Revisiting the Relationship between Competition and Price Discrimination*

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Abstract

We revisit the relationship between competition and price discrimination. Theoretically, we show that, if consumers differ in terms of both their underlying willingness-to-pay and their brand loyalty, competition may increase price differences between some consumers while decreasing them between others. Empirically, we find that competition has little impact at the top or the bottom of the price distribution but a significant impact in the middle, thus increasing some price differentials but decreasing others. Our findings highlight the importance of understanding the relevant sources of consumer heterogeneity and can reconcile earlier conflicting findings.

1 Introduction

Price discrimination occurs when firms charge different mark-ups to different consumers. While intuition might suggest that competition would limit a firm's ability to price discriminate, it is well established that firms can price discriminate in non-monopoly settings. There is now a large theoretical literature on oligopoly price discrimination (for an extensive review, see Stole, 2007). There is also a growing body of empirical work that investigates how market structure impacts equilibrium outcomes under price discrimination.

This empirical literature has developed along several tracks. One track investigates whether competition influences the *type* of price discrimination strategies firms use;

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see, for example, Asplund et al. (2008) and Borzekowski et al. (2009). Another focuses on the impact of competition on price *menus* in settings in which firms practise second-degree price discrimination; see Busse and Rysman (2005) and Seim and Viard (2011). The third, and largest, set of studies considers the impact of competition on price *differences* or price dispersion in settings where firms practice third-degree price discrimination or when only data on prices are available. This line of work dates back to Borenstein and Rose (1994) who first documented that competition was associated with increased price dispersion. However, the subsequent literature has delivered conflicting findings. Most notably, Gerardi and Shapiro (2009) revisit the analysis in Borenstein and Rose (1994) and find precisely the opposite pattern.[1]

Given this ambiguity, in this paper we revisit the relationship between market structure and price discrimination. We have three points of departure from the earlier literature. First, we build directly on early theoretical work on oligopoly price discrimination which shows that competition can increase or decrease price differences. In particular, Borenstein (1985) and Holmes (1989) show that the effect of competition on price differences depends on whether discrimination is based on differences in consumers' underlying willingness-to-pay or differences in their degree of brand loyalty. We develop a simple model in which consumers differ along both dimensions and show that, with more than two types of consumers, competition may increase the price differential between some consumers while reducing it between others. Second, empirically, we estimate the impact of competition on price differentials rather than on overall price dispersion, which has been the focus of most previous studies. Since our theoretical model demonstrates that competition may increase price differences between some consumers while decreasing them between others, the impact on overall price dispersion is not necessarily informative about the changes in prices that take place. Finally, we exploit a novel source of data and study the Canadian airline industry, rather than the U.S. industry which was the setting for many previous studies. There are a number of advantages to studying the Canadian setting. Most importantly, the small number of carriers operating in the domestic Canadian market means that the changes in market structure that we observe map much more closely to the simple comparison between monopoly and duopoly which is the basis of our theoretical model and, indeed, much of the theoretical work in this area.

Borenstein (1985) was the first to point out that, while monopoly price discrimination is based on differences in consumers' underlying value of a good, oligopoly price

[1]While Gerardi and Shapiro (2009) attribute the different findings to the more credible identification strategy that they use, more recent empirical work has also delivered conflicting findings. Stavins (2001) finds that price dispersion due to ticket restrictions increases with competition. Using data from the Irish airline industry, Gaggero and Piga (2011) find that competition reduces fare dispersion. Hernandez and Wiggins (2014) find that competition from Southwest compresses the menu of fares. Dai et al. (2014) find a non-monotonic relationship between competition and fare dispersion, with competition increasing dispersion in concentrated markets but decreasing it in competitive markets.

discrimination can also be based on differences in the strength of consumers' brand preferences. Holmes (1989) then showed that a firm's price elasticity of demand in a market can be expressed as the sum of the industry-demand elasticity and the cross-price elasticity and that, with more than one firm, price discrimination can be based on differences in either elasticity. In his review article, Stole (2007) explicitly shows that, with third-degree price discrimination, the relationship between competition and the price differential between consumer types will depend on whether consumers have similar or different cross-elasticities of demand. In particular, he shows that if all consumers have high cross-elasticities of demand, competition will push all prices towards marginal cost and reduce price differentials. On the other hand, if consumers with a low industry elasticity also have a low cross-elasticity while those with a high industry elasticity have a high-cross elasticity, prices will remain high for the former but fall for the latter and price differentials will grow with competition.

Using the set-up in Holmes (1989) and Stole (2007), we develop a simple model of third-degree price discrimination with three types of consumers. In our model, consumers differ in terms of both their underlying willingness-to-pay and their degree of brand loyalty to particular firms. To match our empirical setting, we describe our model in the context of the airline industry but believe that it would apply in a broader set of industries. Like much of the previous literature, we distinguish between 'business travelers' and 'leisure travelers' and assume that business travelers have both a higher underlying willingness-to-pay as well as greater brand loyalty due, perhaps, to frequent flyer programs. However, we also allow 'business travelers' to themselves be heterogeneous in their degree of airline loyalty, perhaps as a result of different corporate travel policies. To capture this, we introduce an intermediate type of traveler whom we refer to as a 'brand indifferent business traveler'.

We show that, in this set-up, competition will have the largest impact on the fares of the intermediate type since these are the consumers who will be charged high prices by a monopolist but whose price will move towards marginal cost with competition. The intuition for this result is simple: brand indifferent business travelers need to fly, similar to brand-loyal business travelers; however, they are willing to switch carriers, similar to leisure travelers. This implies that a monopoly airline can charge these travelers high prices, but must reduce prices to them once competition arises. In contrast, brand-loyal business travelers' fares will remain high even under competition, while leisure travelers' fares will be low regardless of market structure. It follows directly that competition will reduce the fare differential between some groups of travelers while increasing it between others.

Empirically, we test the predictions of this model using data on the Canadian airline industry. Our analysis uses data from the Airport Data Intelligence (ADI) database produced by Sabre Airline Solutions. The ADI database provides monthly fare and booking information for most itineraries worldwide and provides one of the only available sources of systematic data on the Canadian market.[2] The ADI data

[2]The Canadian government does not disseminate detailed data on airfares in the way that the

provide monthly average fares by cabin class and fare code. These data allow us to investigate how competition affects the fares paid for tickets in different cabins as well as tickets at different points of the fare distribution.[3] Since Canada had only a single legacy price-discriminating airline—Air Canada—operating during our sample period, our empirical analysis consists of a series of reduced-form regressions in which we relate Air Canada's fares for different types of tickets to measures of route-level market structure. All of our regressions include route, year and month fixed-effects and therefore capture how Air Canada differentially adjusts its fares for a given type of ticket, as the degree of competition on a route changes over time.

A clear pattern of results emerges from our empirical analysis. When we compare the impact of competition across cabin classes, we find that having an additional competitor on a route has no impact on Air Canada's Business fares but reduces its average Coach fares by approximately 6%, suggesting that competition has little impact on Air Canada's very expensive tickets. When we focus just on Coach class fares and estimate the impact of competition on the percentiles of the Coach fare distribution, we uncover a U-shaped relationship between competition and fare reductions. Competition has the largest impact on fares between the 15th and 75th percentiles of the Coach fare distribution and a smaller impact on fares below and above these percentiles.

In extensions of our empirical analysis, we exploit the one multi-airport city in our data—Toronto—which, in addition to having a major international airport, has a small downtown airport as well as an airport about an hour out of the city, in neighboring Hamilton. When we estimate the impact of competition on Air Canada's fares on flights out of Toronto, we find that Air Canada's median fares fall by 29% when it faces competition from Porter Airlines at Toronto's downtown airport, which is likely to particularly appeal to business travelers, but by only 6% on other routes. Similarly, Air Canada's median fares fall by 12% when Westjet's competition at Toronto occurs at Pearson airport, but by a statistically insignificant amount when WestJet competes from Hamilton airport, which is likely to attract leisure, rather than business, travellers. Overall, our empirical findings suggest the existence of more than two types of travelers and indicate that competition serves to reduce fare differentials between some while increasing differentials between others.

This work makes several important contributions. First, within the empirical literature on competition and price discrimination, we are the first to document a U-shaped relationship between competition and price decreases. Our findings indicate that, in our setting, competition has little impact on prices at the bottom or top of the distribution but a statistically and economically significant effect on prices

U.S. government does through the Department of Transportation's Databank 1B (DB1B), which is a random 10% sample of domestic tickets.

[3] Recently, other studies have also employed airline data with information on ticket characteristics, although the source and setting is different from ours; see Hernandez and Wiggins (2014) and Sengupta and Wiggins (2014).

in the middle of the distribution. Note that this result is different from that in Dai et al. (2014). They also document a U-shaped pattern but they measure the impact of increased competition on dispersion, starting from different levels of market concentration, while we focus on how a given change in competition impacts different parts of the fare distribution.

Second, our model and results offer a way of reconciling the conflicting results in the earlier literature. Although the early theoretical literature shows that the relationship between competition and price differentials is, in fact, ambiguous, the empirical literature has nevertheless focused on measuring the direction of that relationship, typically using aggregate measures of dispersion. Our simple extension of the theory as well as our empirical results show that not only is the direction of the relationship ambiguous but—with more than two types of consumers—some differentials may increase while others decrease. Thus, the different findings in the literature, especially when based on aggregate measures of dispersion like the Gini index, may all be possible.

Finally, this work contributes to the broader literature on oligopoly price discrimination. Early models of price discrimination were developed in a monopoly setting where only differences in consumers' underlying willingness-to-pay are relevant. Yet, as Borenstein (1985), Holmes (1989) and Stole (2007) all highlight, a fundamental difference between monopoly and oligopoly price discrimination is that, in the latter, differences in consumers' willingness-to-switch become relevant as well. Our paper shows that understanding the relevant sources of consumer heterogeneity in an industry is critical to understanding and estimating the relationship between market structure and equilibrium outcomes. While we focus on a particular empirical setting, the same issues are likely to arise in other industries. The hotel industry, for example, also has consumers with different underlying values of a good as well as different degrees of brand loyalty and firms with tools for discriminating among them. Price discrimination is also common in the software industry where customers are likely to differ in terms of their overall value of a product (for example, depending on whether the software is for personal or commercial use) as well as their willingness to switch among software products, due to heterogeneity in switching and learning costs.

The remainder of this paper is organized as follows. The next section lays out the theoretical considerations. In Section 3, we describe our empirical setting and data. Section 4 presents our empirical strategy. The results of our empirical analysis are presented in Section 5. A final section concludes.

2 Theoretical Considerations

In this section, we present a simple model to illustrate how competition may increase price differences between some groups of customers while decreasing price differences between others. The intuition that drives our results is similar to Borenstein (1985), which is explored further in Holmes (1989). Specifically, the key insight that we build on is that the effect of competition on price differentials depends on whether price discrimination is based on differences in consumers' tendency to drop out of the market or their tendency to switch suppliers.

We first summarize the key result from Holmes (1989), with slight modifications to fit our extension. Assume that two differentiated firms, A and B, face a set of potential consumers of two types, 1 and 2. Firms can practice third-degree price discrimination, implying that they can set separate prices for the two different groups of consumers. Holmes makes two assumptions, which we follow. The first is the *symmetry assumption* by which Firm A's demand by a given type when it sets a price p_1 and B sets p_2, is the same as Firm B's demand by that type when prices are reversed. The second is that there exists a unique equilibrium to the price game in which both firms set the same price for a given type. Given these two assumptions, the results that follow in this Section hold for all demand functions. Thus, rather than specifying demand for each consumer type, we follow Holmes and directly consider the various demand elasticities at the equilibrium prices.

Holmes shows that the demand for each firm's output, by each type of consumer, has an elasticity that can be decomposed into an industry-elasticity component and a cross-price elasticity component. Specifically, for either firm, the elasticity of demand by consumers of type i is given by:

$$e_i^{\mathcal{F}}(p) = e_i^{\mathcal{I}}(p) + e_i^{\mathcal{C}}(p) \tag{1}$$

Here, $e^{\mathcal{I}}$, the industry elasticity, measures how responsive aggregate industry demand is to changes in prices while $e^{\mathcal{C}}$, the cross-price elasticity, measures the impact on one firm's demand from changes in the other firm's price.

Holmes then shows how the familiar inverse elasticity pricing rule determines equilibrium prices for each group of consumers:

$$\frac{(p_i^* - c)}{p_i^*} = \frac{1}{e^{\mathcal{F}}(p_i^*)} = \frac{1}{e^{\mathcal{I}}(p_i^*) + e^{\mathcal{C}}(p_i^*)} \tag{2}$$

As Holmes points out, this expression shows that, in symmetric oligopoly, price discrimination can be based on differences in consumers' industry-demand elasticity and/or differences in consumers' cross-price elasticities.

Stole (2007) uses Holmes' set-up to illustrate why the relationship between competition and price differentials is ambiguous. Stole explains that if the goods are close substitutes (i.e.: both types of consumers have high cross-elasticities of demand), then competition will drive prices in both segments towards marginal cost and the price differential across segments will be negligible. On other hand, if consumers with a high industry elasticity consider the goods to be close substitutes while consumers with a low industry elasticity have strong brand loyalty, then competition will lower prices to the former while firms maintain high prices for the latter. In this case, competition will lead to larger price differentials across consumer segments, relative to the case of monopoly. It is thus clear from Stole that both of the empirical findings in the earlier literature are theoretically possible and that the relationship between competition and fare differentials depends on the underlying source(s) of heterogeneity between travelers.

