Title
Essays on Quantitative Marketing and Economics

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Publication Date
2018

Peer reviewed|Thesis/dissertation

Essays on Quantitative Marketing and Economics

by

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A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Business Administration

in the

Graduate Division

of the

University of California, Berkeley

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Spring 2018

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Abstract

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In two essays, I present my work that applies empirical method to real-world problems in quantitative marketing and economics. In the first chapter, I use structural econometrics to investigate airlines' dynamic price competition. I show how widely-used dynamic pricing techniques affect firms profits under a competitive equilibrium. The second chapter is a joint work with Zemin Zhong. We focus on how China's anticorruption effort impact its economy, measured by car consumption and new business registration.

Dynamic pricing is becoming a common practice in many industries, but its effect under competition is uncertain due to the potential for the Prisoner's dilemma. The paper studies profit and welfare implications of competitive dynamic pricing in the context of the airline industry. The paper develops a structural dynamic oligopoly model where firms compete in selling limited capacities when facing demand fluctuations. The supply and demand are jointly estimated using a unique daily-level data on airfares and capacity utilization. The identification leverages a natural experiment of carrier exit. The estimates show that air travel demand exhibits a large degree of temporal heterogeneity and stochastic variability. The counterfactuals show that the ability to perform dynamic pricing increases total welfare. In particular, (i) price discrimination (charging late-arriving consumers higher prices) softens competition in the late market and increases profits substantially and (ii) revenue management (pricing on remaining capacities) intensifies competition and does not increase profits.

Corruption could either benefit economic growth by greasing the wheel, or distort supply of public goods and create inefficiency. Empirically testing the impact of corruption is difficult due to its evasive nature. We take an alternative approach by investigating the economic impacts of anti-corruption policies. We focus on China's recent anti-corruption campaign, the largest of its kind in recent history. As an important initiative of this campaign, the Communist Party's Provincial Committees of Discipline Inspection (PCDI) send inspector teams to investigate municipal governments for potential corruption. The variation in their timing allows us to use a difference-in-difference design to identify their impact on local economy. Using two unique administrative datasets of vehicle and business registration, we find that

PCDI visits have a negative impact on both car sales and new business entry. For vehicles, the effect is surprisingly uniform across different price tiers: Luxury brands exhibit a similar drop as domestic brands, suggesting corruption's impact permeates households across a wide income spectrum. Over time, the effect is strengthening: We observe a 2% drop in the first three months of PCDI visit and a 10% drop one year afterward. The especially large impact cannot be explained by the decline in government officials' consumption behavior, suggesting anti-corruption efforts also affect the private sector. We test the idea using business registration data, and we found PCDI visits indeed discourage new business registration. We validate our empirical strategy by showing that (1) the timing of PCDI visits cannot be predicted by observable county characteristics and (2) car registrations exhibit parallel pre-treatment trends. Our results suggest there may be a trade-off in anti-corruption and economic growth.

To Hsin-Tien,

Acknowledgments

I am indebted to my committee members J. Miguel Villas-Boas, Ganesh Iyer, Minjung Park and Kei Kawai for their support. I thank my advisor Przemysław Jeziorski for his guidance. I also thank my co-author and friend Zemin Zhong. Both of the two chapters benefited from conversations with many other intelligent and kind people from Berkeley and other places. All errors are my own.

Chapter 1

Estimating Airlines' Dynamic Price Competition

1.1 Introduction

Dynamic pricing is becoming a common practice in many industries. These include transportation, hospitality, online retailing, event tickets, entertainment, tourism and so on. In these markets, the distribution of consumers may change over time– consumers entering the markets at different points in time may have different preferences. Firms can use time-dependent prices to price discriminate against consumers. Another common feature among these industries is the presence of capacity constraint– supply is limited whereas demand may fluctuate over time. Thus, firms may reprice in real time based on current availabilities and expected future demand.

Many of these industries are competitive. Not surprisingly, more and more dynamic pricing solutions are designed to help firms compete in prices in real time.[1] Under competition, the effect of dynamic pricing on firms' profits is uncertain. A monopoly firm is likely to benefit from the ability to cut prices in "low states" – (i) when consumers are more price sensitive; (ii) when bad past sales cause excessive idle capacity.[2] In a competitive setting, the ability to cut prices in these "low states" may potentially intensify price competition and lower firms' profits as in the prisoner's dilemma.[3]

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[1]For instance, IBM Dynamic Pricing "helps online retailers respond in real time to changes in competitive prices, product demand and market conditions [...] offering automatically recommends an online retailer's optimal response." See Chen et al. (2016) for Amazon sellers' use of dynamic pricing algorithms.

[2]With patient consumers, a durable-good monopoly may be worse off with the ability of dynamic pricing (Coase (1972)). Related to the current paper, Bagnoli et al. (1989) and Board and Pycia (2014) show, respectively, Coarse conjecture fails with finite consumer pool or the presence of outside option. The current paper abstract away from patient consumers.

[3]See Holmes (1989), Corts (1998), and Winter (1997) for theories on competitive price discrimination. See Deneckere et al. (1997) and Wang and Hu (2014) for theories on price competition under demand uncertainty. See Cabral and Villas-Boas (2005) for other related examples.

This paper attempts to provide a better understanding of profit and welfare implications of dynamic pricing in the competitive setting. The consequences of dynamic pricing practices have clear managerial and regulatory implications. These consequences are theoretically ambiguous or unknown, so I approach this question empirically. My analysis focuses on the airline industry. The industry is an oligopoly with sophisticated dynamic pricing firms. Airlines pioneered the widely known dynamic pricing technique called *revenue management* that re-optimizes based on real-time capacities. In addition, airlines price the same seat more than two times higher one week before departure as opposed to five weeks before departure. This increasing price pattern may be a result of *price discrimination*.[4] Hence, I estimate a rich demand and supply model that encompasses these two forces. Subsequently, I use the estimated model to perform counterfactual simulations quantifying the effects of these dynamic pricing techniques on equilibrium outcome.

To answer my research question, I manually collect real-time airfares and capacity utilization from the websites of several major airlines. The information on real-time prices and capacity utilization enables me to separate the pricing driven by revenue management from that driven by price discrimination. To obtain exogenous price variations, I leverage a natural experiment of carrier exit, which resulted in a change in the market structure. To control for the demand trend before and after the exit, I supply the market (a treated market) with a control market. The control market is a duopoly market that had the closest parallel trend in average price with the treated market before the exit event. Consequently, I implement a structural version of difference-in-differences research design with four conditions (control/treatment route $\times$ before/after the exit). The research design allows the exit decision to be correlated with the aggregate demand trend that was common with the control route.

The exit can be a strategic decision based on the firm's belief on the long-run demand trend in the focal route. To address this, I only look at *flights departing 15 days before and after the exit event*.[5] If the route-specific demand trend is smooth in time, it will vanish when the time interval gets small in a similar way as the regression discontinuity design. Conveniently, the exit was scheduled one year before it took place. If the firm was unable to predict demand shocks within a 30-day window one year beforehand, the exact timing of the exit can be "as good as random."

The empirical evidence provides support to my research design. First, the average prices before the exit event followed a common trend for the control and the treated market. Next, I demonstrate that after the exit, the average price increased substantially in the treated market but changed little in the control market. I show that the exit of its competitor caused the airline to increase its prices significantly. The increases in prices were heterogeneous across different numbers of days to departure. Monopolization increases the middle market

[4]The increasing price path is in contrast with pure capacity-based pricing, in which the value of a seat should decrease as the departure date approaches, because of the diminishing option value to sell it in the future (see Theorem 1 in Gallego and Van Ryzin (1994)).

[5]For each of these flights, I observe daily level historical prices and remaining capacities.

prices the most. The reduced form analysis demonstrates rich intertemporal variation in prices, quantities and capacity utilization.

The estimation results show that the demand elasticity varies significantly across time as the departure date approaches. For a typical flight, own demand elasticity is 1.2-1.4, measured seven weeks before departure. The elasticity decreases to approximately 1 when measured one week before departure. Industry demand elasticity also decreases over time from 1 to 0.6. The estimates suggest that late-arriving consumers have higher valuation for the tickets and substitute less to the outside option than early-arriving consumers. Thus, firms raise prices to price discriminate against late-arriving consumers. Cross-price elasticity ranges from 0.2-0.5. The level of the cross-price elasticity indicates that flights by different carriers departing on the same day are imperfect substitutes. Firms are vertically differentiated – Alaska has larger market power among high willingness-to-pay (high type) consumers, whereas JetBlue dominates the segment of low willingness-to-pay (low type) consumers. Lastly, the model prediction is consistent with the reduced form evidence that the monopolization increases the middle-market prices the most. In the early (late) market, the firms have the common incentive to price low (high) because of low (high) consumer valuations. Thus the exit of the opponent has relatively small effect on the remaining firm's price. However, in the middle market, firms' incentives are misaligned. The firm that has large low-type consumer segment wants to keep low prices, making it hard for the opponent to jack up its prices. When the exit removed this externality, the opponent's price increased dramatically.

I use these estimates to perform a series of counterfactual simulations. I define admissible strategy spaces that reflect different degrees of strategic sophistication. I show that how dynamic pricing techniques affect airlines' profits in a competitive equilibrium. In particular, I consider three pricing regimes: (i) full dynamic pricing when airlines price on the number of days to departure as well as own and the opponent's remaining capacities; (ii) fixed-path pricing when airlines price only on the number of days to departure and do not adjust their prices based on any demand fluctuation; (iii) constant pricing when airlines charge constant prices. I solve the equilibrium for each of them.

Firstly, I compare the equilibrium of full dynamic pricing with the equilibrium of fixed-path pricing. This singles out the impact of revenue management (pricing contingent on demand fluctuations). I find that, surprisingly, revenue management has little impact on airlines' profits. This is in great contrast to the common prior belief. For instance, according to Robert Crandall, the former CEO of American Airlines, "[revenue management is] the single most important technical development in transportation management since we entered deregulation." It turns out that under competition, most of the benefit of revenue management goes to the consumers– revenue management increases total consumer surplus by as much as 14.4%. These findings on airlines' profits and consumers' surplus highlights the strategic effect of revenue management that is not captured under a pure monopoly framework. Revenue management increases efficiency in capacity utilization, but relaxing capacity constraint intensifies price competition. A related intuition dates back to Kreps and Scheinkman (1983).[6] Further investigation shows that revenue management decreases substantially (i) the risk of running out capacities and (ii) prices in the early markets. This is driven by the strategic effect of demand uncertainty: the existence of demand uncertainty can exempt airlines from intensified competition.[7] When revenue management decreases the risk of selling out too soon, airlines compete more aggressively in the early markets.

Secondly, I investigate the effect of price discrimination. I compare the equilibrium of constant pricing with the equilibrium of fixed-path pricing. I find that price discrimination increases airlines' profits by a substantial 9%. Under constant pricing, the two airlines "differentiate" themselves in an attempt to soften competition. JetBlue charges a low price and focuses on the early markets. Alaska charges a high price and focuses on the late markets. When moving to the price discrimination regime, both airlines increase their prices in the late markets. As discussed in Holmes (1989), airlines' price discrimination is aligned with their collective incentives to extract more consumer surplus in the late markets. As the late market becomes less competitive under price discrimination, Alaska is actually able to sell out more seats with higher prices comparing to the constant pricing regim. This is because industry demand elasticity in the late markets is low– the high type consumers in the late markets are unwilling to switch to the outside option even though they face higher discriminatory prices. Overall, consumer welfare decreases by as much as 9.4%. Although the low type consumers are better off under price discrimination, the magnitude is much smaller than the loss of the high type consumers.

All in all, under competition, dynamic pricing benefits both airlines and consumers, and the channels for the two are different. From airlines' perspective, most of the benefits come from price discrimination instead of revenue management. This has significant managerial implications, since both scientific and popular literature on dynamic pricing tend to emphasize capacity throttling over price discrimination. My results suggest that increasing emphasis on price discrimination may be beneficial for firms with the presence of competition. For instance, it can be beneficial for airlines to conduct market research and explore temporal heterogeneity in air travel demand. From consumers' or policy makers' perspective, it is revenue management rather than price discrimination that increases social welfare substantially. Price discrimination mainly shifts the pie from the consumers to the airlines. In settings where the implementation of pricing system involves industry level decision-making, firms, expecting the competitive effect of revenue management, may be unwilling to adopt it.

This paper develops a model of dynamic oligopoly in perishable good market. To the best of my knowledge, the most related work is Sweeting (2015). Sweeting (2015) develops a model of perishable good dynamic pricing in the competitive setting. He looks at the event ticket resale market from a platform design perspective. The different industries and research questions induce different modeling choices. Firstly, the airline markets typically have a small

[6] Kreps and Scheinkman (1983) implies that under price competition, firms' profits can be non-monotonic in their capacities. See, for instance, Osborne and Pitchik (1986).

[7] See, for instance, Wang and Hu (2014).

number of players with (potentially) considerable market power, and the event ticket resale markets typically have many small sellers with little market power. As a result, I use Markov Perfect Equilibrium following Maskin and Tirole (1988) and Ericson and Pakes (1995), and he uses Oblivious Equilibrium (Weintraub et al. (2008)). Secondly, the price dynamics are qualitatively different between the airline markets and the event ticket resale markets. Average price increases dramatically for the former, but decreases for the latter. Researchers generally attribute the decreasing price path to perishability. The increasing price path is usually rationalized by time-varying consumer types.[8] Thus, my model incorporates rich temporal heterogeneity in consumer preferences.

To account for price endogeneity, the demand model allows for product specific demand shocks observed by firms but not by researchers. When doing so, the paper cannot apply the standard tool for demand estimation, that is, BLP market share inversion (Berry et al. (1995)). The market share inversion works well in cases where the sales data is aggregated, usually over time, so that firms' markets shares contain little measurement error. However, since the airline demand and supply changes daily and the capture of these changes is a goal of this paper, normal levels of aggregation can be excessive in my case. An appropriate daily level of aggregation that retains the pricing patterns results in mismeasured market shares. These market shares are frequently equal to zero or are even undefined if no firms sells during a particular day. Instead of applying BLP directly, this paper considers an alternative generalized method of moments (GMM) estimator in which demand and supply are estimated jointly using a nested fixed point approach reminiscent of Rust (1987). In the inner loop, I solve the dynamic system of demand and supply into its reduced form for a selected set of equilibrium outcome variables of interest conditional on all observed and unobserved states. This is done by backward induction starting from the last period. For each period, I integrate out all unobserved states, including unobserved demand and supply shocks.[9] In the outer loop, I match the moments from the model to the corresponding moments from the data. Such an approach requires me to solve a dynamic stochastic game with large state space, including unobserved states. To lower the computation burden, I use Gauss-Hermite quadrature to numerically integrate out unobserved demand and supply shocks. To further reduce the state space, I use cubic interpolation to interpolate firms' value functions over capacity states. Finally, I use *Julia*'s parallel computation on a multiprocessor server.

1.1.1 Related Literature

This paper is related to several streams of literature.

[8]For instance, McAfee and Te Velde (2006) comment the following: "... In particular, the failure of prices to fall as takeoff approaches is devastating to theories, leaving standing only those theories in which late arriving potential passengers have a relatively high willingness-to-pay."

[9]The possibility of unobserved demand and supply shocks makes two-step methods, such as Bajari et al. (2007), difficult to apply. Note that Bajari et al. (2007)'s first-stage estimator would be a hedonic price regression, which is known to fail if unobserved demand characteristics are present.

This paper contributes to the understanding of airline pricing. To my knowledge, it is the first attempt to structurally estimate airline dynamic pricing in the competitive setting. Airline industry is one of the textbook examples of dynamic pricing (McAfee and Te Velde (2006)). Its dynamic pricing techniques inspire followers from many other industries. Although nowadays airline dynamic pricing may be taken for granted by many people, its implication is not well understood.[10] On the other hand, the industry's competitiveness has consequential welfare implication. It receives attention from both policy makers and the research community (Borenstein (1992)). Curiously, no existing paper has empirically examined airlines' dynamic pricing technologies from an equilibrium perspective. My paper confronts the challenge by (i) implementing a research design and collecting a high-frequency data and (ii) modeling and estimating a large stochastic dynamic game. Notably, Berry and Jia (2010) studies air travel demand in differentiated product markets. Confined by the aggregated data, they adopt the static BLP framework. Recently, Lazarev (2013) and Williams (2017) estimate dynamic airline pricing using dynamic programming techniques. Both of them focus on the monopoly markets. Both of them (and this paper) allow for price discrimination. Lazarev (2013) models consumer level demand uncertainty to conceptualize a counterfactual of free ticket cancellation, whereas Williams (2017) (and this paper) models aggregate level demand uncertainty to allow for revenue management. Williams (2017) studies price discrimination and revenue management jointly and quantify their interactions in the single agent setting, whereas this paper studies the equilibrium consequences of introducing these dynamic pricing techniques to competitive firms.

Secondly, this paper adds to the empirical literature on competitive price discrimination, for instance, Besanko et al. (2003), Villas-Boas (2009), Hendel and Nevo (2013), etc.[11] In the current investigation, consumers can differ in both their valuations and their brand preferences. The former determines the industry-demand elasticities, i.e., the tendency to drop out of the market. The latter determines cross-demand elasticities, i.e., the tendency to switch between competitors. Without capacity constraint, the ability to price discriminate may increase or decrease airlines' profits and social welfare depending on the ratio of the two (Holmes (1989) and Corts (1998)). This paper shows empirically that early-arriving consumers' cross-demand elasticities are low relative to their industry elasticities. Thus airlines' price discrimination is more motivated by their collective incentives to sell to more travelers and fill in capacities instead of private incentives to undercut and steal business from each other. Therefore, oligopoly airlines' price discrimination benefits airlines and increases social welfare.

Thirdly, this paper relates to the literature on dynamic competition with capacity constraint. IO theorists have long recognized that quantities are limited and that the capacity

[10] For instance, Borenstein and Rose (2014) makes the following comment: "many industries have learned from the sophistication airlines have developed in peak-load pricing, price discrimination, and revenue management. But the airlines themselves remain uncertain, and often in fundamental disagreement, over how much price segmentation is optimal and precisely how to accomplish it."

[11] See Stole (2007) for a summary.

constraint has important implications for firms' strategic interactions (Edgeworth (1925)). Related to the current work, theorists have looked at multistage price and quantity games (Kreps and Scheinkman (1983) and Davidson and Deneckere (1986)) and repeated pricing games where firms face capacity constraints and demand uncertainty (Staiger and Wolak (1992)). Deneckere et al. (1996) and Deneckere et al. (1997) found that price commitment may increase social welfare by decreasing destructive competition under demand uncertainty. Recent empirical work has studied capacity constrained dynamic auction games (Jofre-Bonet and Pesendorfer (2003) and Jeziorski and Krasnokutskaya (2016)) and demand fluctuation in concrete industry (Collard-Wexler (2013)). Finally, this paper is related to the revenue management literature. The literature has traditionally focused on monopoly cases. As a notable exception, Gallego and Hu (2014) theoretically analyze a revenue management game similar to the current one.[12]

The plan of this paper is as followings: Section 2 presents the empirical setting with some reduced form evidence that motivates the structural model. Section 3 presents the research design. Section 4 sets up the model. Section 5 discusses the empirical strategies and identifications. Section 6 shows estimation results. Section 7 performs counterfactual analysis. Section 8 concludes.

1.2 Empirical Setting

1.2.1 Airline Pricing

The airline industry is an important contributor towards economic development. As in the year 2015, the industry generated \$767 billion revenue and transported \$3.3 billion passengers (the International Air Transport Association, IATA). In addition to the massive economic scale, airlines are also common textbook examples of dynamic pricing.

Historically in U.S., air travel was viewed as a public good, and the industry operated under governmental subsidies and regulations. To avoid destructive competition, the Civil Aeronautics Board (CAB) controlled airfares. "Discounts and promotions were typically disallowed on the grounds that they disadvantaged competitors or were unduly discriminatory across passengers" (Borenstein and Rose (2014)). After the 1970-1974 Domestic Passenger Fare Investigation, CAB developed the so-called Standard Industry Fare Level (SIFL). SIFL was a nonlinear distance-based formula for setting fares based approximately on industry average cost. Not until Airline Deregulation Act of 1978 did airlines begin their innovation on sophisticated dynamic pricing. The market liberalization removed government-imposed entry and price restrictions and spurred fierce price competition (Kahn (1988)).

[12] See also Xu and Hopp (2006).

Dynamic pricing Airlines are capacity constrained. Aircrafts are assigned well before departure date. For each given flight, the cost of adjusting capacities are very high.[13] Air tickets are perishable goods by nature. If a seat is not sold before its departure date, it has no value. Air travel demand is uncertain. Each day when setting prices, airlines do not know how many consumers will actually buy. Airlines frequently adjust prices based on real-time fluctuations in supply and demand. In particular, I single out two key components of airlines' dynamic pricing – revenue management and price discrimination. It is worth pointing out that airlines' pricing problem involves many other strategic considerations. To keep the model simple, many departures are made from precise institutional features, such as multi-fare-class pricing, demand learning, multi-product pricing, network pricing, and so on. These features are important by themselves and can be viewed as separate questions. I leave them to future research.[14]

1. *Revenue Management*. Airlines pioneered the development of revenue management. Revenue management was originally called yield management, although now it is outdated. The meaning of revenue management can be very broad in some cases. However, the fundamental concept of revenue management has not changed, that is, to optimize profits contingent on product availability, i.e. "the actual number of passengers who are currently booked on a specific flight". In 1977, shortly before the deregulation of U.S. airline industry, American Airlines initiated an inventory-based pricing system called Dynamic Inventory Optimization and Maintenance Optimizer (DINAMO). This was the first large-scale dynamic pricing system. DINAMO gave American Airlines a large competitive advantage against their competitors. Over a three-year period starting around 1988, the system generated \$1.4 billion in additional incremental revenue (Smith et al. (1992)). Meanwhile it also caused the bankruptcy of American Airlines' direct competitor People Express. Thanks to the innovation in information technology and computational capability, the practice of revenue management is both prevalent and mature in today's airline industry (Alderighi et al. (2012) and Escobari (2012)).

[13]For most airlines, the schedule design process begins 12 months prior to departure date. Based on this flight schedule, fleet (aircraft type) assignment is done about 12 weeks in advance (Bae (2010)). Last minute aircraft swaps happen mostly because of unscheduled maintenance, bad weather, air traffic control (ATC) delays, etc. As for American Airlines, aircraft swaps are covered in their contract of carriage and thus warrant free ticket cancellation (https://www.aa.com/i18n/Tariffs/AA1.html). There is active research on the concept of demand-driven dispatch (D^3, see Berge and Hopperstad (1993) for the early work). Currently, it is still very expensive and complicated to put D^3 into practice. It requires coordination of network development, schedule construction, fleet assignment, aircraft routing, crew scheduling and ground resource optimization (Shebalov (2009)). There is no D^3 in my estimation data.

[14]For example, in practice airlines offer a discrete distribution of airfares at each point in time (Alderighi et al. (2016)). The pricing department is responsible for creating buckets of fares. The revenue management department will adjust the availabilities of these fares dynamically. My model assumes that airlines choose one price from a continuous set. This is a good approximation if (1) There are many prices. In my data, the number of unique prices observed for each route×firm is 13, 22, 38 and 44. (2) Each period is short enough. In my data, 74% of the time the number of tickets sold in one period is no bigger than 1.

Revenue management is viewed as critical to running a modern airline profitably.[15]

2. *Price Discrimination.* As a well-known industry regularities, airfares are on average more expensive closer to departure date.[16] This is viewed as evidence of intertemporal price discrimination. In 1970, British Airways offered "early bird" discounts to consumers who bought tickets at least four months in advance. Generally, leisure consumers with higher price elasticities arrive early, whereas business travelers who are less price sensitive arrive late. Airlines thus are able to screen consumers based on the times of their arrivals.

Competion and Product Differentiation There has been much discussion on whether or not the industry is subject to "excessive competition". Airlines claim that the industry is too competitive. Indeed, since 1978 there have been well over 100 bankruptcy filings in the U.S airline industry. Every major US interstate airline at the time of deregulation in 1978 has since filed a bankruptcy request. A well-known argument is the problem of industry over-capacity. The internet has facilitated great transparency in airfares, and consumers can search them at minimal cost. Moreover, the marginal cost of selling to an additional passenger is low compared to the marginal consumer's willingness to pay. Thus if flight tickets are not very differentiated across airlines and thus air travel demand is homogeneous, one would expect airlines' competition to be fierce.

Therefore, the degree of airline differentiation is a crucial determinant of the competitiveness of the market. If flights are sufficiently differentiated, monopoly powers will arise. In an effort to mitigate competition, airlines introduced a loyalty-inducing marketing device called frequent flyer program (FFP). In 1981, American Airlines introduced the first FFP. Soon after 1986, FFP has spread to all major airlines. FFP reduces travelers' cross-price elasticities by encouraging them to buy tickets from a single airline. As a result, it increases brand loyalty and switching cost (Borenstein (1992)). Should market power be a significant public policy concern in the airline industry? Concerns about airlines' market power have waxed and waned considerably in the past three decades. For instance, in order to promote competition among its airlines Norway banned domestic FFP in 2002, but lifted the ban later in 2013.[17] On the other hand, the industry's profitability has fluctuated dramatically due to cyclical demand, sticky fixed costs, and repeated disruptive business innovations. Factors like entry/exit and short-run profitability tell us little about airlines' market power. To understand the competition in the industry, it is essential to estimate its demand prim-

[15] It has become a common practice in many other industries of perishable products including energy, hospitality, entertainment, broadcasting, transportation, etc. According to a recent industry report, the revenue management market is estimated to grow from $9.27 billion in 2015 to $21.92 billion by 2020 at a compound annual growth rate of 18.8 % during the forecast period.

[16] This is well documented in the literature. The pattern also holds in my data. Alderighi et al. (2012) presents cases when the price pattern can be different.

[17] http://www.aftenposten.no

itives. The current paper provides empirical insights on airlines industry's competitiveness by estimating a dynamic oligopoly model in differentiated product markets.

Americans' Value Pricing Sophisticated pricing system clearly benefits a monopoly airline. However, its impact is unclear under competition. As noted in Borenstein and Rose (2014), "many industries have learned from the sophistication airlines have developed in peak-load pricing, price discrimination, and revenue management. But the airlines themselves remain uncertain, and often in fundamental disagreement, over how much price segmentation is optimal and precisely how to accomplish it." In April 1992, American Airlines announced its "value pricing" strategy to replace the complicated yield management system with a simple, four-tier price system. The goal was to simplify its existing fare system by eliminating 430,000 out of 500,000 fares in its computerized reservation system – an 86 percent drop.[18] As the industry leader, American Airlines assumed that its competitor would follow. However, their major competitors responded to their simplified fare system by aggressive undercutting. The industry went into a full-fledged price war.[19] In October 1992, Robert L. Crandall admitted publicly that his plan had failed. Americans completely abandoned its "value pricing," after losing $251 million in just two quarters. The industry as a whole lost $1.53 billion in that year (Morrison et al. (1996)).

1.2.2 Data Source

I collect a high-frequency panel data of posted prices and seat maps from airlines' websites. In the airline literature, the widely used data set is the "Airline Origin and Destination Survey" collected by U.S. Department of Transportation (called DB1B). This data report a 10% random sample of all domestic airline tickets at quarter-route level. This data set is highly aggregated, and it does not report the date at which a ticket is priced/purchased and the date at which the flight departs. As a result, it does not contain the intertemporal variations to reflect dynamics in demand and supply. Recently, researchers have obtained higher frequency prices and sales data. Lazarev (2013) use a high-frequency data set of daily-flight-level prices to approximate transaction prices. Escobari (2012) uses a dynamic panel of seat maps obtained from the internet to approximate daily sales.

Posted daily-flight-level prices have been used to approximate transaction prices for several years (McAfee and Te Velde (2006)). Seat maps are used only recently as proxies for sales and inventories.[20] To the best of my knowledge, currently seat maps are the best proxies for airlines' remaining capacities.[21] Technically, airlines hold their real-time inventory information in their computer reservations systems (CRSs). Most airlines have outsourced

[18]See: *"American Airlines' Value Pricing"*, HBS Case No. N9-594-001

[19]*See "The Mother of All (Pricing) Battles: The 1992 Airline Price War"*. HBS Case Number: 5-204-250.

[20]Seat map data has also been used in recent transportation economics, revenue management research, etc. See, for instance, Clark and Vincent (2012) and Mumbower et al. (2014).

[21]See Puller et al. (2012) and Li et al. (2014) for another potential data source for daily sales.

their CRSs to global distribution system (GDS) companies, such as Amadeus, Sabre, Galileo, and Worldspan. A seat map is a public interface connected to airlines' real-time availability data. Reliable availability responses are crucial and inaccuracy could result in lost bookings (Barnhart and Smith (2012)). As stated in Sabre's website, the interactive seat map is to provide real-time "displays for more accurate views of remaining seat availability and seat location".[22] Nevertheless, this data is not ideal and has potential measurement errors. If a consumer did not select a seat at the time of the purchase, then the data may fail to indicate that the seat was sold.[23] Williams (2017) compares collected seat map data with airlines' reported loading factor and finds that the size of the measurement error seems acceptable.[24] The current GMM estimator can account for random measurement errors.

Every day, I manually searched for all nonstop flights that departed within the next 100 days for a selected set of routes. I recorded the prices and the numbers of remaining seats from the source code of the airlines' official websites. Figure 1.17 shows an example from one of the airlines. I used the lowest economy class price as my measure of price. I used the number of remaining economy class seats as my measure of remaining capacity. This is because my analysis focuses on economy class seats only. I admit the simplification I impose here. I do not explicitly model product differentiation within the economy class seats. In reality, airlines may offer different tiers of economy seats. This is less problematic if demand for different tiers of economy seats were more or less uncorrelated with time.

1.2.3 Route Selection

In order to obtain a robust research environment, I follow a systematic procedure for my route selection.[25] I use two major data sources to guide my route selection. Firstly, I analyze the DB1B data collected by DOT in the first quarter of 2014. It gives me summary statistics for most of U.S. domestic airline routes. Meanwhile, I manually collect a separate dataset from Google Flight API. I search for 17,392 randomly generated pairs of domestic airports.

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[22]Similarly on Amadeus's website– "Amadeus Interactive Seat Map allows airlines and travel agents to deliver superior service to passengers by displaying real-time and accurate seat information... Enhance customer service by providing them with seat choices based on accurate, real-time availability."

[23]Possibility of strategic seat blocking is not modeled. Ticket cancellation can cause measurement error in sales. The model assumes away ticket cancellations.

[24]Seat maps understate reported load factor by an average of 2.3% at the flight level, with a range of 0-4%. The aggregate error at monthly level is 0.81% (Williams (2017)).

[25]There was also a practical reason that I had to focus on a small set of routes. The cost of monitoring a large set of routes was high. Airlines' websites usually respond very slowly to each request and frequently return errors. They block an IP if they sense too many "suspicious" searches. I also found that they change the source codes of their websites regularly. In many cases, the changes seemed meaningless but did create problems for data scraping. Since all the data is real-time, any missing data would be lost forever. Avoiding missing data is a costly problem even for firms that specialize in collecting online pricing data and selling this data to airlines (Mumbower et al. (2014)). To keep the data quality, I had to maintain my program in "real-time". To minimize missing data, I scraped the same flights twice a day as a backup.

This covers more than 62% of all possible combinations among 237 major U.S. airports. I record a sample of nonstop tickets for these 17,392 routes.

Step 1: preliminary In the first step, I identify a set of routes that meet my route selection rules. These rules are intended to improve data quality and simplify the structural model. Below I explain each of the major criteria and the motivation behind them.[26]

1. *Free seat assignment*. I only include routes where consumers can select seats for free at the time of purchase. This is because I use seat maps to approximate remaining capacities. Southwest does not allow any advance seat assignment. Some low-cost airlines, such as Spirit, charge consumers for advance seat reservation. I have to restrict my attention to routes with only a subset of the following carriers: American, Delta, JetBlue, Alaska, United, Hawaii, and Virginia. I noted at the time of data collection that some of these airlines, such as American, Delta and United, started to introduce basic economy class seats, and consumers could not reserve seats when purchasing this type of ticket. I manually checked to make sure that the selected routes were not affected by the new policy.

2. *Pricing of round-trip tickets*. I include routes where round-trip tickets are priced close to the corresponding one-way tickets. By doing so, the pricing and purchasing behavior of round-trip tickets can be approximately seen as independent one-way tickets. This criterion help simplify the model and allow me to abstract away from extra complication. Alaska and JetBlue price strictly at the segment level.

3. *High nonconnecting traffic*. I rank the routes by the ratio of traffic that is not connected to other cities. Then I select routes where this ratio is high. There are two reasons for this: (i) when a seat was marked as occupied in a seat map, it was more certain that a nonstop ticket was purchased; (ii) the concern of network pricing is smaller. In the selected routes, the ratio is above 80%.[27]

4. *Minimal number of daily flights*. I choose oligopoly routes where the number of operating airlines and daily flights were as small as possible. I adopt a full solution method when estimating the model, and doing so reduces the computational burden while keeping the key ingredient of competition. In all the selected routes, there were two operating airlines. Each carrier has fewer than two daily flights. In most of the cases, each carrier had exactly one daily flight. To expand the sample, I allow a few exceptions when one firm has an extra flight during peak days.

The selection rules lead me to a final sample of 5 routes: Seattle-Tucson (SEA-TUS), San Diego-Boston (SAN-BOS), New York-Sarasota (NYC-SRQ), New York-Aguadilla (NYC-

[26] My selection procedure is similar to Williams (2017).

