Measuring the Impact of Scheduling Overlap and Market Structure on Prices: Evidence from the Airline Industry

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Abstract

Measuring the degree of competition in markets is important for setting competition and regulatory policies as well as developing management strategies. Commonly used structural indices, such as the HHI, overlook the way in which firms compete and, hence, set their prices in markets. We propose a family of horizontal differentiation measures, which encapsulates firms' portfolio of products as well as the degree of overlap and substitution between competing services. We term this family of measures Schedule Differentiation Metric or SDM. Applied to aviation markets, we illustrate one instance of SDM and demonstrate the significant importance of SDM in explaining price levels and structure. The information captured by SDM also explains fares across fare percentiles depending on the competing airlines' business models.

Keywords: airlines, competition, HHI, flight frequency, product differentiation

JEL Classification: L13, L93, D22

Acknowledgements: We are indebted to Tom Ross for their helpful comments and suggestions. We thank the seminar participants at the Indian Institute for Management 2022, Southern Economic Association 2021 Conference, CRESSE 2018 conference, ATARD 2018 workshop, TSTE Conference 2018 Beijing-Jiaotong University and Bristol IO Workshop 2017. We are also indebted to two anonymous referees for suggestions that greatly improved the paper.

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1. Introduction

Assessing the competition in transportation markets in general, and aviation markets in particular has taken on increasing importance as mergers between carriers become more common and the entry of new firms more challenging. Such metrics affect the direction of competition policy but also public policy generally; market entry restrictions, removing barriers to ownership and trade, and assisting firms in times of economic crises, to name a few examples. Private sector firms also require a clear understanding of the extent and nature of firm rivalry when making decisions regarding market entry, differentiation and assimilation strategies, product positioning and other capacity and service decisions.

Over the years, numerous methods have been devised to measure the degree of competition and concentration in markets. Methods include simple counting of the number of competing firms, concentration ratios $CR(n)$ that capture the market shares of the largest n firms to assess the extent to which a given market is oligopolistic, the price-cost margin (Lerner index) measuring the mark-up in price over marginal cost, relative profits encapsulating the change in competition, or the Herfindahl-Hirschman Index (HHI) concentration measure, which is constructed using the competing firms' market shares. Such competition indices indicate the expectation of competition but do not indicate the extent to which firms or products are rivalrous or the true extent of competition in markets. These measures do not distinguish between market shares that result due to quality variations and do not account for any other features that result from different market segmentations between the competing firms. That is, such measures ignore ***how*** firms compete with each other. The fundamental contribution of this paper is to develop a metric that measures how firms compete. Two markets, for example, may have the same value for HHI, but prices in the two markets may be significantly different. We develop empirical measures of the relative contributions of the structural measure of competition (HHI) and the behavioural measure in explaining the variation in prices across markets.

This concern has been addressed by Hausman et al. (1992, 1994), who refined the HHI by accounting for the heterogeneity of products via estimations of cross-price elasticities. They argue that while "closeness of characteristics" is difficult to measure, cross-price elasticity gives a natural measure for "closeness" for competitive purposes. Nevertheless, the authors admit that calculating the measure requires extensive data that often is not available (such as cost data). The paper by de Palma et al. (2018) further highlights the importance of capturing horizontal differentiation between service providers. Considering the rivalry between transport facilities, they account for two sources of differentiation: geographic location and departure time, suggesting the latter is key for understanding price levels.

Our contribution addresses this point exactly: in many industries, the closeness of product characteristics can be directly measured, and actual products (or services) are easily observed. Accordingly, we propose a new horizontal differentiation measure that considers the degree of closeness between the portfolio of goods (or services) offered by competing firms. To that end, our measure captures two important dimensions of competition that are prevalent in many service industries: the number of different goods (or services) and the horizontal differentiation between them, while varying the weight associated with competing goods based on how closely they are located to each other and, hence, the degree to which they are substitutable. Such a measure can be applied, for example, to the retail industry (where competing stores are horizontally differentiated by the geographical distance from each other) or to the transportation industry (where competing departures are horizontally differentiated by the time intervals from each other).

Our focal interest is the airline industry. This is an industry that is still subject to intense competitive oversight where policymakers are interested in competition-inducing mechanisms. For instance, when approving merger and acquisition (M&A) requests, the European Commission often imposes various constraints, such as slot remedies, which require airlines to limit the number of slots they operate at an airport or the frequency of operations between two specific airports, or fare constraints. An example where horizontal differentiation is subject to regulation in the form of some practical barriers is Egypt, which had prohibited any domestic airline operating a flight within 2 hours of any (government-owned) EgyptAir flight at Cairo Airport (OECD, 2014).

We term our measure Schedule Differentiation Metric or SDM. We let SDM weigh the time differential between each pair of services operated by competing firms while possibly accounting for their ordinal ranking; the nearest competing service (measured by time difference) is more substitutable than the farthest service operated by a competitor. SDM captures the degree of substitution between competing products. We measure the SDM at the market level, an origin-destination airport pair.

SDM can be perceived as the weighted average time between competing services (or flights in our case) normalized for the number of services operated by the competing firms. Thus, SDM is bounded from below by zero indicating the scenario where all competing firms operate a single flight each scheduled at the same time, a not uncommon outcome in some airline markets. The upper limit of SDM is the measure of the maximum possible time difference between two competing services. For example, in a non-circular 24-hour schedule, given for example an 11 pm-5 am operations curfew, the farthest apart two services can be scheduled is 18 hours, giving rise to an SDM—in its simplest form—of 1080 minutes.[1] Our measure possesses several intuitively appealing properties: it generally decreases as the competing firms increase their degree of schedule overlap, and the range of values of SDM generally decreases as firms increase their frequency of operations. Importantly, these aspects—frequency of operations and degree of overlap—interact with each other. When a firm adjusts its frequency of operations, it also influences the degree of substitution between competing services. In practice, we find that with increased frequency of operations, firms seek to distribute their flights during the day, suggesting that their entire schedules are adjusted. Thus, we observe a decrease in the value of SDM as more services are added.

Our family of measures and their consequential impacts on prices are related to the product diversity and the location model literatures (see, e.g., Tirole, 1988, or Church and Ware, 2000, for a full discussion of optimal product diversity and Hotelling and Salop location models). Product diversity in a market depends on the distribution of preferences. There is also a strategic component where firms can enter product space in different ways. They can cluster, which increases substitutability and competition, or they can differentiate, which reduces substitutability and competition, and places a product (or variety) closer to some sub-group preferences for which there may be an elastic or inelastic demand. Church and Ware (2000) discuss the conditions for insufficient vs excessive entry of products.[2] Dixit (1979) for the case of oligopoly, and Spence (1976) and Dixit and Stiglitz (1977) for monopolistic competition, also Anderson et al. (1995) and Anderson and Renault (1999) have shown that the market can produce greater product diversity at higher prices, or less product diversity at lower prices.

In competitive markets increasing substitutability, being closer in features to a competitor product, increases the cross elasticity and the size of the potential surplus (Church and Ware, 2000). However, greater competition will bid down prices as well as the surplus previously appropriated by the suppliers. As markets are more concentrated, different forces are at work affecting the firm's decision to be more, or less, rivalrous. Rivalry increases as

[1] A non-circular schedule implies that a service on Monday is not substitutable with a service on other days. This is consistent with the assumption in the literature that travel dates are fixed (see, e.g., Armantier and Richard, 2008). de Palma et al. (2018) also assume a span of 24 hours. A paper by Brueckner (2010) treats a circular market and takes a maintained position that fares and flight frequency can be varied equally easily, something we disagree with. Using a circular model also implies that passengers are indifferent between a positive and negative schedule delay. Our model, as we have said, is a linear model which implies travel dates are fixed.

[2] Church and Ware (2000) argue that insufficient or excessive entry of products depends on two opposing effects: business stealing and non-appropriability of total surplus. Specifically, when a new product enters the market, it steals some customers from other firms; yet, while the generated surplus exceeds the fixed cost, the latter is greater than the new profit, as some of the benefits from introduction are captured by consumers.

products are closer substitutes. Changes in rivalry can take place by rearranging the degree of variety, determining the closeness of substitute products. There are two effects, the demand effect and the strategic effect. The demand effect incentivizes firms to increase substitution and to increase rivalry so as to capture consumers with a preference for that variety or close to that variety. The strategic effect recognizes that, as variety or distinctiveness decreases, there is more competition and lower prices.

An index of rivalry that considers both the numbers of products or firms and the variety of products (to what extent they are different), can indicate whether prices are likely to be high or low. Increasing variety may not necessarily lead to lower prices. Increased variety may result in higher prices because finer market segmentation firms can extract greater surplus by targeting consumers with different but specific preferences. To that end, our proposed measure, SDM, encapsulates both aspects of competition—product variety offered by each firm and how close they position each with respect to the other—to provide decision makers with the clarity regarding the directional impact of variety and the associated substitution on prices.

We demonstrate our SDM and test its efficacy in capturing the level of prices using data from the U.S. airline industry. In airline markets, schedules are strategically determined well in advance before flights take place whereas prices can be and are adjusted daily and, hence, are operational decisions; that is, fares and schedules are *not* determined simultaneously. de Palma et al. (2018) make the point that setting schedules is a separate decision which precedes the price setting. Belobaba (2009) reinforces this point highlighting that schedule development is a strategic decision component of the planning process, whereas pricing and revenue management is a tactical decision that is related to marketing and distribution which is required closer to flight departure. Airlines basically have two schedules, a winter and summer schedule which are established at twice yearly routes conferences where the airlines seek to establish airport access for their desired schedule of flights. It is after these schedules are established that airlines engage in fare competition in a market given the number and nature of competitors and the market characteristics and given the established schedules. An application of our measure to the more general horizontal differentiation such as retail industry may actually capture strategic decisions as store location decisions which are carefully thought through given their generally longer-term nature similarly in aviation, market entry is a strategic decision.

Using panel data from the first quarter of each of the years 2013-2015,[3] we measure the frequency of operations between competing carriers and the time differentials between flights in close to a thousand U.S. domestic markets on a representative day. Limiting our attention in the empirical analysis to duopoly markets (as in Brueckner and Luo, 2014), SDM proves to capture key aspects of horizontal competition and the relationship between these features and the realized prices in those markets. Importantly, SDM adds results above and beyond HHI, the traditional measure of market competition, as elaborated below.

We demonstrate the efficacy of SDM with an example. As SDM is a family of measures, for the illustration below we consider SDM in its simple form, which is also the same form employed later in the empirical analysis. Consider the Seattle (SEA) – Boston (BOS) market, illustrated in Figure 1. This market was operated by two carriers Alaska Airlines (AS) and JetBlue Airways (B6). In 2013, 2014, as well as 2015, they both operated an identical number of flights, implying they possessed equal market shares—0.5 each, and, hence, HHI equals to 0.5 in all 3 years. However, the average transacted price by Alaska Airlines changed from \$284 in 2013, through \$225 in 2014, to \$271 in 2015, whereas JetBlue Airways prices were \$230, \$178, and \$212 in 2013, 2014, and 2015, respectively. Naturally, given their identical market shares, HHI—which remains constant during this period—cannot explain this variation in fares. Carefully examining the schedules of the two carriers and evaluating the SDM in each of the years, one can notice that in 2013 they operated one flight each which were almost 15 hours apart (SDM=888); in 2014, they doubled their frequencies (SDM=200.5); in 2015 they kept their frequencies but shifted their flights slightly apart from each other (SDM=206). Our SDM captures these scheduling dynamics and their effects on fares.

[3] During this period the U.S. airline industry engaged in capacity discipline, as airlines focused their attention on profit rather than market share. Thereafter, demand has accelerated resulting with a corresponding capacity adjustment. Our focus on a short panel during this period so as to avoid the need to control for the demand fluctuations over time (which we do not measure directly) and limit the number of market entry/exit which occur in longer panels (and as such, allow us to study duopoly settings more thoroughly).

