Analysis of "Does Competition Reduce Price Dispersion? New Evidence from the Airline Industry" by Gerardi and Shapiro

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Introduction

The airline industry is well known for charging its customers different prices for identical services (same journey, same date, same time, same comfort class). Economists have been investigating the root cause of this price variations in the past. Can these price variations be explained by cost differences alone? To address this issue, Stigler (1987) proposed a mechanism of comparison. By comparing the ratio of the prices of two services with the ratio of their marginal production costs, it is possible to observe the existence of price discrimination. Hence, a pricing strategy is considered discriminatory if the two ratios are not equal. According to Phillips (1983), prices are discriminatory if the difference in marginal costs is not equal to the difference in prices. Unlike Stigler (1987), Philips proposed comparison of absolute differences.
According Trole (1988), price discrimination is defined as the practice of charging different prices for the same or very similar products that have the same cost of production based solely on consumers' willingness to pay. On the other hand, product differentiation refers to the practice of charging different prices for products with different service qualities. The airline industry seems to utilize both pricing strategies for maximizing profits.

A perfectly competitive market cannot exercise price discrimination because it's a price taker. According to traditional microeconomic theory, a firm can exercise price discrimination if the following conditions are met:

1. The firm must have some degree of monopoly power.
2. There must be differences in price elasticity of demand. The firm is then able to charge a higher price to the group with a more price inelastic demand and a lower price to the group with a more elastic demand.
3. The firm must be able to prevent re-sell of products.

Stole (2007) documented that price discrimination can be based on differences in consumers' underlying value of a good under competition. In other words, price discrimination can be based on differences in industry-elasticities of demand) and/or differences in consumers' degree of brand loyalty.

Borenstein and Rose (1994) argued that this price variation cannot be solely explained by cost differences. In a nutshell, the relationship between competition and price dispersion has been accorded due attention by researchers particularly in the airline industry. One of the reasons is that the two important prerequisites for price discrimination exist in the airline industry. Customers have different demand elasticities and airlines can differentiate between these two customer groups: demand from business travelers and leisure travelers. Demand from business travelers is less price elastic than leisure travelers. The airline industry uses some form of ticket restrictions such as advance purchase requirements, nonrefundable tickets and Saturday night stay overs to distinguish between these two groups.

Since deregulation of the airline industry in 1978, the existence of public data enabled researchers to empirically test pricing models. However, different empirical researchers have come up with different conclusions regarding the effect of competition on price dispersion in the airline industry.

Previous empirical studies such as Borenstein and Rose (1994) found that competition increased overall price dispersion by utilizing cross-sectional data. They argued that their findings support the brand loyalty pricing theory. This theory is based on firm's ability to cultivate some form of brand loyalty among its customers. When the theory of brand loyalty is applied to the airline industry, it predicts a new entrant will not affect high paying customers segment because they are members of the airlines' frequent flyer reward programs but affects the price conscious customers segment. Hence, the brand loyalty theory predicts a positive relationship between competition and price dispersion.

Gerardi and Shapiro (2009), on the other hand, utilized panel data to investigate what happens to price dispersion when more carriers start to compete on the same route. They found that competition has a negative effect on price dispersion particularly with those routes characterized by heterogeneous customer base but the effect of competition on price dispersion on routes characterized by homogenous customer base is smaller. This finding by Gerardi and Shapiro (2009) seems consistent with microeconomic theory predictions of competition and price discrimination. Being a price taker, a competitive firm cannot price discriminate. However, a firm with some monopoly power can exercise some form of price discrimination if there is difference in demand elasticities. But as competition increases, the level of price discrimination falls over time. Gerardi and Shapiro (2009) claim that competition in the airline industry has changed since the emergence of low cost carriers (LCCs) such as JetBlue or Southwest. Omitted variable bias is also cited as the cause of the discrepancy between Borenstein and Rose (1994) and Gerardi and Shapiro (2009).

Literature Review

The discussion concerning price discrimination and competition continues to be on going. One of the earliest papers to investigate the relationship is Gale (1993). In this paper, he developed a theoretical model of airline price discrimination to evaluate the effects of market concentration on price discrimination. His model shows a greater difference between advance-purchase fares and unrestricted fares in an equilibrium characterized by a non-cooperative duopoly than in an equilibrium characterized by a monopoly. In order to more fervently test this relationship, Borenstein and Rose (1994) empirically test the impact of competition on price dispersion. Using a cross-section of individual airline ticket prices, Borenstein and Rose (1994) calculated Gini coefficients for each airline-market pair. Regressing this measure on market concentration (Herfindahl index) and other factors through instrumental variables, they found that competition increased overall price dispersion. However, there is far from consensus.

