Airline Hubs: Costs, Markups and the Implications of Customer Heterogeneity

by

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March 1997

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1. Introduction.

There is by now a large empirical literature on the post-deregulation airline industry. This literature has focused on a number of issues regarding the provision and pricing of airline services.[1] One of the most debated aspects of the industry restructuring is the almost complete shift in network organization, from “point-to-point” to “hub-and-spoke.” Hub and spoke networks, in which passengers change planes at a hub airport on the way to their eventual destinations, have been criticized as increasing entry barriers and driving up prices for hub-originating passengers (e.g., Borenstein, 1989, 1991).[2] Others, including some airline executives, have suggested that hub-and-spoke networks reduce costs (e.g. Caves, Christensen and Trethway, 1984; Brueckner, Dyer and Spiller, 1992, hereafter, BDS; Brueckner and Spiller, 1994).[3] The claim of the cost-efficiency of hubs has been challenged by the success of non-hub carriers, like Southwest.[4]

These two effects, increasing markups and reducing costs, though, are not mutually exclusive (Berry 1990). Airline hubs could raise prices for some consumers by substantially increasing markups over marginal cost, while at the same time reducing costs. In this paper, we use a differentiated products supply-and-demand model to disentangle the separate effects of hubs on costs and markups. We think of hubs as shifting out the product specific demand curve for flights of the hubbing airline out of its hub city. Flights originating at hubs and provided by the hub-airline may appeal especially to relatively price inelastic consumers. This shift in the level and elasticity of demand can lead to both higher output levels and prices for the hubbing airline, consistent with previous empirical results. On the cost side, we allow for economies of "spoke density:" more densely traveled spokes may have lower marginal costs. Economies of

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[1] Deregulation removed restrictions on entry and exit and gave carriers the freedom to set fares. For discussion of the impact of the new regulatory environment on airline operations, see Bailey and Williams (1988), Bailey, Graham and Kaplan (1985), Brueckner and Spiller (1994), Levine (1988), Moore (1986), and Morrison and Winston (1986).

[2] Critics also mention several other negative features of hub-and-spoke networks, like increased number of connections, and the increase in hub airport congestion (as planes land and depart in bunch).

[3] For an industry defense of the hub-and-spoke system, see Michael Levine’s editorial page article in Northwest Airlines’s February 1995 issue of its in-flight magazine.

[4] Southwest has been the only consistently profitable carrier since deregulation. See, US Department of Transportation, Air Carriers Financial Statistics Quarterly, various issues.

spoke density will lead to economies of scope across itineraries that share a common spoke.[5] These economies of scope in turn imply network economies, so that itineraries that include a hub airport, by increasing spoke density, may have lower costs (see BDS).

In this paper we provide estimates of a model of airline competition which capture the two major features of the industry: product differentiation and economies of density. On the demand side, we attempt to capture the fact that airline customers are heterogenous by allowing customers' preferences over various product specifications to be drawn from a binary distribution. On the cost side, we estimate a very flexible spoke marginal cost function, so as to allow economies of density to vary across different ranges.

Our estimates not only provide support to some of the traditional common wisdom in the industry, but are also useful to understand major puzzles concerning the evolution of the industry and its operational, marketing and pricing practices. First, we provide estimates of the differential willingness to pay for different air travel features by what might be called tourist and business travelers. Indeed, our results are consistent with the existence of two very distinct types of passengers, one with the standard attributes of a tourist traveler (i.e., high price sensitivity, low willingness to pay for frequent flyer features, low willingness to pay for frequency, low disutility from connecting flights, etc) and another with a strong business-traveler flavor (i.e., low price sensitivity, high willingness to pay for frequent-flyer features, high willingness to pay for frequency, high disutility from connecting flights, etc). These estimates are the key to uncovering the ability of hub-airlines to increase their markups in hub-originating flights. In this regard, we provide evidence that hubs provide two major competitive advantages to companies: they reduce costs and allow for higher markups on hub originating passengers.

Second, our estimates show that a hubbing airline's ability to raise prices at its hub is not universal, but rather is focused on tickets that appeal to relatively price-inelastic consumers, (i.e., business travelers). Indeed, we find that hub airlines do not find it profitable to raise prices much to non-business travelers. Thus, business travelers' higher willingness to pay for flying a hub-airline coupled with their price inelastic demands, provides hub airlines with the ability to offer higher priced products to which business travelers will self-select.

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5 For example, the itinerary New York-Chicago-San Diego shares a spoke with New York-Chicago-Seattle. Thus, an increase in demand for the airline's New York-San Diego service, increases traffic in its New York-Chicago leg, and if economies of density are present, it reduces the marginal cost of providing service in the New York-Seattle market. See Brueckner and Spiller (1991, 1994).

Third, our estimates suggest that in spite of the higher markups of the hubbing airlines, the price inelastic consumers (i.e., business travelers) drastically move their flying patterns towards the origin hub airline, even though they have to pay an average premium of 20% or so over the prices charged by the non-hub competitors.

Fourth, our estimates show that the existence of a hub airline does not provide a "monopoly umbrella" to the other non-hub airlines serving the hub airport. Indeed, non-hub airlines competing with a hub-airline face the workings of a particularly strong competitive scissor: a reduction in the proportion of their travelers who are price insensitive, and a reduction in market share. Both are the result of the shift of the price insensitive passengers (business travelers) towards the hub airline. The increased price sensitivity of their average passenger, however, reduces the non-hub airlines' average yield and, as a consequence, the profitability of serving all routes connected to that airport. Thus, competing airlines will reduce service out of an airport where a competitor starts operating a hub. Our results, then, provide a possible explanation for the increase in airport concentration that has taken place following airline deregulation (Brueckner and Spiller, 1994). Such increase in airport concentration, however, is not necessarily the result of increased entry-barriers, but rather of the price insensitivity of business travelers' demands and of their valuation of flying the hub-originating airline.

Finally, on the cost side, we find strong evidence of economies of density. Indeed, airlines operating large hubs are found to have, on average, significantly lower marginal costs, out of the hub, than their competitors in the same routes. We show, however, that economies of density may depend on the nature of the route. In particular, we do not find economies of density at distances less than 500 miles or so. This may help to explain the "Southwest effect," which relates to the apparent profitability of Southwest Airlines, a non-hubbing airline offering frequent flights on short routes. According to our estimates, the "Southwest effect" may not be exclusively the result of lower labor costs, but rather may be the result of Southwest's having found a particularly effective "cost" niche.[6]

2. Costs and Demand: Preliminaries

Costs. The cost efficiencies of hubs may arise from the use of large, cost-effective aircraft on the densely trafficked spokes of a hub-and-spoke system. This idea relies in part on

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[6] This result puts in question Southwest's recent strategy of moving "national." Such move implies moving into a range where economies of density, and hence, hub-and-spoke networks, may be more efficient.

an engineering argument that larger planes are cheaper to fly per seat mile, at least on longer routes. For a given flight frequency, more "dense" spokes can efficiently use larger aircraft. Economies of scale at the level of airline spokes in turn imply network economies, for hubbing airlines can combine passengers who have different final destinations on a single large plane that flies to a hub city. At that hub the passengers switch to different planes, which in turn combine passengers from various initial origins.

There is some empirical evidence in favor of hubs reducing costs. Caves, Christensen and Tretheway (1984), for example, estimate economies of density by analyzing the relationship between airline total costs, route structure, and total passenger traffic. They find that, holding the airline's route structure (e.g., the number of points served) constant, total cost increases only 80% as rapidly as total traffic, indicating significant economies of traffic density. While this is an important finding, the underlying methodology ignores details of a carrier's route structure that critically affect density levels, an omission that may bias the estimate of economies of density.[7] In order to capture such detail, a more disaggregated approach is needed that makes use of density information at the individual route level. Use of such detailed output information, however, is impossible within the traditional cost-function framework because the required cost accounting data are not available at the route level (indeed, route-level total or average cost is not even well-defined.) Therefore, estimation of economies of density using disaggregated data must proceed in a way that does not require direct cost information.[8]

Brueckner and Spiller (1994) provide an alternative method to estimate economies of density that is not based on traditional cost function approaches, but rather directly model the role of spoke densities. In their model, the marginal cost of adding a passenger to a given spoke changes with an airline's total traffic, or density, on that spoke. The marginal cost of a multi-segment passenger is then found as the sum of the marginal costs of each segment. This marginal cost in turn affects price. Thus, the high spoke densities that are a feature of hub-and-spoke networks are allowed to affect costs and prices in a natural way. Brueckner and Spiller

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[7] For example, holding the number of endpoints fixed, densities will fall as the number of hubs operated by the airline increases.

[8] We are not the first to estimate an oligopoly model, including a marginal cost function, without *direct* cost information. For prior attempts, see, for example Porter (1983) and, more generally, Bresnahan’s (1989) survey of structural estimation of oligopoly models. For a different suggestion on how to estimate cost functions for network industries without product level cost information, see Spady (1985).

(1994) focus on flights that pass through hub airports, rather than originating at hubs. (This is an attempt to control for the higher markups that may be found on flights out of hub airports.) They find evidence that by funneling passengers through a hub airport, the switch to hub-and-spoke operations raised traffic densities and allowed carriers to reduce their costs.

For the cost side of our model, we take an approach similar to Brueckner and Spiller (1994). We model the effect of density on the marginal costs of each spoke in the network. The marginal cost of flying a given itinerary is then the sum of the marginal costs of the spokes defining that itinerary. A product’s marginal cost is “observed” as price minus a markup that is derived from our model. In practice, then, we make inferences from the effect of density on prices, holding markups constant via the techniques discussed below.