[27] Specifically, 80.2% for SEA-TUS; 93.2% for SAN-BOS; NYC-SRQ for 87.4%; 90.9% for NYC-SAT; 83.5% for NYC-BQN.

BQN) and New York-San Antonio (NYC-SAT). The operating airlines in these routes included JetBlue, Delta, Alaska, and United. These are among the six largest domestic airlines in U.S. I keep track of all nonstop flights in the selected five routes for a period of six months. My dataset covers 225,704 observations of daily prices and inventories from 4,550 flights.

Step 2: exit route I select a time window in which a route changes from duopoly to monopoly, namely Seattle-Tucson. From December, 2015 to March, 2016, both Alaska and Delta offer direct flights between Seattle and Tucson. Delta exited the market on March 31, 2016, and Alaska remains in the market. The market structure changes from duopoly to monopoly. My data collection period is chosen to contain this exit event.

Alaska has served this route since 2000. It offers daily non-stop flights year-round. Delta started to aggressively build its presence in Seattle airport in 2011 and announced Seattle's hub status in 2014. This created a "turf war" with Alaska, since Seattle airport is Alaska's headquarters and largest hub. Delta first entered the SEA-TUS market and offered a weekly nonstop flight from December 2014 to March 2015. They started to operate at daily level only since my data collection year, i.e. 2016. In the year 2016, they still operated in the December to March interval. The flight was operated under one of Delta's regional carriers, SkyWest Airlines, and Delta was responsible for the pricing and selling.

A concern is the potential of seasonality in demand. As will be clear in the next section, my identification assumption allows for potential seasonalities that are (i) "smooth" in time; (ii) "common with the control route". It is nonetheless useful to have a sense of potential idiosyncratic "sharp" seasonality at either Seattle or Tucson airport. To do so, I discuss relevant air travel supply at the two airports. There is little direct evidence of idiosyncratic sharp seasonality at March for either Seattle airport or Tucson airport.

1. *Tucson airport*. There were a total of 23 nonstop daily-level flights at Tucson airport. 4 of the 23 flights did not operate year-round. Delta's SEA-TUS flight operated from December to March, and all of the other 3 flights started in November and ended in June.[28]

2. *Seattle airport*. Delta had 60 nonstop flights at Seattle airport. 12 of the 60 flights did not operate year-round. 2 of the 12 flights ended in March, including the current one. 4 of the 12 flights ended in April. The other 6 flights ended in August.

Step 3: control route I supply the exit route with a control route, namely SAN-BOS. Both of the two routes are identified in Step 1 following the exact same set of criteria. The control route is chosen because it had the closest parallel trend in average price with the exit route before the exit event. Both the exit route and the control route are long-haul. Conveniently, Alaska operates in both of the routes. Although the identification does not require the two routes share the same set of carriers, this fact is still valuable for my reduced

[28] The other three flights were: Alaska's Portland-Tucson flight, Delta's Minneapolis-Tucson flight, Southwest's Oakland-Tucson flight.

form analysis later. Both JetBlue and Alaska offer direct flights in the SAN-BOS route. JetBlue entered the route in 2007, and Alaska entered only since 2013.

1.2.4 Data Patterns

Table 1.2 reports the summary statistic of the estimation data. The data contains $10,290$ observations of daily-flight-level prices and sales for 210 flights up to 49 days before departure dates. On average, a flight sells 1.11 seat each day. More than half of the days, a flight sells zero tickets. From day $t+1$ to day t, on average the price increases by \$ 7.5. An average flight sells 47.39 seats 7 weeks before departure. The flight-level Gini coefficient in the bottom row captures the intertemporal price dispersion for a given flight. The mean of the flight-level Gini coefficient equals 0.21. This means that an expected absolute difference is 42% between two randomly selected prices for the same flight at two different pricing dates (Siegert and Ulbricht (2015)). The large dispersion of airfares is consistent with existing findings (Borenstein and Rose (1994)).

Figure 1.2 shows the path of prices and remaining seats for one particular flight. The red line shows that the seats were sold out gradually over time. 90 days before departure, the flight had more than 100 remaining seats. On the departure day, there were around 17 seats unsold. The blue line shows the dynamics of prices. The prices range from 150-600 dollars. The shaded regions highlight some suggestive evidence of revenue management. In the light-blue area, seats were sold out quickly (red line dropped quickly), then the price increased. In the light yellow area, seats were sold out slowly (red line was flat), then the price dropped.

Figure 1.18 shows the average path of prices and loading factor by number of days to departure. Loading factor increases smoothly over time. The average loading factor on the departure date is 83%. The corresponding number is between 83%-84% for the U.S airline industry from 2011-2016.[29] On average, price increases as the departure date approaches. Noticeably, the price jumps up at certain threshold such as 4 days, 1 week, 2 weeks, 3 weeks, etc. Prices are relatively stationary more than one month before departure date. The price path looks similar to existing literature.

1.3 Research Design

A common challenge in demand estimation is to find exogenous variations that can identify preference on endogenous variables, i.e. price. In order to address this, I leverage the exit event and pair the exit route with a control route that had the closest parallel trend in the average price before the exit event (see the previous section for route selection procedure and see the remainder of this section for the parallel trend discussion). I implement a structural version of (local) difference-in-differences design. In this section, I formally present the research design. I discuss the assumption under which the treatment (exit event) can

[29] http://airlines.org/dataset/annual-results-u-s-airlines-2/

be viewed as exogenous. I provide reduced form evidence supporting the assumption. I demonstrate that the treatment caused rich variations in prices.

	03/17 — 03/31	04/01 — **04/15**
Treatment route Seattle-Tucson	Delta Alaska N=2940	Alaska N=1470
Control route Boston-San Diego	Alaska JetBlue N=2940	Alaska JetBlue N=2940

Table 1.1: (local) difference-in-differences

Notes: The number of observations in each cell is calculated by N= #firms×#pricing-dates×#departure-dates.

Table 1.1 summarizes the research design. The identification condition is similar to the regular reduced form difference-in-differences design. Recall that difference-in-differences allow the treatment and the control to be different as long as the differences are (i) persistent in time or (ii) random in time. If the differences are persistent in time; they are automatically controlled by the before and after design. It is valuable to allow consumers' preferences and arrival patterns to be different between the two routes. If the time-varying differences are random, they are accounted by the law of large numbers. Importantly, difference-in-differences requires the systematic change after the treatment to be common across the routes. This is the well-known common trend assumption. A regular common trend assumption is admittedly unsatisfactory in my setting. This is because I use exit event as the treatment. Exit is typically viewed as a strategic decision. It is possibly based on the exit firm's expectation on long-run demand in the route. If this is true, the treatment would be correlated with long-run route-specific demand trend that is known by Delta but not by the researcher.

To address this concern, I restrict my estimation sample to only a relatively small neighbor of the exit event, namely 15 days. That is, I only use flights that departed from March 17, 2016, to April 15, 2016, in the treatment route and the control route . In Table 1.1, each block of the 2-by-2 design has $N = \#\text{departure-dates} \times \#\text{firms} \times \#\text{directions} \times \#\text{pricing-dates}$ observations. I assume that the common trend assumption holds in this 30-day time window.

Assumption 1. *Within the 30-day time window, the control route and the treatment route had a common demand trend.*

The (local) difference-in-differences design helps mitigate the concern on the endogeneity of the treatment. Firstly, if the route-specific demand trend is smooth in time, it will vanish when the time interval gets small in a similar way to the regression discontinuity design. Secondly, the exit was scheduled one year before it actually took place. If Delta was unable to predict demand shocks within a 30-day window 1 year beforehand, the exact timing of the exit can be "as good as random". Lastly, the difference-in-differences design allows for one type of endogenous exit. It allows Delta's exit decision to be correlated with aggregate demand trend that was common with the control route. This is valuable if Delta had limited prediction power for one specific route, but it had a prior for industry demand trend and acted on this prior.

Figure 1.3 shows suggestive evidence that the trends in route-level average price were indeed parallel across the two routes before the treatment on March 31, 2016. Each dot is an average price for flights departed on a given departure date in a given route. It is averaged over $N = \#\text{firms} \times \#\text{directions} \times \#\text{pricing-dates}$ observations of prices. The lines are smoothed using Gaussian kernels. From March 01, 2016, to March 31, 2016, the price gap was stable over time between the two routes. The gap changed dramatically after Delta's exit. Route-level mean prices increased substantially in the exit route but did not change much in the control route.

Note that average price in the treatment route could increase "mechanically" when the low-priced firm exited the market. This type of price variation is enough to identify consumer price sensitivity. Nonetheless, it is still valuable to single out how the remaining firm reacted to the exit event. Alaska Airlines operated in both the treatment and the control route before and after the exit event. Figure 1.4 shows Alaska's average prices under the 2-by-2 treatment conditions. Each dot is an average price for flights departing on a given departure date in a given route. It is averaged over $N = \#\text{directions} \times \#\text{pricing-dates}$ observations of prices. Alaska raised its price significantly in the treatment route. Alaska's price did not change significantly in the control route.

Figure 1.4 shows a "point estimate" of the treatment effect. Figure 1.5 goes one step further and zooms in– it shows the heterogeneous treatment effects conditional on different numbers of days to departure. Each dot is an average price for flights departing under a given condition for a given number of days to departure. It is averaged over $N = \#\text{directions} \times \#\text{departure-dates}$ observations of prices. The graph shows that there were rich variations in treatment effects across different numbers of days to departure. Alaska raised its prices significantly in the exit route after the exit event. Interestingly, most of the price increases happened 2-5 weeks before the departure date. The increases in prices are relatively small towards the two ends. Figure 1.6 shows that the model is successful in predicting these variations.

1.4 Model

In the following set up, products can be seen as non-stop economic class tickets for a directional city pair on a departure date, for instance, non-stop economy class tickets from San Diego to Boston on April 01, 2016. To simplify the notation, I omit subscripts for departure dates d and routes r.

1.4.1 Demand

Let $t = 1, 2, .., T$ be the selling periods. Thus time is discrete and T is the deadline of selling, after which the product is assumed to have zero value. I assume that consumers live for only one period and will not wait. This assumption is motivated by price patterns observed in the data. The upper graph in Figure 1.18 shows that on average equilibrium price path increases as the departure date approaches. The lower graph shows that the possibility that price will drop tomorrow is only 0.11 on average. Therefore, consumers' incentive to bet on prices is small.[30] That is, a forward-looking consumer would have behaved in a similar way as a myopic consumer. However, a consumer may wait if by doing so she can learn more about her preference (Dana (1998), Lazarev (2013)). To simplify the model and focus on the supply side, I abstract away from this in the current paper.[31]

Arrival Process Let $I(t)$ be the random variable for the number of consumers arriving t days before departure. I assume that $I(t)$ follows an exogenous Poisson stochastic process and the Poisson parameter takes some functional form $\lambda(t; \gamma_{\text{arrival}})$. Formally:

$$I(t) \;\sim \text{Pois}\left(\lambda\left(t; \gamma_{\text{arrival}}\right)\right),$$

where γ_{arrival} is the parameters on arrival process to be estimated.

Modeling aggregate consumer arrival as a Poisson process is intuitive. The Poisson arrival process has been used widely in many fields, including economics and operations research (McGill and Van Ryzin (1999)). As opposed to Gershkov et al. (2016), I assume the parameters of the arrival process are known to the airlines. Importantly, the exact number of arriving consumers is unknown to airlines.[32]

Choice Process Each consumer who arrives t days before the departure date faces a choice set $\mathcal{J}_t$. $\mathcal{J}_t$ includes (1) nonstop flight for a specific directional route on a specific departure date available t days before departure and (2) an outside option. The subscript t indicates that choice set may change over time depending on availability. If a consumer does not choose any flight, then she chooses the outside option labeled as 0. The outside option is a reduced form way of capturing all other possible alternatives. These include

[30]The consumer who is indifferent between the best inside option and the outside option has the strongest incentive to wait. By waiting, she can still leave the market if the price goes up and buy a ticket if the price drops. Yet for this marginal consumer, the expected gain is only \$5-\$7. Using the estimated preference and assuming zero waiting cost, one can show there are 1.5-2.2 these consumers each market.

[31]I note that the current set up can be extended to incorporate strategic consumers similar to Goettler and Gordon (2011).

[32]McGill and Van Ryzin (1999) discussed other arrival processes that can incorporate batch arrivals.

(1) different means of transportation and (2) different travel dates and/or destinations. By putting flights departing on other dates in the outside option, I abstract away from modeling airlines' multi-product pricing.[33]

Consumers make choices according to the standard discrete choice model. Consumer $i = 1, ..., I(t)$ arriving at time t is endowed with preference $\left\{\boldsymbol{\alpha}_{it}, \{\varepsilon_{ijt}\}_{j\in\mathcal{J}_t}\right\}$, where $\boldsymbol{\alpha}_{it}$ measures her preference over product characteristics (brand and price) and ε_{ijt} is her idiosyncratic choice-specific preference shock. I assume that ε_{ijt} follows type-I extreme value. Assume that $\boldsymbol{\alpha}_{it}$ follows some exogenous distribution:

$$\boldsymbol{\alpha}_{it} \ \sim \ F\left(\cdot\ ;\ t, \gamma_{\text{type}}\right),\ i = 1, ..., I(t),$$

where γ_{type} are the parameters on random taste distributions to be estimated. Note that the preference distribution $F\left(\cdot\ ;\ t, \gamma_{\text{type}}\right)$ is a function of time t. This characterization permits a demand structure that is heterogeneous within each period and non-stationary across periods. It thus allows a rich demand substitution pattern within each period and price discrimination across periods.

To account for price endogeneity, I allow for product-specific demand shock ξ_{jt} that is observed by market participants but not by researchers. The importance of controlling for unobserved product characteristic has been highlighted in previous literature (Villas-Boas and Winer (1999)). In practice, airlines gather real-time information on demand shocks. As a result, observed prices can be correlated with this type of information. This information, however, is not observed by researchers. Thus, without accounting for these unobserved demand shocks, price elasticities will likely be biased downwards (in absolute value).

I obtain the BLP utility specification that combines consumer heterogeneity through latent taste shocks and endogeneity through product-specific demand shocks:

$$\begin{aligned} u_{ijt} = {} & \alpha_{it}^{\text{Firm}_1} \times \mathbf{1}_{\{j=1\}} + \alpha_{it}^{\text{Firm}_2} \times \mathbf{1}_{\{j=2\}} + \alpha_{it}^{\text{Price}} \times p_{jt} + \\ & \beta^{\text{After}} \times \mathbf{1}_{\{\text{Depart after treatment}\}} + \beta^{\text{Weekend}} \times \mathbf{1}_{\{\text{Depart on weekend}\}} + \\ & \xi_{jt} + \varepsilon_{ijt} \\ \equiv {} & \bar{u}_{ijt} + \varepsilon_{ijt}. \end{aligned}$$

$\boldsymbol{\alpha}_{it} \equiv \left\{\alpha_{it}^{\text{Firm}_1}, \alpha_{it}^{\text{Firm}_2}, \alpha_{it}^{\text{Price}}\right\}$ are the random coefficients, where $\alpha_{it}^{\text{Firm}_1}$ and $\alpha_{it}^{\text{Firm}_1}$ are consumer i's preference towards firm 1 and firm 2 respectively and $\alpha_{it}^{\text{Price}}$ is consumer i's price coefficient. Let $\boldsymbol{\alpha}_{it}^{\text{Firm}} \equiv \left\{\alpha_{it}^{\text{Firm}_1}, \alpha_{it}^{\text{Firm}_2}\right\}$ be the vector for consumer i's brand preference. β^{After} is a preference shock between before the exit event and after. This allows a common industry demand trend β^{After} across the two routes. β^{Weekend} is a dummy variable for weekends, and it allows consumers who travel on weekends to be different from those who travel on weekdays. Without loss of generality, normalize outside option such that $\bar{u}_{i0t} = 0$.

I make a simplifying assumption that consumers simply choose the product that maxi-

[33] See Li (2015) for dynamic pricing of complementary products in a monopoly market.

mizes her utility. If the product is sold out during a selling period, then a lottery is used to decide who get the remaining seats. However, consumers do not consider this possibility of sell out when make purchases.[34] Finally, I obtain the familiar expression for market share:

$$s_{jt} = \int_{\boldsymbol{\alpha}_{it}} \frac{\exp\left(\bar{u}_{ijt}\right)}{1 + \sum\limits_{j' \in \mathcal{J}_t \setminus \{0\}} \exp\left(\bar{u}_{ij't}\right)} \times \mathrm{dF}\left(\boldsymbol{\alpha}_{it};\ t, \gamma_{\text{type}}\right).$$

Sales Process Let $\mathbf{q}_{jt}$ be the sales for firm j's flight t days before its departure date. Proposition 1 states that a multinomial choice process conditional on a Poisson arrival process yields mutually independent Poisson sales process.

Proposition 1. *We must have:*

$$\boldsymbol{q}_{jt} \ \sim \ \text{Pois}\left(\lambda\left(t\right) \times s_{jt}\right),$$

$$\boldsymbol{q}_{jt} \ \perp\!\!\!\perp \ \boldsymbol{q}_{j't}.$$

This equivalence simplifies my model. To explain, consider the following simple example. If the number of arriving consumers follows Pois(4). An arriving consumer has 50% chance of choosing firm A from a choice set of firm A and firm B. It is trivial to show that the expected sales value of firm A is 2. If firm B's sales is known to be 4, what do we expect firm A's sales to be? The answer is 2. Proposition 1 says that conditional on demand information the sales of the two firms follow independent Poisson distributions. This result simply comes from the mathematical property of Poisson-Multinomial distribution. It makes the state transition more trackable and reduces the computation substantially.

1.4.2 Supply

In my model, firms play a dynamic pricing game under complete information. Same as in a single-agent dynamic programming problem, prices have to satisfy *intertemporal optimality condition*. Since sales are stochastic, the optimality condition changes constantly. Therefore, airlines continuously re-optimize to account of the changing shadow price of capacity. In addition to this monopolistic dynamic optimization, airlines also rationally expect that today's pricing strategies not only affect all players' sales today but also affect their capacities tomorrow. As a result, airlines adjust their prices dynamically contingent on time as well as each other's remaining capacities. I assume that remaining capacities are common knowledge. This assumption is made in a few recent papers on competitive revenue management. See, for instance, Levin et al. (2009), Gallego and Hu (2014), etc.[35]

[34]Rationing rule is important in Bertrand prcing. See Davidson and Deneckere (1986).

[35]Clark and Vincent (2012) show empirical evidence that all else equal some airlines increase their prices as their rivals' remaining available seats disappear. Their finding holds in my data. In practise, real-time fares

States Firms' payoff relevant state variables are summarized as $\{t, \boldsymbol{c}_t, \boldsymbol{\xi}_t, \boldsymbol{\omega}_t\}$. c_{jt} denotes firm j's remaining capacities t days before departure. ξ_{jt} denotes firm-specific demand shocks. ω_{jt} denotes firm-specific shocks in marginal cost. One may think that airlines' marginal costs are realized at the time of departure. In practice, airlines' optimal prices account for their expected marginal costs at the pricing date. The expected marginal costs depend on current gas prices, the option value of a seat if sold as a connecting ticket, etc. These costs change over time. Thus I allow marginal cost shocks ω_{jt} to have the same subscript t as observed prices p_{jt}. Finally, ξ_{jt} and ω_{jt} put together real-time demand and supply information known to firms but not to researchers.

Under capacity constraint, sales $\tilde{\mathbf{q}}_{jt}$ for firm j at time t follows truncated Poisson distribution. Let $\tilde{\mathbf{q}}_t$ be the $J \times 1$ random vector for sales. The state transition of capacities are governed by the following stochastic sales process:

$$\Pr_t\left(\tilde{\mathbf{q}}_{jt} = \tilde{q}_{jt} \middle| p_t, c_t, \xi_t\right) = \begin{cases} \mathrm{h}\left(\tilde{q}_{jt}; \lambda\left(t\right) \times s_{jt}\right) & \text{if } \tilde{q}_{jt} < c_{jt}; \\ 1 - \displaystyle\sum_{k=1}^{c_{jt}-1} \mathrm{h}\left(k; \lambda\left(t\right) \times s_{jt}\right) & \text{if } \tilde{q}_{jt} = c_{jt}, \end{cases}$$

where $\mathrm{h}\left(k;\lambda\right)$ is the Poisson probability mass function with parameter λ at k. It follows that:

$$c_{jt+1} = c_{jt} - \tilde{q}_{jt}.$$

Timing of the Game In the beginning of each period t, firms observe own and the opponent's capacities $\mathbf{c_t}$ and the remaining time $T - t$. Firms know the distributions of the Poisson arrival process as well as the distribution of consumer preference at any point in time. However, they do not observe how many consumers actually arrive, nor do they know the actual valuation of these consumers. They simultaneously choose prices that maximize their own expected total payoffs, which is the sum of the expected current period profits and the expected continuation value. In the end of the period, demand is realized and seats are filled. Then the game proceeds to the next period until $t = T$. After the final period, all remaining capacities have zero value. A firm is out of the market if it runs out of capacity before the departure date.

Payoff Function I discuss the details of the supply model now. Marginal cost can be written as:

$$\mathrm{mc}_{jt} = \eta^{\mathrm{Firm}_1} \times \mathbf{1}_{\{j=1\}} + \eta^{\mathrm{Firm}_2} \times \mathbf{1}_{\{j=2\}} + \omega_{jt},$$

---

and inventories are indeed public information on GDS platform available to all its subscribers. According to the chief operating officer of Sabre– "At Sabre, we have worked jointly and diligently with airlines to come to mutual agreements that ensure efficient access to their inventory." For related theories, see Vives (1984) and Shapiro (1986), etc. For recent structural work, see Asker et al. (2016).

where ω_{jt} is IID cost shock, $\boldsymbol{\eta} = \left\{\eta^{\mathrm{Firm}_1}, \eta^{\mathrm{Firm}_2}\right\}$ are intercepts for firms' marginal cost. Cost information is common knowledge.

In each period, the expected static payoff is given by:

$$\overline{\Pi}_{jt}\left(\boldsymbol{p}_t, \mathbf{c}_t, \xi_t, \omega_t\right) = \mathbb{E}_t\left[\tilde{\mathbf{q}}_{jt} \times \left(p_{jt} - \mathrm{mc}_{jt}\right)\right].$$

The expected static payoff equals sales times margin. It is a function of firms' current prices. It depends on capacity since the latter decides the maximal sales a firm can have. Current profit also depends on all supply and demand shocks. The expectation is taken over current stochastic sales. The expectation operator has subscript t because the game is non-stationary.

Markov Strategy I consider non-stationary Markov pricing strategies. Airlines' prices are contingent on all current payoff-relevant state variables. Specifically, their prices are contingent on the number of days to departure t, remaining capacities of each firm, demand shocks and cost shocks:

$$g_j : \underbrace{T}_{\text{time}} \times \underbrace{C^J}_{\text{capacities}} \times \underbrace{\Xi^J}_{\text{demand shocks}} \times \underbrace{\Omega^J}_{\text{cost shocks}} \rightarrow \underbrace{\mathcal{R}^+}_{\text{current price}}.$$

Bellman Equation Firm j's Bellman equation is defined recursively:

$$\begin{aligned} V_{jt}\left(\boldsymbol{c}_t, \xi_t, \omega_t \middle| \boldsymbol{g}\right) = \max_{p_{jt}} \Bigg\{ & \overline{\Pi}_{jt}\left(\boldsymbol{p}_t, \boldsymbol{c}_t, \boldsymbol{\xi}_t, \boldsymbol{\omega}_t\right) + \\ & \delta \int \mathrm{EV}_{jt+1}\left(\boldsymbol{c}_{t+1}, \boldsymbol{\xi}_{t+1}, \boldsymbol{\omega}_{t+1} \middle| \boldsymbol{g}\right) \times \prod_{j=1,2} \mathrm{dPr}_t\left(\tilde{\mathbf{q}}_{jt} = \tilde{q}_{jt} \middle| \boldsymbol{p}_t, \boldsymbol{c}_t, \boldsymbol{\xi}_t\right) \Bigg\}, \end{aligned}$$

where $\mathrm{EV}_{jt+1}\left(\boldsymbol{c}_{t+1}, \xi_{t+1}, \omega_{t+1} \middle| \boldsymbol{g}\right)$ the expected value function over future shocks satisfying:

$$\mathrm{EV}_{jt+1}\left(\boldsymbol{c}_{t+1}, \xi_{t+1}, \omega_{t+1} \middle| \boldsymbol{g}\right) = \mathbb{E}_{\{\boldsymbol{\xi}_{t+1}, \boldsymbol{\omega}_{t+1}\}}\left[V_{jt+1}\left(\boldsymbol{c}_{t+1}, \xi_{t+1}, \omega_{t+1} \middle| \boldsymbol{g}\right)\right].$$

Boundary Condition To conclude the model, I specify boundary conditions for airlines' dynamic problem. Naturally, perishability implies that all seats have no value after the end of the selling period.

$$V_{jT} = 0.$$

The second boundary conditions are driven by the existence of capacity constraint.[36]

$$V_{jt} = 0, \text{ if } c_{jt} = 0.$$

[36] Airlines' overbooking strategy is well-known. In my estimation data, the situation of a plane being full but the airline still posting price is rare. It never happened in the treatment route, and happened 0.6% of the times in the control route.

Discussion I have assumed that all error terms are IID in all their respective subscripts and uncorrelated with state variables. The conditional independence assumptions are standard and pragmatic in the context of dynamic models (Rust (1987)). Yet assuming that unobserved product-specific demand shocks are IID across time seems restrictive comparing to static demand estimations. For instance, BLP places little distributional assumptions on ξ. Allowing serially correlated demand shocks is conceptually simple, but it does not seem to add much to the current paper.

One may extend the model to incorporate the learning of demand. The idea is similar to Gershkov et al. (2016). Consider a general Markov process of arrival $\lambda(t, N(t))$ such that a firm can learn demand from cumulative sales. The key assumption is that arrival is orthogonal to valuations.

Finally, recent theoretical papers such as Board and Skrzypacz (2016) and Gershkov et al. (2016) have applied dynamic mechanism design for monopoly revenue management with strategic consumers. Their set ups are related to this current paper. This current paper only looks at simultaneous price posting.

1.4.3 Equilibrium

I look at Markov perfect Nash equilibrium for this dynamic stochastic game.

$$V_j(g_j^*; g_{-j}^*) \geq V_j(g_j; g_{-j}^*), \forall g_j.$$

Note that the game has a finite horizon, therefore one may attempt to argue backward by showing uniqueness for each static subgame. Although a finite horizon can alleviate concerns of the multiplicity of equilibria (Chen et al. (2009)), proving the uniqueness of this game is not easy. Caplin and Nalebuff (1991) establish a set of sufficient conditions for existence and uniqueness of price competition with differentiated products. Unfortunately, the results do not easily generalize to the BLP setting. In a recent paper, Pierson et al. (2013) provide another set of sufficient conditions for uniqueness of the pricing game under mixed multinomial logit demand. Pierson et al. (2013)'s proof mostly relies on restricting market concentrations and/or price spaces. To the best of my knowledge, there is no more general results.[37]

Suppose the static pricing game is indeed unique, the next question is whether the uniqueness remains under a dynamic setting. Now the cost function needs to account for the option value of a sale and is thus more complicated. Without characterising the structure of the value functions, it is unclear how the standard techniques can possibly work. Although it may not be so hard to prove structures of monopoly dynamic programming problems (Gallego and Van Ryzin (1994)), it is significantly harder to do so in dynamic games. In fact, the structure of a RM game with stochastic demand is largely unknown (Lin and Sibdari (2009) and Gallego and Hu (2014)).

[37] Gallego et al 2004, 2006.

When the competition is mild enough, the equilibrium will be unique. In practice, I allow firms to play best response dynamics. At each state, the pair of optimal prices is found when the change of firms' best responses is smaller than a tolerance. The pricing games' solution is robust to different initial values and sequences of moves. I will discuss the numerical algorithm with more details in the appendix.

1.5 Estimation

There are two challenges in the estimation. The first one is how the unobserved product-specific errors in small "non-invertible" markets will be incorporated (I will be more precise later), and the second is how to keep the estimation computationally feasible. I adopt a nested fixed-point approach. In the first step, I solve the system of demand and supply into its reduced form for all market outcomes conditional on all observed and unobserved states. In the second step, I integrate out all unobserved states. In the final step, I match model predicted outcomes and empirical outcomes. I adopt a GMM estimator and interact the predicted errors with a set of covariates. I discuss identification at the end of this section.

1.5.1 Econometric Specification

I use a third order polynomial to approximate the Poisson aggregate arrival rate:

$$\lambda\left(t;\gamma_{\text{arrival}}\right)=\sum_{n=0}^{3}\gamma_{\text{arrival}}^{(n)}\times t^{n}.$$

I allow arrival rates to be different for the two routes.

I approximate the random coefficient demand model with discrete types. This is typical in economic literature. Examples include Berry and Jia (2010) on airline demand and Besanko et al. (2003) on price discrimination. The discretized random coefficient model captures the correlation of tastes but remains computationally cheap under certain circumstances. I allow for two vertical types of consumers $\{H, L\}$ differing in their price sensitivities. In particular, let $\alpha_{\text{H}}^{\text{Price}}$ be the price coefficient for the high type consumers and $\alpha_{\text{L}}^{\text{Price}}$ for the low type. This is a parsimonious way of modeling traveler types as business travelers and leisure travelers.

I allow their arrival process to be correlated with time. The probability that a consumer who arrives at time t is a low type follows:

$$\Pr_{\text{L}}(t;\gamma_{\text{type}})=\frac{1}{1+\exp\left[\sum_{n=0}^{3}\gamma_{\text{type}}^{(n)}\times t^{n}\right]}.$$

It follows that

$$\Pr_{\text{H}}\left(t;\gamma_{\text{type}}\right)=1-\Pr_{\text{L}}\left(t;\gamma_{\text{type}}\right).$$

Note that this parametric assumption is pragmatic in several ways. The logit transformation bounds probabilities in $[0, 1]$. Secondly, the third-degree polynomial flexibly captures the intertemporal variation in consumer types.

Within each vertical type of consumers, I further allow for two segments with possibly different horizontal brand preferences. Strictly speaking, I can not identify brand preference from product preference, so I do not distinguish them in the paper. Let $\gamma_{\text{type}}^{\text{H1}}$ be the proportion of high type consumers that relatively prefer firm 1 and $\gamma_{\text{type}}^{\text{L1}}$ be the proportion of low type consumers that relatively prefer firm 1. Thus I have 2×2 discrete segments. Let $\boldsymbol{\alpha}_{\text{H1}}^{\text{Firm}} = \left\{\alpha_{\text{H}_1}^{\text{Firm}_1}, \alpha_{\text{H}_1}^{\text{Firm}_2}\right\}$ be a 2×1 vector for brand preference of firm-1-leaning high type consumers, where $\alpha_{\text{H}_1}^{\text{Firm}_1}$ is firm-1-leaning high type consumers' preference for firm 1 and $\alpha_{\text{H}_1}^{\text{Firm}_2}$ is firm-1-leaning high type consumers' preference for firm 2. Define $\boldsymbol{\alpha}_{\text{H}_2}^{\text{Firm}} = \left\{\alpha_{\text{H}_2}^{\text{Firm}_1}, \alpha_{\text{H}_2}^{\text{Firm}_2}\right\}$, $\boldsymbol{\alpha}_{\text{L}_1}^{\text{Firm}} = \left\{\alpha_{\text{L}_1}^{\text{Firm}_1}, \alpha_{\text{L}_1}^{\text{Firm}_2}\right\}$, and $\boldsymbol{\alpha}_{\text{L}_2}^{\text{Firm}} = \left\{\alpha_{\text{L}_2}^{\text{Firm}_1}, \alpha_{\text{L}_2}^{\text{Firm}_2}\right\}$ accordingly.

Therefore, I can write out the probability distribution on the four discrete types of consumers:

$$\mathrm{F}\left(\alpha_{it}; t, \gamma_{\text{type}}\right) = \begin{cases} \mathrm{Pr}_{\mathrm{H}}\left(t; \gamma_{\text{type}}\right) \times \gamma_{\text{type}}^{\text{H1}} & \text{if } \alpha_{it}^{\text{Price}} = \alpha_{\mathrm{H}}^{\text{Price}}, \boldsymbol{\alpha}_{it}^{\text{Firm}} = \boldsymbol{\alpha}_{\mathrm{H}_1}^{\text{Firm}}, \\ \mathrm{Pr}_{\mathrm{H}}\left(t; \gamma_{\text{type}}\right) \times \left[1 - \gamma_{\text{type}}^{\text{H1}}\right] & \text{if } \alpha_{it}^{\text{Price}} = \alpha_{\mathrm{H}}^{\text{Price}}, \boldsymbol{\alpha}_{it}^{\text{Firm}} = \boldsymbol{\alpha}_{\mathrm{H}_2}^{\text{Firm}}, \\ \mathrm{Pr}_{\mathrm{L}}\left(t; \gamma_{\text{type}}\right) \times \gamma_{\text{type}}^{\text{L1}} & \text{if } \alpha_{it}^{\text{Price}} = \alpha_{\mathrm{L}}^{\text{Price}}, \boldsymbol{\alpha}_{it}^{\text{Firm}} = \boldsymbol{\alpha}_{\mathrm{L}_1}^{\text{Firm}}, \\ \mathrm{Pr}_{\mathrm{L}}\left(t; \gamma_{\text{type}}\right) \times \left[1 - \gamma_{\text{type}}^{\text{L1}}\right] & \text{if } \alpha_{it}^{\text{Price}} = \alpha_{\mathrm{L}}^{\text{Price}}, \boldsymbol{\alpha}_{it}^{\text{Firm}} = \boldsymbol{\alpha}_{\mathrm{L}_2}^{\text{Firm}}. \end{cases}$$

1.5.2 Endogeneity

Price endogeneity in a simultaneous demand and supply system has been studied for decades in economics. Ignoring the endogeneity problem will cause biased estimates on the price coefficient (Villas-Boas and Winer (1999)), since prices are often strategically chosen in response to demand errors unobserved by researchers, which violates identification conditions. If the demand function is aggregated from discrete choice and thus is nonlinear, a simple IV regression is not immediately applicable. The classic solution to this was developed in Berry (1994) and Berry et al. (1995).[38] The endogenous component in demand is assumed to be captured by an addictive product shock ξ_j observed by market players but not by researchers. The proposed solution is to linearize the demand equation and invert out the unobserved error ξ_j. Once back to a linear setting, the work remaining is to find appropriate instrument variables. Berry et al. (1995)'s inversion method works well when the market size goes to infinity at a certain speed such that observed market shares (1) can approximate choice probabilities, and (2) are bounded away from zero. Neither of this holds in the current setting. In each market (itinerary$\times$departure-date$\times$pricing-date) I observe on average fewer than two prices and two sales. This type of data is a deviation from the standard market-level data, but is not uncommon in dynamic pricing setting (see Sweeting

[38]Control function is another approach, Petrin and Train (2010).