We extend the two-type model from Stole (2007) to consider the possibility that travelers differ in terms of both their underlying value of a trip and their strength of brand loyalty and, moreover, that travelers who are similar on one dimension may still differ on the other. This gives rise to more than two types of travelers and the possibility that competition may increase price differentials between some types while decreasing them between others. We illustrate the intuition using a simple three-type model. In particular, we assume that Type 1 consumers have a low willingness-to-pay for a trip and no brand loyalty. These travelers, whom we call *price-sensitive leisure travelers*, will choose to fly with the cheapest possible airline and, if prices are too high, they will choose not to fly at all. We assume that Type 2 consumers are travelers with a high willingness-to-pay for a given trip but little brand loyalty. These travelers, whom we call *brand-indifferent business travelers*, will purchase a ticket even if fares are high but will choose to fly with the airline offering the cheapest fare. The third type of travelers are *brand-loyal business travelers* who have both a high willingness-to-pay to take their trip and a high degree of brand loyalty.

We focus on these particular segmentations of travelers because we believe they are consistent with key institutional features of the airline industry. A fundamental source of heterogeneity between travelers is their basic willingness-to-pay for a trip. Business travel is conducted to support some type of commercial or income-generating activity and therefore the reservation price for a business-related trip will typically be higher than that of a leisure-related trip. Therefore, we model business and leisure travelers as differing in their underlying willingness-to-pay.[4] In addition, travelers are heterogeneous in their degree of brand loyalty. In the airline industry, brand loyalty can result from both actual differentiation between airlines' offerings as well as perceived differentiation resulting from airlines' use of frequent flyer programs. These programs, which reward travelers for cumulative travel on a given airline, lower the degree of substitutability between otherwise similar flights. Because these programs generally have a non-linear reward structure, they will be more highly valued by business travelers since they fly more frequently.[5] For this reason, business travelers are often assumed to be more brand loyal than leisure travelers. However, we recognize that business travelers themselves may differ in terms of their degree of loyalty, due to differences in corporate travel policies (which may offer the traveler varying amounts of flexibility in his choice of carrier and ticket type), differences in their preferences for in-flight amenities or even differences in their frequency or destination of travel which will impact the value to them of collecting frequent flyer points. We therefore

[4] Note that travelers must differ in terms of their underlying value of a trip for there to be price discrimination in monopoly markets.

[5] See Borenstein (1989), Borenstein (1991), Lederman (2007) and Lederman (2008) for discussion and empirical evidence on how frequent flyer programs impact fares and market shares.

assume that leisure travelers have low brand loyalty and that business travelers differ in terms of their degree of airline loyalty.

We capture these sources of heterogeneity in travelers' willingness-to-pay and willingness-to-switch by assuming that Types 1 and 2 have the same cross-elasticity of demand and differ only in terms of their industry elasticity while Types 2 and 3 have the same industry elasticity and differ only in their cross-elasticity.[6] Specifically:

$$e_1^{\mathcal{I}} > (e_2^{\mathcal{I}} = e_3^{\mathcal{I}}) \tag{3}$$

$$(e_1^{\mathcal{C}} = e_2^{\mathcal{C}}) > e_3^{\mathcal{C}} \tag{4}$$

Similar to Holmes (1989), we assume that airlines are able to set separate prices for each of these three types of travelers, if they so choose. That is, we assume airlines practice third-degree price discrimination. In reality, airlines price discriminate through both third-degree and second-degree strategies, taking advantage of known information about travelers' that correlates with their willingness-to-pay and also offering menus of fare and ticket characteristic bundles for travelers to choose from. For simplicity and for the purposes of motivating our empirical analysis, we abstract from the self-selection problem and assume the airline can observe enough about each traveler's type—for example, from the timing of the search, the search parameters they enter and their frequent-flyer program profile—to charge them a different price. This allows us to build directly on the set-up in Stole (2007). In addition, this approach follows the one taken in most of the previous empirical work in this area which has estimated the impact of competition on fare dispersion, rather than on fare menus, thus also abstracting from the role of self-selection.

We begin by considering a price discriminating monopoly airline facing these three traveler types. In the case of a monopolist, the cross-price elasticity, $e_i^{\mathcal{C}}$, is zero for all consumer types, implying that the firm's elasticity is the same as the industry elasticity. The monopolist will set each group's price, which we denote p^M, according to the standard inverse elasticity rule. Therefore, for each Type i:

$$\frac{(p_i^M - c)}{p_i^M} = \frac{1}{e_i^{\mathcal{I}}} \tag{5}$$

Given equation 3 this implies that $p_1^M < (p_2^M = p_3^M)$.

We now consider the impact on prices when there is competition from a second airline. Each firm in this symmetric duopoly sets a price for each group of consumers, denoted p^D, according to the inverse elasticity rule. Therefore, for each Type i:

$$\frac{(p_i^D - c)}{p_i^D} = \frac{1}{(e_i^{\mathcal{I}} + e_i^{\mathcal{C}})} \tag{6}$$

[6] These equality assumptions may be unrealistic but are used to starkly illustrate how the different sources of heterogeneity affect the relationship between market structure and price differentials. Assuming weak monotonicity in the inequalities below will not change the result.

Given equations 3 and 4 this implies that $p_1^D < p_2^D < p_3^D$. Note that, with competition, the consumers' cross-elasticities of demand become relevant.

We can now compare how the change in market structure affects prices to each group and examine how price differentials between each pair of types changes with competition. Note first that, for all i, $p_i^D < p_i^M$, or that prices are lower in duopoly than monopoly for all consumers. For each Type i, Equations 5 and 6 imply that the ratio of the monopoly to duopoly markup is: $1 + \frac{e_i^{\mathcal{C}}}{e_i^{\mathcal{I}}}$.

Equations 3 and 4 imply that

$$\frac{e_2^{\mathcal{C}}}{e_2^{\mathcal{I}}} > \frac{e_1^{\mathcal{C}}}{e_1^{\mathcal{I}}}, \text{ and } \frac{e_2^{\mathcal{C}}}{e_2^{\mathcal{I}}} > \frac{e_3^{\mathcal{C}}}{e_3^{\mathcal{I}}}$$

Thus, competition reduces Type 2's fares by more than either of the other types.

Note the intuition behind the result that the Type 2 fares fall more than the other two types. Type 2 travelers need to fly, like Type 3's; however, they are willing to switch carriers, like Type 1's. Their low industry elasticity but high cross elasticity means that the airline can charge them high prices when it is a monopolist but not once there is competition. In contrast, Type 1's high industry elasticity means the airline cannot charge them very high prices even under monopoly and so competition does not impact their fares as much. Type 3's low cross elasticity means that the airline can charge them high prices even under competition and so competition also does not impact their fares as much.

What does this imply for how competition affects price dispersion? It is clear that whether competition increases or decreases price dispersion will depend on which groups' fares are compared. Since fares for Type 2's fall by more than the other two types, competition should decrease the differential between Type 2's and Type 1's and increase the differential between Type 3's and Type 2's. Without additional structure on the model, we cannot determine whether competition lowers Type 1 or Type 3 fares more. However, we know that competition should either increase the differential between Type 3's and Type 1's (which will occur if fares to leisure travelers fall by more than fares to brand loyal business travelers) or decrease the differential between them but by less than the change between Type 2's and Type 1's. More generally, the model suggests that, if airlines are able to segment travelers based on both their underlying value of a trip and their degree of brand loyalty, competition will increase the price differential between travelers who have different levels of brand loyalty but decrease the differential between travelers whose only source of heterogeneity is their underlying willingness-to-pay.[7]

[7] For completeness, we could also consider a fourth type of traveler with a low willingness-to-pay to travel but high brand loyalty, whom we could call a *brand-loyal leisure traveler*. Assume that the brand loyal leisure traveler had the same industry elasticity as our leisure traveler above but the same cross-elasticity as the brand loyal business traveler. Using the same logic as above, we can show that competition has the smallest effect on these travelers. Intuitively, this is because their prices are already relatively low under monopoly and, due to their high brand loyalty, fall little

This simple model illustrates two key points that impact an empirical analysis of the relationship between competition and price discrimination. First, we have shown that with more than two types of consumers, competition may increase the price differential between groups while decreasing it between others. This implies that empirical analyses that measure changes in overall price dispersion using a metric like the Gini coefficient may not be informative about the underlying changes in price differentials that have occurred. Second, we have shown that the largest impact of competition may be on neither the cheapest nor most expensive fares but rather on fares in the middle. Since it is typically not possible to know which tickets are sold to which types of travelers, previous work has compared the impact of competition on the top and bottom of the fare distribution as a way to distinguish tickets sold to business and leisure travelers. Our simple model suggests that it may more informative to estimate the impact of competition on the overall distribution as focusing on the extremes may miss the largest effects.

Finally, while our model assumes that airlines practice third-degree price discrimination, in reality airlines use a mix of second-degree and third-degree price discrimination. For example, price discrimination based on cabin class or ticket characteristics (such as refundability) is clearly a form of second-degree discrimination since, at the time of booking, the traveler can choose from a menu of tickets with different features and fares. However, airlines also price discriminate based on features of the transaction including how far in advance the ticket was purchased and the day-of-week and time-of-day on which the ticket was purchased (for evidence, see Puller and Taylor, 2012; Escobari et al., 2016). While this is not quite the same as price discriminating based on immutable characteristics of the consumer, it is also not equivalent to offering the consumer a clear menu of price and quality combinations to actively choose from. A traveler who learns of her travel plans at the last minute will not likely have contemplated purchasing that ticket weeks in advance of the plans becoming known such that she can be considered to have (even implicitly) chosen from a menu of options. Similarly, a traveler who books his flight on a Sunday does not know what the price of fare code that flight would be if he booked it on every other possible day of the week. Thus, many forms of price discrimination by airlines lie somewhere in between second- and third-degree discrimination. They are not based on characteristics of the consumers but are also not based on self selection into a menu of choices presented to the consumer.

Figure 1 reproduces an Air Canada document, published in 2009, which summarizes its North American fare structure. The document shows the various ways the

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with competition. In terms of differentials, competition would increase the differential between these travelers and the (brand-indifferent) leisure travelers and the brand indifferent business travelers but decrease the differential between these travelers and the brand loyal business traveler. These patterns are consistent with the more general implication of our model that the impact of competition on fare differentials between consumers will depend on whether those consumers differ in terms of their industry elasticities, cross elasticities or both.

airline price discriminates. Specifically, it shows that Air Canada offers different *fare types* (e.g.: Tango, Latitude) which are clearly associated with different characteristics and quality levels. Consumers are presented with a menu of these fare types and associated prices at the time of booking. At the same time, each fare type is associated with a number of *fare codes* (for example, Tango fares are associated with the K, N, G, P T and E codes) over which travelers have no direct ability to choose. These fare codes represent different 'buckets' (or versions) of the fare type which are offered by the airline at varying times, with varying conditions and varying prices. For example, fare codes might distinguish the same Tango ticket sold with varying advance purchase requirements. These fare codes are never presented to the consumer as a menu; rather, different fare codes will be made available based on characteristics of the consumer's search such as days remaining before departure or day of booking. This type of price discrimination, we argue, more closely resembles third-degree than second-degree.

Our model and empirical analysis abstract from price discrimination via self-selection for two reasons. First, theoretically, the third-degree model allows us to illustrate, a simple way, the intuition for why competition may increase price differentials between some consumers while decreasing them between others. In contrast, there are no clear predictions for the effect of competition on prices in an environment of second-degree price discrimination. As Stole (2007) discusses, most prior research in this area has focused on the effects of competition on quality or quantity, rather than on prices. It is difficult to obtain clear predictions of the effect of competition on prices, given that firms can adjust quality or quantity.[8] Second, our data contain no information on ticket characteristics. While we do observe fare codes, we cannot match those codes to particular types of tickets in a systematic way. As a result, we are limited to estimating the impact of competition on prices though we recognize that some of the changes in the price distribution that we document may reflect Air Canada adjusting its menu and/or consumers choosing different products from that menu. It is worth noting, though, that the fare structure represented in Figure 1 is used by Air Canada on all North American routes regardless of the level of competition faced.

[8]Some research suggests that greater competition reduces welfare distortions between high- and low-valuation consumers and also reduces the dispersion in prices (Stole, 1995). The results of Rochet and Stole (2002) also suggest that prices decrease more for high-valuation consumers. Yang and Ye (2008) have a similar finding although they suggest that the result depends on the initial level of competition.

3 Empirical Setting and Data

3.1 Empirical Setting: The Canadian Airline Industry

Our empirical setting is the Canadian domestic airline industry. The Canadian market has several features that make it well suited for a study of market structure and price discrimination. First, Canada had only one legacy airline—Air Canada—operating in our sample period. Air Canada is, by far, the largest airline in the country, in terms of both the number of routes served and passengers carried. Unlike the other airlines in the industry at the time, Air Canada operated a hub-and-spoke network including a large international network and offered multiple cabin classes on its aircraft. Air Canada provides service on virtually all of the top domestic routes in Canada. We therefore focus our empirical analysis on Air Canada's pricing behavior, investigating how its fares for different types of tickets change as it faces varying levels of competition on a route.

