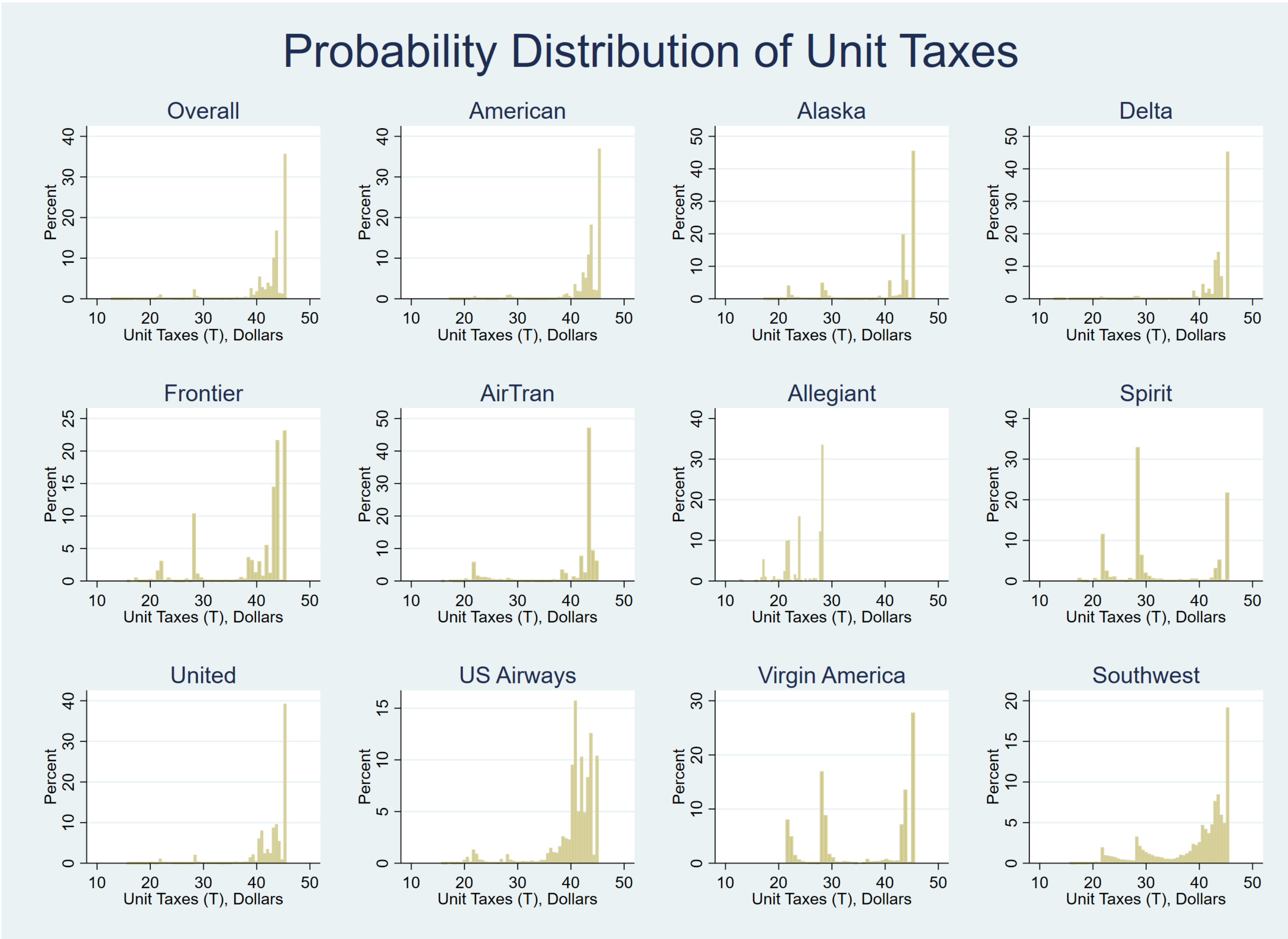


Figure 5: Distribution of the Unit Taxes by Carriers

5 Analysis

5.1 Empirical Strategy

We reference our estimation strategy from the current literature (e.g. Chetty, Looney, and Kroft (2009); Li, Linn, and Muehlegger (2014); etc.).

Let us establish some notations first. Consider an air travel ticket x. p denotes the before-tax price of x. Tickets are subject to a variety of the ad valorem tax τ and unit taxes T. Therefore, the tax-inclusive price of x is $p^\tau = (1+\tau)p + T$.

As previously described, all airfares posted are tax inclusive now. As is evident from Figures 6 and 7, major airlines only report taxes collectively during the online checkout. Customers would have to hover over the items to obtain detailed descriptions of each tax. Although on the checkout page, both the base fare and the tax-inclusive fare are presented, we believe that, since consumers have been presented with the tax-inclusive fare first, this price is that which factors into their purchasing decision. As a result, the tax-inclusive price is at least as salient as, and potentially more salient than, the pre-tax price p. When purchasing tickets, customers often simply jointly consider all taxes. As a result, we further assume that consumers consider only the collective tax but not necessarily each component of the collective tax. Therefore, the collective tax should be more salient than the airfare. Since the ad valorem tax rate remains at 7.5 percent during our sample timeframe, it does not provide any variations. We subsequently hypothesize that customers react fully (or even overreact) to the unit taxes since they are more salient. We denote by $x(p, T)$ the demand for air travel as a function of the base fare and the unit taxes. For a carrier-route pair i at time t (in quarters), consider the following estimating equation[13]:

$$\log x_{it} = \gamma + \alpha p_{it} + \beta T_{it} + \rho Z_{it} + \omega_t + \eta_i + \varepsilon_{it} \tag{1}$$

[13] In the main text, we will briefly present results in the log-log form to report elasticities, which allow us to compare our estimates with the literature.

