Consumer Heterogeneity and Markups over the Business Cycle: Evidence from the Airline Industry*

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Abstract

We analyze price dispersion in the airline industry in order to determine the effects of the business cycle on markup variations. We find that the cycle can affect the degree to which airlines can price discriminate between different consumer types, ultimately affecting the degree of price dispersion. Performing a fixed-effects panel analysis on 17 years of data covering two business cycles, we find that price dispersion is highly procyclical. Estimates show that a rise in the output gap of one percentage point increases the interquartile range by 1.6 percent. These results suggest that markups move procyclically in the airline industry, such that during booms in the cycle, the firm can significantly raise the markup charged to those with high willingness to pay. Our analysis suggests that this impact on the firm's ability to price discriminate imposes extra profit risks over and above cost variations.

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1 Introduction

One step in being able to subdue a business cycle is to understand how firms can possibly accentuate it. Thus, comprehending how firms react to business cycle fluctuations is of critical importance to economists. It is generally thought that firms react to fluctuations in aggregate demand by altering their pricing and competitive behavior, and there have been many theories put forth on how they do so. For instance, Rotemberg and Saloner (1986) theorize that, during booms firms may be less likely to collude since the cost of cheating is much higher, causing firms to cut prices. Another set of theories, based on switching costs and brand loyalty, show that during booms new customers may enter the market causing demand to become more elastic and firms to lower prices (see Bils (1989), Klemperer (1995), and Stiglitz (1984)). A third set, set forth by Greenwald, Stiglitz, and Weiss (1984) and analyzed by Chevalier and Scharfstein (1996), show that during recessions cash-strapped firms may forego offerering low prices to attract new customers in order to generate more cash flow.

These theories all explain why firms would raise markups during a recession, however, understanding how firms behave in the marketplace is ultimately an empirical question. The results from empirical studies looking at the cyclicality of markups have varied. Domowitz, Hubbard, and Peterson (1986), for instance, proxy marginal cost with average cost and find that markups are procyclical, while Bils (1987) models the production function with overtime and adjustment costs and finds that markups are countercyclical. Rotemberg and Woodford (1991) use a more flexible production function and decompose output variations into labor,wage and markup deviations from trend. They also find that markups move countercyclically. More recently, using less aggregated and higher frequency data, Nekarda and Ramey (2009) find evidence of procyclical markups.

In this study, we analyze the behavior of price dispersion in the airline industry in order to determine the effects of business cycles on markup decisions. We focus on airlines because the industry offers a rich laboratory to study pricing dynamics. First, the Bureau of Transportation Services (BTS) provides rich panel data on ticket prices over a 17 year time span, 1993q1 to 2009q4. This allows us to accurately control for market-specific factors such as competition and cost at the route level over two business cycles. Second, there is a large degree of heterogeneity in prices for a given airline on a specific route.

Like firms in many other industries, airlines are known to price discriminate between consumers with differing degrees of willingness to pay. Such price discrimination results in differing degrees of route-specific price dispersion over time. Ultimately, this variation in the degree of price dispersion over the business cycle helps us identify the firms pricing mechanism.

To help understand this aspect of airline pricing behavior, we develop a simple theoretical model of second-degree price discrimination based on Mussa and Rosen (1978). The model shows that as long as consumers have diminishing marginal utility of income, price discrimination will cause price dispersion to positively covary with aggregate income. Specifically, during booms in the cycle, the difference between incentive compatible prices charged to high- and low income consumers increases, causing the degree of price dispersion to rise.

Using various measures of price dispersion and the business cycle, we perform a fixed-effects panel estimation controlling for variation in competition and costs. The estimates show that price dispersion exhibits highly procyclical behavior, corroborating the mechanism delineated in the model. During booms in the business cycle, airlines are better able to exploit the larger difference in willingness-to-pay between differing consumer types. This subsequently allows them to raise the markup charged to the more price inelastic consumers. This finding suggests that business cycle variations can induce a large fluctuations in profits over and above variations in cost. Specifically, as markups are tied to the degree to which the airline can successfully price discriminate, recessions significantly hinder this profitable pricing mechanism. This story is corroborative to the highly procyclical nature of profits in the airline industry as seen in Figure 1.

Although our empirical analysis is confined to one industry, our model indicates that this phenomenon is likely to occur in many other industries as well. Specifically, as diminishing marginal utility of income is inclusive to a broad class of utility specifications, procyclical markup variation should occur in industries in which firms have market power and can successfully price discriminate. Researchers have found many other industries in which firms have been successful at price discrimination such as hotels, stadiums, restaurants, theaters (Leslie 2004), yellow-page advertising (Busse and Rysman 2005), and personal computers (Shapiro and Aizcorbe 2010).

Our study also gives potentially interesting insight to macroeconomists who have had a longstanding interest in the cyclicality of markups. In macroeconomic models of perfect competition, fluctuations in aggregate demand do not shift the labor demand schedule, thus, to generate movements in employment the models rely on outward shifts in the labor supply curve (see Hall 1980). To generate labor demand shifts, models of imperfect competition (for example, Rotemberg and Woodford (1992), Goodfriend and King (1997)) were developed which introduced an endogenous variable, the markup of price over marginal cost.[1] In particular, a countercyclical markup will act in a similar manner to a positive productivity shock during booms in the business cycle, shifting the labor demand curve out and raising real wages.[2] Our estimates provide some evidence against this hypothesis, at least as an exhaustive possibility.

The study is structured as follows: Section 2 reviews the theoretical framework by which price discrimination can lead to procyclical markup variation. Section 3 discusses possible effects of cost on price dispersion. Section 4 contains a detailed discussion of the data. In Section 5 we perform our fixed-effects panel estimation and in Section 6 we conclude.

2 Theoretical Framework

Price dispersion is a common characteristic of the airline industry, and one of the leading explanations for such dispersion at the flight level is the practice of price discriminating between different types of consumers. Specifically, airlines implement second and third-degree price discrimination in which they segment heterogeneous groups of individuals and charge them distinct prices for the same product. Advance-purchase requirements, non-refundable tickets, and Saturday-night layovers are a few examples of restrictions that airlines use to isolate passengers with different price elasticities of demand. Since high-income or business consumers tend to place a high value on their time, they are more likely to purchase more expensive tickets without such restrictions.

[1] Including labor hoarding in the framework as in Burnside, Eichenbaum, and Rebelo (1993) has also been a way to explain procyclical labor productivity.

[2] Other reseearch in this area include Gali (1994), Edmunds and Veldkamp (2006), and Jaimovich (2007).

By making use of these techniques, airlines are able to separate price-sensitive travelers from price-insensitive travelers.

According to a 1993 Gallup Survey, 49% of air travel in the U.S. was for business, and those respondents cited a rise in new business activity or improved financial conditions in their respective firms as the primary reason for increased business travel (Busse, 2002).[3] This suggests that when aggregate demand conditions are good, high-income or business consumers have higher demand for air travel, and are also more likely to pay higher prices for tickets attached with less restrictions and preferred flight times. Thus, during periods of high aggregate demand, carriers will likely experience both a higher proportion of price inelastic travelers demanding tickets, and a higher willingness-to-pay for those price inelastic consumers. If the fraction of tickets sold to price inelastic consumers increases and the difference in ticket prices between price inelastic consumers and price elastic travelers increases in periods of high aggregate demand, then both the average markup and price dispersion will follow the business cycle.

We illustrate this relationship between price discrimination and the business cycle with a simple model of monopoly pricing. While an oligopolistic model would prove more realistic, it also complicates the analysis and moves away from the scope of our empirical study—the effect of aggregate conditions on pricing patterns. Furthermore, in our empirical analysis we control for variations in competition over time, and thus any effect of the business cycle on prices, in a dynamic sense, will be measured under the setting where the degree of competition is fixed. One could extend our theoretical framework to an oligopolistic game by adding a horizontal dimension on the consumer's valuation of the product (e.g. brand) as in spatial models such as Schmalensee (1978), Salop (1979) and Brito (2003). Such brand differentiation would allow firms to compete in price and also have some degree of market power. One should therefore think of the theoretical model below as a market in which brand preference is strong enough to allow firms to price above marginal cost, and that consumers' preferences over brand are distributed independently of income.

[3]On the flip side, respondents who indicated less business travel attributed it to decreasing business activity or bad financial conditions in their respective firms.

