RISE | RICE INITIATIVE *for the* STUDY *of* ECONOMICS

RISE Working Paper 15-023

"Measuring Market Power When Firms Price Discriminate"

By Levent Kutlu and Robin C. Sickles

RICE Department of Economics
Baker Hall, MS22
6100 Main Street, Houston, Texas 77005
https://economics.rice.edu

Measuring Market Power When Firms Price Discriminate

Levent Kutlu
Department of Economics
Antalya International University

Robin C. Sickles
Department of Economics
Rice University

November 23, 2015

Abstract

We propose a conduct parameter based market power measure within a model of price discrimination, extending work by Hazledine (2006) and Kutlu (2012) to certain forms of third degree price discrimination. We use our model to estimate the market power of U.S. airlines in a price discrimination environment. Market power estimates from our single-price conduct model are larger than those estimated from the standard price discrimination model.

Keywords: Price discrimination, market power, conduct parameter, productivity, cost efficiency

JEL codes: C57, L13, L40, L93

1 Introduction

A widely used market power measure is the Herfindahl-Hirschman index (HHI). One potential issue with the HHI is that it ignores whether or not firms price discriminate. A simple example illustrates this problem. Consider two duopoly markets where in one market firms charge a single price and in the other market firms price discriminate. If the market shares of the duopolists are the same, then the HHI would indicate that these two markets have the same market power. This is a questionable conclusion. We address this issue by proposing a conduct parameter measure of market power in the price discrimination framework.[1]

The relationship between price discrimination and market power has been extensively researched. In a theoretical setting, Dana (1999) shows that when capacity is costly and prices are set in advance, firms facing uncertain demand will sell output at multiple prices. As the market becomes more competitive, the prices become more dispersed. Hence, the model of Dana (1999) supports a negative relationship between market power and price dispersion. On the other hand, McAfee, Mialon, and Mialon (2006) find no theoretical connection between the strength of price discrimination and market power. Dai, Liu, and Serfes (2014) show that the relationship between the unit transportation cost (intensity of competition) and price dispersion (measured by the Gini coefficient) is non-monotonic and can be inverse U-shaped. As for the empirical literature, Borenstein and Rose (1994) and Stavins (2001) find a negative relationship between price dispersion and market power. Gerardi and Shapiro (2009) show a positive relationship, while Dai, Liu, and Serfes (2014)[2], and Chakrabarty and Kutlu (2014) show a non-monotonic relationship between market power and price dispersion. These studies rely on the HHI when

[1] See Perloff, Karp, and Golan (2007) and Stole (2007) for extensive surveys on market power and price discrimination, respectively.

[2] Dai, Liu, and Serfes (2014) study price dispersion both theoretically and empirically.

examining this relationship.[3] It would seem, however, that for these studies a term such as price dispersion would be more appropriate than price discrimination. This is due to the need to control for the effect of costs in order to properly identify price discrimination, which these studies do not do as they utilize reduced form regressions to estimate the degree of price discrimination instead of using a structural empirical model.[4] In contrast we estimate a structural model that is consistent with our theoretical model of third degree price discrimination.

Our market power measure is specifically designed to capture price discrimination. Hence, when firms price discriminate our measure is designed to better identify the presence of market power compared with measures ignoring price discrimination. By utilizing our conduct parameter game, we can show that for a variety of sensible scenarios a positive relationship is supported. Earlier studies (e.g., Stavins 2001) relate the breakdown in this positive relationship to differences in the demand structures of high-end and low-end consumer segments. In contrast to this view, our model illustrates that such a breakdown can be due to different rates of changes for the conducts of high-end and low-end segments and/or different demand structures. Conduct is a supply related concept and is associated with the way firms play the game. By saying "conducts of high-end and low-end segments" we differentiate potentially different conducts of firms that the firms implement for different consumer segments.

The presence of price discrimination using a single-price index also can lead to biased estimation results. The first estimation problem concerns the demand equation. Consistent estimation of the price elasticity of demand is important for deriving consistent conduct parameter estimates. A second estimation problem involves the supply equation.

[3] See Kutlu and Wang (2015b) for a study using conduct parameter estimates that are obtained from single price models.

[4] Price dispersion may happen for reasons other than cost differences and market power. For example, in a framework with identical firms (same marginal costs), Kutlu (2015) shows that if the consumers have limited memories even when each firm sets a single price, price dispersion may exist.

While the single-price version of the conduct parameter game necessitates some functional form assumptions on the marginal cost so as to identify the conduct parameter, in the price discrimination framework we do not have to make any such assumptions.[5] The reason is that the price discrimination version of the conduct model can be written in a form that does not require knowledge of marginal costs. However, the researcher must specify the high-end and low-end prices as well as corresponding quantities. These prices and quantities can be obtained in an ad hoc way or can be determined by econometric analysis.

We consider the U.S. airline industry in order to illustrate how our theoretical model can be applied to measure the market power of firms who price discriminate. We estimate the market power of U.S. airlines under both price discrimination and single-price settings during the period $1999I$ to $2009IV$. This enables us to examine the consequences of ignoring price discrimination. The market power estimate when price discrimination is ignored is equal to 0.23, which is close to the theoretical market power level for a symmetric Cournot game. However, when we control for price discrimination, the market power of the U.S. airlines turns out to be considerably lower. In particular, the conduct estimates for high-end and low-end segment are 0.133 and 0.098, respectively. This indicates that the high-end segment is relatively competitive and the low-end segment is very competitive. An important implication of these results is that if the antitrust authorities ignore price discrimination in their market power estimation, they might incorrectly block beneficial mergers. We observe that the conducts of high-end and low-end consumer segments are statistically different. Hence, a single-conduct-parameter model might not be able to capture market power properly.