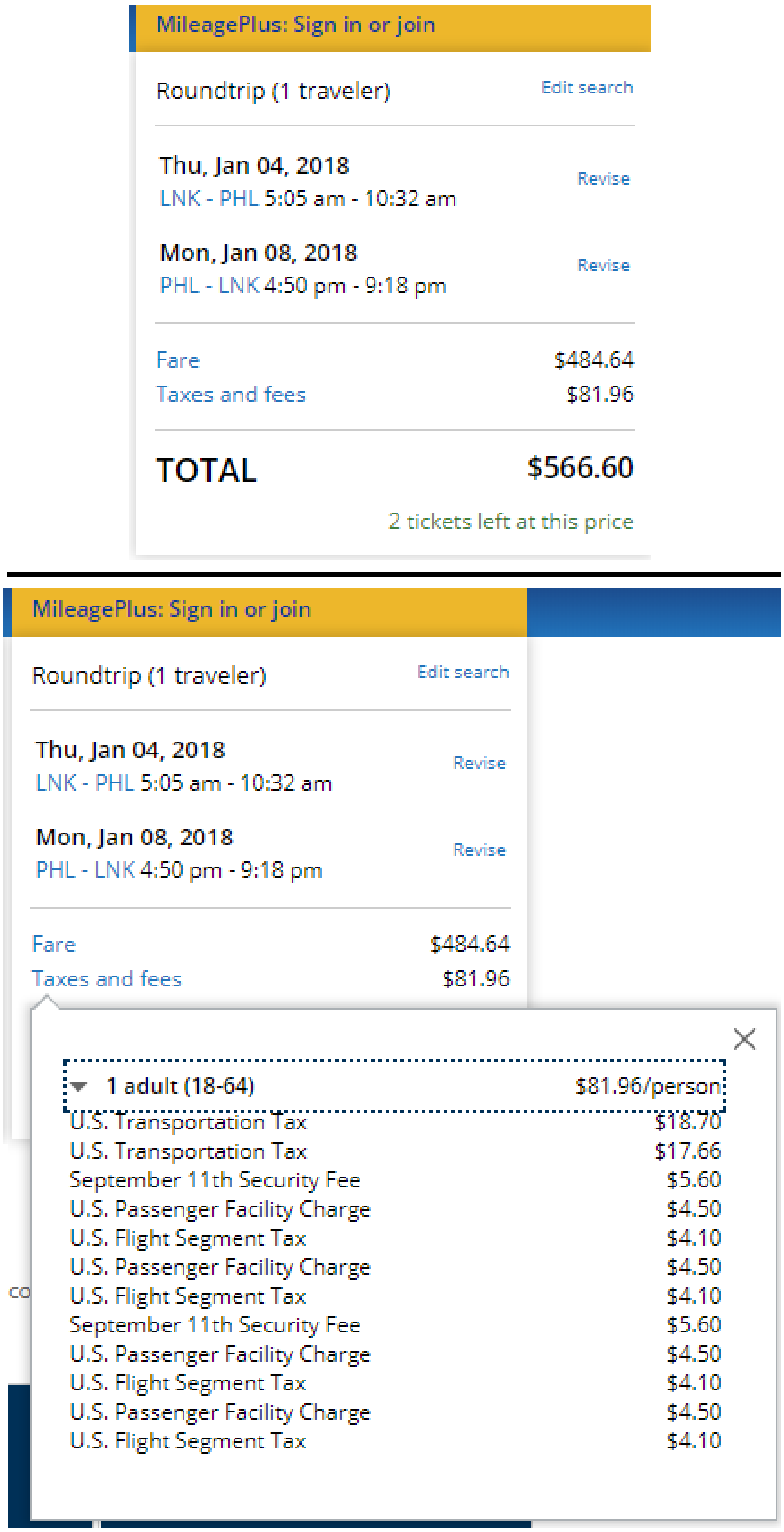
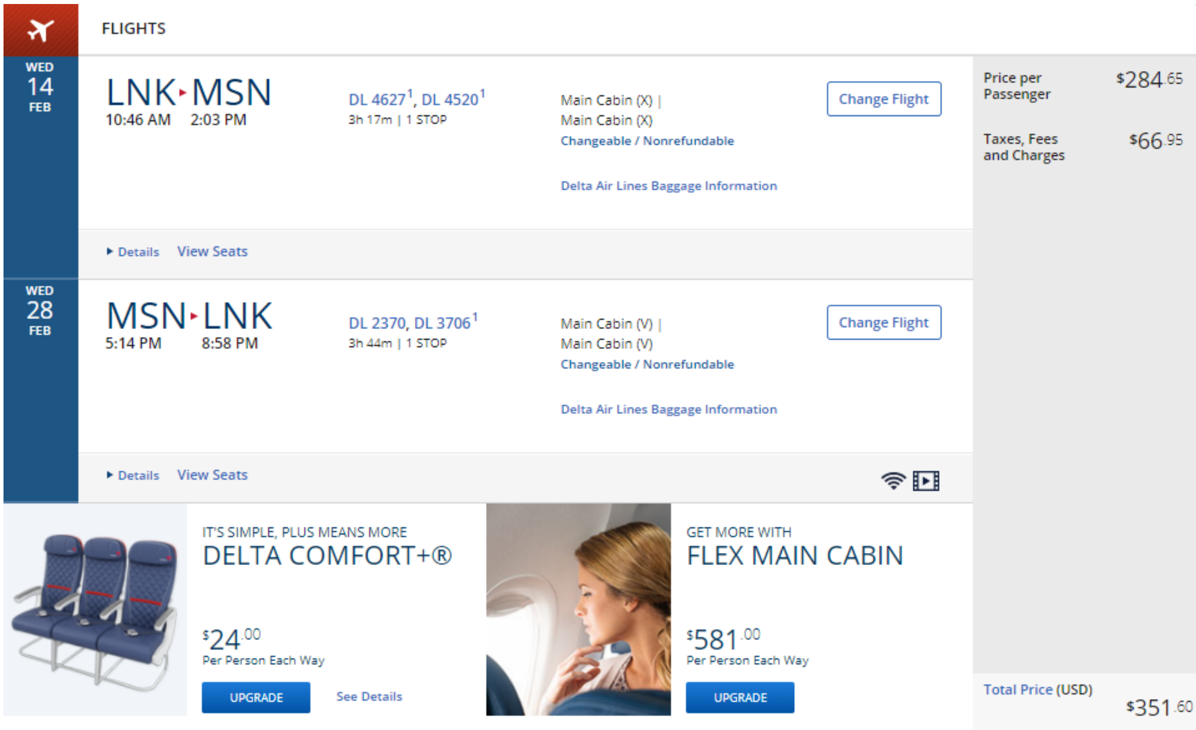