Stavins (1996) documented a negative relationship between concentration and price discrimination. The data from the paper is from the Official Airline Guide. Information included when tickets were bought and other restrictions. Her other main finding was that, holding market share constant, higher market concentration leads to less price discrimination on a particular route. Likewise, Gerardi and Shapiro (2009) observed a negative relationship. They analyzed the effect of competition on price dispersion in the U.S airline industry using a panel data. Previous studies, leaned on cross-sectional data. Thus, panel data is an interesting contribution. As far as findings are concerned, Gerardi and Shapiro find as competition increases, competition decreases especially in those routes characterized by heterogeneous customer base. In addition, they found the effect of competition on price dispersion is less in those routes characterized by homogeneous customer base.

Most recently, Ambarish Chandra and Mara Lederman (2015) have empirically tested the effect of competition on price dispersion in the Canadian airlines industry and came up with different conclusion with the previous empirical research outcomes. They argued that both Borenstein and Rose (1994) and Gerardi and Shapiro (2009) effects can operate simultaneously. In general, their empirical findings showed two components: the impact of competition on price dispersion between brand indifferent business travelers and leisure travelers is likely to fall while price dispersion between brand loyal business travelers and leisure travelers is likely to rise. They assumed customers differ in terms of both their underlying value of a good and their degree of brand loyalty. They found that competition may increase price dispersion between some types of customers while decreasing in other types.

Other research has been focused on defining the functional relationship between price dispersion and competition. Mian Dai, Qihong Liu and Konstantinos Serfes (2012) investigated the effect of competition on price dispersion in the airline industry using a panel data from 1993-2008.They found a non-monotonic effect of competition on price dispersion. According to their findings, in concentrated markets, an increase in competition is associated with greater price dispersion. In less concentrated markets, however, an increase in competition is associated with less price dispersion (an inverse-U relationship). Their finding is consistent with oligopolistic second-degree price discrimination.

The goal of the research in this paper is to contribute to the debate. The research endeavor is to leverage the time-series element of cross-sectional data to observe fluctuations of ticket prices and dispersion overtime and the tendencies of airlines to decide pricing in relation to dispersion.

Data

In our analysis, our data covers 1993: Q1 -2008Q:4. The data is pooled from two central databases: the DB1B and T100. The T-100 data includes observations on enplaned passengers who originate and end their trips at the origin and destination airports and passengers with connection flights from other flights at the respective airports. The DB1B data contains only direct flights passengers who originate and end their flights at the respective origin and destination airports. The DB1B data set comprises three subcomponents: market data, coupon data and ticket data. Variables were combined from three of the above. Only domestic coach class itineraries and tickets containing direct flights were considered in the analysis. Direct flights constitute 30% of the itineraries in the DB1B sample. The most significant difference between the two the T100 and the DB1B is related to passenger counts.

The data in our analysis is most concerned around ticket prices. Ticket prices data were obtained from DB1B database which is a 10 percent random sample of all domestic tickets issued by the airlines. Tickets believed to be frequent flier tickets were eliminated from the sample. A cross-section was constructed in such a way that 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). The ticket price is defined as a single direction fare listed in the itineraries while prices of round-trip flights are one- half of the prices listed on the itineraries. The maximum was 34.2% in 2006Q1 and the minimum percentage was 22.8% in 1994Q2. Tickets arising from code- sharing arrangements (when the operating and ticketing carriers are different), were also removed. After filtering the ticket data from each quarter, tickets from the DB1B were combined and collapsed in to airline route observation. Overall, there are 606,015 airline route observations between 1993: Q1 -2006: Q3. After merging the 55 airline route data of the DB1B with the T-100, there are 274,821 airline route observations. The merge between the DB1B data and the T-100 data matched around 45% allowing for a robust sample to perform analysis.

Gerardi and Shapiro (2009) utilized direct coach class data of domestic airline tickets for the period of 1993: Q1-2006. Our analysis is therefore more of an expansion of their analysis and will be able to update the literature with current analysis of trends.

Model Construction and Methodology

Variables

There are several specifications that are of use in the analysis. Throughout the construction of the model, the estimation method has varied, but the variables that are core to the analysis will remain fairly unchanged. To measure price dispersion, the odds-log ratio of the gini-coefficient is used. This statistic is used to make the interpretation of the coefficients easier as it is an unbounded statistic. The gini itself is a measure of price dispersion amongst fare prices. The logs of the ticket prices at the 90th and 10th percentile are included for a separate reason. They are included to provide information concerning differentiated consumers. The 90th percentile is supposed to more indicative of consumers that are leisure travels, while the 10th percentile models the behavior of business and luxury travelers. The Herfindahl-Index is used as a measure of competition. It is found by squaring the market share of each firm and summing the results. Airline is an indictor variable. Date encapsulates 1993 quarter one to 2008 quarter four. It provides a cross-sectional element to data and enables for time-series analysis to be conducted.