In the next section we introduce our theoretical model. This is followed by the em-

[5]This assumes a homogeneous product market. If high-end and low-end products have different cost structures, then we still have to make some functional form assumptions on the marginal cost.

pirical model and estimations, and finally our conclusions.

2 Theoretical Model

2.1 Supply Side

In this section, we introduce a conduct parameter model, which enables us to measure market powers of firms in the price discrimination framework. There are N firms in the market. Each consumer buys no more than one unit of the good. The distribution of customer valuations is known to the firms and resale of the good is not possible. The customers are segmented into *bins* based on their reservation prices. The price of the good for the k^{th} bin is given by:

$$P_k = P(\sum\nolimits_{i=1}^{k} Q_i) \tag{1}$$

where $q_{i,n}$ is the quantity sold in bin i by firm n; $Q_k = \sum_{n=1}^{N} q_{k,n}$ is the total quantity sold in the bin $k = 1, 2$; and P is an inverse demand function that represents consumers' valuations.[6] In our empirical illustration the market is segmented into two bins ($K = 2$) and we discuss our model using the two bin segmentation in the discussion to follow. The total quantity demanded in the market is denoted by $Q = Q_1 + Q_2$. Hence, $P_1 = P(Q_1)$ and $P_2 = P(Q_1 + Q_2) = P(Q)$. Following earlier studies that use this demand structure, we concentrate on the airline industry. The valuation of a buyer is a function of characteristics of the ticket including the time of the purchase. The business travellers, whose plans are often made with relatively minimal lead times and which tend to be

[6] Varian (1985) [Section I], Formby and Millner (1989), Hazledine (2006, 2010), Kumar and Kutlu (2015), and Kutlu (2009, 2012) use this demand structure based on the valuations of consumers. None of these models are based on the conduct parameter approach.

relatively inflexible, have high valuations whereas the tourists, whose plans are generally flexible, have relatively low valuations. Hence, the airlines can optimally group the buyers based on the day they want to buy a particular airline seat and the lead time in reserving the seat.

In our conduct parameter model the consumer segmentation is optimal in the sense that the size of each bin is determined by the firm. This contrasts with price discrimination models wherein each segment is taken to be exogenous to the firms so that each segment is taken as a separate market. In a commonly used third degree price discrimination scenario we would have two separate markets determining each segment so that the demands of consumers belonging to these segments are independent of each other. This sort of price discrimination may be reasonable were the segments fixed, say by gender or race. Segmentation by race is considered by Graddy (1995), among others, in her work on third degree price discrimination.

However, in a market where reservation prices depend on the age of customers, firms could choose quantities indirectly by choosing a threshold age. In this setting, customers who are older than the threshold age would be assigned to bin 1 and the rest assigned to bin 2. The firm could then implicitly decrease the size of bin 1 by increasing the age threshold. In the airline context, airlines can segment customers by choosing the number of days before the flight. If the firms can adjust the segment size then our model can capture this behavior.

2.2 Demand Estimation

Demand estimation is an essential part of market power measurement and below we examine how demand estimates are biased when price discrimination is ignored. As Nash equilibrium is a special case of the conduct parameter setting, we illustrate the

problems in demand estimation using this special case. The qualitative results are the same for the conduct parameter setting. As in the earlier section, assume that the firms segment their customers based on their reservation prices. The researcher observes the average price, $\bar{P}$, rather than the demand function, P, representing the valuations of customers. While for the single-price scenario there is no distinction between $\bar{P}$ and P, for the price discrimination scenario $\bar{P}$ and P are not the same. If the researcher assumes that a single-price index, $\bar{P}$, constitutes the demand function, then this would lead to a systematic measurement error. We consider a linear inverse demand function:

$$P(Q) = \alpha + \beta Q \tag{2}$$

where $\beta < 0$. Based on our price discrimination model, in the Nash equilibrium we have $\frac{Q_1}{Q_1+Q_2} = \frac{N}{N+1}$. Hence, the corresponding average price function is:[7]

$$\begin{aligned} \bar{P}(Q_1, Q_2) &= \frac{P_1 Q_1 + P_2 Q_2}{Q_1 + Q_2} \\ &= P_2 + (P_1 - P_2)\frac{Q_1}{Q} \\ &= P(Q) - \beta \frac{N}{N+1} Q_2. \end{aligned} \tag{3}$$

The relevant first order conditions for the conduct parameter setting, which is more general than a Cournot competition, is given in the next section. To estimate this relationship the researcher would collect data for total revenue, $\bar{P}Q$, and total quantity, Q, in order to construct the dependent variable for the demand function. The $(\bar{P}, Q)$ pair then would be viewed as constituting the demand function and thus it would be assumed by the researcher that $\bar{P}(Q) = \alpha + \beta Q$, which of course excludes Q_2 and thus coefficient estimates for the demand function are (asymptotically) biased.

[7]Recall that $P_1 = P(Q_1)$ is the high-end price, $P_2 = P(Q_1 + Q_2)$ is the low-end price, and $Q = Q_1 + Q_2$ is the total quantity.

We conclude that using a single-price index may seriously bias estimates of the demand equation parameters. One of the consequences of estimating the demand elasticity incorrectly may be flawed market power estimates. Without the knowledge of β the conduct parameter approach cannot identify market conduct. Similarly, if β is biased, then conduct parameter estimates as a market power measure may be biased as well. In the next section, we construct a market power measure in the price discrimination framework that addresses this issue.