Figure 6: Checkout Process on the Website of United Airlines
Top Panel: Regular Checkout Screen
Bottom Panel: Regular Checkout Screen with Details of Taxes after Clicking "Taxes and Fees"



Top: Checkout Process

Bottom: Checkout Process with a Click to Show Detailed Taxes

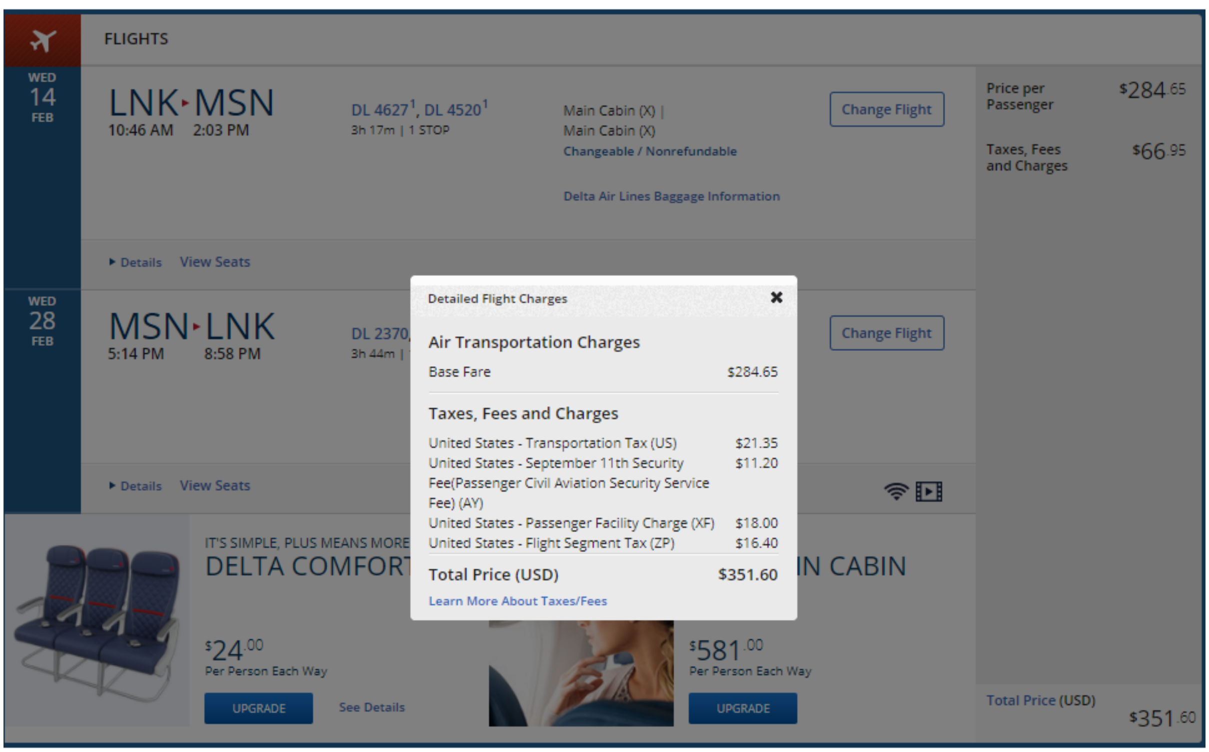


Figure 7: Checkout Process on the Website of Delta Air Lines

In this equation, all x, p, and T are averaged and weighted by the number of passengers in an given itinerary within the same i. Base fares differ even if the itineraries are identical. Different itineraries involve different sets of airports, which charge different levels of the Passenger Facility Charge and possibly different segment fees and September 11 Security Fees (with different number of segments) in different time periods. Z represents a set of demand shifters, which includes per capita personal income, real GDP, and the unemployment rate at the state of origin and destination levels. ω and η represent time and route-carrier fixed effects, respectively.[14] ϵ is the standard error term, which we cluster at the carrier and route level.[15] The identification rests on the variations in tax-exclusive airfares and unit taxes across itineraries and within routes, (ticketing) carriers and times. Note that a route (market) is a given airport-pair (city-pair).[16] With this equation, the effect of tax-exclusive fares on (log) demand is given by:

$$\frac{\partial(\log x)}{\partial p} = \alpha \tag{2}$$

and the effect of the tax T on (log) demand is given by:

$$\frac{\partial(\log x)}{\partial T} = \alpha\frac{\partial p}{\partial T} + \beta \tag{3}$$