Second, market structure is straightforward to measure in the Canadian setting. There is little connecting service in Canada because Canadian airlines do not generally operate large hub-and-spoke networks.[9] Rather, they mostly operate point-to-point flights, focusing on the larger cities in the country. By contrast, in the U.S., there are typically multiple carriers offering connecting service between any two cities, leading to different measures of market structure depending on whether the researcher focuses on only direct service or on direct and connecting service. In addition, there is no domestic codesharing between Canadian carriers so there is no need to distinguish between operating and marketing carriers when measuring competition. With the exception of Air Canada, there is also no use of regional partners. Finally, there is only one multi-airport city in Canada (Toronto). The existence of multi-airport cities can make market structure measures sensitive to the researcher's decision about market definition.

Third, the Canadian market offers the opportunity to examine changes in fares and fare differentials as routes move between monopoly and duopoly. Because of the small number of carriers serving the domestic Canadian market, and Air Canada's long-standing dominance, there are many routes in our dataset—over 50%—on which the airline is a genuine monopolist for at least part of our sample period. By contrast, even with recent consolidation, it is rare to find routes in the U.S. with only a single airline offering direct service, especially when restricting attention to travel between large cities, as we do in this paper. Moreover, as argued above, the importance of connecting service in the U.S. and the prevalence of multi-airport cities means that there are often four or even five airlines offering service in some form between large cities. The Canadian setting therefore maps much more closely to the comparison between monopoly and duopoly which forms the basis of our model as well as much

[9] Air Canada does have a hub in Toronto. However, Air Canada also offers non-stop service between all of Canada's large cities and the vast majority of its passengers fly non-stop itineraries.

Table 1: Top Canadian Airports, and Comparable US airports

Canada			U.S. Comparable	
Rank	Airport	Enplanements	Airport	Rank
1	Toronto Pearson	32,278,458	Chicago O'Hare	2
2	Vancouver	16,394,986	Newark	14
3	Montreal Trudeau	13,228,564	Boston	19
4	Calgary	12,073,264	New York LaGuardia	20
5	Edmonton	6,156,730	St. Louis	31
6	Ottawa	4,359,055	Sacramento	40
7	Halifax	3,482,421	Cincinnati	51
8	Victoria	1,456,782	El Paso	72
9	Kelowna	1,355,975	Tulsa	76
10	Quebec City	1,343,021	Manchester	77

Source: Statistics Canada's "Air Carrier Traffic at Canadian Airports" (2011); Federal Aviation Administration's "Passenger Boarding and All-Cargo Data" (2011). Both sources include domestic and international passengers.

of the theoretical work in this area.

Since there is little previous empirical work on the Canadian industry, we provide some background information to illustrate how the Canadian industry compares with the U.S., which has been extensively researched. Table 1 presents the 10 largest Canadian airports based on total annual enplanements in 2011. To demonstrate how Canadian airports compare to U.S. airports in size, we also show, for each Canadian airport, a U.S. airport of comparable size and indicate the rank of that airport. As the table shows, Canadian airports are generally significantly smaller than U.S. airports, with the third largest airport in Canada roughly the same size as the 19th largest in the U.S. and the tenth largest roughly the same size as the 77th largest in the U.S.[10]

3.2 Data and Construction of Sample

The primary source of data for our empirical analysis is the Airport Data Intelligence (ADI) database, compiled by Sabre Holdings. Sabre is a travel technology company that owns a global distribution system (GDS) used by thousands of travel agents (including several of the large online agencies). Based on its GDS bookings, as well as data it collects to capture bookings that do not go through its GDS, Sabre produces the ADI database, which contains fare and booking information for most passengers and flights worldwide, from January 2002 until the present.

Our analysis uses data on travel within Canada from 2002 until 2011. The level of

[10]These rankings are based on enplanements, not originations or trips. The low enplanement numbers at Canadian airports reflect both the smaller number of passengers in the market as well as the lack of connecting service since connecting itineraries generate multiple enplanements per trip.

observation in the ADI data is the airline-route-year-month-cabin class-fare code.[11] This means that—for each month and for each pair of airports in Canada—we observe every airline that offered direct or connecting service between those airports, the number of passengers who travelled that route on the airline in that month in a given cabin and fare code, and the average fare they paid. The data are further broken down by direction of travel so that passengers flying from Toronto to Vancouver, for example, can be distinguished from those flying from Vancouver to Toronto, and are also broken down by point of origin.

We complement the ADI data with flight schedule data from the Official Airlines Guide (OAG). The OAG data provide the complete flight schedule of flights between all Canadian airports for one week in each month between January 2002 and December 2011. Specifically, we have the complete schedule of flights for the week beginning with the first Monday of each month. We use the OAG data as a second source of data on entry and exit dates which is useful for constructing and checking our market structure measures. We assume that airlines' schedules during the week that we observe reflect their schedules throughout the month and we match the variables we construct from the OAG data to the Sabre data at the airline-route-month level. We also use the OAG data to construct a measure of Air Canada's average plane size on a route and use this as a control in one of our robustness checks.

For our regression analysis, we limit our sample to routes between the top 15 cities in Canada.[12] Travel between these 15 cities accounts for approximately 65% of all domestic travel in Canada. The average route in this sample has about 8,000 monthly passengers in the ADI data and about 7,000 direct monthly passengers. The largest route in the sample (Toronto-Montreal) has, on average, over 100,000 monthly passengers in the ADI data. Averaging across routes in this sample, 59% of the passengers on a route travel on direct itineraries. However, in this sample as a whole, direct passengers account for over 87% of passengers, indicating that connecting passengers are concentrated on the smaller routes.

Our empirical analysis thus focuses on the impact of competition on Air Canada's fares for direct itineraries on routes between the top 15 cities. Air Canada provided service on 158 routes between the top 15 cities, with 118 of these routes being served non-stop. These 118 routes form the basis of our regression sample. We impose two additional sample restrictions. First, we drop route-months where Sabre reports fewer than 400 passengers on Air Canada (across all fare codes), which would correspond to fewer than 100 a week. Second, we exclude fare codes with average one-way fares below $50 on a given route-month.[13] After imposing these restrictions, we find that

[11] Airlines may offer multiple itineraries on a given route. For example, an airline may provide both direct and connecting service between two airports. For simplicity, and because our regressions include only direct service, we will refer to observations as being at the airline-route-month level.

[12] These 15 cities contain 17 airports, since there are three airports in the Toronto area. The top ten airports appear in Table 1.

[13] These may reflect coding errors or frequent-flyer awards and employee discounts. The results are not sensitive to small changes in either this cut-off or the passenger count cut-off. The online

across all route-months in our data, Air Canada's average share of direct or one-stop passengers on a route is 47% and its average share of direct passengers on a route is 48%.

3.3 Cabin Class and Fare Code Data

A novel and important feature of the ADI data is that it includes information on the cabin class and fare code of tickets. The cabin class refers to the actual cabin of service on the aircraft and distinguishes between Coach and Business class service. This allows us to investigate whether competition impacts Coach and Business class tickets differently.[14] Aggregating across all route-months in our regression sample, we find that the majority of Air Canada's passengers travel in Coach class with only 4% in Business class. Air Canada does not necessarily sell tickets in both cabins on every route as some of its smaller planes do not have separate business class cabins. In our sample, we observe Business tickets on 30% of route-months.

Fare codes are a finer level of categorization than cabin classes and multiple fare codes will be associated with a given cabin class. Fare codes are typically designated using a single letter of the alphabet, as discussed in Section 2. As Figure 1 showed, Air Canada offered several *fare types* within Coach and Business class (e.g.: Tango, Latitude) with each type being associated with several different *fare codes*. In our data, we observe tickets by cabin class and fare code though we are not able to match fare codes to the specific fare types in Figure 1. As Figure 1 indicates, fare codes are used to distinguish tickets with different features (i.e.: tickets in different fare types) and to distinguish tickets which are identical from the customers' point of view but which are associated with different restrictions or requirements such as advance purchase periods.

Table 2 shows how the tickets in our data map to cabin classes and fare codes on Air Canada. Our data cover about 54 million total passengers who fly on Air Canada over the 10-year sample period. The table shows their distribution across cabins and fare codes. The vast majority of passengers fly in the Coach cabin. The table also shows that, even within Coach class, Air Canada uses a large number of different fare codes.

appendix presents the results of our main specifications using a $25 cutoff, with very similar results.

[14]This is not done in most papers which use DB1B data as it is generally believed that the cabin class indicator in that data is unreliable.

Table 2: Total Air Canada Passengers, 2002–2011 (000s)

Code	Business	Coach	Total
A	0	3,177	3,177
B	0	1,687	1,687
C	885	0	885
D	98	0	98
E	0	906	906
F	0	1	1
G	0	1,110	1,110
H	0	1,761	1,761
I	52	312	364
J	1,075	0	1,075
K	0	325	325
L	0	4,441	4,441
M	0	1,532	1,532
N	0	962	962
P	0	469	469
Q	0	3,441	3,441
R	0	439	439
S	0	1,634	1,634
T	0	1,067	1,067
U	0	978	978
V	0	3,251	3,251
W	0	961	961
X	0	14	14
Y	0	22,307	22,307
Z	71	1,027	1,098
Total	2,181	51,802	53,984

Notes: Table shows the distribution of AC passengers by Class and code, on the top 15 domestic routes, 2002–2011.

4 Empirical Approach and Identification

The goal of our empirical analysis is to investigate whether competition differentially impacts the fares charged to different types of passengers. While previous work in this area has largely focused on the impact of competition on the overall amount of fare dispersion on a route (captured by an index such as the Gini coefficient), we instead estimate how competition impacts different parts of the overall fare distribution.[15]

4.1 Regression Specification

Our main estimating equation is a simple reduced-form specification. Denoting routes by r and time-periods by t, we estimate the effect of competition on a specific fare, i using:

$$\log p^i_{rt} = \beta_0 + \beta^i_1 \text{Competition}_{rt} + \lambda_r + \theta_t + \epsilon_{rt} \tag{7}$$

where λ and θ denote route and time fixed-effects, respectively. The i's denote different types of fares on a given route; for example, the average coach or average business class fare, or else specific percentiles of the overall fare distribution. An observation is a route-month combination.[16] We cluster standard errors at the route level.

We express prices in logs to measure the proportional effect of competition on various fare measures. Doing so allows us to compare differences in the estimated coefficients in order to determine the effect of competition on the ratio of fares for different tickets. In particular, assume that for two distinct types of fares, i and j, the estimated coefficients on the competition variable are $\hat{\beta}^i_1$ and $\hat{\beta}^j_1$. Since these estimated coefficients represent the proportional effect of competition on fares, price dispersion will rise or fall depending on the value of $\hat{\beta}^i_1 - \hat{\beta}^j_1$.[17]

4.2 Variables used in the Regressions

Fare Measures

We explore the relationship between market structure and fare differentials in two ways. First, we compare the impact of competition on the average fare of tickets in the two different cabin classes: Business and Coach. This allows us to examine, at a broad level, whether the prices of Air Canada's tickets in different cabin classes are affected differently by competition.

Second, we estimate how competition affects the full distribution of fares within Coach class. Coach accounts for the vast majority of Air Canada's passengers and

[15] Borenstein (1989) estimated the impact of hub dominance on different percentiles of the fare distribution. In their analysis, Gerardi and Shapiro (2009) estimate the impact of competition on both the Gini coefficient and various percentiles of the fare distribution.

[16] Recall that the regression sample only includes observations on Air Canada's fares.

[17] We present a formal test of the equality of the coefficients in Appendix B.

there are over 20 different fare codes within Coach. Thus, most of Air Canada's price discrimination is taking place across passengers within Coach class. Since the ADI data are not available at the ticket level, we use the fare code information to approximate the empirical distribution of fares for each route-month. Specifically, we assume that every passenger in a fare code paid the average fare of that class and use this to construct a route-month level fare distribution. We then calculate every fifth percentile of this fare distribution.[18] Following the methodology developed in Chetverikov et al. (2016), we estimate equation 7 above using each of these percentiles as the dependent variable. This allows us to trace out the impact of competition on the distribution of fares.[19]

Because we approximate the true fare distribution with the one we construct from the fare code information, we expect that our percentiles may be measured with error. While the methodology of Chetverikov et al. (2016) is robust to left-hand side measurement error, it is nevertheless useful to consider the possible sources of this error. Measurement error will arise if not all passengers who purchased a ticket in a given fare code (on a given route in a given month) paid the average fare of that class. To understand when this may occur requires some institutional background on airline pricing. As discussed by Lazarev (2013), airlines establish a set of fares for each flight, with different types of fares denoted with different fare codes. As we discussed above, and as illustrated in the Air Canada document in Figure 1, fare codes distinguish tickets that have different characteristics or restrictions. Airlines then determine how many seats (if any) to make available in each fare code on each flight at each point in time.

Variation in fares across passengers within a fare code will therefore arise for two reasons. First, passengers flying in the same fare code on the same flight might pay different prices if, in the time leading up to departure, the airline varies the price it sets for that fare code on that flight. Second, passengers flying the same fare code on different flights within the month may pay different prices if the airline sets different fares for the same fare code on different flights. While it is not possible for us to know how frequently these occur, we expect that airlines do set different prices for the same fare code across flights on a route. We also expect, at least on routes with competition, airlines may adjust the fares for tickets in a fare code on a given flight during the time leading up to departure.[20] Given this, we expect that our

[18] Table 13 in Appendix A presents an example using a specific route-month.