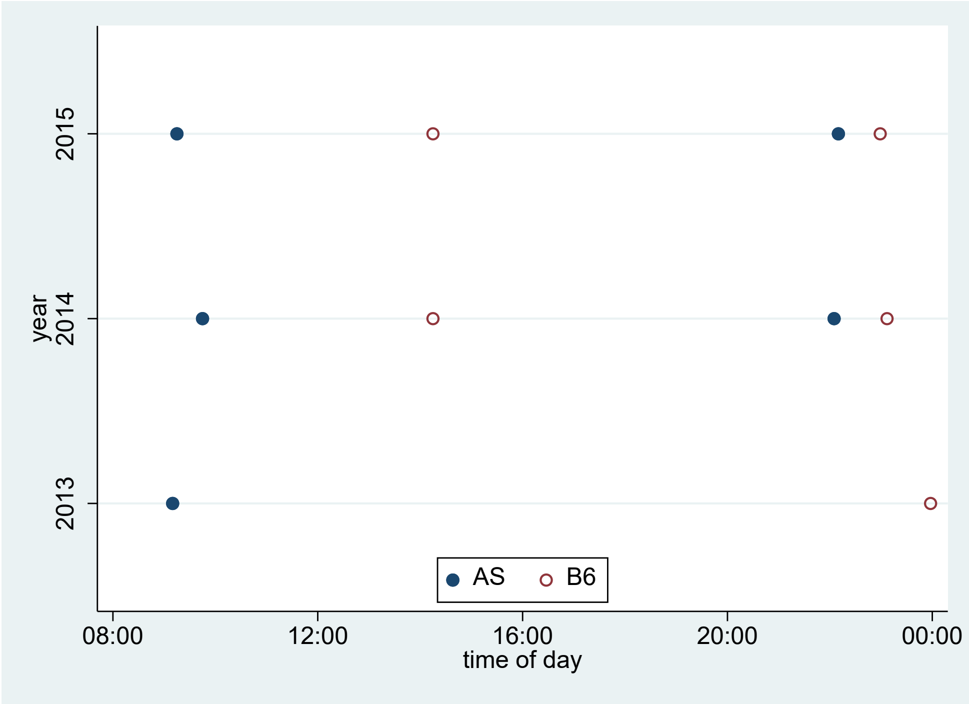


Figure 1. SEA-BOS daily flights operated by Alaska Airlines (AS) and JetBlue Airways (B6)

More generally, our key result is that in duopoly markets an increase in SDM, reflecting greater weighted average horizontal differentiation between competing products (and which may not necessarily reflect a change in the value of HHI), is associated with higher fares. While intuitive, this is an important tool that can support decision makers in understanding the implications of rivalry in aviation markets. We also find the effect of HHI and SDM differ significantly based on the type of rivalry in the market. For example, HHI explains pricing outcomes for most fare percentiles (except for low and very high percentiles) when two network carrier compete, however, its explanatory power diminishes when a network carrier competes with an LCC; and it bears no power in explaining fare percentiles in markets with two competing LCCs (although the latter could be driven by the low number of observations—197 such markets).

Importantly, SDM is significant in explaining the fare levels in the various percentiles when two network carrier compete with each other. The effect of SDM is consistent and substantial across most of the fare percentiles showing apparent fare matching and competition in frequency and timing of flights. By contrast, SDM has no explanatory power when a network carrier competes with an LCC or when two LCCs compete with each other, this type of service competition is of no value to carriers operating under these market structures. Again, this is an important result which is driven by the fact that in such markets the schedule of flights plays minimal, or no role, in customers' choices. In particular, a rivalry between LCCs is essentially price-based competition. Evidently, the type and extent of rivalry between carriers depends on whether a carrier is competing with an LCC, or with a network carrier.

The SDM developed here can support and guide regulatory, antitrust and policy and decision making in any network industry as well as other service industries. As an example, in the airline industry one can consider a policy imposed by the government to limit the operations from carriers other than the home carrier at the primary airport or how slots might be reallocated from network to LCCs. Our SDM indicates that such a policy, which restricts the degree of overlap between schedules, and limits the frequency operated by the competitors, has the potential of increasing the premium the home carrier can charge its passengers and reduce economic welfare. Similarly, restricting numbers of flights in international bilaterals, such as three flights weekly rather than single daily, will also result in higher prices.[4]

The remainder of the paper is organized as follows. Section 2 reviews the literature on competition intensity measurement. Section 3 introduces our proposed measure, SDM, along with some examples. Section 4 describes the data used for the application of SDM. Section 5 outlines the empirical methodology whereas Section 6 provides the empirical estimations. Section 7 discusses the results and Section 8 concludes.

2. Measuring Competition Intensity

In this section, we provide additional insights into the measurement of competition, in general (§2.1), and in aviation markets, in particular (§2.2).

2.1. General approaches to measuring competition

Firms compete in a variety of ways including pricing, quality, accessibility and networking. When firms compete, there is a resultant market structure characterized by the number of competing firms and the distribution of market shares across these firms. There has been a number of metrics of 'expected' competition based on the number and size distribution of firms; expected in the sense larger numbers of firms are expected to result in more competition in the market. The most popular metric is the Hirschman-Herfindahl index (HHI) which is an ex post measure of the degree of competition based on how a market is structured. Empirical studies that use the HHI as an explanatory variable interpret its influence on a variable, price, for example, should the value of the HHI change (e.g., Gerardi and Shapiro, 2009, Borenstein

[4] A similar outcome can result at slot-controlled airports if a carrier controls clusters of slots to create more distance (time) between rival flights.

and Rose, 1994, and Evans et al., 1993).

Although the HHI correctly indicates a decrease in concentration due to entry, it may not necessarily indicate the change in the actual level of effective competition in the market. For example, abolishment of a cartel may result in a market exit due, for example, to inefficiencies, in which case market concentration increases, while the actual level of competition intensifies. Also, when efficient firms behave more aggressively, they end up with an increased market share, although this may result in a higher HHI, the actual level of competition intensifies.[5] That is, the HHI is sensitive to the product and geographic market definition used, and secondly, it gives equal weight to the market share inequality and numbers of competitors (Hannan, 1997, and Lijesen, 2004).

Rivalry refers to the actions of firms (or products), that try to take market share and profits from another firm or product. The *intensity* of this rivalry can refer to the amount of pressure one firm or product places on another. Fierce rivalry can lead to capturing more market share whereas less rivalry can result in simply sharing the market. One way of considering the intensity of competition is to see the extent to which products are substitutes or the degree that their characteristics overlap. For example, Lijesen (2004) tests his model on aviation data using a single quality feature, non-stop versus one-stop flights between an origin and destination. Behrens and Lijesen (2015) measure the intensity of competition using conduct parameters. Their index, labelled a best-response-measure (BRM), assumes that any overlap will entice a response from the other firm; the closer substitutes, or more overlap, the greater the response.

In another paper, Bloom et al. (2013) use a multivariate distance function that identifies a firm's position in technology space (how similar were the firm's technologies) and its position in product market space (how similar were products). The paper compares the strengths and weaknesses of several measures of the proximity of firms to one another and proposes certain properties as metrics for evaluation purposes. All of the measures are designed to be applied when there are two or more types of spillovers; our paper has one spillover, rivalry in product markets where the trade-off is increasing distance to create differentiation and increasing proximity to steal rivals' customers.

Boone et al. (2007) have proposed an alternative metric of competition intensity by measuring the profit elasticity (PE), the elasticity of profit with respect to cost levels, noting that a higher PE signals more intense competition. In a related article, Boone (2008) has

[5] Only in the case of a homogeneous good and a Cournot market is the link between concentration and profitability assured (see Cowling and Waterson, 1976).

proposed another measure: the relative profit differences. This metric relies on the firms' varying degrees of efficiency and how these differences translate into varying degrees of profit. A significant drawback of this metric is the requirement that each firm have different efficiency level.

2.2. Measuring competition in the airline industry

In aviation markets firms primarily focus their competition on the prices and/or qualities of their services. Those services amount to a collection of features such as the amenities offered on board, the seating, connectivity, or the loyalty plan. One of the most important features in aviation markets, like in many other transportation markets, is the timing and frequency of the flights offered by the airline.

Flight frequencies and schedules play an important role in the competitive environment faced by airlines as noted in the literature. Richard (2003) modeled airline rivalries in flight frequency, arguing that passengers have the desired departure time, and multiple departures allow passengers to find a more appropriate flight that reduces their (time) inconvenience, or schedule delay (a concept introduced by Douglas and Miller, 1974); Ivaldi et al. (2015) described a flight accessibility variable, which is inversely proportional to an airline's flight frequency and found that passenger demand increases with frequency. Additional support to this notion comes from Peeters et al. (2005) who found that frequency is an important consideration as high-yield passengers are willing to pay for reducing the schedule delay. This may result in duopoly aviation markets exhibiting an S-curve effect (Wei and Hansen, 2005), where a high proportion of flight frequency translates into an even higher share of passenger traffic. Thus, as airlines engage in competition, they end up increasing their frequencies, and as they increase their frequencies, they may use smaller aircraft. This presents airlines with a trade-off: while larger aircraft offer cost economies of aircraft size and energy use savings (Wei and Hansen, 2003; Givoni and Rietveld, 2010), it may result in schedule delay for passengers.

Richard (2003) provided estimates of the relative importance of price and frequency in passengers' decisions. He showed that airline consumers significantly value the convenience of a flight schedule with multiple departure times. Martin et al. (2008) estimated a stated preference model revealing that the willingness-to-pay (WTP) for an additional flight was €3 for leisure passengers but €15 for business passengers.

To that end, we recognize there are differing airline business models where low-cost carriers (LCCs) focus entirely on low cost and low fares whereas full-service carriers (FSCs) tend to operate hub-and-spoke networks. Even within LCCs there is a degree of differentiation: some carriers offer low frequency (e.g. Ryanair) and others offer higher frequencies (e.g.

Easyjet); see Klophaus et al. (2012) for the diverse business strategies among European LCCs. Accordingly, the literature finds that hub-and-spoke network carriers have higher route frequencies than point-to-point networks. These frequencies depend, for example, on density economics (Caves et al. 1984), on the capacity to attract connecting passengers (Wei and Hansen, 2006) and on the nature of the contract between network carriers and regional airlines (Forbes and Lederman, 2009, Gillen et al., 2015).

Borenstein and Netz (1999) is a closely related paper. Recognizing that airlines trade off the incentive to minimize differentiation (i.e., schedule flights closer to the competitor) in order to steal demand from each other, and an alternative incentive to maximize differentiation, they first measure average time differentiation as the mean of time differences between flights pairs raised to the power of α, where α (which takes values between 0 and 1) reflects the importance of schedule differentiation. They, then divide this value by the maximum time differentiation—that is, corresponding value if all flights were to be equally spaced out—to yield their schedule differentiation index. Given the number of flights in a market, they find that product differentiation declines in the degree of competition (measured as the inverse of HHI).[6] Their measure captures the time difference between each and every pair of flights in the market. Our measure, instead, only account for competing pairs of flights while allowing for weights to be assigned to different pairs based, e.g., on their relative proximity ranking, as our focus is on how competing flights are positioned throughout the day.[7]

The competition measure we propose in the next section accounts not only for the frequency of flights operated by a carrier, but also for the degree of schedule overlap with competing carriers operating the same route. By contrast to Borenstein and Netz (1999), we are concerned with the impact of our measure on the realized prices in the market. Further, while they have carried out a cross-section analysis, we expand to a short panel to demonstrate the dynamics of competition and differentiation over time, while further capturing the rivalry types (i.e., whether the competing carriers are a FSC or a LCC). Lastly, our empirical analysis is not conditional on the number of flights in a market.

[6] Borenstein and Netz caution that while strategic interaction is a plausible explanation, such behavior may also be subject to network effects as airlines seek to coordinate their flights across the network and accordingly may result with crowding of flights at certain points of time.

[7] Thus, while Borenstein and Netz (1999) measure is not impacted by how competing firms split the market between them. Assume, for example, a market with 4 flight slots (8am, 10am, 6pm, and 8pm) and two airlines, each operating two these flights. Borenstein and Netz's measure yields the same value regardless which airline operates which flight. Our measure can easily produce a higher value for the case where one carrier operates the morning flights and the other the evening flights, as in this case they split the market by differentiating apart from each other as much as possible.

3. The Schedule Differentiation Metric (SDM)

In this section, we outline the construction of our measure, followed by several examples that illustrate this metric in various scenarios.

3.1. Construction of SDM

Schedule Differentiation Metric, or SDM, is a family of horizontal differentiation measures adjusted for two key aspects of differentiation in transportation markets: frequency and timing of services offered by competing firms. To that end, we construct a family of measures that assigns a weight to each pair of competing flights such that flights that are temporally closer to each other are closer substitutes and, hence, compete more intensely and accordingly are assigned a higher weight. This weighted average time difference, unlike simple average, allows for capturing the degree of substitution between competing flights. In that respect, we shall highlight that increasing frequency does not necessarily result with lower fares for two reasons: (i) given the capacity-frequency trade-off, airlines may switch to smaller aircraft (or reduce seating density) when they increase frequency into a market, resulting with possibly lower total seating capacity in a market, (ii) increasing the frequency of operations reduces passengers schedule delay which may allow airlines to increase their fares.