2.1 Consumers

We consider a model with multiple types of consumers, where consumers are heterogeneous along their level of income, y_i. Specifically, we suppose that consumers are differentiated by income, y_i, where a consumer of type i, solves the following maximization problem:

$$\max_{d \in \{0,1\}} d \cdot x_v + u(m) \tag{1}$$

$$\text{subject to:}$$
$$y_i = m + d \cdot p$$

where x_v is valuation of the ticket where $v \in 1, 2$ indicates its attributes. For instance, $v = 2$ would indicate the ticket has an advance purchase requirement or saturday-night stayover, while $v = 1$ would be a less restrictive ticket or ticket purchased closer to the date of departure. It follows that with positive time costs, $x_1 > x_2$. The variable m represents the numeraire commodity and d represents the consumer's decision to buy or not buy. Note that $u(\cdot)$ is the functional form representing the manner in which the consumer values the numeraire commodity relative to the discrete good. It follows that the indirect utility function for the case in which the consumer purchases the discrete good ($d = 1$) is given by:

$$U = x_v + u(y_i - p). \tag{2}$$

As in Tirole (1988), we make the assumption that a consumer's income is very large relative to the valuation, x_v, and subsequently to the equilibrium price charged. This allows us to take a Taylor expansion around $p^* = 0$ which, under the assumption that $y_i - p \approx y_i$, yields:

$$U = x_v + u(y_i) - u'(y_i)p. \tag{3}$$

It follows that for a given consumer to be better off consuming the good, it must be the case that $x_v + u(y_i) - u'(y_i)p \geq u(y_i)$, which means demand for the good is:

$$d_i(p_v) = \begin{cases} 1 & \text{if} \quad p_v \leq \frac{x_v}{u'(y_i)} \\ 0 & \text{if} \quad p_v > \frac{x_v}{u'(y_i)} \end{cases} \tag{4}$$

2.2 Firm behavior

To simplify the firm problem we assume two types of consumers: a high income, y_h and a low income, y_l consumer. The firm's problem in the two-consumer-type case is to maximize profits given consumer, will purchase if $p_v \leq \frac{x_v}{u'(y_i)}$. The firm has the option to separate the market by offering different types of tickets in order to increase its profits. For the separating equilibrium to occur, the firm must be able to separate the market and also find it profit-maximizing to do so. It follows from Mussa and Rosen (1978) prices must satisfy:

$$p_1^* = b_h x_1 - (b_h - b_l)x_2 \tag{5}$$

$$p_2^* = b_l x_2. \tag{6}$$

where $b_h = \frac{1}{u'(y_h)}$ and $b_h = \frac{1}{u'(y_l)}$. As the high-income consumer values x_2 more than the low-income consumer, the firm must lower the price of x_1 to dissuade the high-income consumer from deviating and purchasing x_2. Specifically, the bound is lowered by the extra utility the high-income consumer would have received over the low-income consumer of consuming x_2, $(b_h - b_l)x_2$. This lowering of the price ensures that the high-income consumer does not purchase x_2 instead of x_1 (that is, that ensure the equilibrium is incentive compatible). In either case, the firm will find it profit-maximizing to separate the market as long as the number of low-income consumers is sufficiently large (see Tirole (1988)).

Note that the price range between the high and low price ticket (a simple measure of price dispersion) will be:

$$D = p_1 - p_2 = b_h(x_1 - x_2). \tag{7}$$

It follows that the elasticity of price dispersion relative to a change in income is:

$$\varepsilon_{D,y} = \frac{\partial D}{\partial y}\frac{y}{D} = \left[-\frac{u''(y_h)}{u'(y_h)}y_h\right] \tag{8}$$

which is simply the coefficient of relative risk aversion (CRA). As long as the CRA is positive (i.e. diminishing marginal utility of income), price dispersion will widen with an increase in aggregate income. Thus, under very general conditions on the consumer's utility of income will price dispersion follow aggregate income. It is also relevant to note that dispersion will also be procyclical if $x_1 - x_2$ follows aggregate income. This implies that the effect of aggregate income on price dispersion will be pronounced if nonrestrictive tickets become more valuable during booms in the cycle.

To show the linkage between price dispersion and markups we first denote the average markup as:

$$\bar{\mu} = \alpha_h * \mu_1 + (1 - \alpha_h) * \mu_2 \tag{9}$$

where α_h is the proportion of high-income consumers purchasing tickets and $\mu_v = p_v - c_v$ is the markup charged on ticket of type v with marginal cost c_v. Assuming that marginal costs do not covary with aggregate demand, it follows from (8) that the ratio of the markups charged to each type of consumer, $\frac{\mu_1}{\mu_2}$, will rise with aggregate demand, and so will the average markup.

Overall, the model indicates that, ceterus paribus, procyclical price dispersion is indicative of a procyclical average markup. It is this relationship between price dispersion and aggregate demand that we will explore in the airline ticket price data. Specifically, we will study the cyclicality of markups in the airline industry using price dispersion as a proxy for average markups. If the model assumptions are reasonable, then we expect to find a positive correlation between price dispersion and aggregate demand. This linkage of price dispersion and markup variation, however, is dependent on the assumption that marginal cost does not vary with the business cycle. We address this issue in the following section.

3 Capacity and Marginal Cost Issues

There are two plausible reasons as to why marginal cost may be procyclical. First, if the carrier is constrained by capacity, then as more flights reach full capacity, the expense of an additional passenger becomes very large as either a bigger aircraft or an extra flight is needed to supply the extra seat-mile. Thus, marginal cost is apt to rise in periods of peak aggregate demand when carriers need to expand capacity. Second, wages of crew and maintenance workers are apt to rise during booms in the cycle, which would also cause marginal costs to rise. We tackle these two scenarios in this section.

3.1 Effective Capacity Cost

In discussing the effect of capacity constraints on pricing, it is easiest to decompose marginal cost into its two primary components, which we refer to as the passenger cost and the capacity cost. If the aircraft is not operating at full capacity, then marginal cost is simply equal to the passenger cost; the cost of adding an additional passenger to the airplane. This cost is mostly made up of the extra fuel required to transport the additional weight of the passenger, while other, lesser components include the in-flight costs of serving the additional passenger (i.e. meals, snacks, etc.). However, if the airplane is operating at full capacity, then marginal cost is equal to the direct cost of an additional passenger as well as the more substantial cost of an additional flight. This cost is incurred regardless of whether or not seats on the airplane are filled with passengers, while the passenger cost is only incurred on seats that are sold. This implies that marginal cost at the route level is given by,

$$c_{ij} = \beta_{ij} + \lambda_{ij} \tag{10}$$

where β_{ij} is the passenger cost of serving an additional passenger one mile on route j by carrier i, and λ_{ij} is the cost of an additional flight (in seat-miles).

If airlines price according to stochastic demand concerns, then aggregate demand could alter the firm's expected probability of selling a ticket, and subsequently alter the "effective" capacity cost. Specifically, if the carrier is uncertain about expected demand, then under price-setting commitments and costly capacity, profit-maximizing behavior

induces a distribution of prices rather than a single price. The intuition is that if the firm were allowed to change price after the realization of the state, then it would set a low price in the low-demand state and a high price in the high-demand state. However, because the firm must commit to a menu of prices ex-ante, its profit maximizing strategy is to assign multiple prices to specified quantities of the good.[4] That is, if firm must pay costs irrespective of whether or not its output is sold, then it has a large incentive to set higher prices on goods that are less likely to be sold.[5]

Eden (1990) formalized a model in a setting of perfect competition where there is uncertainty regarding the number of agents who will show up to exchange goods in the marketplace. In such a setting, goods are characterized by the probability that they will be sold, and in equilibrium firms face a tradeoff between price and the probability of sale. In the model, equilibrium prices are given by the condition,

$$p_s = \beta + \underbrace{\frac{\lambda}{prob(sale)_s}}_{\lambda_s^{eff}} \tag{11}$$

where p_s is the price of the sth good, β is an operating cost that the firm must pay for each good that it sells, λ is the unit capacity cost, and $prob(sale)$ is the probability that good s is sold. The second term on the right-hand side of the equation can be interpreted as an "effective" capacity cost of good s, λ_s^{eff} . In competitive equilibrium, it is the case that firms are indifferent between selling a high-priced good with low probability and selling a low-priced good with high probability. Dana (1999) extended Eden's model to monopoly and oligopoly market structures. In this setting, the monopolist sets a higher

[4]It should be pointed out that more subtle factor is also needed to induce such pricing behavior by firms. The firm's ex-post optimal price must be positively correlated with the level of demand (Dana 1999, 2001). That is, if the firm's optimal price in the high-demand state is larger than it's optimal price in the low-demand state, then it should use multiple prices to achieve some of the benefits that it would have if it were able to adjust price in response to demand. If instead, the ex-post optimal price is constant or decreasing in demand, the firm's optimal strategy will be to set one price.