There are several issues to be faced in using such a model. First, depending on demand conditions, airlines may respond to increased density by increasing flight frequency rather than by increasing plane size. Therefore, in the empirical work we try to control for flight frequencies. Second, high traffic, and thus low cost, on some spokes may be a consequence of high demand for associated itineraries, resulting in low prices as well as high markups. This suggests that densities are endogenously determined, together with price. Our estimation procedure tries to account for this endogeneity. Third, density may affect fixed as well as marginal costs, an effect that we will simply not capture. Finally, marginal cost may vary with factors that we do not observe, such as capacity levels that vary across time of day. We do not observe these factors and so cannot account for them.

Demand. Many authors have suggested reasons why flights on hubbing airlines originating out of hub airports may be associated with higher markups (e.g. Borenstein, 1989, Levine, 1987). It has been suggested that various marketing programs, such as frequent flier programs and non-linear travel agent commission programs, both build brand loyalty and may exploit various principal-agent problems. Hubbing airlines may also offer superior service via their control over airport resources: for example more convenient gates and better departure times.

Evidence for this markup effect has been provided in various regressions of price on characteristics of routes and markets, including whether the flight originates from a hub. Borenstein (1989), for example, finds that flights on airlines with a hub at one or both endpoints command higher prices. This effect seems to be particularly large at the high end of the price distribution. Borenstein (1989) does not provide a model of costs or demand, but attempts to control for market-level unobservables by, for example, introducing city-pair level fixed effects. In Borenstein (1991), he introduces *directional* city-pair effects, looking at the difference between routes into and out of the hub city. He finds higher prices on flights out of the hub which might, for example, be consistent with the effect of marketing efforts such as frequent flyer programs.

Reduced form regressions, however, do not allow us to make statements about how prices relate to costs, or what are the determinants of markups over cost. Our approach is to introduce hubs as one characteristic in a differentiated products model of demand for airline flights. When combined with the cost model and a notion of market equilibrium, we will obtain estimates of markups for various products. In such a model, high markups can result both from a lack of competition and from high levels of product-specific demand.

To obtain an empirically implementable model of product differentiation, we adapt recent advances in empirical models of such markets (Berry, 1994, Berry, Levinsohn and Pakes, 1995 --henceforth BLP). In these models, consumers differ in their valuations of the characteristics of different products. In particular, we model two types of potential consumers ("business" and "tourist", perhaps) who differ in their "taste" for direct flights, low fares, and other features of airlines' products. A ticket on a direct flight with few restrictions, for example, can be sold to business travelers at a high price, while other tickets may be sold primarily to tourists at low prices. Our model of markups allows for the possibility that flights out of hub airports are offered at higher prices, even if costs are low.

We believe that the restrictions placed on tickets, such as advance purchase requirements and Saturday stayover rules, are an important explanation for the wide variety of fares offered within given routes. Unfortunately, our data do not contain information on ticket restrictions. Previous authors have generally used this same data set and have not been able to control for such restrictions. We do introduce an explicit unobserved product characteristic, which is correlated with prices, to help control for these unobserved restrictions.

Equilibrium. Following Berry’s (1990) equilibrium model of airline prices, we assume that prices are set according to a static Nash equilibrium in prices. It is this equilibrium assumption, together with the models of cost and demand, that allows us to construct markups for various products. The equilibrium accounts for a wide variety of interactions across and within firms. In particular, we take account of the multi-product nature of production. A given airline frequently offers a variety of products (defined, for example, by different itineraries and restrictions) within a given market. In a Nash equilibrium, the optimal price vector for the firm takes into account the positive effect a price increase on the sales of other products offered by the same firm. Similarly, a given spoke carries passengers who have paid for many different products. A change in the price of any one of these products affects the costs of all products sharing this spoke.

3. The Model.

Our general strategy is to model costs and demand for individual products within a cross-section of markets. The model outlined in this section is "structural" both in the sense that it is derived from economic primitives like cost and utility, and in that unobservable factors are explicitly discussed. The use of economic primitives allows us to separate out cost and demand effects. As for unobservables, some discussion of these is always important in empirical work, for the properties of the various possible estimation strategies rely on the properties of the unobservable "errors" of the model. Even more important, perhaps, we believe that our data simply do not measure a number of important variables, such as the restrictions placed on a ticket. Ignoring such unobserved factors might lead to substantially misleading results.

We should note, however, that the model suffers from a reliance on a variety of functional form and behavioral assumptions. We are able, though, to substantially relax the very restrictive functional form assumptions that have been frequently employed in past work on airline markets (such as in Brueckner and Spiller, 1992, or Morrison and Winston, 1986). The estimation strategy employs a number of exogeneity restrictions, but in contrast to much past work we treat prices and spoke densities as endogenous variables.

We begin by defining notions of markets and products. Many of our definitions and modeling choices are motivated by the available data, so in this section we sometimes indicate the general nature of our data. A later section will provide details on the data.

Markets and Products. Markets are defined as round-trip air travel between an origin and a destination city. Thus, one market is for round-trip travel with New York as the origin and San Francisco as the destination. Our markets are *directional* origin-destination markets: New York-Los Angeles is a different market than LA-NY. This allows characteristics of the origin city to affect demand.

Within each market there is a set of products. Motivated by our data, we define products as a unique combination of airline, fare and itinerary. Thus three products in the NY-LA market might be (1) a direct United flight at $399, (2) a direct United flight at $299 and (3) a United flight through Chicago, also at $299. Our data, most unfortunately, do not provide information on restrictions such as advance purchase requirements, Saturday night stayover rules and limits on the number of seats sold. To deal with this, we introduce an explicit, unobserved variable to capture restrictions; this variable explains why different fares co-exist on the same airline-itinerary.

For each such product, we observe (with some sampling error) the number of passengers. Note that the number of passengers associated with a single product does not correspond directly to spoke density. Spoke density is defined as the sum of the number of passengers taking all itineraries that include the given spoke as one flight segment. The density of United's NY-Chicago spoke thus includes passengers with many destinations out of New York apart from Chicago.

Demand. Following earlier authors, such as Morrison and Winston (1986), we adopt a discrete choice model of demand. We extend the standard logit model by adding heterogeneous tastes for product characteristics, unobserved product characteristics, and a nested logit formulation that takes into account the decision not to fly.

The utility function is:

$$u_{ij} = x_j \beta_i - \alpha_i p_j + \xi_j + \nu_i(\lambda) + \lambda \epsilon_{ij},$$

where the fare is denoted by p_j and the vector x_j contains the other observed product characteristics and market-level demand factors. The term ξ_j captures unobserved (to us) characteristics of the product, such as advance purchase restrictions, and $\nu_i + \lambda\varepsilon_{ij}$ is additive error term.

The "taste" vectors β_i and α_i vary across consumers, yielding a random coefficients specification similar to Hausman and Wise (1978) and BLP (1995). There is an important question of how to model the distribution of the random coefficients. One traditional model would assume that (β_i, α_i) are distributed i.i.d. normal across consumers. The correlation of tastes across characteristics is often assumed to be zero for simplicity (as in BLP). However, we believe that the distribution of consumer tastes may be bi-modal. This is because there is a group of business travelers for whom the price of a ticket is not an important consideration in their decision to fly. There is another, probably much larger, group of potential travelers for whom the price of a ticket is, however, an important factor.[9] Furthermore, business travelers may have

[9] This difference in price sensitivity may arise from several factors including the urgency or need of the trip, tax considerations (travel is a deductible expense for business but not for tourists), and even the extent by which business travelers fully internalize the costs of their tickets.

systematically different tastes for observed *x*'s, such as flight frequency and whether the flight is direct. This last point suggests that tastes are correlated across characteristics.

Throughout the paper we adopt the simplest distribution that is bi-modal and features correlation in tastes across characteristics.[10] This is a two point distribution. We estimate two different taste parameters, (β_1, α_1) and (β_2, α_2), together with the probability, γ, that a potential consumer is of "type 1". Note that this distribution has $2K+1$ parameters if there are K characteristics with random coefficients. In contrast, the simplest normal distribution would have $2K$ parameters -- a mean and a variance of tastes for each characteristic. Our discrete distribution also has the advantage that it will provide a simple closed form expression for market shares. In contrast, the normality assumption requires numeric integration to obtain market shares.[11] We also provide results assuming a tri-modal distribution of customers.

Unlike the simple logit model, our specification allows markups to systematically vary with observed characteristics. In the random coefficients model the tastes of consumers who purchase a product vary systematically with *x* and *p*. Thus, a change in price will have systematically different effects on products with different characteristics and prices. For example, a high priced product will be purchased, on average, by consumers who do not care much about price. Thus, a price increase may not have a large effect on the demand for this product. In contrast, in the logit model price effects (measured by the slope of demand) are always equal for products with equal market shares, regardless of the values of *x* and *p*. Indeed,

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[10] There is some evidence that the distribution of fares may be a bi-modal mixture of distributions. Looking at the distribution of fare per mile (available from the authors upon request) we observe that such distribution has a fat upper tail, which is inconsistent with a normal distribution. Fitting fare per mile to a mixture of normal distributions we find that it provides a much better fit than a simple normal distribution (adj R^2 of .999 against 0.972). The linear combination is given by Fare = 0.5987*N(0.2375,0.0781) + (1-0.5987)*N(0.5946,0.2752). It is interesting to note that the fare/mile means from the full estimation match these distributions fairly well. As will be presented in more detail below, our full estimation provides a type 1 mean fare/mile of 0.237 the same mean as estimated through this method. The type 2 mean fare/mile from the full estimation is 0.414, against 0.589 using this method. The proportions are a bit different, 0.73 are from the type 1 distribution in the full estimation and only 0.598 using this simple estimate.