Specifications

1. Log(P90) = $\beta_0 + \beta_1 \ln(\widehat{HHI}) + \beta_2 \widehat{Log(P10)} + \beta_3 \widehat{Ginilo} + \beta_4 \widehat{airline} + \beta_5 \widehat{date}$

2. Log(P10) = $\beta_0 + \beta_1 \ln(\widehat{HHI}) + \beta_2 \widehat{Log(P90)} + \beta_3 \widehat{Ginilo} + \beta_4 \widehat{airline} + \beta_5 \widehat{date}$

3. Ginilo $= \beta_0 + \beta_1 \ln(\widehat{HHI}) + \beta_2 \widehat{Log(P90)} + \beta_3 \widehat{Ginilo} + \beta_4 \widehat{airline} + \beta_5 \widehat{date}$

Motivating IV Regression

The initial model uses OLS to estimate the relationship between price dispersion and competition. The goal of this regression to motivate the use of Instrumental variables. Several regressions were run to this end. The first regression used ticket prices in the 10^{th} percentile as the dependent variable. In the second regression, ticket prices in the 90^{th} percentile were used. In the last regression, the Herfindahl index was used as the dependent variables. The explanatory variables were simply rotated from the previous dependent variables. To evaluate the regressions, a Durbin-Wu Hausman test was conducted per regression. This test determines if OLS estimates are consistent and evaluates endogeneity. To conduct this test, the regression uses the variable of interest as the dependent variables and regresses on the other variables. By taking the residual of the regression and using it as a dependent variable in the original regression, it is possible to test the significance of the variable. Also, though conducting a post-estimation F-test, the consistency of the OLS estimation may be determined. The interpretation of the result is that a rejection of null suggests that the estimates for OLS are inconsistent. This test was conducted as well with the price paid by the 90^{th} particle as the dependent variables. Both tests suggested that OLS estimates were inconsistent. This result suggests that an alternative approach is necessary.

VARIABLES	(1) 10th Percentile	(2) 90th Percentile	(3) HHI
ginilo	2.736***	4.727***	0.204
	(0.00836)	(1.22e-09)	(0)
lp10	5.677***	6.705***	0.122
	(0.0181)	(1.78e-09)	(0)
lp90	-4.421***	-7.460***	-0.276
	(0.0136)	(1.93e-09)	(0)
lp10_res	-5.677***		
	(0.0183)		
date	-0.00672***	-0.00313***	9.67e-05
	(3.84e-05)	(0)	(0)
lp90_res		7.460***	
		(1.97e-09)	
nlhhi_res			1
			(0)
Constant	4.020***	18.20***	1.516
	(0.0127)	(4.65e-09)	(0)
Observations	250,505	250,505	250,505
R-squared	0.320	1.000	1.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Instrumental Variable Approach

Given that OLS estimates are inconsistent, a different estimator should be used. The underlying issue is covariance with the error term. Using instruments provides a remedy for this issue. However, instruments must be both the relevant and valid. This approach is used by adding a variable that is correlated with the beta-hat that is to be recovered but is also simultaneously not correlated with the error term. If this is possible, then the estimation will consistently estimate beta-hat. A secondary approach uses two-stage least squares with Instrumental Variables. This process regresses each endogenous variable on the exogenous variables including each of the instruments being used. These predicted values are used as the basis in the second stage. By regressing these predicted values on the exogenous variables, a more consistent estimator can be obtained than by only OLS estimation. Thus, TSLS with IV may yield more consistent results and is the second estimation method used.

Arguments for Instruments

The instruments being used are the log of total passengers enplaned, the log geometric mean of Metropolitan statistical area population of end-point cities, and the geometric mean of enplaned passengers. The log of total passengers enplaned is an effective instrument. It is meant to instrument competition on HHI. Since the price that is being charged in the top 10^{th} percentile is related to the willingness of firms to fly specific routes, total passengers enplaned is able to encapsulate supply. It is also not likely correlated with other exogenous variables that are related to demand shifters. Consider the effect of a successful advertising campaign. While advertising may cause demand to shift through preferences, there are still fixed-inputs in terms of airlines. There are only so many seats and airplanes available at a given time. Since firms that have larger market share are likely to have higher amounts of these fixed-inputs, enplaned passengers to able to able to be correlated without picking-up on the static from other shifters in the error term.