2.3 Market Power Estimation

We now consider a conduct parameter model in the price discrimination framework and propose market power measures consistent with this model. Assume that firm n is choosing quantities for each bin, (q_{1n}, q_{2n}). The optimization problem of the representative firm is given by:

$$\max_{q_{1n},q_{2n}} \pi_n = P_1 q_{1n} + P_2 q_{2n} - C_n(q_{1n}, q_{2n}) \tag{4}$$

where C_n stands for the total cost of firm n. The first order conditions are:

$$\begin{aligned} \frac{\partial \pi_n}{\partial q_{1n}} &= P_1 + P_1' \frac{\partial Q_1}{\partial q_{1n}} q_{1n} + P_2' \frac{\partial Q}{\partial q_{1n}} q_{2n} - c_n(q_{1n}, q_{2n}) \\ &= P_1 + P_1' \eta_1 q_{1n} + P_2' \eta_1 q_{2n} - c_n(q_{1n}, q_{2n}) = 0 \end{aligned} \tag{5}$$

$$\begin{aligned} \frac{\partial \pi_n}{\partial q_{2n}} &= P_2 + P_2' \frac{\partial Q}{\partial q_{2n}} q_{2n} - c_n(q_{1n}, q_{2n}) \\ &= P_2 + P_2' \eta_2 q_{2n} - c_n(q_{1n}, q_{2n}) = 0 \end{aligned} \tag{6}$$

where c_n stands for the marginal cost of firm n. After summing over n and rearranging these first order conditions, we have:

$$P_1 - P_2 = -P_1' Q_1 \theta_1 - P_2' Q_2 (\theta_1 - \theta_2) \tag{7}$$

where $\theta_i = \frac{\eta_i}{N}$ for $i = 1, 2$. Here, θ_1 and θ_2 represent the market power in the high-end and low-end segments, respectively. The conducts $(\theta_1, \theta_2) = \left\{(0,0), \left(\frac{1}{N}, \frac{1}{N}\right), (1,1)\right\}$ correspond to perfect competition, price discriminating Cournot competition, and price discriminating monopoly (joint profit maximization), respectively. When $(\theta_1, \theta_2) = (0, 0)$, as perfect competition suggests, there is only one price and this price is equal to the marginal cost.

We consider only the firm's optimization problem with respect to a particular route and do not consider the complications inherent in modeling the decision to optimize with respect to all of its and its competitor's routes. For example, the number of directional routes in our data sets is 850. This is consistent with a large body of theoretical and empirical work on the airline industry that assumes independence of city-pair markets.

A special case is when high-end and low-end segment conducts are the same, in which case $\theta \equiv \theta_1 = \theta_2$. Given that the segment sizes are determined by the firms, the common conduct assumption seems to be a relatively sensible assumption for our homogenous product setting. Note that although the high-end and low-end segments would likely have different demand elasticities, which affects the price-marginal cost markups, this difference does not necessarily imply distinct conducts. Nevertheless, a common conduct is an empirically testable assumption. For now, in order to investigate the implications of this condition, we assume that it holds. Equation (7) then becomes:

$$P_1 - P_2 = -P_1' Q_1 \theta. \tag{8}$$

This expression can be generalized to a setting where there are more than two prices. The generalized version of this equation is $P_j - P_{j+1} = -P_j'\theta Q_j$ for $j = 1, 2, ..., K-1$, where K is the number of prices and Q_j is the total quantity for segment j. In what follows we concentrate on the case where the number of price segments is two. Here, $\theta = \left\{0, \frac{1}{N}, 1\right\}$ correspond to perfect competition, price discriminating Cournot equilibrium, and price discriminating monopoly (joint profit maximization), respectively.

Bresnahan (1989) argues that one should consider θ as a parameter that can take values consistent with existing theories. If the researcher considers θ as a parameter coming from several theories, the estimated parameter value can be used to categorize the market using statistical tests. For example, one can test whether the market outcome is consistent with Cournot competition or not by testing $\theta = \frac{1}{N}$. Another approach is considering θ as a continuous-valued parameter. An interpretation of this approach is that the conduct is described in terms of firms' conjectural variations, which are the "expectations" about other firms' reactions. This interpretation allows θ to take a continuum of values. The important point in this interpretation is that the "conjectures" do not refer to what firms believe will happen if they change their quantity levels. In the conjectural variations language, what is being estimated is what firms do as a result of their expectations. As Corts (1999) mentions the conduct parameter can be estimated "as if" the firms are playing a conjectural variations game that would give the observed price-cost margins. We consider θ as a market power index that can take a continuum of values and measures the size of the elasticity adjusted price cost markup. For instance, we may interpret a market with θ value between 0 and $\frac{1}{N}$ as a market level that is more competitive than a symmetric Cournot competition.

We define price discrimination as:

$$PD = P_1 - P_2. \tag{9}$$

Hence, the conduct parameter is given by:

$$\begin{aligned} \theta &= \frac{P_1 - P_2}{-P_1' Q_1} \\ &= \epsilon_1 \frac{PD}{P_1} \end{aligned} \tag{10}$$

where $\epsilon_1 = -\frac{1}{P_1'}\frac{P_1}{Q_1}$ is the price elasticity of demand for the high-end bin.[8] Our price discrimination measure is reminiscent of the price-marginal cost markup for the Lerner index:

$$L = \frac{P - MC}{P} \tag{11}$$

where MC is the "marginal cost" for the market. Generally MC is defined as a weighted average of the marginal costs of the firms in the market. For the single-price conduct parameter game, the conduct parameter is nothing more than the elasticity adjusted Lerner index:

$$\tilde{\theta} = \epsilon L \tag{12}$$

where $\epsilon = -\frac{1}{P'}\frac{P}{Q}$ is the price elasticity of demand. The price-cost markup takes a central role for the Lerner index. In our case, the relevant markup is $PD = P_1 - P_2$. An important implication of this is that marginal cost information is not required. This condition relies on the assumption that the high-end and low-end market powers are represented by a single conduct parameter, i.e., $\theta = \theta_1 = \theta_2$. In the single-price conduct parameter setting the firms determine the price in such a way that the equilibrium price lies above the marginal cost. Hence, the optimal price lies somewhere at or above the marginal cost. In the price discrimination setting, the firms choose quantities for low-end and high-end segments and these quantities determine the prices for these segments. In our model,