[11] There are obvious extensions of our finite point discrete distribution. For example, one could model tastes as being drawn from different normal distributions. This would allow for within type variance in tastes, as seems reasonable, but would also return us to the problem of numeric integration.

this last feature is true of any discrete choice model in which consumer tastes enter only as an additive i.i.d. term.

We also recognize that the publicly available data do not tell us what restrictions are placed on a ticket. To account for this, we follow Berry (1994) and introduce an unobserved (to us) product characteristic, ξ_j. The term ξ_j, which is perfectly observed by firms and consumers, will also capture other unmeasured characteristics of the product, such as the quality of the food and the service. This characteristic enters utility in much the same way as the observed *x*'s. Since there is one unobserved characteristic for each product, we cannot consistently estimate the ξ_j from product level data. Therefore, as the estimation section will make clear, we must place some restrictions on their distribution. We could assume some parametric distribution for the unobserved product characteristics, but instead we will use the weaker assumption that the ξ_j are uncorrelated with some vector of instruments.

We do not want to assume that the unobserved product characteristics are uncorrelated with price, because we believe that tickets with different restrictions have systematically different prices. We will assume that the ξ_j are uncorrelated with other observed demand variables, such as the distance between the two cities and a dummy variable for whether the flight is direct. Whether these exogeneity restrictions are reasonable depends on the economic process that generates restrictions on tickets. To give one extreme case, if the same restrictions are offered on each airline/itinerary, then the exogeneity restrictions are correct. For example, an airline might always offer an unrestricted fare, an advanced-purchase Saturday night stayover fare and an advanced purchase fare with no stayover restriction. In this case, there will be no correlation between the (un)restrictiveness of the ticket and *x*. On the other hand, it is not hard to think of stories which would violate our exogeneity restriction.[12]

Following BLP (1995), we introduce an explicit "outside" good, which might include auto travel and the use of the phone. The outside good has utility

$$u_{io} = \varepsilon_{ij}.$$

The mean of this utility, then, is normalized to zero. Coefficients on market level factors that enter the utility for "inside" the market goods are therefore interpreted as being relative to the

[12] One example is where airlines’ choice of capacity for various fares categories on a particular market depends on realization of demand. In this case, our estimated ξ will reflect a mixture of demand shock and the endogenous capacity constraint. In the paper we consider no endogenous choice of ξ by the airline, although such would be an interesting, albeit difficult, extension.

outside good. Market shares now are defined as the share of a given product out of all potential trips between these two cities. The number of such potential trips is not observed, although we believe it to be related to the population of the cities Formally, we assume that in origin-destination market n there is some number of potential passengers who consider air travel. In the empirical specification, this number is assumed to be proportional to the geometric mean of the population of the origin and destination cities. The use of the geometric mean has both empirical and (weak) theoretical precedents in the literature on travel demand. Denoting this mean population as M_n and the factor of proportionality as μ, the number of potential passengers is then μM_n. Note that M is data, while μ is a parameter to be estimated. We realize that the "number of potential trips" is a rather abstract concept, but we must introduce some such concept to allow for the outside good in the model. We will generally think of each potential trip as representing a different consumer, although this need not be so if a single consumer might take several trips in the same market. For simplicity, we will not model any correlation in tastes across potential trips.

Our use of random coefficients introduces a correlation in utility between products with similar characteristics. We believe that the outside good is not at all similar to the "inside" goods, so we also want to introduce correlation among the utilities of the inside goods. To do this in a simple way, we use a nested logit framework, where the only "nest" groups products into an inside group and an outside good; the latter group, of course, has only one element.[13]

The additive error, represented by the sum $\nu_i + \lambda\varepsilon_{ij}$ is chosen to yield the familiar nested logit market share function (see McFadden, 1978 and Cardell, 1992). The distribution of this sum is parameterized by λ, which is to be estimated. As in the logit, ε captures idiosyncratic tastes for a particular product; for example, consumer I may prefer a particular departure time. In contrast, ν_i does not vary across products and represents the random taste for air travel, relative to the outside good. Cardell (1992) gives the distributional assumption that implies the nested logit market share function, conditional on values of β_i and α_i. Under this assumption, as λ goes to 1 the within market correlation goes to zero while as λ goes to zero, the correlation of choices within the market goes to one.

Conditional on β_i and α_i, the nested logit market share function is given by the product of the within group market shares (the share of this product out of the total number of tickets sold) times the group share (the number of tickets sold in the market divided by the number of

[13]The nested logit assumption could be extended to include other nests -- on airports within cities, firms within markets, etc. -- but we have not yet estimated such a model.

$$s^1_{j/g} = \frac{e^{(x_j\beta_1 - \alpha_1 p_j + \xi_j)/\lambda}}{\sum_j e^{(x_j\beta_1 - \alpha_1 p_j + \xi_j)/\lambda}}$$

potential consumers). For consumer type 1, the within market share is:whereas total share of the market, the group share, is

$$\bar{s}^1 = \frac{D_1^\lambda}{1 + D_1^\lambda}$$

where the term D_1 is just the denominator of $s^1_{j/g}$. The market share for type 1 customers of product j, s^1_j , is then simply the multiplication of the group share and the within group share. The market share of product j is then given by the appropriate weighted average across the two types of consumers:

$$s_j = \gamma s_j^1(\boldsymbol{p},\boldsymbol{x},\boldsymbol{\xi}) + (1-\gamma)s_j^2(\boldsymbol{p},\boldsymbol{x},\boldsymbol{\xi}),$$

where γ is the proportion of type 1 consumers in the population.

Costs. In our model, the total and marginal cost, respectively, of operating a given spoke, *s*, are given by $C(Q_s,w_s)$ and $c(Q_s,w_s)$, where Q_s is spoke density and w_s is a vector of exogenous variables. These exogenous variables include distance between the endpoint cities and characteristics of the origin and destination airports. In addition to modeling spoke costs, we assume that there is a random, idiosyncratic component to product cost. In particular, we will assume that the product specific component of total cost for product *j* in market *m* is given by $\omega_{jm}q_{jm}$, where q_{jm} reflects the output of product j in market m. The only reason for this particular specification is so that marginal cost of product j will have a linear random error term, ω_{jm}. This makes for a convenient empirical specification.

Total variable cost for the firm is the sum of the total costs of each spoke flown by the firm plus the product-specific costs. Let S_f be the complete set of spokes flown by firm *f*, $S_f(j,m)$ be the set of spokes in the itinerary of firm *f* for product *j* in market *m*, and $J(f,m)$ be the set of products offered by firm *f* in market *m*. Then total firm cost is given by:

$$C_f = \sum_{s \in S_f} C(Q_{sf}, w_{sf}) + \sum_m \sum_{j \in J(f,m)} \omega_{jm} q_{jm} + FC_f \ .$$

Note that fixed costs, FC_f could be affected in some way by hubbing, but our empirical work will make use only of estimates of marginal cost and so will not capture any such effect.

In this specification, there are common costs across products because the same spoke can enter into the production of many demand-side products. Thus, is it not possible to speak of a well-defined total cost for any given product. However, product marginal cost is well-defined and is given by sum of spoke marginal cost across the spokes in the itinerary, plus the product-specific component.

$$mc_{jmf} = \left[\sum_{s \in S_f(j,m)} c(Q_s, w_s) \right] + \omega_{jm} \ .$$

To derive an estimator, we will assume that ω is uncorrelated with the exogenous variables of the model. We treat price and spoke density as endogenous, and other observed variables as exogenous.

Our prior belief is that there may be a complicated relationship between distance, density. and flight frequency. At shorter distances, air travel competes heavily with auto travel (and, in a few places, with trains). There may be pressure in these markets to use any potential cost savings that stem from density to increase flight frequency, so as to the better compete with auto travel that allows travelers to choose a fairly precise departure and arrival time. We think of the East and West Coast air shuttles, as well as Southwest airlines, as potential examples of this.[14] Also, in shorter markets it may not be cost effective to fly larger planes, because a large fraction of cost involves take-offs and landings. In short markets, this fixed-cost with respect to distance is not offset by large savings once in the air. We do not have a model of flight frequency, but we do have data on the number of flights flown per quarter on each spoke. Ideally, we would like to treat flight frequency as an endogenous variable, but in this paper we merely include it in some specifications as an exogenous cost shifter.

[14] Southwest Airlines is not in our data set, as it reports all its sales as being composed of one way tickets. As a consequence, it does not fit our product definitions. See Data section below.

To avoid imposing much structure on spoke costs, we want to use a fairly flexible functional form in distance, density and flight frequency. In the empirical work reported below, we use polynomials of these variables. Consider, for example, a case where spoke costs are quadratic in distance and density and d_s is the distance of spoke s. Then, for a multi-spoke ticket, product marginal cost is given by a linear combination of $\Sigma_s d_s$, $\Sigma_s Q_s$, $\Sigma_s d_s^2$, $\Sigma_s Q_s^2$ and $\Sigma_s d_s Q_s$, plus the error term ω.

Note that we provide no role in costs for capacity constraints or for firms' uncertainty about future costs and demand. This is in large part because we have no information at the level of individuals flights at a particular day and time. The data are aggregated to the level of the airline/route/fare on a quarterly basis. Therefore we cannot identify which flights might be subject to capacity constraints. Nor can we tell how uncertainty about the number of passengers on a flight is resolved as the time of departure approaches.

Capacity constraints, together with demand uncertainty, have been proposed as possible explanations for some features of airline pricing, such as the apparent price discrimination in favor of tickets purchased in advance. Other features of pricing, such as Saturday stayover rules appear to be harder to explain as purely cost-based phenomena. In any case, there is always that possibility that some of what we label as a markup in fact represents a shadow price of capacity.