A secondary instrument is the population of end-point cities. The population of end-point cities is correlated with the competition for smaller flights. For instance, there are likely far fewer airlines that fly smaller flights and are able to form a less competitive market that influences HHI. This is because airlines have less incentive to make these trips. What is the benefit of flying a route to Harrisburg to Pittsburg? Since few people are flying, it limits the amount of profit that can be obtained from flying this route, and thus there are a limited number of airlines that would fly it in the first place. This suggests that a monopoly may be more likely to form on these routes. Just as likely is that airlines are incentivized to fly between cities with the largest population. However, because there are more airlines flying these routes, there is less market share. Thus, HHI is correlated with population through competition.

Lastly, the number of total number of passengers on route is the last instrument. It correlates with HHI, since the firms with the most market share will have the most amount of customers per route. Likewise, the reasoning from the previous variable may be applied. If there are viewer options for less traveled flights, consumers may have fewer options to choose from the correlation is strengthened. While this relationship is apparent, this instrument may not be particularly strong. One concern that it may be affected by seasonality. For instance, in the summer, some leisure routes may be more popular. Tourists from Philadelphia are more likely to go to Miami in the summer for vacation than in other times for instance.

VARIABLES	(1) 10th Percentile	(2) 90th Percentile	(3) Log-Odds Gini
nlhhi	-0.248***	-0.156***	0.259***
	(0.0247)	(0.0300)	(0.0293)
air	- 0.00231* **	-0.00460***	-0.00476***
	(0.00033)	(0.000407)	(0.000397)
Constant	4.640***	5.691***	-1.252***
	(0.0134)	(0.0163)	(0.0159)
Observations	3,716	3,716	3,716
R-squared		0.028	0.059
Instrumented: nlhhi			
Instrument: ltot_route			
Instrument: lgmeansa			
Instrument: genp			

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Testing of Specifications

First Stage Statistics

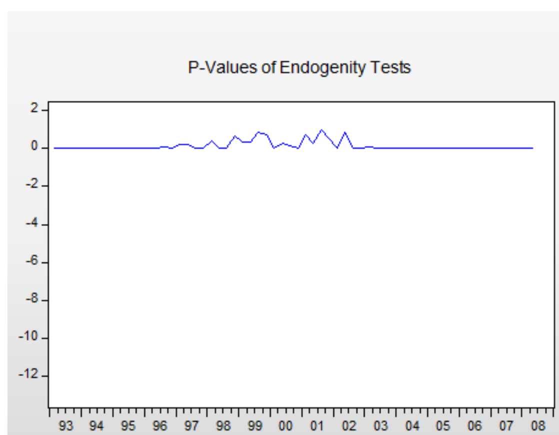
To further evaluate these specifications, robustness testing is required. The initial step taken is to review the First-Stage summary statistics from the two-stage IV regression. The first statistic of note is the R-squared from the first stage. This described the fit from the first-stage by OLS. Adjusted R-squared is also reported via the fit from the same regression. These statistics should not have much weight attached to their interpretation. Any variable that is forced into a regression will inflate the R-squared by the virtue of how it is calculated. Thus, the partial-R-squared should be used as a stronger indictor of the relevance of instruments. The partial-R-squared measures correlation between the variable being instrumented and additional instruments after partialling out the effect of other regressors. Lastly, F-statistics should be reviewed. It is a joint-significance test. If the null is rejected and that the difference between regressors is non-zero, then the instruments being used are relevant. This evaluation of statistics was conducted on each model throughout the entire time period. In each instance, an inspection of these statistics suggest that the instruments are relevant.

Overidentification Testing

Overidentification tests seek to evaluation the validity requirement for using instruments. While first stage statistics are used to test the relevance requirement. Both must be met to use a specific instrument. The tests for overidentification are used to test that excluded instruments are uncorrelated with the error term and are right in excluding them. The Baseman Chi Test and the Hansen J test are found by regressing upon the residuals of the IV estimation on the full set of instruments. Essentially, the test is attempting to determine if you have more instruments than endogenous variables. The results of the testing seem to suggest that the model may be overidentifed. In each specification under all time-periods with the cross-section, the Overidentifcation test is rejected. While this endows a sense of skepticism on the instruments being used, it may suggest that heteroskedasticity is an issue. It also may be overstated as an issue considering that an overidentifed model will be biased towards OLS estimates. Given that the specifications were already estimated using OLS, a comparison between coefficients provided through OLS and coefficients produced through a rotation of instruments will provide a robust model for analysis.

Endogeneity Testing

Endogeneity testing is required to evaluate if regressors that fit previous iterations of the model are still endogenous to the model. It provides a stronger sense of confirmation. The test that is conducted is a Wu-Hausman test. This test has already been explained when motiving IV regression. The result of the testing in the third specification with the logs-odd gini as the dependent variable has an unexpected result from testing. The test shows no issues with endogenity in certain time periods and is problematic in others. It appears that heteroskedacity may be influencing the validity of the



results. Given the amount of variation in certain time periods and the consistency of results in others, it seems likely to be a factor. This analysis effectively motivates for tests of heteroskedasticity.