The term $\frac{\partial p}{\partial T}$ captures the effect of tax on price, or tax incidence. In particular, $\frac{\partial p}{\partial T} > 0$ means that, as a result of tax increases, tax-exclusive fares increase as well, demonstrating over-shifting. $\frac{\partial p}{\partial T} < 0$ depicts under-shifting or incomplete pass-through of taxes. Full shifting of taxes requires $\frac{\partial p}{\partial T} = 0$. It can be shown that consumers react more strongly to tax changes than to price-equivalent changes as long as $\alpha(1 - \frac{\partial p}{\partial T}) < \beta$ in magnitude.[17] Under the Neoclassical model, the two effects are the same, showing that consumers react to taxes

[14]For example, in a given time period (quarter), LAX-SFO by Delta Air Lines and LAX-SFO by United Airlines are two separate observations. Here "carrier" refers to the ticketing carrier.

[15]Similar results are obtained with standard errors clustered at the route level.

[16]We also conduct the analysis at the market level, where a market is a given city-pair. We omit the results at the market level in the main text, and they are quantitatively and qualitatively the same.

[17]Under full-shifting, this condition is simplified to $\alpha < \beta$, as depicted in the log-log framework in Li, Linn, and Muehlegger (2014).

as strongly (or weakly) as they do to price-equivalent changes. When the effect of taxes on demand is lower in magnitude than the effect of fares on demand, it points to under-optimization of consumers, or that tax is not as salient as prices – a phenomenon found in Chetty, Looney, and Kroft (2009). Conversely, if the tax effect is greater in magnitude than the price effect, we have consumers reacting to tax changes more strongly to price-equivalent changes. In a working paper, Chuang (2019) finds evidence of over-shifting in the unit taxes and $\frac{\partial p}{\partial T}$ ranges from 0.6 to 0.8. As a result, in the current study, we can simply compare α and β in order to detect passengers' optimization with regards to prices and taxes.

We also attempt to capture any idiosyncratic route (market)-specific demand shocks by re-estimating (1) in first-differences. Specifically,

$$\Delta \log x_{it} = \alpha' \Delta p_{it} + \beta' \Delta T_{it} + \rho' \Delta Z_{it} + \Delta \omega_t + \Delta \varepsilon_{it} \tag{4}$$

5.2 Endogeneity

When estimating demand under the framework presented in the preceding subsection, it is critical to address the problems that an endogenously determined price creates. Demand estimation has been at the core of the empirical industrial organization literature in recent decades. Beginning with the pioneering work of Berry, Levinsohn, and Pakes (known as BLP, 1995), researchers have made various suggestions for valid instruments for endogenously determined prices. BLP suggests the use of functions of characteristics of other products that correlate with markups, which ultimately affect the price. Hausman (1996) argues for the prices of the same goods in other markets (national) since their correlation is due to common cost shocks ("Hausman-type" instruments), although Bresnahan (1997) criticizes their use because their correlation might be due to common demand shocks (such as a national campaign). Nevo (2001) employs such Hausman-type instruments, focusing on regional prices as instruments, while Crawford and Yurukoglu (2012) adopt a similar type of instrument, namely the prices of other goods in the same market. Waldfogel (2003) considers features of the distribution of consumer characteristics in the market, which Berry and Haile (2010) subsequently terms Waldfogel instruments.[18]

In the spirit of Hausman-type instruments, our main instrument is the average one-period-lagged fares from the same carrier in other non-competing routes of similar distances. In each quarter, we partition routes into the following distance groups: $< 1,000$ miles, $> 6,000$ miles, and 35 other in 200-mile increments if the distance is in between $1,000$ and $6,000$ miles. In total, there are 37 distance groups. We define routes to be non-competing if they fall in the same distance group and are not from the same origin or destination airport in order to remove any potential concerns with common demand shocks at the airport level.[19][20] Common cost structures within the same carrier suggest that fares, even if one-period lagged, are likely to be strongly correlated. It is common for carriers to run promotions across the nation for a limited time, which could render the contemporaneous fare endogenous. However, such promotions would usually never last for more than a few days long. In addition, there is no apparent relation regarding how the promotion for this period might be correlated with the next period. Furthermore, given that the carriers are all well established, it is unlikely that any sudden changes in quality (impacting demand) will occur. Based on this reasoning, we believe the exclusion restriction is satisfied.[21]

[18] For more literature using different instruments, please see the discussion by Berry and Haile (2016).

[19] We are able to construct such an instrument for the vast majority of observations. Only 58 of the more than one million observations are excluded from 2SLS regressions due to the missing instrument.

[20] For example, even if two routes are in the same distance group, as long as the origin or the destination is/are the same, one would not qualify as a similar route to the other. By constructing the instrument in this way, we exclude the potential common demand shock from the same (or nearby) origin or destination.

[21] We also considered a different main instrument: average lagged fares from competitors in the same or nearby routes. Instrument validity requires that airfare be correlated with the one-period lagged fare by competitors, and that it be uncorrelated with the error term (i.e., common demand shocks). Pricing decisions can affect other carriers' load factors or seat occupancy rates, which in turn affect airfares. Given strategic interactions according to which airlines observe what others do and that carriers always foresee how competitors may react after decisions are made, the first requirement should be satisfied. The second requirement points to the importance of no serial correlation in the error term. It is true that, in a given time period, carriers might face similar demand shocks within the route or in the entire country. However, since the time period is a quarter in our dataset, any common demand shocks should have been reflected in the airfare, given how constantly they change on a given day. For example, a newly proposed Amazon headquarters in the DC area will surely increase demand between Seattle and DC. However, construction itself will not be completed within a quarter, and this demand shock should have been captured in the airfare. It is also less common for people to purchase tickets more than a few months ahead given that consumers are aware of the high change fees and/or restricted refund options, if any. We believe that the argument

Also included in our instrument set are cost shifters such as the unit fuel cost, cost per available seat-mile (CASM), dummies for whether the origin or destination is a hub for the ticketing carrier, and the number of competitors in the route. Similar instruments were utilized in Berry and Jia (2010), and Granados, Gupta, and Kauffman (2012).[22] In the next section, we present our results under both fixed effects and first-differences and with OLS and 2SLS estimates. With 2SLS estimates, we also report the results with a single instrument (just-identified) and with a different set of multiple instruments (over-identified).