Markups and the Pricing Equation. To close the model, we assume price-setting behavior by the multi-product firms in each origin and destination market. In the pricing equation that we derive, each firm takes into account the effect of a change in price on the demand and cost of its own products in this market, and (through the spoke densities) on the cost of its products in other markets.

Our assumption of a static Nash equilibrium in prices is obviously a simplification. Airline "yield management" techniques attempt to allocate seats across different fare classes in a complicated fashion that depends on the sales history of a particular flight. Therefore, the true equilibrium involves more choices than just prices and it has some dynamic component. This dynamic component would be even more complicated if, as some allege, airlines engage in some form of tacit collusion. Unfortunately, these interesting extensions to our equilibrium model are very difficult to implement and are left for future research.

In our model, profits of firm *f*, which in each market m produces the products in the set *J(f,m)* are given by the sum over the revenue generated by each product minus total cost:

$$\pi_f = \sum_m \sum_{j \in J(f,m)} q_{jm}(p_m) p_{jm} - \sum_{s \in S_f} C(Q_s, w_s) - \sum_m \sum_{j \in J(f,m)} \omega_{jm} q_{jm}(p_m) - FC_f$$

Differentiating with respect to the price of product *j* in market *m* gives a first order condition of

$$\frac{\partial \pi_f}{\partial p_{jm}} = q_{jm} + \sum_m \sum_{k \in J(f,m)} \frac{\partial q_k}{\partial p_{jm}} [p_{km} - \omega_{jm} - \sum_{s \in S(k,m)} c(Q_{sf}, w_{sf})] = 0 .$$

But since the marginal cost of product *k* in market *m* is

$$mc_k = [\sum_{s \in S_f(k,m)} c(Q_s, w_s)] + \omega_k,$$

we can rewrite the first order condition in the more familiar form of

$$\frac{\partial \pi_f}{\partial p_{jm}} = q_{jm} + \sum_{k \in J(f,m)} \frac{\partial q_k}{\partial p_{jm}} (p_k - mc_k) = 0.$$

Then, following BLP, define the matrix Δ which has elements *(j,k)* equal to $\partial s_k / \partial p_j$, if *j* and *k* are produced by the same firm, and equal to zero otherwise. In vector notation, the pricing equation is then:

$$p = \Delta^{-1} s + mc$$

where the first term on the right-hand side is the markup.

To derive the matrix Δ, note first that it is possible to get analytic forms for the derivatives of shares conditional on each type, $\partial s^1_k / \partial p_j$ and $\partial s^2_k / \partial p_j$. Let Δ_1 be the matrix of derivatives of market share with respect to mean utility for consumers of type 1, (with j,k elements not produced by the same firm again set to zero). Then, using the analogous definition for Δ_2, the derivative matrix is:

$$\Delta = \gamma \alpha_1 \Delta_1 + (1 - \gamma) \alpha_2 \Delta_2$$

which is enough to give us the markup term. The calculation of the markup depends only on the derivatives of market shares with respect prices and therefore does not depend on any cost-side parameters.

Remember that we should not confuse markups with profits. Airlines may not be profitable even if markups over marginal cost are large, because fixed costs are potentially large and because marginal may be declining in output over a substantial range.

4. Estimation.

The estimation techniques are taken from Berry (1994) and Berry, Levinsohn and Pakes (1995). These depend on an assumption that the two "errors" in the model, ξ and ω, are mean independent of some vector of observed instruments. (This is analogous to the OLS assumption that the error is mean independent of x.) We want to allow for the endogeneity of price and density, so we do not include these in the instrument vector. However, we do treat the other product characteristics (and indeed the network structure of each firm) as exogenous. While our econometric assumptions are still restrictive, they are in many ways less restrictive than the assumptions found in previous work.[15]

Estimation of the parameters of the model is undertaken by the method of moments, which exploits the mean independence assumption on the errors of the model. In particular, at the true parameter vectors, the errors of the model should be orthogonal to the vector of instruments. Thus, we choose the vector of parameters which sets the covariance of the errors and the instruments "as close as possible" to zero.

Because the basic procedure is described in much detail in BLP (1995), we will not belabor it here. The method of moments framework requires us to solve for unique values of the unobservables as a function of the data. On the demand side, unique values of ξ are guaranteed by a result in Berry (1994). We calculate them using a slight variation of a contraction mapping technique used in BLP. This calculation requires us to compute the market share function itself. Unlike the BLP specification, our assumptions on demand give us analytic market shares and so, unlike BLP, we do not require any Monte Carlo integration techniques. Given the size of our data set, this is fortunate. On the cost side, we note that marginal cost can be computed simply as price minus the markup, where the markup is a function of demand side parameters and of ξ. The cost side unobservable is then just a linear term in marginal cost.

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[15] Entry into airline networks was modeled in previous work undertaken separately by two of the current authors. These attempts, though, involved much less detailed models of product markets and, in any case, did not endogenize the entire network structure. See, Reiss and Spiller (1989) and Berry (1992).

Thus, for any values of the parameters, θ, we can compute two vectors of unobservables, $\xi(\theta)$ and $\omega(\theta)$. At the true value of θ, these unobservables have mean zero, conditional on our assumed vector of instruments. This is the restriction that drives the estimation procedure.

To calculate standard errors of the estimates, we have to make some assumptions on the correlation structure of the errors. Across markets, the errors are assumed to be independent. Within markets, we decompose the demand and cost errors into a market mean and a deviation from the mean. The within market demand and cost shock means are allowed to be correlated, but the deviations are assumed to be uncorrelated. This factor structure is used in calculating the variance matrix of the moment conditions, which is one component of the formula for the variance of the estimates.

Berry (1994) makes a simplifying assumption that the econometrician observed the expected market share. In actual data, we observe this only with sampling error. In BLP (1995), this sampling error in observed market shares was not large, because the shares were calculated as a fraction of the population of U.S. households, which on the order of 100 million. In this paper, we also have a large sample size, of more than one million. Unfortunately, this sample is divided into more than 120,000 products across more than 14,000 markets. Thus, the average number of sampled passengers choosing a given product is less than 10. While in other contexts a sample size of one million might lead one to ignore sampling error, in our case it is not so obvious. However, we must leave the topic of how to correct our standard errors for this source of variation for future research. Our current standard errors correct for the very large variation across products and markets.

Instruments. Our estimation procedure requires us to specify a vector of exogenous instruments. As noted, we treat product price, product market shares and spoke densities as endogenous, but treat all other product and market characteristics as exogenous shifters of cost and/or demand. Instruments for spoke densities include population and network characteristics at the endpoint cities. Additional instruments for price and markups include the characteristics of other products in the market. To create our instrument vector, we experimented with various combinations of the exogenous data on simple versions of our model on a 10% sample of our data. We then held this vector fixed as we moved onto estimating our full model on the entire data set

"Identification". Some readers of early versions of this paper have inquired as to how data can identify two unobserved types of consumers. Note that our model is a special case of a general random coefficients discrete choice model; our random coefficients are assumed to take on one of two values. There is an extensive literature on why such models are likely to fit data

better than models without random coefficients, see, e.g. Hausman and Wise (1978), McFadden (1981) and BLP (1995). We will only briefly review that literature here, in the context of our data.

Let us begin by considering what sort of data would allow us to estimate two different coefficients on price, while the other coefficients were held equal across consumer types. Imagine two identical city-pair markets, with products that are identical except for price. The first market has two products, one priced at $200 and one at $100. The second market has three products, one at $200 and two at $100. In a logit model without random coefficients, it is well known that if the two market shares in the first market are equal, then the three market shares in the second market will also be equal. The general problem carries over to any discrete choice model in which the error structure is additive i.i.d. across products. However, in real markets the two low-priced products in the second market are likely to compete for many of the same consumers and the market share of the $200 product will be higher than the individual shares of the $100 products. Our model will fit this sort of data by estimating two coefficients on price. The farther apart are these coefficients, the better substitutes are similarly priced goods. In our dataset the prices and product characteristics vary a lot (see Table 1). Therefore, it is easy for us to pick up violations of the i.i.d. error model and easy to estimate two coefficients on price.

Estimating two coefficients on price also has an affect on markups. In the case without random coefficients, markups and prices will not respond to the number of similar products in the market. With random coefficients, markups will change: introducing similar products will drive prices down.

Now let us consider letting several coefficients change across consumer types. It may be obvious from the prior argument that we could find large and small coefficients on both price and on our “hub” variable. But should the large coefficient on hubbing be associated with the price sensitive type or with the price insensitive type? If the price sensitive type likes hubs more (less), then the derivative of market share with respect to hubbing will be larger (smaller) for low priced goods. In our data, we can see how market shares change with hubbing for both low and high priced goods, and so, intuitively, the estimation procedure can assign the hub-loving coefficient to the “correct” type.

5. Data.

The spoke density data used in the empirical work are drawn from the Department of Transportation's Service Segment Databank DB27R, which shows a carrier's total monthly traffic on each nonstop route segment that it serves (traffic is aggregated across individual flights). Data on fares and traffic levels in individual city-pair markets also used below, are drawn from Databank 1A (DB1A) of the Department of Transportation's Origin and Destination Survey (O&D). This databank shows fare and route information for a quarterly 10% sample of all airline tickets sold in the U.S. Each record of the databank contains an airline itinerary (a route flown on a given carrier, with the direction of travel indicated), a dollar fare, the distance of the trip, and a number of passengers flown on the itinerary at the given fare during the quarter.