(2015) for event ticket). [39]

I adopt a "reduced form method" discussed in Berry (1994). Let $\mathcal{I}$ be all the relevant states for the joint system of demand and supply. Let $\mathcal{I} = \{\mathcal{I}^o, \mathcal{I}^u\}$ such that $\mathcal{I}^o$ is observed in the data while $\mathcal{I}^u$ is not. So $\mathcal{I}^u = \{\xi, \omega\}$. I first solve the game and translate the structured system into a reduced form. Let $\Psi(\mathcal{I}, \vartheta)$ be such an operator that takes structural parameters ϑ as well as all payoff relevant states $\mathcal{I}$ and returns a vector of market outcome (prices, quantities, prices interacting with quantities, etc). Then I integrate out unobserved shocks $\mathcal{I}^u$ and obtain the expected market equilibrium variables $\boldsymbol{\psi}$ conditional on only observables $\mathcal{I}^o$ and the structural parameters ϑ. Let $\vartheta = \{\vartheta^o, \vartheta^u\}$ be the structural parameters on observables and unobservables respectively. Note that the conditional independence assumption implies that $\Phi(\mathcal{I}^u|\mathcal{I}^o, \theta^u) = \Phi(\mathcal{I}^u|\theta^u)$. Therefore:

$$\boldsymbol{\psi}(\mathcal{I}^o|\vartheta) = \int_{\mathcal{I}^u} \Psi(\mathcal{I}|\vartheta^o) d\Phi(\mathcal{I}^u|\theta^u).$$

Note that Ψ takes ξ and ω as its arguments and jointly solves demand and supply. It implicitly accounts for the dependence of prices on unobserved demand error ξ. This is different from integrating out ξ separately for the demand equation while using observed prices. The latter approach, as pointed out by Berry (1994), is not consistent since it assumes that price does not respond to ξ.

The drawbacks of the reduced form method are discussed in Berry (1994). BLP does not impose any distributional assumption on ξ and ω. In practice, I assume that ξ and ω are independent normal and use numerical integration method to calculate $\boldsymbol{\psi}(\mathcal{I}, \vartheta)$. In addition, as in other full solution method, a stronger assumption is needed to address potential multiple equilibria.[40] Lastly, in order to avoid the identification from functional form, the reduced form method by Berry (1994) requires an exclusion restriction – a variable that enters supply equation (supply shifter) but is excluded from the demand equation. I use current gas price as a supply shifter.

In practice, I solve for model predicted prices and sales and allow for the following

[39] Outside of the dynamic pricing context, Goolsbee and Petrin (2004) looked at survey data with small (but non-zero) market size in the cable industry. They confirmed the importance of allowing unobserved demand shock and proposed a method for dealing with the measurement error in market shares.

[40] Villas-Boas (2007) provides a more general perspective.

interaction terms:

$$\boldsymbol{\psi}_{jtdr}\left(\mathcal{I}^{o}_{jtdi}\middle|\vartheta\right)=\begin{bmatrix}\hat{p}_{jtdr}\\ \hat{q}_{jtdr}\\ \hat{p}_{jtdr}\times\hat{q}_{jtdr}\\ \hat{p}_{jtdr}\times\hat{q}_{j'tdr}\\ \hat{p}_{jtdr}\times c_{jtdr}\\ \hat{q}_{jtdr}\times c_{jtdr}\\ \hat{p}_{jtdr}\times c_{j'tdr}\\ \hat{q}_{jtdr}\times c_{j'tdr}\end{bmatrix}.$$

1.5.3 Identification

I adopt a method of moments estimator by minimizing the differences between the model predicted market outcomes, $\boldsymbol{\psi}_{jtdr}\left(\mathcal{I}^{o}_{jtdi}\middle|\vartheta\right)$, and the observed market outcomes, $\boldsymbol{\psi}_{jtdr}$. I match a set of observed moments with corresponding predicted moments jointly for the system of supply and demand. The prediction errors by construction have mean zero. To translate data variations into model parameters, I allow the market outcomes to interact with a set of observed covariates. Now I discuss the selection of these covariates.

1. *Supply Covariates.* $\mathbf{z}^{\text{supply}}$ include current gas price and dummy variables indicating the identities of the two firms. Note that the demand side allows product differentiation, and the supply side does not place restrictions on firms' relative capacities. Thus firms can differ in size, market power, etc. Firms' identity dummies help identify the relative position of the two firms.

2. *Demand Covariates.* $\mathbf{z}^{\text{demand}}$ denote exogenous covariates in consumers' utility function. Firstly, I let $\mathbf{z}^{\text{demand}}$ include weekday/weekend dummies, which help identify the relative preference for weekend flights. This is one way to control for departure day fixed effects. Secondly, I allow $\mathbf{z}^{\text{demand}}$ to contain dummies for weeks to departure, which helps identify temporal (cross-period) demand heterogeneities. The reduced form evidence shows rich cross-period heterogeneities. Moreover, these heterogeneities can be captured well with weekly time windows.

3. *Treatment Conditions.* To implement the difference-in-differences design, I use the treatment conditions $\mathbf{z}^{\text{treatment}}$ as the third set of shifters. Thus $\mathbf{z}^{\text{treatment}}$ includes interactions between treatment/control routes and before/after exit. This set of covariates (1) create exogenous variations in prices to identify within-period preferences and (2) infer route-specific demand structures.

Finally, I allow these covariates to interact with each other and obtain the full covariate vector $\mathbf{z}$. Thus, a covariate is a dummy vector that indicates, for instance, JetBlue's weekday flight in the exit route before the exit five weeks before the departure:

$$\mathbf{z}_{jtdr} = \mathbf{z}_j^{\text{supply}} \times \mathbf{z}_{td}^{\text{demand}} \times \mathbf{z}_{dr}^{\text{treatment}}.$$

The moment restriction is:

$$\boldsymbol{g}\left(\vartheta_0\right) = \mathbb{E}_{\{\boldsymbol{\xi},\boldsymbol{\omega},\tilde{\boldsymbol{q}}\}}\left[\left(\boldsymbol{\psi}\left(\theta_0\right) - \boldsymbol{\psi}_{jtdr}\right)\Big|\mathbf{z}_{jtdr}\right] = 0.$$

In the end, I have 469 moments and $|\vartheta| = 38$ parameters. I use a two-step generalized method of moments and assume that the necessary regularity condition holds for the GMM. As a first step, I estimate the model with each moment weighted by its empirical counterpart. This estimator is consistent but not efficient. With the first-step estimates $\hat{\vartheta}_1$, I can calculate the estimator for the optimal weighting matrix $\hat{W}_T(\hat{\vartheta}_1)$. With this weighting matrix, I update the estimators and calculate the standard error using the asymptotic variance matrix for the two-step feasible GMM estimator.

$$\hat{\vartheta} = \underset{\vartheta\in\Theta}{\operatorname{argmin}}\left[\hat{\boldsymbol{g}}_T\left(\vartheta\right)\right]'\hat{W}_T\left(\hat{\vartheta}_1\right)\left[\hat{\boldsymbol{g}}_T\left(\vartheta\right)\right].$$

The parameters are jointly identified from the demand and supply of the model. Price variations before and after the exit identify consumers' price coefficients. In addition, the random demand fluctuations create variations in remaining capacities, which shift firms' optimal prices through revenue management. These variations in prices will also help identify price coefficient. The mixture of consumer types is identified from violations of the IIA properties of simple logit demand. Temporal preference heterogeneity is identified by the temporal variations of high-frequency prices and quantities.

In many applications, market size M is directly observed. For instance, researchers set M for automobile and TV cable equal to the number of households in the whole population (Berry et al. (1995), Goolsbee and Petrin (2004)). When there is information in a number of markets, M can be parameterized as depending on market level data (Berry (1990), Berry and Jia (2010), Lazarev (2013)). In my setting, the number of potential air travelers could potentially affect my inference on market competition and welfare. It is unobserved by the researcher.[41] Informally, the current identification on market size can come from two sources. Firstly, the dependence of firms' optimal prices on remaining capacities helps identify market size. In addition, the current difference-in-differences research design also helps. [42]

[41]In a related dynamic setting, Nair (2007) looked at intertemporal price discrimination in monopoly video-game markets. Similarly, he does not assume the market size to be the whole population (all users for the game platform), otherwise, the relatively small sales would imply that the game has almost zero market share at any period.

[42]The change in relative sales in response to the change in relative prices across the two periods helps identify the price coefficient. This tells me the change of the utility for product 1 across the two periods. I

1.6 Results

1.6.1 Estimates

In this section, I discuss the estimates from the structural model. Table 1.3 – Table 1.6 report the estimates from the structural model. In particular, Table 1.3 shows consumers' preference parameters in the exit route. Table 1.4 shows consumers' preference parameters in the control route. Table 1.5 shows consumers' arrival rates and the distributions of their types for the two routes. Table 1.6 shows estimates on other common parameters for the two routes.

All the estimates are precise and significant at 1% level, suggesting that the model parameters are well identified by the data variations. The estimates seem intuitive. Early-arriving consumers' price coefficients are about three times bigger (in absolute value) than late-arriving ones. This confirms one's prior that late-arriving consumers are so-called "high types"' – less sensitive to prices. Figure 1.7 plots the estimated Possion arrival rates for the two routes. The upper graph is for the exit route and the lower one is for the control route. The different colors indicate the distribution of different consumer types. This distribution indeed changes over time. It suggests that Alaska has a relatively larger loyal segment in the exit route than in the control route. In reality, Alaska is the relatively bigger player in the exit route but the smaller one in the control route. This is also consistent with the observation that Alaska is the incumbent in the exit route but the newer firm in the control route. Estimates of the ratios of each player's loyal segments are consistent with their relative sales.

As shown in Figure 1.7, the estimated arrival patterns are similar for the two routes. On average, 4-7 travelers arrive at the market for a particular flight on a particular day. The number of arriving consumers is the lowest 3 weeks before departure. It then increases to its highest level just one week before departure. The estimated ratio of high-type travelers is increasing with time. In particular, in the exit route, the ratio of high-type travelers starts from close to 7% seven weeks before departure. It increases gradually to more than 80 percent one week before departure. In the last day, about 87% of the arriving travelers are high-type travelers. Meanwhile, in the control route, the ratio of high-type travelers starts at around 23 percent. It then gradually increases to around 60% just one week before departure. On the last day, the ratio of high-type travelers is around 85%. Figure 1.7 also summarizes the probability distribution of consumers' brand preferences conditional on the

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also observe the change of the share for product 1 across two periods, since it is inferred from the change of product 1's sales under the assumption that market size is constant. Thus I know (1) the change of the utility for product 1 (after identifying price coefficient); (2) the change of the utility for the outside option (equals zero by assumption); (3) the change of the share for good 1 (observed from sales); and I can infer the change of the share for the outside option. The absolute change of sales for the outside good is observed (from the absolute change of sales for the inside goods). This helps to infer market size. See the appendix illustrates more when demand is a simple logit.

arrival time. In the exit route, the incumbent firm Alaska has a larger loyal segment for both high-type consumers and low-type ones. 88% of high-type consumers prefer the incumbent firm Alaska to Delta, whereas 84% of low-type consumers prefer the incumbent firm Alaska to Delta. In the control market, 26% of high-type consumers and 38% of low-type consumers prefer the incumbent firm JetBlue. In both routes, Alaska seems to have relatively larger loyal segments than its opponents in high-type consumer segments.

The estimates on the firm-specific constant terms in the consumer utility function confirm that there is great heterogeneity in consumers' relative brand preferences. These estimates are reflected by firms' relative average price levels. On average, high type consumers have stronger brand preference than low type consumers, as measured by the amount of money that can induce an "average" consumer to switch. In the exit route, an average Alaska-leaning high-type consumers would pay an extra of \$457 to fly with their preferred provider Alaska instead of Delta. An average Delta-leaning high-type consumers would pay an extra of \$768 to fly with their preferred provider Delta instead of Alaska. These numbers suggest that high-type travelers' brand preferences are very strong. As a result, the competition in the late market is weak and the late market is close to monopoly – this is the reason why the exit had no effect on the prices one week before departure. On the other hand, in the control route, an average Alaska-leaning high type consumers would pay an extra of \$168 to fly with their preferred provider Alaska instead of JetBlue. It suggests that although Alaska has a larger loyal segment of high-type consumers, the average degree of loyalty is not very high. An average JetBlue-leaning high type consumers would pay an extra of \$678 to fly with their preferred provider JetBlue instead of Alaska.

The relative brand preference for leisure travelers differs substantially from only \$5 to as much as \$207. In the exit route, an average Alaska-leaning low-type consumer would pay an extra of \$100 to fly with their preferred provider Alaska instead of Delta; an average Delta-leaning low-type consumers would pay an extra of \$163 to fly with their preferred provider Delta instead of Alaska. In the control route, the low-cost carrier JetBlue dominates the low-type consumer segment. In fact, even the Alaska-leaning low type travelers are almost indifferent between Alaska and JetBlue – on average, it only takes \$5 to make them switch to JetBlue. On the other hand, JetBlue seems to have a "very loyal" low-type segment– on average it takes \$207 to make them switch to the opponent Alaska.

1.6.2 Competition

In this section, I zoom in on one route and investigate its competitive landscape in more detail.[43] Figure 1.8 shows the choice probabilities of the four segments choosing between Alaska and JetBlue. It is simulated using the empirical distribution of the initial capacities under the optimal dynamic pricing strategies. Loosely speaking, Alaska faces more competitive pressure than JetBlue. This is because Alaska's loyal segments have lower loyalty than

[43]For simplicity and for consistency with the counterfactual analysis, I focus the discussion on the control route. I conduct similar examination in the treatment route, and the insight is qualitatively similar.

JetBlue's in both the high-end and the low-end market.

Figure 1.8 also suggests that there is more substitution across firms in the middle periods than in the two ends. In the very early periods, consumers valuation is low and the firms try to fill in their capacities and price very low. It would be too costly for either one of them to price even lower in order to capture the opponent's consumers. There is some sense that they are competing more against the outside option than against the opponent. In the very late market, it would also be very costly to attack the competitor. The reason is different. Late market has so much "fat" that attacking the opponent aggressively would lose ones' own profit and thus is almost never optimal. Overall, both firms want to price high (low) in the late (early) market. However, in the middle market, the firm with more high-type consumers (Alaska) wants to increase its price, and the firm with more low-type consumers (JetBlue) wants to keep its low price. The price gap becomes large and it induces more substitution across firms. Figure 1.9 shows the ratio of consumers who choose JetBlue among all Alaska's consumers who buy tickets. It shows that the ratio of Alaska's consumers who choose JetBlue over Alaska changes as the departure date approaches. The ratio is relatively low in the early market. It increases in the middle market as the price gap between the two firms becomes wider. It decreases to the lowest level when JetBlue also jacks up its price in the late market.

Figure 1.10 shows own price elasticity and industry elasticity (in absolute values) using the empirical distribution of capacities. The elasticities are evaluated at the optimal dynamic prices. Own demand elasticity is defined as the percentage change of own sales with respect to a one percentage change in own price. Industry demand elasticity is defined as the percentage change of industry sales when both firms increase their prices by one percentage. The estimated values are consistent with previous literature. The commonly cited Gillen et al. (2003) suggests that airline travel demands elasticity ranges from 0.181-2.01 with a median of 1.3 for a sample of 85 city-pairs. Previous literature also points out that demand in long-haul routes like the current one is less elastic. The median own demand elasticity of long-haul domestic leisure consumer is 1.228. Similarly, my estimates range from 1-1.4.

My result also highlights the intertemporal variations in elasticity. Own demand elasticity decreases as departure date gets closer. Industry demand elasticity also decreases over time. It starts from just below 1 7 weeks before departure and starts to drop substantially at 3 weeks to departure. This confirms the belief that the demand in the late market is very inelastic. The gap between own demand elasticity and industry demand elasticity is informative. It suggests that the firms would collectively benefit if they can increase their prices together since the industry demand is much less elastic.

1.6.3 Fitting

Figure 1.19 shows the fitting errors in percentage for all the 469 moments. The mean fitting error in percentage is 11.5%. This suggests that the data can be reasonably well explained by the structural model. Figure 1.20 compares the model predicted price paths with their empirical counterparts conditional on the 2-by-2 treatment conditions. It suggests that the model captures the upward-slopping trend for prices. The estimates also reflect the relative price levels between firms. Moreover, the model captures differences across the 2-by-2 treatment conditions. It fits reasonably well the changes in prices caused by the change in market structure in the exit route. This is presented in Figure 1.6.

1.7 Counterfactuals

I present some results of my counterfactual simulations. The discussion focuses on the route where Alaska competes against the low-cost carrier JetBlue. Under my previous assumption of myopic consumers, the estimated arrival patterns would not change when airlines' pricing policies change. This remains reasonable because in the equilibrium for each of the scenarios I consider below, the expected price path does not decrease as departure date approaches (in fact, it strictly increases except for the constant pricing regime). To reduce unnecessary computation, I fix unobserved demand errors ξ and supply errors ω at zero and focus on isolating other forces.

I study how dynamic pricing affects airlines' profits and consumer welfare. I consider possible policy interventions that fix admissible pricing policies. By comparing different pricing regimes I single out the effects of different dynamic pricing techniques such as price discrimination and revenue management. Let c_0 be firms' initial capacities. In this exercise, I use the empirical distribution of capacities at period 0 (i.e., 49 days before departure). I assume that this distribution of capacities is exogenous.[44] I consider the following three different pricing regimes.

1. *Static pricing* Each firm j can only charge a constant price $p_j \in \mathcal{R}^+$. They choose p_j simultaneously at period 0 before any realization of demand uncertainty. They (know that both of them) cannot change prices later on. In equilibrium, their prices are mutual best responses that maximize own expected profits given the opponent's strategy. The expectation is taken over all future demand uncertainty.

$$p_j^* = \text{argmax}_{p_j \in \mathcal{R}^+} \mathbb{E}_0 \left[\sum_{t=0}^{T} \Pi_j^t \left(p_j, p_{-j}^*, \boldsymbol{c}_t \right) \middle| p_{-j}^*, \boldsymbol{c}_0 \right], \quad j = 1, 2.$$

   The equilibrium constant prices are the fixed points (p_1^*, p_2^*). Define V_j^{CST} as the total expected discounted profit in the constant-pricing equilibrium.

2. *Fixed-path pricing* Firms can set prices conditional on the number of days to departure. At period 0, each firm submits a price policy that is a function of the number of days

[44] Ideally, one can start to keep track of a flight once it opens up to sale. This requires a horizon of more than 300 days and is impractical. Another practical approach is to collapse all the periods more than 49 days before departure into one "big" period. As long as the "big" period fits well with the empirical data, the amount of demand uncertainty 49 days before departure shall be similar with my current treatment. Thus it will not change the current result qualitatively. As a robustness check, it will come in the next version of the paper.

to departure:

$$g_j^{\mathrm{CMT}} : \underbrace{T}_{\text{time to departure}} \rightarrow \underbrace{\mathcal{R}^{+}}_{\text{current price}} .$$

The two firms (know that both of them) cannot deviate from their price policies. In equilibrium, their price policies are mutual best responses that maximize own expected profits given the opponent's strategy. The expectation is taken over all future demand uncertainty.

$$g_j^{\mathrm{CMT}*} = \operatorname{argmax}_{g_j^{\mathrm{CMT}}} \mathbb{E}_0 \left[\sum_{t=0}^{T} \Pi_j^t \left(g_j^{\mathrm{CMT}}(t), g_{-j}^{\mathrm{CMT}*}(t), \boldsymbol{c}_t \right) \middle| g_{-j}^{\mathrm{CMT}*}, \boldsymbol{c}_0 \right], \quad j = 1, 2.$$

The equilibrium price policies are the fixed points $\left(g_j^{\mathrm{CMT}*}, g_j^{\mathrm{CMT}*}\right)$. Define V_j^{CMT} as the total expected discounted profit in the equilibrium of fixed-path pricing.

3. *Full dynamic pricing* Firms can set prices conditional on the number of days to departure and can adjust prices based on each other's cumulative sales (or remaining capacities). At period 0, each firm submits a price policy that is a function of the number of days to departure and the remaining capacities of both players:

$$g_j^{\mathrm{DYN}} : \underbrace{T}_{\text{time}} \times \underbrace{C^J}_{\text{capacities}} \rightarrow \underbrace{\mathcal{R}^{+}}_{\text{current price}} .$$

This game is subgame perfect. In equilibrium, firms' price policies are mutual best responses that maximize own expected profits given the opponent's strategy. The expectation is taken over all future demand uncertainty.

$$g_j^{\mathrm{DYN}*} = \operatorname{argmax}_{g_j^{\mathrm{DYN}}} \mathbb{E}_0 \left[\sum_{t=0}^{T} \Pi_j^t \left(g_j^{\mathrm{DYN}}(t, \boldsymbol{c}_t), g_{-j}^{\mathrm{DYN}*}(t, \boldsymbol{c}_t), \boldsymbol{c}_t \right) \middle| g_{-j}^{\mathrm{DYN}*}, \boldsymbol{c}_0 \right], \quad j = 1, 2.$$

The equilibrium price policies are the fixed points $\left(g_j^{\mathrm{DYN}*}, g_j^{\mathrm{DYN}*}\right)$. Define V_j^{DYN} as the total expected discounted profit in the equilibrium of full dynamic pricing.

1.7.1 Price Discrimination

The estimates show that late-arriving consumers are indeed less price sensitive. Thus airlines charge higher prices in the late market to price discriminate against these high-valuation consumers. The existing theoretical work shows that under competition price discrimination has ambiguous effects on consumer welfare and firms' profits. In this section, I empirically quantify these effects. In particular, I consider two relevant policy interventions. In the first scenario, airlines can only charge constant prices over time. In the second one, airlines can charge time-dependent prices. By comparing these two, I single out the effects of price discrimination.[45]

Figure 1.11 compares the optimal fixed price paths with the optimal constant prices. Not surprisingly, each airline's optimal constant price lies in between its highest and lowest discriminatory prices. Specifically, Alaska charges \$450 and JeBlue charges \$319. The \$131 price gap suggests that the airlines are vertically differentiated under constant pricing. JetBlue keeps a low price and sells mostly to low valuation consumers. Alaska focuses on high valuation consumers by charging a high price. This pattern is driven by the fact that JetBlue has bigger market power in the segment of low type consumers whereas Alaska has bigger market power in the segment of high type consumers.

In the fixed-path pricing scenario, Alaska's price starts from \$366 seven weeks before departure. It quickly increases to \$415 around six weeks before departure. It rises above Alaska's constant price around two weeks before departure. JetBlue's fixed price path starts at \$288 seven weeks before departure. It stays roughly at this level and increases slowly over time. Until around two weeks before departure, JetBlue's price jumps to around \$600 for the last two weeks before departure. In my numerical analysis, I find that under price commitment, firms' optimal price paths always converge to "step functions". The result is robust and stable – A firm charges a low price in the early periods and increases its price slowly over time. Then at a certain point, the firm increases its price substantially. This jump in price is especially interesting since the consumers' distribution is "smooth" in time. Indeed, this pattern disappears under full dynamic pricing – the average price paths under full dynamic pricing are smooth.

More than two weeks before departure, constant prices are lower than fixed price paths. This reflects that price discrimination intensifies price competition in the low-end market. The price gap between the two firms looks similar with and without price discrimination. Within the last two weeks before departure, JetBlue raises its price substantially in order to extract more profit from its high valuation consumers. Its price is even higher than Alaska's. This is because although JetBlue has a smaller high-type loyal segment than its opponent, its high-type consumers are more "loyal" (willing to pay more for its tickets). In the late market, both airlines price higher under price discrimination than under constant pricing. All in all, price discrimination softens competition in the late market because of airlines' collective incentives to jack up prices in the late market.

Figure 1.12 shows the airlines' sales paths under constant pricing and under price discrimination. Alaska sells more seats under price discrimination. Figure 1.12 shows that the incremental sales of Alaska under price discrimination mainly comes from the late market. Interestingly, Alaska prices higher in the late market under price discrimination than under constant pricing. This is because price discrimination softens competition – under price discrimination, the airlines collectively raise their prices in the late market. After JetBlue

[45]Strictly speaking, when firms are able to charge time-dependent prices, their prices would also account for the time value of a seat. I performed similar analysis when assuming away the capacity constraint. The result is similar– price discrimination shifts a substantial amount of consumer welfare to industry profit.

jacks up its price in the late market, Alaska-leaning high-type consumers who choose JetBlue under constant pricing find it less appealing. Some of them switch back to Alaska (industry demand elasticity is relatively low).

In addition, price discrimination causes a misallocation of seats. More seats are allocated to low valuation consumers under price discrimination than under constant pricing. The left panel of Figure 1.12 shows that under price discrimination JetBlue allocates more seats to the early market and allocate fewer seats to the late market.

Table 1.7 summarizes the change of consumer welfare by consumer segments. Consistent with the standard intuition of price discrimination, high-type consumers suffer from price discrimination. The welfare of Alaska-leaning high-type consumers decreases by -9.7%. The welfare of JetBlue-leaning high-type consumers decreases by -12.9%. Although low-type consumers' welfare increases substantially in percentage, their monetary gain is much smaller than the monetary loss of high valuation consumers. Overall, consumer welfare decreases by -9.4%.

Meanwhile, the airlines' revenues increase considerably. Table 1.8 shows that Alaska's revenue increases by +\$1567.38 per flight, which amounts to +13.6% of its total revenues. JetBlue's revenue increases by +\$1155.57 per flight, which amounts to +6.2% of its total revenues. These gains in revenue are significant comparing to the magnitudes of airlines' margins. According to IATA, airlines' margin is around 8% of its revenue in the past three years.[46] Thus, my estimates suggest that the amount of gains in profit from price discrimination is substantial.

Overall, price discrimination is aligned with airlines' collective incentives to raise prices in the late market. It softens competition and helps airlines extract more consumer surplus. As a result, social welfare decreases by -1.6%, or $-\$1135.16$.

1.7.2 Revenue management

The estimates suggest that air travel demand is uncertain and can fluctuate substantially. Therefore, revenue management (pricing on remaining capacities) may have significant welfare implications. This exercise attempts to single out the effect of revenue management. To do so, I compare two pricing regimes– full dynamic pricing and fixed-path pricing. Under full dynamic pricing, the airlines are able to adjust prices based on remaining capacities. Under fixed-path pricing, the airlines submit their pricing policies at period zero, and cannot change their prices regardless of how good or bad their sales turn out to be. This removes the airlines' ability to smooth the impacts of demand fluctuations on capacity utilization.

Figure 1.13 compares the fixed pricing paths with the average price paths under full dynamic pricing. When the airlines cannot adjust prices conditional on remaining capacities, they increase prices in the early periods. The effect is especially strong for Alaska. This is because Alaska has a large segment of high valuation consumers and many of them arrive late.

[46]Globally, the numbers are 4.6% 8.5%, 8.8%,7.5% for 2014-2017. These recent numbers are much higher than historical numbers. In general, the North American airlines' margins are higher than average.

When revenue management is turned off, Alaska raises its price substantially in the early market to save seats for its late-arriving high type consumers. To highlight this incentive, Figure 1.14 shows that if each firm were to commit to its average price path of full dynamic pricing, Alaska would be twice more likely to sell out all its seats comparing to the case when each firm commits on its optimal fixed price path. Thus, low price in the early market hurts Alaska, since it increases the probability of selling out all seats. Figure 1.15 shows the sales path under the two pricing regimes. It suggests that Alaska indeed tries to reserve more seats for its high valuation consumers. Its sales decrease in the early market but do not change much in the late market.

Figure 1.16 shows the probability of selling out with and without revenue management. Under revenue management, the airlines are able to raise their prices when they are selling out too soon. Therefore, the probability of selling out all the seats early on is very low. Without revenue management, the probability of selling out all the seats very early on becomes nontrivial. Figure 1.16 shows that without revenue management JetBlue is twice more likely to sell out all its seats before departure. In particular, there is a positive probability that JetBlue may sell out all its seats one month before departure.

Table 1.9 summarizes the effect of revenue management on consumer welfare. It shows that revenue management increases welfare substantially for all the four consumer segments. This result is driven by two effects: lower prices and higher supply. The two consumer segments that benefit the most from revenue management are Alaska's high type consumers and JetBlue's low type consumers. JetBlue's low type consumers benefit from lower prices in the early market. Alaska's high type consumers benefit from higher supply because revenue management allows Alaska to manage capacity more efficiently. These "extra" seats are allocated to consumers in the early market.

Table 1.10 shows that overall consumer welfare increases by a substantial 14.4%. Interestingly, firms' revenues change little under revenue management. This is the result of two competing forces. On one hand, airlines manage their capacities more efficiently. This enables the firms to expand the market and sell to more consumers. On the other hand, this incentive intensifies price competition in the early market. The extra seats that the airlines can supply to the market are sold at low prices. Overall, the positive effect of increased sales is canceled out by the negative effect of intensified competition.

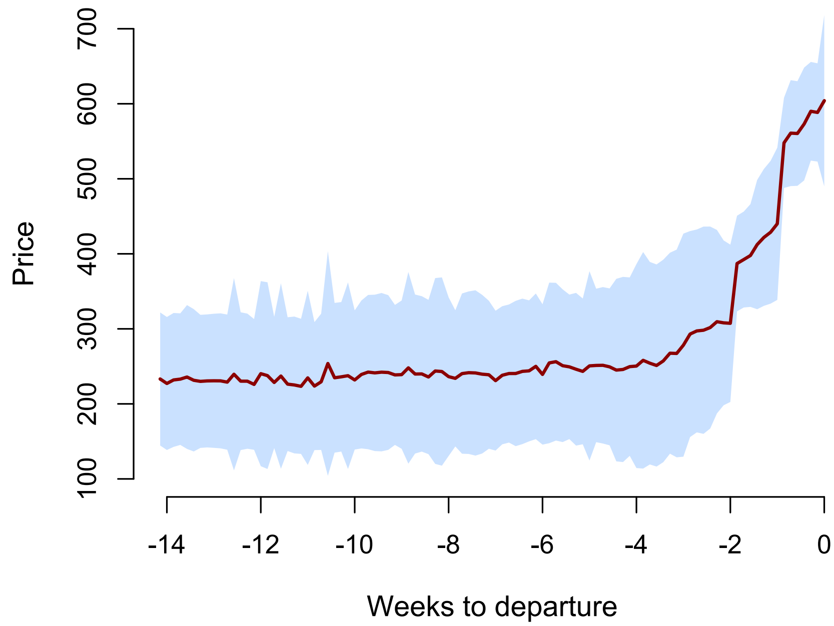
1.8 Conclusion

The digitalized marketplace allows firms to monitor demand and supply in real time and to continuously re-price. Dynamic pricing has become a common practice in many industries. Under competition, the effect of dynamic pricing is unclear due to the prisoner's dilemma. This paper empirically investigates the competitive effects of dynamic pricing in the context of oligopolistic airline markets. I develop a dynamic oligopoly model where firms sell limited capacities under demand fluctuations. I estimate the model and show that (i) price discrimination softens competition in the high-end market and increases profits substantially and

(ii) revenue management (pricing on remaining capacities) intensifies competition and does not increase profits.

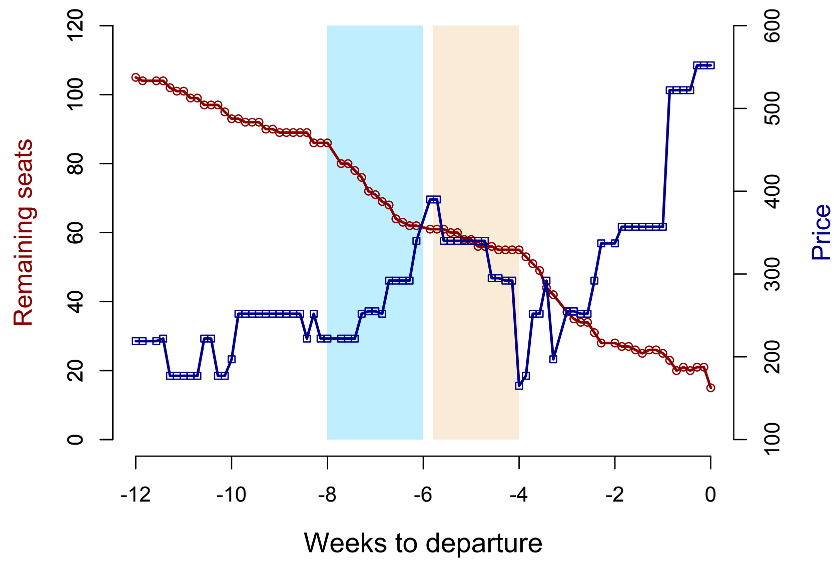
Future research may look at the competitive effect of information sharing. The current paper abstracts away from strategic information sharing, although the fixed-path pricing can be viewed as an extreme case when all demand information is turned off. In addition, endogenizing capacity choices may also yield interesting results.