[5]Prescott (1975), was the first study to address this issue in the economic literature. His paper was more focussed on the theory of unemployment, and his model was more of an example rather than a formal model of pricing.

price for a good that sells only in high demand states since its effective cost is higher.[6]

Under this setting, where the carrier commits to prices ex-ante, the highest priced tickets—tickets with the highest effective capacity cost—are not purchased until demand rises sufficiently high to purchase all of the low priced tickets. Thus, if the carrier is pricing solely with stochastic demand concerns, then peaks in aggregate demand will induce higher price dispersion through the higher effective capacity cost of the remaining seats on crowded aircrafts. In this case, it could be argued that procyclical price dispersion is not evidence of a procyclical markup, it is evidence that the effective capacity cost rises during periods of peak demand due to low available capacity.

While we believe that carriers do take effective capacity cost into account, we discount its prominence at the business cycle frequency. If stochastic demand pricing was causing price dispersion to follow the business cycle, then aircraft capacity utilization should positively follow the business cycle. Figure 4 shows that the mean aircraft capacity utilization rate has been steadily increasing over the course of the sample period, and is not necessarily positively correlated with the business cycle.[7] Rather, there is significant seasonal variation in this variable, indicating that effective capacity concerns are likely important at high frequency levels, but not necessarily at middle and low frequency levels. Overall, this figure makes it apparent that at the business cycle frequency, carriers are more likely altering capacity as opposed to letting the effective capacity cost vary, which corroborative of findings by Puller, Sengupta and Wiggins (2010).

3.2 Using Average Variable Cost as a Proxy for Marginal Cost

In general, marginal cost may vary over the business cycle for reasons other than changes in aircraft utilization. For instance, wages of pilots and flight attendants may

[6]Indirect evidence found by Stavins (1996) is consistent with stochastic demand pricing. Stavins found that even controlling for advance purchase requirements, ticket prices increase as the number of days to departure decreases.

[7]As a robustness check, we estimate an instrumental-variable fixed-effects regression, similar in fashion to the estimator discussed in the next section. We ran (1) $\ln(util)_{ijt} = \alpha + \beta_1 YGAP_t + \gamma_{ij} + \varepsilon_{ijt}$ and then ran (2) $\ln(util)_{ijt} = \alpha + \beta_1 YGAP_t + \beta_2 \ln \widehat{HHI}_{ij} + \gamma_{ij} + \varepsilon_{ijt}$. The coefficient β_1 was estimated to be -.44 with a standard error of .04 in the first specification (1) and -.43 with standard error .03 in the second (2). This negative coefficient indicates that utilization moves countercyclically.

rise during booms, as may the price of fuel. For this reason, in our empirical analysis below we proxy for variations in marginal cost using a measure of the carrier's average variable cost. Numerous studies, such as Caves, Christensen, and Trethaway (1984) and Gillen, Oum, and Tretheway (1985, 1990), have found that the carriers' passenger output displays constant returns to scale in firm size. Due to these findings, we believe average variable cost is a valid approximation to marginal cost in this context. Specifically, the BTS's P-52 database defines a measure called the "total aircraft operating cost," which includes fuel, crew wages, maintenance, aircraft leasing, and depreciation.[8] This variable measures the tangible cost to the carrier of operating in a given quarter. Figure 3 plots this variable as a proportion of total seat-miles for three carriers in our sample. The figure shows that cost per seat-mile is correlated between firms, and has generally increased throughout the sample period. The large rise and fall in 2008 can be attributed to the spike in oil prices that occurred during that summer. Overall, including a proxy for marginal cost in the empirical specification removes any variation in price dispersion induced by tangible cost variations. This leaves our estimation of the effect of business cycle on prices in line with that of the theoretical model whereby marginal cost is not varying.

4 Data

Our study focuses on domestic, direct, coach-class airline tickets over the period 1993q1 to 2009q4. Our sample includes nine major domestic airlines, often referred to as "legacy carriers,"[9] as well as a number of low-cost carriers[10] (LCCs) and regional carriers. Ticket prices represent 10-percent of all domestic tickets issued by airlines and

[8] As described in the next section, in the fixed-effects specification we decompose this variable between its fuel component and its other components because fuel is relatively much more volatile.

[9] The legacy carriers in our sample include United, US Airways, Delta, American, Alaskan, TWA, Continental, Northwest, and America West.

[10] The list of LCCs, obtained from Ito and Lee (2003), includes Air South, Access Air, AirTran, American Trans Air, Eastwind, Frontier, JetBlue, Kiwi, Morris Air, National, Pro Air, Reno, Southwest, Spirit, Sun Country, ValuJet, Vanguard, and Western Pacific. For a more detailed discussion of LCCs see Goolsbee and Syverson (2005).

are obtained from the DB1B database. In addition to ticket prices, the DB1B includes other quarterly itinerary information, such as origin and destination airports, passenger quantities, number of stops (plane changes), and fare class.[11] Tickets less then $20 are believed to be frequent-flyer tickets and are eliminated.

The data is a panel, where an observation is a flight conducted by a specific airline, between an origin and destination airport (route), in a specific time period (year and quarter). For example, an American Airlines direct, coach-class ticket, from Dallas (DFW) to San Francisco (SFO) in the first quarter of 1999 is considered an observation in our data. Our direct ticket data include both one-way flights and round-trip flights. The DB1B contains numerous itineraries and fares for the same flight by the same carrier, reflecting the quarterly frequency of the data, as well as the many different fares found within the same fare class, on the same flight, at a given point in time. Thus, our data comprise distributions of prices for carrier-route itineraries. Price dispersion is measured using three separate proxies: the interquartile range, the Gini coefficient, and the 90th and 10th price percentiles estimated separately. The interquartile range and gini coefficient are advantageous in that they summarize dispersion with one statistic, while the price percentiles have the advantage that they give more detailed information about the tails of the distribution.

The median Gini in our entire sample is 0.25. To get a better handle on the dynamics of price dispersion, we present a few graphical examples of the pricing patterns seen in the data. Figure 2 plots price percentiles of two routes routes along with a plot of the output gap.[12] It is noteworthy that the top percentiles follow the output gap. Specifically, the top portion of the price distribution rises and falls with boom in cycle in the late 1990s and then begins to gradually fall as aggregate demand deteriorates. In Section 5 we conduct a more systematic analysis using panel data methods in an effort to confirm these observations.

[11]There are three different sub-components to the DB1B data set. They are market data, coupon data, and ticket data; and we combine variables from all three. For further reference, see the BTS's website http://www.transtats.bts.gov.

[12]The output gap is defined as the log difference between the actual nominal GDP and the CBO's measure of potential output.

5 Estimation

We exploit the panel dimension of the data in order to assess the effects of business cycle variations on price dispersion while holding fixed time-invariant route specific factors, as well as any route-specific variation in the degree of competition and carrier-specific variation in fuel and other operating costs. Specifically, we use a fixed-effects panel estimator which exploits only the times-series variation along a specific route in the estimation routine.[13] We use two different approaches in measuring the effect of business cycle variations on price dispersion. Our first specification takes the form:

$$\text{DISP}_{ijt} = \theta_0 + \beta_1 * YGAP_t + \beta_2 * \ln \widehat{HHI}_{jt} + \beta_3 * \ln FUEL_{it} + \beta_4 * \ln COST_{it} + \gamma_{ij} + \varepsilon_{ijt}. \quad (12)$$

where i indexes the carrier, j the route, and t the time period. Carrier-route fixed effects are represented as γ_{ij}, and $\widehat{HHI}_{jt}$ is the market concentration of the route as measured by the Herfindahl index and is instrumented using the same variables as in Borenstein and Rose (1994) and Gerardi and Shapiro (2009).[14] We control for costs using the logarithm of the carrier's average fuel cost per gallon, $\ln FUEL_{it}$, as well as the remaining operating cost per seat-mile, $\ln COST_{it}$, measured by the BTS for a specific carrier. In this specification, we proxy the the business cycle with the output gap, $YGAP_t$, as measured by the Congressional Budget Office (CBO).