We follow the earlier studies of spoke density, BDS and Brueckner and Spiller (1994), by using data from the fourth quarter of 1985. However, these two studies focused on 4-segment round-trip flights that do not originate out of hub cities. This restriction is intended to avoid demand-side effects of hubs. In the present work, we allow for markups which vary with hubs and so we do not restrict ourselves to non-hub origins, nor to 4-segment fares. We do use only round-trip itineraries. We eliminate itineraries that are chosen by only one passenger, as these may represent coding errors. For similar reasons, we eliminate very low and very high prices from the data.

Our data set contains 122,871 unique Origin-Destination-Carrier-Fare products in 14,122 unique Origin-Destination directional markets. These products comprise 4,963 unique Carrier-Legs flown by 32 carriers from 262 Origins representing the itineraries of 1,107,894 passengers. Approximately 30% of the markets have only one product and another 30% have between one and five products. About 1% of the markets have more than one hundred products, the maximum number being 874 products in the New York City to Miami market. In approximately 50% of the markets with more than one product, fares vary less than 20% from the mean fare but in 10% of the markets fares vary more than 50% from the mean.

As noted, the "population potential", or market size, M_m, of each market is measured as the geometric mean of the population of the endpoint cities, measured in millions (in the tables, this variable is MPOP.) Sampled output of each product is the number of passengers (NPASS) in the O&D sample. Price (or FARE) is the observed fare in the O&D.

The *x* variables that determine consumer utility relative to the outside good include a constant, distance between the origin and destination cities (MDIST), distance squared and a dummy variable (DIRECT) equal to one if the flight is direct. To capture the possibility that consumers may avoid congested airports we include a variable (CONGEST-D) equal to the number of the origin or destination airports (0, 1 or 2) that are slot controlled[16]. We have experimented with a number of measures of hub size, including a dummy variable for hubs and the number of points served by an airline out of an airport. However, neither of these measures accounts for the relative importance of the city-pair. Therefore, if an airport is a hub for a given carrier, our HUBSIZE variable is equal to the sum of the population potential for all city-pairs connected -by that airline- through that hub. If the airport does not serve as a hub for a carrier, then the hubsize measure is zero. Our measure of appeal to tourists is the (signed) January temperature difference (TEMPDIFF) between the origin and destination. Since TEMPDIFF is the same for all products in a given market, it has no power to explain the choice between products, but it helps explaining the choice between flying and the outside good. Furthermore, it may help separate customer types. There is no direct measure of flight frequency in the data. However, from the Service Segment Databank, one observes the number of trips (per quarter) between the two cities comprising the route. As a demand-side flight frequency variable (TRIPS-D) we include the minimum number of such trips across the one or two segments of the flight. We allow the coefficients on the direct, hub size, tourist and flight frequency variables, together with the coefficient on price, to vary across consumer types.

On the cost side, segment marginal cost depends on a the number of spoke end-points (0, 1 or 2) that are congested (CONGEST-C), segment distance (DIST) and spoke density (DENS). We also include a second cost-side measure of congestion, (DOT-CONGEST), equal to the number of takeoffs and landings which occur at one of the twenty-four airports which operate under FAA "flow control."[17] Finally, a cost-side flight frequency variable (TRIPS-C) is included in some specifications. This is just the segment number of trips per quarter from the Service Segment Databank.

Remember that product marginal cost is the sum of spoke marginal costs, so that a linear specification for marginal cost would include the sum of distance and density across segments. We include a constant (equal to one) in the specification of segment marginal cost and so the number of segments (NSEG), which is just the sum of this constant across segments, enters product marginal cost. The mean of any product-specific marginal costs that are unrelated

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[16] The FAA has established slot allocation mechanisms at Chicago O'Hare, Kennedy and La Guardia in New York City and Washington National in Washington D.C.

[17] This list of 24 airports also includes Orange County and Long Beach, California, each of which is under strict local limits on takeoffs and landings.

to segment costs (*i.e.* the mean of ω) is then captured by including a additional constant in the specification for product marginal cost.

Since we expect that any cost-reducing effect of density would be greater at longer distances, we experiment with different functional forms for the interaction between distance, density and frequency. In particular, we use second and third order polynomials as approximations to more general functional forms. A quadratic specification adds the sum across spokes of squared distance, the sum of distance times density and so forth.

Table 1 presents some descriptive statistics on the data, including means, maximums, standard deviations, etc, as measured across products in the sample. (The spoke 2 densities, which refer to the second outbound leg, are set to zero on direct flights.) The variables in Table 1 are scaled so as to give easy-to-present coefficients in the later tables. Table 2 presents some simple correlations between exogenous variables, taking products as the unit of observation. (The two densities are for up to two outbound segments.) Note that in the raw sample, densities are positively correlated with price, which is consistent with the idea that it is necessary to correct for the effects of markups and distance if we are to find any evidence of economies of density.[18]

Table 3 presents some simple regressions of price on other variables. These regressions are for descriptive purposes only, as the estimated coefficients bear little necessary relationship to the parameters of the model. There are two price regressions. The first involves only the "cost" variables of distance and density. Density has the expected sign, but a small magnitude, about a $9 decrease in price for a 100,000 passenger increase in spoke density. As measured by the R^2, distance and density do not "explain" much of the variance in price. When some demand variables are added, the magnitude of the coefficient on density decreases further. Both direct and the hubsize variable are positive and significantly different than zero. The positive coefficient on hubsize is consistent with early descriptive regressions that have been used to support the "Borenstein" effect of hubs on markups.

These results suggest room for improvement, and we turn next to results from our model.

6. Results.

[18] When we look only at a subsample of small 4-segment markets, consistent with the Brueckner-Spiller sampling framework, we do find a negative raw correlation between price and density.

We begin by briefly characterizing the demand and cost parameters and then move on to the more interesting implications of those parameters.

The Estimated Parameters. Table 4 summarizes the results for the demand side for various versions of the model. Table 5 provides the estimated parameters and standard errors for both demand and cost for the various estimated models. In each case marginal cost includes a cubic in distance and density. In addition, the marginal-cost specification includes the number of segments in the itinerary and the two variables measuring airport congestion. In both Tables the first column provides estimates for a special case with only one type of consumer. The second column lets the coefficient on price vary across two types of consumers, while the third column lets a number of the demand parameters vary. The fourth column differs from the third in adding flight frequency ("trips") to the cost function.

There are so many parameters to be estimated that Table 5 is broken into three panels. The first two panels present the demand parameters, while the third panel presents the cost estimates.

Columns one of Tables 4 and 5 give results from a nested logit with only one type of consumer. We can reject the pure (non-nested) logit model, as the coefficient λ is less than one, indicating the expected result that the values of within market choices are correlated. The other demand-side coefficients are of the expected sign. The coefficient on FARE applies to the negative of price; the positive coefficient indicates that consumers do not like price increases. They prefer direct flights out of uncongested airports on the hubbing airline. The signs of DIST and DIST^2 have the expected inverse U shape: as distance increases, air travel becomes more attractive relative to auto travel, but total demand for travel may fall. At short distances we expect the first effect to dominate, but the second to dominate at longer distances.

In columns two, we allow the coefficient on FARE to differ across two groups of consumers. The coefficients on the other variables continue to have sensible signs. Looking at the coefficient on FARE, we find evidence in favor of the existence of different types of consumers with differing disutility from price increases. The type 1 consumers place a much greater negative weight on price increases, as the coefficient on price is nearly ten times as large for group one as opposed to the group two. The price sensitive consumers make up about 92.4% of the potential travelers. However, such price sensitive potential consumers are much less likely to actually buy a ticket; we shall see in the last panel of the table that they make up a much lower percentage of the actual travelers.

Column three allows the coefficients on FARE, DIRECT, HUBSIZE, TEMPDIFF and TRIPS to vary across customer type. This additional differentiation reduces the population of type 2 customers from almost eight percent of the population to less than three percent of the population. The price insensitive type 2 consumers exhibit tastes, relative to type 1, that we might expect from business travelers. They care more about direct flights, more about the size of hub at the origin and more about flight frequency. Their valuation of the tourist variable, TEMPDIFF, is a little less than that of type 1 customers, but is less precisely estimated. Thus, even though we have no customers' characteristics in our data set, the data and the model together can identify two types of consumers that can sensibly be labeled "tourist" and "business."

In column four, the demand side specification does not vary but the cost side specification does: the trips variable is added to the cubic portion of segment marginal cost. Here the only puzzling result is that the type 1 HUBSIZE coefficient is larger than the type two coefficient. This puzzle can be resolved by considering the marginal willingness to pay for HUBSIZE. Our linear utility specification implies linear indifference curves in HUBSIZE/FARE space, with a slope given by the ratio of the coefficient on HUBSIZE to the coefficient on FARE. It is easy to see that the marginal willingness to pay for increases in hub size is much greater for the type 2 business traveler.

The third panel of Table 5 gives the estimated parameters of segment marginal cost. Given the flexible functional form on our cost side, it is hard to interpret the these parameters. In all specifications but the last, congestion appears to raise segment marginal cost. The negative sign on NSEGS indicates a negative intercept in the segment marginal cost function, which may indicate problems with the cost specification for distances and densities near zero. The estimated coefficient on the linear term in DIST is positive, which seems reasonable. The coefficient on the linear term in DENSITY is also positive, which by itself does not support economies of density. However, the other terms do lend support to the presence of economies of density at many distances and densities, as we will see below.

We turn next to the economic implications of these parameters. The demand parameters have important implications for pricing behavior and markups, while the cost side parameters determine the extent of economies of density.