[8] To be more precise this is the absolute value of the price elasticity of demand, which we use throughout.

when $\theta = \theta_1 = \theta_2$, if the price of the low-end segment, P_2, were a function of Q_1 so that Q_2 is fixed (i.e., Q_2 is given) and the firms choose high-end market quantities, then their optimal choice (conditional on Q_2) would be to choose Q_1 treating P_2 as if it is the marginal cost. This is because in reality P_2 is the effective opportunity cost for the high-end market pricing option. Similar to the standard single-price setting, for a given Q_2 level, the optimal P_1 value lies somewhere at or above this effective (marginal) opportunity cost, i.e., P_2.[9] The derivation of our market power measure is based on this idea that, for any given low-end quantity, the choice of high-end quantity is determined so that the low-end price represents the effective (marginal) opportunity cost. In principle, this is a market power measure for the high-end market. If the high-end and low-end market powers are represented by a single conduct parameter, this measure can be considered as a single parameter representing the market power for the market. Whenever the single conduct parameter assumption is questionable, L and θ may not be used as market power measures. However, (θ_1, θ_2) estimates from Equation 7 are still valid in terms of measuring market power. In our empirical section we allow market power measures to be different for different segments.

Identification is an important issue in the conduct parameter approach and the constant marginal cost assumption is widely used in order to overcome this difficulty.[10] For our $\theta = \theta_1 = \theta_2$ case, since we do not need cost information, we need not make functional form assumptions on the cost function. However, we do require data for group specific prices. If the indices are constructed from ticket specific price data, the researcher must either identify the group to which each individual passenger belongs or divide the sample based on some characteristics of the customers. For example, in case of movie theaters

[9] Here, by optimal P_1 for a given Q_2, we mean the equilibrium for the conduct parameter game when Q_2 is treated as given.

[10] For more details about identification in the framework of conduct parameter approach see Bresnahan (1982), Lau (1982), Perloff, Karp, and Golan (2007), and Perloff and Shen (2012).

this criteria can be based on the age of customers. In case of airlines, the segmentation can be based on length of time between the flight and purchase of ticket. However, such information can be hard for the researcher to acquire. An indirect way to segment the customers might be to use information on ticket characteristics. The airlines can control ticket quantities for different customer segments by adjusting the characteristics of tickets or by simply restricting the number of seats, e.g., configuring the cabin for a particular allocation of business/first class seats vs coach class seats. We could then consider coach class and business/first class tickets as low-end and high-end tickets. We use this approach in our empirical illustration. One difficulty with this approach is that the product is not likely to be homogeneous. Therefore, our empirical model must take this complication into account.

We utilize Equation (10) to examine the relationship between price discrimination and market power. The derivative of price discrimination with respect to conduct is given by:

$$\begin{aligned} \frac{\partial PD}{\partial \theta} &= \left(\frac{1}{\tilde{\epsilon}_1}\right)^2 (\tilde{\epsilon}_1 - \tilde{\epsilon}_{1\theta}\theta) > 0 \Leftrightarrow \\ \tilde{\epsilon}_1 &> \tilde{\epsilon}_{1\theta}\theta \end{aligned} \tag{13}$$

where $\tilde{\epsilon}_1 = \frac{\epsilon_1}{P_1}$ and $\tilde{\epsilon}_{1\theta} = \frac{\partial \tilde{\epsilon}_1}{\partial \theta}$. The conduct would be changing $\tilde{\epsilon}_1$ through its effect on the equilibrium quantities and prices. If $\tilde{\epsilon}_1$ is relatively non-responsive to changes in conduct and market power is relatively low, then price discrimination is likely to increase as market power increases. An example of a positive correlation between PD and θ is a situation in which the inverse demand function is in lin-log form as this would imply that $\tilde{\epsilon}_1 > 0$ is a constant. Two less obvious examples of a positive relationship are situations in which the inverse demand function is in lin-lin or log-lin form.[11] Hence, for a variety of

[11]For the log-lin demand form we assumed zero marginal cost for the sake of getting a closed form solution for the equilibrium. Similarly, for the lin-lin demand functional form we assume that marginal costs are constant.

demand function scenarios, price discrimination and market power are positively related.

When the conducts for the high-end and low-end segment are not restricted to be the same, the analysis is less trivial. One way to examine this relationship is to develop a directional derivative of PD with respect to (θ_1, θ_2) in the direction of $(1, 1)$. This provides us with price discriminating behavior when both of the conducts change at the same rate. For the log-lin inverse demand function this directional derivative is positive. However, for the lin-lin demand function the directional derivative is positive if and only if $\theta_1 < \frac{1}{2}\left(\sqrt{4\theta_2 + 5} - 1\right)$. Hence, if the market power for the high-end segment is sufficiently high and the market power for the low-end segment is sufficiently low, then price discrimination and market power can be negatively related. For example, if the low-end segment is competitive, i.e., $\theta_2 = 0$, and the high-end segment has a market power greater than $\theta_1 = \frac{1}{2}\left(\sqrt{5} - 1\right) \simeq 0.618$, then price discrimination and market power would be negatively related. Therefore, $\theta_1 > \frac{1}{2}\left(\sqrt{5} - 1\right)$ is a necessary condition for a negative relationship when the inverse demand function is in lin-lin form. Roughly speaking a conduct of 0.618 corresponds to a market power level that is somewhat higher than that of a symmetric Cournot duopoly, which equals 0.5. A negative relationship requires a large discrepancy in the market powers of the high-end and low-end segments. The intuition is that when market power for the high-end segment is high and market power for the low-end segment is low, the effect of a unit increase in the market power for the high-end segment can be small relative to the effect of a unit increase in the market power for the low-end segment. Hence, if the market powers of high-end and low-end markets increase at the same rate, then after some market power level the low-end segment prices begin to catch up with the high-end segment prices. This leads to a decrease in price discrimination. However, if the rate of change in market power is proportional to the initial conduct values for the high-end and low-end segments, then the positive relationship prevails. That is, if the directional derivative of the price discrimination is

taken in the direction of (θ_1, θ_2) rather than $(1, 1)$, then price discrimination increases. Therefore, for a variety of interesting cases, our market power measure agrees with the conventional wisdom that price discrimination and market power are positively related.