Our second specification takes the form:

$$\text{DISP}_{ijt} = \theta_0 - \beta_1 * UR_{jt} + \beta_2 * \ln \widehat{HHI}_{jt} + \beta_3 * \ln FUEL_{it} + \beta_4 * \ln COST_{it} + \gamma_{ij} + \varepsilon_{ijt}. \quad (13)$$

where we proxy the business cycle with the (negative value of the) average unemployment rate of the two endpoint states on the route, UR_{jt}. In both specifications, price

[13] In order to determine initially whether time-invariant, route-specific effects would be important in our context, we performed Hausman tests for each sample and specification of our model. In all cases the null hypothesis of zero correlation between the residuals and the vector of explanatory variables was soundly rejected.

[14] See appendix for a description of the instruments .

dispersion, $DISP_{ijt}$, is measured in three different ways: the logarithm of the interquartile range, the Gini log-odds ratio,[15] and the 90th and 10th percentiles, each estimated in separate regressions. Analyzing the top and bottom of the price distribution separately provides additional information regarding the source of the change in price dispersion. Observations are weighted by the total number of passengers on the route over the entire sample period and standard errors are clustered by route in order to control for autocorrelation as well as correlation between carriers on the same route.

6 Estimation Results

Table 1 contains estimation results for both specifications, using the logarithm of the interquartile range and the gini log-odds ratio as the dependent variable. We report results for all direct routes in our 17-year sample[16]. The model reviewed in Section 2 predicts that under certain functional forms of the utility function, high-income consumers' price elasticity will be more sensitive to business cycle variations than low-income consumers.

The effect of a rise in the business cycle—as measured by the output gap—on price dispersion is positive and significant at the 1-percent significance level. The estimate indicates that a one percentage point rise in the output gap (i.e. from .01 to .02) increases the interquartile range by 1.6 percent and the Gini log odds by .015. The results from the second specification are similar to the first, indicating that a decrease in the unemployment rate induces an increase in the amount of price dispersion on a given route.[17] Specifically, a one percentage point fall in the unemployment rate raises

[15]We measure price dispersion using the Gini log-odds ratio given by given by $G_{ij}^{lodd} = \frac{ln(G_{ij})}{1-ln(G_{ij})}$, which produces an unbounded statistic. No results change using the log of the Gini coefficient. See Hayes and Ross (1998) for further discussion.

[16]This sample includes 154,407 carrier-route observations when using $\ln(IQR)$ as the dependent variable and 156,038 carrier-route observations using the gini log-odds ratio. The reason for the fewer observations in the first specification is that observations in which the interquartile range were equal to zero were necessarily dropped.

[17]This sample includes 153,706 carrier-route observations when using $\ln(IQR)$ as the dependent variable and 155,331 carrier-route observations using the gini log-odds ratio. We have fewer observations in this specification because we do no have unemployment information for American Samoa or St. Thomas.

the interquartile range by 2.1 percent. Linking this rise in price dispersion to rise in markups, this indicates that the elasticity of markups to the business cycle are quite strong.

A look at the estimates from the percentile regressions in Table 2 shed more light on the manner in which price dispersion follows the business cycle. The estimates show that an increase in the output gap raises the 90th-percentile price level but has no significant effect on the 10th-percentile price level. Specifically, a rise in the output gap by one percentage point raises the 90th percentile price by 1.10 percent and has no significant effect on the 10th percentile price. Similar, to the output gap a fall in the unemployment rate by 1 percentage point raises the 90th percentile price by 1.3 percent, however, there is significant, yet small -.35 percent , negative effect of a fall in the unemployment rate on the 10th percentile. Thus, the estimates indicate that during booms in the cycle, carriers are raising prices to those consumers with high willingness to pay.

As in Gerardi and Shapiro (2009), we find that the effect of a decrease in competition—as measured by an increase in market concentration $\ln \widehat{HERF}$—on price dispersion is positive and significant at the 1-percent significance level.[18] We also find interesting dynamics occurring on the cost side. Specifically, fuel costs seem to filter into the 10th percentiles and 90th percentiles equally, while the other operating costs filter more into the 90th percentile prices. There are many plausible stories that could explain this result. One reason may be that carriers find it easier to pass on costs to the more inelastic consumers in fear of losing those who are less elastic.

Overall, the fixed-effects, panel estimates provide evidence of a positive relationship between the business cycle and price dispersion in the airline industry. Furthermore, the results show that variations in the business cycle have a large positive effect on the 90th price percentile. These results are suggestive of the mechanism outline by the model delineated in Section 2, whereby carriers are raising the markup charged to those consumers who are least price elastic during booms in the business cycle.

[18] All instruments were relevant at the 1 percent level as measured by the Cragg-Donald statistic.

6.1 Time Dummy Plots

As our next exercise, we replace the output gap proxy with time-dummies in our fixed-effects panel estimation. Specifically, we estimate:

$$\ln IQR_{ijt} = \theta_0 + \beta_1 * \ln \widehat{HHI}_{jt} + \beta_2 * \ln FUEL_{it} + \beta_3 * \ln COST_{it} + \gamma_t + \gamma_{ij} + \varepsilon_{ijt}, \quad (14)$$

which imposes no parametric form on the manner in which time affects price dispersion. In order to assess how well the time-dummy coefficients, $\hat{\gamma}_t$ match aggregate demand conditions, we plot the coefficients alongside the output gap in Figure 5. The estimates on the time dummies follow the output gap pretty well, slowly rising from the mid 1990s to the late 1990s, then falling in the early 2000s during the recession. The coefficients rise again from 2004 through 2007 and then subsequently fall with the latest recession. The correlation between the moving average of the coefficients and the output gap is 0.64 and -0.47 with the unemployment rate.[19] Overall, the variation seems to match the first cycle better than the second. As discussed above, this is likely due to the smaller peak in 2007 than in 2001 whereby carriers were less able to price discriminate against the price inelastic consumers.

6.2 Big-City versus Leisure Routes

As discussed in Gerardi and Shapiro (2009), we can decompose the full sample into routes that with a heterogeneous consumer base and routes with a heterogeneous base. As routes between big cities tend to attract both business and leisure consumers they also tend to have a bimodal distribution of consumers while the routes to leisure destinations tend to have unimodal price distributions and lower median prices.[20] Thus, airlines may have more opportunities to implement price discrimination strategies on big-city routes since they include relatively more high-income business consumers. Furthermore, note that equation (8) implies that dispersion on big-city routes will be more sensitive to the

[19]This is taken with the three-month moving average of the coefficients. The correlation with actual dummies on the output gap is .51.

[20]For a full list of the cities in each sample as well as a detailed description of these subsamples are created please refer to Gerardi and Shapiro (2009).

cycle if the utility over income displays increasing relative risk aversion and less sensitive to the cycle if it displays decreasing relative risk aversion.

To test whether the business cycle has a different impact on big-city routes than leisure routes we split the sample into two subsamples. The estimates using the logarithm of the interquartile range are reported in Table 4. The specification using the output gap as the business cycle proxy show that the effect is much stronger on the big-city route sample, while the estimates with the city unemployment rate show a negligible difference between the two samples. Specifically, in the big-city sample, a one percentage point rise in the output gap induces a 2.7 percent increase in the interquartile range, while it has an insignificant .19 percent rise on leisure routes. In the leisure sample, a 1 percentage point fall in the average endpoint city unemployment rate causes a 2.2 percent increase on both samples.

6.3 Legacy Carriers versus Low-Cost Carriers

Legacy carriers, sometimes called "hub-and-spoke carriers," tend to implement different price discrimination strategies than do low-cost carriers (LCCs). For instance, some legacy carriers offer "economy-plus," which offer the passenger more leg room, separate access through security, and/or early boarding. To determine whether different types of carriers price differently over the business cycle, we divide the sample between legacy and LCCs. The estimates are reported in Table 4 and show that most of the effects from the business cycle on price dispersion are stemming from the legacy carriers. The effect of the output gap on the interquartile range is roughly twice the magnitude ($\hat{\beta}_1 = 2.3$ compared to $\hat{\beta}_1 = 1.0$) on the sample of legacy carriers than on the sample of LCCs. Legacy carriers pricing considerations are thus more sensitive to the movements in willingness to pay of the price inelastic consumers, while the LCCs price more sensitively to variations in cost.