Implications of the demand parameters. In this section we focus on implications of the demand side results in column III of Table 4. The last panel of that table summarizes the demand side results. First note that both types of consumers are important in the market. While type 2 consumers make up less than three percent of the potential travelers, the column III estimates imply that they make up more than a quarter of actual passengers (and this percentage increases to almost 40% in column IV.) These proportions are consistent with the results of a recent Gallup survey which reports that in 1993, 8 percent of air travelers accounted for 44 percent of all trips.[19]

Based on results shown in column III, the mean price paid by type 1 consumers is $204 while the mean price paid by the “business” travelers is almost $150 higher. However, the business traveler is getting something for these extra dollars. In particular, consider the demand unobservable, ξ, which captures, for example, the unrestrictiveness of the ticket. Across all products, ξ is mean zero (i.e. its mean is captured by the constant in the utility function.) Passengers have a preference for high "quality" flights and so the mean across all tickets sold is estimated to be about 0.98. The level of ξ is 30% higher for type two customers and about 12% less for the type 1s.

Table 6 considers the implication of the parameters for the relationship between prices, markups and hubs. Specifically we examine in some detail the effect of a carrier's usage of an airport as a hub on the demand and fare paid for products in markets originating at those airports Given our estimates, for each product in each market we can estimate the proportion of each type of consumer buying the product. We can then discuss the average product characteristics bought by different types of consumers flying different airlines in different markets.

Table 6 presents a summary of product characteristics across categories of markets, consumers and airlines using the results of Table 5 Column III. Within a market, we take weighted averages of product characteristics, where the weights are the predicted number of passengers of each type. The weighted product characteristics are separately averaged (within market) across hubbing and non-hubbing airlines. These market averages are then averaged across market (weighting by the number of passengers in each market) to produce summary statistics. The point of taking averages of within market averages is to control for across market variation in distance, populations size and other market characteristics. However, such variation in market-level variables makes it dangerous to compare levels the different market categories (*i.e.* across the vertical panels of the table.) Therefore we will focus on the hub/non-hub differences within market categories.

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[19] See, Air Travel Association, Air Travel Survey 1993, Washington, DC, 1993.

The first (horizontal) panel of Table 6 divides the products into three categories of markets. The first category, non-hub markets, includes all markets in which no carrier uses the origin as a hub airport. The other two categories are comprised of all hub markets, those in which at least one carrier uses the origin as a hub. The hub markets are distinguished by the size of their connected network, as measured by HUBSIZE. Large hub markets include all those in which at least one of the hub carriers has a HUBSIZE of 0.01, approximately the largest third of all hubs. Small hubs then include all other hub markets. The second panel of the table divides the customers into the two estimated types (with average percentage of each type given in the third panel.) The fourth panel then further separates the products into the products of non-hubbing and (where appropriate) hubbing airlines. The next panel then gives the averaged product characteristics

Note that although 82% of the markets are non-hub markets, these markets include only 31% of the total passengers flown. The remaining markets and passengers are distributed almost evenly between the large and small hub markets. The makeup of the passengers in each type of market is also notable, with non-hub markets having the highest percentage of Type 1, "tourist", passengers, and the large hub markets having the highest percentage of Type 2, "business", passengers.

Even more interesting is the distribution, within hub markets, of customer types between the hub and non-hub carriers participating in each market. In small hub markets the distribution of customer types, "Pct of Car Tot", is almost identical for each carrier type. In the large hub markets, however, the hub carrier, or carriers, serve a higher percentage of TYPE 2 customers, 33.0% versus 23.2% for non-hub carriers. In all markets the fare paid by TYPE 2 customers is higher than that paid by TYPE 1 customers. In the small hub markets these fares are almost identical for hub and non-hub carriers. In the large hub markets, however, the average fare realized by the hub carriers is almost 19 % higher than that of the non-hub carriers for TYPE 2 customers and only 5% higher for TYPE 1 customers. This advantage is labeled the "Hub Premium" and is shown not only for fare but also for estimated Marginal Cost and markup.

Also shown in TABLE 6 are the average values of DIRECT, TRIPS and then unobserved characteristic, ξ, for each customer type in each market. Note that in small hub markets, where the non-hub carriers carry 60 percent of the passengers, average TRIPS is higher for non-hub carriers than for hub carriers. In all markets, however, TYPE 1 customers fly, on average, less frequent products than do TYPE 2 customers. Similar comments can be made about DIRECT. Hub carriers generally provide a higher percentage of direct flights and TYPE 2 customers consume more direct flights than TYPE 1 customers from both carrier types. In the small hub markets, the products of non-hub carrier's products have 14 to 18 percent higher values for the unobserved characteristic. In large hub markets, however, their products have values 35 percent smaller than those of the hub carriers.

The last panel of Table 6 then decomposes the fare premium obtained by hubbing airlines. In large hubs, type 2 passengers are paying 19% more ($319 vs. $268) originating from a large hub on the hubbing airline. However, the average marginal cost of the hubbing flights is 26% *less* ($98 vs. $133). An interesting part of the “hub premium” is then that markups are 63% higher ($221 vs. $133).

Figure 1 provides these results in a visual way.[20] We see that for small hub markets, hub carriers are able to charge type 2 customers 4% above non-hub carriers. Hub carriers also have 4% lower marginal costs for these traveler types. On the other hand, the average type 1 customer pays the same to a hub or a non-hub carrier. Furthermore, carriers have similar marginal cost of providing type 1 service. Because the hub premia for type 2 customers is so small, type 1 and type 2 customers divide themselves evenly between hub and non-hub carriers.

In large hub markets, however, we observe the working of the hub premium. First, type 2 customers are not just willing to pay the 20% premia that hub airlines charge, but that price differential does not deter them from flying more often with a hub than a non-hub carrier. Hub carriers are even able to extract a small premium over type 1 customers (5%).

Figure 1 shows, then, the origins and the workings of the origin hub premium. The hub premium originates in type 2 (business) customers. They value flying an airline with a larger network much more than type 1 customers do. In large hubs, then, hub-airlines are able to charge type 2 customers a substantial premium over non-hub airlines. That premium, however, is very small for type 1 (tourist) travelers.

The ability to charge a large premium and still capture a larger share of the business travel, implies that non-hub airlines in hub markets have a strong competitive disadvantage. Not only does the hub airline not create a "monopoly umbrella" (the price non-hub carriers are able to charge type 1 or type 2 customers is indeed found to be smaller than in non-hub markets), but the hub airline takes a larger share of the type 2 customers. Thus, the average yield of a non-hub airline is smaller in hub markets than in non-hub markets, reducing the profitability of serving hub-markets.

[20]Some readers have found this representation useful and some have not; in any case all the relevant numbers are in Table 6.

This result may suggest a dynamic explanation (untested here) to the increase in airport concentration that has taken place since deregulation. Once an airline decides to develop a major hub in a given airport, their competitors find business customers moving away, reducing their average yield. Marginal airlines, then, will find it profitable to drastically cut service to that city. On the other hand, hubs do provide substantial price and cost benefits to airlines, facilitating entry out of hubs into new city-pair markets, thus potentially explaining the decrease in market level concentration that has taken place since deregulation (for a start on empirical models of airline entry, see Reiss and Spiller, 1989, and Berry, 1992).

Implications of the Cost Parameters. We have just seen that flights by hubbing airlines out of hubs are associated with lower costs. Our proposed explanation for this is economies of density. Figure 2 presents plots of estimated marginal cost, corresponding to the estimates in column III, in distance and density space. Information similar to that depicted in the figures is also found in Table 7. The surface of the plot is shaded where the partial derivative of Marginal Cost with respect to density is less than zero. Darker areas indicate higher returns to density. At distances less than 500 miles, marginal cost increases as density increases up to about 150,000 passengers per quarter and then begins to decline. Increasing returns to density are thought to result from the ability to carry additional passengers through the use of larger, more efficient aircraft. At short distances this may not possible, because over short distances the increased cruising efficiency of larger aircraft may not make up for their higher takeoff and landing cost. Increases in density must in that case be met with increases in frequency. We call this result the "Southwest Effect," after the largest non-hubbing airline that offers frequent service on shorter, dense routes.

At distances of 500 to 1,500 miles there are returns to density throughout the range of density. However, above distances of 1,500 miles, marginal cost is increasing except at very low levels of density. We interpret this last result as perhaps stemming from the tendency of polynomials to curl up (or down) at the corners of the data. Alternatively, the increasing marginal cost at high distances may be due to a similar loss of flexibility which occurs when the leg distance limits the choice of aircraft to the largest types. Since there are no larger, more efficient aircraft than those already in use, increases in density can only be met with increases in frequency.

In fact, most legs are either under 500 miles in length, or within the area where there are returns to density. Very few observations actually fall in the high distance, high density area where marginal cost increases rapidly. However, the magnitudes of the estimated derivatives of marginal cost with respect to density in Table 7 are fairly large. This may reflect problems with the polynomial specification resulting in a cost surface that is too “curvy”. Thus, while we take our results as consistent with the idea of economies of density over a wide range, we will not perform the kind of detailed analysis of implications for the cost side that we performed for the demand side.

7. Robustness.

Our results depend on a number of functional form and exogeneity restrictions. We examine the robustness of our results in two ways, using a statistical test and by relaxing the distributional assumptions. We calculate a traditional (Hansen, 1982) specification test. This test is conditional on all the assumptions of the model and therefore tests the over-identifying moment restrictions together with all the functional form and distributional assumptions. Since our model is obviously stylized and the sample is large, it would be surprising if we could not formally reject the model and indeed we do so.