1.9 Figures



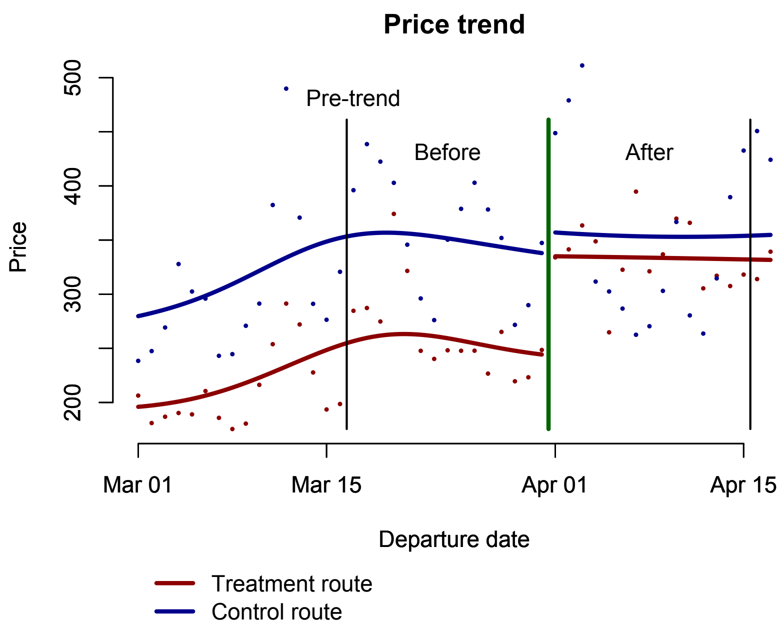
This grahp shows average price path for JetBlue Flight 19, which departed from March 01, 2016, to June 01, 2016. The red line shows average price conditional on the number of days to departure. The light-blue area shows one standard deviation of prices.

Figure 1.1: Average price path: an example



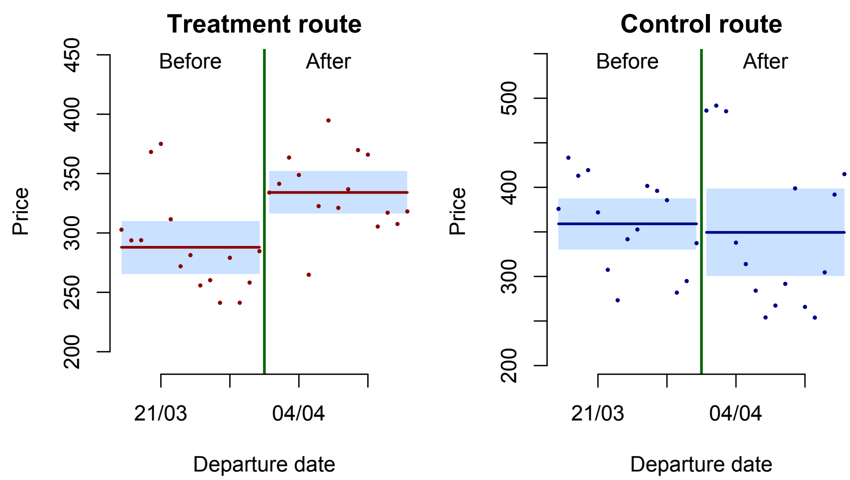
This grahp shows the history of prices and remaining seats for a particular flight – JetBlue Flight 19, which departed on March 25 2016. The red line shows the path of remaining seats. The blue line shows the path of prices. The shaded regions highlight some suggestive evidence of revenue management. In the light-blue area, seats were sold out quickly (the red line with circles dropped quickly), then the price (the blue line with squares) was increased. In the light-yellow area, seats were sold out slowly (the red line with circles was flat), then the price (the blue line with squares) dropped.

Figure 1.2: Data on price and remaining capacity: an example



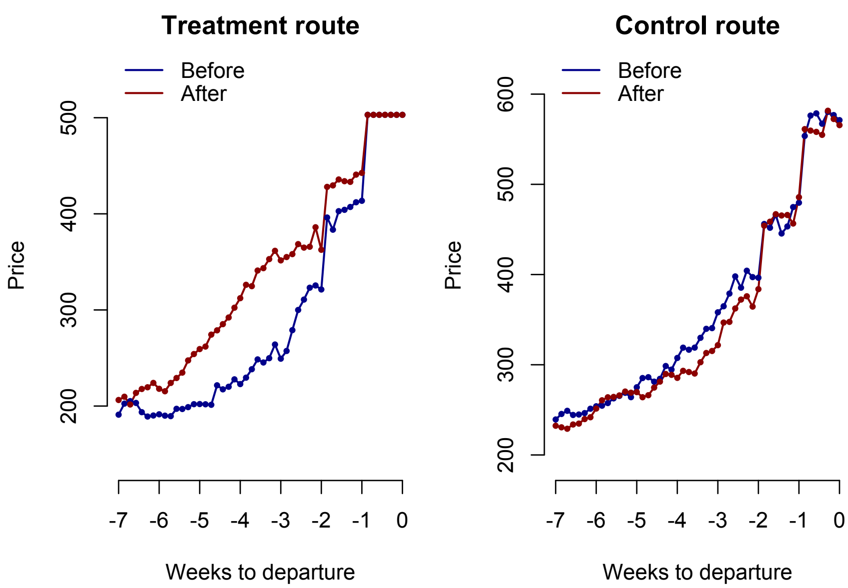
This graph provides suggestive evidence that the trends in average prices were parallel across the treatment route and the control route. Each dot is an average price for flights departing on a given departure date in a given route. It is averaged over $N = \#\text{firms} \times \#\text{directions} \times \#\text{pricing-dates}$ observations of prices. Each line is smoothed using Guassian kernels. Before March 31, 2016, price gaps were stable over time across the two routes. The gap changed after Delta's exit. Route-level mean prices increased substantially in the exit route but did not change as much in the control route.

Figure 1.3: Parallel trend in average price for the treatment route and the control route before the exit event (local difference-in-differences design)



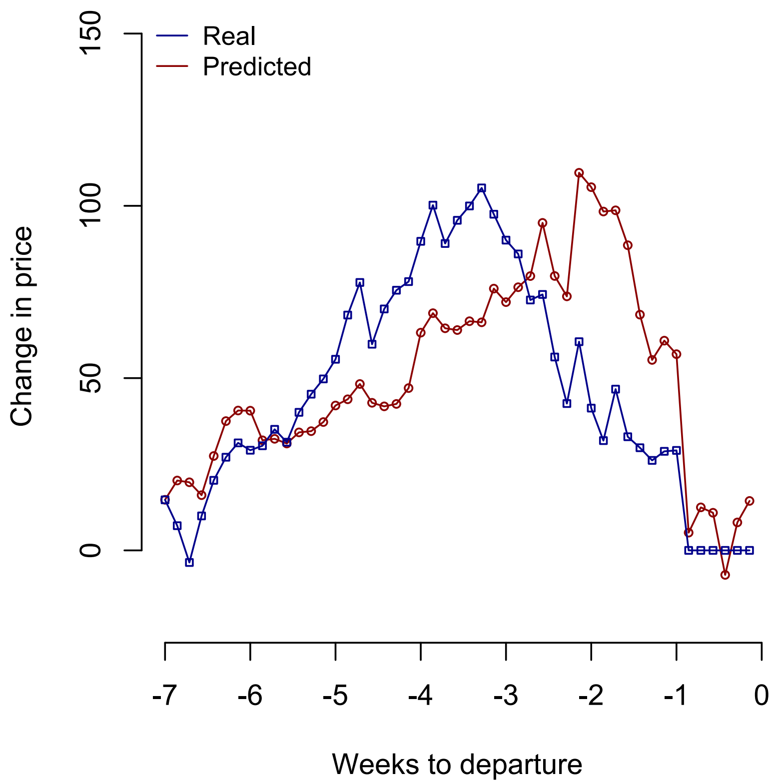
This graph singles out Alaska's price response to Delta's exit. It compares Alaska's average prices under the 2-by-2 treatment conditions. Alaska raised its price significantly only in the route where its competitor exited. Each dot is an average price for flights departing on a given departure date in a given route. It is averaged over $N = \#\text{directions} \times \#\text{pricing-dates}$ observations of prices. The light blue areas are at 95% confidence interval (N=15, i.e. the number of departure dates).

Figure 1.4: Treatment effect on Alaska's mean price (regression discontinuity design)



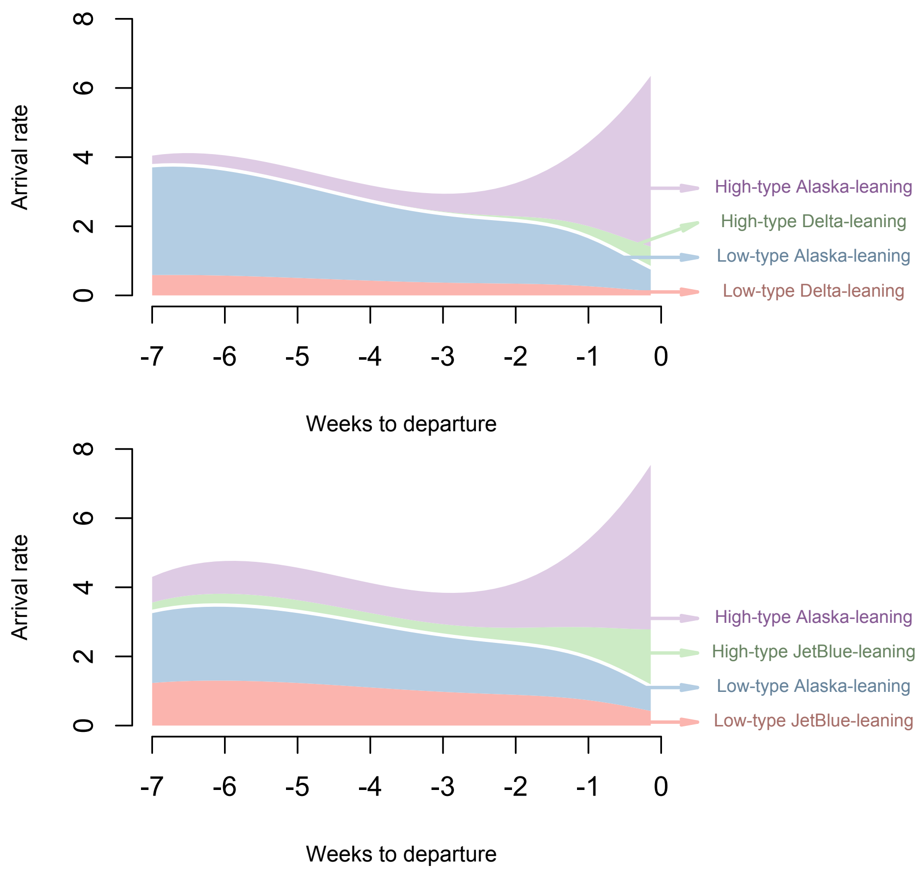
The graph shows Alaska's average price paths under the 2-by-2 treatment conditions. It illustrates heterogeneous treatment effects across different numbers of days to departure. Each dot is an average price for flights departing under a given condition for a given number of days to departure. It is averaged over $N = \#\text{directions} \times \#\text{departure-dates}$ observations of prices.

Figure 1.5: Heterogeneous treatment effects on Alaska's average price path



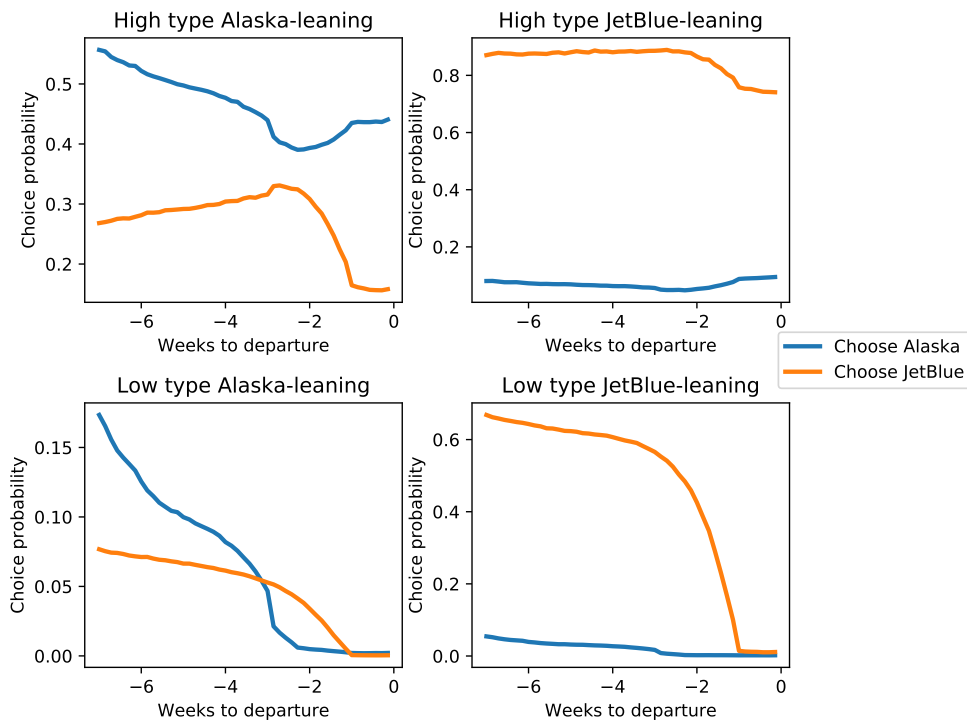
Note: This graph shows how Delta's exit affects Alaska's price. The blue line with squres is the change in prices observed in the data. The red line with circles is the change in prices predicted by the model.

Figure 1.6: Effect of exit on Alaska's price: predicted vs real



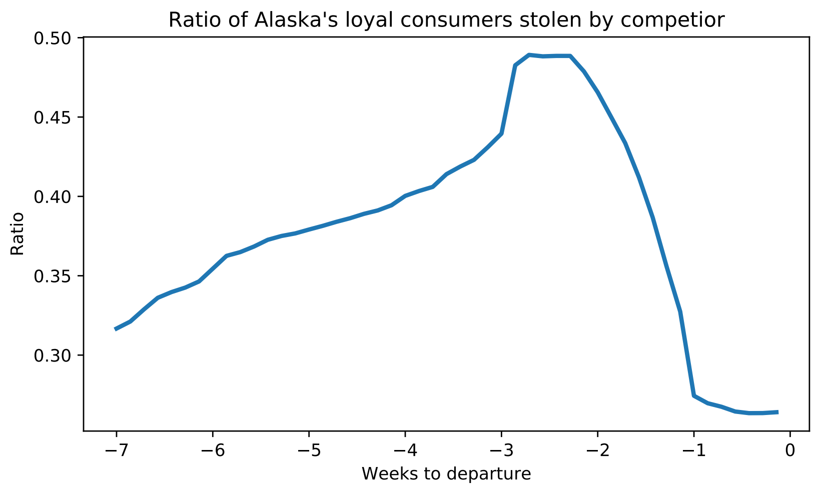
Note: The graph plots Poisson arrival rates for different segments of consumers in the two routes. The upper graph shows the arrival distribution in the exit route. The lower graph shows the arrival distribution in the control route.

Figure 1.7: Estimated arrival by consumer segments



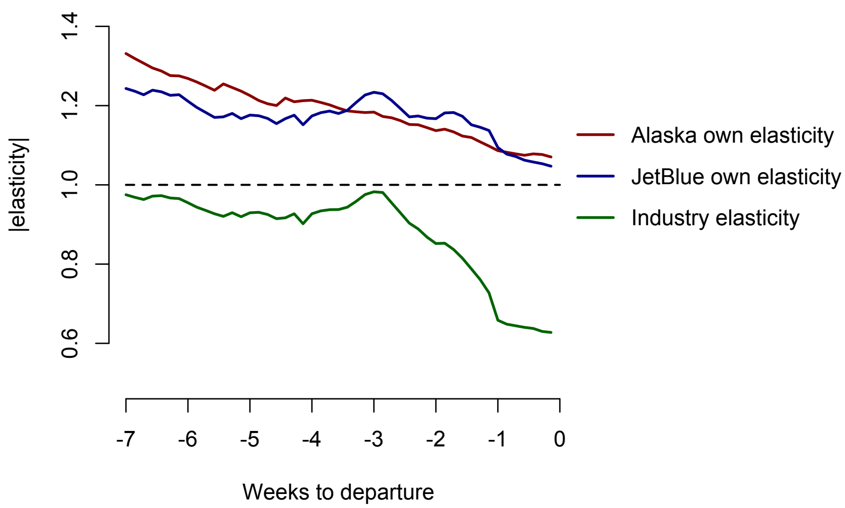
Note: This graph shows how estimated choice probabilities change over time by consumer types in the control route. The blue line shows the probability of choosing Alaska and the red line shows the probability of choosing JetBlue.

Figure 1.8: Estimated choice probability by segments



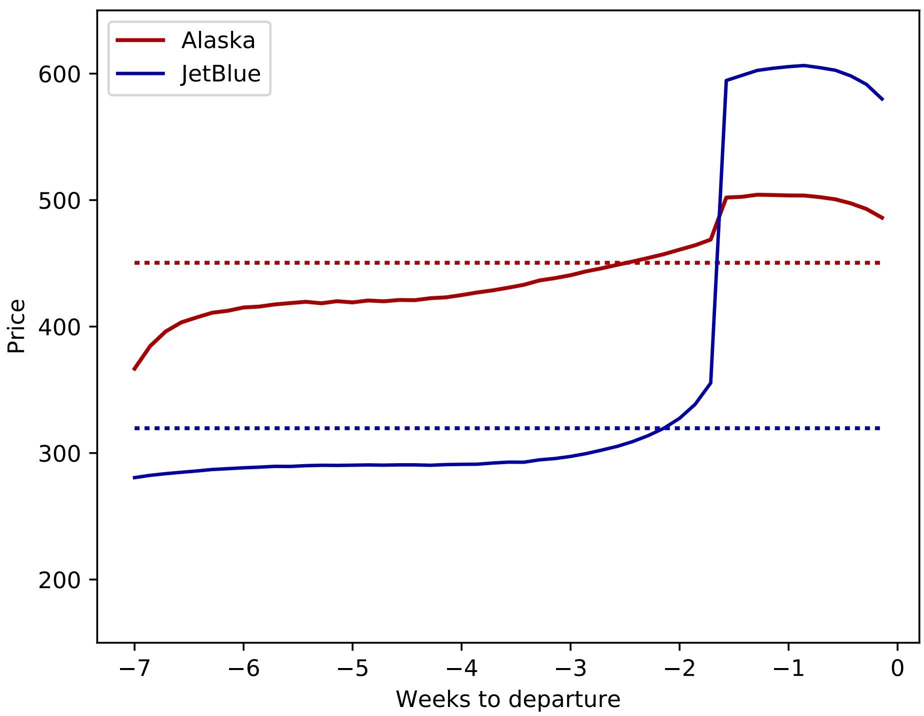
Note: This graph shows the ratio of consumers who choose JetBlue among all Alaska's consumers who buy tickets. It is calculated as the number of Alaska's consumers that choose JetBlue divided by the number of Alaska's loyal consumers that choose inside options. For example, 7 weeks before departure around 32% of Alaska-leaning consumers who buy tickets choose the oppennet. The ratio is low in the two ends.

Figure 1.9: Business stealing by number of days to departure



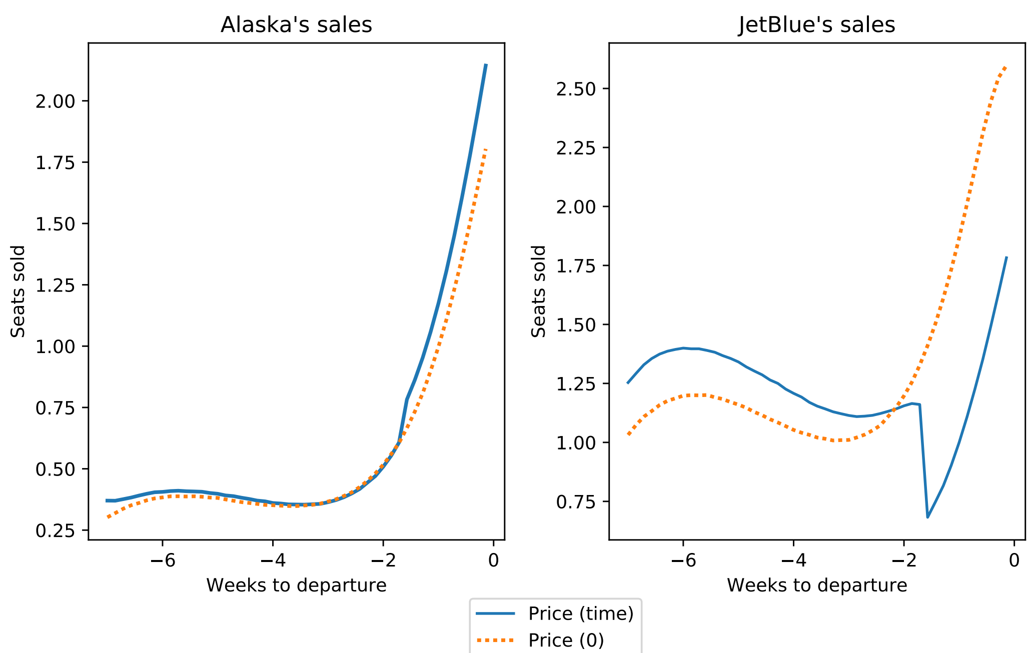
Note: This graph shows own price elasticity and industry elasticity (in absolute values) using the empirical distribution of capacities. The elasticity is evaluated at the optimal dynamic prices. Own demand elasticity is defined as the percentage change of own sales with respect to one percentage change in own price. Industry demand elasticity is defined as the percentage change of industry sales when both firms increase their prices by one percentage.

Figure 1.10: Estimated elasticities



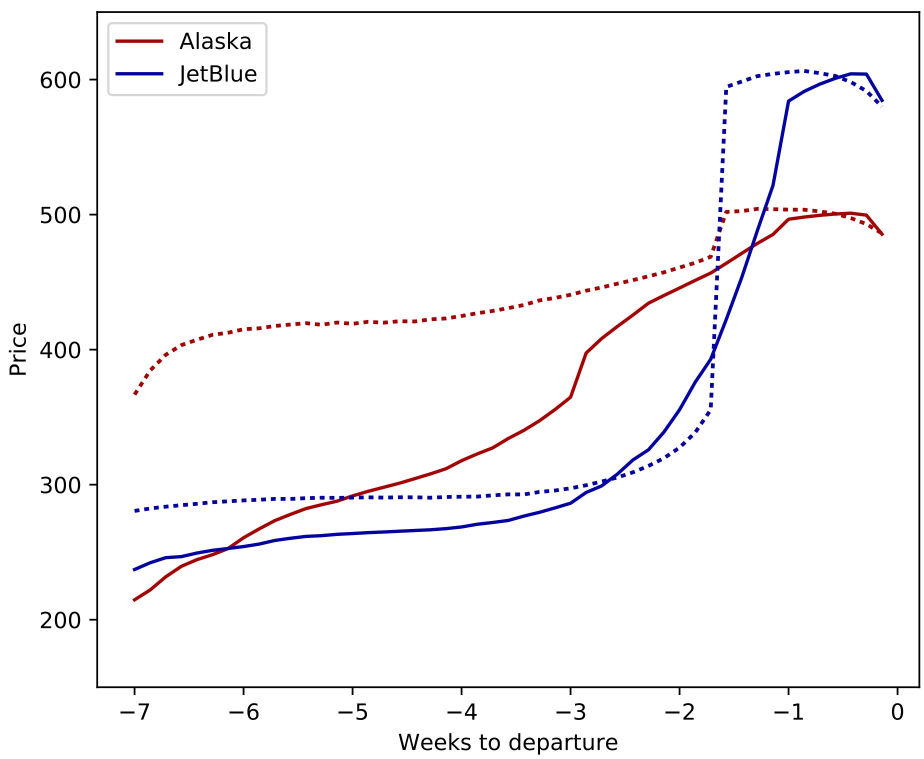
Note: This graph compares the case of fixed-path pricing with the case of constant pricing. The solid lines are optimal fixed price paths and the the dashed lines are optimal constant prices. Alaska's prices are in red, and JetBlue's prices are in blue.

Figure 1.11: Constant price vs price on time only



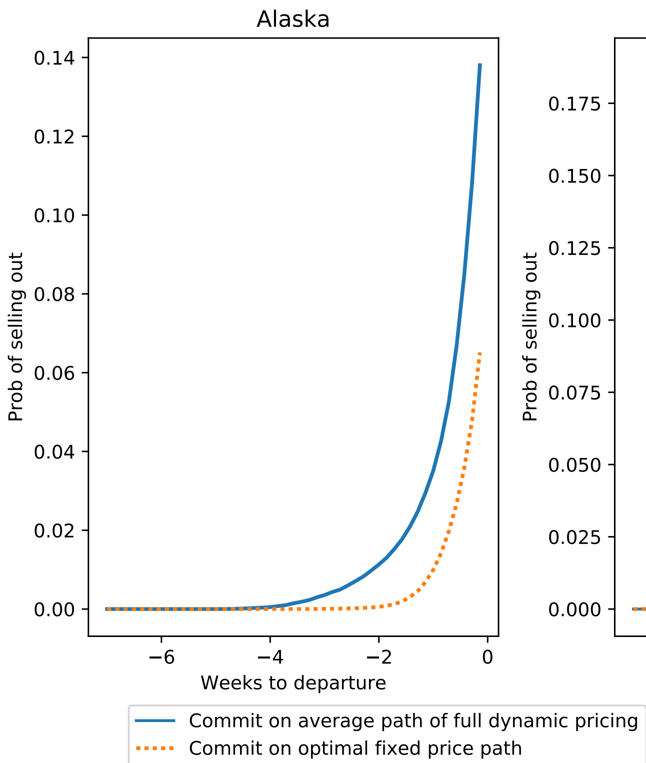
Note: this graph shows the average number of seats sold each day as departure date approaches. The solid line (blue) is for the case of fixed price path. The dashed line (yellow) is for the case of constant pricing. The left panel is for Alaska, and the right panel is for JetBlue.

Figure 1.12: Sales: constant price vs price on time



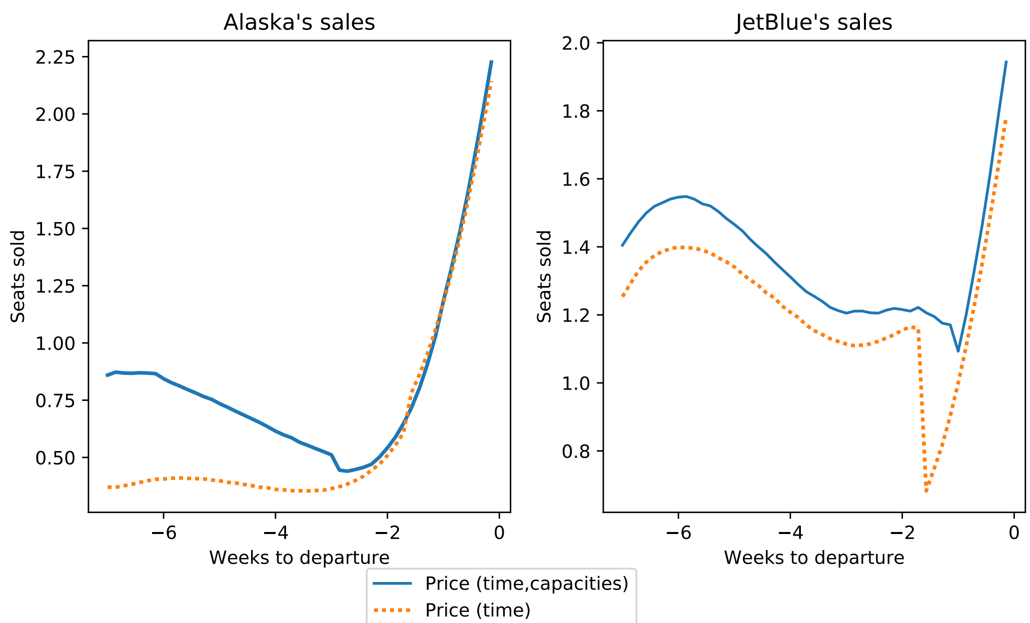
Note: This graph compares the case of full dynamic pricing (with revenue management) with the case of fixed-path pricing (without revenue management). The solid lines are average price paths under full dynamic pricing and the the dashed lines are optimal fixed price paths. Alaska's prices are in red, and JetBlue's prices are in blue.

Figure 1.13: Pirce on time and capacities vs price on time only



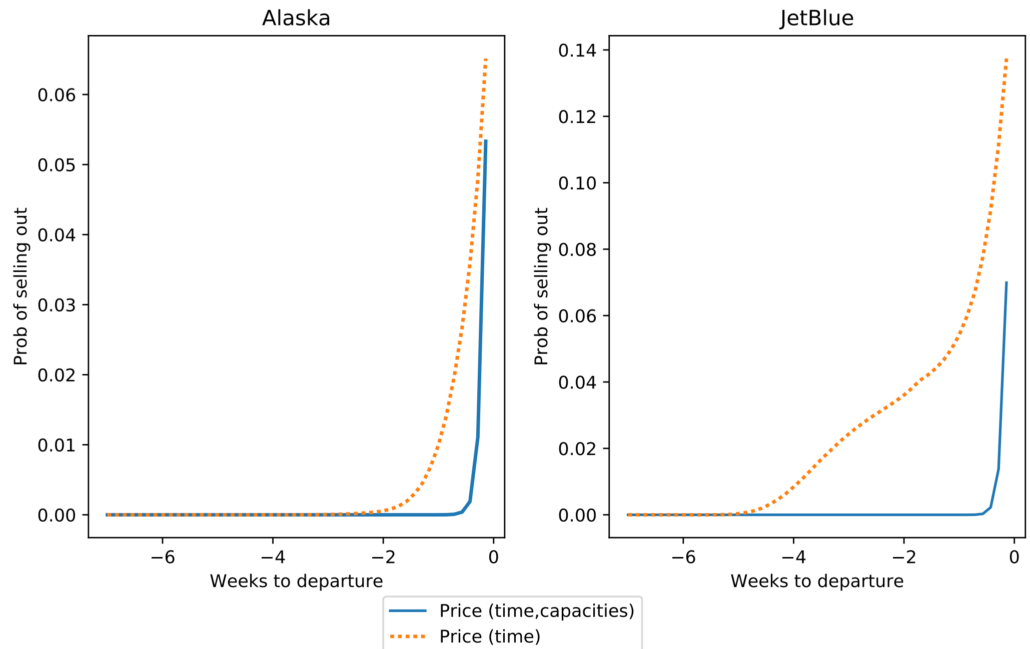
Note: This graph shows the probability of selling out all seats under fixed-path pricing. It compares the case when firms commit on optimal price path (yellow-dashed) with the case when they commit on average price path of full dynamic pricing (blue-solid). Alaska is on the left, and JetBlue is on the right.

Figure 1.14: Probability of selling out all seats: commit on optimal fixed price path vs commit on average price path of full dynamic pricing



Note: this graph shows the average number of seats sold each day as departure date approaches. The solid line (blue) is for the case of full dynamic pricng (with renvenue management). The dashed line (yellow) is for the case of fixed-path pricing (without revenue management). The left panel is for Alaska, and the right panel is for JetBlue.

Figure 1.15: Sales: price on time and capacities vs price on time



Note: This graph shows the probability of selling out all seats. It compares the case of full dynamic pricing (blue-solid) with the case of fixed-path pricing (yellow-dashed). Alaska is on the left, and JetBlue is on the right.