Classic horizontal differentiation literature suggests that firms may seek to differentiate their schedule to the largest degree possible. Data, however, reveals that in some markets, airlines indeed space their flights several hours apart, whereas in other markets they slot their competing flights close to each other, sometimes even completely overlapping.[8] One such example is demonstrated in Figure 2 for the Philadelphia (PHL) – Boston (BOS) market, where in 2014, the two carriers in this market (Alaska – AS and US Airways) slotted their flights only a few minutes apart from each other. As they introduce more flights, the degree of overlap may either increase, if they offer flights close to each other, or decrease, if they move their competing flights apart from each other. Our measure, then, aims to capture both the number of flights operated by each firm and how they compete with each other.

[8] While rare, examples where service is offered at any point by each of the competing firms include, for instance, the case in Australia in the 1980s when Qantas and Annsett had nearly perfectly overlapping schedules.

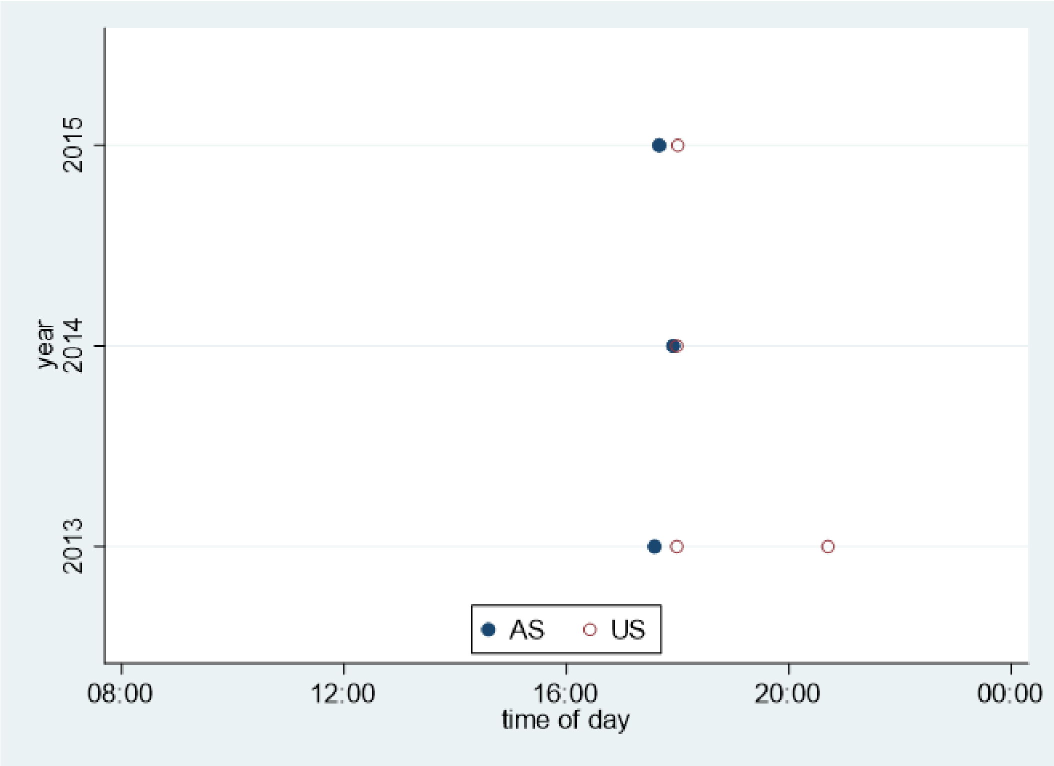


Figure 2. PHL-SEA: example of an (almost) perfect overlap; flights are operated by Alaska Airlines (AS) and US Airways (US)

We use matrix notation to construct the SDM and demonstrate using the case of duopoly, although the concept can be generalized to oligopolistic settings (see §0). Assume the two competing carriers—Airline i and Airline j—which operate N and M flights, respectively. Let $T_{i,n}$ denote the scheduled departure time of the n^{th} flight of Airline i, and similarly let $T_{j,m}$ denote the scheduled departure time of the m^{th} flight of Airline j. We then let $d_{m,n}$ denote the absolute time difference between the scheduled departure times of the m^{th} and n^{th} flights operated by Airline j and Airline i, respectively, that is, $d_{m,n} = |T_{i,n} - T_{j,m}|$. These time differences are stored in the matrix **DIFF**.

To account for the degree of substitution between competing flights, we allocate different weights to competing flights based on their temporal adjacency. We create two matrices—both having a size of M by N. The first is **WEIGHTM** which captures the weights of Airline i's flights with respect to Airline j's flights, $w^M_{m,n}$. And the second, **WEIGHTN**, captures the weights of Airline j's flights with respect to Airline i's flights, $w^N_{m,n}$.

The product of these three matrices yields the matrix **SDMM**:

$$\mathbf{SDMM} = \mathbf{WeightM} \cdot \mathbf{Diff}^{\boldsymbol{T}} \cdot \mathbf{WeightN},$$

where $\mathbf{Diff}^{\boldsymbol{T}}$ is the transposed matrix. These can be summarized

$$\begin{pmatrix} w_{1,1}^M & \cdots & w_{1,N}^M \\ \vdots & \ddots & \vdots \\ w_{M,1}^M & \cdots & w_{M,N}^M \end{pmatrix} \begin{pmatrix} d_{1,1} & \cdots & d_{M,1} \\ \vdots & \ddots & \vdots \\ d_{1,N} & \cdots & d_{M,N} \end{pmatrix} \begin{pmatrix} w_{1,1}^N & \cdots & w_{1,n}^N \\ \vdots & \ddots & \vdots \\ w_{m,1}^N & \cdots & w_{m,n}^N \end{pmatrix}$$

Finally, **SDM** is calculated by aggregating over the entries of **SDMM** and normalized by the scale of operations, $f(M,N)$:

$$\boldsymbol{SDM} = \frac{\sum_{m=1}^{M} \sum_{n=1}^{N} \mathbf{SDMM}_{m,n}}{f(M,N)}.$$

The beauty of the family of measures is that it allows for a broad range of weights and normalizations to take place. Specifically, weights can take different forms, such as:

1. Equal weights, in which case, $\mathbf{WeightN}_{m,n} = \mathbf{WeightM}_{m,n} = 1, \forall m, n.$
2. Inversely decreasing weights, whereby the closest competing departure is assigned a weight of 1, the 2nd closest competing departure – a weight of $\frac{1}{2}$, the 3rd – a weight of $\frac{1}{3}$ and so on.
3. Inverse quadratically decreasing weights. Similar to the above, the closest competing departure is assigned a weight of 1, the 2nd closest competing departure – a weight of $\frac{1}{2^2} = \frac{1}{4}$, the 3rd – a weight of $\frac{1}{3^2} = \frac{1}{9}$ and so on.
4. Weights associated with time blocks: this could be manifested by splitting the day into specific blocks of times, reflecting the attractiveness of flights during those time blocks, such as morning flights (between 6am and 8am) and evening flights (between 6pm and 8pm), while giving a common weight, say 1, for all competing flights within the same time block and a different, lower weight, say $\frac{1}{2}$, for all competing flights associated with other time blocks.

We shall note that all these weighing measures can be normalized within the **WEIGHTM** and **WEIGHTN** by ensuring the sum of weights in each column and row, respectively, sums up to 1. This is achieved by reassigning $w_{m,n}^M := \frac{w_{m,n}^M}{\sum_{n=1}^{N} w_{m,n}^M}$ and $w_{m,n}^N := \frac{w_{m,n}^N}{\sum_{m=1}^{M} w_{m,n}^N}$. However, in that case, the sum of entries in **SDMM** is identical to that of **DIFF**, implying that the calculation of the **WEIGHTM** and **WEIGHTN** can be avoided.[9]

Further normalization that takes into account the scale of operations, $f(M,N)$ which can assume various formulations, such as:

1. An additive form: $f(M,N) = M + N$ which accounts for total number of flights
2. A multiplicative form: $f(M,N) = M \cdot N$ which captures the total number of competing

[9] We thank the anonymous reviewer who highlighted this simplification opportunity.

flight pairs in the markets

3. Other combinations, $f(M,N) = M^2 \cdot N^2$ or $f(M,N) = M^2 + N^2$ and so forth, though such normalizations may be harder to interpret.

For convenience, we express this index in minutes, although it can easily be quantified in any other time units. This measure, SDM, is effective in capturing the dimensions of competition that arise when firms operate substitutable schedules. We will demonstrate the different values that can be generated, and in subsequent sections, illustrate the strength of SDM in explaining realized prices in markets.[10]

It is important to highlight that SDM is quite distinct from the HHI metric. The HHI which is traditionally used to capture the expected degree of competition, is a measure of market concentration based on market shares offered (e.g., how many flights) or captured (e.g., number of seats sold) by the competing firms. By contrast, SDM captures *the way in which* the firms compete with each other in those markets. As such, HHI is an ex-post measure since it is constructed on what has happened in the market from more, or less, competition whereas SDM is an ex-ante measure as it shows how airlines position themselves in order to compete. Thus, HHI and SDM are complementary measures, as we demonstrate in subsequent sections.

3.2. Illustration of SDM

Consider a market served by two airlines, where Airline i operates two daily flights at 10am and at 5pm and Airline j operates three daily flights at 8am, 12:30pm and at 6pm. These flights are illustrated in Figure 3.

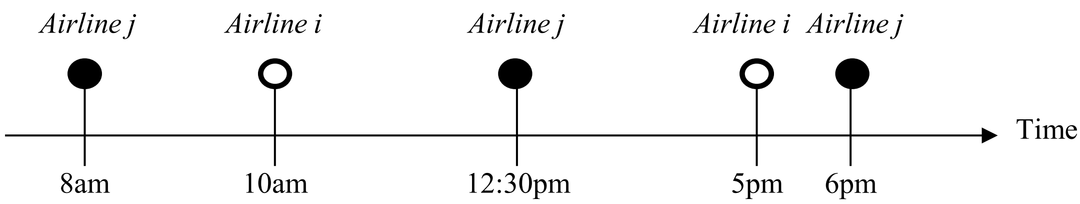


Figure 3. Example of flight schedules by two competing airlines

[10] This measure can be formulated in alternative ways, generally resulting with qualitatively similar insights. We prefer the proposed mechanism due to its properties (presented later in this section) and as it is rather intuitive and can be simply communicated as the weighted average of schedule overlap. Here we limit our construct to duopoly markets, in §7.1 we demonstrate how to generalize it.

The Diff matrix is derived by calculating the time differential (in minutes) between every pair of flights operated by the two airlines. The entries in the first column in the matrix are the times between Airline j's first flight (at 8am) to Airline i's flights (at 10am and at 5pm); 120 minutes and 540 minutes, respectively. The entries in the second column are the times between Airline j's second flight (at 12:30pm) to Airline i's flights: 150 minutes and 270 minutes. The entries in the final column are the times between Airline j's third flight (at 6pm) to Airline i's flights: 480 minutes and 60 minutes. Hence,

$$\mathbf{Diff} = \begin{pmatrix} 120 & 150 & 480 \\ 540 & 270 & 60 \end{pmatrix}.$$

To calculate the entries in the **WeightM** and **WeightN** matrices, we first need to determine the weighing mechanisms. For illustration purposes, we assume inversely decreasing weights. Thus, the entries in the first column of **WeightM** reflect the weights associated with Airline i's two flights with respect to Airline j's first flight. Specifically, since Airline i's 10am flight is closer, it is assigned a weight of 1 and Airline i's 6pm is assigned a weight of $\frac{1}{2}$. Working out the remaining pairs, we obtain:

$$\mathbf{WeightM} = \begin{pmatrix} 1 & 1 & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & 1 \end{pmatrix}.$$

Similarly, we work out the entries of **WeightN** starting with the first row, which gives the weights of Airline j's flights with respect to Airline i's flights. For instance, the first row focuses on Airline i's 10am flight. Thus, Airline j's 8am flights is the closes and, hence, is assigned a weight of 1, the 12:30pm flight is the second closest and, hence, receives a weight of $\frac{1}{2}$ and lastly, the 6pm flight is associated with a weight of $\frac{1}{3}$. Continuing with this process, we have:

$$\mathbf{WeightN} = \begin{pmatrix} 1 & \frac{1}{2} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{2} & 1 \end{pmatrix}.$$