6.4 Subsample Analysis

As a final exercise, we divide the sample between two sample periods based on the National Bureau of Economic Research (NBER) business cycle dates. Our first sample

period, 1993q1 to 2001q4 covers one peak (March 2001) and one trough (November 2001). Our second sample period, 2001q1 to 2009q4, also covers one peak (December 2007) and one trough (November 2001). The estimation results indicate that cyclically of dispersion was stronger in the first sample period than it was on the second. Specifically, the effect was about twice as strong in the first sample period ($\hat{\beta}_1 = 2.3$) than the second ($\hat{\beta}_1 = 1.1$). This reduction in the size of the coefficient is mostly likely due to the larger and more lengthy boom in the first sample period relative to second, giving carriers more room to raise prices to the price inelastic consumers.

7 Conclusion

Our analysis has shown that price dispersion is significantly procyclical in the airline industry. This result is indicative that markups of price over marginal cost are also procyclical, in line with the recent findings of Nekarda and Ramey (2010). Our estimates are in sync with a parsimonious theoretical model of second-degree price discrimination. The model has shown that as long as firms have the ability to price discriminate and consumers have diminishing marginal utility of income, price dispersion will follow aggregate demand. Thus, we believe our results can be extrapolated to other industries in which price discrimination over willingness to pay is apparent. Overall, our analysis indicates that airlines undertake great profit risk over the business cycle in the form of variations in the ability to price discriminate. This may be one reason why low-cost carriers, such as Southwest and JetBlue, who target a more homogeneous consumer base may have reported more stable profit patterns than legacy airlines.

One difference between our work and the macroeconomic literature on markup variations is that we use a partial equilibrium framework while most macroeconomic models are in a setting of general equilibrium. However, a number of these general-equilibrium models require homothetic preferences to obtain clear-cut predictions on the behavior of markups. This assumption is made even though work on static models of monopolistic competition dating back to Robinson (1932) had already emphasized how markups vary as a function of aggregate demand (or deviations from trend output), so long as preferences are not homothetic. Gali (1992) and others have tackled this issue com-

prehensively, positing that changes in demand composition can explain the relationship between markup variation and aggregate demand. Our microeconomic model should be interpreted as an illustration of this same effect, although embedded in a standard industrial organization model of second degree price discrimination.

Future work on the issue would involve examining whether other microeconomic mechanisms are at work in determining markup cyclicality, as well as looking at industries with different types of firm pricing strategies. For instance, Miller and Osborne (2010) find evidence of price discrimination in the cement industry to be based on the spatial location of the consumer. In the healthcare industry, players are involved in a bargaining game over price. Markup cyclicality is therefore likely distinct for certain classes of industries.

A Variable Definitions

- $\ln P(k)_{ijt}$ - The logarithm of the kth price percentile of carrier i on route j in period t, obtained from the DB1B.
- $\ln IQR_{ijt}$ - The logarithm of the interquartile range, given by $P(75)_{ijt}$ - $P(25)_{ijt}$, where $P(k)_{ijt}$ is the price percentile of carrier i on route j in period t, obtained from the DB1B.
- G^{lodd}_{ijt} - The Gini log-odds ratio, given by $G^{lodd}_{ijt} = \ln(\frac{G_{ij}}{1-G_{ij}})$, where G_{ijt} is the Gini coefficient of carrier i's price distribution on route j in period t, calculated using data from DB1B.
- $\ln HHI_{jt}$ - The logarithm of the Herfindahl index of route j in period t, calculated using passenger shares obtained from the DB1B.
- $YGAP_t$ - The log of nominal GDP in period t minus the log of nominal potential GDP in period t, as measured by the Congressional Budget Office (CBO).
- UR_{jt} - The average metropolitan unemployment rate in period t of the origin and destination state of route j, obtained from Bureau of Labor Statitics (BLS).
- $\ln FUEL_{it}$ - The average cost per gallon fuel by carrier i in period t, obtained from the BTS P-52 database.
- $\ln COST_{it}$ - Total operating costs minus total fuel costs divided by total seat-miles for carrier i in period t, obtained from the BTS P-52 database.

Instruments

- $\ln PASSRTE_{jt}$ - The logarithm of total enplaned passengers on route j in period t from the T-100 Domestic Segment Databank.
- $IRUTHERF$ - This instrument is identical to one used by Borenstein and Rose (1994). This variable is the square of the fitted value for $MKTSHARE_{ijt}$ from its first-stage regression, plus the rescaled sum of the squares of all other carrier's

shares. See Borenstein and Rose (1994) for a more detailed explanation. It is equal to $\widehat{MKTSHARE_{ijt}}^2 + \frac{HERF_{jt} - MKTSHARE_{ijt}^2}{(1-MKTSHARE_{ijt})^2} * (1 - \widehat{MKTSHARE_{ijt}})^2$.

- $GENSP$ - $\frac{\sqrt{ENP_{j1} * ENP_{j2}}}{\sum_k \sqrt{ENP_{k1} * ENP_{k2}}}$, where k indexes all airlines, j is the observed airline, and ENP_{k1} and ENP_{k2} are airline k's average quarterly enplanements at the two endpoint airports. This instrument is similar to one used by Borenstein and Rose (1994), with the difference being that Borenstein and Rose use average daily enplanements, while we use average quarterly enplanements, as a result of data availability. Data on enplanements were obtained from the T-100 Domestic Segment Databank.

B Data Construction

In this appendix, we discuss our methods and assumptions involved in constructing our panel of airline-route ticket observations from the DB1B and T-100 Domestic Segment databases maintained by the BTS at their online website, Transtats. There are three different sub-components to the DB1B data set. They are market data, coupon data, and ticket data, and we combine variables from all three sources.[21]

We use only domestic, coach-class itineraries and keep only tickets containing direct flights.[22] Direct flights typically account for 30 percent of the itineraries in the DB1B over the course of our sample, with no apparent trend.

The BTS includes a variable that describes the reliability of each ticket price ("dollar cred"). The variable takes on a value of 0 if the fare is of questionable magnitude, based on a set of limits defined by the BTS, and it takes a value of 1 if it is credible. We drop all tickets for which this variable takes a value of zero.

The DB1B also provides limited information regarding the fare class of each ticket. Each ticket is labeled as either coach-class, business-class, or first-class, and we eliminated all first-class and business-class itineraries. Unfortunately, the DB1B does not have any

[21]For further reference, see the BTS's website http://www.transtats.bts.gov.

[22]The sample of direct flights encompasses both non-stop flights and flights in which there is a stop but no change of plane.

direct way of identifying frequent-flyer tickets, but there are indirect methods that have been used in the previous literature, and we follow these in our analysis. First, we drop all fares coded as 0. Next, we dropped all fares that are less than or equal to $20 ($10 for one-way tickets).

In addition to eliminating frequent-flyer tickets and higher-class tickets, we also eliminate tickets in which the operating and ticketing carriers are different due to code sharing arrangements. Code sharing is a practice where a flight operated by an airline is jointly marketed as a flight for one or more other airlines. Due to the uncertainty regarding the actual airline who is setting the price schedule in such an arrangement, we decided to eliminate these itineraries. Code sharing first appears in the data in 1998:Q1. On average, approximately 80 percent of the original number of direct tickets in the DB1B is retained in the analysis.

After filtering the ticket data for each quarter of the DB1B, we combined tickets from all 55 quarters and collapsed the data into airline-route observations. For example, if we had 10,000 United Airline tickets between Boston and Los Angeles in 1993:Q1, we calculated summary statistics (such as the Gini coefficient), and collapsed the data into a single observation corresponding to a United Airlines flight between Boston and Los Angeles in 1993:Q1.

The merge between the DB1B and T-100 Segment databases was not exact (around 45 percent matched). First, since the DB1B does not provide complete coverage for all airlines and routes, there are a number of direct routes in the T-100 data that we do not find in the DB1B (especially low-volume routes). Second, the DB1B does not allow us to distinguish between a non-stop, direct ticket and a ticket that involves a stop without a plane change. For example, if a passenger takes a flight from Boston to Orlando that stops in Atlanta, but does not involve a plane change, his itinerary will look identical to that of a passenger who flies from Boston to Orlando without any stops. For this reason, we identified some airline routes as direct in the DB1B, that are not non-stop, and therefore do not have segment information in the T-100 data. While we lose many airline-route observations during the merge as a result, we believe that this merge actually provides a nice filter, since we would ideally like to use only non-stop, direct flights. Thus, by merging data between the DB1B and the T-100, we likely eliminate a

large proportion of flights that are direct, but not non-stop due to a plane change.