6 Results

6.1 Main Results

We first present results from our pooled dataset under both estimating Equations (1) and (4). As Section 5 suggested, we compare α (α') and β (β') to detect consumers' over-optimization. One would expect that, as taxes increase, the demand for a good decreases. Therefore, β (or β') is expected to be negative. Similarly, based on the law of demand, quantity demanded decreases as price increases, holding everything else constant. One should also expect α (or α') to be negative. Following the framework outlined in Section 5.1, we test to check whether these values are statistically different.

We first use all roundtrip tickets as observations and report the results in Table 4 with a variety of fixed effects. We choose not to include a specification without quarter fixed effects because we believe that seasonal impact on demand should be incorporated at all times.

for the exclusion restriction is satisfied as well. One could argue that a further-lagged fare by competitors strengthens the arguments for the exclusion restriction. However, it might also weaken the correlation between current airfare and lagged prices. The result with this instrument does not qualitatively change our results, although they yield generally higher elasticity estimates (in magnitude). In case of monopoly routes, we use fares from nearby routes instead. Nevertheless, there are a significant number of routes for which we cannot successfully determine an instrument for. Overall, this instrument is generally weaker than the instrument of choice in the main text.

[22] Here, we treat focus cities for low-cost carriers the same as hubs for legacy carriers. We acknowledge the potential shortcomings underlying this approach. For example, for smaller low cost carriers like Frontier, a focus city might not be the same as a focus city for Southwest.

Columns (1) through (3) provide results with OLS estimates, whereas Columns (4) through (6) present 2SLS estimates under the just-identified case. Corresponding elasticities are displayed toward the bottom of the table under each column. OLS estimates systematically underestimate the price elasticity of demand, although the unit level estimates do not appear significantly different. The 2SLS estimates suggest that a one-dollar increase in the base fare leads to a 0.1-percent decrease in demand, where as a one-dollar increase in the unit taxes leads to an 8-percent decrease in the demand. The log-log version of estimates conveys a similar story: a one-percent increase in the base fare leads to a 0.4-percent decrease in the demand, while a one-percent tax increase leads to a 2.3-percent demand decrease. These measures point to the finding that consumers react to tax changes more strongly to price-induced equivalent changes. This finding is consistent with Tiezzi and Verde (2016), who report that higher gasoline taxes (in levels) can cause consumers to react more to tax changes than to price-equivalent changes. At the same time, this finding contrasts with Chetty, Looney, and Kroft (2009), who find that sales tax on groceries is not salient. Given how differently grocery taxes and aviation taxes are displayed, this finidng should not be surprising. Column (7) uses the specification from Column (6) with the only difference being the instrument(s) used. In Column (7) we use CASM, the number of competitors, and the carrier-level unit fuel cost, in addition to the lagged average fare of the carrier's other routes, as the set of instruments. With over-identification, we report the Hansen J statistic at the bottom of the table. However, we reject the null hypothesis that all of the instruments are valid.[23]

[23] We have conducted over-identification tests for our models with different combinations of the instruments. The Hansen J statistics, under most specifications for over-identifying restrictions, rejects the null that all instruments are valid. However, we would be cautious in interpreting this result. Based on how the chi-squared distributed statistic is calculated, it might not be surprising to see this outcome given our large sample and clusters. See also Nevo (2001), and Ellis, Martins, and Zhu (2017). In addition, there has been a growing debate over the validity and information yielded by such Hansen J statistics. For example, Parente and Silva (2012) argue that the test does not provide significant information on the validity of the moment conditions. Similar arguments are also made in Heckman, Urzua, and Vytlacil (2006); Deaton (2010); and Angrist and Pischke (2009). In the just-identified case, both elasticity measures, as well as the over-optimization parameter, remain quantitatively and qualitatively unchanged compared to most over-identified cases. Estimates and cluster-robust standard errors are also qualitatively and quantitatively unchanged under the Limited Information Maximum Likelihood estimator (LIML).

Insert Table 4 here.

In Table 5, we present the results with the same specifications shown in Table 4, but with first differences. As previously shown, OLS estimates underestimate the true price elasticity of demand, although α' and β' are not necessarily different as shown. In levels, it is apparent that β' is significantly larger than α'. Depending on the fixed effects included, the respective price elasticity of demand changes. In our preferred specification, as shown in Column (6), in terms of elasticities, a one-percent increase in the base fare leads to a 1.26-percent decrease in the demand, whereas an equivalent tax increases leads to a 1.9-percent decrease in the demand. We also reject that the two elasticities are equal at the 1 percent significance level.[24] The optimization parameter, as defined in Chetty, Looney, and Kroft (2009), is 1.517. Level estimates and elasticity estimates also do not qualitatively change when we include more instruments in the set (Column (7)). Hence, we find that both fixed effect and first-difference models support our hypothesis that consumers react to tax changes more strongly than to price-equivalent changes.

Insert Table 5 here.