[19] Chetverikov et al. (2016) develop a methodology for estimating the impact of a group-level treatment on the within-group distribution of a micro-level outcome variable. In our case, the group is the route-month, the micro outcome is fare and we are estimating the impact of market structure (which varies at the group-level) on the percentiles of the fare distribution. Because their approach is implemented as a linear regression of the percentiles on the group-level treatment, the endogeneity of the treatment can be dealt with through standard two-stage least squares and group-level fixed effects can be included.

[20] Lazarev (2013), whose data allows him to observe fare codes at the flight level, reports that this is more common on very competitive routes but much less so on routes with few operating carriers.

percentiles will be measured with error.[21] However, we assume that the level of the measurement error is uncorrelated with market structure, although we expect that the variance of the error may be larger on more competitive routes (since these may invite more frequent fare changes within a fare code on a flight). As this may give rise to heteroskedasticity, we account for this with robust standard errors.

Market Structure Measures

We measure the competition faced by Air Canada on a given route-month in three ways: (i) the number of carriers, other than Air Canada, that provide direct service on the route in the month, (ii) indicators for whether the market is a duopoly or competitive (which we define as having three or more carriers), with AC's monopoly routes being the omitted category, and (iii) the negative of the log of the Herfindahl Index in the route-month.[22]

When constructing the market structure measures, we restrict the sample to the main nationwide carriers that existed during our sample period. Along with Air Canada, there were four such carriers, all of which were essentially low-cost carriers: WestJet, Porter, CanJet and Jetsgo.[23] All of these four carriers offer only a single class of service on their aircraft. Together, these five airlines account for over 85% of domestic airline passengers in Canada, and over 99% of passengers within our sample of routes between the top 15 cities.[24]

To confirm our measures of market structure, we cross-check Sabre's data against data from the OAG. While there is generally clear agreement between the two sources, there are occasional differences, due to missing data in either Sabre or OAG. We therefore measure a carrier as providing service on a route-month if it shows up in either dataset for the corresponding route-month.

On the latter, most of the variation in fares comes from the availability of different fare codes while fares within a class do not change much.

[21]There are a number of route-months on which Y-code tickets, which usually denotes a refundable Coach class ticket, account for an unusually high share of passengers. We believe that this classification is an error but that the underlying passenger and fares numbers are reliable as they are consistent with other months. We include these route-months in our analyses but recognize that they may also introduce measurement error to our fare percentiles. As a robustness check, we re-estimate (and present in Appendix C) our main regression specifications excluding the problematic route-months and find that the results are unchanged.

[22]These are the same measures used in Gerardi and Shapiro (2009) although they use the log of the number of rival carriers and we use the level since Air Canada is a monopolist on a number of routes.

[23]Porter is not exactly a low cost carrier; it features amenities that are more commonly associated with a 'Premium Economy' class of service, such as leather seats and free snacks on board and in its airport lounges. However, Porter offers a single aircraft cabin, similar to most LCCs. See Chandra and Lederman (2014) for a note on Porter Airlines and its effects on Air Canada's fares.

[24]Note, in particular, that we drop charter airlines, as well as small carriers such as Bearksin Airlines which operate small planes on some of the routes in our sample.

Table 3: Summary Statistics: Regression Sample

	Mean	SD	Min.	Max.	N
Business Fare	867.7	459.3	89	2648	3144
Coach Fare	252.9	102.1	65	739	11064
Num. Direct Rivals	0.83	0.64	0	3	11064
Duopoly	0.59	0.49	0	1	11064
Competitive	0.11	0.32	0	1	11064
HHI	0.70	0.22	0	1	11064
Selected Percentiles (Coach Cabin):					
1st Percentile	141.8	68.1	50	539	11064
25th Percentile	211.4	99.9	50	783	11064
50th Percentile	233.8	105.6	59	783	11064
75th Percentile	265.8	108.9	65	783	11064
99th Percentile	565.8	304.1	81	3234	11064

Note: An observation is a route-month.

Summary Statistics

Table 3 presents summary statistics on our fare and market structure variables. The level of observation in the table is the route-month and we have a total of 11,064 observations in the regression sample. Air Canada serves all of these routes in all months by construction. As the table indicates, across route-months, the average Coach and Business fares are \$253 and \$868, respectively.[25] On average, Air Canada faces fewer than one direct competitor on its routes. About 59% of route-months have Air Canada facing one competitor in direct service while 11% of route-months have two or more rivals. Based on the distribution of passengers across carriers, the average Herfindahl index on a route is a very high 70%.

The lower panel of Table 3 presents summary statistics for selected percentiles of the Coach cabin distribution. Again, the level of observation is the route-month. On average, the 99th percentile fare within Coach is about four times as expensive as the first percentile and the 75th percentile is about 25% more expensive than the 25th percentile. Note that all fare values are in nominal U.S. dollars.

4.3 Identification

Our empirical analysis consists of a series of reduced-form regressions in which we relate various fare measures to route-level market structure. All of our regressions include route, year and month fixed-effects. Thus, our analysis exploits variation in market structure within routes over the 120 months of our sample and our estimates

[25] As mentioned in Section 3, not all routes have Business class service which explains the lower number of observations for these fares.

capture how Air Canada changes its fares for different types of tickets as market structure on a route changes.

While the route fixed-effects control for route-level unobservables that may be correlated with market structure and fares, changes in market structure over time—which result from the entry and exit decisions of competing airlines—could still be correlated with time-varying unobservables which could also affect Air Canada's fares. For example, entrants may enter or exit routes following unobservable demand or cost shocks which also impact Air Canada's fares. Alternatively, entrants' decisions and Air Canada's pre-entry pricing decisions may be linked as demonstrated by Goolsbee and Syverson (2008). Given this, we begin by estimating our pricing regressions using ordinary least squares (OLS) and then go on to develop an instrumental variables (IV) approach to account for the potential endogeneity of the market structure variable. We describe the IV strategy in detail below. Our results are consistent across the two approaches.

5 Results

Our main results are presented in Tables 4 and 5. Table 4 investigates the impact of competition on cross-cabin price differentials while Table 5 investigates how competition impacts within Coach price differentials. We then present a number of extensions and robustness checks including an instrumental variables estimation strategy. We conclude the section with a discussion of how our results relate to the theoretical considerations laid out in Section 2.

Table 4 presents estimates of the relationship between market structure and average fares, by cabin class. For each cabin class, we show the results of estimating equation 7 using the three market structure variables described above. Looking first at the specifications that use the number of non-stop rivals as the measure of competition (columns 1 and 4), the coefficient estimates indicate that having an additional non-stop rival on a route lowers Air Canada's average Coach class fares by about 6%, but has no statistically significant effect on average Business class fares. When we measure market structure using dummy variables for a duopoly or competitive market structure (columns 2 and 5), we find that competition has a modest and marginally significant impact on Business class fares but a large and statistically significant impact on Coach class fares. The estimates in column 2 suggest that moving from a monopoly to duopoly reduces Air Canada's average Coach fares by about 7%, and that the introduction of additional competition reduces fares by another 7 percentage points. The estimates using the Herfindahl index as the measure of competition (columns 3 and 6) show a similar pattern.

Since competition significantly reduces Coach fares but has little or no impact on Business class fares, the findings in Table 4 indicate that competition increases cross-cabin fare differentials, relative to monopoly. These results are consistent with the finding in Borenstein and Rose (1994) who found that competitive routes were

Table 4: Regression of Cabin Level Average Fares on Competition Measures

	Coach			Business		
	(1)	(2)	(3)	(4)	(5)	(6)
Num. Direct Rivals	-0.059***			-0.009		
	(0.014)			(0.013)		
Duopoly		-0.066***			-0.038*	
		(0.016)			(0.020)	
Competitive		-0.135***			-0.023	
		(0.029)			(0.027)	
-Ln(HHI)			-0.114***			-0.062**
			(0.025)			(0.025)
Constant	5.099***	5.103***	5.097***	6.177***	6.188***	6.189***
	(0.016)	(0.015)	(0.015)	(0.024)	(0.025)	(0.023)
R^2	0.898	0.898	0.898	0.947	0.947	0.947
Obs	11064	11064	11064	3144	3144	3144

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include route, month and year FEs. Standard errors, clustered by route, in parentheses. R^2 excluding the competition vars is .894 for Coach and .946 for Business.

associated with greater fare dispersion, albeit in a different setting and using a cross-sectional estimation strategy.

As described above, over 90% of Air Canada's passengers travel in Coach class and there is considerable within-Coach class price dispersion. Therefore, we next estimate how market structure impacts different parts of the Coach class fare distribution. In Table 5 we estimate the effect of the number of rival carriers on selected percentiles of Air Canada's Coach fare distribution.[26] The coefficient estimates suggest that competition has a different impact on tickets at different points in the Coach distribution. In particular, the greatest impact of competition on Air Canada's fares lies somewhere in the middle of the Coach fare distribution. Among the selected percentiles, each additional competitor leads to a 7% to 8% reduction in fares on tickets between the 25th and the 75th percentile, but at most a 2% effect on the fares of tickets in the tails of the distribution. In all cases, the data reject the hypothesis that the coefficients on percentiles in the middle of the distribution (the 25th, 50th and 75th) are equal to the coefficients on the percentiles at the tails of the distribution (the 1st, 5th, 95th and 99th).[27]

To visually represent the impact of competition across the full Coach fare distri-

[26]From this point on, we use the number of rival carriers as our sole measure of competition, though the results are, in all cases, very similar using the other two competition measures.

[27]See Table 14 in Appendix B in which we estimate these effects in a single model which allows us to formally test the equality of the coefficients.

Table 5: Regression of Coach Percentiles

	(1) 1	(2) 25	(3) 50	(4) 75	(5) 99
Num. Direct Rivals	-0.025***	-0.080***	-0.073***	-0.069***	-0.022
	(0.009)	(0.013)	(0.014)	(0.021)	(0.015)
Constant	4.309***	4.742***	4.919***	5.213***	5.818***
	(0.015)	(0.016)	(0.026)	(0.030)	(0.020)
R^2	0.824	0.877	0.846	0.769	0.831
R^2 excluding Rivals	0.823	0.872	0.841	0.764	0.831
Obs	11064	11064	11064	11064	11064

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include route, month and year FEs. Standard errors, clustered by route, in parentheses.

bution, in Figure 2 we plot the coefficient estimate on the number of rival carriers variable, for every fifth percentile in the fare distribution. The figure has a clear U-shape, indicating that the greatest effect of competition occurs between the 15th and 75th percentiles of the fare distribution. By contrast, competition has a much smaller effect at either end of this distribution. This implies that competition reduces the differential between some tickets but increases the differential between others.

5.1 Instrumental Variables Estimation

We develop an instrumental variables (IV) strategy to ensure that our findings are not driven by the possible endogeneity of the market structure variables. Given the inclusion of route fixed effects in all of our models, our regressions identify the impact of market structure on fares by exploiting changes in the number of carriers serving a route over time. These changes in market structure result from the entry and exit decisions of airlines. Much of the variation in market structure in our sample comes from the expansion of WestJet, CanJet and JetsGo early in our sample and the expansion of Porter Airlines in latter years of our sample.[28]

WestJet, CanJet and JetsGo were all low-cost carriers operating one (or, in JetsGo's case, two) aircraft type(s) and operating mostly point-to-point flights. Taking their business model as fixed, they could only enter routes that were appropriate for the plane types in their fleet and that had large enough populations to provide sufficient point-to-point traffic. In addition, WestJet, CanJet and JetsGo each began with a particular geographic focus and expanded outward from their headquarters.

[28]Specifically, between 2002 and 2004, WestJet entered 39 routes, CanJet entered 21 routes and JetsGo entered 32 routes. Between 2007 and 2010, Porter Airlines, which began operations out of Toronto's Billy Bishop Airport, entered 18 routes. See Table 18 in Appendix E for information on the entry, exit and expansion of each of these airlines and how they affected the degree of competition faced by Air Canada.

Porter Airline began operations out of Toronto's Billy Bishop Airport in 2007. This is a small airport in downtown Toronto that had not been used for commercial flights for many years. Porter operates only Bombardier Q400 planes and has been constrained in adopting any other type of aircraft due to both the runway length at the airport and city regulations. As a result, as Porter expanded, it could only enter routes that are within the flying range of the Q400 and appropriate for its 70-seat capacity. In addition, Porter's expansion has been largely focused out of its headquarters at Billy Bishop Airport.

Our IV strategy takes advantage of these technological and geographic influences on these airlines' entry decisions. In particular, our IV strategy is based on an implicit entry model which assumes that airlines choose which routes to enter, and in what order, based on their expected profitability. We include two types of instruments: variables that we expect will impact the suitability of a route for a particular airline's fleet type and variables that we expect will impact the expected costs to a particular airline of entering a particular route. Specifically, we predict the likelihood that an airline serves a given route in a given month with the following variables: the population of the endpoint cities of the route at the start of the sample (to capture suitability with the airline's aircraft size and business model), the distance of the route as well as squared and cubed distance terms (to capture suitability with the airline's aircraft range), the distance of the route from the airline's headquarters (to capture the fact that the costs of entry likely increase as an airline moves further from its headquarters of operation) and an interaction between the distance of the route from the airline's headquarters and the airline's age (to capture the fact that airlines will enter less profitable routes as they get older).[29] After predicting each airline's likelihood of serving a route in a given month, we use these predictions to calculate the predicted number of competitors on each route in each month. We then use the predicted number of carriers as an instrument for the actual number of competitors in a two-stage least squares estimation.[30]

This IV strategy involves a number of assumptions. First, while we predict which routes an airline is likely to serve in each month once they have entered the industry, we do not predict the full-scale entry of Porter Airlines or full-scale exit of CanJet and Jetsgo. Rather, we assume that their entry and exit dates are exogenous to route-level time-varying unobservables.[31] Second, we assume that airlines' decisions

[29] The population data are Census Metropolitan Area data for 2001, from Statistics Canada's Table 051. All of the distance variables are calculated based on latitude and longitude information which was obtained from www.openflights.org. Information on each airline's headquarters was found on the web. We also include the airline's age uninteracted.