3 An Empirical Illustration to Analyze U.S. Airline Industry

In this section, we illustrate our methodology for estimating market powers of firms in the price discrimination framework. The U.S. airline industry serves well for this purpose. We estimate the market powers of the U.S. airlines utilizing our conduct parameter framework and compare our market power estimates with traditional market power estimates ignoring price discrimination. First, we introduce our data set. Then, we present our empirical model and results.

3.1 Data

Our quarterly data set covers a sample of airline tickets from reporting carriers over the period from $1999I$ to $2009IV$. The U.S. airlines faced serious financial troubles during this period. Historically, the demand for the U.S. airline industry grew steadily. However in our sample period there were exceptions to this pattern. The effect of these negative shocks is boosted by sticky labor prices and exogenous cost shocks such as increased taxes and jet fuel prices. The financial implications of these factors on domestic airline operations were stark–the airlines lost an order of magnitude more (in 2009 dollars) during our sample period, the decade of $1999 - 2009$ compared to the entire previous two decades of $1979 - 1999$.[12]

[12]For more information about the financial situations of the U.S. airlines, see Borenstein (2011) and Duygun, Kutlu, and Sickles (2014).

Our data set is compiled from a variety of data sources. Price indices are constructed from the Airline Origin and Destination Survey (DB1B) data provided by the Bureau of Transportation Statistics. The DB1B is a 10% sample of airline tickets from reporting carriers collected by the Office of Airline Information of the Bureau of Transportation Statistics. Information on the number of enplanements is obtained from the T100 database. In general, the cost related data set is obtained from the firm level data of DOT's airline production data sets (Form 41 and T100). We concentrate on direct one-way or round-trip itineraries. The round-trip fares are divided by two in order to derive corresponding one-way fares.[13] Three different groups of prices and quantities are calculated. The low-end group consists of coach class tickets. The high-end group consists of business class and first class tickets. The final group is the aggregation of these two groups. Prices are the average ticket prices for a given category. When the average price is based on a limited number of ticket specific observations or when routes had a very small number of passengers the observations were dropped. Outliers, such as observations based on itineraries with "incredible" fare data according to the variable "DollarCred" are dropped as well.

When calculating prices multi-destination tickets are excluded because it is not possible to identify the ticket's origin and destination. Also, following Bruecker, Dyer, and Spiller (1992) we excluded any ticket that does not have the same fare class for all segments of the trip. One potential issue is that coach class tickets are not always consistently reported across carriers. For example, our ticket level raw data set includes some small carriers that designate all their tickets as only first class and business class (high-end). We consider the quality for these tickets as coach class. This may cause a downwards bias in our price discrimination measure. However, similarly, dropping such airlines may cause some upwards bias in the price discrimination measure. In any case, the share of

[13]Borenstein and Rose (1994) and Kutlu and Wang (2015a) also divide the round-trip price by 2.

such airlines is small and we expect the bias to be negligible. Finally, sometimes the class information for a ticket is not available and we drop such tickets.

Our data set also includes city specific demographic variables such as population weighted per capita income (PCI) and the average population for each city-pair (POP) based on Metropolitan Statistical Area (MSA) data from the U.S. Census. As the MSA data are annual, interpolations were used to generate quarterly versions of the PCI and POP variables. When merging the MSA data with the airline data, we lost some cities as we had Census information on just the metropolitan areas.

The final database contains 850 directional routes. We deflated nominal prices by the CPI. The first quarter of 2005 is the base quarter. Our data set includes information about distance ($DIST$) between of city-pairs and the average size ($SIZE$) of the fleets. The larger sized fleets can help airlines provide more services without a proportional increase in costs. Also, larger aircraft are generally perceived as safer and thus improves service quality. On the other hand, larger aircraft carry more people, which might cause congestion, increase the possibility that luggage is mishandled, and increase waiting time for baggage claims. Therefore, the net quality effect of aircraft size is ambiguous. Flight distance is one of the more important determinants of flight cost. It also captures the indirect competition effects from other modes of transportation. Finally, in order to provide easier interpretation of results the quantity and PCI variables are divided by 1000, POP variable is divided by 10^6, and the $DIST$ variable is divided by 100 so that, for example, a unit of $DIST$ is 100 miles and a unit of POP is one million people.