In an effort to eliminate possible coding errors, we drop certain airline-route observations from the data that we believe do not have adequate coverage to calculate reliable price dispersion statistics. We drop any airline-route observation that does not have at least 100 passengers in the DB1B. Furthermore, for each airline route observation, we calculate the average number of passengers over time in both the DB1B and the T-100 Segment databases. If the number of passengers on an airline route in a given quarter falls below 25 percent of its mean over time in one of the databases, but not in the other, then we drop the observation from our data, on the basis that its value is most likely measurement error. However, if the number of passengers on an airline route in a given quarter falls below 25 percent of its mean in both the DB1B and the T-100 Segment databases, then we keep the observation in our data.

Finally, we addressed the issue of "double counting." Since we defined a route as a directional trip in our data, any round-trip ticket would count twice. For example, a round-trip fare from Boston to San Francisco would appear twice in the data — once as BOS-SFO and once as SFO-BOS. Since this would have no effect on the consistency of our estimates, but a significant effect on the size of our standard errors, we chose to drop one of the directions. Of course, the drawback of this assumption is that some one-way fares were dropped from the data as a result. In our judgment, the first issue outweighed the second issue.

References

[1] Borenstein, S., Rose, N., 1994. Competition and Price Dispersion in the U.S. Airline Industry. *The Journal of Political Economy* Vol. 102(4), 653-683.

[2] Bils, M., 1987. "The Cyclical Behavior of Marginal Cost and Price. *American Economic Review* 77(5): 83855.

[3] Bils, M., 989. "Pricing in a Customer Market." *Quarterly Journal of Economics*, 104(4), pp. 699-718.

[4] Burnside, C, Eichenbaum, M., and Rebelo, S. 1993. "Labor Hoarding and the Business Cycle." *The Journal of Political Economy* Vol. 101, No. 2 pp. 245-273.

[5] Busse M., 2002. Firm Financial Condition and Airline Price Wars. *The RAND Journal of Economics* 33(2): 298-318.

[6] Busse, M., and Rysman, M., 2005. Competition and Price Discrimination in Yellow Pages Advertising. *The RAND Journal of Economics* 36(2): 378–390.

[7] Chevalier, J. and Scharfstein, D., 1996. "Capital-Market Imperfections and Countercyclical Markups: Theory and Evidence," *American Economic Review*, vol. 86(4), pages 703-25, September.

[8] Caves, D., L. R. Christensen, and M. W. Tretheway, 1984. "Economies of Density versus Economies of Scale: Why Trunk and Local Service Airline Costs Differ, *Rand Journal of Economics*, 15 (4), Winter, 471-489.

[9] Dana J., 1999. "Equilibrium Price Dispersion Under Demand Uncertainty: The Roles of Costly Capacity and Market Structure." *The RAND Journal of Economics* Vol. 30(4), 632-660.

[10] Dana J., 2001. "Monopoly Price Dispersion Under Demand Uncertainty." *International Economic Review* Vol. 42(3), 649-670.

[11] Domowitz, I., Hubbard,G. and Petersen, B. 1986. "Business Cycles and the Relationship between Concentration and Price-Cost Margins. *The RAND Journal of Economics* 17(1): 117.

[12] Eden, B., 1990. "Marginal Cost Pricing When Spot Markets Are Complete." *The Journal of Political Economy* Vol. 98(6), 1293-1306.

[13] Edmunds, C., and L. Veldkamp. 2006. "Income dispersion and countercyclical markups, *Journal of Monetary Economics* vol. 56(6), pages 791-804.

[14] Gali, J., 1994. "Monopolistic Competition, Business Cycles, and the Composition of Aggregate Demand," *Journal of Economic Theory*, 63(1), 7396

[15] Gerardi, K., and Shapiro, A.H., 2009. "Does Competition Reduce Price Dispersion? New Evidence from the Airline Industry." *Journal of Political Economy.* vol. 117(1), pages 1-37, 02.

[16] Gillen, D.W., T.H. Oum, and M.W. Tretheway, 1990. "Airline Cost Structure and Policy Implications: A Multi-Product Approach for Canadian Airlines, *Journal of Transport Economics and Policy.*

[17] Goodfriend, M. and King, R., 1997. The New Neoclassical Synthesis and the Role of Monetary Policy. In *NBER Macroeconomics Annual*, pp. 23183. MIT Press.

[18] Goolsbee, A. and Syverson,C. 2008. "How do Incumbents Respond to the Threat of Entry? Evidence from the Major Airlines," *The Quarterly Journal of Economics*, vol. 123(4), pages 1611-1633.

[19] Greenwald, B., Stiglitz, J. and Weiss, A. 1984. "Informational Imperfections in the Capital Market and Macroeconomic Fluctuations." *American Economic Review*, Papers and Proceedings), 74(2), pp. 194-99.

[20] Hall, R., 1980. Employment Fluctuations and Wage Rigidity. Brookings Papers on Economic Activity.

[21] Hayes, K., Ross, L., 1998. "Is Airline Price Dispersion the Result of Careful Planning or Competitive Forces?" *Review of Industrial Organization* 13: 523–542.

[22] Jaimovich, N., 2008. "Firm Dynamics, Markup Variations, and the Business Cycle." *Journal of Monetary Economics* vol. 55(7), pages 1238-1252.

[23] Miller, N. and Osborne, M., 2010. "Competition among Spatially Differentiated Firms: An Empirical Model with an Application to Cement", EAG Working Paper 10-2.

[24] Mussa, M. and Rosen, S. 1978. "Monopoly and product quality", *Journal of Economic Theory* 18, 301-317.

[25] Nekarda, C. and Ramey, V.,2009. "The Cyclical Behavior of the Price-Cost Markup," UCSD Working paper.

[26] Prescott, E., 1975. "Efficiency of the Natural Rate." *The Journal of Political Economy* Vol. 83(6), 1229-1236.

[27] Puller, S., Sengupta, A., and Wiggins, S. 2009. "Testing Theories of Scarcity Pricing in the Airline Industry," NBER Working Papers 15555.

[28] Rotemberg, J. and Saloner, G. 1986. "A Super-game Theoretic Model of Business Cycles and Price Wars During Booms." *American Economic Review*, 76(3), pp. 390-407.

[29] Rotemberg, J., J., and Woodford,M., 1991. "Markups and the Business Cycle," in *O.J. Blanchard, and S. Fischer (eds.), NBER Macroeconomics Annual 1991 Cambridge, MIT Press*

[30] Rotemberg, J. and Woodford,M., 1992. "Oligopolistic Pricing and the Effects of Aggregate Demand on Economic Activity," *Journal of Political Economy*, 100(6), 11531207.

[31] Shapiro, A.H. and Aizcorbe, A., 2010. "Implications of Consumer Heterogeneity on Price Measures for Technology Goods" *BEA Working Paper*.

[32] Stavins, J., 1996. Price Discrimination in the Airline Market: The Effect of Market Concentration. *Review of Economics and Statistics* Vol. 83(1).

[33] Stiglitz, J. 1984. "Price Rigidities and Market Structure." *American Economic Review*, 74(2), pp. 350-55.