Heteroskedasticity

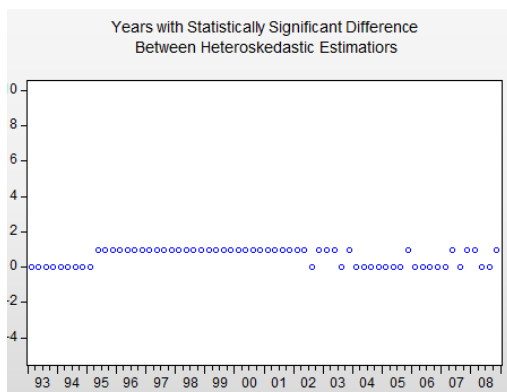
The Hall-Pagan test can be used to determine the presence of heteroscedasticity in IV regression. When this test among various other tests for heteroscedasticity (Breusch-Pagan, White/Koenker…) the results of the testing reject the null of homoskedascity in each specification and during all segments of the cross-section. Thus, the presence of heteroskedatic data suggests that GMM should be used as it is the more efficient estimator under these conditions.

Competing Heteroscedastic Estimation Methods

GMM is the preferred estimator under heteroscedasticity. There are two models derived from basic GMM that were considered. The first estimation method considered is IV-GMM. The second estimator considered is two-step GMM with IV. The IV-GMM estimator is analogous to the to the two-step IV approach. By using GMM instead of OLS in the first stage, the estimator is more efficient. Also, in heteroscedasticity, IV-GMM provides more efficient in overidentifed models[1]. Given the concern about overidentifcation, this estimator is effective.

The two-step GMM with IV with robust standard errors is the model that was selected. The main reason for opting for the two-step GMM is that it has been found to yield stronger results than only GMM.[2] Given the concern over previous robustness testing, two-step GMM may be preferred the estimator to use.

To compare the results from the regressions, a Hausman test was conducted. This test essentially compares the difference in variance to determine if it is positive definite. The results from this test were problematic. The data fails to meet the asymptotic assumptions of the Hausman test during many segments. This occurs in 1993-1994 and from 2004-2008. The differences in the model seem to be more pronounced from 1995-2003. In the years that are able to be tested upon, the null hypothesis is that there is no systematic difference between coefficients is rejected. The "1" in the graph significant when this null was rejected. The "0"'s signify when the test could not be conducted. Given that there is a difference



in the results from these two estimation methods for the majority of quarters, the more reliable estimator is more reasonable of the two to use. Thus, two-stage GMM with IV is selected over

[1] http://fmwww.bc.edu/EC-C/S2014/823/EC823.S2014.nn02.slides.pdf
[2] https://econweb.ucsd.edu/~yisun/Unified_paper_one_two_July24_2015_longer_version.pdf

GMM-IV, given the properties of two-stage GMM to yield more definitive results from statistical testing.

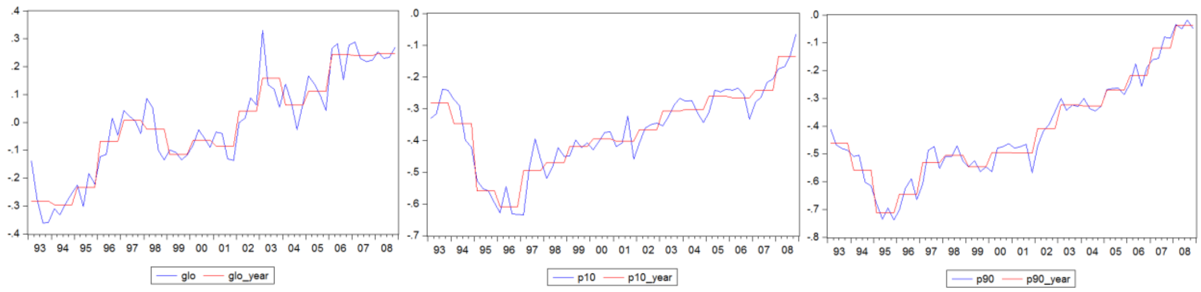
Rotation of Instruments and Refinements

The last procedure in refining the specification is the rotation of instruments. Even after correcting of heteroscedasticity, the overidenifcation tests suggest the model was over identified. By estimating the regression with various combinations of instruments, the exclusion of the log geometric mean of the population of Metropolitan Statistics Areas as an instrument may improve the model. When excluded from the regression the overidenification tests were no longer problematic. This did not occur while excluding the other instruments. One point of consideration is that overidentification tend to yield false positives with highly grouped data used as an instrument.[3] This is the results of intra-class correlation. However, the structure of the data was not conducive to testing. An intra-class coefficient could only be calculated with the non-transformed HHI and gini. Thus, without an effective means to test for the degrees of intra-class correlation, it is safer to remover a potentially invalid instrument then include it as an instrument on the chance tests are being biased. Thus, the final specifications are only using the geometric mean of enplaned passengers and total passengers on a route as instruments with two-sage GMM.