3.2 Empirical Model

In the theoretical section we assumed a homogeneous product market. For the empirical example we relax this assumption by allowing the marginal costs of the seats and effi-

ciencies to differ for different groups. In order to estimate the demand equation and the conduct parameters we must segment the customers. As mentioned earlier, this either can be done econometrically or by using some criteria that identifies segments. We use the latter approach and divide those purchasing airline tickets into two groups: high-end and low-end (bin 1 and bin 2, respectively). We assume that the low-end segment consists of coach class ticket buyers and that the high-end segment consists of business class and first class ticket buyers. We then calculate average prices and the relevant quantities for each segment. Although the homogeneous product version of our model does not require cost data, for our empirical study that does not impose homogeneity, we do require cost data. We specify the inverse demand function in log-lin form as:

$$\begin{aligned} \ln P_{krt} &= \beta_{k0} + \beta_{k1} Y_{krt} + \sum\nolimits_i \beta_{ki} X_{rti} + \sum\nolimits_{j>1} \delta_{kj} TD_{tj} \\ &\quad + \frac{1}{2} \sum\nolimits_{i,j} \beta_{kij} X_{rti} X_{rtj} + \varepsilon_{krt} \end{aligned} \tag{14}$$

where P_{krt} is the average route specific price for bin $k = 1, 2$, route r, and time t; Q_{krt} is the quantity for bin k; $Q_{rt} = Q_{1rt} + Q_{2rt}$ is the total quantity; $Y_{1rt} = Q_{1rt}$; $Y_{2rt} = Q_{1rt} + Q_{2rt} = Q_{rt}$; X_{rti} are the control variables (POP_{rt}, PCI_{rt}, $SIZE_{rt}$, and $DIST_{rt}$); TD_{tj} are the time dummies; and ε_{krt} is the error term. We impose the usual symmetry condition for the β_{kij} parameters so that $\beta_{kij} = \beta_{kji}$.

Since in our empirical example the high-end and low-end segments may show different characteristics, we assume different conducts for each segment. From Equation (5) and Equation (6) it follows that:

$$\begin{aligned} P_{1rt} &= -P'(Q_{1rt})\,\theta_1 Q_{1rt} - P'(Q_{rt})\,\theta_1 Q_{2rt} + MC_{1rt} \\ P_{2rt} &= -P'(Q_{rt})\,\theta_2 Q_{2rt} + MC_{2rt} \end{aligned} \tag{15}$$

where MC_{krt} represents the route–time-specific aggregate of the marginal cost bin $k = 1, 2$, route r, and time t. Given our log-linear inverse demand function this implies that:

$$\begin{aligned} P_{1rt} &= \alpha_{11} R_{1rt} + \alpha_{12} R_{2rt} + MC_{1rt} \\ P_{2rt} &= \alpha_{21} R_{2rt} + MC_{2rt} \end{aligned} \tag{16}$$

where R_{krt} is the level of revenue for bin $k = 1, 2$. We control for the marginal costs. After substituting the demand parameters into Equation (16) and adding error terms, the supply equations become:

$$\begin{aligned} P_{1rt} &= -\beta_{11}\theta_1 R_{1rt} - \beta_{21}\theta_1 R_{2rt} + EMC_{1rt} + v_{1rt} \\ P_{2rt} &= -\beta_{21}\theta_2 R_{2rt} + EMC_{2rt} + v_{2rt} \end{aligned} \tag{17}$$

where v_{krt} is an error term.

We also estimate the conduct parameters from the single-price version of our model. In this version, the prices are calculated by taking the overall averages of ticket prices for high-end and low-end bins. The quantities are the sum of high-end and low-end quantities. Estimation of the general model is carried out using 3SLS while for the single price model 2SLS is used.[14]

Instruments include the explanatory variables of the model as well as total high-end and total low-end quantities for the industry (excluding the relevant carrier's route quantity). These latter instruments are based on the quantities in other route markets. As we are measuring aggregate market power then for a given route we consider the total quantity for a given route market as our quantity variable. Thus, the quantity for market A and sum of all quantities for the other markets are assumed to be independent. A

[14]For the single price version we estimate a single equation and for the price discrimination version we jointly estimate a system of two equations.

similar set of instruments were used in Kutlu and Sickles (2012).

3.3 Results

Demand estimates for the price discrimination and single-price scenarios are given in Table 1. The variables $QHIGH$ and $QTOT$ are total quantity for the high-end segment and sum of quantities for both segments, respectively. Similarly, the variables $PHIGH$, $PLOW$, and P are the average price for the high-end segment, average price for the low-end segment, and overall average price for both segments, respectively. The time dummies are not shown in the output to conserve on space. In order to capture quality differences, the demand equation for the price discrimination scenario is estimated by a piecewise linear function where each piece represents a consumer segment. The explanatory variables for the low-end segment and single-price scenarios are the same. However, the dependent variables are different. The dependent variable for the single-price scenario is the overall average price whereas the dependent variable for the low-end segment is the average price for the low-end segment only. It appears that the parameter estimates are not very different for the low-end segment and single-price models.

Table 1: Demand Estimation

	Price Discrimination		Single Price
	log(PHIGH)	**log(PLOW)**	**log(P)**
QHIGH	-2.1616***		
	(0.0971)		
QTOT		-0.0335***	-0.0280***
		(0.0014)	(0.0016)
POP	0.1852***	0.1178***	0.1195***
	(0.0239)	(0.0130)	(0.0137)
PCI	0.0270	0.1816***	0.1679***
	(0.0195)	(0.0111)	(0.0116)
SIZE	0.0578***	-0.0136**	-0.0196***
	(0.0067)	(0.0043)	(0.0046)
DIST	0.1128***	0.0319***	0.0323***
	(0.0128)	(0.0071)	(0.0075)
POP SQUARED	0.0139***	0.0058***	0.0053***
	(0.0010)	(0.0003)	(0.0004)
PCI SQUARED	-0.0018***	-0.0015***	-0.0016***
	(0.0002)	(0.0001)	(0.0001)
SIZE SQUARED	-0.0003***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)
DIST SQUARED	-0.0135***	-0.0011	-0.0012
	(0.0015)	(0.0008)	(0.0008)
DIST CUBED	0.0003***	-0.0001	-0.0001
	(0.0001)	(0.0000)	(0.0000)
DIST^4	0.0000	0.0000**	0.0000**
	(0.0000)	(0.0000)	(0.0000)
DIST^5	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)
POP*PCI	-0.0090***	-0.0039***	-0.0030***
	(0.0006)	(0.0003)	(0.0004)
POP*SIZE	0.0001	0.0002	-0.0001
	(0.0002)	(0.0001)	(0.0001)
POP*DIST	0.0045***	-0.0022***	-0.0017***
	(0.0002)	(0.0001)	(0.0001)
PCI*SIZE	0.0010***	-0.0003***	-0.0002**
	(0.0001)	(0.0001)	(0.0001)
PCI*DIST	0.0014***	0.0003***	0.0004***
	(0.0001)	(0.0001)	(0.0001)
SIZE*DIST	0.0003***	0.0001***	0.0002***
	(0.0000)	(0.0000)	(0.0000)
TIME DUMMY	YES	YES	YES
R-squared	0.2866	0.3883	0.4950
# obs.	26246	26246	26246