Since our analyses produce price elasticities of air travel demand, it is worthwhile for us to compare our price elasticity estimates to those in the literature. The International Air Transport Association (2008) provides a survey of elasticity estimates for domestic and international travel, showing that, on routes that are highly competitive, demand elasticity is approximately -1.2 to -1.5. Using market-level DB1B data that focuses on top-100 routes, Berry and Jia (2010) report an upward trend (in absolute value) for demand elasticities, increasing from -0.78 in 1999 to -1.05 in 2006 in their baseline estimation, reflecting the effects of the introduction of online booking. Gillen, Morrison, and Stewart (2003) discovered that

[24] At the market level, the corresponding demand elasticity and tax elasticity are -1.424 and -1.966, respectively. Both are significant at the 1 percent significance level. The equality of the two elasticities can be rejected at the 10 percent significance level. The ratio of the two lies within the 95 percent confidence interval [0.821, 1.940].

the price elasticities of demand ranged from -0.18 to -2.01 across 85 cross-sectional meta-studies. Our elasticity measure under the preferred specification at approximately -1.26 is generally reasonable and is in line with the literature.

A natural question arising from our finding of over-optimization regards the source of such a response. To the best of our knowledge, this is the first paper to examine tax salience for domestic trips in the airline industry. For international trips, Bradley and Feldman (2018) document full optimization after the full-fare disclosure.[25] In recent decades, empirical and theoretical papers have addressed similar questions and provided some explanations in other industries, often using the concept of over-optimization parameters and the ratio of tax elasticity to price elasticity of demand, to detect over-reaction. Chetty, Looney, and Kroft (2009) posit that having a tax response that is more sensitive than a price-equivalent response can lead to negative pass-through rates, or tax incidence. Hanson and Sullivan (2016) find that for alcohol taxes, the over-optimization parameter is between 1.35 and 1.40. In addition, there have been a few papers focusing on the retail gasoline industry that find statistical evidence of over-reaction to taxes. Tiezzi and Verde (2016) find the optimization parameter under certain specifications to be more than 8. They attribute the over-optimization in part to potential consumer tax aversion. Li, Linn, and Muehlegger (2014) find that the parameter ranges from 2 to 8. Davis and Kilian (2011) obtain a parameter value as high as 7. They posit that gasoline price changes caused by tax hikes are more persistent than those due to other factors. In addition, such a response might also be amplified by extensive media coverage, causing consumers to become even more aware of the tax hike and thus more substantially reducing consumer demand for gasoline, as is also mentioned in Li, Linn, and Muehlegger (2014). Rivers and Schaufele (2014) find the tax elasticity to be almost five times the price elasticity. As presented above, our over-optimization parameter estimate ranges from 1.5 to 7, which is qualitatively and quantitatively comparable with what others have found.

[25] To be precise, Bradley and Feldman (2018) suggest that the over-optimization parameter after the full-fare disclosure for international travel is 1.59 with the 95 percent confidence interval of $[0.90, 2.28]$, which they view as full-optimization.

Note that the explanations provided in earlier works, as suggested by Coglianese et al. (2017), need not be mutually exclusive. In fact, we believe that the source of our over-optimization finding could be a combination of all of the aforementioned explanations. Tax changes are common in the airline industry, although they might not be noticed by the general public. For example, the rate of the passenger facility charge changes frequently and varies across airports. The segment fee has been increasing (and has never decreased) in recent years. The September 11 Security Fee experienced its first increase during our sample period. All of these tax increases accumulate and become more persistent than price fluctuations. Among the different tax increases, the increase in the September 11 Security Fee likely received the most media attention.[26] To investigate how the September 11 Security Fee might have affected passengers' price and tax responses, we allow both price and tax effects to be different before and after the tax change. Specifically,

$$\begin{aligned} \log x_{it} =& \gamma + \alpha_1 p_{it} + \alpha_2 p_{it} \times I[Post911Tax]_t + \beta_1 T_{it} + \beta_2 T_{it} \times I[Post911Tax]_t + \\ & \lambda I[Post911Tax]_t + \rho Z_{it} + \omega_t + \eta_i + \varepsilon_{it} \end{aligned} \tag{5}$$

In this equation, $I[Post911Tax]_t$ is a time period indicator that equals 1 in all periods in or after the third quarter of 2014, when the September 11 Security Charge experienced its first legislative increase, or 0 otherwise. We report results in Table 6, with 2SLS estimates under the just-identified case. Column (1) presents the level results, with Column (2) showing the corresponding elasticity measures. Columns (3) and (4) shows similar results, but under first-differences. From both the level measures and the elasticity measures, we find that, after the September 11 Security Fee increase in July 2014, passengers' responses to tax changes increased, while price response has decreased. Under the preferred specification in Column (4), we fail to reject the null that the two elasticity measures are the same prior to the tax

[26]Less media coverage would be given or noticed if the segment tax increased by ten cents per year. The magnitude of the change meant that the increase in the September 11 Security Fee received more media attention. Media attention is also lower if the tax increase only applies to certain airports, such as in the case of the Passenger Facility Charge.

change at conventional significance levels. After the change, the difference between the two elasticity measures becomes truly significant.

Insert Table 6 here.

In addition to the aforementioned rationale, ongoing debate of aviation tax increase would also affect consumers' perception on these taxes. For example, the ongoing debate of potentially increasing the cap of the Passenger Facility Charge has been a highly debated proposal. Since these (hypothetical) increases have received extensive media coverage, tax aversion and public complaints against the TSA (for example, potential privacy violations) arising from the extensive security screenings and their efficiency could have adverse effects on consumer demand for air travel, with the perception that such tax increases could further exacerbate problems. One more possible explanation for the over-optimization might stem from how "taxes and fees" are displayed. Since most consumers do not necessarily click on it to find out what the relevant taxes and fees are, they might opt for the false impression that taxes are for the government to collect, and fees are carrier-imposed fees.[27] The psychological factor of seeing continuous increases in product fees (baggage fees, change fees, etc.) would certainly lead to further over-optimization, although consumers might not actually be charged with these fees.