Second, we re-estimated the model assuming a tri-modal distribution of consumer preferences. We are able to distinguish three consumer types. The first resembles our prior tourist type and the last resembles our prior business type. In general, the second type falls in the middle, with price sensitivity clearly between the other two types. Table 8 shows some demand-side coefficient estimates from this specification. The Hubsize coefficient for the new type 2 resembles that of type 3, but type 2 consumers do not seem to care as much about flight frequency as type 3. The markups from this specification are almost perfectly correlated with the markups from the prior specifications.

8. Conclusions.

In this paper we take a new approach to the empirical analysis of differentiated product markets. We attempt to estimate the tastes of a discrete set of unobserved (by us) consumer types and we provide an explicit model of economies of scope at the network level. Our methods show signs of success, particularly in distinguishing economically interesting consumer types.

We have not addressed all the issues of potential importance in the airline industry. There may be important dynamic aspects in the pricing and production decisions. On the pricing side, there may be some sort of tacit or explicit collusion. On the production side, some of what we call markups or marginal cost may reflect capacity constraints on some flights at some times of day. Also, network structure may affect entry and exit decisions in important ways. Finally, we have not modeled any agency problems related to frequent flier programs or travel agent commissions. These marketing devices might exploit differences in incentives between decision-makers and the ultimate consumers of the product.

This paper, though, provides a first attempt to analyze the role of hub-and-spoke operations in a product differentiation framework. Our results confirm that hubs are an important production and marketing tool for the airlines. First, the existence of economies of density implies that hubs provide important cost savings. Second, hubs provide the airlines with an ability to charge a hub-premium. Their ability to raise prices, however, is much greater for price-insensitive business-type travelers. When flying out of large hubs, these travelers pay a premium of approximately 20%, while the hub-premium for non-business travelers is estimated to be only 5% or less. The welfare consequences of this hub premium need not be negative. Business travelers are seen to receive a higher quality good, in terms of observed and unobserved (by us) characteristics and, indeed, business travelers represent a higher percentage of total passengers for hub-carriers than for non-hub carriers. Add to this the low demand elasticities of business travelers and, aside from the unmodeled issues mentioned in the last section, the negative welfare consequences of hubs appear to be rather small.

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TABLE 1
DESCRIPTIVE STATISTICS
122,871 Unique Origin-Destination-Fare-Carrier Observations

	MEAN	STD DEV	MIN	MAX
FARE ($100)	2.764	1.488	0.110	18.33
NPASS (Passengers)	9.017	31.299	1.000	2798.0
DIRECT (Fraction)	0.466	0.498	0.000	1.000
HUBSIZE	0.017	0.045	0.000	0.210
TEMPDIFF (10°F)	0.286	2.077	-6.520	6.520
TRIPS-D (MIN 1,000/QTR)	0.293	0.179	0.001	1.595
CONGEST-D(# of airports)	0.202	0.413	0.000	2.000
MDIST (1,000 MI)	1.009	0.608	0.030	2.776
DIST (1ST Outbound Leg) 1,000 MI	0.710	0.503	0.021	2.704
DIST (2ND Outbound Leg) 1,000 MI	0.351	0.479	0.000	2.611
DENS (1ST Outbound Leg) 100,000 PASS/QTR	0.593	0.475	0.00003	4.553
DENS (2ND Outbound Leg) 100,000 PASS/QTR	0.361	0.493	0.000	4.553
TRIPS-C (1ST Leg) 1,000 DEP/QTR	0.349	0.214	0.001	1.595
TRIPS-C (2ND Leg) 1,000 DEP/QTR	0.212	0.249	0.000	1.594

TABLE 2
CORRELATION OF ENDOGENOUS VARIABLES

	PRICE	QUANTITY	DENS(1)	DENS(2)
PRICE	1.000	-0.063	0.084	0.122
NPASS		1.000	0.068	-0.120
DENS(1)			1.000	0.164
DENS(2)				1.000

DENS(1) refer to the density of the first outbound leg, while DENS(2) refers to the density of the second outbound leg.

TABLE 3
REGRESSION OF PRICE ON COST AND DEMAND VARIABLES

	Cost only		Cost and Demand	
	Parm	S.E.	Parm	S.E.
CONSTANT	1.704	0.013	1.545	0.022
NSEGS	-.113	0.013	-0.011	0.017
CONGEST-DOT	0.084	0.007	0.082	0.008
CONGEST-C	0.012	0.005	0.012	0.005
DIST	1.004	0.008	1.004	0.008
DENS	-.088	0.012	-0.094	0.012
TRIPS-C	0.362	0.029	0.310	0.037
CONGEST-D			0.009	0.013
HUBSIZE			2.097	0.094
TEMPDIFF			-0.011	0.002
TRIPS-D			0.019	0.040
R^2		0.173		0.177

TABLE 4
SUMMARY OF DEMAND RESULTS

	I Single Type of Consumer	II 2 Types of Consumers Differ only in Price		III 2 Types of Consumers No Trips in MC		IV 2 Types of Consumers Leg Trips in MC	
VARIABLE		TYPE 1	TYPE 2	TYPE 1	TYPE 2	TYPE 1	TYPE 2
FARE	0.455	0.696	0.068	0.829	0.077	0.986	0.111
DIRECT	0.656	0.542	-	0.414	1.014	0.293	0.876
HUBSIZE	0.437	0.213	-	0.285	0.761	0.616	0.368
TEMPDIFF	0.050	0.049	-	0.052	0.049	0.049	0.050
TRIPS	0.551	0.393	-	0.329	0.954	0.388	0.493
PERCENTAGE OF PASSENGERS	100%	70.99%	29.01%	73.19%	26.81%	60.13%	39.87%
PERCENTAGE OF POPULATION	100%	92.35%	7.65%	97.48%	2.52%	95.21%	4.79%
AVERAGE FARE	-	$205	$338	$204	$351	$191	$323
AVERAGE ξ	-	0.97	1.19	0.86	1.30	0.87	1.22
AVERAGE TRIPS	-	0.39	0.36	0.37	0.39	0.39	0.36

TABLE 5
RESULTS OF ESTIMATION

	I Single Type of Consumer		II 2 Types of Consumers Differ only in Price		III 2 Types of Consumers No Trips in MC		IV 2 Types of Consumers Leg Trips in MC	
	Parm	S.E.	Parm	S.E.	Parm	S.E.	Parm	S.E.
LAMBDA	0.605	0.020	0.638	0.020	0.599	0.027	0.617	0.026
MU	4.766	0.464	8.652	2.079	8.651	2.471	9.532	1.625
PROB TYPE 1	1.000	Fixed	0.924	0.018	0.975	0.013	0.952	0.019
DEMAND								
FARE 1	0.455	0.039	0.696	0.054	0.829	0.075	0.986	0.084
FARE 2	-	-	0.068	0.014	0.077	0.017	0.111	0.024
DIRECT 1	0.656	0.023	0.542	0.022	0.414	0.060	0.293	0.063
DIRECT 2	-	-	-	-	1.014	0.070	0.876	0.070
HUBSIZE 1	0.437	0.026	0.213	0.013	0.285	0.047	0.615	0.075
HUBSIZE 2	-	-	-	-	0.761	0.423	0.368	0.127
TEMPDIFF 1	0.050	0.003	0.049	0.003	0.052	0.005	0.049	0.007
TEMPDIFF 2	-	-	-	-	0.049	0.017	0.050	0.016
TRIPS-D 1	0.551	0.058	0.393	0.041	0.329	0.055	0.388	0.061
TRIPS-D 2	-	-	-	-	0.954	0.395	0.493	0.231
CONSTANT	-10.305	0.034	-10.621	0.033	-10.207	0.034	-10.172	0.034
CONGEST-D	-0.158	0.030	-0.215	0.030	-0.186	0.031	-0.203	0.030
MDIST	0.528	0.070	0.562	0.069	0.772	0.071	0.752	0.070
MDIST^2	-0.126	0.029	-0.176	0.028	-0.206	0.029	-0.209	0.029
COST								
NSEGS	-1.453	0.157	-0.922	0.088	-0.656	0.095	0.081	0.234
CONGEST-S	0.125	0.030	0.046	0.017	0.060	0.019	-0.033	0.015
CONGEST-C	0.041	0.012	0.073	0.007	0.071	0.008	0.072	0.010
DIST	4.510	0.395	2.965	0.223	3.181	0.241	0.155	0.631
DIST^2	-2.117	0.241	-1.297	0.136	-1.420	0.147	1.117	0.446
DIST^3	0.402	0.044	0.168	0.247	0.178	0.027	-0.410	0.096
DIST*DENS	-5.229	0.794	-3.540	0.448	-3.891	0.486	-6.651	1.287
DIST^2*DENS	1.419	0.254	1.045	0.143	1.270	0.155	2.986	0.454
DENSITY	2.060	0.506	1.818	0.282	1.584	0.307	4.827	1.259
DENSITY^2	0.376	0.384	-0.252	0.213	0.164	0.232	1.537	0.522
DENSITY^3	-0.379	0.081	-0.102	0.046	-0.238	0.050	-1.012	0.341
DENS^2*DIST	1.140	0.277	0.564	0.156	0.524	0.169	0.392	0.361
TRIPS	-	-	-	-	-	-	-4.544	2.536
TRIPS^2	-	-	-	-	-	-	13.540	4.826
TRIPS^3	-	-	-	-	-	-	-13.612	2.524
TRIPS*DIST	-	-	-	-	-	-	6.989	3.868
TRIPS*DIST^2	-	-	-	-	-	-	-5.075	1.374
TRIPS^2*DIST	-	-	-	-	-	-	4.913	2.360
TRIPS*DENS	-	-	-	-	-	-	-14.381	3.247
TRIPS^2*DENS	-	-	-	-	-	-	9.237	2.114
TRIPS*DENS^2	-	-	-	-	-	-	2.008	1.605