[30] This approach mimics the approach used for binary endogenous variables which involves using a nonlinear model such as a logit or probit to generate a predicted value for the binary variable and then using the predicted value as an instrument in a two-stage least squares with a linear first-stage. See Angrist and Pischke (2008) for details.

[31] These airlines' 'birth' and 'death' dates effectively serve as an additional instrument in our first-stage model.

about where to locate their headquarters are not driven by time-varying unobservable characteristics of the routes close to their headquarters. This allows us to use the distance of a route from an airline's headquarters as an instrument, capturing the cost advantages that may come with expansion to nearby routes. Given that the airlines in our sample chose different cities in different parts of the for their headquarters, this assumption seems reasonable. Finally, we assume that the airlines' business models—for example, the decision of what type of aircraft to operate and the number of aircraft types to employ—are exogenous.

To implement the IV strategy, we construct an airline-route-month level dataset which includes all of the airlines in our sample other than Air Canada and all of the 118 routes in our sample in each month. We construct a variable that equals one if the airline serves the route-month and zero otherwise. We estimate a logit model which relates an airline's decision to serve a route in a given month to the variables described above. We allow each of the variables to have a different effect for each airline, in order to capture differences in their business models. For example, we expect that route distance will have a different effect on the likelihood of Porter Airlines serving a route than the likelihood of WestJet serving a route, given the different types of aircraft each uses. This means that the route level characteristics such as endpoint population and distance become airline-route level variables and are still identified even with the inclusion of route fixed effects in the model. The variables measuring age and the interaction of age with distance from headquarters provide time-varying instruments which help predict changes in the likelihood of airline serving a given route in one month compared to another.

We estimate a single logit model where each of the independent variables is interacted with a dummy variable for each of the four airlines. Table 6 presents the results of this estimation. Each column of the table displays the coefficients on the independent variables for a different airline. The coefficients generally have the expected signs and match institutional features of the industry and the individual carriers. For example, all of the carriers other than Porter Airlines are more likely to serve routes between cities with larger populations. This is consistent with the fact that WestJet, CanJet and Jetsgo all operate aircraft with about 100 seats or more while Porter operates planes with 70 seats. Similarly, WestJet, CanJet and JetsGo are more likely to serve longer routes while Porter is more likely to serve shorter routes, again matching the constraint it faces by only operating Bombardier Q400 planes. All airlines other than JetsGo are less likely to serve routes that are further from their headquarters. Finally, all of the airlines become more likely to serve routes further from their headquarters as they grow older. The fit of the first-stage logit model is very good with a Pseudo-R^2 of 0.57.[32]

[32] If we estimate the model separately for each airline—which produces identical coefficients—we obtain a somewhat lower fit for WestJet than for the other carriers, which is not surprising given that WestJet was already a mature airline at the start of our sample period and had already entered most of the routes that matched its initial expansion strategy.

Table 6: Predicted Service by Carrier: Logit Regression

	Westjet	Porter	Canjet	Jetsgo
Origin Population (mill)	0.915***	0.018	0.901***	2.652***
	(0.016)	(0.062)	(0.051)	(0.152)
Dest. Population (mill)	0.908***	0.017	0.924***	2.650***
	(0.016)	(0.062)	(0.051)	(0.152)
Route Dist (1000 km)	3.519***	-39.826***	4.279***	3.239***
	(0.143)	(4.882)	(0.747)	(0.847)
Min. Distance to HQ (1000 km)	-5.483***	-22.411***	-32.568***	-1.591
	(0.145)	(1.467)	(1.830)	(1.090)
Age (months)	0.013	0.061**	0.006	0.053
	(0.009)	(0.030)	(0.029)	(0.035)
Age $\times$ Min. Distance to HQ	0.001***	0.025**	0.037***	0.114***
	(0.000)	(0.011)	(0.009)	(0.021)
Carrier Intercepts	-3.074***	3.857*	-2.801***	-18.137***
	(0.647)	(2.088)	(0.397)	(1.058)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Coefficients are from a single logit regression where the identity of each airline is interacted with the corresponding variable in the left column. The regression includes polynomials in distance measures, and month and year FEs, all of which are also interacted separately for each airline. Standard errors are in parentheses. N=57960; Pseudo-R^2=0.569.

Because our right-hand variables vary at the airline-route or airline-route-month level, we are also able to estimate the logit model including route fixed effects. This is a demanding specification in that it is estimating each airline's tendency to serve routes with particular characteristics, over and above the average tendency of all airlines to serve that route.[33] Nevertheless, we estimate this specification so that our equation includes all of the same fixed effects as our second-stage regression. The results of this specification are presented in Table 17 in Appendix D, where we also replicate the results from Table 6. The pattern of estimates is qualitatively quite similar though the magnitudes change, as expected given the inclusion of the fixed effects. Not surprisingly, the inclusion of the route fixed effects improves the fit of the model.[34]

Using the estimates in Table 17, we calculate each airline's predicted probability of serving a route and sum these to obtain the predicted number of competitors in a market in a month. Table 7 presents summary statistics of the predicted number of competitors, based on the actual number of competitors. The logit model predicts

[33] Intuitively, if we observe Porter Airlines provide service on the Toronto to Montreal route which is served, at various times, by all of the airlines in our sample, it is difficult for the regression to determine whether Porter serves this route because its short distance makes it suitable for Porter's aircraft or because it has a high route fixed effect.

[34] We have also estimated these equations using probit models and the results are almost identical.

Table 7: Predicted Number of Rivals by Actual Rivals

Actual Rivals	Predicted Rivals			
	Mean	SD	Min.	Max.
0	0.20	0.26	0.00	1.40
1	0.91	0.26	0.00	2.07
2	1.79	0.37	0.27	2.91
3	2.69	0.30	2.10	2.99

Table 8: IV Regression of Coach Percentiles

	(1) 1	(2) 25	(3) 50	(4) 75	(5) 99
Num. Direct Rivals	-0.013	-0.089***	-0.078***	-0.069**	-0.007
	(0.012)	(0.017)	(0.022)	(0.032)	(0.028)
Constant	4.978***	5.345***	5.408***	5.601***	5.765***
	(0.022)	(0.024)	(0.037)	(0.040)	(0.032)
R^2	0.822	0.876	0.845	0.769	0.831
Obs	10986	10986	10986	10986	10986

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include route, month and year FEs. Standard errors, clustered by route, in parentheses.

values in a continuous distribution, which is bounded between zero and one, producing a more compressed distribution than the original discrete distribution of actual rivals. Therefore, we slightly over-predict the number of rivals on Air Canada's monopoly routes, and slightly under-predict them when it has one or more rivals in the market. Overall, though, the predictions are excellent, with an 88% correlation between the predicted and actual number of competitors.[35]

Table 8 presents the results of estimating our percentile regressions via two-stage least squares, using the predicted number of competitors as an instrument for the actual number of competitors (thus, the table is analogous to the regressions in Table 5 presented earlier). The pattern of estimates in Table 8 is very similar to that in the original table and the same U-shaped relationship emerges. The point estimates are generally slightly larger in absolute value than those in the original table suggesting perhaps a slight upward bias in the original. Figure 3 plots the coefficients from the IV regressions and it looks very similar to the original version in Figure 2.

Overall, the findings in Table 8 suggest that the results presented thus far are not influenced by the potential endogeneity of the market structure measures.

[35]Using the specification without route fixed-effects—i.e. the results of Table 6, provides a correlation of 60%.

5.2 Extensions

We now present a number of extensions and robustness checks. We first examine the effect of competition from two specific rivals to Air Canada: Porter Airlines and WestJet Airlines. There are reasons to believe that these two carriers may have had distinct effects on Air Canada's fares for certain types of tickets.

As described earlier, Porter Airlines is a relatively new, regional airline focused on travel out of its hub in Toronto. Porter uses the Billy Bishop airport in downtown Toronto, which is often much more convenient for travelers than Air Canada's hub at Pearson Airport. Porter is believed to appeal especially to business travelers who work downtown, for whom the airport is a short distance from their offices. In addition, Porter provides very high frequency service on routes that are commonly traveled for business purposes (in particular, Toronto-Ottawa and Toronto-Montreal). Thus, if competition has the largest impact on business travelers who have a high willingness-to-pay to travel but are willing to switch between airlines, this effect should be particularly strong when the competition is from Porter Airlines on routes in or out of Toronto.

To investigate this, we estimate our percentile regressions with separate variables to capture the impact of competition from Porter on Toronto routes, the impact of competition from Porter on routes that do not involve Toronto as an endpoint and the impact of competition from other carriers. Table 9 presents the results of these regressions. The estimates indicate that the U-shaped pattern of fare reductions that we found earlier is most pronounced when Air Canada faces competition from Porter on its Toronto routes. The impact of competition from Porter on those routes is much larger than the impact of Porter on other routes or the impact of other carriers. This pattern is easily seen in Figure 4 which plots the coefficient estimates for the impact of competition from Porter in Toronto and the impact from Porter on other routes. The figure shows that the U-shaped pattern is both more pronounced and deeper. This suggests that travelers who purchase tickets in the middle and upper portions of the Discount Coach distribution have a greater cross-elasticity with respect to Porter in Toronto than they do to other carriers or to Porter in other markets.

We now turn to effects of competition from WestJet Airlines, which is a low-cost carrier competing nationally with Air Canada on most major routes. In the early part of our sample, WestJet's service from the Toronto area was from the Hamilton airport, which is located about 40 miles from downtown Toronto. Over time, WestJet shifted operations from Hamilton to Toronto's Pearson airport. This means that, for a sample of routes to and from Toronto, we observe periods when WestJet's operations were from a considerably less desirable location than Air Canada's flights from Toronto. This might imply lower substitutability with Air Canada's flights on these routes, especially for business travelers (even ones with little brand loyalty) who would not be expected to commute to Hamilton for a flight.

To explore this, we re-estimate our percentile regressions allowing competition from WestJet at Hamilton to have a different impact than competition from WestJet

Table 9: Regression of Coach Percentiles: The Effect of Porter Airlines

	(1)	(2)	(3)	(4)	(5)
	1	25	50	75	99
Porter Toronto	0.041*	-0.224***	-0.343***	-0.360***	0.000
	(0.023)	(0.026)	(0.027)	(0.033)	(0.043)
Porter non-Toronto	-0.072	-0.010	-0.060*	-0.195***	-0.057*
	(0.045)	(0.027)	(0.035)	(0.030)	(0.030)
Other direct carriers	-0.029***	-0.071***	-0.048***	-0.033**	-0.022
	(0.010)	(0.011)	(0.011)	(0.015)	(0.016)
Constant	4.311***	4.736***	4.905***	5.193***	5.817***
	(0.016)	(0.015)	(0.021)	(0.028)	(0.021)
R^2	0.824	0.879	0.853	0.780	0.831
Obs	11064	11064	11064	11064	11064

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include route, month and year FEs. Standard errors, clustered by route, in parentheses.

at Toronto and controlling for the number of other carriers serving a route.[36] Table 10 presents results of this analysis. The results show that competition by WestJet from Hamilton has a smaller impact on Air Canada's fares at all points in the distribution, with most of the coefficients capturing competition from WestJet in Hamilton not being statistically significant (although the point estimates are still suggestive of a U-shape). A pronounced U-shape pattern emerges from the coefficients on the variable capturing competition from WestJet in Toronto, as illustrated in Figure 5. These results suggest that competition from WestJet at Toronto has a larger impact on Air Canada's fares that competition from Hamilton and this difference is most pronounced for fares in the middle of the distribution, consistent with these tickets being purchased by travelers who may be willing to switch between carriers but less so if the competing carrier operates out of a distant airport.

We also carry out a number of robustness checks which we describe here. The results of these checks are available in the online appendix. First, we split our sample by routes that involve Toronto and routes that do not and our findings are similar across both samples. Second, we break up the sample into the periods before and after 2007 and find that the U-shaped pattern emerges in both time periods. Third, we add a control for the average size of the planes used by Air Canada on each route, using data from OAG, since this variable was identified by Gerardi and Shapiro (2009) as an explanation for the discrepancy between their finding and that of Borenstein and Rose (1994). Our results are robust to including this control. Finally, our findings are robust to ignoring the direction of travel and estimating our regressions at the

[36]For this analysis, we limit the sample to routes into or out of Toronto, hence the much smaller sample size. If WestJet provided service on a given route-month from both Pearson and Hamilton, we code this as service from Pearson.

Table 10: The Effect of WestJet's Competition from Hamilton Airport

	(1) 1	(2) 25	(3) 50	(4) 75	(5) 99
Westjet at Pearson	-0.039***	-0.064**	-0.131***	-0.141***	-0.035
	(0.010)	(0.023)	(0.043)	(0.043)	(0.022)
Westjet at Hamilton	0.029	-0.073*	-0.056	-0.074	0.015
	(0.018)	(0.037)	(0.069)	(0.063)	(0.034)
Other direct carriers	-0.023*	-0.070***	-0.038*	-0.044*	-0.025*
	(0.013)	(0.020)	(0.021)	(0.024)	(0.014)
Constant	4.417***	4.930***	5.074***	5.234***	5.677***
	(0.013)	(0.022)	(0.038)	(0.050)	(0.038)
R^2	0.836	0.887	0.848	0.815	0.815
Obs	2208	2208	2208	2208	2208

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include route, month and year FEs. Standard errors, clustered by route, in parentheses.

city-pair level.