Results

In the following section we will discuss the changing nature over time of our 2-stage GMM coefficients. To recall, for each of the 3 sets of regressions in our model, for observations for each year-quarter separately, we regress log-odds Gini Index $ln(\frac{Gini}{1 - Gini})$ (constructed to span from -∞ for a value of Gini = 0 or no dispersion, to +∞ for a value of Gini = 1 or total dispersion,) logged 10^{th} percentile of ticket prices, and logged 90^{th} percentile of ticket prices, on a full set of carrier dummies, as well as the fitted value, $-\ln(\hat{HHI}_{route})$, from the first stage where we instrumented for $-\ln(HHI_{route})$ with LTOT_ROUTE, the logged value of the total number of enplaned passengers along the route, and GENP, Gerardi and Shapiro's instrument consisting of the geometric mean of enplaned passengers at the endpoints of the route, using $-\ln(HHI_{route})$ for ease of understanding with respect to an analysis of competition (as a value of 0 for HHI= 1 represents no competition, with the value increasing towards +∞ as HHI decreases towards 0 represents increasing levels of competition, measured by a greater split of market share.)   From here, for the sake of brevity, we will refer to each of our coefficients as: $\boldsymbol{\gamma_{glo}}$ for the coefficient on $-\ln(\hat{HHI}_{route})$ in the regression of log-odds Gini Index, $\boldsymbol{\gamma_{p10}}$ for the coefficient on $-\ln(\hat{HHI}_{route})$ in the regression of logged 10^{th} percentile ticket price, and $\boldsymbol{\gamma_{p90}}$ for the coefficient on $-\ln(\hat{HHI}_{route})$ in the regression of logged 90^{th} percentile price.

[3] Overidentifcation tests with Grouped Data file:///C:/Users/ram478/Downloads/SSRN-id226633.pdf



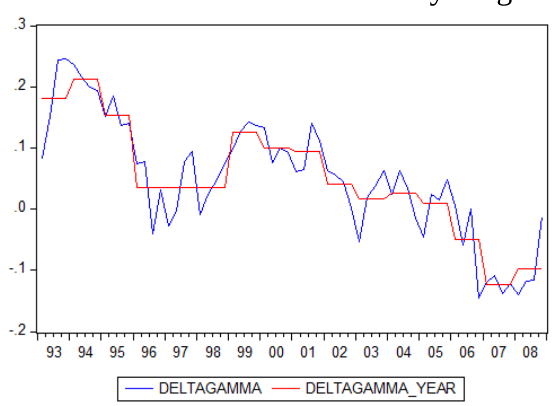
Shown above, from left to right, are the time series plots from 1993Q1 to 2008Q4 of $\boldsymbol{\gamma_{glo}}$, $\boldsymbol{\gamma_{p10}}$, and $\boldsymbol{\gamma_{p90}}$, respectively, with seasonal cycles shown in blue, and year averages shown in red. Looking at the time series for $\boldsymbol{\gamma_{glo}}$, we can see that our results appear to be partially in opposition to those of Gerardi and Shapiro, who found in their paper that the coefficient on $-\ln(H\hat{H}I_{route})$ was negative, indicating that increasing amounts of competition had the effect of reducing dispersion. We find that, while from 1993Q1 through 2001Q4 (which is when the September 11 terror attacks occurred,) except for a brief period consisting of the year of 1997, the year-average coefficient is negative like Gerardi and Shapiro's, in 1997, and after 2002Q1, it becomes positive, which would seem to indicate that more competition increases dispersion after this point. On average for all year-quarters, the effect is still slightly negative, albeit at -0.01, an entire order of magnitude smaller than their coefficient. For the time series of $\boldsymbol{\gamma_{p10}}$ and $\boldsymbol{\gamma_{p90}}$, our results alight with their findings that competition reduces ticket prices for both the 10th and 90th percentile. In order to elucidate further, we regressed each of our three coefficients thrice on, respectively, indicator variables for route presence of monopoly, duopoly, and competiveness (the latter meaning any time there are more firms present than the 2 in a duopoly.) In each of these total 9 regressions, both the intercept as well as the coefficients on [mono, duo, comp] were significant at better than the 1% significance level. For $\boldsymbol{\gamma_{glo}}$, the respective coefficients on mono, duo, and comp were 0.011, 0.007, and -0.009; for $\boldsymbol{\gamma_{p10}}$, they were 0.001, -0.006, and 0.007, and for $\boldsymbol{\gamma_{p90}}$ they were 0.007, -0.011, and 0.004. (Appendix)