Note that, depending on the industry investigated and the purpose of a tax, there might be apparent contextual differences, and one should not be surprised to see different results in this paper. Chetty, Looney, and Kroft (2009) examine the salience of sales taxes, which are not included in the posted prices. Collected sales taxes become general revenues of the state, city, or county. Gasoline excise taxes, which are included in the posted price, are levied not only to raise funds for bridges and roads but also to correct for negative externalities of pollution emissions or congestion. In the current paper, however, airline taxes are user fees, which are used to provide services to passengers. Consequently, depending on the context

[27] In some situations, some fees are indeed carrier-imposed. Carriers can choose to impose carrier-specific fuel surcharges or mileage close-in booking fees.

of the paper, the behavioral response could very well be different.

Note further that Coglianese et al. (2017) attribute the high elasticity of demand that they find in the gasoline market to the endogeneity of tax changes. They suggest that the tax changes could be easily predicted, allowing consumers to purchase additional gasoline with the anticipation of future tax increases. The same pattern is also observed among those able to store gasoline, such as wholesale distributors and operators of retail gasoline stations. Such reasoning, however, might not necessarily fit the airline industry. In particular, tax changes cannot be easily predicted. Consumers do not purchase tickets in bulk prior to changes in taxes, nor do they "store" tickets. Travel agencies or websites do not purchase tickets in advance for tax savings either. Gasoline is a necessity for driving, but individuals likely do not fly as often as they drive. The behavioral response to tax changes is, of necessity, likely to differ from that for other goods. One can also argue that the demand for gasoline is more inelastic than that for air tickets due to the availability of substitutes. It is common for consumers to purchase gasoline for immediate use. Such immediate usage is (mostly) not price discriminated. However, it is rare for consumers to purchase air tickets for tomorrow's use, for example, due to high ticket prices prior to departure.[28] Therefore, the arguments made in Coglianese et al. (2017) might not necessarily apply to the airline industry.

In summary, we find conclusive evidence to suggest that passengers react more strongly to tax changes than to price-equivalent changes. In our preferred specification using 2SLS estimates, demand changes as a result of tax increases are approximately 1.52-times greather than price-induced equivalent changes.

7 Conclusion

Topics related to tax salience in the economic literature have attracted considerable interest in recent decades. Despite the rich literature in this area, little research has been conducted

[28]Even if people purchase tickets for immediate use, these demands are highly inelastic, and a tax increase most likely would not affect demand to any meaningful extent.

in the context of the airline industry. Specifically, taxes in the airline industry have been under-studied. In this paper, we study the salience of US air travel taxes. We follow the theoretical and empirical framework suggested in Chetty, Looney, and Kroft (2009) and adopt instrumental variable strategies commonly used in field of Industrial Organization. We contribute to the literature by exploring the tax structure in the airline industry and extend the knowledge of tax salience by focusing on an industry in which the posted price is tax inclusive. We find that, on average, passengers react more strongly to the effective ticket tax rate than to price-equivalent changes. The over-optimization parameter is estimated to be approximately 1.5 in our preferred specification. We reference possible explanations from the existing literature and apply them specifically in the context of the airline industry. This paper sheds light on the tax structure in the airline industry and complements recent studies on the topic of tax salience, providing evidence of over-optimization.

Our findings have major implications for tax policies and carriers' strategies. Given the result that responses to tax changes are stronger than those to price changes, it is imperative for the relevant authorities to examine tax policies to find a balance between tax revenue from different taxes and using them to combat negative externalities or terrorism. Such efforts could require the coordination of government agencies at multiple levels, commercial carriers, and airports. Furthermore, for passengers, such responses to taxes could easily translate into responses to fee changes or anything other than "fare" changes. Anecdotal evidence has documented consumers' aversion to fee changes, such as baggage fees or change fees. It is therefore critical for carriers to realize this aversion so that they can continue to revise their product offerings and optimize strategically.

We conclude with potential caveats and future research directions. The demand shifters included in this paper are all at the state level, so they do not necessarily provide sufficient variation within the state across airports.[29] Hence, more comprehensive results might be obtained were county-level variation is available for use. Second, theoretically, it is clearly

[29] For instance, what happens in the southern-most parts of Texas might not affect the demand for air travel in the northern-most parts of Texas as much as local effects.

demonstrated that the prices of substitutes or complements can affect the demand for those goods for which they complement or substitute. It might also prove valuable to control for the prices of goods that complement or substitute for air travel. Referencing explanations from the existing literature, we apply them to our context and show how they could complementarily explain over-optimization in the airline industry. Our research, finally, calls for future work to quantitatively investigate how these factors play roles in shaping consumers' tax responses in the airline sector and other industries.