Multiplying the three matrices, we have:

$$\mathbf{SDMM} = \mathbf{WeightM} \cdot \mathbf{Diff}^{\boldsymbol{T}} \cdot \mathbf{WeightN}$$

$$= \begin{pmatrix} 1 & 1 & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & 1 \end{pmatrix} \begin{pmatrix} 120 & 540 \\ 150 & 270 \\ 480 & 60 \end{pmatrix} \begin{pmatrix} 1 & \frac{1}{2} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{2} & 1 \end{pmatrix}$$

$$= \begin{pmatrix} 790 & 675 & 1010 \\ 770 & 540 & 670 \end{pmatrix}.$$

Next, we sum up the entries of **SDMM** and normalize the measure. For the illustration, we set $f(M,N) = M \cdot N$. Thus, we have

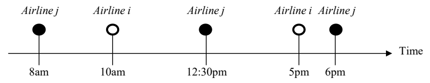
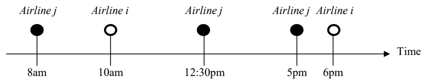
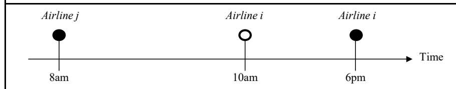
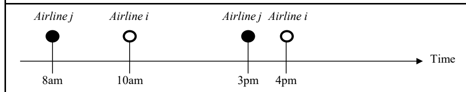
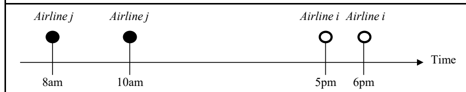
$$\boldsymbol{SDM} = \frac{4455}{3 \cdot 2} = 742.5.$$

In Table 1 we illustrate several operationalizations of the SDM and the values it obtains for different market constellations. Specifically, we consider three weighing methods: normalized inversely decreasing weights (first set of columns), inversely decreasing weights (second set of columns), and inverse quadratically decreasing weights (third set of columns). We also capture three normalization alternatives for each of these methods: additive, multiplicative, and quadratic. These diverse combinations demonstrate the wealth of options available for regulators in changing their focus of attention. The final two columns of the table also provide the corresponding values derived by Borenstein and Netz's (1999) mechanism, which take into account the time difference between every pair of flights in the market (and not just competing pairs), while assigning the same weight to all pairs.

We illustrate using eight constellations. The first is the benchmark example described earlier. The second example removes the middle flight from the schedule of flights, the third removes another flight (Airline i's second flight) from the schedules. The fourth example returns to the benchmark while switching the timing of the latest flights operated by the two airlines and repeating the same logic as above for the 5th and 6th examples. The 7th constellation demonstrates how the values of SDM shrink as flights come closer to each other, when compared with the 5th constellation. We have added an 8th constellation to illustrate the difference between our contribution and that of Borenstein and Netz (2005). They treat all flights as substitutes whereas we take account of how substitutable the flights are using our weights. Note in constellation 8 the flights are clustered for each airline to be in the morning or evening whereas in constellation 2 or 5, the airlines are more rivalrous by having flights closer to one another. In moving to constellation 8, the numbers for Borenstein and Netz do not change whereas ours change to reflect the difference in the degree of competition in the market.

Our preferred normalization is $M^2 \cdot N^2$ as it maintains consistency across the different operationalizations of SDM. It is also consistent across the different constellations and the relative values intuitively represent the changes and substitutability of the flights in the constellations. We proceed with normalized inversely decreasing weights with $f(M,N) = M^2 \cdot N^2$.

Table 1. The SDM in different configurations

Method	**SDM**									**Borenstein & Netz**	
Weighing	**Normalized**			**Inverse**			**Inverse quadratic**			$\alpha = 0.5$	$\alpha = 1$
$f(M,N)$	$M \cdot N$	$M + N$	$M^2 \cdot N^2$	$M \cdot N$	$M + N$	$M^2 \cdot N^2$	$M \cdot N$	$M + N$	$M^2 \cdot N^2$		
	270	324	45	742.5	891	123.75	459.38	551.25	76.563	17.21	324
	300	300	75	675	675	168.75	468.75	468.75	117.19	18.14	370
	300	200	150	450	300	225	266.67	177.78	133.33	19.12	400
	280	336	46.67	770	924	128.33	476.39	571.67	79.40	17.21	324
	300	300	75	675	675	168.75	468.75	468.75	117.19	18.14	370
	300	200	150	450	300	225	266.67	177.78	133.33	19.71	400
	240	240	60	540	540	135	375	375	93.75	15.28	252
	510	510	127.5	1147.5	1147.5	286.88	796.88	796.88	199.22	18.14	370

Note: The grey shaded column presents the normalisation used in our analysis.

4. Data

After establishing the SDM and some of its properties, we demonstrate its importance in explaining fare levels in the U.S. domestic airline industry. Our reference timeframe is the first quarter of 2013-2015. This is a period where the industry has been experiencing growth in traffic and expansion of destinations.

4.1. SDM and HHI

To construct the SDM, we assume normalized inversely decreasing weights with $f(M,N) = M^2 \cdot N^2$, and use schedule information from the U.S. Department of Transportation's (DOT) On Time Performance dataset. This dataset assembles detailed information at the flight level. While schedules may change from one day to another, the core schedule of airlines does not change dramatically during the week. Hence, in order to simplify the construction of SDM, we decided to pick one day of the week—the first Wednesday of March—as a representative of the daily schedule. Focusing on a single day of operations rather than the entire week of flights, while assuming that travel dates are fixed (see, e.g., Armantier and Richard, 2008), allows us to simplify the analysis as we can consider substitution only within the same day of operations and avoid substitution across days.

Similar to Brueckner and Luo (2014), we limit our attention to duopoly markets. Since some duopoly markets are occasionally serviced by other carriers, the data is cleaned in the following manner. We consider a market to be a duopoly if (i) the combined number of total number flights operated by the two competing carriers during the quarter exceeds 80% of the total number of flights in the market; (ii) the third airline operates less than 10% of the flights in the market; and (iii) the second airline operates significantly more flights than the third airline; the share of flights operated by the second airline exceeds that of the third airline by at least 10%. Additionally, we have dropped overly monopolistic markets where one of the duopoly carriers operated less than 5% of the flights.[11] Those restrictions guarantee that the market is dominated by two airlines and that other smaller players are indeed of a minor scale compared with the two major players in the market, effectively a duopoly market.[12] This elimination results with a final unbalanced panel consisting of 968 markets. We define a market as the origin-destination airport pair.

[11] We have 9 such observations, so inclusion of these markets shall not impact the qualitative results of the analysis.

[12] Our cleaning is more restrictive than the method in Brueckner and Luo (2014), who removed all airlines with less than 20 monthly departures. While this might be an effective measure in thick markets, we believe that it may overlook some of the competition in thinner markets.

The distribution of the SDM measure is illustrated in Figure 4. The histogram shows how the SDM follows a rather truncated normal distribution with the majority of observations having an SDM value less than 200 coupled with a long thin tail of observations exceeding an SDM of 400. This informs us that in many markets, given the number of flights they operate, the competing carriers maintain relatively low degree of schedule differentiation, but the distribution of such differentiation varies significantly across markets. Also, since there is only a limited number of markets with high values of SDM suggests that competing flights are generally not too far apart.

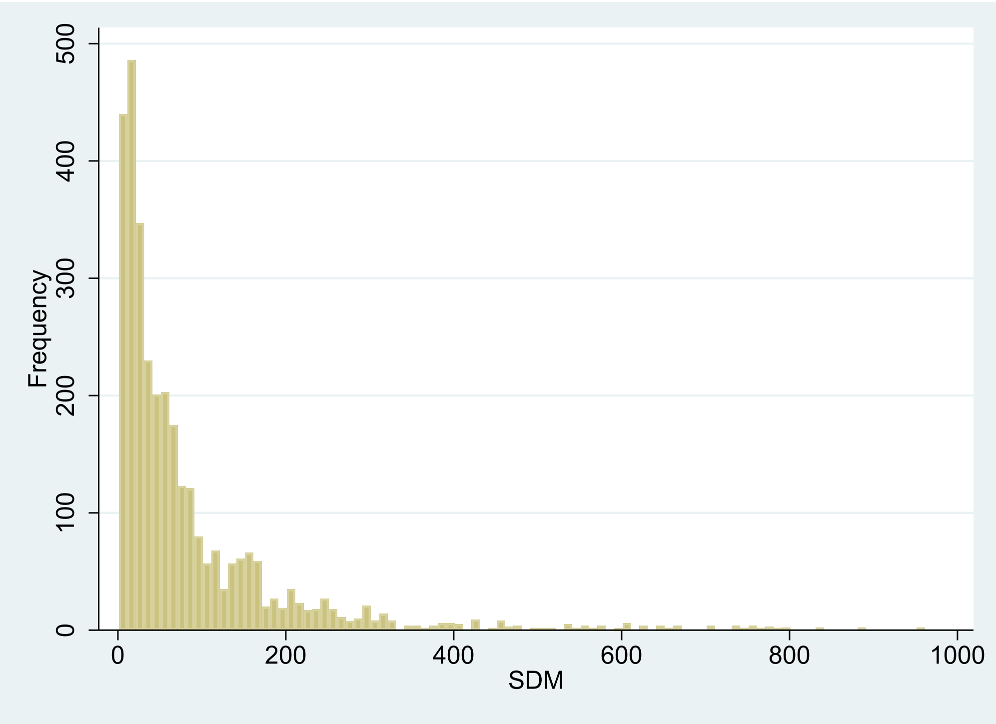


Figure 4. A histogram of SDM (assuming normalized inversely decreasing weights with $f(M,N) = M^2 \cdot N^2$

One of the characteristics of SDM, as was discussed, is that it captures both the frequency of operations as well as the substitution between competing flights. We demonstrate the former aspect in Figure 5. Specifically, this figure depicts SDM against the total daily number of flights in the market; the minimum value of daily flights in our dataset is 2—one for each competing airline—and the thickest market has 32 daily flights. As can be observed from Figure 5, as the number of operations increases, quite intuitively, the amount of variation in SDM diminishes; with a single daily flight, the carriers can position their flights at the same time slot to directly compete with each other (in which case SDM can be as low as 0) or can maximize the time differential with a morning flight vs a night flight (in which case SDM can easily exceed a value of 600). With a larger number of flights during the day, as airlines start spreading their flights over the day to account for scheduling and operational considerations, the range of alternative schedules diminishes and the magnitude of SDM drops as well.

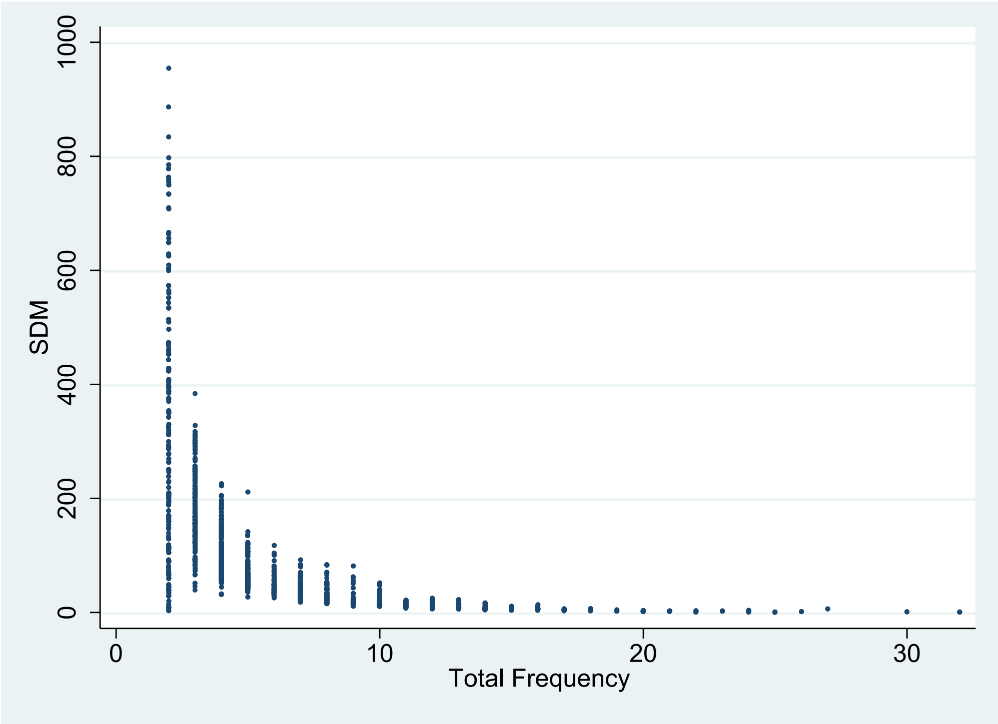


Figure 5. SDM vs. Total daily frequency (assuming normalized inversely decreasing weights with $f(M,N) = M^2 \cdot N^2$

SDM complements the traditional measure of competition intensity, HHI, which is commonly used in analyzing aviation markets. The HHI measure is constructed based on flight market shares on a quarterly basis as recorded in the On-Time performance dataset.[13,14] Figure 6 depicts the degree of competition as captured via the HHI measure versus the SDM measure. This figure does not reveal any strong relationship between the two measures. This is a natural outcome of our measure which captures how firms compete by accounting for both the number

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[13] The reason that HHI is on a quarterly basis is two-fold. First, fare data, is provided on a quarterly basis and we need to align the two measures. Second, our SDM is based on a representative day of flights. We recognize that flight schedules might change (slightly) based on day of the week and possibly during the quarter, thus a quarterly based HHI will more closely reflect the rivalry between airlines and hence it will be consistent with the observed transacted fares. Note, even though HHI is derived in a manner closely aligned with observed fares, and SDM is based on a single representative day, we show that SDM has a great power in explaining fares. Thus, reconstructing the SDM based on the entire quarter's schedule data (which is a rather challenging endeavour) could possibly yield an even more precise SDM with improved power in explaining fares.