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Supply Estimation

	Price Discrimination		Single Price
	log(PHIGH)	**log(PLOW)**	**log(P)**
REVHIGH	0.2872***		
	(0.0098)		
REVLOW	0.0044***	0.0033***	
	(0.0002)	(0.0004)	
REVTOT			0.0065***
			(0.0004)
SIZE	36.6253***	-9.1506***	-9.9545***
	(2.0456)	(0.5708)	(0.6014)
DIST	1.3559	0.1830	-0.3593
	(3.8323)	(1.0469)	(1.1025)
SIZE SQUARED	-0.1249***	0.0326***	0.0353***
	(0.0070)	(0.0020)	(0.0021)
SIZE*DIST	-0.0123	0.0065	0.0120**
	(0.0143)	(0.0039)	(0.0041)
DIST SQUARED	5.0865***	0.9765***	1.0232***
	(0.4723)	(0.1284)	(0.1354)
DIST CUBED	-0.3431***	-0.0718***	-0.0745***
	(0.0265)	(0.0072)	(0.0076)
DIST^4	0.0084***	0.0020***	0.0020***
	(0.0006)	(0.0002)	(0.0002)
DIST^5	-0.0001***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)
TIME DUMMY	YES	YES	YES
R-squared	0.4650	0.4253	0.4516
# obs.	26246	26246	26246

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The supply estimates for the price discrimination and single-price scenarios are given in Table 2. Again, the time dummies are not displayed. The variables $REVHIGH$, $REVLOW$, and $REVTOT$ are revenue from the high-end segment, revenue from the low-end segment, and total revenue from these two segments, respectively. The conduct estimates for the high-end and low-end segments are 0.133 and 0.098, respectively.[15] A question of interest is whether we can assume that there is a single common conduct for high-end and low-end segments. We implemented a bootstrap test with 1000 replications and at the 1% significance level the equality of the conducts is rejected. In any case, both of these values indicate a relatively competitive environment. These conduct parameter values are roughly comparable to that of a symmetric Cournot market with $7-8$ and

[15] We calculate the conduct estimates using Equation (16) and Equation (17). That is, we solve $\hat{\alpha}_{11} = -\hat{\beta}_{11}\hat{\theta}_1$ and $\hat{\alpha}_{21} = -\hat{\beta}_{21}\hat{\theta}_2$ for $\hat{\theta}_1$ and $\hat{\theta}_2$.

10 firms, respectively.[16] The average number of firms in the data set is 4.84. This would correspond to a conduct parameter value of 0.207 for a symmetric Cournot game.[17] Hence, the estimated market power for the high-end segment is about half of a symmetric Cournot competition when firms price discriminate. The conduct parameter estimate for the single-price framework is 0.23. An implication of these results is that ignoring price discrimination when measuring market power might lead to over estimation of market power. This could in principal result in blocking a potentially socially beneficial merger.

4 Conclusion

In many industries price discrimination is prevalent yet often mergers are analyzed in a single-price framework. If antitrust authorities ignore price discrimination, then they may end up blocking socially beneficial mergers or accepting socially harmful mergers. A conduct parameter measure of market power specific for the price discrimination environment can potentially prevent such suboptimal decisions. For this purpose we designed a conduct parameter model that enables estimation of market power in the presence of price discrimination. Like many other market power measures our measure is static. In dynamic environments, this might result in inconsistent parameter estimates. This is a general criticism for concentration measures, such as the Lerner index, and in conduct parameter models.[18] A possible solution would be to extend our model to a framework such as that in the single-price model of Kutlu and Sickles (2012) so that the firms play a dynamic efficient super-game. However, such an extension is beyond the scope of this paper.

[16] We are comparing price discriminating (single-price) Cournot with price discriminating (single-price) conduct game.

[17] We assume that the number of firms is equal to 4.84. For 5 firms the corresponding conduct is 0.2. In general, the theoretical conduct parameter value for a symmetric Cournot competition is equal to $1/N$.

[18] See Corts (1999) for a criticism of static conduct parameter models.

An important aspect of our model is that it enables us to examine the relationship between price discrimination and market power. In contrast to many of the earlier studies, when studying this relationship we allow the market powers of high-end and low-end markets to differ. For this purpose we used a variety of (widely used) functional forms that lead to a closed form solution for the equilibrium. For all of these scenarios there is a positive relationship between market power and price discrimination when the conduct can be captured by a single parameter. If conducts cannot be captured by a single parameter, then under some special conditions a negative relationship is possible. In particular, if the high-end and low-end segment conducts increase at the same rate, the inverse demand function is in lin-lin form, and if the high-end segment conduct is sufficiently larger than that of the low-end segment, then price discrimination would decrease. However, if the high-end and low-end segment conducts increase at rates that are proportional to the initial market power level, then price discrimination would increase. Hence, while we do not have compelling theoretical evidence for such a positive relationship, it appears that for many of the sensible scenarios a positive relationship is likely to hold.