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Table 4: Pooled Results: All Roundtrip Tickets (with Fixed Effects)

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Passengers)	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
(α) Base Fare	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(β) Unit Tax (T)	-0.079***	-0.081***	-0.083***	-0.077***	-0.078***	-0.080***	-0.078***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(Real GDP)	-0.231***	0.165***	-0.160**	-0.306***	0.003	-0.233***	-0.218***
	(0.056)	(0.059)	(0.063)	(0.063)	(0.067)	(0.071)	(0.072)
Log(Per Capita Personal Income)	1.750***	0.972***	1.087***	1.650***	1.086***	1.102***	1.157***
	(0.046)	(0.057)	(0.064)	(0.050)	(0.062)	(0.069)	(0.071)
Log(Population)	2.223***	1.186***	1.579***	2.160***	1.190***	1.433***	1.279***
	(0.102)	(0.119)	(0.122)	(0.113)	(0.131)	(0.134)	(0.139)
Unemployment Rate	-0.008***	-0.003*	-0.002	-0.013***	-0.003	-0.002	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Quarter FE	X			X			
Year, Quarter FE		X			X		
Year-Quarter (Time) FE			X			X	X
Demand Elasticity (log (Base Fare))	-0.142***	-0.141***	-0.144***	-0.389***	-0.302***	-0.395***	-0.198***
Tax Elasticity (log(T))	-2.439***	-2.444***	-2.501***	-2.309***	-2.316***	-2.383***	-2.290***
p-value: $\alpha = \beta$	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
p-value: Equality of Elasticities	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
First Stage F-Statistic	-	-	-	6,936.99	6,541.32	7,313.01	1,853.45
Hansen J Statistic	-	-	-	-	-	-	623.94
Instrument(s) Used	-	-	-	a	a	a	b
Observations	1,713,268	1,713,268	1,713,268	1,395,459	1,395,459	1,395,459	1,314,206

Note:

Time and carrier-route fixed effects included. Robust standard errors clustered by Route × Carrier in the parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Instrument Sets: a: [lagged average base fare of the same carrier's other routes in the same distance group]
b: [Set a, CASM, Number of Competitors, Unit Fuel Cost]

Table 5: Pooled Results: All Roundtrip Tickets (with First-Difference)

Dependent Variable: Δ Log(Passengers)	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS
(α') Δ Base Fare	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.002***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(β') Δ Unit Tax (T)	-0.053***	-0.054***	-0.057***	-0.052***	-0.053***	-0.056***	-0.051***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δ Log(Real GDP)	0.071	-0.433***	-0.925***	0.543***	-0.181**	-0.716***	-0.621***
	(0.075)	(0.081)	(0.096)	(0.095)	(0.092)	(0.112)	(0.134)
Δ Log(Per Capita Personal Income)	0.480***	1.173***	0.627***	0.430***	1.300***	0.738***	0.703***
	(0.057)	(0.079)	(0.112)	(0.062)	(0.085)	(0.127)	(0.151)
Δ Log(Population)	1.865***	2.879***	3.434***	0.443*	1.793***	2.244***	1.263***
	(0.207)	(0.213)	(0.224)	(0.230)	(0.225)	(0.251)	(0.318)
Δ Unemployment Rate	-0.023***	-0.028***	-0.020***	-0.010***	-0.015***	-0.003	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Quarter FE	X			X			
Year, Quarter FE		X			X		
Year-Quarter (Time) FE			X			X	X
Demand Elasticity ($\Delta \log$ (Base Fare))	-0.030***	-0.030***	-0.031***	-0.667***	-0.492***	-1.256***	-1.225***
Tax Elasticity ($\Delta \log(T)$)	-1.854***	-1.868***	-1.985***	-1.797***	-1.867***	-1.905***	-1.795***
p-value: $\alpha' = \beta'$	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
p-value: Equality of Elasticities	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.009	0.024
First Stage F-Statistic	-	-	-	971.13	996.45	219.98	54.22
Hansen J Statistic	-	-	-	-	-	-	964.619
Instrument(s) Used	-	-	-	a	a	a	b
Observations	1,406,161	1,406,161	1,406,161	1,218,430	1,218,430	1,218,430	1,146,272

Note:

Time and carrier-route fixed effects included. Robust standard errors clustered by Route × Carrier in the parentheses. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Instrument Sets: a: [lagged average base fare of the same carrier's other routes in the same distance group]
b: [Set a, CASM, Number of Competitors, Unit Fuel Cost]

Table 6: Effects of September 11 Security Charge Increase

Dependent Variable: Log(Passengers)	(1) Fixed Effects	(2)	(3) First-difference	(4)
Panel A. Effects in Levels				
(a) Base Fare	-0.001***		-0.003***	
	(0.000)		(0.000)	
(b) Base Fare $\times I[Post911Tax]_t$	0.001***		0.001***	
	(0.000)		(0.000)	
(c) Unit Taxes	-0.078***		-0.050***	
	(0.001)		(0.001)	
(d) Unit Taxes $\times I[Post911Tax]_t$	-0.028***		-0.018***	
	(0.001)		(0.001)	
Panel B. Elasticities				
(e) Log (Base Fare)		-0.324***		-1.388***
		(0.047)		(0.220)
(f) Log (Base Fare $\times I[Post911Tax]_t$)		0.207***		0.228***
		(0.014)		(0.024)
(g) Log (Unit Taxes)		-2.687***		-1.765***
		(0.033)		(0.041)
(h) Log (Unit Taxes $\times I[Post911Tax]_t$)		-1.471***		-0.898***
		(0.022)		(0.033)
p-value: $(a) = (c)$	< 0.001	-	< 0.001	-
p-value: $(a) + (b) = (c) + (d)$	< 0.001	-	< 0.001	-
p-value: $(e) = (g)$	-	< 0.001	-	0.115
p-value: $(e) + (f) = (g) + (h)$	-	< 0.001	-	< 0.001
First Stage F-Statistic	3,516.60	111.34	3,574.89	86.94
Instrument(s) Used	a	a	a	a
Time FE	X	X	X	X
Demographic Controls	X	X	X	X
Observations	1,395,459	1,395,459	1,218,378	1,218,378

Note:

Time and carrier-route fixed effects included.

Robust standard errors clustered by Route × Carrier in the parentheses.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Instrument Set:

a: [lagged average base fare of the same carrier's other routes in the same distance group]