5.3 Discussion

In Section 2, we developed a simple model of airline price discrimination in which travelers differed in terms of both their underlying value of a trip and their degree of brand loyalty. We distinguished between leisure travelers and two types of business travelers: 'brand loyal business travelers' and 'brand indifferent business travelers'. We showed that, in this setup, competition would have the largest impact on the fares charged to brand indifferent business travelers and, as a result, would reduce the fare differential between these travelers and leisure travelers but increase the fare differential between them and the brand loyal business travelers. Consistent with existing results in Borenstein (1985), Holmes (1989) and Stole (2007), our simple model illustrated that competition increases price differences between consumers when discrimination is based on differences in cross-price elasticities (or the strength of brand preferences) but decrease price differences between consumers when discrimination is based on differences in industry-demand elasticities.

While our data do not allow us to directly link tickets to traveler types, our results indicate that different parts of the fare distribution are differentially impacted by competition. Moreover, the U-shaped pattern that we uncover is consistent with the existence of (at least) three broad types of travelers. In particular, our finding that the fares for Air Canada's very cheap tickets are hardly impacted by competition suggests that these tickets are sold to highly price sensitive travelers who are charged low prices even when Air Canada is a monopolist. Our finding that the fares for

Air Canada's very expensive tickets (both expensive Coach tickets and Business class tickets) are hardly impacted by competition suggests that these tickets are sold to travelers with both a high willingness-to-pay and strong brand loyalty. Finally, our finding that fares for the remainder of Air Canada's tickets do fall with competition suggests the existence of a set of travelers with a high enough underlying willingness-to-pay that they are charged relatively high prices under monopoly but a high enough willingness-to-switch that their prices fall with competition. This set of travelers is consistent with the brand indifferent business travelers that we consider in our model.

Furthermore, consistent with our model, our results indicate that fare differentials between some tickets fall with competition while other rise. To illustrate this, in Table 11 we estimate the impact of competition on the ratios of various fare percentiles. The estimates in the table show that competition lowers the ratio of fares in the middle of the distribution (the 25th, 50th and 75th percentiles) to fares at the bottom of the distribution by about 10%. On the other hand, the ratio of fares at the top of the distribution to fares in the middle of the distribution increases with competition.[37] These patterns suggest that price differences between tickets in the middle and bottom of the distribution is likely based on differences in underlying willingness-to-pay while price discrimination between tickets at the top and in the middle of the distribution is, at least partly, based on differences in brand loyalty.

Table 11: Regression of Fare Ratios

	(1) 25:1	(2) 50:1	(3) 75:1	(4) 99:25	(5) 99:50	(6) 99:75
Num. Direct Rivals	-0.098***	-0.108***	-0.140**	0.191***	0.142***	0.091*
	(0.019)	(0.034)	(0.066)	(0.056)	(0.053)	(0.050)
Constant	1.587***	1.965***	2.757***	3.197***	2.750***	2.081***
	(0.030)	(0.073)	(0.127)	(0.085)	(0.090)	(0.088)
R^2	0.258	0.295	0.367	0.472	0.459	0.392
Obs	11064	11064	11064	11064	11064	11064

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include route, month and year FEs. Standard errors, clustered by route, in parentheses.

One concrete way to illustrate the differing effects of competition on fares is to consider the entry of Porter airlines, starting in 2008, into 18 routes. All of these were served by Air Canada, and a number of these were routes where Air Canada was a monopolist. Thus Porter's entry would be expected to reduce fares. In Table 12 we show the estimated effect of Porter's entry on selected percentiles of Air

[37]We also estimated these regressions using less extreme percentiles; e.g.: 5th and 95th. When we do so, we find a very similar pattern, however the standard errors are larger—likely due to the measurement error in the percentiles we construct, as discussed earlier—making the point estimates either only marginally significant or insignificant.

Canada's fare distribution. We do this by estimating how Porter's presence on a route affected Air Canada's fares, controlling for the number of other carriers on the route, restricting attention to the routes that were entered by Porter at some point during our sample period. The table shows that Porter's entry was associated with around

Table 12: Effect of Porter Airlines on Air Canada's fares

Percentile	Original Fare	New Fare [Range]	Reduction
P1	102	101 [96,106]	0
P25	169	147 [134,160]	21
P50	199	156 [137,174]	43
P75	254	181 [163,198]	72
P99	443	432 [403,461]	11
Mean	219	180 [168,192]	39

Notes: Predicted values of Porter Airlines' entry calculated using coefficients from a regression of Air Canada's fares on indicators for competition by Porter and the sum of all other carriers.

a $40 drop in Air Canada's mean fares across the routes that eventually experienced entry. However, these figures are strikingly different at various percentiles. For the very cheapest tickets on Air Canada, Porter's entry had no effect, while the largest effect—a $72 reduction, with a confidence interval of +/-$18—occurred at the 75th percentile. Thus, this simple exercise highlights why focusing on mean effects, or effects at the tails of the fare distribution, can obscure the considerable heterogeneity in the impact of competition across the fare distribution.

Finally, while our findings are consistent with our simple model of price discrimination, it is worth considering the role that cost-based explanations of price dispersion could play. Variation in the fares observed on a given route-month will reflect both price discrimination and differences in the marginal costs of a seat. While it is likely the case that the marginal costs of Business class tickets and expensive Coach tickets are somewhat higher than the marginal costs of cheaper Coach tickets—for example, due to the costs of providing greater in-flight service, more frequent flier points or refundability—it is unlikely that these cost differences are large enough to account for the fare differences between these types of tickets. Moreover, there is no reason that competition would differentially impact the costs of different types of tickets.

A more significant source of cost variation can arise from differences in the shadow cost of capacity. Because capacity is hard to adjust and demand is uncertain, the marginal cost of an airline seat includes a shadow cost—i.e.: the cost of not being able to sell that seat at a later time. Shadow costs will vary across flights in both predictable and unpredictable ways. For example, the shadow cost of capacity will be higher at peak times of the day, peak times of the season and when airline and/or airport resources are scarce. This will result in fare differences across flights on a given route, reflecting the higher expected shadow cost of capacity on certain flights. In addition, the shadow cost of a seat may change over time as demand for a flight is realized. Since airlines can adjust fares as demand is realized, fares will be adjusted to reflect the shadow cost of a seat at the time that the seat is sold.

It is likely that some of the within route-month fare variation observed in our data reflects differences in the shadow costs of seats. Since we are unable to match tickets to particular flights and do not have data on expected or realized load factors, it is not possible for us to directly control for the factors that affect the shadow cost of a seat. Most previous studies of competition and price discrimination in the airline industry face a similar problem as the standard database on U.S fares, the DB1B, also does not allow tickets to be matched to particular flights.[38] Instead, one strategy that has been used to distinguish price dispersion due to price discrimination from price dispersion due to differences in marginal cost is to identify routes where the heterogeneity in willingness-to-pay is expected to be large. For example, Gerardi and Shapiro (2009) identify "big city" routes and tourist routes and argue that the former are more likely than the latter to have both business and tourist travelers. They show that their findings with respect to market structure and price dispersion are more pronounced on big city routes, suggesting the operation of price discrimination.

The Canadian setting does not lend itself to this strategy as there are fewer big cities and no obvious tourist routes (like Las Vegas and Orlando). Instead, we view our analyses that consider the impact of Porter Airlines (at Toronto's Billy Bishop Airport) and WestJet (at Hamilton airport) as suggesting the operation of price discrimination. Specifically, our findings—that the U-shaped pattern of fare reductions is larger when Air Canada faces competition from Porter Airlines out of downtown Toronto and smaller when it faces competition from WestJet out of Hamilton Airport—are consistent with a high cross price elasticity between Air Canada and Porter but a low cross price elasticity with WestJet when it flies out of a distant airport.

6 Conclusions

In this paper, we have revisited the relationship between market structure and price discrimination in the airline industry. This industry has been the focus of much of the previous empirical work on competition and price discrimination; yet, this literature has delivered conflicting findings. These findings have, thus far, been reconciled based on differences in empirical strategies used. To be sure, these differences are important. However, we have offered a new way to understand the different findings

[38]A number of recent papers have data that links fares to flights and that includes information on load factors. However, these papers focus only on monopoly routes in order to simplify their structural estimation. See, for example, Lazarev (2013) and Williams (2013).

that have emerged. Building on early theoretical work in this area which shows that competition can increase or decrease price differences between consumer types, we developed a simple model with three types of travelers. Our model allowed travelers to differ in terms of both their underlying value of a trip and their degree of brand loyalty and, further, allowed travelers with a high value of travel to differ in terms of their brand loyalty. We have shown that, in this set-up, competition may have the largest impact on the fares charged to travelers who have a high underlying value of completing their trip but little airline loyalty. Because these travelers' fares fall by more than those of other types of travelers, competition reduces the fare differential between some types of tickets while increasing the differential between others. This makes it clear that the resulting relationship between competition and overall fare dispersion is ambiguous.

Our empirical analysis estimated how changes in market structure on routes served by Air Canada affected the airline's fares for different types of tickets. The results indicate that competition has little impact on Air Canada's very cheap fares or very expensive fares, including both Business class and high-end Coach class tickets. On the other hand, competition leads to a 7-8% reduction in fares of tickets in the middle of the Coach distribution. Overall, we find a U-shaped relationship between competition and fare reductions over the fare distribution. This implies, and indeed we show, that competition reduces some fare differentials while increasing others, thus encompassing both sets of findings in the earlier literature. More generally, the paper highlights the fact that, in non-monopoly settings, the impact of competition on price discrimination will depend on whether price discrimination is based on differences in industry-elasticities or cross-elasticities or both and that measuring this relationship requires a nuanced understanding of the sources of consumer heterogeneity in an industry.

Both our theoretical model and our empirical results are rooted in a model of third-degree price discrimination, where airlines charge different prices to travelers who are likely to possess different characteristics. However, as we acknowledge in the paper, airlines use a mix of second- and third-degree price discrimination strategies, as do firms in a range of industries. Thus far, the empirical literature on price discrimination has not separated out the effect of competition on each type of price discrimination. We believe that a productive area of future research would be to identify a setting where data was available that allowed the effects of competition on firms' second-degree and third-degree price discrimination strategies to be disentangled.

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Figure 1: Air Canada Document showing fare codes across Service Levels