Figure 1.16: Probability of selling out all seats: price on time and capacities vs price on time

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▶<div class="seat seat-core right regularSeat occupiedSeat" title="07C" style="left:189px;top:335px;">…</div>
▶<div class="seat seat-core left regularSeat occupiedSeat" title="07D" style="left:274px;top:335px;">…</div>
▶<div class="seat seat-core mid regularSeat availableSeat" style="left:317px;top:335px;" id="plane_seat_7E" title="07E">
…</div>
▶<div class="seat seat-core right regularSeat occupiedSeat" title="07F" style="left:360px;top:335px;">…</div>
▶<div class="seat seat-core left regularSeat occupiedSeat" title="08A" style="left:103px;top:377px;">…</div>
▶<div class="seat seat-core mid regularSeat availableSeat" style="left:146px;top:377px;" id="plane_seat_8B" title="08B">
…</div>
▶<div class="seat seat-core right regularSeat occupiedSeat" title="08C" style="left:189px;top:377px;">…</div>
▶<div class="seat seat-core left regularSeat occupiedSeat" title="08D" style="left:274px;top:377px;">…</div>
▶<div class="seat seat-core mid regularSeat occupiedSeat" title="08E" style="left:317px;top:377px;">…</div>
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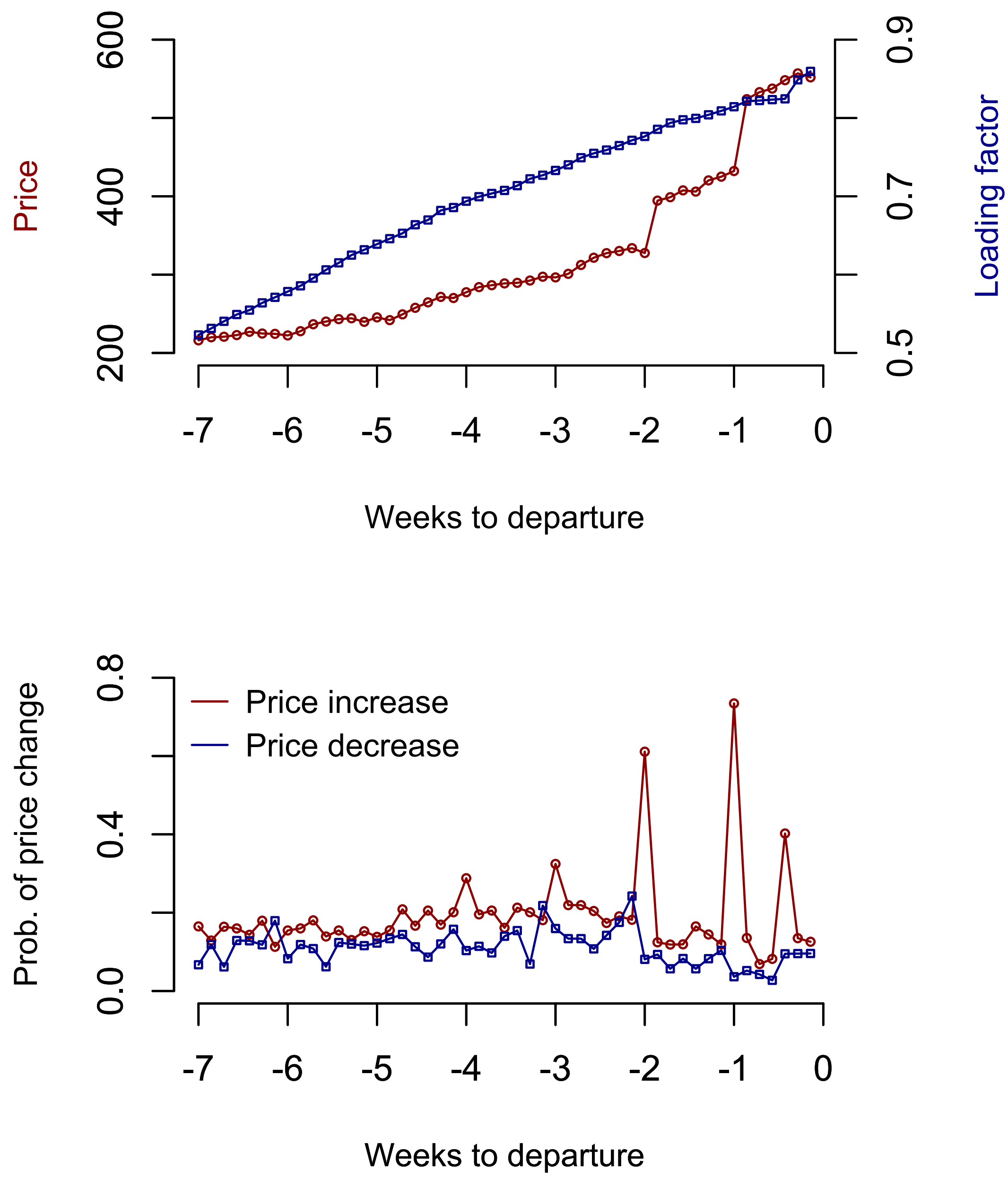
"plane_seat_9A" title="09A">…</div>
▼<div class="seat seat-core mid regularSeat availableSeat" style="left:146px;top:419px;" id="plane_seat_9B" title="09B">
```

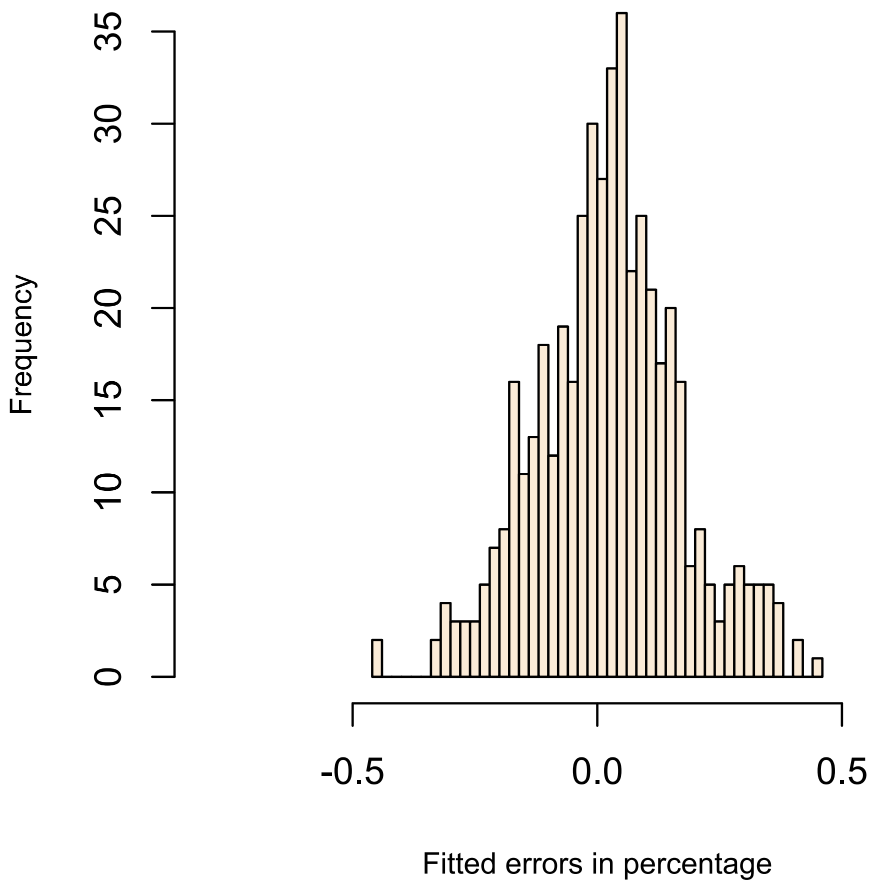
Note: this graph shows a screenshot of some source codes of one major airline. From these data, one can learn the price, the characteristics and the status of each individual seat for a particluar flight at any point in time. It is the information source for seat maps.

Figure 1.17: Source code from an airline's official website



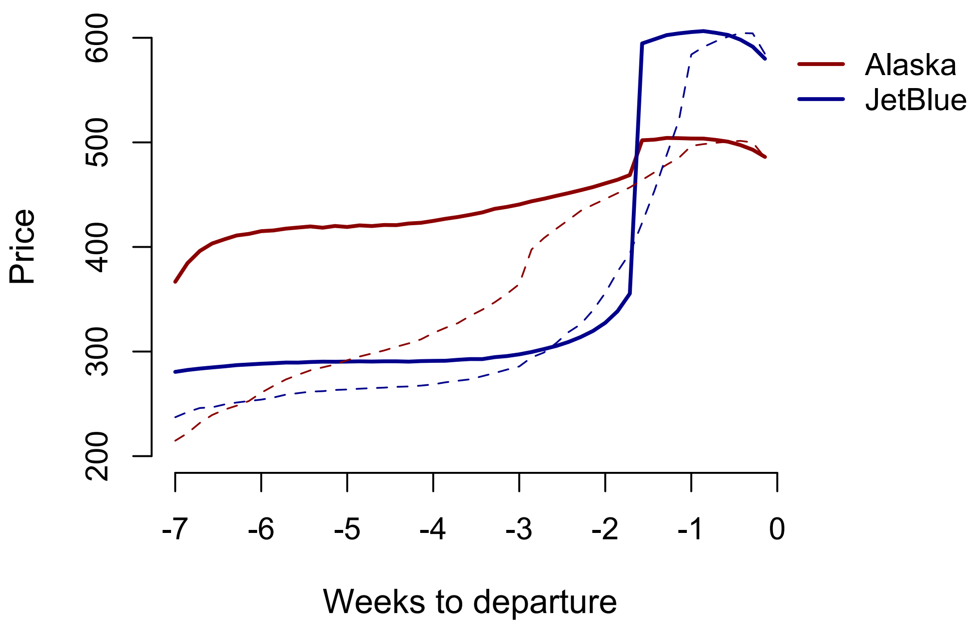
Note: this graph shows the dynamic patterns for prices and sales. The upper graph shows the average paths for price (red-circle) and loading factor (blue-square). The lower graph shows the probability of a price hike (red-cirlce) or drop (blue-square) in a given day.

Figure 1.18: Dynamic patterns for prices and sales (estimation data)



Note: this graph shows the fitting errors for the GMM. It is calculated as the absolute value of the residuals divided by their empirical means.

Figure 1.19: Fitted error for all (469) moments



Note: this graph compares the model predicted prices with the real prices conditional on the number of days to departure. It is organized by the 2-by-2 research design. The dashed lines are model predicted prices and the solid lines are the observed prices.

Figure 1.20: Fitted price path

1.10 Tables

Table 1.2: Estimation data summary

Statistic	Mean	Median	St. Dev.
Observations (N=10,290)			
Price ($)	310.51	268.00	154.63
Number of seats sold daily	1.11	0	1.87
Price change ($)	+7.49	0	62.03
Products (N=210)			
Capacity	64.27	64.00	23.28
Average total sales	47.39	46.00	21.12
Load factor	0.85	0.87	0.08
Gini coefficient	0.21	0.22	0.08

Notes:

1. Market: directional city pair×departure date. (N=4×30=120)
2. Product: market×firm. (N=120×1.75=210)
3. Observation: product×pricing date. (N=210×49=10,290)

Table 1.3: Consumers' preferences in the exit route

	Estimates	
	High type	Low type
Price coefficients	-0.556	-1.528
	(0.007)	(0.019)
Alaska's consumers' preference to		
Alaska	2.578	1.649
	(0.042)	(0.072)
Delta	0.035	0.121
	(0.085)	(0.042)
Delta's consumers' preference to		
Alaska	0.131	0.323
	(0.065)	(0.091)
Delta	4.400	2.820
	(0.049)	(0.060)

Note: Price coefficients on $100.

Table 1.4: Consumers' preferences in the control route

	Estimates	
	High type	Low type
Price coefficients	-0.383	-1.535
	(0.001)	(0.009)
Alaska's consumers' preference to		
Alaska	1.077	0.821
	(0.010)	(0.017)
Jetblue	0.434	0.741
	(0.009)	(0.009)
JetBlue's consumers' preference to		
Alaska	0.703	0.087
	(0.026)	(0.019)
Jetblue	3.300	3.257
	(0.020)	(0.027)

Note: Price coefficients on $100.

Table 1.5: Consumer arrival and segmentation

	Estimates	
	Exit route	Control route
Probability of preferring Alaska		
High type	0.889	0.740
	(0.005)	(0.004)
Low type	0.830	0.623
	(0.014)	(0.008)
Poisson arrival		
$\gamma^0_{arrival}$	4.136	4.063
	(0.130)	(0.013)
$\gamma^1_{arrival}$	0.409	1.074
	(0.017)	(0.009)
$\gamma^2_{arrival}$	-0.383	-0.563
	(0.004)	(0.004)
$\gamma^3_{arrival}$	0.053	0.067
	(7e-4)	(6e-4)
Probability on types		
γ^0_{type}	-2.665	-1.245
	(0.021)	(0.009)
γ^1_{type}	0.472	0.369
	(0.004)	(0.004)
γ^2_{type}	-0.147	-0.155
	(0.002)	(0.002)
γ^3_{type}	0.024	0.024
	(4e-4)	(2e-4)

Table 1.6: Other common parameters

	Estimates
Preference shock	
After dummy	0.059
	(0.006)
Weekend dummy	-0.074
	(0.006)
Unobserved shock	
σ_ω	11.514
	(0.039)
σ_ξ	0.410
	(0.010)
Cost parameter	
Alaska	32.10
	(0.075)
Delta	24.130
	(0.150)
JetBlue	30.937
	(3.960)

Table 1.7: The effect of price discrimination on consumer welfare by segment

Welfare Change	High Type	Low Type
Alaska-leaning	-$ 2082.88 (-9.7%)	+$47.3135 (+29.8%)
JetBlue-leaning	-$ 2087.95 (-12.9%)	+$265.382 (+15.9%)

Table 1.8: The effect of price discrimination on profits and welfare

	Constant pricing	Fixed-path pricing	Change
Alaska's Profits	$11503.38	$13070.76	+$1567.38 (+13.6%)
JetBlue's Profits	$18694.74	$19850.32	+$1155.57 (+6.2%)
Consumer Surplus	$ 39584.58	$35726.46	-$3858.12 (-9.4%)
Total Welfare	$69782.71	$68647.55	-$1135.16 (-1.6%)

Table 1.9: The effect of revenue management on consumer welfare by segment

Welfare Change	High Type	Low Type
Alaska-leaning	+$2601.22 (+13.3%)	+$581.16 (+282.3%)
JetBlue-leaning	+$951.67 (+6.7%)	+$1022.92 (+53.0%)

Table 1.10: The effect of revenue management on profits and welfare

	Fixed-path pricing	Full dynamic pricing	Change
Alaska's Profits	$13070.76	$13031.33	-$39.43 (-0.3%)
JetBlue's Profits	$19850.32	$19726.35	-$123.97 (-0.6%)
Consumer Surplus	$ 35726.46	$40883.43	+$5156.97 (+14.4%)
Total Welfare	$68647.55	$73641.11	+$4993.55 (+7.3%)

Chapter 2

The Economic Impact of China's Anti-corruption Campaign

[1]

2.1 Introduction

Despite its pervasiveness, how corruption affects economic growth and distribution remains largely unknown. The theoretical literature highlights two competing intuitions: on the one hand, corruption may induce a more efficient provision of government services and raise efficiency by circumventing pre-existing distortions; on the other hand, it may create inefficiency by discouraging private investment and insufficient supply of public goods. The impact of corruption and its mechanism remains an empirical question. Yet corruption, by its very nature, is illicit and secretive, posing challenges to its measurement. Moreover, the level of corruption is endogenous, making it difficult to identify its impact on the economy.

We address these challenges by investigating the economic impact of anti-corruption efforts. China is a natural setting for such a test. Indeed, one of the biggest puzzles in studying corruption is that why China could enjoy sustained economic growth despite widespread corruption. We focus on Chinas recent anti-corruption campaign led by the Communist Party of China (CPC) after its 18th National Congress under the new President Xi Jinping. The campaign is considered, unprecedentedly, the most far-reaching anti-corruption effort in the history of the Communist rule in China. The campaign is a politically driven one. *"If we cannot manage the party well and govern the party strictly, leaving prominent problems within the party unsettled, our party will sooner or later lose its qualifications to govern and will unavoidably be consigned to history."* As stated by the highest leader Xi.[2] This campaign is an ideal setting for our study, because it not only has rich variation in its roll-out,

[1]This is a joint work with Zemin Zhong.

[2]https://www.ft.com/content/02f712b4-8ab8-11e6-8aa5-f79f5696c731

helping us to find plausibly exogenous shocks, but also has a significant impact that induces a large effect size.

We focus on a major component of this campaign with rich variations in its roll-out. After the 18th National Congress, the CPC's Provincial Committee of Discipline Inspection (PCDI) in each province sent out inspection teams to investigate potential misconduct of local government officials. We test how these inspection teams visits affected the local economy. To do so, we first construct a data set of the timing of all inspection visit from the year 2012-2016. The data set covers 2,686 visits to 1,846 counties. We then use a data set of county-level statistics from China Statistical Yearbook for Regional Economy from 2012 to 2014 to show that the visit times across counties within each province is random conditional on all observable county attributes.

With these plausibly exogenous treatments of anti-corruption efforts, the challenge remains as to find a highly granular data set of economically relevant variables. This task is particularly hard in the context of China, since to the best of our knowledge, such data hardly exist. To overcome this challenge, we obtain access to two unique administrative datasets. The first dataset we used is vehicle registration from China's Department of Transportation. Similar to the DMV in the United States, the department is in charge of vehicle registration in mainland China. The registration data contains 24,708,544 observations of 99 million vehicle registrations aggregated at vehicle model, county and monthly level. It recorded all new personal registrations in mainland China from 2008 to 2015. The reason we use car sales data is that it is both an important economic outcome on its own [3], and highly correlated to household income. The second dataset we used is business registration from China's National Enterprise Credit Information Publicity System (NECIPS), managed by the State Administration of Industry and Commerce. The current dataset has 765, 434 observations of business registrations in Shanxi Province during 2010 to 2016. Moreover, for each observation, we have name, date, address, industry, registered capital at the time of registration. This dataset is an important economic outcome on its own because it measures a significant portion of investment, and it helps us to understand how anti-corruption affects the economy.

Our identification strategy is based on a standard Difference-in-Difference design based on the timing variation of PCDI visits. We found that each PCDI visit causes local car sales to drop by 3-4%. Surprisingly, we find that the drop in car sales is uniform across different price tiers. Luxury car sales experienced a drop in a similar magnitude as much cheaper domestic cars. We then show the dynamic effect of PCDI visit on local car sales. We find that the drop in car sales is not a short run effect and is strengthening over time. PCDI visits lead to 2% drop in the first three months after their arrivals, and the effect gradually increases to more than 10% fifteen months later.

We show three pieces of evidence in support of our empirical strategy. First, we show that observable county characteristics can not predict PCDI visits. Second, we show that car sales exhibit parallel pre-treatment trend for the counties that get visited earlier vs. later.

[3] In 2015, automobile constituted 12% of China's manufacture sector total output.

This test provides supportive evidence to our common trend assumption that is required in DiD design. Third, we perform placebo test by randomizing the visits using the empirical distribution within each province. We find that placebo visits do not affect car sales or business registrations. Also, we perform a series of robustness check, showing our result is robust to multiple alternative model specifications and sample selections.

How should we understand the effect? PCDI visits plausibly increase monitoring efforts, therefore raise the cost of corruption (Becker and Stigler, 1974). Officials would react by reducing the corruption activities, leading to less expected income, which could drive the decline in car sales. Moreover, the similar effects of luxury, economical, and domestic brands suggests that corruption in China does not only benefit the elite class. Instead, it permeates different social-economic classes with a wide spectrum of income. The magnitude of the effect is large, which can hardly be explained the changes in the officials' income alone. Therefore, our results suggest that anti-corruption may affect the growth of private sector as well. Indeed, we find that PCDI visits reduce new business registration by 7% in numbers and 12% in total registered capital. Taking together, this suggests anti-corruption faces a trade-off: while it is effective in reducing corruption, it also changes the incentive of the bureaucracy, making them less accommodating to the private sector, which hurts the total investment. The drop of car consumption across different brands suggests that the impact is remarkably uniform for the rich and middle-class alike.

Our study contribute to the large and growing literature on corruption (Bardhan, 1997; Olken and Pande, 2012). Recent empirically studies on anti-corruption focus on the effect of government audits on the level of corruption and electoral outcomes (Ferraz and Finan, 2008, 2011; Bobonis et al., 2016; Avis et al., 2017). We contribute to this literature by studying a large-scale anti-corruption campaign in an authoritarian regime, and we focus on its impact on the economy to show its effectiveness (Meagher, 2005). We also contribute to the studies of corruption in China. Corruption is widely believed to be rampant in China that has been documented in housing markets (Fang et al., 2014), land auction (Cai et al., 2013), entertainment (Cai et al., 2011), and tax evasion (Fisman and Wei, 2004). We are among the first to study the effect of the anti-corruption campaign after the 18th CPC Congress, and both our mechanism of PCDI visits and the outcome measures are novel.

Our central results on how anti-corruption affects growth are related to the importance of institutions in economic growth. The focus on the incentives of bureaucracy is related to many recent studies. [4] Previous studies suggest regulation could affect firm entry. [5] This study links the two streams of literature, pointing an unintended consequence of anti-corruption: it changes the incentive of bureaucracy and increases the cost of entry for the private sector. The negative impact of anti-corruption on business registration suggests corruption may help reduce entry barrier. This is in contrast to the seemingly positive correlation between corruption and entry cost widely found in cross-country studies (Svensson,

[4]For example, see Acemoglu et al. (2005); Acemoglu and Verdier (2000).

[5]See Djankov et al. (2002),Bertrand and Kramarz (2002),Aghion et al. (2008), Bruhn (2011), Kaplan et al. (2011), and Branstetter et al. (2014).

2005). The idea of why China could sustain high economic growth despite corruption, or as our result suggests, *because of* corruption, has been raised repetitively (Svensson, 2005). As far as we could tell, we are the first to provide empirical evidence supporting some positive role of corruption. In China, the relationship between local governments and private sector could be nuanced. Consistently, Allen et al. (2005) document survey evidence that local Chinese governments generally support the growth of private sector, and sometimes invest in the firms, despite demanding profit sharing.

2.2 Background

Political corruption is a major problem in China. Since the establishment of the economic reforms in 1978, China has faced increasing levels of corruption. The 2016 report of Corruption Perception Index of Transparency International ranks China at 79th place among 176 countries. According to a recent PEW poll in 2016, corruption is a top concern of the Chinese public. 49% of the respondents believe that the corruption of officials is a "very big problem" and another 34% believe it is a "moderately big problem". The percentage is even higher than (i) gap between rich and poor, (ii) crime, (iii) safety of food and medicine and (iv) air/water pollutions.[6]

Not surprisingly, throughout several generations of its leadership, the Communist Party of China has viewed political corruption as a major threat to its legitimacy. Although fighting corruption has been one of the Party's top priorities for three decades, it has not made much progress until Xi's regime. Right after taking power since CCP's 18th National Congress in 2012, the party under Xi Jinping's leadership launched the largest anti-corruption campaign in recent history. Xi vowed to "crackdown both tigers and flies together", where the former refers to top-ranking party and government leaders and the latter refer to low-ranking local officials.

Xi's anti-corruption becomes his political brand and generates unprecedented social and political impact in mainland China. As of 2016, the campaign has "netted" over 120 high-ranking officials, including about a dozen high-ranking military commanders, several senior executives of state-owned companies and five nation-level leaders.[7] In one of the most notable cases, Zhou Yongkang, a former Politburo Standing Committee (PSC) member, was given a life sentence. This incident has made Zhou the first PSC member to be charged with criminal conduct for more than three decades. At the local level, over 100,000 petty civil servants have been indicted for corruption. According to the state-run news outlet Xinhua,"The battle against corruption has gained crushing momentum. Recent years have seen huge progress and improved public confidence in the campaign to strictly govern the Party and fight corruption."

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[6]http://www.pewglobal.org/2016/10/05/chinese-public-sees-more-powerful-role-in-world-names-u-s-as-top-threat/10-4-2016-9-39-43-am/

[7]http://chinapower.csis.org/can-xi-jinpings-anti-corruption-campaign-succeed/

However, some think tanks and political analysts believed that the anti-corruption campaign might have impeded economic growth by incentivizing officials to stay safe by doing nothing.[8] In 2015, the Chinese premier Li Keqiang repeatedly criticized officials for being slack and lazy in implementing Beijing's policy directives as they "kept their heads down" to stay out of trouble during Xi's sweeping anti-graft campaign.[9] Following Li's comment, a special investigation team of People's Forum surveyed 8,896 citizen and officials. 71.7% of the respondents said they often met officials who were "not doing their duties", while 26% respondents said it happened to them occasionally. More than 50% of the respondents thought the reason that the officials were "not doing their duties" is that they "did not want to get into trouble". Both government officials and ordinary people held a very similar view on this. 19% of officials thought government officials were lazy because there are too many rules but not enough incentives; 15.7% believed that officials were lazy because doing more causes more mistakes.

In this paper, we look at a specific anti-corruption institution called Provincial Committee of Discipline Inspection (PCDI) visit. The inspection visit system was written into Constitution of the Communist Party of China since CCP's 17th National Congress in 2008. It was formalized and firmly executed until after Xi took power, and constituted as a major component of Xis effort to institutionalize the anti-corruption campaign. PCDI in each province selects teams of inspectors and sends them to all county-level local governments within its jurisdiction. The team members are selected to avoid conflict of interest. They shall focus on finding out problems related to the following: (i) violation of political discipline and political rules, forming cliques and related issues; (ii) abuse of power, corruption and bribery and related issues; (iii) violation of organizational discipline, illegal promotion of people, canvassing bribes, buy and sell government positions, canvassing bribes, and related issues; (iv) violation of work discipline, life discipline, engage in formalism, bureaucracy, hedonism and extravagance and related issues.

Before their visit, the team members shall visit same-level PCDI, Audit Office, and Office for Letters and Calls to learn about the Party leaders in the targeted local government. Upon arrival, they should send out notices to the local Party leaders and then take their duties to perform the inspection visit. After a typical visit of 1-3 months, the inspection team shall summarize their findings, then analyze and report to the provincial-level inspection leading group. After being authorized by the provincial-level inspection leading group, the inspection team will provide feedback to the local government. Local government is required to make necessary changes and provide corresponding feedbacks promptly. If necessary, law enforcement agencies will initiate formal investigations on potentially corrupted individuals. For how PCDI works in its investigation, see interviews with CDI officials in Li and Deng (2016).

The inspection schedules will typically be announced to the public on PCDIs official

[8] http://www.ftchinese.com/story/001060886; http://theory.people.com.cn/n/2015/0526/c112851-27059033.html

[9] http://uk.reuters.com/article/uk-china-economy-corruption-idUKKCN0PJ08S20150709

websites several days before the actual visits. Local citizens are encouraged to provide any leads or evidence regarding potential political corruption. PCDI inspection teams are not authorized to initiate or perform formal investigations. Instead, they are in charge of gathering information on any wrongdoing and misconduct of local officials. Depending on its nature, the information shall be handed to either the Provincial Organization Department or PCDI. In particular, during their stay, the inspection teams conduct independent auditing and "learn from the reports from local party committees; participate in party disciplinary meetings; manage whistleblower letters, phone calls and visits regarding issues of party members or officials; organize forums to understand public opinions of local leaders; communicate with individuals; review relevant documents and records; conduct surveys and evaluate the opinions of the public; visit the local bureau or individual department; and consult with other government departments to gain better understanding of the issues".[10]

2.3 Data

2.3.1 Data Overview

Our study focuses on estimating the economic impact using market outcomes, in particular vehicle and business registrations. Compared to other measures of economic outcomes such as GDP, our two sets of registration data has several key advantages. First, both datasets are highly granular in several important dimensions. In the vehicle data, we know the exact car model down to its engine size. Moreover, for business registration data, we have the name, industry and registered capital for each business. Equally important to our analysis, both datasets are aggregated at county level, which enables us to use rich variations across different counties and prefectures. The vehicle data is aggregated at monthly level dimension, and the business registration data has an exact date of registration. The timing dimension allows us to study the dynamics of the impact of anti-corruption. Second, both are highly reliable and centralized administrative data. We cross-checked both datasets with multiple data published by either trade media or vehicle manufactures, and we can confirm that the vehicle and business registration data is accurate. It is much less likely to suffer from any manipulation that plague various regional statistics in China, both because of the institutional reason (the traffic administration bureau is more vertically managed compared to the statistics bureau) and the lack of incentive for local officials to manipulate. Similar logic applies to the business registration data.