Table 1: Full Sample Estimates

	$\ln(IQR)$		G^{lodd}	
YGAP	1.556***		1.149***	
	(0.199)		(0.103)	
-UR		2.073***		1.612***
		(0.286)		(0.149)
$\ln \widehat{HERF}$	0.256***	0.253***	0.085***	0.082***
	(0.042)	(0.042)	(0.023)	(0.023)
$\ln FUEL$	0.039***	0.026	-0.044***	-0.053***
	(0.015)	(0.016)	(0.009)	(0.009)
$\ln COST$	0.175***	0.154***	0.459***	0.444***
	(0.060)	(0.057)	(0.029)	(0.029)
Observations	154407	153706	156038	155331

Notes: All regressions include carrier-route-specific dummies. Standard errors are in parentheses and are clustered by route to account for both autocorrelation and correlation between carriers on the same route. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

Table 2: Full Sample Estimates: Percentiles

	ln(90)		ln(10)	
YGAP	1.144***		-0.040	
	(0.103)		(0.061)	
-UR		1.299***		-0.349***
		(0.149)		(0.103)
$\ln \widehat{HERF}$	0.299***	0.296***	0.218***	0.218***
	(0.029)	(0.029)	(0.015)	(0.014)
$\ln FUEL$	0.033***	0.022*	0.097***	0.097***
	(0.011)	(0.012)	(0.005)	(0.005)
$\ln COST$	0.293***	0.276***	-0.021	-0.022
	(0.033)	(0.032)	(0.015)	(0.015)
Observations	156038	155331	156038	155331

Notes: All regressions include carrier-route-specific dummies. Standard errors are in parentheses and are clustered by route to account for both autocorrelation and correlation between carriers on the same route. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

Table 3: Panel Estimates by Carrier Type

	Big-City Routes		Leisure Routes	
YGAP	2.690***		0.194	
	(0.350)		(0.467)	
-UR		2.184***		2.248***
		(0.474)		(0.605)
$\ln \widehat{HERF}$	0.347***	0.344***	0.195***	0.209***
	(0.078)	(0.078)	(0.048)	(0.053)
$\ln FUEL$	-0.062**	-0.090***	0.190***	0.194***
	(0.024)	(0.026)	(0.027)	(0.031)
$\ln COST$	0.120*	0.076	-0.085	-0.075
	(0.067)	(0.066)	(0.162)	(0.151)
Observations	43614	43614	35312	34611

Notes: The dependent variable is the logarithm of the interquartile range. All regressions include carrier-route-specific dummies. Standard errors are in parentheses and are clustered by route to account for both autocorrelation and correlation between carriers on the same route. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

Table 4: Panel Estimates by Route Type

	Legacy Carriers		Low-Cost Carriers	
YGAP	2.308***		1.007***	
	(0.223)		(0.174)	
-UR		2.307***		1.868***
		(0.313)		(0.269)
$\ln \widehat{HERF}$	0.191***	0.186***	0.307***	0.312***
	(0.049)	(0.049)	(0.039)	(0.039)
$\ln FUEL$	-0.013	-0.035**	0.217***	0.207***
	(0.016)	(0.016)	(0.012)	(0.012)
$\ln COST$	0.113***	0.075*	0.620***	0.640***
	(0.043)	(0.043)	(0.041)	(0.043)
Observations	105636	104994	40941	40926

Notes: The dependent variable is the logarithm of the interquartile range. All regressions include carrier-route-specific dummies. Standard errors are in parentheses and are clustered by route to account for both autocorrelation and correlation between carriers on the same route. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

Table 5: Panel Estimates by Subsample

	1993q1 - 2001q4		2001q1-2009q4	
YGAP	2.308***		1.094***	
	(0.468)		(0.159)	
-UR		2.494***		1.233***
		(0.796)		(0.207)
$\ln \widehat{HERF}$	0.457***	0.478***	0.211***	0.210***
	(0.053)	(0.053)	(0.043)	(0.043)
$\ln FUEL$	0.174***	0.147***	0.092***	0.091***
	(0.022)	(0.023)	(0.012)	(0.012)
$\ln COST$	0.220***	0.237***	0.297***	0.282***
	(0.046)	(0.047)	(0.050)	(0.048)
Observations	71276	70999	90889	90438

Notes: The dependent variable is the logarithm of the interquartile range. All regressions include carrier-route-specific dummies. Standard errors are in parentheses and are clustered by route to account for both autocorrelation and correlation between carriers on the same route. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

Figure 1: Operating Profits



Total operating profits are taken from the BTS's P-12 database and includes profits for carriers with annual operating revenues of $20 million or more. The output gap is the difference between actual and potential output as measured by the Congressional Budget Office (CBO) and the Bureau of Economics Analysis.