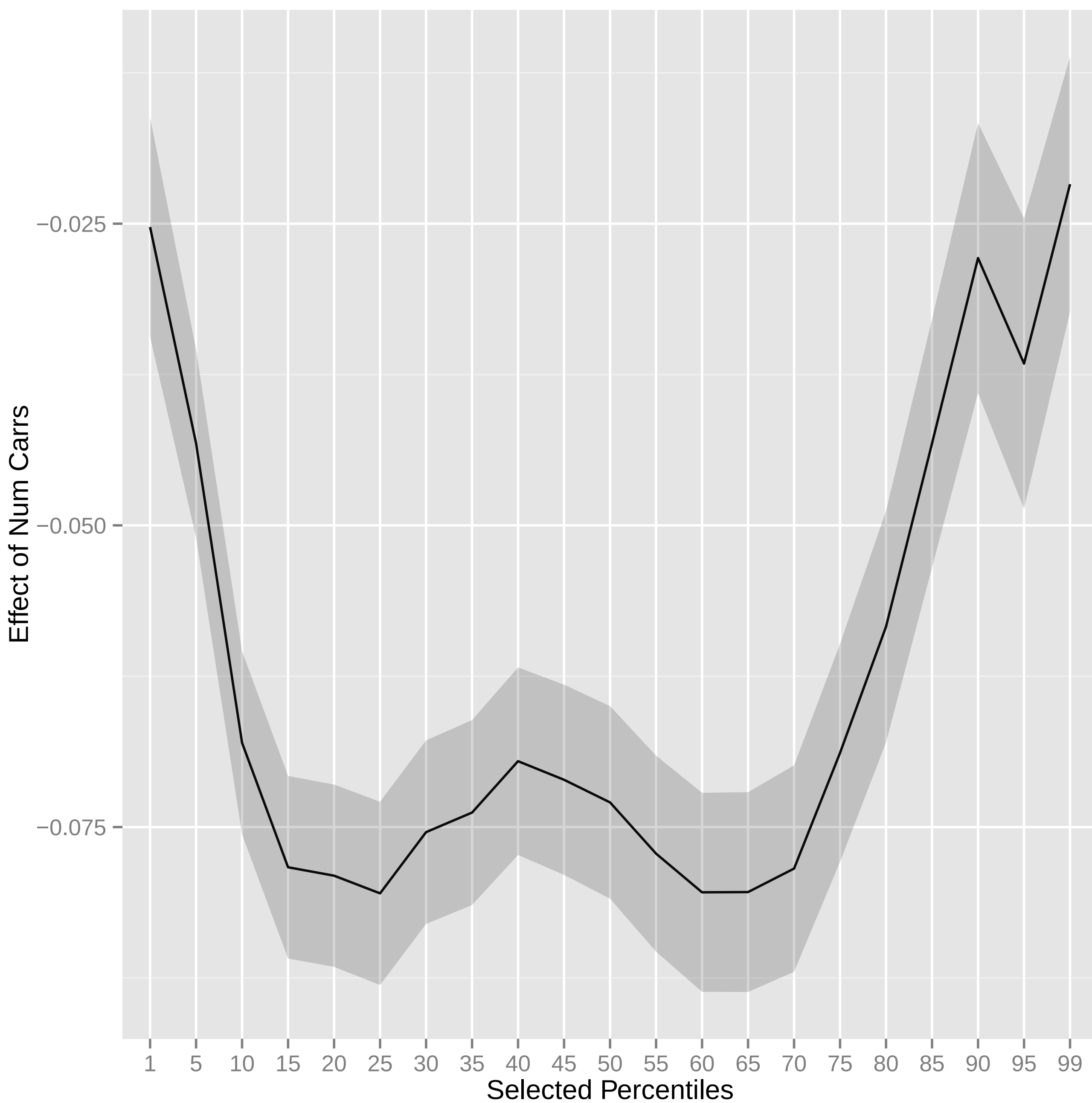
AIR CANADA

North American Fare Structure

	TANGO K, N, G, P, T, E	TANGO PLUS M, U, H, Q, V, W, S, L	LATITUDE Y, B	EXECUTIVE CLASS® LOWEST D, Z	EXECUTIVE CLASS® FLEXIBLE J, C
Changes	$ 75 + difference in fare	$ 50 Canada, $ 75 Transborder + difference in fare	Difference in fare may apply	$ 50 Canada, $ 75 Transborder + difference in fare	Difference in fare may apply
Same Day Change Upon Check-in	$ 150 $ 75 on Rapidair routes	$ 75	Complimentary	$ 75	Complimentary
Same Day Airport Standby	n/a	Available only on Rapidair	Available	Available	Available
Refunds	Non-Refundable	Non-Refundable	Refundable	Non-Refundable	Refundable
Advance Seat Selection	$15, $17, $22[1] (Optional)	Complimentary	Complimentary	Complimentary	Complimentary
Maple Leaf™ Lounge Access	$ 45	$ 35	$ 30	Yes	Yes
Onboard Café	Prepay $7 for $9 value, at aircanada.com/agents.		Complimentary	Complimentary Executive Class meal	Complimentary Executive Class meal
Aeroplan® Accumulation	25 % Aeroplan Miles	100 % Air Canada Status Miles	100 % Air Canada Status Miles	150 % Air Canada Status Miles	150 % Air Canada Status Miles
Air Canada Top Tier Upgrade Certificates	n/a	As per the terms and condition on the certificates	As per the terms and condition on the certificates	n/a	n/a
Priority Service Check-in, Bags, Boarding	No	No	At airports in Canada, where available	Yes	Yes
On My Way™	$ 25: up to 1,000 miles $ 35: 1,000 + miles	$ 25: up to 1,000 miles $ 35: 1,000 + miles	$ 25: up to 1,000 miles $ 35: 1,000 + miles	$ 25: up to 1,000 miles $ 35: 1,000 + miles	$ 25: up to 1,000 miles $ 35: 1,000 + miles

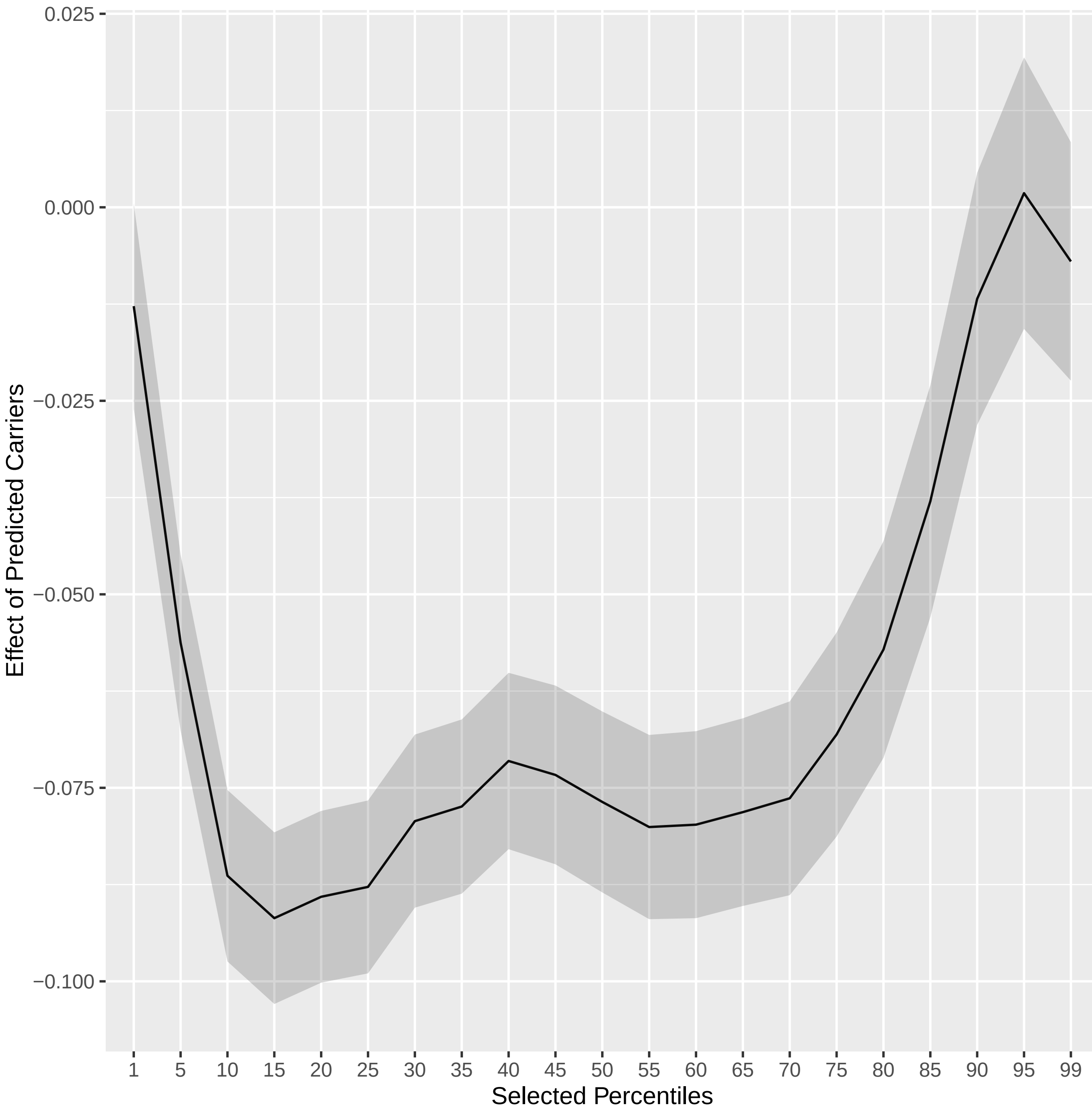
[1] $15, 0- 350 miles, $17, 351 – 1000 miles, $22, 1001 + miles. This is a summary of the fare attributes for travel within North America when purchased on the Air Canada website. ®Aeroplan is a Registered Trademark of Aeroplan LP. ® Executive Class is a Registered Trademark of Air Canada. ™ Maple Leaf is Trademark of Air Canada. ™On My Way is a Trademark of Air Canada. Information subject to change without prior notice. Sales Communication, Updated Nov. 24, 2009.

Figure 2: Effect of the Number of Rivals on Percentiles of AC's fare distribution



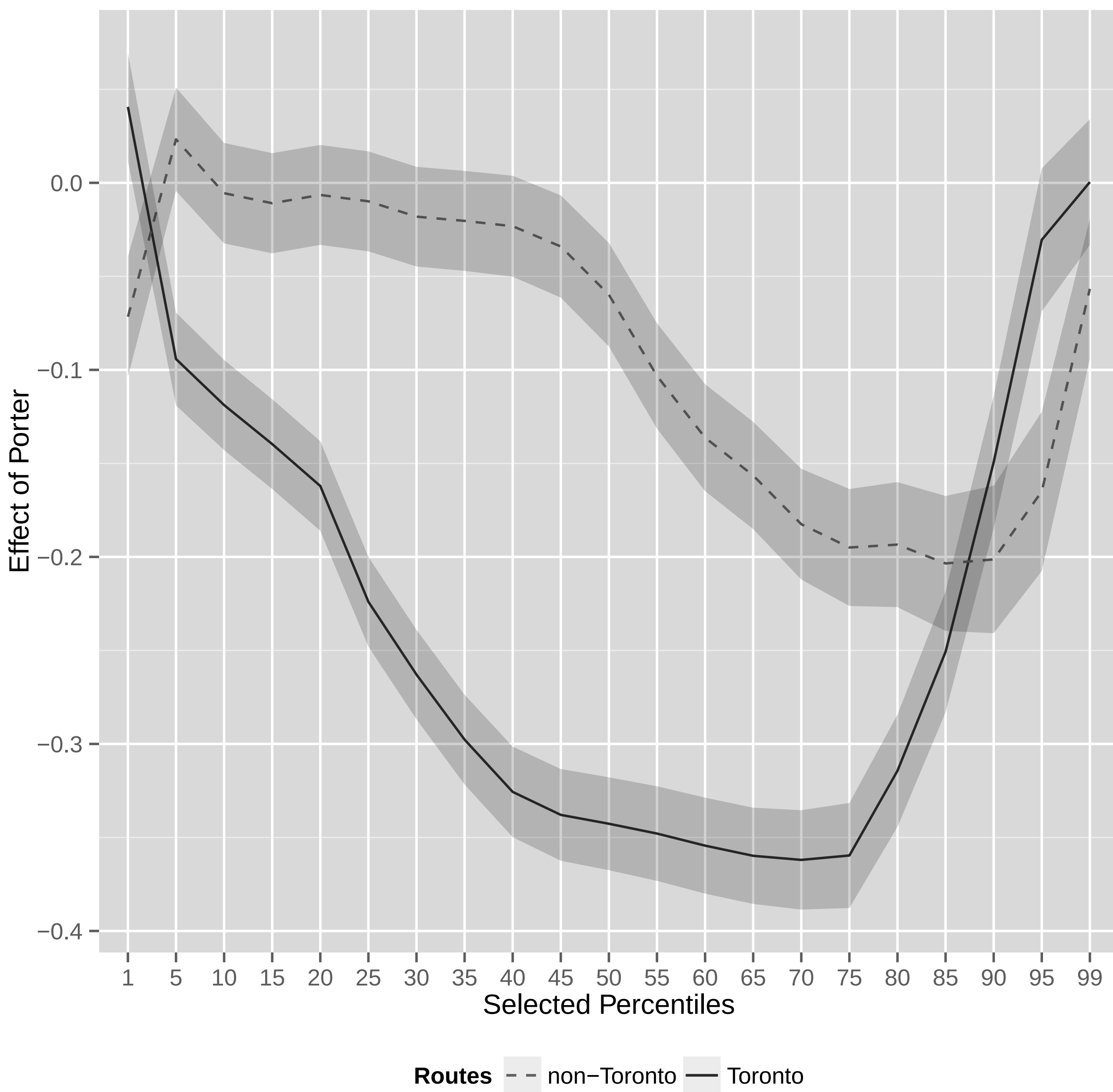
Notes: Values represent coefficients from regressing every fifth percentile in the fare distribution on the number of direct rivals faced by AC on a route. Other controls include route, month and year FEs. Shaded area represents the 95% confidence interval.