[14] Note that given our definition of duopoly markets, there may, in fact, be more than two operating carriers in a market and, therefore, the measure of HHI captures their respective market shares as well. This means that the value of HHI may be lower than 0.5.

of competing flights and how they are organized against each other whereas HHI only accounts for the number of competing flights in a market. This is best illustrated by the observations along the horizontal line where HHI=0.5. In these markets the two airlines operate the same number of flights. However, despite the concentration of observations with values of HHI equals to 0.5, we witness a wide distribution of SDM values. Evidently, our proposed measure of competition captures another dimension that is entirely omitted from the calculation of traditional competitive measures, such as HHI.

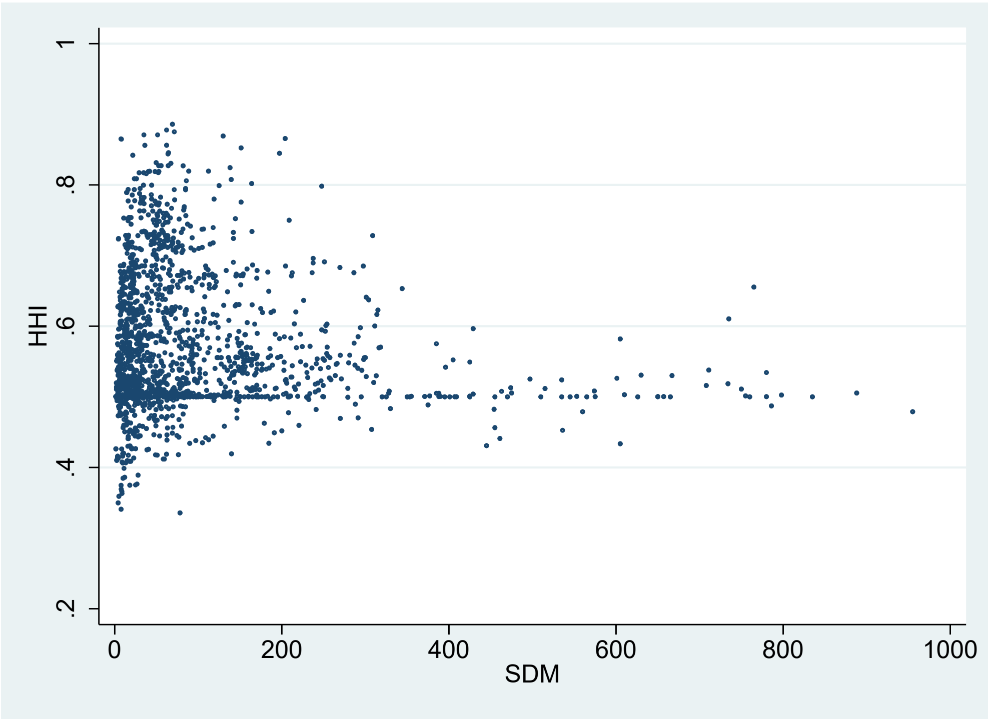


Figure 6. HHI vs. SDM (assuming normalized inversely decreasing weights with $f(M, N) = M^2 \cdot N^2$

4.2. Dependent and control variables

Our interest is in revealing the importance of SDM in affecting fare levels, distinct from the structure of the market in the various markets. To that end, we have aggregated data from the U.S. Department of Transportation's DB1B dataset which is a sample of 10 percent of all airfares. Using this data, we generate a mean fare and the fares at different percentiles.

Economic market characteristics, measured by population and income per capita, are defined as the average across the metropolitan areas at the origin and destination airports. Data from the U.S. Bureau of Economic Analysis (BEA) are used to derive the arithmetic means of the population, AvgPop, and the average income per capita, AvgIncCap, of the origin and destination metropolitan areas.

To complement the DB1B data with carrier characteristics, we use the Air Carrier Financial Reports (Form 41 Financial Data) which contain quarterly data on operating cost (OpExp), maintenance material cost (MainMatExp), Aircraft fuel cost (AircraftFuel) and total current assets (Assets), for the U.S. carriers' domestic services. We have further accounted for the unique characteristics of low-cost carriers (LCCs) by using a dummy to indicate the type of the carrier of interest (LCCDummy which equals 1 if a carrier is an LCC and 0 otherwise).[15]

To account for heterogeneity between aircraft in terms of seating capacity among the routes operated by a carrier, we construct an aircraft dispersion measure utilizing the DOT's Air Carrier Statistics report. We group aircraft into clusters of common configurations so that aircraft of similar types with similar seating capacity are considered to be one type. We end up with five categories based on seating capacity: less than 50, up to 100, up to 150, up to 170, and greater than 170 (these are also corresponding to features of aircraft types, such as turbo-prop, jet engine, single aisle). The corresponding shares of flights operated by aircraft from each category are then squared and all are summed in the same way the traditional HHI is calculated. This gives us the Aircraft Dispersion measure which is bounded from below by 0.2 (equal shares in each of the categories) and from above by 1 (all flights are from the same category type). We provide detail on the construction of this measure in Appendix A.

Our final sample contains 3223 observations on 15 different carriers in 968 markets for the first quarters of 2013, 2014 and 2015. An observation in our data represents a carrier-route-year combination. Summary statistics of the variables used in the empirical analysis are provided in Table 2.

[15] The following airlines were coded as LCCs: Frontier, JetBlue Airways, Southwest Airlines, Spirit Airlines, and Virgin America. (Note that other LCCs—AirTran Airways, Allegiant Air, Sun Country Airlines, USA3000 Airlines—are not represented in our final data selection.)

Table 2. Summary statistics

Variable	N	Mean	Std. Dev.	Min	Max
SDM	3223	87.61	121.26	1.20	955.00
HHI	3223	0.57	0.10	0.34	0.89
Fare ($)	3223	214.00	66.09	26.47	625.00
AvgPop (million)	3223	5.15	3.17	0.66	16.50
AvgIncCap (million $)	3223	0.05	0.01	0.04	0.07
Assets (million $)	3223	20400.00	18900.00	590.33	57000.00
OpExpense (million $)	3223	3703.00	3171.68	263.92	9036.98
MaintMatExp (million $)	3223	69.95	56.37	1.70	178.06
AircraftFuel (million $)	3223	955.55	855.89	0.06	2469.77
ACDisp	3223	0.60	0.21	0.24	1.00
LCCDummy	3223	0.27	0.44	0.00	1.00

Source: Authors' analysis of U.S. Department of Transportation's DB1B dataset, On Time Performance dataset, as well as Air Carrier Financial Reports and Air Carrier Statistics Reports

5. Empirical Approach and Identification

Our empirical analysis investigates how the extent of competition affects the price level in a given market while controlling for several variables described in Section 4.2. The two variables of most interest are HHI and SDM. HHI, as a structural measure of competition, is used regularly in proposed merger cases and anti-trust hearings to assess how market concentration may affect price levels and whether a policy change might be needed to reduce or protect against increased concentration levels. How much of the price variation in markets is explained by this variable? How firms compete may be just as important as market concentration in affecting market price levels. SDM is the measure of how firms are rivalrous and essentially measures substitutability. To measure the relative contributions of each of HHI and SDM to variations in price levels, it is essential that both variables be included in the estimating equation.

5.1. Model Specification

In the estimation equation we let i denote the market, c denote the carrier, and t denote the year, we estimate the effect of the competition measure, SDM, via the following log-log equation:

$$
\begin{aligned}
ln(Fare_{ict}) = \alpha_0 &+ \alpha_1 ln(HHI_{it}) + \alpha_2 ln(SDM_{it}) + \alpha_3 ln(AvgIncCap_{it}) \\
&+ \alpha_4 ln(AvgPop_{it}) + \alpha_5 (LCCDummy_{it}) + \alpha_6 ln(Assets_{ct}) \\
&+ \alpha_7 ln(OpExp_{ct}) + \alpha_8 ln(MainMatExp_{ct}) \\
&+ \alpha_9 ln(AircraftFuel_{ct}) + \gamma_i + \gamma_c + \gamma_t + \varepsilon_{ict}
\end{aligned} \tag{1}
$$

where $\mathrm{Fare}_{\mathrm{ict}}$ is the average fare paid for a ticket in market i for carrier c during the first quarter of year t. γ_{i}, γ_{c} and γ_{t} are the market, carrier and time fixed effects, respectively. The $\mathrm{LCCDummy}_{\mathrm{it}}$ variable indicates whether the carrier of interest is a low-cost model and, hence, likely to offer lower fares. We include airline total current assets, operating expenses, maintenance material costs, and aircraft fuel expenses in the model in order to control for time-varying carrier characteristics. Such variables could capture carriers' economies of scale: as carrier expand their offering, they increase the portfolio of their assets, their expenses—both operational and fuel related—increase, but possibly due to economies of scale they could pass through some of their savings to their passengers through lower fares. The route and carrier specific time-invariant unobservable γ_i and γ_{c} (such as hub status) and time fixed effects that can be considered as common shocks to all carriers and will be absorbed by fixed effects and year dummies, respectively. This eliminates any biases in our estimates arising from cross-sectional variations.

5.2. Identification

The econometric problem that we are concerned with is the potential endogeneity of HHI and SDM because both are functions of the carriers' frequencies since the market performance feeds back to market structure (Evans et al., 1993). The classical solution is to estimate the model by using instruments which are orthogonal to the unobservable variables of the equation. We address the possible endogeneity of HHI and SDM , by employing three instruments: (i) the total enplaned passengers in a route as used in Gerardi and Shapiro (2009). Specifically, the total number of non-stop passengers in the origin-destination market, NS Pax; (ii) an exogenous characteristic of the competing airlines as captured via the aircraft dispersion of the carriers in the market, AC Dispersion. The fleet structure of a carrier provides implicit information about the airlines' frequency, which are predetermined, predict well the market shares while being independent of the price shocks (i.e. uncorrelated with the error term of price equation); and (iii) an additional exogenous population measure variable, as used in Borenstein and Rose (1994), which is not correlated with the variable average population. To that end we use the geometric mean of the population at the origin and destination, GeoMeanPop. We estimate the specified model with fixed effects by instrumental variable.

Since the instrument aircraft dispersion is, to the best of our knowledge, a measure that is introduced for the first time we elaborate on its relevance. Recognizing that carriers may enter different types of markets with different aircraft, with this measure we wish to capture the degree of heterogeneity between the aircraft with regard to their seating capacity. This overcomes the simplicity of only counting the number of flights and treating all flights as homogeneous. Fleet planning is a long-term strategic decision, and airlines decide far in advance what fleet they will operate. Scheduling is set out twice yearly when they present their summer and winter schedules. Pricing decisions, on the other hand, are dynamic, are at the operational level and can be determined on a daily or even hourly basis. Accordingly, frequency and pricing are not simultaneous decisions. We provide details on the construction of this measure in Appendix A.

Given this construction of aircraft dispersion, we elaborate on its importance as an instrument. It may have an impact on HHI in two opposing ways. On the one hand, one might expect a negative relationship as carriers that enter a market with uniform aircraft type (such as is the case for LCCs), might be limited in their ability to adjust capacity in thin markets whereas carriers with aircraft diversity might be able to utilize different aircraft types to attract passengers with different preferences. We expect the latter effect to dominate and result with a positive relationship with HHI. The relationship with SDM is expected to be in the opposite direction as a more diverse fleet implies the airlines are able to enter the market with fewer aircraft or fewer seats as they can serve the market with a more suitable fleet composition and, hence, they can better differentiate from each other, resulting with higher SDM. These feature of aircraft dispersion affect SDM and HHI, but are not expected to affect prices directly.