2.3.2 Vehicle Registration

We obtain access to an administrative dataset from China's Traffic Administration Bureau, Ministry of Public Security. Similar to the state DMV in the United States, the bureau is in charge of all vehicle registration. The data covers all the jurisdictions in all China, from

[10]See *Provisions of the Chinese Communist Party Regarding On-Site Inspections (2015 Revision).*

2008 to 2015. From 2011 onwards, it is aggregated at car model-county-month level. For example, our record shows that on there were 254 Toyota Camry (2.0L engine) registered in Yuexiu District, Guangzhou City, Guangdong Province, for November 2014. The data includes all new personal vehicle registrations, and special plates such as commercial or military plates are not included. In total, we have data for 24,708,544 model-county-month observations, recording registrations for 99 million vehicles.

Figure 2.1 shows all brands with larger than 1 million vehicles sold during 2008 to 2015. Figure 2.3 shows the growth of total vehicle registrations for 2011-2015. Overall there is strong growth with seasonality (spikes at each January before the Chinese new year). For this study, we classify vehicles into three categories according to their prices. We define luxury brands as those with typical prices above ¥300,000 (around $44,000). In China, the largest luxury brands are Mercedes-Benz, BMW, and Audi. We define economic brands as mass-market foreign brands, including Volkswagen, Toyota, Hyundai, Honda, Nissan, Ford, GM. Their typical prices range from ¥100,000 to ¥300,000 (around $15,000 to $44,000). Domestic brands, such as BYD, Changan, JAC, and Geely, typically have prices below ¥100,000. Figure 2.2 shows the share of luxury vehicles at county level for the 2011-2015 data. Not surprisingly, richer counties in the east and south coasts have the highest share of luxury vehicles. Figure 2.2 shows the monthly national share of luxury vehicles for 2008 to 2015, and there is a growing share of luxury vehicles for the 2008-2012 period, after which the shares have plateaued. The variations of vehicle registrations across counties, time, and type of vehicles will be the dependent variable as key measures of economic outcomes.

In our sample, we aggregate the registration data at the brand level, and we only use brands with larger than 1 million total registrations (24 brands). In Table 2.2 we show the summary statistics at brand-county-month level. An average county has 322.2 total vehicle registrations per month, including 7.4 registrations per luxury brand, 14.4 per economic brand, and 6.5 per domestic brand. There are very large variances across different county-months. This observation motivates us to include rich fixed effects and to use log transformation.

2.3.3 Business Registration

The business registration data is gathered from China's National Enterprise Credit Information Publicity System (NECIPS), which is managed by the State Administration for Industry and Commerce. The dataset covers all business entities that are registered for any level of administration for industry and commerce. Each record shows the name, registration date, address, managing administration, registered capital, broad and narrow industry, and the name of its legal representative. For this study, we use the data from the time window of 2010 to 2016. As of August 2017, all the results are based on Shanxi province. In total, we have 765,434 observations, and most of which are in the following industries: retail (37%), agriculture (11%), non-metallic mineral products (5%), household services (5%), and business services(4%). To make it consistent with the vehicle registration data, we aggregate the business registration data at the county-month level for different industries and different scales of registered capital.

2.3.4 PCDI Visits

At the provincial level, PCDI is responsible for coordinating inspection visits through the Leading Group on Inspection Works, which is under the direct leadership of PCDI secretary. We collect data on the PCDI visits directly from the websites of PCDI in provincial level jurisdictions. For each visit, we record the arrival time and duration for each county and county-level jurisdiction. Table 2.3 shows the summary statistics. On average, a county was first visited by PCDI in late 2014, and an average visit lasts two months. Notice there are rich variations in the timing of the first visit. To visualize it, Figure 2.5 shows the timing of PCDI visits for a random sample of 50 counties. Most counties were first visited by PCDI during 2014 and 2015, with rich variation in the timing across different counties. Most visits lasted 2-3 months, although sometimes it can take longer.

2.3.5 Other supplementary data

To supplement the analysis, we include some data on the local economy and other attributes. And the summary statistics can be found in Table 2.4. The county-level statistics are from China Statistical Yearbook for Regional Economy, 2012 to 2014. It includes statistics such as population, government expenditure, fiscal income, and investment in fixed assets. Notable, this dataset does not always include GDP. We add the GDP and some other income measures from the Statistical Yearbook of Economy in each province. Unfortunately, the data for the year of 2015 is not yet available. Therefore we are unable to include the statistics in our model. It is worth pointing out that the local economy statistics suffer from severe manipulation. We use them for heterogeneous effect only.

We also include measures of distances to capture the differences in monitoring cost. Specifically, we first use BaiduMap's Geocoding API to obtain the coordinates of county, prefecture, and province government sites. We then use its Route Matrix API to get the shortest driving distances from county government to its corresponding prefecture and province government sites.

2.4 Model and Identification

2.4.1 Identification

For our difference-in-differences approach, the most crucial identifying assumption is parallel-trend assumption: absent the treatment, the treated counties have the same trend compared to the control. In our setting, it requires that the timing of PCDI to be uncorrelated with the differences in trends of how vehicle registrations evolve. For example, if a PCDI send inspectors to counties that will have lower future economic growth, it would bias for finding a spurious effect of PCDI visits. Testing this hypothesis is often difficult.

We address this challenge by showing that the treatment and control groups have similar pre-treatment trends, and we find little evidence of systematic differences for counties that were visited earlier vs. counties that were visited later. We discuss the timing of visits in this section while leaving the discussion of testing pre-treatment trends in the Result section.

Timing of PCDI visits If counties that get visited earlier are systematically different from those visited later, it may invalidate the parallel trend assumption of our difference-in-difference design. To show whether such systematic difference exists in observable county statistics, we define a county as being visited "early" if it is visited earlier than the median visit date within the province that it belongs, and vice versa. Table 2.5 shows the comparisons of economic statistics between counties that were visited earlier versus later. We find no significant difference between the "early" versus "late" counties in any of the available economic and social statistics. **??** further shows the distributions of visit dates and select economics statistics (GDP, Fiscal Income, etc) of "early" and "late" counties. Despite the difference visit dates, the two groups of counties show very similarly distributed economic statistics. The findings support our difference-in-difference empirical strategy.

2.4.2 Empirical Model

We estimate a difference-in-differences model as follows:

$$y_{ijt} = \beta d_{it} + \delta_1 x_{ij} + \delta_2 z_{jkt} + \epsilon_{ijt} \tag{2.1}$$

in which y_{ijt} is the (logged) outcome variable: the number of vehicle registrations for brand j at county i and month t, or the number of business for type j at county i. We focus on the effect of d_{it} that is an indicator (or a set of indicators with different lags) of whether PCDI inspectors have visited county i at time t.[11] In studying dynamics, we also decompose d_{it} to test for pre-treatment effects and lagged effects. We include a rich set of fixed effect: x_{ij} is the brand-county fixed effect, z_{jkt} is province-brand-time fixed effect (province indicated by subscript k). The error term ϵ_{ijt} will be allowed to be both serially correlated across time t and counties within the same prefecture by clustering standard errors at prefecture level.

By taking the log of registrations as y_{ijt}, we model the effect of PCDI visit as a change in the growth rate of the vehicle or business registration. The log transformation helps because different counties could vary greatly in their size of the economy. To show the robustness, we also include results using the raw data. For the vehicle data, we include brand-county fixed effect to capture county specific factors for each brand/type, such as the geography and persistent brand preference. We also include province-brand-time fixed effect to capture province-wide common shocks such as national supply shocks for each brand, or a provincial supply shock such as distribution cost shock, as well as national or

[11] We tried other specifications of the treatment effect, such as separating the entry and exit of each visit, and in general, we find the dynamics of the effect suggests that the impact is sustained after entry, but not changing after exit. Therefore, for the main model we define $d_{it} = 1$ for county i if t is no smaller than its first visit arrival time T_i.

provincial level demand shocks such as monetary and fiscal policy shocks. Similarly, when we use business registrations as the outcome variable, we include type-county fixed effect and province-type-time fixed effects. We also take a conservative clustering approach, because variations in PCDI visits are mostly at the county level, and we go beyond it to allow for counties within the same prefecture to have correlations to account for some visits that cover a whole prefecture.

2.5 Results on PCDI visits

Main effect Table 2.6 shows the first key finding: PCDI visits to counties lead to 3.4% drop in the number of vehicle registrations. It translates to on average 12.6 vehicles per county-month. In the second column, we show the effects for brands in different price tiers. Moreover, we find PCDI visits lead to a -2.9% effect for luxury brands (such as BWM and Audi), -3.3% for economy brands (such as Toyota and Volkswagen), and -3.8% for domestic brands (such as BYD and Changan). Table 2.7 shows that (1) using raw registration data instead of log leading to similar effect despite some loss in efficiency, and (2) placebo visits do not affect the outcomes as desired.

The similar effect sizes across luxury, economy and domestic vehicles also shed light on the distributional implications of the anti-corruption campaign. As President Xi declared, the campaign targets both "tigers" and "flies". Moreover, the result suggests that even at the county level, the effect of PCDI visits is pretty uniform across the income spectrum for at least the top 20% to 30% who are potential car buyers.

Dynamics Figure 2.6 plot the PCDI visit effects for each three-month period before and after the treatment date, with both 90% and 95% confidence intervals (the same result can be found in Table 2.8). It highlights two notable features of the PCDI visit effect. First, the effect is only getting stronger over time. In the initial three to six months after PCDI visits, the effect is marginally significant at around -2%. However, it gets stronger in 6-9 months (-3%) and especially 9-12 months (-7%) after PCDI visit. Moreover, after 15 months of PCDI visits, relative to counties that have not been visited, the treated counties experience an over 10% drop in vehicle registrations. Second, this effect is remarkably similar across different price tiers of vehicles. As a reference, Figure 2.7 shows the same figure for placebo visits, and we find no effect.

Several factors possibly drive the delayed response to PCDI visits. There are two mechanic reasons. First, most PCDI visits last two to three months. Moreover, how PCDI inspectors enforce the rules may not be revealed after they conclude their visit. Moreover, the inspectors themselves do not enforce the law. Rather, they collect leads and information for PCDI to decide whether to start investigations, leading to a potential delay (see Section Section 2.2). Second, the process of buying a vehicle and getting it registered may induce a mechanic delay of one or two months.

There could also be a strategic reason for the delay. For example, it may take the local officials and their associates some time to learn the persistence of the enforcement level.

To test the idea, we test whether earlier PCDI visits have a larger effect compared to later visits. We interact treatment dummy with a dummy for late visits, indicating whether a county is visited after the median visit date of the province it belongs. After adding the interaction, the results are in Table 2.14. The finding is consistent with county officials learning of the PCDI visits. As more and more counties get visited, the remaining counties raise the expectation of being visited shortly and a higher expectation of the escalation of future monitoring efforts. They seemed to react before they were visited, attenuating the PCDI visit effects.

Interpretation The most notable finding is that PCDI visits have very large impact on consumer vehicle purchases (2% for the first three months, and 10% after a year). A simple back-of-the-envelope calculation suggests that the effect can hardly be explained by vehicle purchases of government officials alone: government employees constitute only 0.5% of the population. Adding all public institutions employees (such as teachers and doctors), we have around 3.5%. Given that on average each household owns 0.36 vehicle, and assuming a generous 5-year replacement, it would require every single one of public institutions employees to stop purchasing vehicles to produce a 10% drop in vehicle registration. This unlikely scenario is greatly beyond the power of PCDI.

The large effect size suggests that PCDI has an indirect impact on the private sector, which could drive the large drop in vehicle sales. To test the idea, we investigate how PCDI affect business registration using similar models. First of all, we test whether PCDI visits affect all types of business registration. Table 2.10 shows that while PCDI visits do not affect smaller enterprises with registered capital below ¥2 million (around $ 300,000), it reduces the number of new enterprises with over ¥2 million registered capital by 7%. Table 2.11 further shows that (1) the effect is large and significant for the total registered capital and (2) it is robust to placebo test.

Pre-treatment trend One might worry that counties visited earlier have different trend versus counties visited later regardless of the treatment. If so, this could violate the parallel trend assumption in the difference-in-differences design. Given that we have pre-treatment data, we can test for whether the trends are indeed different before PCDI visits. We use the same specification as in Equation 2.1, and add pre-treatment dummies for 0-3 month and 3-6 month before PCDI visits. Table 2.9 shows the results, and Figure 2.8 visualizes it. Clearly, before PCDI visits, our treated and control counties have no significant differences conditional on the same set of fixed effects. Moreover, the post-treatment effects remain mostly the same, despite some loss in statistical power leading to wider confidence intervals post-treatment. Figure 2.6 further extends the pre-treatment dummies for up to 12 months before PCDI visits, and we get similar results of no difference in pre-treatment trends. This finding suggests that when a PCDI decide the sequence of visits, its decision is not correlated with the growth of past vehicle registrations. Therefore, it is unlikely for a PCDI to decide its visit schedule based on *future* lower growth rate in vehicle registrations.

Heterogeneous effects We further test whether the effect is the same for counties with different characteristics.[12] We tested whether there are heterogeneous treatment effect for several economic indicators (1) counties with higher GDP-per-capita, (2) counties with higher government expenditure, (3) counties with higher investment in fixed assets. We find the effects for those counties groups are indistinguishable from the main effect, either for its dynamics or across different tiers of brands (see **??**).

We also test whether monitoring cost before regular PCDI visits might drive possible heterogeneous PCDI visit effect. To test the idea, we collect the driving distances from county government sites to its prefecture government sites. We then divide counties into two groups by the median distance to prefecture sites. Similarly, we did it for the distance from county to provincial government sites. Again, we did not find any significance in the interaction between the treatment and the dummy for far-away counties, either from prefecture or province government (see **??**).

Supply response One alternative explanation is that the decline in car sales might be driven by the supply side response. We believe supply response is unlikely because most dealers are located at prefecture level. PCDI visit can only lead to such a sizable drop if they somehow increase the marginal cost of selling vehicles substantially only in the counties where they sell the vehicles. We did not find that plausible, nor do we manage to find any media reporting such an impact. Even if there are supply response, it is more likely to strengthen our results: facing declining demand, dealers or manufacturers will react by reducing prices, partially offsetting the impact on the demand side.

2.6 Concluding Remarks

We study how China's recent anti-corruption campaign affect the local economy, by measuring how the visits of party discipline officials affect the car sales. We find that PCDI visits cause car sales to drop by 3.4% at the county level. Notably, the effect gets larger over time, leading to 10% drop one year after the PCDI visits. This particularly large effect can hardly be explained by consumption of government officials alone. Instead, the magnitude, as well as the uniformity of effect affect different price tiers of brands suggests that anti-corruption campaign has a more far-reaching impact on the economy by discouraging official efforts. This suggests that anti-corruption in China faces a trade-off. On the one hand, it is quite effective in reducing corruption; on the other hand, its effectiveness also thwarts economic growth.

[12] To make sure our parallel trend assumption would hold, we split the counties into different groups within each province, and for each group, we allow a group-specific trend for each brand.

Figures and Tables

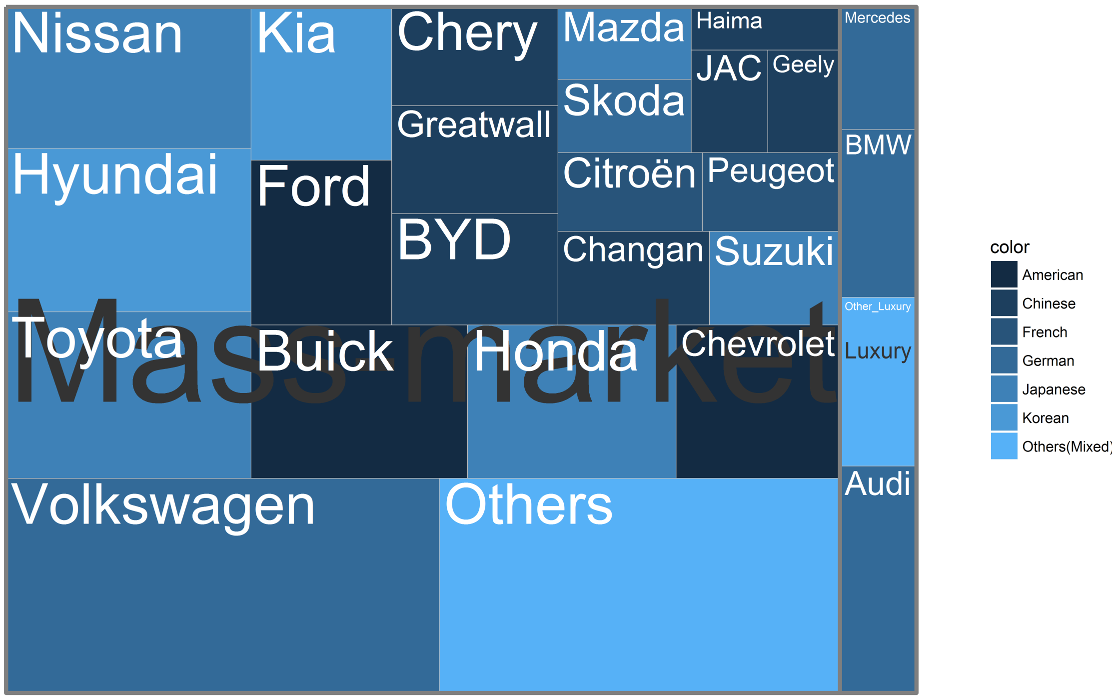

Figure 2.1: Top brands in China, 2008-2015 (sized to market share)

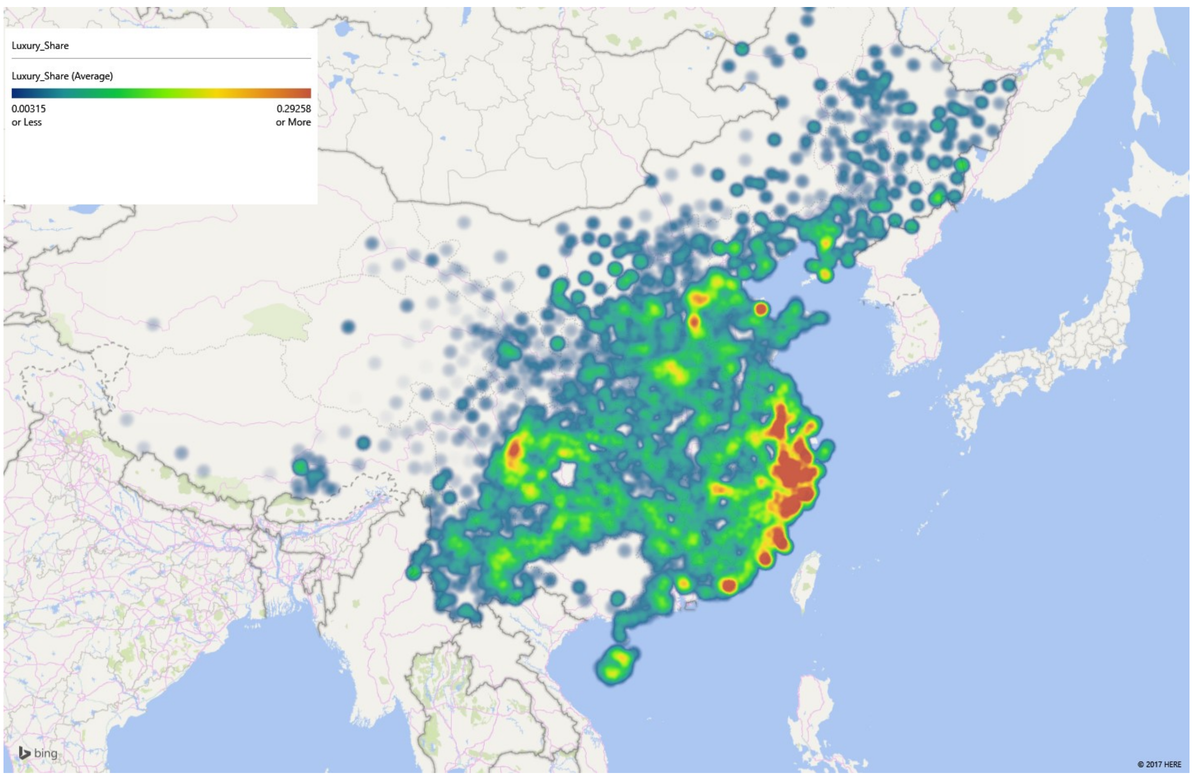

Figure 2.2: Share of luxury vehicles, 2011-15

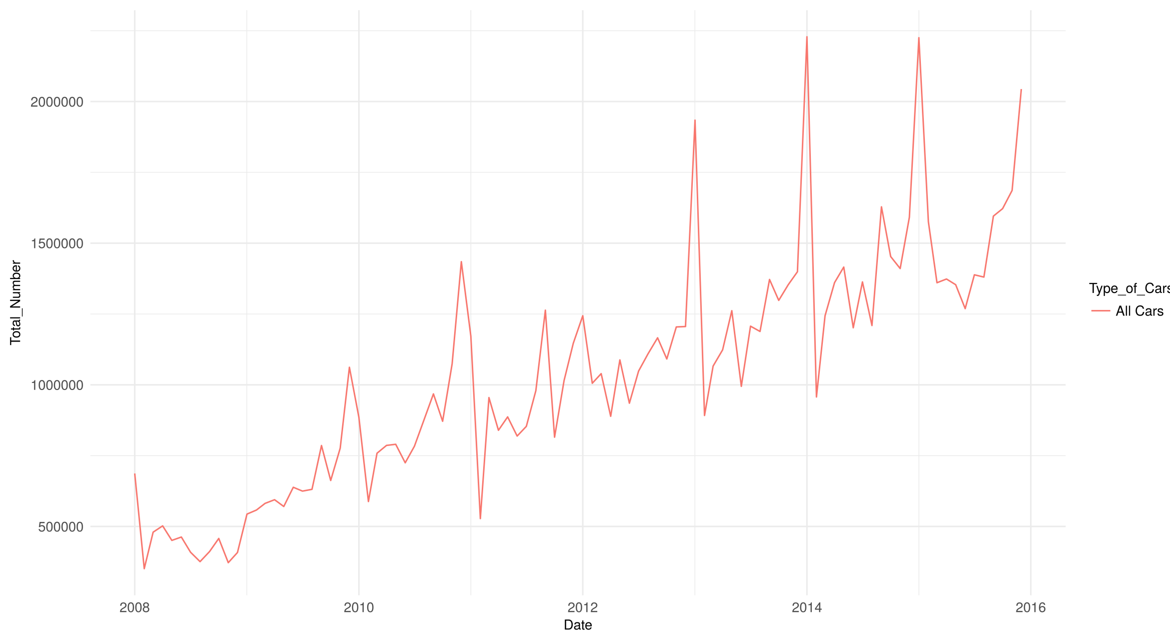

Figure 2.3: Total number of vehicle registrations

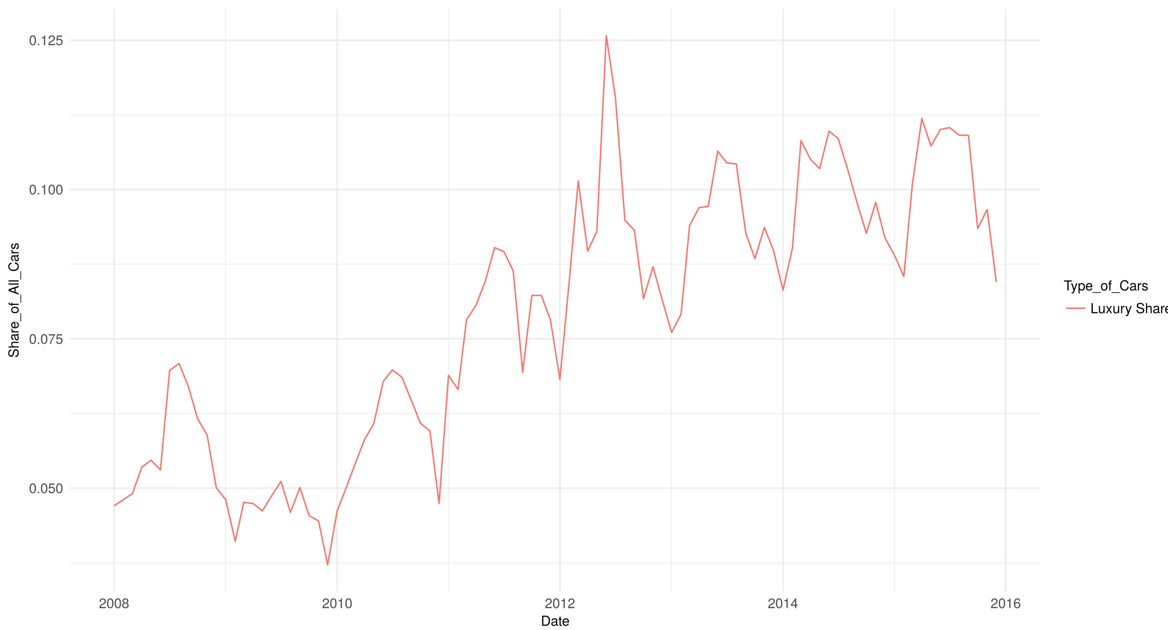

Figure 2.4: Share of luxury vehicles for all China

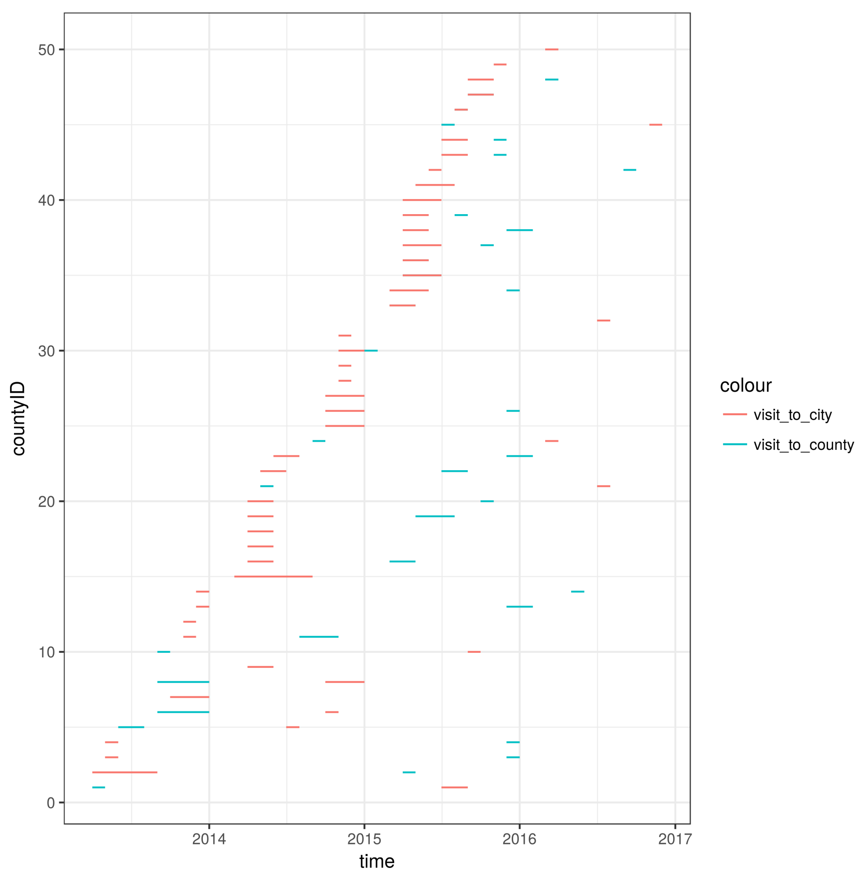

Figure 2.5: PCDI visits after 18th CPC Congress, a random 50-county sample

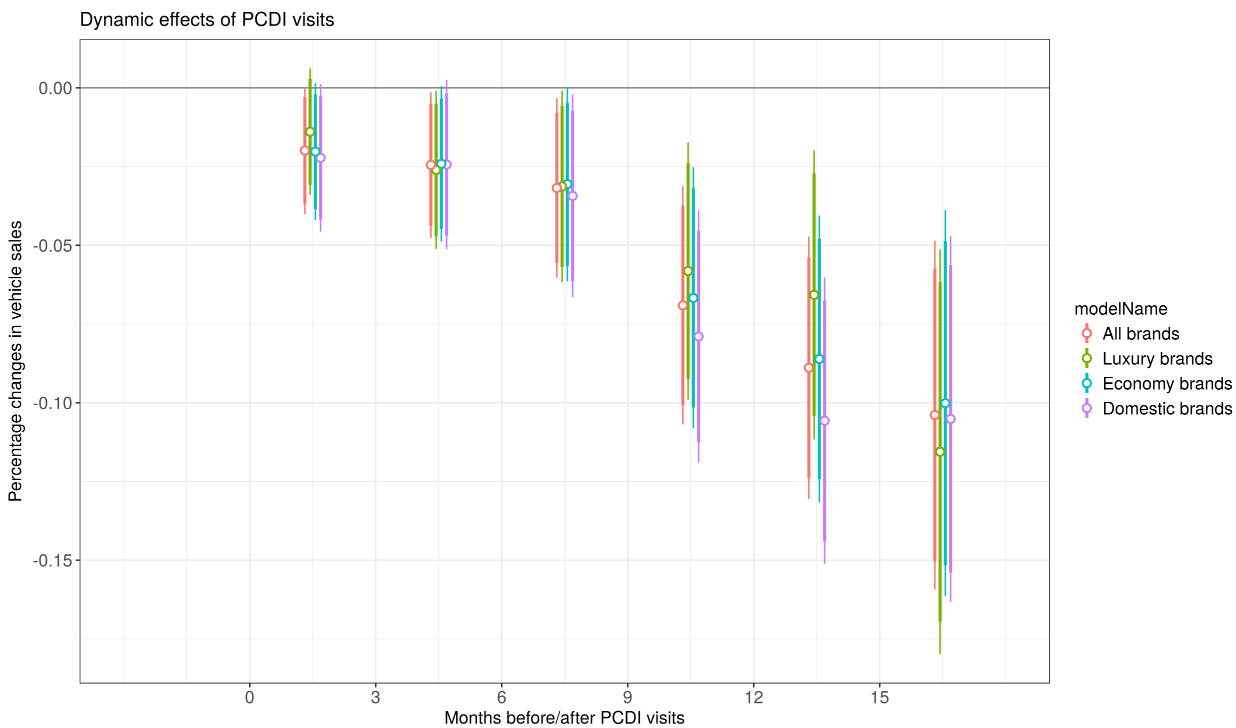

Figure 2.6: The dynamics of PCDI visit effects

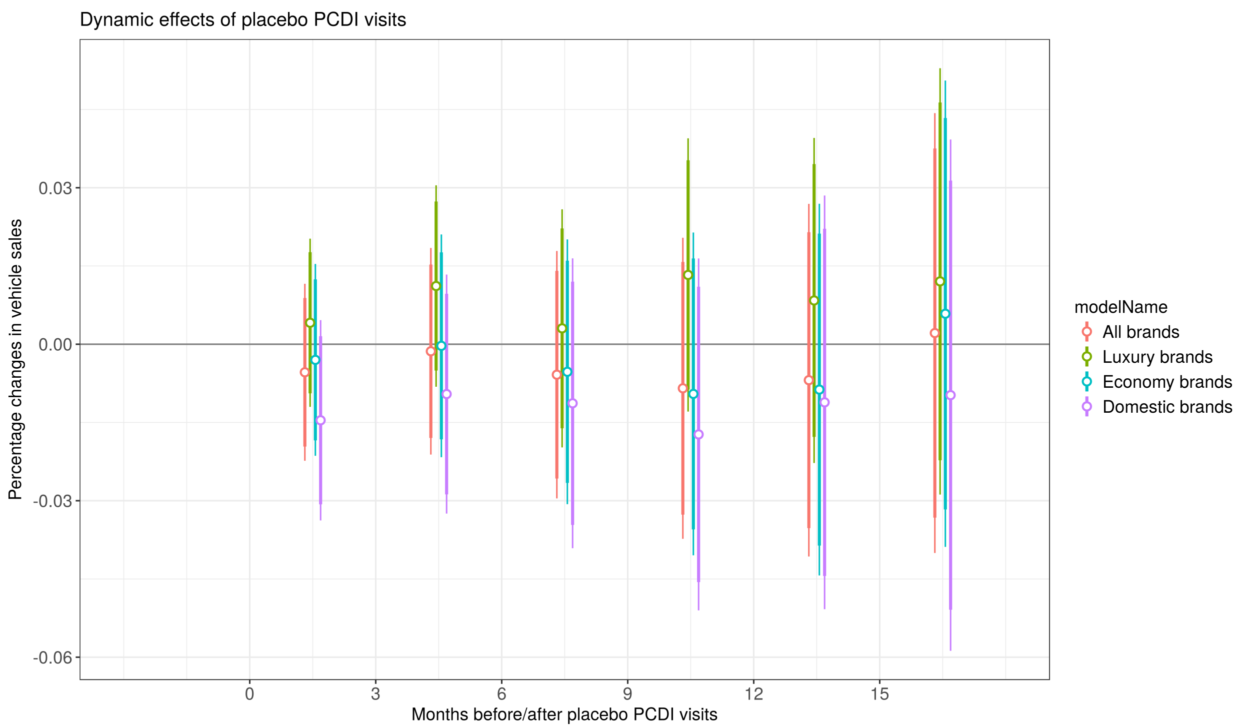

Figure 2.7: The dynamics of placebo PCDI visit effects

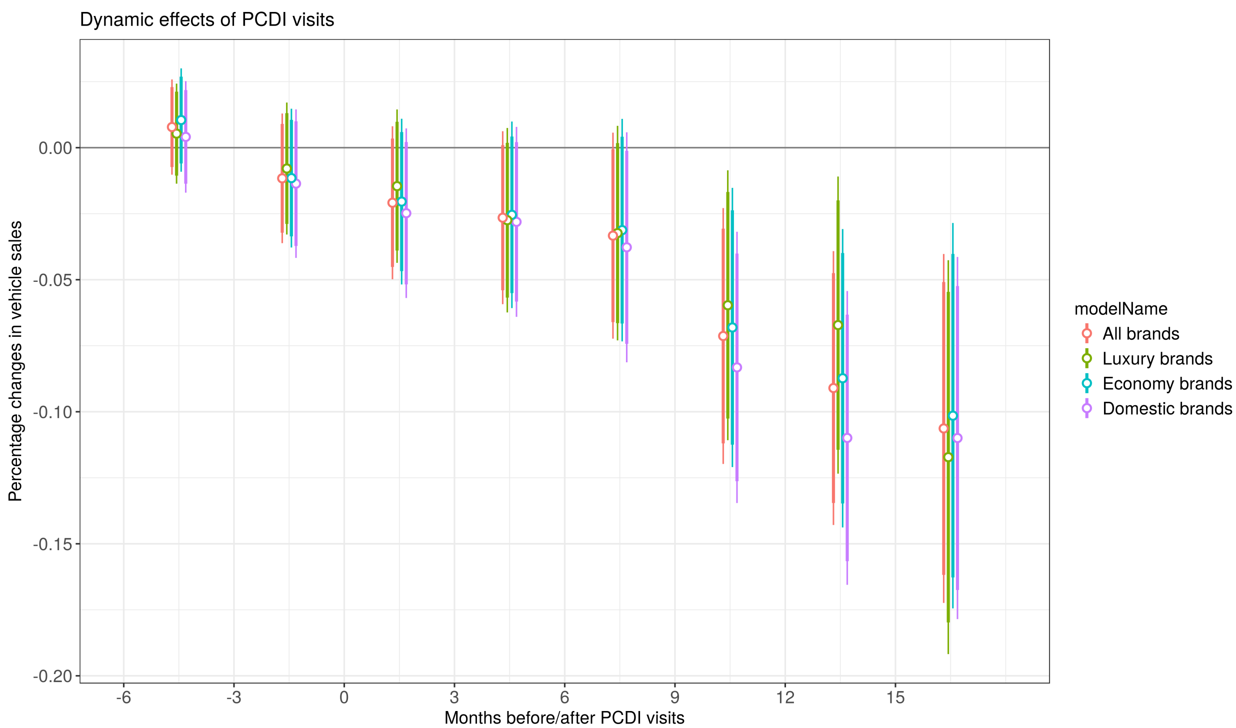

Figure 2.8: The dynamics of PCDI visit effects with pre-treatment trends

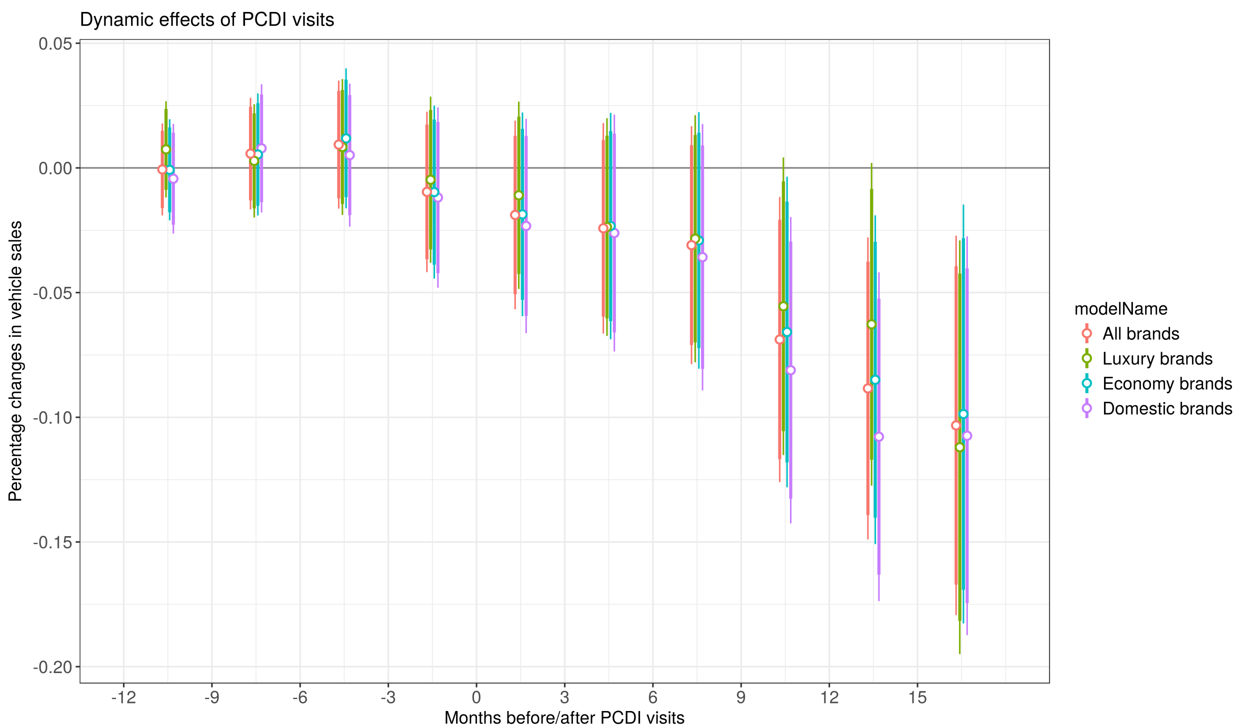

Figure 2.9: The dynamics of PCDI visit effects with pre-treatment trends

Table 2.1: Number of Jurisdictions

Jurisdictions	Provincial	Prefecture-Level	County-Level	County	County-level-city	District
N	31	374	2833	1567	374	835

Table 2.2: Registrations per county-month

	N	Mean	Median	StDev	Min	Max
Total	203640	369.8	147	857	0	45898
Luxury Brands	610920	8.7	1	33	0	1907
Economy Brands	2850960	16.5	4	56	0	6424
Domestic Brands	1425480	7.3	2	20	0	4087

Table 2.3: PCDI Visits Summary Statistics

Stats	N	Mean	Median	StDev	Min	Max
First Visit Date	2686	2014-09-11	2014-10-01		2010-08-01	2016-12-01
Second Visit Date	2686	2015-08-12	2015-10-01		2013-04-01	2016-11-01
First Visit Duration	2686	59	61	28	7	184

Table 2.4: County Summary Statistics

Stats	N	Mean	Median	StDev	Min	Max
2011 GDP	1846	1342651	775220	3654662	14212	115055298
2011 Population	1846	48	39	35	1	236
2011 gdppercap	1846	26489	18661	28795	3411	337697
2011 second_value	1846	615601	345638	955574	2994	15100600
2011 gov_exp	1846	171311	145756	114271	10053	1745761
2011 fixed_inv	1846	625243	456590	629488	0	7119153
2011 fixedinv_gdppercentage	1846	67	60	42	0	423
2012 GDP	1846	1471833	827656	4109114	6376	129500601
2012 Population	1846	48	39	35	1	238
2012 gdppercap	1846	28982	20000	34256	101	393885
2012 second_value	1846	695314	397687	1041492	4098	16312500
2012 gov_exp	1846	206454	176454	130489	38288	1951473
2012 fixed_inv	1846	856617	653106	831949	12949	8342829
2012 fixedinv_gdppercentage	1846	192	74	547	6	6599
2013 GDP	1846	1615742	951300	4100690	0	129500601
2013 Population	1846	48	39	35	1	242
2013 gdppercap	1846	32833	23123	36250	0	435378
2013 second_value	1846	750977	435101	1105936	3914	16910900
2013 gov_exp	1846	233815	198927	146533	32097	2217013
2013 fixed_inv	1846	1070167	830738	999241	35033	9487872
2013 fixedinv_gdppercentage	1846	Inf	83		7	Inf
Distance to Prefecture Government	1997	90902	68181	86432	11	826234
Distance to Province Government	1997	297011	230742	253403	2	1838622

Table 2.5: Statistics For Early vs Late Counties

index	earlymean	latemean	earlymedian	latemedian	p_value
Date	16037	16429	16010	16375	0.0
GDP_2012	1347087	1372012	800000	851000	0.8
GDP_2013	1520544	1508654	911450	980356	0.9
GDP_growth_rate	11	11	12	11	0.1
GDP_percapita_reported	114171	82727	25235	24848	0.2
Urban_income_Wages	29923	28729	31503	31766	0.3
Urban_income_Disposable	22250	21594	19087	18763	0.4
Rural_Income	7867	8010	7398	8059	0.5
Population	48	48	39	39	1.0
Rural_Population	39	39	32	32	1.0
Fiscal_Income	86862	76348	43273	44381	0.1
Fiscal_Spending	211667	202483	175208	176285	0.2
Land_Area	4619	4067	2042	2174	0.4
Employed_Persons	33186	29283	20747	20698	0.1
Rural_Laborers	213144	217293	172294	174552	0.6
Value_added_of_Primary_Industry	214000	216023	162326	170232	0.8
Value_added_of_Secondary_Industry	751400	701012	407014	409204	0.4
Balance_of_Savings_Deposit	756779	748718	542146	521249	0.9
Total_Grain_Yield	203519	185533	101644	86946	0.2
Investment_in_Fixed_Assets	879485	852373	636750	672684	0.6
Number_of_Fixed_Telephone	60322	61807	39206	43087	0.7
Enrollment_of_Regular_Secondary_Schools	25275	23539	18725	17978	0.1
Enrollment_of_Primary_Schools	35096	35014	26166	25632	1.0
Number_of_Beds_of_Hospitals	1283	1325	1052	1068	0.4

Table 2.6: The effect of PCDI visit on vehicle registration

	Dependent variable:	
	Log of Total Registration, all brands pooled	
	(1)	(2)