TABLE 6
COMPARISON OF SHARES AND FARES
Based on Column III, Table 5

Market Type	Non-Hub 31% of Pass. 82% of Mkts Av Dist 800mi		Small-Hub 32% of Passengers 9% of Markets Avg Dist 954mi Avg Pop 3.8 Million				Large-Hub 37% of Passengers 9% of Markets Avg Dist 842mi Avg Pop 3.0 Million			
Customer Type	Typ 1	Typ 2	Type 1		Type 2		Type 1		Type 2	
Pct of Mkt	75.8%	24.2%	73.2%		26.8%		70.4%		29.6%	
Carrier Type	N/Hub	N/Hub	Hub	N/Hub	Hub	N/Hub	Hub	N/Hub	Hub	N/Hub
Pct of Car Tot	100%	100%	73.6%	73.0%	26.4%	27.0%	67.0%	76.8%	33.0%	23.2%
Pct of Typ	100%	100%	40.0%	60.0%	39.3%	60.7%	62.3%	37.7%	72.9%	27.1%
Avg Fare $	224	296	206	206	306	295	215	205	319	268
Avg MC $	93	111	96	95	111	106	91	109	98	133
Avg Markup	58.6%	62.4%	53.4%	53.8%	63.7%	63.9%	57.8%	46.7%	69.2%	50.4%
Ave Fare $/mi	0.387	0.488	0.301	0.302	0.398	0.398	0.336	0.313	0.474	0.403
Avg ξ	0.601	1.005	0.650	0.771	0.942	1.074	0.875	0.566	1.321	0.836
Avg Direct	0.522	0.542	0.792	0.778	0.809	0.819	0.922	0.622	0.927	0.665
Avg Trips	336	340	399	404	410	430	469	362	484	371
Hub Premium		Fare	0.1%		3.7%		5.0%		19.0%	
		Marginal Cost	-1.1%		-4.5%		16.8%		26.1%	
		Markup	-0.8%		3.3%		29.9%		63.4%	

Notes on Table 6

Markets There is a total of 14,122 Origin-Destination markets in the data. Of that number, 778 are markets,representing 5.2% of total passengers, in which only Hub carriers participate. These markets are not used in the compilation of these tables.

Market Type The distinction among market types is based on the maximum HUBSIZE of all carriers participating in the market. The specific division used is:

Non-Hub - HUBSIZE = 0.0 (93.5% of all unique Origin-Carrier combinations).
Small-Hub - 0 < HUBSIZE < 0.01
Large-Hub - HUBSIZE >= 0.01 (Approximately 34% of all unique Origin-Carrier combinations with non-zero HUBSIZE)
See Description of Variables for a complete description of HUBSIZE. See Appendix 1 for a list of all Origin-Carrier combination withnon-zero HUBSIZE.

Averages are calculated as follows: first the passenger weighted average is calculate for each of the O & D markets within each market type. The average, weighted by the total number of passengers in the O & D market, of these averages is then calculated to produce the final values. This method was chosen to best represent the average relationship among the various components of each market.

Markup is calculated as (Avg Fare - Avg MC) / Avg Fare.

Hub Premiums are calculated as follows:

Fare: [Fare(Hub) - Fare(N/Hub)] / Fare(N/Hub).
MC: [MC(N/Hub) - MC(Hub)] / MC(N/Hub).
Markup: [Fare(Hub) - MC(hub) - Fare(N/Hub) - MC(N/Hub)] / [Fare(N/Hub) - MC(N/Hub)].

TABLE 7
DERIVATIVE OF MARGINAL COST WRT DENSITY
$100/100,000 PASS/QTR
BASED ON COLUMN III TABLE 5

DIST\DENS	0.25	0.50	0.75	1.00	1.50	2.00
250 Mi	0.794	0.808	0.733	0.568	-0.27	-0.980
500 Mi	0.125	0.204	0.194	0.096	-0.369	-1.190
1,000 Mi	-0.737	-0.527	-0.406	-0.373	-0.576	-1.135
1,500 Mi	-0.964	-0.623	-0.371	-0.207	-0.148	-0.446
2,000 Mi	-0.556	-0.084	0.299	0.593	0.914	0.879

TABLE 8
ESTIMATION OF THREE TYPE CUSTOMER SPECIFICATION

	Est.	S.E.
LAMBDA	0.522	-0.023
GAMMA-1	0.942	-0.053
GAMMA-2	0.048	-0.054
MU	7.433	-8.101
FARE-1	1.007	-0.304
FARE-2	0.396	-0.192
FARE-3	0.064	-0.042
DIRECT-1	0.790	-0.183
DIRECT-2	0.028	-0.011
DIRECT-3	1.508	-0.549
HUBSIZE1	-0.033	-0.019
HUBSIZE2	2.476	-0.684
HUBSIZE3	2.173	-1.074
TMPDIF-1	-0.405	-0.133
TMPDIF-2	1.163	-0.295
TMPDIF-3	-0.531	-0.171
TRIPS-1	0.657	-0.351
TRIPS-2	0.337	-0.357
TRIPS-3	2.117	-1.045
CONSTANT	-9.561	-0.053
CONGEST	-0.124	-0.047
MDIST	-0.687	-0.109
MDIST^2	0.300	-0.044

APPENDIX
DESCRIPTION OF VARIABLES

Descriptions are for product ***j***, in market ***i***, carrier ***k***.

DEMAND VARIABLES

MPOP	Population Potential[21] for market ***I***.
FARE	Fare paid for product ***j***. UNITS - $100.00
DIRECT*	1 if product ***j*** is a direct flight, 0 otherwise
HUBSIZE*	If the origin is a hub airport for carrier ***k*** then HUBSIZE is the Population Potential for all city pairs connected through the origin city. If the airport does not serve as a hub for carrier ***k*** then HUBSIZE is zero.
TEMPDIFF*	Difference between origin and destination mean January temperatures. UNITS - 10 Degrees Fahrenheit
TRIPS*	Minimum of the number of trips flown by carrier ***k*** on each leg of the route. UNITS - 1000 Departures/Quarter
CONSTANT*	1.0
CONGEST-D*	Sum, over the origin and destination, of a dummy variable indicating that an airport is "slot controlled"[22]
MDIST*	Great circle distance between origin and destination airports. UNITS - 1000 Miles
MDIST^2*	MDIST squared.

COST VARIABLES

NSEGS	Number of segments in the route of product ***j*** . (1 or 2)
CONGEST-C*	Number of takeoffs and landings at "slot controlled" airports in the route of product ***j***.
DOT-CONG*	Number of takeoffs and landings at airports which operate under FAA "flow control"[23]
DISTANCE	Sum of actual leg distances over the one or two legs of the route. UNITS - 1000 Miles
DENSITY	Sum of the number of passengers per month flown by carrier ***k*** on each leg[24] of the route. UNITS - 100,000 Passengers/Quarter
TRIPS	Sum over both legs of the number of trips flown per quarter by carrier ***k***. UNITS - 1000 Departures / Quarter.

[21] SQRT(origin population * destination population).

[22] The FAA has established slot allocation mechanisms at Chicago O'Hare, Kennedy and La Guardia in New York City and Washington National.

[23] This list of 24 airports also includes Orange County and Long Beach, California, each of which is under strict local limits on takeoffs and landings.

[24] Because trips are round trips, we measure densities as the sum of the two directions.

APPENDIX -- CONT

DESCRIPTIVE STATISTICS DEMAND/COST VARIABLES

Variable	Mean	Std Dev	Minimum	Maximum
MPOP	227387.12	192268.08	1130.40	1191781.00
FARE	2.7638407	1.4880484	0.1100000	18.3300000
DIRECT	0.4666602	0.4988892	0	1.0000000
TEMPDIFF	0.2864697	2.0774947	-6.5200000	6.5200000
TRIPS	0.2934735	0.1795864	0.0010000	1.5950000
HUBSIZE	0.0170110	0.0448443	0	0.2106280
CONGEST	0.2022039	0.4130535	0	2.0000000
MDIST	1.0090688	0.6084302	0.0300000	2.7760000
MDIST^2	1.3884041	1.5944844	0.000900	7.7061760
NSEGS	1.5333398	0.4988892	1.0000000	2.0000000
CONGEST	0.3149401	0.6041807	0	3.0000000
DOT-CONG	1.7655997	0.9916804	0	4.0000000
DISTANCE	1.0621377	0.6249192	0.0300000	5.0610000
DIST^2	1.1119420	1.2418665	0.000900	12.8130210
DIST^3	1.5190454	2.6297537	0.0000270	32.4545279
DIST*DEN	0.6679041	0.7026942	0.00001674	5.2785213
DIST^2*DEN	0.7055024	1.1366410	4.67046E-6	13.0132275
DENSITY	0.9544737	0.7384137	0.0000300	7.9023200
DENSITY^2	0.9511442	1.3970802	9E-10	31.9492227
DENSITY^3	1.3074138	3.5029454	2.7E-14	131.9727217
DENS^2*DIST	0.6751575	1.1904563	5.256E-10	11.4191792
TRIPS	0.5610866	0.3638758	0.0010000	3.0850000
TRIPS^2	0.2753029	0.3046792	1E-6	4.7639170
TRIPS^3	0.1679641	0.3080066	1E-9	7.3647064
TRIPS*DIST	0.3382569	0.2554679	0.00012900	2.2982620
TRIPS*DIST^2	0.3175201	0.3843447	9.8E-6	3.3692860
TRIPS^2*DIST	0.1479861	0.1695250	1.29E-7	2.8692971
TRIPS*DENS	0.4777567	0.5866136	3E-8	12.1272763