6. Empirical Results

We undertake an empirical analysis to understand the impact of SDM on the average fare (§6.1) and the various fare percentiles (§6.2). We next refine the analysis to gain a deeper understanding of the relevance of SDM by distinguishing competition between airlines with different business models (§6.3).

6.1. Impact of SDM

Table 3 summarizes the estimation results. Estimation 1 is based on the fixed effect model, FE, whereas Estimations 2-4 employ the fixed effect with instrumental variable method, IVFE. For each of the IV estimations (i.e., Estimations 2-4), the table also provides the results of the first stage regressions, as well as the First stage F-Statsistics and the Hansen-Sargan overidentifying restrictions. We generally observe that the traditional variables behave as expected. Intuitively, average prices transacted by a low-cost carrier are lower. Market structure effects, as measured by the HHI, reveal that as concentration in the market increases, the average transacted fare increases as well. Assets and fuel are both significant and positive indicating a carrier's economies of scale due to larger size and hence ability to offer lower prices. Average income per capita and operating expenses generally have the expected signs (with population being negative possibly suggesting greater attraction to competition and hence lower fares, and operating expenses being negative reflecting, again, a carrier's economies of scale), but they are insignificant.

The SDM captures both frequency of operations and the substitution between competing flights. Recall that an increase in SDM indicates a decreased overlap or less substitution in the schedule of the competing carriers in a market. Thus, one expects an increase in the value of SDM to correspond to an increase in the average transacted fare as the supply of flights into the market diminishes and/or the flights become weaker substitutes. Indeed, the results in Table 3 show exactly that: SDM is significant in capturing the effects on prices. This is an important result. Our measure, SDM, captures crucial aspects of competition in service markets and the service markets relationship to the realized prices in those markets. Furthermore, the significance of SDM could suggest that although passengers may be willing to pay more for greater flight frequency, carriers need to weigh carefully the added benefit of reduced time schedule delay to consumers as this could be shadowed by losses due to increased substitution with competing flights.

Our empirical results suggest that prices would decrease as the competing flights become closer substitutes (while maintaining the same market shares). Recall that our preferred normalization is the one using the inverse weighing of M^2N^2 as it maintains consistency across different operationalizations of SDM.

From Table 1, when the number of competing flights is fixed, as they become closer substitutes, HHI does not change while SDM decreases. It is also consistent across different constellations and the relative values intuitively represent the changes. Accordingly, a coefficient of 0.183 (in the IVFE(3) column) implies that a 10% reduction in SDM translates into a 1.8% reduction in fares.

Table 3. Model Estimates: Fixed Effects and Instrumental Variable Fixed Effects

	FE	IVFE (1)		IVFE (2)		IVFE (3)		
Dependent variable	**MeanPrice**	**1st stage: HHI**	**2nd stage: MeanPrice**	**1st stage: SDM**	**2nd stage: MeanPrice**	**1st stage: HHI**	**1st stage: SDM**	**2nd stage: MeanPrice**
HHI	0.009		1.345**					0.646**
	[0.040]		[0.190]					[0.205]
SDM	0.024**				0.223**			0.183**
	[0.009]				[0.022]			[0.026]
AvgIncCap (M)	-0.844	-0.576*	0.316	0.038	0.030	-0.646*	0.039	0.467
	[0.565]	[0.251]	[0.603]	[0.062]	[0.531]	[0.252]	[0.062]	[0.569]
AvgPop (M)	-0.359	0.617*	-1.027*	0.125*	-0.415	0.434	0.126*	-0.729+
	[0.379]	[0.267]	[0.399]	[0.058]	[0.352]	[0.291]	[0.058]	[0.379]
LccDummy	-0.184**	-0.032	-0.156**	-1.771	-0.169**	-0.032	-1.864+	-0.157**
	[0.052]	[0.023]	[0.053]	[1.098]	[0.048]	[0.023]	[1.099]	[0.050]
Assets	0.098**	0.011	0.097**	3.002*	0.112**	0.010	3.145*	0.109**
	[0.031]	[0.014]	[0.032]	[1.233]	[0.029]	[0.014]	[1.250]	[0.030]
OpExpense	-0.077	-0.132+	0.023	-0.114	-0.090	-0.119+	-0.109	-0.040
	[0.152]	[0.067]	[0.156]	[0.100]	[0.141]	[0.067]	[0.100]	[0.147]
Maintenance	0.070*	-0.003	0.083*	-0.001	0.079**	-0.006	-0.005	0.084**
	[0.032]	[0.014]	[0.033]	[0.061]	[0.030]	[0.014]	[0.061]	[0.031]
Aircraft Fuel	-0.059*	0.062**	-0.127**	-0.386	-0.058*	0.057**	-0.373	-0.091**
	[0.030]	[0.013]	[0.032]	[0.294]	[0.028]	[0.013]	[0.294]	[0.031]
NS Pax		-0.131**		-1.125**		-0.097**	-1.106**	
		[0.011]		[0.052]		[0.012]	[0.052]	
AC Dispersion		0.048**		-0.137**		0.069**	-0.189**	
		[0.007]		[0.031]		[0.008]	[0.034]	
GeoMeanPop		-0.004		-2.680*		0.218	-2.917*	

		[0.264]		[1.259]		[0.302]	[1.286]	
Constant	19.182*	-2.074	17.285*	28.190+	9.485	-2.074	30.215+	9.936
	[8.455]	[3.791]	[8.649]	[16.579]	[7.911]	[3.802]	[16.600]	[8.215]
Adjusted R-sq	0.857		0.876		0.940			0.922
First-stage F-statistics		34.06		111.54		27.27		
Hansen-Sargan Chi2			45.160		11.731			0.923
(p-value)			(0.000)		(0.003)			(0.337)
N	3223		3223		3223			3223

Notes: Standard errors in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$; (M) indicates the variables are measured in millions of units. IVFE models are estimated by Three-Stage Least Squares and adjusted R^2 is based on McElroy (1977). All estimations include carrier, market, and time fixed effects. The Hansen-Sargan test is a statistical test used in the context of instrumental variable (IV) regression models to assess the validity of instruments. Failing to reject the null hypothesis suggests that the instruments are exogenous or valid. It is also known as the overidentification test or Hansen J test. As we exclude SDM in IVFE1 and HHI in IVFE2, we reject the null hypothesis implying that the instruments are not exogenous. This is likely because when the instrumental variables are correlated with the excluded variable SDM in IVFE1 and HHI in IVFE2. As seen in IVFE3, when both SDM and HHI are included, we fail to reject the null hypothesis of J-test, confirming the validity of instrumental variables. The first-stage F-statistic is compared to critical values from the F-distribution to determine statistical significance, the rule of thumb is 10. A high F-statistic indicates that the instruments are strong and have a significant impact on the endogenous variable, supporting the validity of the instrumental variables.

6.2. SDM and distribution of fares

We further explore how SDM performs in explaining the fares at different fare percentiles. The results of these estimations are provided in Table 4. In this table we provide only the comprehensive estimation for each of the models (that is, the estimation that includes both HHI and SDM corresponding to Estimation IVFE (3) in Table 3. The estimation results at the various quartiles reveal that SDM is a significant measure in explaining fare levels. We find that the coefficients of SDM and HHI exhibit some variations across the different quartiles.

To further explore the variations in the behavior SDM and HHI, we estimate the full specification of equation (1) with both HHI and SDM (i.e., IVFE (3)), for a number of other percentiles; from the 5th to 95th in 5 percentile increments as well as the 1st and 99th percentiles. For parsimony reasons, we focus our attention only on the estimated coefficients of HHI and SDM, which are illustrated in Figure 7 along with their degree of statistical significance. One can observe that, generally, significance is maintained throughout the range of most percentiles for both SDM and HHI.

Table 4. Model Estimates: Dependent variables are Log of Prices at 25th, 50th and 75th-Percentiles

	IVFE(3)	IVFE (3)	IVFE (3)
Dependent variable	**Price 25th**	**Price 50th**	**Price 75th**
HHI	1.319**	0.990**	0.864**
	[0.296]	[0.251]	[0.243]
SDM	0.172**	0.186**	0.194**
	[0.037]	[0.032]	[0.031]
AvgIncCap (M)	1.903*	0.182	0.175
	[0.821]	[0.697]	[0.675]
AvgPop (M)	-1.231*	-0.350	-1.016*
	[0.547]	[0.464]	[0.449]
LccDummy	-0.049	-0.037	-0.082
	[0.072]	[0.061]	[0.059]
Assets	0.142**	0.077*	0.080*
	[0.044]	[0.037]	[0.036]
OpExpense	-0.070	0.024	0.036
	[0.212]	[0.180]	[0.174]
Maintenance	0.106*	0.116**	0.078*
	[0.044]	[0.038]	[0.037]
Aircraft Fuel	-0.131**	-0.128**	-0.094*
	[0.044]	[0.038]	[0.036]
Constant	2.390	6.875	17.050+

	[11.860]	[10.065]	[9.751]
Adjusted R-sq	0.910	0.914	0.916
First-stage F-statistics	27.24	27.27	27.27
Hansen-Sargan Chi2	0.208	0.624	0.536
(p-value)	(0.648)	(0.430)	(0.464)
N	3220	3223	3223

*Notes: Standard errors in parentheses; + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$; (M) indicates the variables are measured in millions of units. IVFE models are estimated by Three-Stage Least Squares and the adjusted R^2 is based on McElroy (1977). All estimations include carrier, market, and time fixed effects. The Hansen-Sargan test is a statistical test used in the context of instrumental variable (IV) regression models to assess the validity of instruments. Failing to reject the null hypothesis suggests that the instruments are exogenous or valid. It is also known as the overidentification test or Hansen J test. We fail to reject the null hypothesis of J-test, confirming the validity of instrumental variables. The first-stage F-statistic is compared to critical values from the F-distribution to determine statistical significance, the rule of thumb is 10. A high F-statistic indicates that the instruments are strong and have a significant impact on the endogenous variable, supporting the validity of the instrumental variables.*

One can observe that the effect of market structure (HHI) on fare levels exhibits a down-sloping behavior, with the effect consistently decreasing at higher percentiles. This may suggest the limited impact that competition has on fares at higher percentiles, possibly suggesting that carriers are able to post higher prices for those loyal passengers regardless of the degree of competition in the market. The impact of scheduling and flight frequency (SDM) is rather consistent throughout most of the fare percentiles with some drop in the effect at very low and very high percentiles thereby exhibiting an overall an inverted flat U-shape behavior. This suggests the impact brought by schedule overlap brings more consistent impact on fares.

Importantly, we have found that SDM adds net explanatory value to the explanation of fare levels so one interpretation of our results is that given market structure and given schedules, fare levels will be affected by the schedule structure since that determines how airlines can compete in fare space given they have established a given flight schedule.

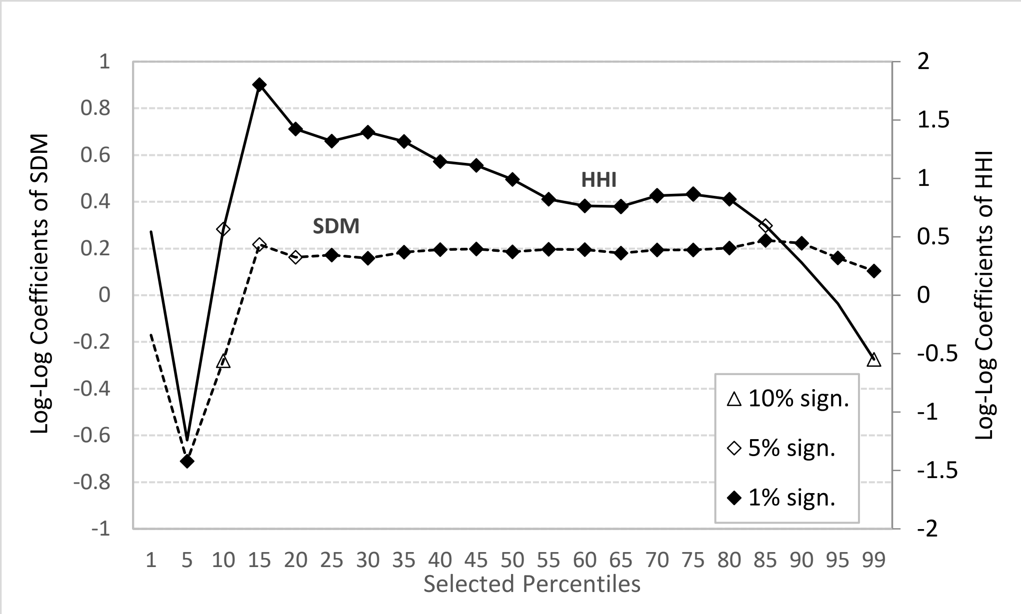


Figure 7. Effect of HHI and SDM at different transacted fare percentiles

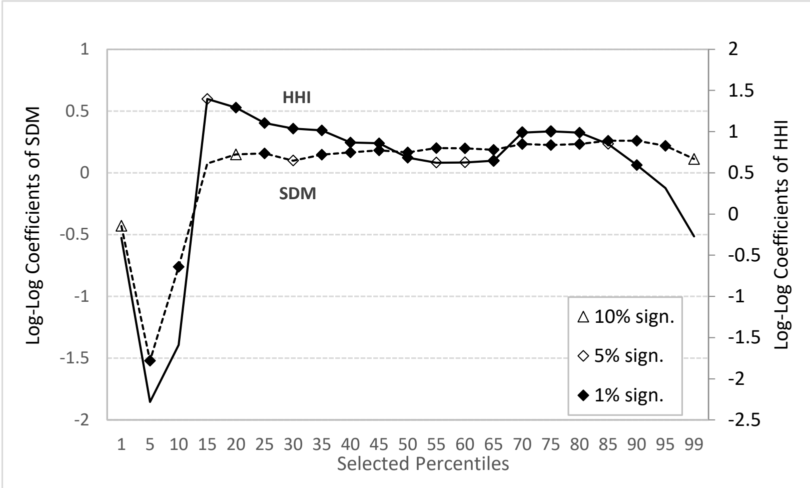
One possible explanation to the pattern of coefficients of SDM and HHI across the different percentiles is that schedule overlap may play a different role for different passenger types. Accordingly, we further explore the impact driven by the rivalry structure between the airlines in the market.