Figure 2: Pricing Dynamics

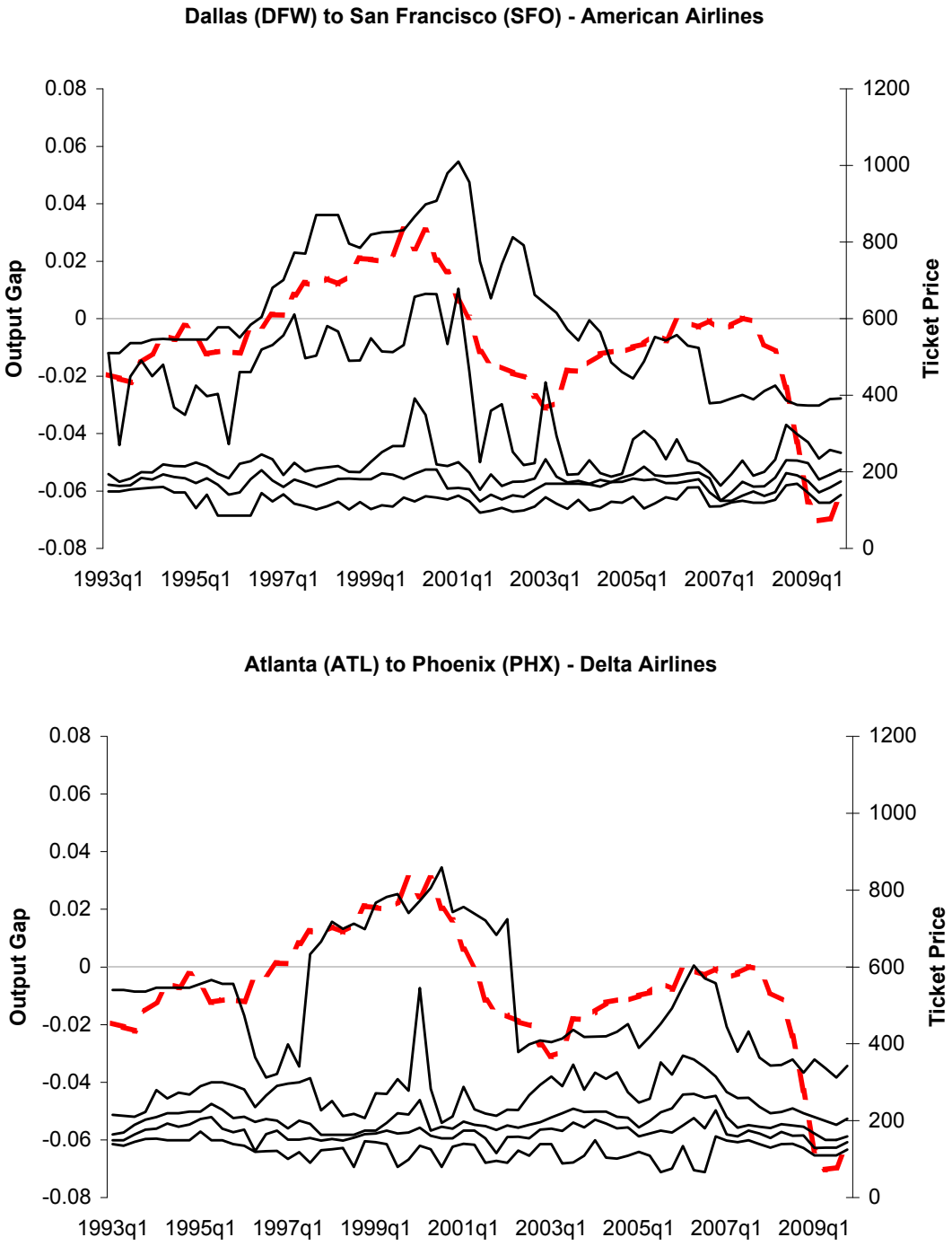


Figure 3: Aircraft Operating Costs

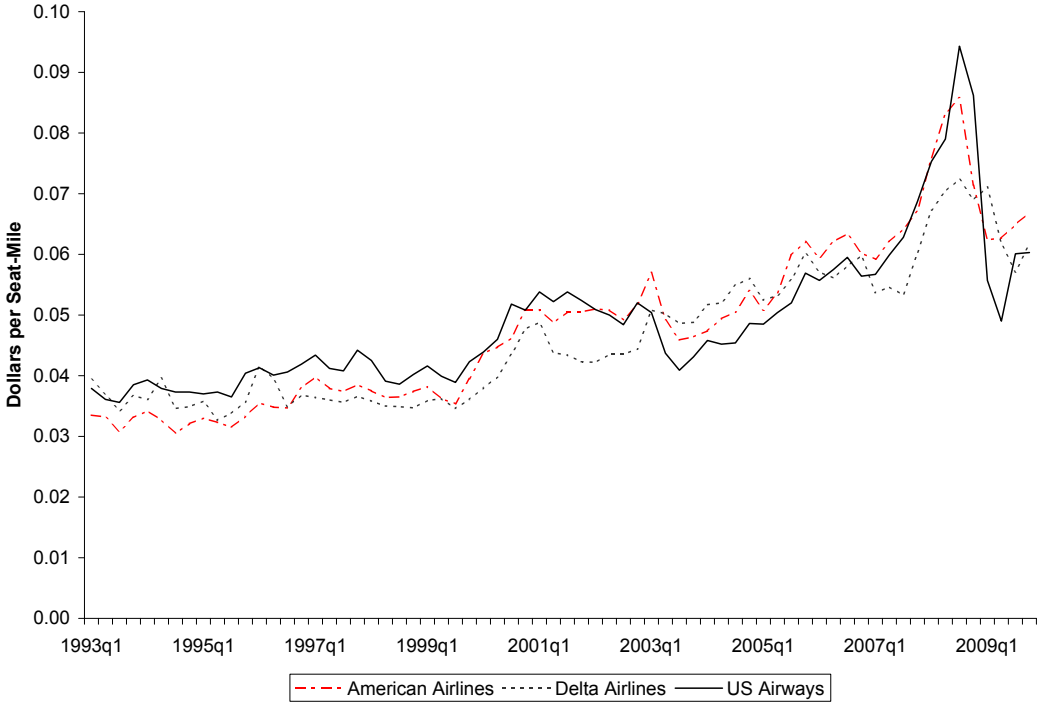


Figure 4: Aircraft Utilization Rate

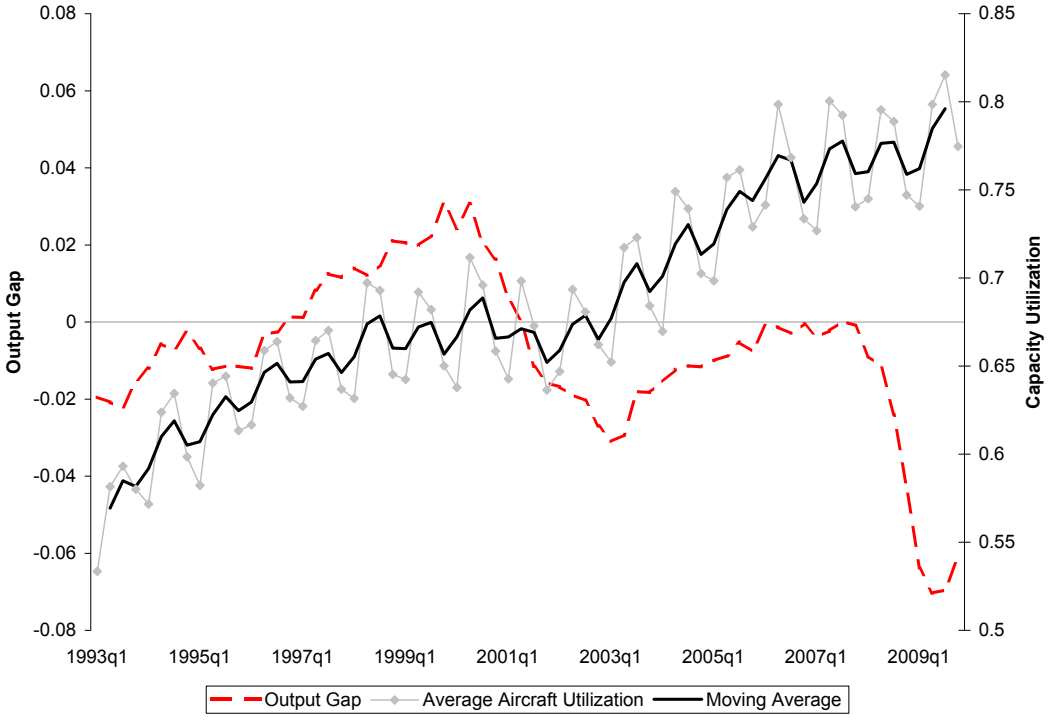
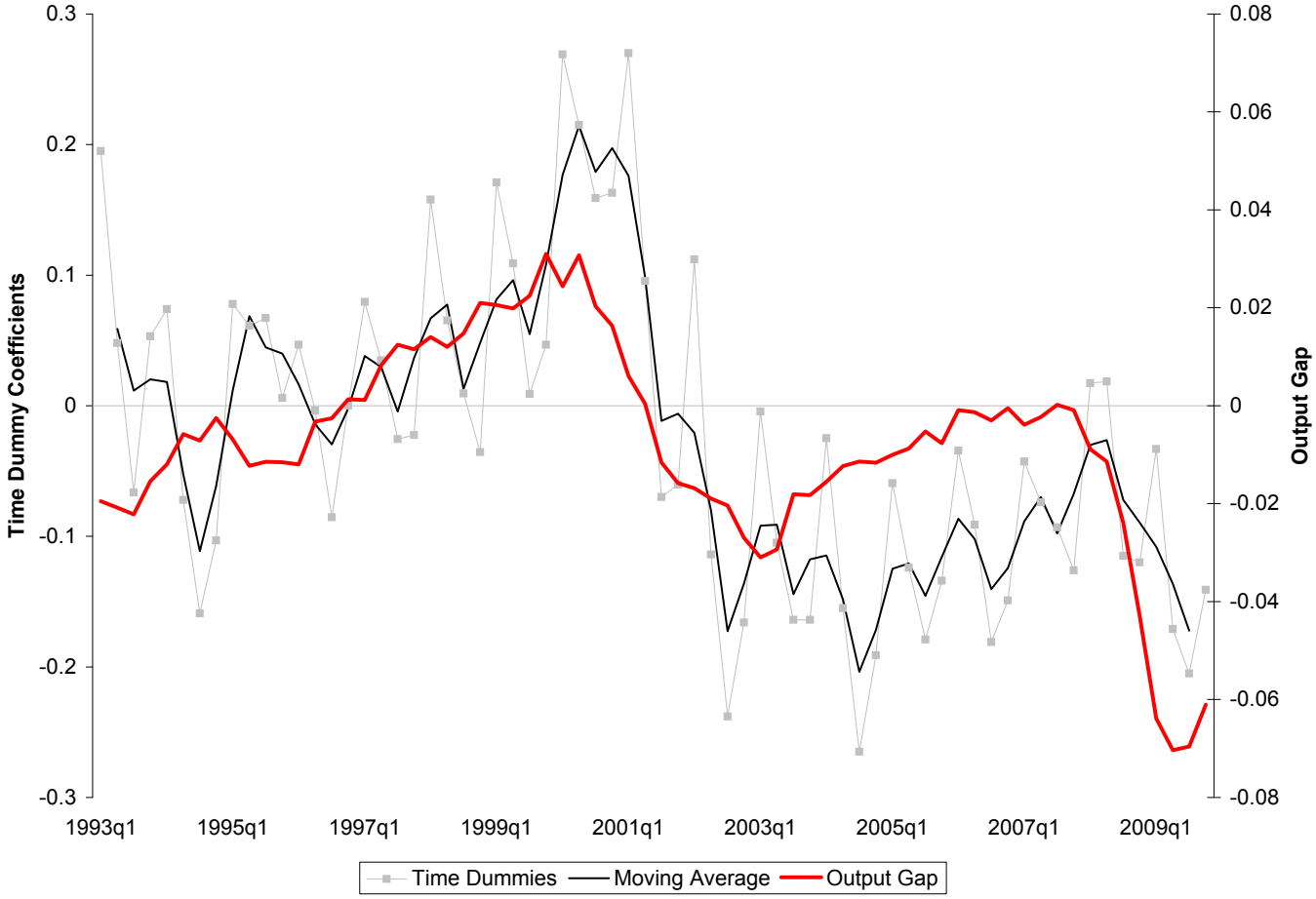


Figure 5: Time Dummies: Logarithm of Interquartile Range



Notes: Plotted in gray squares are the time dummies, γ_t, estimated from the following regression: $\ln IQR_{ijt} = \theta_0 + \beta_1 * \ln \hat{HHI}_{jt} + \beta_2 * \ln FUEL_{it} + \beta_3 * \ln COST_{it} + \gamma_t + \gamma_{ij} + \varepsilon_{ijt}$ on the sample of Legacy and Low-Cost carriers. The solid black line represents a three-month centered moving average of the time dummies.