$T > PCDI\_visit\_date$	-0.034^{***}	
	(0.012)	
$T > PCDI\_visit\_date$, Luxury brands		-0.029^{**}
		(0.013)
$T > PCDI\_visit\_date$, Economy brands		-0.033^{**}
		(0.013)
$T > PCDI\_visit\_date$, Domestic brands		-0.038^{***}
		(0.014)
County-by-Brand fixed effects	Yes	Yes
Time-by-Province-by-Brand fixed effects	Yes	Yes
Observations	2,974,320	2,974,320
R^2	0.823	0.823
Adjusted R^2	0.817	0.817
Note:		*p<0.1; **p<0.05; ***p<0.01
		Clustered Standard Errors (Prefecture-level) in parenthese

Table 2.7: The effect of PCDI visit and place visit on vehicle registration

	Dependent variable:			
	Log of Total Registration		Total Registration	
	(1)	(2)	(3)	(4)
$T > PCDI\_visit\_date$	-0.034^{***}		-0.407^{**}	
	(0.012)		(0.204)	
$T > Placebo\_visit\_date$		-0.005		0.033
		(0.010)		(0.225)
County-by-Brand fixed effects	Yes	Yes	Yes	Yes
Time-by-Province-by-Brand fixed effects	Yes	Yes	Yes	Yes
Observations	2,974,320	2,977,560	2,974,320	2,977,560
R^2	0.823	0.823	0.815	0.815
Adjusted R^2	0.817	0.817	0.809	0.809

Note: *p<0.1; **p<0.05; ***p<0.01

Clustered Standard Errors (Prefecture-level) in parenthese

Table 2.8: The dynamics of PCDI visit effect on vehicle registration

	Dependent variable:			
	Log of Total Registration			
	All	Domestic	Economy	Luxury
	(1)	(2)	(3)	(4)
Treatment_0_3m	−0.020*	−0.022*	−0.020*	−0.014
	(0.010)	(0.012)	(0.011)	(0.010)
Treatment_3_6m	−0.024**	−0.024*	−0.024*	−0.026**
	(0.012)	(0.014)	(0.013)	(0.013)
Treatment_6_9m	−0.032**	−0.034**	−0.031*	−0.031**
	(0.015)	(0.016)	(0.016)	(0.016)
Treatment_9_12m	−0.069***	−0.079***	−0.067***	−0.058***
	(0.019)	(0.020)	(0.021)	(0.021)
Treatment_12_15m	−0.089***	−0.106***	−0.086***	−0.066***
	(0.021)	(0.023)	(0.023)	(0.023)
Treatment_15m	−0.104***	−0.105***	−0.100***	−0.116***
	(0.028)	(0.030)	(0.031)	(0.033)
Time-by-Province-by-Brand fixed effects	Yes	Yes	Yes	Yes
Brand-by-County fixed effects	Yes	Yes	Yes	Yes
Observations	2,974,320	881,280	1,652,400	440,640
R^2	0.823	0.805	0.825	0.779
Adjusted R^2	0.817	0.799	0.819	0.773

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered Standard Errors (Prefecture-level) in parenthese

Table 2.9: The dynamics of PCDI visit effect on vehicle registration

	Dependent variable:			
	Log of Total Registration			
	All	Domestic	Economy	Luxury
	(1)	(2)	(3)	(4)
Treatment_pre6_pre3	0.008	0.004	0.010	0.005
	(0.009)	(0.011)	(0.010)	(0.010)
Treatment_pre3_0m	−0.012	−0.014	−0.012	−0.008
	(0.013)	(0.014)	(0.013)	(0.013)
Treatment_0_3m	−0.021	−0.025	−0.020	−0.015
	(0.015)	(0.016)	(0.016)	(0.015)
Treatment_3_6m	−0.027	−0.028	−0.025	−0.027
	(0.017)	(0.018)	(0.018)	(0.018)
Treatment_6_9m	-0.033^{*}	-0.038^{*}	−0.031	−0.032
	(0.020)	(0.022)	(0.021)	(0.021)
Treatment_9_12m	-0.071^{***}	-0.083^{***}	-0.068^{**}	-0.060^{**}
	(0.025)	(0.026)	(0.027)	(0.026)
Treatment_12_15m	-0.091^{***}	-0.110^{***}	-0.087^{***}	-0.067^{**}
	(0.026)	(0.028)	(0.029)	(0.029)
Treatment_15m	-0.106^{***}	-0.110^{***}	-0.101^{***}	-0.117^{***}
	(0.034)	(0.035)	(0.037)	(0.038)
Time-by-Province-by-Brand fixed effects	Yes	Yes	Yes	Yes
Brand-by-County fixed effects	Yes	Yes	Yes	Yes
Observations	2,974,320	881,280	1,652,400	440,640
R^2	0.823	0.805	0.825	0.779
Adjusted R^2	0.817	0.799	0.819	0.773

Note: *p<0.1; **p<0.05; ***p<0.01

Clustered Standard Errors (Prefecture-level) in parenthese

Table 2.10: The effect of PCDI visit on business registration

	Dependent variable:				
	Log of Registration Number				
	All types	Unknown	0-.5M	.5M-2M	>2M
	(1)	(2)	(3)	(4)	(5)
$T > PCDI\_visit\_date$	−0.007	0.049	−0.006	−0.004	−0.072*
	(0.037)	(0.065)	(0.046)	(0.045)	(0.040)
County-by-Type fixed effects	Yes	Yes	Yes	Yes	Yes
Time-by-by-Type fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	27,266	7,069	6,718	6,783	6,696
R^2	0.654	0.714	0.406	0.498	0.534
Adjusted R^2	0.645	0.707	0.390	0.485	0.522

Note: *p<0.1; **p<0.05; ***p<0.01

Clustered Standard Errors (Prefecture-level) in parentheses

Table 2.11: The effect of PCDI visit on business registration (> 2M capital)

	Dependent variable:			
	Log of Registration Number		Log of Registration Capital	
	(1)	(2)	(3)	(4)
$T > PCDI\_visit\_date$	-0.072^{*}		-0.123^{**}	
	(0.040)		(0.052)	
$T > Placebo\_visit\_date$		0.036		0.041
		(0.037)		(0.047)
County-by-Type fixed effects	Yes	Yes	Yes	Yes
Time-by-by-Type fixed effects	Yes	Yes	Yes	Yes
Observations	6,696	6,696	6,696	6,696
R^2	0.534	0.534	0.304	0.304
Adjusted R^2	0.522	0.522	0.286	0.286

Note: *p<0.1; **p<0.05; ***p<0.01

Clustered Standard Errors (Prefecture-level) in parentheses

Table 2.12: The effects of two PCDI visits on vehicle registration

	Dependent variable:	
	Log of Total Registration	
	(1)	(2)
Treatment	-0.034^{***}	-0.033^{***}
	(0.012)	(0.012)
Treatment_secondvisit		-0.005
		(0.014)
County-by-Brand fixed effects	Yes	Yes
Time-by-Province-by-Brand fixed effects	Yes	Yes
Observations	2,974,320	2,974,320
R^2	0.823	0.823
Adjusted R^2	0.817	0.817
Note:		*p<0.1; **p<0.05; ***p<0.01
		Clustered Standard Errors (Prefecture-level) in parentheses

Table 2.13: Heterogeneous PCDI visit effect on vehicle registration

	Dependent variable:		
	Log of Total Registration		
	(1)	(2)	(3)
$T > PCDI\_visit\_date$	-0.034^{***}	-0.031^{*}	
	(0.012)	(0.016)	
$T > PCDI\_visit\_date \cdot\ GDP > Median$		0.006	
		(0.022)	
$T > Placebo\_visit\_date$			-0.002
			(0.012)
$T > Placebo\_visit\_date \cdot\ Distance > Median$			-0.011
			(0.019)
Time-by-Province-by-Brand fixed effects	Yes	Yes	Yes
Brand-by-County fixed effects	Yes	Yes	Yes
Time-Province-Brand-GDP fixed effects		Yes	Yes
Observations	2,974,320	2,726,460	2,726,460
R^2	0.823	0.815	0.815
Adjusted R^2	0.817	0.806	0.806

Note: *p<0.1; **p<0.05; ***p<0.01

Clustered Standard Errors (Prefecture-level) in parentheses

Table 2.14: The effects of early versus late PCDI visits on vehicle registration

	Dependent variable:	
	Log of Total Registration	
	(1)	(2)
Treatment	−0.051***	
	(0.018)	
Treatment:LateTreatment	0.045**	
	(0.023)	
Placebo		−0.009
		(0.013)
Placebo:LatePlacebo		0.010
		(0.016)
County-by-Brand fixed effects	Yes	Yes
Time-by-Province-by-Brand fixed effects	Yes	Yes
Observations	2,974,320	2,977,560
R^2	0.823	0.823
Adjusted R^2	0.817	0.817

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered Standard Errors (Prefecture-level) in parentheses

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Appendices

A.1 Appendix to Chapter 1

A.1.1 Equilibrium discussion

Before going to details of the discussion, I shall point out that the proof below uses standard techniques but relies a set of assumptions that are too strong. An ongoing project is to relax some of the assumptions.

As the game is finite horizon in nature, to establish the existence and uniqueness of the equilibrium, it is sufficient to prove the existence and uniqueness of equilibrium for each one of the subgames. This reduces the dynamic model to finite simple oligopoly pricing games with mixed multinomial logit demands.[13]

Allon et al (2013) establish general conditions for the existence and uniqueness of equilibrium in oligopoly pricing games with mixed multinomial logit demand. The main condition is that each single firm shall not capture more than half of any segment. In addition to assumption on market concentration, it also assumes reasonably bounded strategy spaces as well as the classical dominant-diagonal condition. Provided these conditions, they show that the pricing game is supermodular and its equilibrium can be uniquely identified with a Tatonment scheme. Although these demand conditions can be easily verified or established to the current setting, a complication arises from the supple side – their results are derived from cost functions that are affine in the sales volume, however in a dynamic setting like ours the cost function is typically non-linear.

Under convex cost and other mild assumptions, Gallego et al (2006) show the existence and uniqueness of an oligopoly price competition using asymmetric attraction demand model. They further show that the unique equilibrium is globally stable and guarantee a linear convergence rate of tatonement. Although their cost structure is applicable to this setting and their demand model includes simple logit as a special case, but discrete consumer segmentation is not discussed in their paper.[14]

Assumption 2. *Firm i's pricing strategy has an upper bound:* $p_i^{max} \leq -\frac{3}{2\alpha_k} + c_i, \forall i, k.$

Assumption 3. *In each segment* $k = 1, ..., K$*, each firm* i *captures less than* $\frac{1}{3}$ *of the market:* $S_{ik} < \frac{1}{3}, \forall i, , k.$

Allon et al (2013) prove that Assumption 1 and is sufficient for the uniqueness of price competition game under mixed multinomial logit demand function. It consists of excluding

[13] See Mizuno (2003), Bernstein and Federgruen (2004) for more examples.

[14] As pointed out by Allon et al (2013),"there is no guarantee that the aggregate profit functions share the same property as their segmen-by-segment components." Quah and Strulovici (2012) recently established a necessary and sufficient condition for aggregation of the single crossing property in Milgrom and Shannon (1994).

the possibility of excess market concentration. For the equilibrium to be unique, every single firm captures less than one third of the potential market in each segment when pricing at some upper bound of its feasible price.

Next we make a set of assumptions on the structural properties of the value function. Holding all other arguments constant, let $\Delta^1_{ii}(\mathbf{s},t) = V_i(\mathbf{s}+\mathbf{e}_i,t) - V_i(\mathbf{s},t))$ be the marginal value for firm i if firm i itself has one additional seat, and $\Delta^1_{ij}(\mathbf{s},t) = V_i(\mathbf{s}+\mathbf{e}_j,t) - V_i(\mathbf{s},t)$ be the marginal value for firm i if its competitor j has one additional seat. Then let $\Delta^2_{ii}(\mathbf{s},t) = \Delta^1_{ii}(\mathbf{s}+\mathbf{e}_i,t) - \Delta^1_{ii}(\mathbf{s},t)$ be the incremental marginal value of firm i's own capacity and $\Delta^2_{ij}(\mathbf{s},t) = \Delta^1_{ij}(\mathbf{s}+\mathbf{e}_j,t) - \Delta^1_{ij}(\mathbf{s},t)$ be the incremental marginal value of competitor j's capacity on firm i.

Assumption 4. *Firm's value function is "concave" in its own capacity and "convex" in its competitor's capacity. That is:*

$$\Delta^1_{ii}(\boldsymbol{s},t) > 0; \quad \Delta^1_{ij}(\boldsymbol{s},t) < 0; \quad \Delta^2_{ii}(\boldsymbol{s},t) < 0; \quad \Delta^2_{ij}(\boldsymbol{s},t) < 0 \quad \forall i,j,\boldsymbol{s},t \tag{2}$$

The concavity of own capacity is a common monotonicity result in dynamic programming. Assuming diminishing marginal revenue, Gallego and van Ryzin (1994) show this in a continuos time monopoly problem under stochastic demand. In a duopoly competition model, Gallego and Hu (2014) showed negative capacity externality in the case of deterministic substitutive demand. Ideally, one could prove these properties from the model primitives. Some of them might be simple, but some, as commented in Li and Sibdari (2009), can be complicated. I will postpone it to future research. Nevertheless, these assumptions seem to be both intuitively and numerically correct.

Assumption 5.

$$\left|\frac{\partial \lambda_i}{\partial p_i}\Delta^2_{ii}(\boldsymbol{s},t)\right| > \left|\frac{\partial \lambda_j}{\partial p_j}\Delta^2_{ij}(\boldsymbol{s},t)\right| \quad \forall i,j,\boldsymbol{s},t,p_i,p_j \tag{3}$$

Assumption 4 is technical and more restrictive, and it yields the dominant-diagonal condition we need for uniqueness. One sufficient condition is that the second order effect of externality of competitor's capacity is negligible. It excludes the situation when firm j can influence firm i so much by changing firm j's own capacity.

Theorem 1. *Provided Assumption 1-4, the equilibrium of the dynamic game exists and is unique.*

A.1.2 Properties on equilibrium

In this section, I show that this dynamic game has unique equilibrium. The game is finite horizon, thus it reduces to finite number of one-shot games at each state $\{t, c_1, c_2\}$. State subscripts are omitted for simplicity. We can write out the period objective function as:

$$f_i(p_i) = \mathbb{E}\big[\Pi_i + V_i\big] \quad \forall i = 1,2. \tag{4}$$

Where $\mathbb{E}\Pi_i$ is the current period expected profit and $\mathbb{E}V_i$ is the expected future value. Let $\mathbf{k}_i \sim \text{Pois}(\lambda_i)\forall i$ be the random variable for number of buyers of firm i. Note that some buyers may not be able to get seats because of finite capacity, thus the actual demand $\mathbf{D}_i$ should be a truncated variable. For ease of exposure, let $V_1(k_1, k_2) = 0$, if $k_1 > s_1$ and $V_2(k_1, k_2) = 0$, if $k_2 > s_2$, thus avoid truncation of probability distribution over future value function:

$$\mathbb{E}\big[V_i\big] = \mathbb{E}_{\mathbf{\Lambda}|\mathbf{p}}\Big[V_i\big(\mathbf{k}_1, \mathbf{k}_2\big)\Big] \quad \forall i = 1, 2. \tag{5}$$

However, we still have to explicitly deal with truncations on the current sales. Let c_i be the marginal cost of firm i and s_i be the current remaining capacity of firm i, we have:

$$\begin{aligned}
\mathbb{E}\big[\Pi_i\big] &= (p_i - c_i) \times \mathbb{E}_{\mathbf{\Lambda}|\mathbf{p}}\big[\mathbf{D}_i\big] && (6)\\
&= (p_i - c_i) \times \left[\sum_{k_i=0}^{s_i} k_i \frac{e^{-\lambda_i}\lambda_i^{k_i}}{k_i!} + \sum_{k_i=s_i+1}^{\infty} s_i \frac{e^{-\lambda_i}\lambda_i^{k_i}}{k_i!}\right] && (7)\\
&= (p_i - c_i) \times \left[\lambda_i \sum_{k_i=1}^{s_i} \frac{e^{-\lambda_i}\lambda_i^{(k_i-1)}}{(k_i-1)!} + s_i \sum_{k_i=s_i+1}^{\infty} \frac{e^{-\lambda_i}\lambda_i^{k_i}}{k_i!}\right] && (8)\\
&= (p_i - c_i) \times \left[\lambda_i \sum_{k_i=0}^{s_i-1} \frac{e^{-\lambda_i}\lambda_i^{k_i}}{k_i!} + s_i\left(1 - \sum_{k_i=0}^{s_i} \frac{e^{-\lambda_i}\lambda_i^{k_i}}{k_i!}\right)\right] && (9)\\
&= (p_i - c_i) \times \left[\lambda_i \frac{\Gamma(s_i, \lambda_i)}{(s_i-1)!} + s_i\left(1 - \frac{\Gamma(s_i+1, \lambda_i)}{s_i!}\right)\right] && (10)\\
&= (p_i - c_i) \times \left[s_i + \frac{\lambda_i\Gamma(s_i, \lambda_i) - \Gamma(s_i+1, \lambda_i)}{(s_i-1)!}\right] && (11)
\end{aligned}$$

Where $\Gamma(s, \lambda)$ is the incomplete gamma function, satisfying $\frac{\Gamma(s+1,\lambda)}{s!} = \sum_{k=0}^{s} \frac{e^{-\lambda}\lambda^k}{k!}$.

The proof adopts the classic argument for existence and uniqueness in Bertrand game, e.g. Economides (1989), Caplin and Nalebuff (1991) and Allon et al (2013), etc.[15] For existence, I show that player i's objective function is concave in its own actions, i.e. $\frac{\partial^2 f_i}{\partial p_i^2} < 0, \forall i$. Provided general technical conditions, a Kakutani fixed point theorem applies for the existence for a pure strategy equilibrium. The proof for uniqueness is based on dominant diagonal argument, i.e. $|\frac{\partial^2 f_i}{\partial p_i^2}| > |\frac{\partial^2 f_i}{\partial p_i \partial p_j}|, \forall i, j$, which, in combination with the existence result, establishes uniqueness.

In the following part of this section, I first establish useful properties on the demand functions and value functions. After that I show existence and uniqueness respectively.

[15] See the seminal paper Rosen (1965) for general conditions for N-person concave games.

A.1.3 Structure on demand

The random variable for buyers for firm i follows independent poisson process, λ_i satisfying:

$$\lambda_i = \sum_{k=1,..,K} M_k S_{ik} \quad \forall i = 1, 2. \tag{12}$$

Where S_{ik} is the market share for firm i in segment k and M_k is the size of segment k. Since conditional on segment, consumers have simple logit preference, thus it follows from standard results:

$$\frac{\partial \lambda_i}{\partial p_i} = \sum_{k=1,..,K} M_k \alpha_k S_{ik}(1 - S_{ik}) < 0 \quad \forall i. \tag{13}$$

$$\frac{\partial \lambda_i}{\partial p_j} = \sum_{k=1,..,K} -M_k \alpha_k S_{ik} S_{jk} > 0 \quad \forall i, j. \tag{14}$$

$$\frac{\partial^2 \lambda_i}{\partial p_i^2} = \sum_{k=1,..,K} M_k \alpha_k^2 S_{ik}(1 - S_{ik})(1 - 2S_{ik}) > 0 \quad \forall i. \tag{15}$$

$$\frac{\partial^2 \lambda_i}{\partial p_i \partial p_j} = \sum_{k=1,..,K} -M_k \alpha_k^2 S_{ik} S_{jk}(1 - 2S_{ik}) < 0 \quad \forall i, j. \tag{16}$$

$$\frac{\partial^2 \lambda_i}{\partial p_j^2} = \sum_{k=1,..,K} -M_k \alpha_k^2 S_{ik} S_{jk}(1 - 2S_{jk}) < 0 \quad \forall i, j. \tag{17}$$

The last three inequalities follow from no excess market concentration assumption. It follows immediately that:

$$\left|\frac{\partial \lambda_i}{\partial p_i}\right| > \left|\frac{\partial \lambda_i}{\partial p_j}\right| \tag{18}$$

$$\left|\frac{\partial^2 \lambda_i}{\partial p_i^2}\right| > \left|\frac{\partial^2 \lambda_i}{\partial p_i \partial p_j}\right| \tag{19}$$

Next we show some results useful for later proofs:

Lemma 1.

$$2\frac{\partial \lambda_i}{\partial p_i} + (p_i - c_i)\frac{\partial^2 \lambda_i}{\partial p_i^2} < 0 \tag{20}$$

$$\left|2\frac{\partial \lambda_i}{\partial p_i} + (p_i - c_i)\frac{\partial^2 \lambda_i}{\partial p_i^2}\right| > \left|\frac{\partial \lambda_i}{\partial p_j} + (p_i - c_i)\frac{\partial^2 \lambda_i}{\partial p_i \partial p_j}\right| \tag{21}$$

Proof. To see the first inequality:

$$2\frac{\partial\lambda_i}{\partial p_i} + (p_i - c_i)\frac{\partial^2\lambda_i}{\partial p_i^2} = \sum_{k=1,..,K}\Big[M_k 2\alpha_k S_{ik}(1-S_{ik})\Big] + \sum_{k=1,..,K}\Big[(p_i-c_i)M_k\alpha_k^2 S_{ik}(1-S_{ik})(1-2S_{ik})\Big] \tag{22}$$

$$= \sum_{k=1,..,K} M_k\alpha_k S_{ik}(1-S_{ik})\Bigg[2+\alpha_k(p_i-c_i)(1-2S_{ik})\Bigg] \tag{23}$$

$$< \sum_{k=1,..,K} M_k\alpha_k S_{ik}(1-S_{ik})\Bigg[2+\alpha_k(p_i-c_i)\Bigg] < 0 \tag{24}$$

On the other hand:

$$\left|\frac{\partial\lambda_i}{\partial p_j} + (p_i-c_i)\frac{\partial^2\lambda_i}{\partial p_i\partial p_j}\right| = \left|\sum_{k=1,..,K} -M_k\alpha_k S_{ik}S_{jk} + \sum_{k=1,..,K} -(p_i-c_i)M_k\alpha_k^2 S_{ik}S_{jk}(1-2S_{ik})\right| \tag{25}$$

$$= \left|\sum_{k=1,..,K} -M_k\alpha_k S_{ik}S_{jk}\Big[1+\alpha_k(p_i-c_i)(1-2S_{ik})\Big]\right| \tag{26}$$

$$\leq \sum_{k=1,..,K} -M_k\alpha_k S_{ik}S_{jk}\Big|1+\alpha_k(p_i-c_i)(1-2S_{ik})\Big| \tag{27}$$

$$< \sum_{k=1,..,K} -M_k\alpha_k S_{ik}(1-S_{ik})\Big|1+\alpha_k(p_i-c_i)(1-2S_{ik})\Big| \tag{28}$$

$$< \sum_{k=1,..,K} -M_k\alpha_k S_{ik}(1-S_{ik})\Bigg[2+\alpha_k(p_i-c_i)(1-2S_{ik})\Bigg] \tag{29}$$

$$= \left|2\frac{\partial\lambda_i}{\partial p_i} + (p_i-c_i)\frac{\partial^2\lambda_i}{\partial p_i^2}\right| \tag{30}$$

Note that the first inequality uses triangular inequality and the last inequality follows from the fact that $\Big|1+\alpha_k(p_i-c_i)(1-2S_{ik})\Big| < 2+\alpha_k(p_i-c_i)(1-2S_{ik})$. To see this, first if $\Big[1+\alpha_k(p_i-c_i)(1-2S_{ik})\Big] > 0$ then the inequality holds trivially. Otherwise, we must have:

$$2+\alpha_k(p_i-c_i)(1-2S_{ik}) - \Big|1+\alpha_k(p_i-c_i)(1-2S_{ik})\Big| = 3+2\alpha_k(p_i-c_i)(1-2S_{ik}) \tag{31}$$

$$> 3+2\alpha_k(p_i-c_i) \geq 0 \tag{32}$$

Where the last inequality is an exact restatement of Assumption 1.

□

A.1.4 Structure of value function

Lemma 2. $\mathbb{E}V_i = \sum_{(k_1,k_2)} V_i(k_1,k_2)\frac{e^{-\lambda_1}\lambda^{k_1}}{k_1!}\frac{e^{-\lambda_2}\lambda^{k_2}}{k_2!}$, *we have the followings:*

$$\frac{\partial\mathbb{E}V_i}{\lambda_i} < 0; \quad \frac{\partial\mathbb{E}V_i}{\lambda_j} > 0; \quad \frac{\partial^2\mathbb{E}V_i}{\lambda_i^2} < 0; \quad \frac{\partial^2\mathbb{E}V_i}{\lambda_j^2} > 0. \tag{33}$$

$$\left|\frac{\partial^2 \mathbb{E}V_i}{\partial\lambda_i^2}\frac{\partial\lambda_i}{\partial p_i}\right| > \left|\frac{\partial^2 \mathbb{E}V_i}{\partial\lambda_j^2}\frac{\partial\lambda_j}{\partial p_j}\right| \tag{34}$$

Proof. The first derivatives are very simple to see. The expected future value decreases with current period own sales because seats are valuable. It increases with current period competitor's sales because of capacity externality – the more the seats the worse the competition. Without lose of generality, let $i = 1$ and omit it for ease of exposure when possible:

$$\frac{\partial \mathbb{E}V}{\lambda_1} = \sum_{k_2=0}\left\{\frac{e^{-\lambda_2}\lambda^{k_2}}{k_2!} \times \left[\sum_{k_1=0} V(k_1,k_2) \times \left[-\frac{e^{-\lambda_1}\lambda^{k_1}}{k_1!} + \frac{e^{-\lambda_1}\lambda^{k_1-1}}{(k_1-1)!}\right]\right]\right\} \tag{35}$$

$$= \sum_{k_2=0}\left\{\frac{e^{-\lambda_2}\lambda^{k_2}}{k_2!} \times \left[\sum_{k_1=0} V(k_1,k_2) \times \left(-\frac{e^{-\lambda_1}\lambda^{k_1}}{k_1!}\right) + \sum_{k_1=1} V(k_1,k_2) \times \left(\frac{e^{-\lambda_1}\lambda^{k_1-1}}{(k_1-1)!}\right)\right]\right\} \tag{36}$$

$$= \sum_{k_2=0}\left\{\frac{e^{-\lambda_2}\lambda^{k_2}}{k_2!} \times \left[\sum_{k_1=0} V(k_1,k_2) \times \left(-\frac{e^{-\lambda_1}\lambda^{k_1}}{k_1!}\right) + \sum_{k_1=0} V(k_1+1,k_2) \times \left(\frac{e^{-\lambda_1}\lambda^{k_1}}{(k_1)!}\right)\right]\right\} \tag{37}$$

$$= \sum_{k_2=0}\left\{\frac{e^{-\lambda_2}\lambda^{k_2}}{k_2!} \times \left[\sum_{k_1=0} \left[V(k_1+1,k_2) - V(k_1,k_2)\right] \times \frac{e^{-\lambda_1}\lambda^{k_1}}{k_1!}\right]\right\} \tag{38}$$

Similarly, one can show that

$$\frac{\partial \mathbb{E}V}{\lambda_2} = \sum_{k_1=0}\left\{\frac{e^{-\lambda_1}\lambda^{k_1}}{k_1!} \times \left[\sum_{k_2=0} \left[V(k_1,k_2+1) - V(k_1,k_2)\right] \times \frac{e^{-\lambda_2}\lambda^{k_2}}{k_2!}\right]\right\} \tag{39}$$

The marginal effect of the sales intensity is a probability-weighted sum of the marginal effect of a seat. Follow a similar argument, we can show that the second derivative of the expected future value to sales intensity is determined by a probability-weighted sum of "curvature" of the value function. That is:

$$\frac{\partial^2 \mathbb{E}V}{\lambda_1^2} = \sum_{k_2=0}\left\{\frac{e^{-\lambda_2}\lambda^{k_2}}{k_2!}\left[\sum_{k_1=0}\Big(\big[V(k_1+2,k_2) - V(k_1+1,k_2)\big] - \big[V(k_1+1,k_2) - V(k_1,k_2)\big]\Big)\frac{e^{-\lambda_1}\lambda^{k_1}}{k_1!}\right]\right\} \tag{40}$$

$$\frac{\partial^2 \mathbb{E}V}{\lambda_1^2} = \sum_{k_2=0}\left\{\frac{e^{-\lambda_2}\lambda^{k_2}}{k_2!}\left[\sum_{k_1=0}\Big(\big[V(k_1+2,k_2) - V(k_1+1,k_2)\big] - \big[V(k_1+1,k_2) - V(k_1,k_2)\big]\Big)\frac{e^{-\lambda_1}\lambda^{k_1}}{k_1!}\right]\right\} \tag{41}$$

□

Therefore, the sign of the second derivative of expected future value with respect to own sales intensity depends on whether the marginal cost of a seat increases with sales or not.

A.1.5 Existence

Proof. I show that the expected current profit is concave in own price and expected future value is concave in own price separately. The objective function is a sum of two concave functions and thus is concave. This establishes existence.

The expected profit function $\mathbb{E}\big[\Pi_i\big]$ is very similar to Allon et al (2013). However, here I face the complications of stochastic demand and finite capacity. Fortunately, as I will show below, the result in Allon et al (2013) still holds with some stronger assumption. The first derivative is:

$$\frac{\partial \mathbb{E}\big[\Pi_i\big]}{\partial p_i} = \frac{\partial \left\{ (p_i - c_i)\mathbb{E}D_i \right\}}{\partial p_i} \tag{42}$$

$$= \mathbb{E}D_i + (p_i - c_i)\frac{\partial \mathbb{E}D_i}{\partial p_i} \tag{43}$$

Where

$$\mathbb{E}D_i = s_i + \frac{\lambda_i \Gamma(s_i, \lambda_i) - \Gamma(s_i + 1, \lambda_i)}{(s_i - 1)!} \tag{44}$$

Thus

$$\frac{\partial \mathbb{E}D_i}{\partial p_i} = \frac{\Gamma(s_i, \lambda_i) + \lambda_i \frac{\partial \Gamma(s_i, \lambda_i)}{\partial \lambda_i} - \frac{\partial \Gamma(s_i + 1, \lambda_i)}{\partial \lambda_i}}{(s_i - 1)!} \frac{\partial \lambda_i}{\partial p_i} \tag{45}$$

$$= \frac{\Gamma(s_i, \lambda_i)}{(s_i - 1)!} \frac{\partial \lambda_i}{\partial p_i} \qquad < 0 \tag{46}$$

Also:

$$\frac{\partial^2 \mathbb{E}D_i}{\partial p_i^2} = \frac{\frac{\partial \Gamma(s_i, \lambda_i)}{\partial \lambda_i}}{(s_i - 1)!} \left(\frac{\partial \lambda_i}{\partial p_i} \right)^2 + \frac{\Gamma(s_i, \lambda_i)}{(s_i - 1)!} \frac{\partial^2 \lambda_i}{\partial p_i^2} \tag{47}$$