Our empirical example illustrated how our methodology for the estimating market power of firms in the price discrimination framework can be applied by estimating the market power of U.S. airlines and comparing our market power estimates with those based on a traditional single-price. It is not surprising that the market power estimates differed for these two approaches. The single-price model appeared to over-estimate market power.

References

Borenstein, S. and Rose, N.L., 1994, Competition and Price Dispersion in the U.S. Airline Industry, *Journal of Political Economy*, 102, 653-683.

Borenstein, S., 2011, Why Can't US Airlines Make Money?, *American Economic Review*, 101, 233-37.

Brander, J.A., and Zhang, A., 1990, Market Conduct in the Airline Industry: An Empirical Study, *RAND Journal of Economics*, 21, 567-583.

Bresnahan, T.F. (1982), The Oligopoly Solution is Identified, *Economics Letters*, 10, 87-92.

Bresnahan, T.F. (1989), Studies of Industries with Market Power, The Handbook of Industrial Organization. Amsterdam: North-Holland.

Brueckner, J.K., Dyer, N.J., and Spiller, P.T. (1992), Fare Determination in Airline Hub-and-Spoke Networks, *RAND Journal of Economics*, 23, 309-333.

Chakrabarty, D. and Kutlu, L., 2014, Competition and Price Dispersion in the Airline Markets, *Applied Economics*, 46, 3421-3436.

Corts, K.S., 1999, Conduct Parameters and the Measurement of Market Power, *Journal of Econometrics*, 88, 227-250.

Dai, M., Liu, Q., and Serfes, K., 2014, Is the Effect of Competition on Price dispersion Non-monotonic? Evidence from the U.S. Airline Industry, *Review of Economics and Statistics*, 96, 161-170.

Duygun, M., Kutlu, L., Sickles R.C., 2014. Measuring Efficiency: A Kalman Filter Approach, *Unpublished manuscript.*

Eaton, B.C. and Schmitt, N., 1994, Flexible Manufacturing and Market Structure, *American Economic Review*, 84, 875-888.

Farell, J. and Shapiro, C., 1990, Horizontal Mergers: An Equilibrium Analysis, *American Economic Review*, 80, 107-126.

Féral, A. and Renault, R., 2009, Mergers with Efficiency Gains and Perfect Spatial Price Discrimination, Working Paper.

Formby, J.P. and Millner, E.L., 1989, Output and Welfare Effects of Optimal Price Discrimination in Markets Segmented at the Initiative of the Seller, *European Economic Review*, 1175-1181.

Gerardi, K.S., and Shapiro, A.H., 2009, Does Competition reduce Price Dispersion? New Evidence from the Airline Industry, *Journal of Political Economy*, 107, 1-37.

Graddy, K., 1995, Testing for Imperfect Competition at the Fulton Fish Market, *RAND Journal of Economics*, 25, 37-57.

Hazledine, T., 2006, Price Discrimination in Cournot-Nash oligopoly, *Economics Letters*, 93, 413-420.

Hazledine, T., 2010, Oligopoly Price Discrimination with Many Prices, *Economics Letters*, 109, 150-153.

Kumar, R. and Kutlu, L., 2015, Price Discrimination in Quantity Setting Oligopoly, *Manchester School*, Forthcoming.

Kutlu, L., 2009, Price Discrimination in Stackelberg Competition, *Journal of Industrial Economics*, 57, 364.

Kutlu, L., 2012, Price Discrimination in Cournot Competition, Economics Letters, 117, 540-543.

Kutlu, L., 2015, Limited Memory Consumers and Price Dispersion, *Review of Industrial Organization*, 46, 349-357.

Kutlu, L. and Sickles, R.C., 2012, Estimation of Market Power in the Presence of Firm Level Inefficiencies, *Journal of Econometrics*, 168, 141-155.

Kutlu, L. and Wang, R., 2015b, Price dispersion, Competition, and Efficiency in the U.S. Airline Industry, *Unpublished manuscript.*

Lau, L.J., 1982, On Identifying the Degree of Competitiveness from Industry Price and Output Data, *Economics Letters*, 10, 93-99.

McAfee, R.P., Mialon, H.M., and Mialon, S.H., 2006, Does Large Price Discrimination Imply Great Market Power?, *Economics Letters,* 92, 360-367.

McAfee, R.P., Simons, J.J., and Williams, M.A., 1992, Horizontal Mergers in Spatially Differentiated Noncooperative Markets, *Journal of Industrial Economics*, 40, 349-358.

Perloff, J.M., Karp, L.S., and Golan, A., 2007, Estimating Market Power and Strategies, Cambridge University Press.

Perloff, J.M., and Shen, E.Z., 2012, Collinearity in Linear Structural Models of Market Power, *Review of Industrial Organization*, 40,131-138.

Reitzes, J.D. and Levy, D.T., 1995, Price Discrimination and Mergers, *Canadian Journal of Economics*, 28, 427-436.

Rothschild, R., Heywood, J.S., and Monaco K., 2000, Spatial Price Discrimination and the Merger Paradox, *Regional Science and Urban Economics*, 30, 491-506.

Salant, S.W., Switzer, S., and Reynolds R.J., 1983, Losses from Horizontal Merger: The Effects of an Exogenous Change in Industry Structure on Cournot-Nash Equilibrium, *Quarterly Journal of Economics*, 98, 185-199.

Stavins, J., 2001, Price Discrimination in the Airline Market: The Effect of Market Concentration, *Review of Economics and Statistics*, 83, 200-202.

Stole, L.A., 2007, Price Discrimination and Competition, M. Armstrong and R. Porter (ed.), Handbook of Industrial Organization, vol. 3, Elsevier, chapter 34, 2221-2299.

Varian, H.R., 1985, Price Discrimination and Social Welfare, *American Economic Review*, 75, 870-875.