Figure 3: Effect of the Number of Rivals on Percentiles of AC's fare distribution: IV Estimation



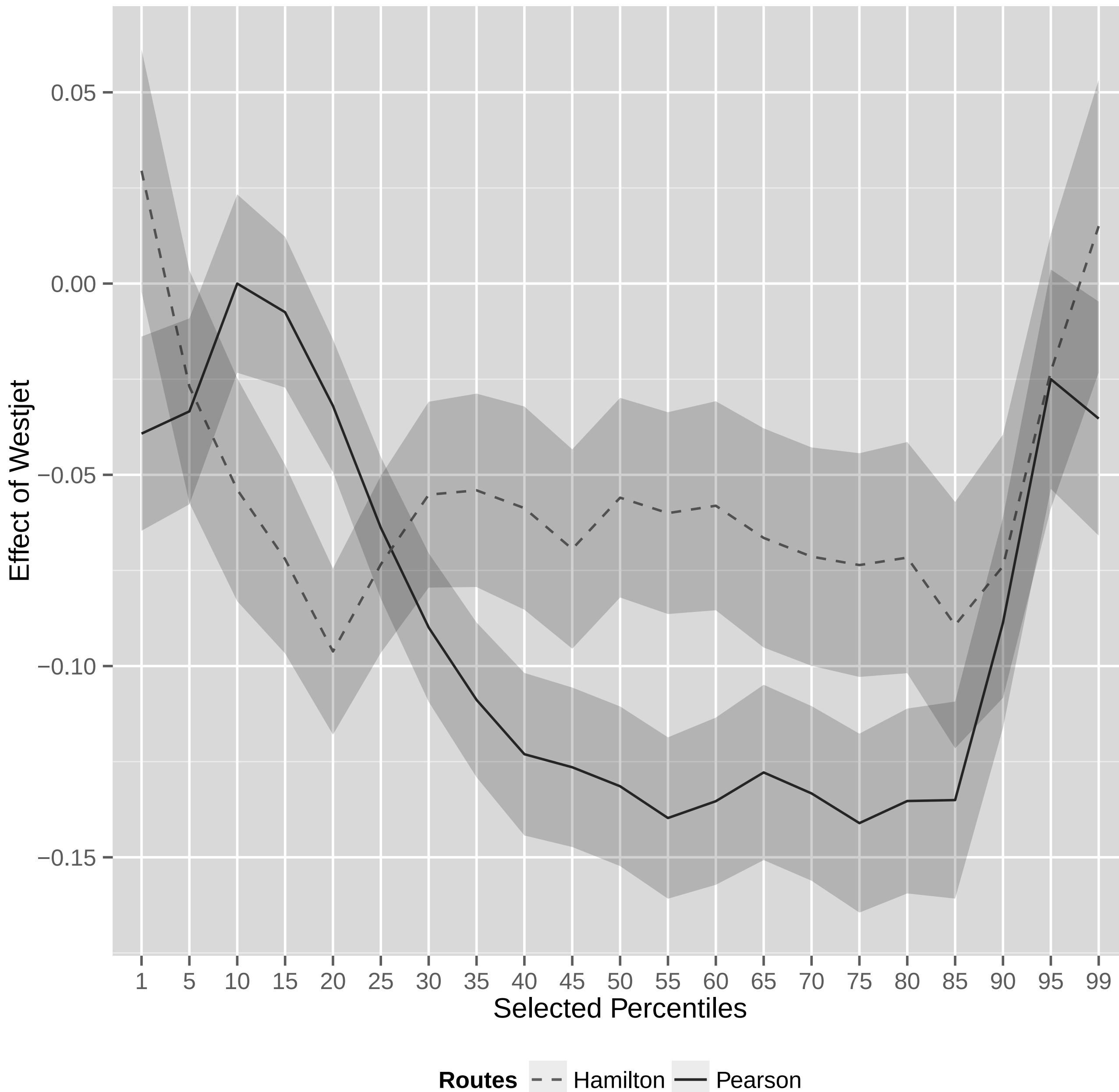
Notes: Values represent coefficients from regressing each percentile in the fare distribution on the predicted number of direct rivals faced by AC on a route. Other controls include route, month and year FEs. Shaded area represents the 95% confidence interval.

Figure 4: Effect of Porter Airlines on Percentiles of AC's fare distribution



Notes: Values represent coefficients from regressing each percentile in AC's fare distribution on the presence of Porter airlines in Toronto and elsewhere. Other controls include route, month and year FEs. Shaded area represents the 95% confidence interval.

Figure 5: Effect of WestJet Airlines on Percentiles of AC's fare distribution



Notes: Values represent coefficients from regressing each percentile in AC's fare distribution on the presence of WestJet airlines at Pearson and Hamilton airports. Other controls include route, month and year FEs. Shaded area represents the 95% confidence interval.

A Appendix A: Constructing fare percentiles from Fare Code data

Below we provide an example which illustrates how we use the information in the Sabre data to construct the percentile variables which we use in our regression analysis. We illustrate this for a specific route-month in our data: travel on Air Canada from Quebec City to Ottawa in October 2002. Table 13 shows the set of fare codes which appear in the Sabre data and the associated fare and passenger variables. The bottom panel shows selected percentiles of the fare distribution which we approximate from the Sabre data.

Table 13: Example of Constructing Percentiles from Fare Code Data

Code	Passengers	Average Fare
Z	9	71.7
A	168	199.1
L	11	212.3
Q	129	227.8
V	132	236.7
H	104	255.3
B	166	295.8
Y	189	347.0
U	134	357.6
Percentile		**Average Fare**
P1		199.1
P25		227.8
P50		255.3
P75		347.0
P99		357.6

Note: This example shows travel from YQB to YOW in October 2002.

B Appendix B: Hypothesis Tests

In Table 14 we present a single regression that pools together the multiple regressions presented in Table 5. By doing so, we can test whether the relevant coefficients are significantly different from each other. Note that the coefficients in the upper panel are identical to those in Table 5. The lower panel presents p-values from tests of the hypothesis that coefficients in the middle of the distribution are equal to those at the tails. All hypotheses are rejected, at the 5% level for the 75th percentile, and at the 1% level for the others.

Table 14: Regression of Fare Ratios

	Log(Fare)
Pctile=1 × Num. Direct Rivals	-0.025***
	(0.009)
Pctile=25 × Num. Direct Rivals	-0.080***
	(0.013)
Pctile=50 × Num. Direct Rivals	-0.073***
	(0.014)
Pctile=75 × Num. Direct Rivals	-0.069***
	(0.021)
Pctile=99 × Num. Direct Rivals	-0.022
	(0.015)
Constant	5.088***
	(0.011)
R^2	0.910
Obs	55320
H_0: P25=P1	0.000
H_0: P25=P99	0.001
H_0: P50=P1	0.001
H_0: P50=P99	0.009
H_0: P75=P1	0.039
H_0: P75=P99	0.036

Top panel: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Route, month, year FEs included. Standard errors, clustered by route, in parentheses. Bottom panel: Each hypothesis displays the associated p-value.

C Appendix C: Robustness to Dropping Certain Route-Months

In Tables 15 and 16 we re-estimate the specifications in Tables 4 and 5, excluding route-months in which the share of Y-code passengers seems implausibly high, as discussed in Section 3.3. Specifically, we exclude any route-months in which the fraction of Y-code passengers exceeds 17%, which is the maximum share of passengers accounted for by Y fares in any route-month prior to 2008, which was when we first observed these irregularities in the data. This drops a total of 3755 route-months from our sample. The results in Tables 15 and 16 are extremely similar to those in Tables 4 and 5, indicating that, while the problematic observations may introduce some measurement error into our data, they do not meaningfully affect our results.

Table 15: Regression of Cabin Level Average Fares on Competition Measures

	Coach			Business		
	(1)	(2)	(3)	(4)	(5)	(6)
Num. Direct Rivals	-0.058***			-0.006		
	(0.013)			(0.012)		
Duopoly		-0.075***			-0.035*	
		(0.016)			(0.020)	
Competitive		-0.134***			-0.016	
		(0.025)			(0.026)	
-Ln(HHI)			-0.133***			-0.069***
			(0.023)			(0.024)
Constant	5.100***	5.109***	5.105***	6.183***	6.195***	6.198***
	(0.016)	(0.015)	(0.015)	(0.026)	(0.027)	(0.025)
R^2	0.897	0.898	0.899	0.945	0.945	0.946
Obs	7308	7308	7308	2574	2574	2574

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include route, month and year FEs. Standard errors, clustered by route, in parentheses.

Table 16: Regression of Coach Percentiles

	(1) 1	(2) 25	(3) 50	(4) 75	(5) 99
Num. Direct Rivals	-0.035***	-0.082***	-0.077***	-0.069***	-0.010
	(0.008)	(0.012)	(0.013)	(0.017)	(0.014)
Constant	4.321***	4.720***	4.904***	5.172***	5.932***
	(0.011)	(0.014)	(0.025)	(0.033)	(0.019)
R^2	0.838	0.898	0.851	0.768	0.856
Obs	7308	7308	7308	7308	7308

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include route, month and year FEs. Standard errors, clustered by route, in parentheses.

D Appendix D: First-stage Regressions–with and without Route FEs

Table 17 presents two kinds of first-stage regressions for use in the Instrumental Variables estimation. The first column simply replicates the results of Table 6. Recall that this was a logit regression of whether each carrier served a certain route in a given month. The right hand side interacts the identity of each of the four carriers with the exogenous variables that we believe to be good predictors of airlines' expansion strategies.

The second column of Table 17 adds route fixed-effects to the specification in the first column. Doing so improves the fit of the logit regression considerably, and also improves the prediction of the number of carriers in each route-month as discussed in the text. Note that the magnitudes of the coefficients change substantially with the addition of route fixed-effects—this is to be expected as each coefficient now represents the deviation from the (unreported) route fixed-effect for the corresponding airline with respect to each exogenous characteristic. Nevertheless, the pattern of coefficients is similar to that of Column 1. For example, within a given route, all airlines are more likely to provide service as endpoint populations grow.

Table 17: Predicted Service by Carrier: Pooled Logit Regression

	(1) Pooled		(2) Pooled with Route FEs	
served_route				
Westjet × Origin Pop.	0.915***	(0.016)	7.549***	(0.511)
Porter × Origin Pop.	0.018	(0.062)	5.699***	(0.520)
Canjet × Origin Pop.	0.901***	(0.051)	8.236***	(0.551)
Jetsgo × Origin Pop.	2.652***	(0.152)	9.242***	(0.556)
Westjet × Dest. Pop.	0.908***	(0.016)	8.652***	(0.540)
Porter × Dest. Pop.	0.017	(0.062)	6.719***	(0.545)
Canjet × Dest. Pop.	0.924***	(0.051)	9.302***	(0.578)
Jetsgo × Dest. Pop.	2.650***	(0.152)	10.354***	(0.584)
Westjet × Route Dist.	3.519***	(0.143)	6.680***	(1.951)
Porter × Route Dist.	-39.826***	(4.882)	38.836***	(13.052)
Canjet × Route Dist.	4.279***	(0.747)	-49.172***	(4.620)
Jetsgo × Route Dist.	3.239***	(0.847)	0.000	(.)
Westjet × Min. Distance to HQ	-5.483***	(0.145)	-8.527***	(1.316)
Porter × Min. Distance to HQ	-22.411***	(1.467)	-13.728***	(2.422)
Canjet × Min. Distance to HQ	-32.568***	(1.830)	-45.974***	(9.527)
Jetsgo × Min. Distance to HQ	-1.591	(1.090)	-7.164***	(1.515)
Westjet × Age	0.013	(0.009)	0.034**	(0.014)
Porter × Age	0.061**	(0.030)	0.097**	(0.044)
Canjet × Age	0.006	(0.029)	-0.045	(0.048)
Jetsgo × Age	0.053	(0.035)	0.179***	(0.056)
Westjet × Age × Min. Distance to HQ	0.001***	(0.000)	0.003***	(0.001)
Porter × Age × Min. Distance to HQ	0.025**	(0.011)	0.149***	(0.025)
Canjet × Age × Min. Distance to HQ	0.037***	(0.009)	0.113***	(0.024)
Jetsgo × Age × Min. Distance to HQ	0.114***	(0.021)	0.238***	(0.034)
Constant	-3.074***	(0.647)	-13.393***	(1.667)
Pseudo R^2	0.570		0.759	
Obs	57750		27775	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Regressions include polynomials in distance measures, and route, month and year FEs. Standard errors in parentheses.

E Appendix E: Additional Details on Market Structure

Table 18: Routes served, by Carrier, and Competition on AC routes

Year	Routes served by:				AC routes:			
	Westejet	CanJet	Jetsgo	Porter	Monopoly	Duopoly	Competitive	Total
2002	44	18	8	0	32	46	12	90
2003	62	18	23	0	20	46	26	92
2004	70	18	31	0	18	41	34	93
2005	66	20	27	0	20	51	26	97
2006	66	17	0	0	29	61	11	101
2007	74	0	0	10	30	68	8	106
2008	82	0	0	10	25	72	10	107
2009	88	0	0	12	20	76	12	108
2010	82	0	0	18	24	68	16	108
2011	80	0	0	18	26	70	14	110

Note: The sample period is 2002–2011 (inclusive). WestJet was in the industry throughout the sample period. Jetsgo and CanJet entered in June and July of 2002, respectively. They exited in April 2005 and September 2006, respectively. Porter entered the industry in March 2007 and remained until the end of the sample. Values in the first 4 columns refer to the maximum number of non-stop routes served by each airline in that year.

F Robustness to changing cutoffs

In our original data we dropped itineraries with fares below \$50 to avoid including free or deeply discounted tickets that may arise from frequent-flyer rewards or employee discounts. Our results are not sensitive to small changes to this cutoff in either direction. As an example, Tables 19 and 20below repeat the results of Tables 4 and 5 using a \$25 cutoff. The results are very similar.

Table 19: Regression of Cabin Level Average Fares on Competition Measures ($25 cutoff for fares)

	Coach			Business		
	(1)	(2)	(3)	(4)	(5)	(6)
Num. Direct Rivals	-0.060***			-0.009		
	(0.014)			(0.013)		
Duopoly		-0.071***			-0.038*	
		(0.016)			(0.020)	
Competitive		-0.138***			-0.023	
		(0.029)			(0.027)	
-Ln(HHI)			-0.118***			-0.062**
			(0.025)			(0.025)
Constant	5.086***	5.091***	5.084***	6.177***	6.188***	6.189***
	(0.016)	(0.015)	(0.015)	(0.024)	(0.025)	(0.023)
R^2	0.899	0.900	0.899	0.947	0.947	0.947
Obs	11064	11064	11064	3144	3144	3144

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include route, month and year FEs. Standard errors, clustered by route, in parentheses.

Table 20: Regression of Coach Percentiles ($25 cutoff for fares)

	(1)	(2)	(3)	(4)	(5)
	1	25	50	75	99
Num. Direct Rivals	-0.040***	-0.083***	-0.075***	-0.070***	-0.022
	(0.010)	(0.013)	(0.014)	(0.021)	(0.015)
Constant	4.213***	4.718***	4.904***	5.208***	5.817***
	(0.013)	(0.015)	(0.026)	(0.030)	(0.020)
R^2	0.806	0.880	0.850	0.771	0.831
Obs	11064	11064	11064	11064	11064

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include route, month and year FEs. Standard errors, clustered by route, in parentheses.