These estimates provide a possible explanation for why our results seem to differ from those of Gerardi and Shapiro. For monopoly, we can see that the effect of its presence is larger for the 90th percentile than it is for the 10th, and both are positive, meaning that for some given span of prices, a monopoly increases the top of the distribution more than the bottom of the distribution, leading to greater dispersion. For duopoly, the effect is again larger for the 90th percentile than it is for the 10th; however, these effects are negative, and so have the effect of decreasing the top of the distribution more than the bottom, which leads to a narrower (i.e., less dispersed) distribution. For competition, like monopoly, the effect is to raise both ends of the distribution. However, in contrast to the monopolistic findings, competitiveness raises the top end of the distribution *less* than the bottom, which results instead in a narrower distribution. Interestingly, duopoly shares effects with both monopoly and competition, but in different ways:

like monopoly, its effects are of a greater magnitude for the top of the distribution than the bottom, but, like competiveness, it has the effect of narrowing the distribution.

However, even though these interesting effects of duopoly are not discussed in the paper by Gerardi and Shapiro, our findings do align with their idea that competition reduces dispersion, at least in the idea that the more competitive schema of 'duo' and 'comp' reduce the coefficient on $-\ln(\hat{HHI}_{route})$ in the log-odds Gini regression. Why, then, do we see that, from 2002 onwards, more competition appears to increase dispersion? One possible explanation steps from the fact that the average number of carriers declines over our sample period, though only from around 1.8 to around 1.7. But this change should enter HHI, and thus be accounted for when determining the coefficients. Perhaps, given that we begin to see the positive effects after September 11, 2001, there is something that changes afterwards regarding the effects of competitive structure. But since they accounted for time, what remains is the thing that they said they did not completely account for—carrier-specific factors besides bankruptcy. In particular, given the large increase in security restrictions after September 11, one might consider that smaller airlines incurred costs of a greater percentage of their income than larger airlines did. In other words, the reduction in dispersion which they ascribed to greater competition could actually be a consequence of the ticket prices of smaller carrier increasing more across all routes compared to the prices of larger carriers, along with the fact that more competition—more carriers operating on a route—would then show this differential to a larger degree than routes with few carriers.

Given that the change in $\boldsymbol{\gamma_{glo}}$ appears to be largely attributable to the changes of $\boldsymbol{\gamma_{p10}}$ and $\boldsymbol{\gamma_{p90}}$, we next determined to look at the time-series of the difference equal to $\boldsymbol{\gamma_{p90}}$ minus $\boldsymbol{\gamma_{p10}}$, which will from here be referred to as $\boldsymbol{\Delta\gamma}$. This is interpreted as the percent change of [a percent change of p90 with respect to a percent change in p10] with respect to a percent change in HHI. In other words, for a given change in HHI, $\boldsymbol{\Delta\gamma}$ tracks how much the 90th percentile price changes as compared to how much the 10th percentile price changes. For ease of understanding, we plot, in the following chart, the negative of this number (as well as the negative of the year average), as these two coefficients are always negative. When the graph is above 0, $\boldsymbol{\gamma_{p90}}$ is lower than $\boldsymbol{\gamma_{p10}}$, meaning an increase in competition will decrease 90th percentile prices more than it decreases 10th percentile prices; when below 0, it is the opposite. As we can see, there is a strongly decreasing trend here, meaning that as time goes on, the magnitude of changes to the 10th percentile become larger when compared to the 90th percentile; the periods where this plot is negative (where the magnitude of 10th percentile changes is greater than of 90th percentile changes) coincides with the periods when



our original plot of γ_{glo} is positive—meaning the periods where increasing competition increases dispersion appear to be the same as the periods where increasing competition decreases 10th percentile prices more than it decreases 90th percentile prices.