The second derivative is:

$$
\begin{aligned}
\frac{\partial^2 \mathbb{E}\big[\Pi_i\big]}{\partial p_i^2} &= 2\frac{\partial \mathbb{E} D_i}{\partial p_i} + (p_i - c_i)\frac{\partial^2 \mathbb{E} D_i}{\partial p_i^2} && (48)\\
&= 2\frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!}\frac{\partial \lambda_i}{\partial p_i} + (p_i - c_i)\left\{\frac{\frac{\partial \Gamma(s_i,\lambda_i)}{\partial \lambda_i}}{(s_i-1)!}\left(\frac{\partial \lambda_i}{\partial p_i}\right)^2 + \frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!}\frac{\partial^2 \lambda_i}{\partial p_i^2}\right\} && (49)\\
&= \frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!}\left[2\frac{\partial \lambda_i}{\partial p_i} + (p_i - c_i)\frac{\partial^2 \lambda_i}{\partial p_i^2}\right] + (p_i - c_i)\frac{\frac{\partial \Gamma(s_i,\lambda_i)}{\partial \lambda_i}}{(s_i-1)!}\left(\frac{\partial \lambda_i}{\partial p_i}\right)^2 && (50)\\
&< \frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!}\left[2\frac{\partial \lambda_i}{\partial p_i} + (p_i - c_i)\frac{\partial^2 \lambda_i}{\partial p_i^2}\right] < 0 && (51)
\end{aligned}
$$

Where the first inequality holds by $\frac{\partial \Gamma(s_i,\lambda_i)}{\partial \lambda_i} = -\lambda_i^{s_i-1}e^{\lambda_i} < 0$ and last one follows from Lemma 2.

Now we showed that the expected period utility is concave. Next we move to the expected value function. The first derivative is given by chain rule:

$$
\frac{\partial \mathbb{E} V_i}{\partial p_i} = \frac{\partial \mathbb{E} V_i}{\partial \lambda_i}\frac{\partial \lambda_i}{\partial p_i} + \frac{\partial \mathbb{E} V_i}{\partial \lambda_j}\frac{\partial \lambda_j}{\partial p_i} \qquad (52)
$$

The second derivative is thus:

$$
\begin{aligned}
\frac{\partial^2 \mathbb{E} V_i}{\partial p_i^2} &= \frac{\partial\left\{\frac{\partial \mathbb{E} V_i}{\partial \lambda_i}\frac{\partial \lambda_i}{\partial p_i} + \frac{\partial \mathbb{E} V_i}{\partial \lambda_j}\frac{\partial \lambda_j}{\partial p_i}\right\}}{\partial p_i} && (53)\\
&= \frac{\partial^2 \mathbb{E} V_i}{\partial \lambda_i^2}\left(\frac{\partial \lambda_i}{\partial p_i}\right)^2 + \frac{\partial \mathbb{E} V_i}{\partial \lambda_i}\frac{\partial^2 \lambda_i}{\partial p_i^2} + \frac{\partial^2 \mathbb{E} V_i}{\partial \lambda_j^2}\left(\frac{\partial \lambda_j}{\partial p_i}\right)^2 + \frac{\partial \mathbb{E} V_i}{\partial \lambda_j}\frac{\partial^2 \lambda_j}{\partial p_i^2} && (54)\\
&< \frac{\partial^2 \mathbb{E} V_i}{\partial \lambda_i^2}\left(\frac{\partial \lambda_i}{\partial p_i}\right)^2 + \frac{\partial^2 \mathbb{E} V_i}{\partial \lambda_j^2}\left(\frac{\partial \lambda_j}{\partial p_i}\right)^2 && (55)\\
&< \frac{\partial^2 \mathbb{E} V_i}{\partial \lambda_i^2}\left(\frac{\partial \lambda_i}{\partial p_i}\right)^2 + \left|\frac{\partial^2 \mathbb{E} V_i}{\partial \lambda_j^2}\right|\left(\frac{\partial \lambda_i}{\partial p_i}\right)^2 < 0 && (56)
\end{aligned}
$$

Where the first and last inequalities come from Lemma 3.

Finally, we can sum up the two component and see the objective function is concave:

$$
\frac{\partial^2 f_i(p_i)}{\partial p_i^2} = \frac{\partial^2 \mathbb{E} V_i}{\partial p_i^2} + \frac{\partial^2 \mathbb{E}\big[\Pi_i\big]}{\partial p_i^2} < 0 \qquad (57)
$$

$\square$

A.1.6 Uniqueness

Proof. First:

$$\frac{\partial^2 \mathbb{E}D_i}{\partial p_i \partial p_j} = \frac{\partial \left(\frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!} \frac{\partial \lambda_i}{\partial p_i} \right)}{\partial p_j} \tag{58}$$

$$= \frac{\frac{\partial \Gamma(s_i,\lambda_i)}{\partial \lambda_i}}{(s_i-1)!} \frac{\partial \lambda_i}{\partial p_i} \frac{\partial \lambda_i}{\partial p_j} + \frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!} \frac{\partial^2 \lambda_i}{\partial p_i \partial p_j} \tag{59}$$

Therefore:

$$\frac{\partial^2 \mathbb{E}[\Pi_i]}{\partial p_i \partial p_j} = \frac{\partial \left\{ \mathbb{E}D_i + (p_i - c_i) \frac{\partial \mathbb{E}D_i}{\partial p_i} \right\}}{\partial p_j} \tag{60}$$

$$= \frac{\partial \mathbb{E}D_i}{\partial p_j} + (p_i - c_i) \frac{\partial^2 \mathbb{E}D_i}{\partial p_i \partial p_j} \tag{61}$$

$$= \frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!} \frac{\partial \lambda_i}{\partial p_j} + (p_i - c_i) \left\{ \frac{\frac{\partial \Gamma(s_i,\lambda_i)}{\partial \lambda_i}}{(s_i-1)!} \frac{\partial \lambda_i}{\partial p_i} \frac{\partial \lambda_i}{\partial p_j} + \frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!} \frac{\partial^2 \lambda_i}{\partial p_i \partial p_j} \right\} \tag{62}$$

$$= \frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!} \left[\frac{\partial \lambda_i}{\partial p_j} + (p_i - c_i) \frac{\partial^2 \lambda_i}{\partial p_i \partial p_j} \right] + (p_i - c_i) \frac{\frac{\partial \Gamma(s_i,\lambda_i)}{\partial \lambda_i}}{(s_i-1)!} \frac{\partial \lambda_i}{\partial p_i} \frac{\partial \lambda_i}{\partial p_j} \tag{63}$$

So we must have:

$$\left| \frac{\partial^2 \mathbb{E}[\Pi_i]}{\partial p_i \partial p_j} \right| \leq \left| \frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!} \left[\frac{\partial \lambda_i}{\partial p_j} + (p_i - c_i) \frac{\partial^2 \lambda_i}{\partial p_i \partial p_j} \right] \right| + \left| (p_i - c_i) \frac{\frac{\partial \Gamma(s_i,\lambda_i)}{\partial \lambda_i}}{(s_i-1)!} \frac{\partial \lambda_i}{\partial p_i} \frac{\partial \lambda_i}{\partial p_j} \right| \tag{64}$$

$$< \left| \frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!} \left[\frac{\partial \lambda_i}{\partial p_j} + (p_i - c_i) \frac{\partial^2 \lambda_i}{\partial p_i \partial p_j} \right] \right| + \left| (p_i - c_i) \frac{\frac{\partial \Gamma(s_i,\lambda_i)}{\partial \lambda_i}}{(s_i-1)!} \left(\frac{\partial \lambda_i}{\partial p_i} \right)^2 \right| \tag{65}$$

$$< \left| \frac{\Gamma(s_i,\lambda_i)}{(s_i-1)!} \left[2\frac{\partial \lambda_i}{\partial p_i} + (p_i - c_i) \frac{\partial^2 \lambda_i}{\partial p_i^2} \right] \right| + \left| (p_i - c_i) \frac{\frac{\partial \Gamma(s_i,\lambda_i)}{\partial \lambda_i}}{(s_i-1)!} \left(\frac{\partial \lambda_i}{\partial p_i} \right)^2 \right| \tag{66}$$

$$= \left| \frac{\partial^2 \mathbb{E}[\Pi_i]}{\partial p_i^2} \right| \tag{67}$$

Next we show same relation holds for expected value functions. First:

$$\frac{\partial^2 \mathbb{E}V_i}{\partial p_i p_j} = \frac{\partial \left\{ \frac{\partial \mathbb{E}V_i}{\partial \lambda_i} \frac{\partial \lambda_i}{\partial p_i} + \frac{\partial \mathbb{E}V_i}{\partial \lambda_j} \frac{\partial \lambda_j}{\partial p_i} \right\}}{\partial p_j} \tag{68}$$

$$= \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_i^2} \frac{\partial \lambda_i}{\partial p_i} \frac{\partial \lambda_i}{\partial p_j} + \frac{\partial \mathbb{E}V_i}{\partial \lambda_i} \frac{\partial^2 \lambda_i}{\partial p_i \partial p_j} + \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_j^2} \frac{\partial \lambda_j}{\partial p_i} \frac{\partial \lambda_j}{\partial p_j} + \frac{\partial \mathbb{E}V_i}{\partial \lambda_j} \frac{\partial^2 \lambda_j}{\partial p_i \partial p_j} \tag{69}$$

$$\tag{70}$$

We consider two cases below.
Case 1. If $\frac{\partial^2 \mathbb{E}V_i}{\partial p_i p_j} \geq 0$, we must have:

$$\left| \frac{\partial^2 \mathbb{E}V_i}{\partial p_i \partial p_j} \right| = \left| \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_i^2} \frac{\partial \lambda_i}{\partial p_i} \frac{\partial \lambda_i}{\partial p_j} \right| + \left| \frac{\partial \mathbb{E}V_i}{\partial \lambda_i} \frac{\partial^2 \lambda_i}{\partial p_i \partial p_j} \right| - \left| \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_j^2} \frac{\partial \lambda_j}{\partial p_i} \frac{\partial \lambda_j}{\partial p_j} \right| - \left| \frac{\partial \mathbb{E}V_i}{\partial \lambda_j} \frac{\partial^2 \lambda_j}{\partial p_i \partial p_j} \right| \tag{71}$$

$$< \left| \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_i^2} \frac{\partial \lambda_i}{\partial p_i} \frac{\partial \lambda_i}{\partial p_j} \right| + \left| \frac{\partial \mathbb{E}V_i}{\partial \lambda_i} \frac{\partial^2 \lambda_i}{\partial p_i \partial p_j} \right| - \left| \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_j^2} \frac{\partial \lambda_j}{\partial p_i} \frac{\partial \lambda_j}{\partial p_j} \right| \tag{72}$$

$$< \left| \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_i^2} \left(\frac{\partial \lambda_i}{\partial p_i} \right)^2 \right| + \left| \frac{\partial \mathbb{E}V_i}{\partial \lambda_i} \frac{\partial^2 \lambda_i}{\partial p_i^2} \right| - \left| \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_j^2} \left(\frac{\partial \lambda_j}{\partial p_i} \right)^2 \right| \tag{73}$$

$$< \left| \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_i^2} \left(\frac{\partial \lambda_i}{\partial p_i} \right)^2 \right| + \left| \frac{\partial \mathbb{E}V_i}{\partial \lambda_i} \frac{\partial^2 \lambda_i}{\partial p_i^2} \right| - \left| \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_j^2} \left(\frac{\partial \lambda_j}{\partial p_i} \right)^2 \right| + \left| \frac{\partial \mathbb{E}V_i}{\partial \lambda_j} \frac{\partial^2 \lambda_j}{\partial p_i^2} \right| \tag{74}$$

$$= \left| \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_i^2} \left(\frac{\partial \lambda_i}{\partial p_i} \right)^2 + \frac{\partial \mathbb{E}V_i}{\partial \lambda_i} \frac{\partial^2 \lambda_i}{\partial p_i^2} + \frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_j^2} \left(\frac{\partial \lambda_j}{\partial p_i} \right)^2 + \frac{\partial \mathbb{E}V_i}{\partial \lambda_j} \frac{\partial^2 \lambda_j}{\partial p_i^2} \right| \tag{75}$$

$$= \left| \frac{\partial^2 \mathbb{E}V_i}{\partial p_i^2} \right| \tag{76}$$

Where the equalities and inequalities come from realizing the signs of the terms.

Case 2. If $\frac{\partial^2 \mathbb{E}V_i}{\partial p_i p_j} < 0$, we must have:

$$\left|\frac{\partial^2 \mathbb{E}V_i}{\partial p_i \partial p_j}\right| = -\left|\frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_i^2}\frac{\partial \lambda_i}{\partial p_i}\frac{\partial \lambda_i}{\partial p_j}\right| - \left|\frac{\partial \mathbb{E}V_i}{\partial \lambda_i}\frac{\partial^2 \lambda_i}{\partial p_i \partial p_j}\right| + \left|\frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_j^2}\frac{\partial \lambda_j}{\partial p_i}\frac{\partial \lambda_j}{\partial p_j}\right| + \left|\frac{\partial \mathbb{E}V_i}{\partial \lambda_j}\frac{\partial^2 \lambda_j}{\partial p_i \partial p_j}\right| \tag{77}$$

$$< -\left|\frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_i^2}\frac{\partial \lambda_i}{\partial p_i}\frac{\partial \lambda_i}{\partial p_j}\right| + \left|\frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_j^2}\frac{\partial \lambda_j}{\partial p_i}\frac{\partial \lambda_j}{\partial p_j}\right| + \left|\frac{\partial \mathbb{E}V_i}{\partial \lambda_j}\frac{\partial^2 \lambda_j}{\partial p_i \partial p_j}\right| \tag{78}$$

$$= \left|\frac{\partial \lambda_i}{\partial p_j}\right|\left\{ -\left|\frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_i^2}\frac{\partial \lambda_i}{\partial p_i}\right| + \left|\frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_j^2}\frac{\partial \lambda_j}{\partial p_j}\right|\right\} + \left|\frac{\partial \mathbb{E}V_i}{\partial \lambda_j}\frac{\partial^2 \lambda_j}{\partial p_i \partial p_j}\right| \tag{79}$$

$$< \left|\frac{\partial \mathbb{E}V_i}{\partial \lambda_j}\frac{\partial^2 \lambda_j}{\partial p_i \partial p_j}\right| \tag{80}$$

$$= \left|\frac{\partial \mathbb{E}V_i}{\partial \lambda_j}\frac{\partial^2 \lambda_j}{\partial p_i^2}\right| \tag{81}$$

$$< \left|\frac{\partial \mathbb{E}V_i}{\partial \lambda_i}\frac{\partial^2 \lambda_i}{\partial p_i^2}\right| + \left|\frac{\partial \mathbb{E}V_i}{\partial \lambda_j}\frac{\partial^2 \lambda_j}{\partial p_i^2}\right| \tag{82}$$

$$< \left|\frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_i^2}\left(\frac{\partial \lambda_i}{\partial p_i}\right)^2\right| + \left|\frac{\partial \mathbb{E}V_i}{\partial \lambda_i}\frac{\partial^2 \lambda_i}{\partial p_i^2}\right| - \left|\frac{\partial^2 \mathbb{E}V_i}{\partial \lambda_j^2}\left(\frac{\partial \lambda_j}{\partial p_i}\right)^2\right| + \left|\frac{\partial \mathbb{E}V_i}{\partial \lambda_j}\frac{\partial^2 \lambda_j}{\partial p_i^2}\right| \tag{83}$$

$$= \left|\frac{\partial^2 \mathbb{E}V_i}{\partial p_i^2}\right| \tag{84}$$

To conclude, we must have that:

$$\left|\frac{\partial^2 f_i}{\partial p_i \partial p_j}\right| = \left|\frac{\partial^2 \mathbb{E}\left[\Pi_i\right]}{\partial p_i \partial p_j} + \frac{\partial^2 \mathbb{E}V_i}{\partial p_i \partial p_j}\right| \tag{85}$$

$$< \left|\frac{\partial^2 \mathbb{E}\left[\Pi_i\right]}{\partial p_i \partial p_j}\right| + \left|\frac{\partial^2 \mathbb{E}V_i}{\partial p_i \partial p_j}\right| \tag{86}$$

$$< \left|\frac{\partial^2 \mathbb{E}\left[\Pi_i\right]}{\partial p_i^2}\right| + \left|\frac{\partial^2 \mathbb{E}V_i}{\partial p_i^2}\right| \tag{87}$$

$$= \left|\frac{\partial^2 \mathbb{E}\left[\Pi_i\right]}{\partial p_i^2} + \frac{\partial^2 \mathbb{E}V_i}{\partial p_i^2}\right| \tag{88}$$

$$= \left|\frac{\partial^2 f_i}{\partial p_i^2}\right| \tag{89}$$

$\square$

A.1.7 Data

In this section, I use the whole sample to show some stylized facts in the airline industry.[16] On the demand side, I use simple reduced-form regression analysis to confirm that sales are less elastic as it gets closer to the departure date. Moreover, my regression results suggest that early demand also has higher cross price elasticity. These motivate my later structural assumption on demand. On the supply side, I show evidence that supports my anecdotal discussion on airline pricing practice. Specifically, my regression results are consistent with stochastic pricing based on realized demand. It suggests that firm is more likely to increase its price in response to its own past sales as well as its competitor's sale. These motivate my later structural assumption on supply.

Data Patterns Table 15 reports the summary statistic of the data. The data covers $225,704$ observations of daily-flight-level prices and sales for $4,550$ flights up to 100 days before departure dates. On average, a flight sells 0.91 seat each day. From day $t+1$ to day t, airlines increase price 15% of the time and decrease price 9% of the time. An average flight sells 45 seats since 100 days before departure. Flight-level Gini coefficient in the bottom row captures the intertemporal price dispersion for a given flight. The mean of the flight-level Gini coefficient in my data equals Siegert and Ulbricht (2015), although they study European airline industry whereas I look at the U.S. one. A flight-level Gini coefficient of 0.12 means that an expected absolute difference is 24% between two randomly selected prices for the same flight at two different pricing dates.

Figure 10 shows the average path of prices and loading factor by number of days to departure. Loading factor increases relatively smoothly over time. The average loading factor is 83%. The average loading factor for the U.S airline industry is between 83%-84% from 2011-2016.[17] Price increases as it gets closer to departure day. Noticeably, price jumps up at certain threshold such as 4 days, 1 week, 2 weeks, 3 weeks, etc. Prices are relatively stationary more than one month before departure date. For later analysis, I will focus on seven weeks (49 days) before departure. The price path looks similar to existing literature. However I note that it is steeper than Williams (2017). If one is willing to extrapolate from his monopoly markets to the current duopoly markets, this suggest that competition increase the slope price path. Siegert and Ulbricht (2015) find that the rate at which prices increase over time decreases in competition.

Sales are smooth over time. More than seventy percent of the seats are available 100 days before departure. On average, airlines fill in more than 50% of their capacities within this time window. In summary, the general patterns of data is very consistent with existing literatures. As we move to the next section, I will discuss the research design of the paper.

[16] My goal is to show some general demand and supply patterns to motivate our structural assumptions, and I will discuss the formal research design in the following section.

[17] http://airlines.org/dataset/annual-results-u-s-airlines-2/

Table 15: Data Summary

Statistic	Mean	Median	St. Dev.
Flight number × Departure date × Pricing date			
N=120,510			
Price ($)	270.38	233.000	131.391
Number of seats sold	1.153	0	1.871
Probability of price increase	0.192	0	0.394
Probability of price decrease	0.305	0	0.460
Price change ($)	+5.923	0	53.592
Flight number × Departure date			
N=3,864			
Capacity	66.45	72.00	27.85
Average sales	35.97	33.00	23.67
Load factor	0.8251	0.8562	0.16
Gini coefficient	0.14	0.14	0.08
Flight number × Days to departure			
N=1,054			
Gini coefficient	0.16	0.17	0.06

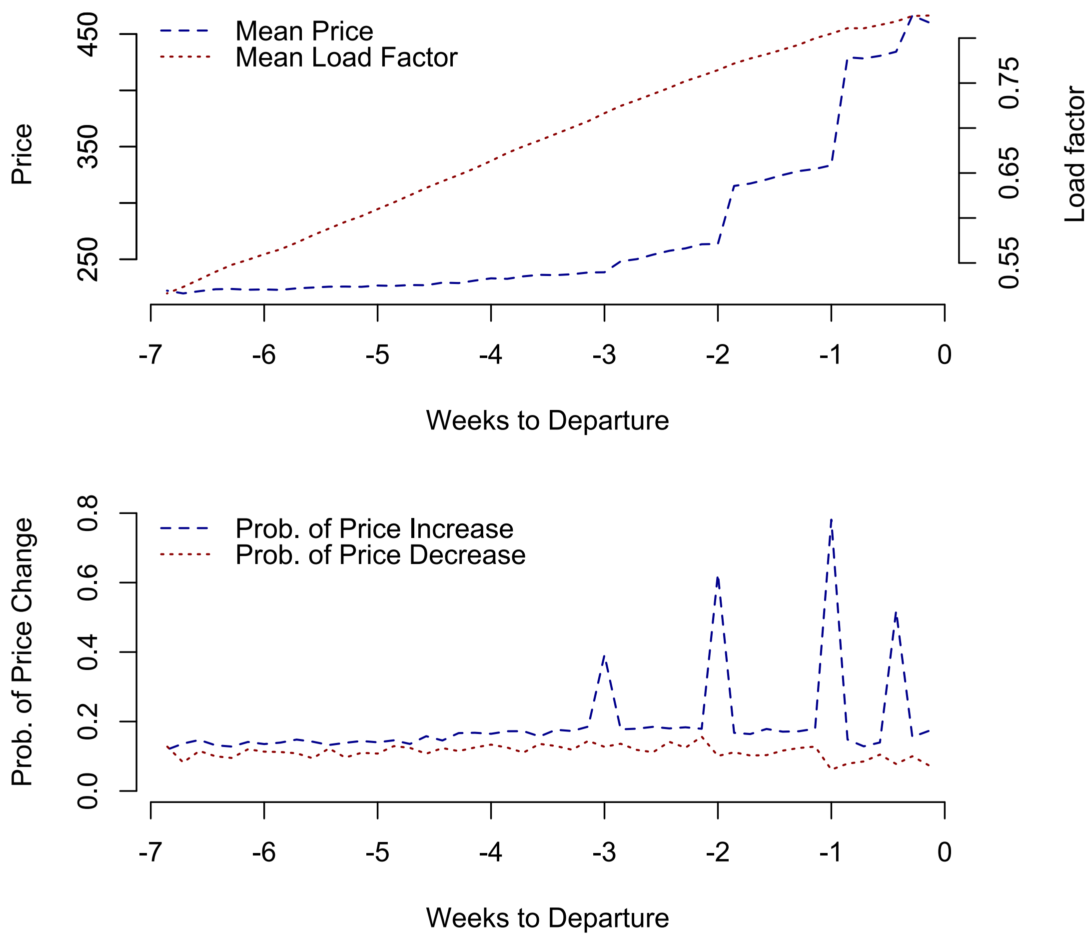

Figure 10: Average path for prices and sales (whole sample)

Capacity Constraint Capacity constraint is important in the airline industry. Generally, equilibrium prices are higher when capacities are more constrained (Osborne and Pitchik (1986)). Figure 11 demonstrates this using price and capacity variation for flights between New York and Aguadilla. Each dot is a mean price for a flight on a departure date, and the solid line plots industry total capacity. Before May 4th, JetBlue used an Airbus A320 with 150 seats. They temporarily switched to an Airbus A321 with 190 seats during May 5th to June 15th. Meanwhile on July 1st, UA switched from an Airbus A320 with 138 economy seats to a Boeing 737-700 Micronetia with 106 economy seats. Other fluctuations are because UA sometimes changed their planes conditional on weekdays. I normalize price by its airline-day-to-departure mean because of a missing data issue. My data collection started at Feb-15th and was interrupted for 3 weeks from June-6th to June-27th. I note that this missing data is not random, for instance for a flight departure at June 26th, I only observed its prices more than 3 weeks from its departure. The normalization should take out intertemporal variations in prices. I note that the graph is similar without normalization.

It suggests that mean prices are negatively correlated with industry capacity. Since the endogeneity of capacity is likely to reverse this correlation, this graph provides causal evidence on the role of capacity constraint.

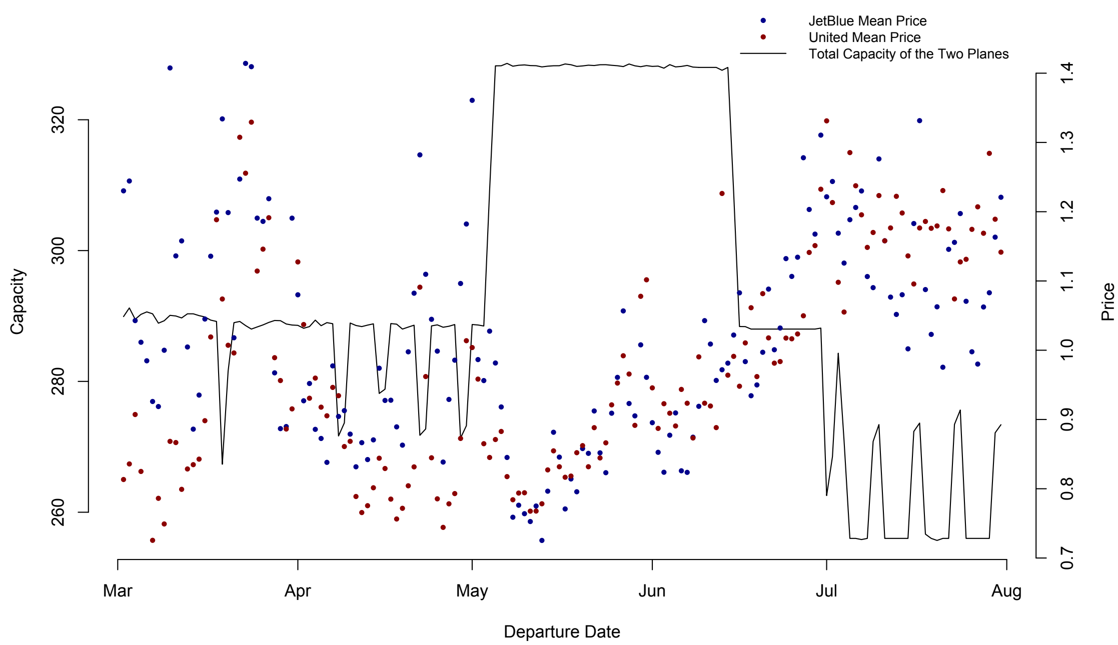

Figure 11: When airlines change planes (New York-Aguadilla)

A.1.8 Demand Elasticities

On the demand side I consider separate regressions for each firm $j = 1, 2$:

$$\begin{aligned}\text{logit}\left[\mathbb{1}\{\text{Sale}^j_{i,d,t} > 0\}\right] = a_1 \times \log\left(\text{Price}^1_{i,d,t}\right) + a_2 \times \log\left(\text{Price}^2_{i,d,t}\right) \\ + \text{Flight}_{i,d} + \text{Trend}_{i,t}\end{aligned}$$

Since daily sales are very small with an average of 0.91, I adopt a logit specification with binary response. The subscripts i denotes itinerary (or directional route), d denotes departure date, and t denotes days to departure. The upper-script $1, 2$ denote firms' identities. $\text{Sale}^j_{i,d,t}$ is the observed sale(s) for firm j's flight in itinerary i, t days before the departure date d. For this reduced form demand regression, I control for endogeneity in a pragmatic way by including more control variables. Specifically, $\text{Flight}_{i,d}$ is itinerary interacted with departure date, and it controls for flight-specific effect. $\text{Trend}_{i,t}$ is itinerary interacted with days to departure, and it captures itinerary-specific trend.

I split the data into two parts by the number of days to departure. For each half, I do two independent logit regressions for the two firms. I pool across all itineraries, so I need to decide how to match the asymmetric firms across the itineraries. I simply denote the bigger firm in each itinerary as firm 1.

Table 16 showed the results for these regressions. The results suggest that five to seven weeks before departure, demand are more elastic. Cross-elasticities are significantly greater than zero five to seven weeks before departure, and the coefficients are no longer significant for consumers arrive less than three weeks before departure.

A.1.9 Stochastic Pricing

On the supply side I would like to show some suggestive evidence that firms are pricing based on scarcity. One straightforward way is to regress prices on capacities, and show that flights sold better are priced higher. However, I am concerned about the endogeneity of capacities. Instead I consider the following regressions for each firm $j = 1, 2$:

$$\begin{aligned}\text{Price}^j_{i,d,t} = b_1 \times \mathbb{1}\{\text{Sale}^1_{i,d,t-1} > 0\} + b_2 \times \mathbb{1}\{\text{Sale}^2_{i,d,t-1} > 0\} \\ + \text{Price}^1_{i,d,t-1} + \text{Price}^2_{i,d,t-1} \\ + \text{Flight}_{i,d} + \text{Trend}_{i,t} + \epsilon_{i,d,t}\end{aligned}$$

Here I do a fixed effect regression, with $\text{Flight}_{i,d}$ capturing itinerary$\times$departure date fixed effect and $\text{Trend}_{i,t}$ capturing itinerary$\times$ days to departure fixed effect. I pool across all itineraries and run the regression for each of the two firms which I labeled in a same way as before.

Table 17 shows results of these regressions. The result is mostly consistent with stochastic pricing. Though one of the coefficient is not significant. Note that I control for $\boldsymbol{p}_{t-1}$ to

Table 16: Sales on Prices

	Logit			
	$\mathbb{1}\{\text{Sale}^1 > 0\}$		$\mathbb{1}\{\text{Sale}^2 > 0\}$	
Week to departure	$5-7$	$1-3$	$5-7$	$1-3$
$\log(\text{Price}^1)$	-3.638^{***}	-2.125^{***}	0.509^{***}	-0.054
	(0.153)	(0.108)	(0.144)	(0.106)
$\log(\text{Price}^2)$	0.295^{**}	0.091	-3.827^{***}	-1.202^{***}
	(0.120)	(0.071)	(0.151)	(0.081)
Controls				
Flight	Yes	Yes	Yes	Yes
Trend	Yes	Yes	Yes	Yes
Observations	18,451	17,320	18,451	17,320
Log Likelihood	−10,765	−10,450	−10,302	−9,230
Akaike Inf. Crit.	24,373	23,755	23,447	21,315

Note: S.E clustered at flight level. *p<0.1; **p<0.05; ***p<0.01

control for endogeneity. I try to make a point that an airline increases its price if it sells or if its competitor sells. I note that ruling out serial correlation of unobserved errors is very challenging. A sufficient condition is that airlines observed all ξ_{t-1} when setting prices.

Table 17: Pricing on Realized Demand

	Linear	
	Price_t^1	Price_t^2
$\mathbb{1}\{\text{Sale}_{t-1}^1 > 0\}$	2.614***	0.587
	(0.431)	(0.517)
$\mathbb{1}\{\text{Sale}_{t-1}^2 > 0\}$	1.080***	4.120***
	(0.396)	(0.597)
Controls		
Price_{t-1}^1	0.664***	0.060***
	(0.015)	(0.008)
Price_{t-1}^2	0.040***	0.644***
	(0.005)	(0.016)
Fixed Effects		
Flight	Yes	Yes
Trend	Yes	Yes
Observations	47,931	47,931
R^2	0.912	0.861
Adjusted R^2	0.908	0.854

Note: S.E. clustered at flight level. *p<0.1; **p<0.05; ***p<0.01

A.2 Appendix to Chapter 2

Table 18: The effect of PCDI visit on vehicle registration, different specifications

	Dependent variable:			
	Log of Total Registration, all brands pooled			
	(1)	(2)	(3)	(4)
$T > PCDI\_visit\_date$	-0.015	-0.034^{***}	-0.035^{**}	-0.003
	(0.016)	(0.012)	(0.014)	(0.007)
County-by-Brand fixed effects	Yes	Yes		
County-by-Brand-Month fixed effects			Yes	
County-by-Brand-Year fixed effects				Yes
Time-by-Brand fixed effects	Yes			
Time-by-Province-by-Brand fixed effects		Yes	Yes	Yes
Observations	2,974,320	2,974,320	2,974,320	2,974,320
R^2	0.801	0.823	0.850	0.877
Adjusted R^2	0.798	0.817	0.810	0.864

Note: *p<0.1; **p<0.05; ***p<0.01

Clustered Standard Errors (Prefecture-level) in parenthese