6.3. The effect of the Business Model within the Duopoly Structure

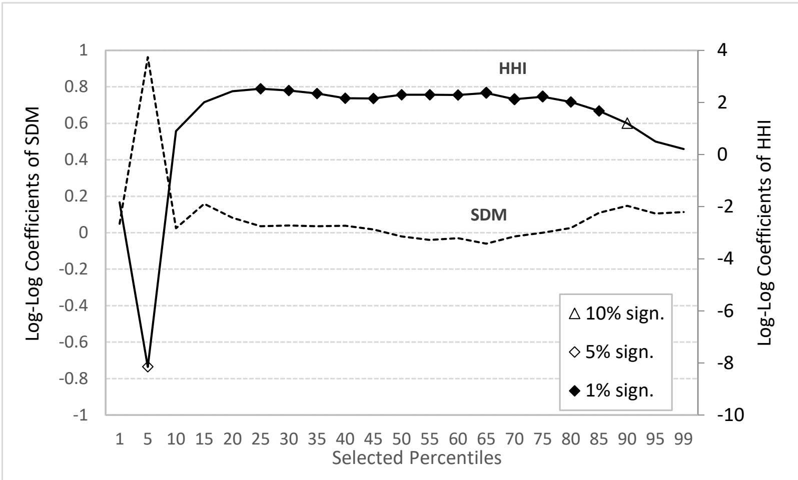
To explore the duopoly structure, we distinguish between markets where both competing carriers are network carriers, where both are low cost carriers, and when we have a mixture of each type. We estimate specification IVFE (3) separately for each of these market structures and illustrate the coefficients of HHI and SDM in the three panels of Figure 8.

The main observation is that once we account for the type of competitor (business model) in the market, the effect of HHI and SDM differ significantly based on the type of rivalry in the market. Consider, for instance, the effect of HHI: it explains fairly well pricing outcomes for most fare percentiles (except for low and very high percentiles) when two network carrier compete; its explanatory power diminishes when a network carrier competes with an LCC; and it bears no power in explaining fare percentiles in markets with two competing LCCs (although the latter could be driven by the low number of observations—197 such markets).

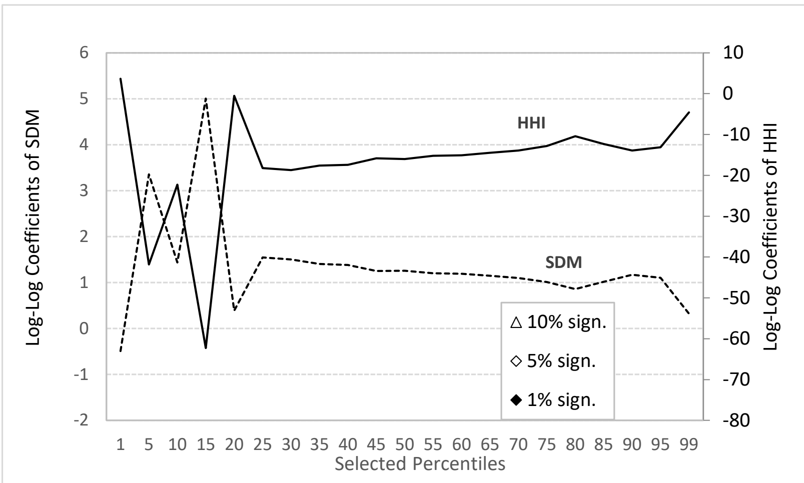
Importantly, SDM is significant in explaining the fare levels in the various percentiles when two network carrier compete with each other. The effect of SDM is consistent and high across most of the fare percentiles showing seeming fare matching and competition in frequency and timing of flights. By contrast, SDM seem to have no explanatory power when a network carrier competes with an LCC or when two LCCs compete with each other. This is an important result which is driven by the fact that in such markets the schedule of flights plays minimal, or no role, in customers' choices. In particular, a rivalry between LCCs is essentially price-based competition. Evidently, the type and extent of rivalry between carriers depends on whether a carrier is competing with an LCC, or with a network carrier.



(a) Two network carriers (1619 markets)



(b) One Network and One LCC (1407 markets)



(c) Two LCCs (197 markets)

Figure 8. Effect of HHI and SDM at different transacted fare percentiles: Different rivalry types

7. Robustness and extensions

Like other competition measures, our SDM metric has potential drawbacks. First, we note that we have limited our attention to duopoly markets, and accordingly, our empirical insights are relevant in such contexts. However, our model can be extended into oligopoly settings (§7.1). We have also abstracted away from two dimensions that could be important to the observed SDM in markets: the distribution of demand throughout the day and the seating capacity of flights offered in markets. Presumably, these two aspects should go hand in hand in the sense that when demand peaks during the day, an aircraft with denser distribution of seats is put into service. We have intentionally elected to abstract away from these two aspects in the context of aviation, as the distribution of demand throughout the day is not publicly available. A generalization of our measure into other industries, such as in the retail industry, may be able to account for these considerations. For instance, in locating stores, decision-makers can account for the geographical density of demand (and possibly for the size of stores). Such problems are inherently difficult; see for example Granot et al. (2010). We elaborate on this consideration in §7.2.

We also explored how the impact of SDM might differ depending on the level of competition in the market as measured by HHI. The sample was divided into those markets that were less concentrated with an HHI<.6 and more concentrated markets with an HHI >.6; Figure 6 illustrates HHI versus SDM. We find that SDM explains a greater proportion of price variation in markets with a dominant carrier; that is, more concentrated markets. This result suggests that airlines leverage their time differentials in more concentrated markets.

7.1 Extension of the SDM into an Oligopoly

We have proposed a measure to capture the degree of horizontal differentiation between two competing carriers based on their schedules of flights. An important generalization of this measure is to allow SDM to encapsulate competitive environments that entertain more than two competitors.

To generalize to any number of competing carriers, n, in a market, one could expand the original methodology by employing n-dimensional matrices, which are more challenging to work with and the ultimate measure requires a correction to account for the number of competing firms. To circumvent this difficulty, we propose, instead, to measure the SDM by focusing at one firm at a time, derive the SDM while assuming all other carriers form a single entity, and average out. Specifically, let SDM_i denote the SDM were carrier i to compete with all other carriers in the markets as if they were a single carrier. Then, we aggregate these measures to yield the market level SDM. That is, $SDM = \frac{1}{n}\sum_{i=1}^{n} SDM_i$.

We illustrate using a simple example. Consider a triopoly setting with two carrier each operating two flights and a third carrier operating only one flight. We consider two constellations as depicted in Figure 7. The flights are three hours apart and staggered with subsequent time slots operated by different carriers. In the first constellation (top) the third carrier operates the flight at the end of the day whereas in the second constellation (bottom) it operates the mid-day time slot.

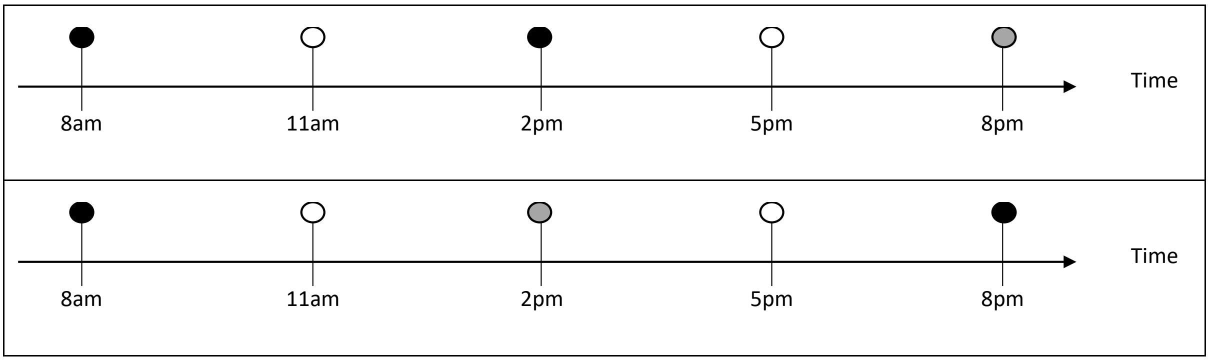


Figure 9. Illustration of SDM for a triopoly

As we employ normalized inversely decreasing weights with $f(M,N) = M^2 \cdot N^2$, the sum of **SDMM** entries equal that of the **DIFF** matrix. Consider the first constellation. For the black (denoted by subscript B), white (W) and grey (G) carriers, respectively we have

$\mathbf{Diff_B} = \begin{pmatrix} 180 & 540 & 720 \\ 180 & 180 & 360 \end{pmatrix}, \mathbf{Diff_W} = \begin{pmatrix} 180 & 180 & 540 \\ 540 & 180 & 180 \end{pmatrix},$ and $\mathbf{Diff_G} = (720 \quad 540 \quad 360 \quad 180),$

resulting with $\mathbf{SDM_B} = \frac{2160}{2^2 3^2} = 60$, $\mathbf{SDM_W} = \frac{1800}{2^2 3^2} = 50$, and $\mathbf{SDM_G} = \frac{1800}{1^2 4^2} = 112.5$ and ultimately to the market level **SDM**=74.16. Replicating the analysis for the second constellation, we obtain **SDM**=59.16. This demonstrates that regardless of the relative size of the competing carriers (that is, how many flights they operate), our measure captures how they compete in the market as the value of our **SDM** changes with the way the schedules differentiate from each other. Note, again, that existing measures of competition such as HHI and the one proposed by Borenstein and Netz (1999) produce the same value for either constellation whereas our measure—by construction—captures the nuanced differences between the two.

7.2 Accounting for underlying demand

Although the distribution of demand is not directly observable in aviation markets, below we resort to a proxy that can reflect the demand in a market: the number of flights operated by the competing carriers in a market (NumFlights). The Fare variable is the fare for each carrier in the market. Accordingly, we estimate the following specification:

$$
\begin{aligned}
ln(Fare_{ict}) = \alpha_0 &+ \alpha_1 ln(HHI_{it}) + \alpha_2 ln(SDM_{it}) + \alpha_3 \ln(NumFlights_{it}) \\
&+ \alpha_4 ln(AvgPop_{it}) + \alpha_5 ln(AvgIncCap_{it}) \\
&+ \alpha_6 (LCCDummy_{it}) + \alpha_7 ln(Assets_{ct}) \\
&+ \alpha_8 ln(OpExp_{ct}) + \alpha_9 ln(MainMatExp_{ct}) \\
&+ \alpha_{10} ln(AircraftFuel_{ct}) + \alpha_{11}\text{year2014} + \alpha_{12}\text{year2015} \\
&+ \gamma_c + \gamma_t + \varepsilon_{it}
\end{aligned}
\tag{2}
$$

Similar to HHI and SDM, 'NumFlights' is also subject to potential endogeneity, and hence it is instrumented.[16] The estimation results are provided in Table 5. We see from IVFE(3) that the inclusion of the market size proxy, Number of Flights, results in SDM still being significant but the coefficient is somewhat smaller than the results reported in Table 3. As pointed out earlier in the paper, SDM is constructed from information on total operations as well as the substitutability between carrier flights. The significance of HHI is illustrating that fares will be higher in concentrated markets even if adding frequency since the dominant firm will still dominate and will have even more product to offer passengers.