To attempt to inform our findings as to whether relatively individually determined pricing attitudes are the source of changes in dispersion with respect to competition, or the other way around, we decided to perform pairwise Granger Causality Tests on our 3 coefficients. (Appendix) We found statistically significant findings that γ_{glo} causes γ_{p10} and γ_{p90}, as well as γ_{p10} and γ_{p90} causing each other. From this, we deduce that the source of pricing differentials is internal (unobservable-to-econometricians) firm attitudes for reacting to competition—i.e., that firms seek a certain pricing differential for given amounts of competition. But which prices do they tend to change? We know that for most of the time period, the changes in the 90th percentile with respect to competition are bigger than the changes in the 10th—as the average value shows γ_{p90} being more negative than γ_{p10} overall From this, we can claim that the reasoning for the F-statistic values in our Granger tests is the following: overall, there are firm attitudes towards dispersion for certain levels of competition. In the beginning of our sample period, these attitudes entered through γ_{p90}; the reason for the apparently larger effects of dispersion attitudes on 10th percentile pricing attitudes comes from the fact that the tests are only pairwise, and so exaggerate the effect of γ_{glo} directly on γ_{p10}, when actually the effect occurs with γ_{p90} as a mediator. However, as the sign of the difference of these coefficients changes towards the end of the sample period, we believe that attitudes have been changing towards those that favor alteration of lower percentile prices with respect to competition. To be more succinct as to the differences from Gerardi and Shapiro's conclusions, would be the following: whereas towards the beginning of the sample period, firms decrease higher-percentile prices in response to competition, narrowing the distribution, as time goes on they are increasingly choosing to decrease lower-percentile prices, thus widening the distribution.

What might be the airlines' reasons for this shift? It seems illogical, going off modern airlines' claims that is cheaper to travel today than it was before air industry deregulation in the 70s—why reduce the cost of the lowest end of tickets, especially when more lower-income travellers are flying as time goes on? If one only looks at fares, it does not seem to make sense to decrease those lowest ones, especially as the markup on business-class tickets is going to be much higher than coach-class—after all, once those comfy seats have been paid to be installed, the only difference between coach and business is a thin curtain, plus amenities like food and drink that can be charged more for anyway. But it is not ticket prices that have seen the rise of airline profits, but 'PRASM'—passenger revenue per available seat. Airlines have chosen to shift profit-making away from overt fare, and instead charge for a bevy of amenties—remote booking, excess baggage fees, early boarding, and the like—which, taken all together, make a modern flight cost more than a pre-deregulation flight, given identical amenities. And now, many of those cheapest tickets which comprise the 10th percentile are now marked by one enormous difference from cheap fares of yore—the fact that they are often non-refundable. Given modern obsessions with coupon-clipping and 'on-sale', and the prevalence of websites allowing consumers to find the cheapest ticket prices, airlines have found a way to oblige these penny-pinching habits while still increasing profits, which is to perform a bit of a bait-and-switch, hoping that customers' pursuit of 'the deal' will have them click first and ask questions later, or, ideally, to not ask any questions at all as they fail to make a strict ledger of small amenity payments and so fail to see the full costs of travel. The reason for the change, then, is that profits come less and less from markup on expensive seats, and more on markup on amenities for inexpensive seats. The period after 9/11 seems to make sense as the time to widely institute these changes, as it could prevent leisure travellers—who, unlike business travellers, are not obliged by their companies to travel regardless of recent air terror incidents—from fleeing air travel, by dropping fares enough that their fears will be allayed in the face of these low ticket prices, while simultaneously taking advantage of these travellers relatively more lacking abilities to judge how much their flights truly cost. After all, unlike companies, the standard coach traveller does not have a bookkeeping department.

These conclusions can guide potential policy changes for the new decade to come. One way of fighting this new form of price discrimination (in ways, a reverse-price-discrimination, based on the fact that those who segment themselves into the want-to-pay-less tier actually pay more than they think) could be to set certain benchmark ratios of highest to lowest fares for a given carrier flying a given route. In this way, firms would have to decrease upper-percentile fares by a particular amount if they decrease lower-percentile fares, and it will be harder for them to take advantage of poor bookkeeping for business travellers. It would be hoped that they would choose to decrease those higher fares in this situation, as increasing the lower fares would cause the sale-seeking travellers to take their business elsewhere. Or, a very direct approach could be to mandate that firms make very clear exactly how much a ticket can cost with amenities, at the point of sale, or to have to list all possible fare additions, so people could do the calculations themselves. Perhaps a better idea is to place a tax on the difference between minimum and maximum fare for a given seat; or, to better encourage competition in the free market, tax deductions or other preferential treatments—for example, giving more choices on things like gates to fly into and out of, more beneficial taxi schedules, etc.—could be given to firms who make their amenities cost a smaller percentage of ticket fare.

What Gerardi and Shapiro may fail to realize when they make the claim that "It is clear that [the erosion of carriers' ability to segment markets] is due to a loss of market power that typically accompanies the entry of a new competitor…" is that neither market segmentation nor price discrimination has to be wholly revealed by ticket prices. Instead, since websites allowing comparison of ticket price virtually force firms to perfectly compete with respect to ticket fare vs. ticket fare, airline profits increasingly stem, instead, from optional amenity fares—the costs of which are so obfuscated, and the abstainence of which is so heavily mourned by economyclass travellers—which do not enter consumers' airline vs. airline calculations exactly because of their optional nature.