Adding flights reduces fares while increasing SDM (reducing substitutability) increases fares. Why should this be the case? Given HHI and SDM, adding flights has a small downward impact on fares. Because SDM is based on number of operations (flights) and substitutability between flights, if number of operations increases, increasing SDM, the only way to hold SDM constant is to reduce the substitutability between flights putting downward pressure on SDM. It appears the downward pressure on SDM from reducing flight substitutability dominated the impact of increasing numbers of operations which puts downward pressure on fares.

[16] We use instrumental variables so that equation is solved in two stages. First, SDM and HHI are separately regressed over the IVs and other exogenous variables. Second, Fare is regressed against the fitted values for HHI and SDM as well as other exogenous variables.

Table 5. Model Estimates: Dependent Variable is Log of Mean Price

	FE	IVFE (1)	IVFE (2)	IVFE (3)
Dependent variable	**MeanPrice**	**MeanPrice**	**MeanPrice**	**MeanPrice**
HHI	0.103**	1.064**		0.796**
	[0.021]	[0.189]		[0.185]
SDM	0.011+		0.434**	0.154+
	[0.006]		[0.078]	[0.080]
NumFlights	-0.067**	-0.385**	0.546**	-0.054
	[0.017]	[0.058]	[0.192]	[0.182]
AvgIncCap (M)	-0.350	0.941	-0.293	0.604
	[0.297]	[0.591]	[0.621]	[0.591]
AvgPop (M)	-0.827**	-1.121**	-0.145	-0.829*
	[0.199]	[0.386]	[0.415]	[0.400]
LccDummy	0.032	-0.141**	-0.182**	-0.153**
	[0.027]	[0.051]	[0.055]	[0.051]
Assets	0.004	0.093**	0.132**	0.107**
	[0.016]	[0.031]	[0.034]	[0.031]
OpExpense	0.083	-0.016	-0.078	-0.030
	[0.080]	[0.151]	[0.162]	[0.149]
Maintenance	0.014	0.098**	0.063+	0.087**
	[0.017]	[0.032]	[0.034]	[0.032]
Aircraft Fuel	-0.053**	-0.092**	-0.086*	-0.095**
	[0.016]	[0.032]	[0.033]	[0.031]
Constant	20.919**	12.233	7.211	10.227
	[4.435]	[8.396]	[9.126]	[8.361]
Adjusted R-sq	0.946	0.950	0.948	0.989
First-stage F-statistics		33.80	14.383	11.174
Hansen-Sargan Chi2		5.622	19.71	1.891
(p-value)		(0.060)	(0.000)	(0.169)
N	3223	3223	3223	3223

Notes: Standard errors in parentheses; + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$; (M) indicates the variables are measured in millions of units. R^2 in IVFE model the 2SLS estimation is based on Pesaran and Smith (1994). All estimations include carrier, market, and time fixed effects. *All estimations include carrier, market, and time fixed effects. The Hansen-Sargan test is a statistical test used in the context of instrumental variable (IV) regression models to assess the validity of instruments. Failing to reject the null hypothesis suggests that the instruments are exogenous or valid. It is also known as the overidentification test or Hansen J test. As we exclude SDM in IVFE1 and HHI in IVFE2, we reject the null hypothesis implying that the instruments are not exogenous. This is likely because when the instrumental variables are correlated with the excluded variable SDM in IVFE1 and HHI in IVFE2. As seen in IVFE3, when both SDM and HHI are included, we fail to reject the null hypothesis of J-test, confirming the validity of instrumental variables. The first-stage F-statistic is compared to critical values from the F-distribution to determine statistical significance, the rule of thumb is 10. A high F-statistic indicates that the instruments are strong and have a significant impact on the endogenous variable, supporting the validity of the instrumental variables.*

8 Concluding remarks

The SDM metric is an innovative approach to measure effective market competition and product differentiation. The results here highlight important aspects of competition intensity in the context of aviation markets. For management, it reveals when and how schedule overlap is important in facilitating higher fares. For policy makers, our insights can stimulate more careful consideration of aviation policies as the impact of schedules and their degree of overlap can influence fares in substantial ways that complements the traditional measure of market concentration, HHI.

Traditional methods of measuring competition (e.g., HHI) can overlook the rivalry between competing firms in that they ignore *how* firms compete with each other. Our measure offers an avenue to overcome this gap by capturing the degree of horizontal differentiation between competing firms. Applied to aviation markets, SDM encapsulates the differentiation in the schedules operated by competing carriers. By scheduling their flights at different time slots throughout the day, airlines differentiate themselves horizontally which in turn can support demand segmentation across users. Fundamentally, HHI captures the importance of the number and size distribution of firms, while SDM captures the number and differentiation of products.

The analysis provides compelling evidence that the SDM is an important instrument in assessing the degree of effective competition in markets; specifically, SDM explains fare levels above and beyond fare levels captured by the market concentration variable, HHI. Keeping the level of HHI in a market fixed, the value of SDM may change, if, for example, both airlines increase their frequency by one additional flight. Since this affects their degree of overlap, the dynamics of the change will command a correction in the fares in this market.

Another insight is the competing business models in the market interact with SDM. Distinguishing three duopoly structures: one where both firms are network carriers, another where both are LCCs, and a third where one is a network carrier and the other is an LCC, illustrates the role of SDM in the various duopoly market structures. LCCs have a low fare strategy and capture the more elastic lower yield demand segments; SDM plays no role as the focus of competition is pricing. Network carriers structure their schedules to serve a variety of customers. Therefore, for network carriers, the degree of schedule overlap, as captured by the SDM, has an impact on fare levels.

For competition authorities, SDM adds an additional check on the expected impact on prices under proposed mergers, acquisitions or joint ventures. For example, firms entering a joint venture may pledge to maintain the number of flights in the markets but the joint venture allows them to collude on scheduling, which, as we have seen in this paper, can lead to higher fares. Oftentimes merger and acquisition approvals are subject to the giving up of landing slots at specified airports. Our results show the approval may not only determine the number of slots to be released (based on HHI analysis) but may also indicate which slots should be released (based on SDM analysis). In the case of slot concentration airfares may be higher on some flights since they are insulated from rivals' alternative flights.

The importance of both of who is competing in a market as well as how they have positioned flights speaks to an entrenched view that allocating free slots to LCCs at slot constrained airports may provide effective competitors to incumbent firms. Our results show that numbers of slots matters but as importantly where the slots are taken from and where they are reallocated in the schedule will have an impact on 'effective' competition. In particular, the positioning of flights can offset the competitive effect of reallocating more slots.

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Appendix A: Construction of the dispersion of aircraft types instrument

The concept of this instrument echoes that of HHI, only that it is applied to the aircraft types and their corresponding capacities. From the U.S. T-100 database, we estimate the average capacity of each aircraft type. Based on the average configuration we split these types into 5 categories: under 50 seats, up to 100 seats, up to 150, up to 170, and above 170. This ensures the seating capacities are aligned with aircraft types. Note the last category includes aircraft with the largest capacities. However, such aircraft (the largest 6 in the table, e.g., Boeing 777 and Airbus A-380) are rarely employed on U.S. domestic routes. Following the construction of HHI, we count the share of flights associated with each capacity category and sum their squared values.

Table 6. Typical Aircraft Capacities

Description	Seat Capacity	Capacity category
Aerospatiale/Aeritalia ATR-42	24.0	1
Embraer EMB-120 Brasilia	30.0	1
Saab-Fairchild 340/B	33.4	1
De Havilland DHC8-100 Dash-8	37.0	1
Embraer-135	37.0	1
De Havilland DHC8-200Q Dash-8	37.0	1
Embraer-140	44.0	1
Aerospatiale/Aeritalia ATR-72	48.7	1
Embraer-145	50.0	1
Canadair RJ-200ER /RJ-440	50.0	1
De Havilland DHC8-300 Dash 8	50.0	1
Canadair RJ-700	65.7	2
Embraer 170	69.5	2
De Havilland DHC8-400 Dash-8	74.3	2
Boeing 767-200/ER/EM	76.5	2
Embraer ERJ-175	77.3	2
Canadair CRJ 900	77.7	2
Airbus Industrie A-318	89.4	2
Embraer 190	99.3	2
Boeing 717-200	118.1	3
McDonnell Douglas DC-9-50	120.0	3
Boeing 737-500	121.3	3
Airbus Industrie A319	127.8	3
McDonnell Douglas DC9 Super 87	130.0	3
Boeing 737-400	133.4	3
Boeing 737-300	137.7	3
Boeing 737-700/700LR	139.9	3
McDonnell Douglas DC9 Super 80/MD81/82/83/88	144.2	3
Airbus Industrie A320-100/200	150.6	4
Boeing 757-200	153.2	4
Boeing 737-800	156.6	4
McDonnell Douglas MD-90	160.0	4
Boeing 737-900	169.9	4
Boeing 767-300/300ER	174.9	5
Airbus Industrie A321	186.7	5
B787-800 Dreamliner	214.9	5
Boeing 757-300	219.0	5
Boeing 767-400/ER	244.2	5
Boeing 747-400	255.4	5
Airbus Industrie A330-200	259.7	5
Boeing 777-200ER/200LR/233LR	266.7	5
Airbus A330-300	288.6	5
Boeing 777-300/300ER/333ER	318.9	5

Appendix B: Regression for different ranges of HHI[17]

Based on the two regressions, the results indicate that in more concentrated markets (we only look at duopolies), with one dominant carrier and one weak carrier, changes in schedule overlaps have less significant effects on prices. The SDM variable tends to explain a greater portion of price variation in more competitive markets, one without a dominant carrier, i.e., less concentrated markets, compared to less competitive markets assessed using the HHI. The results suggest that airlines strategically leverage time differentials in less concentrated markets. When the SDM increases (indicating an increase in the time differential), this leads to higher price increases in less concentrated markets compared to more concentrated ones, all else being equal.

We estimate specification IVFE (3) separately for each of the ranges of HHI and provide them in Table 7

Table 7. Model Estimates: Dependent Variable is Log of Mean Price

	Full Sample	**0.4≤HHI<0.6**	**0.6≤HHI**
Dependent variable	**MeanPrice**	**MeanPrice**	**MeanPrice**
HHI	0.646**	2.181**	0.254
	[0.205]	[0.717]	[0.536]
SDM	0.183**	0.243**	0.187**
	[0.026]	[0.032]	[0.056]
AvgIncCap (M)	0.467	1.288	1.533
	[0.569]	[0.806]	[1.525]
AvgPop (M)	-0.729+	-1.875**	0.247
	[0.379]	[0.560]	[0.976]
LccDummy	-0.157**	-0.069	-0.582**
	[0.050]	[0.065]	[0.103]
Assets	0.109**	0.073+	0.337**
	[0.030]	[0.038]	[0.070]
OpExpense	-0.040	0.092	-0.956**
	[0.147]	[0.191]	[0.307]
Maintenance	0.084**	0.044	0.166**
	[0.031]	[0.041]	[0.060]
Aircraft Fuel	-0.091**	-0.067	-0.049
	[0.031]	[0.041]	[0.063]
Constant	0.646**	17.843+	-7.484
	[0.205]	[10.604]	[17.957]
Adjusted R-sq	0.922	0.937	0.925
First-stage F-statistics	27.27	16.217	11.957
Hansen-Sargan Chi2	0.923	0.044	0.652
(p value)	(0.337)	0.834	0.430
N	3223	2168	1028

[17] We are indebted to an anonymous referee for suggesting splitting the data in this way.

Notes: Standard errors in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$; (M) indicates the variables are measured in millions of units. IVFE models are estimated by Three-Stage Least Squares and adjusted R^2 is based on McElroy (1977). All estimations include carrier, market, and time fixed effects. *All estimations include carrier, market, and time fixed effects. The Hansen-Sargan test is a statistical test used in the context of instrumental variable (IV) regression models to assess the validity of instruments. Failing to reject the null hypothesis suggests that the instruments are exogenous or valid. It is also known as the overidentification test or Hansen J test. We fail to reject the null hypothesis of J-test, confirming the validity of instrumental variables. The first-stage F-statistic is compared to critical values from the F-distribution to determine statistical significance, the rule of thumb is 10. A high F-statistic indicates that the instruments are strong and have a significant impact on the endogenous variable, supporting the validity of the instrumental variables*