Inventory pooling technique from the car rental industry: now and in the autonomous future

Kuangnen Cheng*

Department of Management,
Marist College,
NY, USA
Email: kuangnen.cheng@marist.edu
*Corresponding author

Byunghoon Jin

Department of Economics, Accounting, and Finance,
Marist College,
NY, USA
Email: byunghoon.jin@marist.edu

Abstract: This investigation studies the current car rental industry's inventory pooling technique to understand its potential impact on the industry's future survival and success possibility once autonomous vehicles (AVs) requiring no human input. The research utilises live pricing data from the US car rental and ridesharing industry to detect: 1) how players from the car rental industry apply pricing strategy to reduce inventory shuttling activities and balance the demand with supply; 2) whether the current pooling model can be transferred into the future assuming the business model and pricing strategy of the future robotaxi market is similar to those of today's ridesharing industry. Data reveals that between locations within a pool, pricing fluctuations correlate to weekends or weekdays demand pending on its discrete or complimentary relationship. Hypotheses are developed; consequently, determinants impacting inventory pooling are utilised to analyse their compatibility in the future robotaxi market.

Keywords: autonomous vehicles; car rental industry; complementary demand; inventory pooling; robotaxi.

Reference to this paper should be made as follows: Cheng, K. and Jin, B. (2021) 'Inventory pooling technique from the car rental industry: now and in the autonomous future', *Int. J. Business Environment*, Vol. 12, No. 1, pp.37–63.

Biographical notes: Kuangnen Cheng is an Assistant Professor of Operations Management and Supply Chain Management and teaches at Marist College, NY. His research focuses on supply chain, operations, logistics and operations strategy.

Byunghoon Jin received his PhD in Accounting from Temple University, Master's in Professional Accounting from University of Texas at Austin, and his Bachelors of Science in Business-Accounting from Indiana University Bloomington. He worked for PwC as an internal/external auditor and a consultant. At Marist College, he has taught various financial and managerial accounting courses including intermediate accounting and cost accounting. His main research interests include accruals behaviour, earnings management, cost behaviour, executive compensation, corporate governance, and business ethics.

1 Introduction

The car rental industry is facing new challenges:

1 it is losing customers to ridesharing service (such as Uber or Lyft)

2 it is expected to be disrupted in the near future once the capability of autonomous vehicles (AVs) reaches level 5 (fully autonomous and requiring no human input) according to Society of Automotive Engineers (SAE) International.

However, the vast majority of scholarly articles concerning the paradigm shift in the automotive industry focus on issues such as autonomous technology development, implementation procedures, regulations or public acceptance. How will self-driving vehicles impact the $93 billion value of global car rental industry is rarely studied. As ridesharing firms, automakers and technology giants are gradually entering into the new market, the rental car industry is at a crucial moment in winning the fight. Fortunately, AVs will still require to be managed such as fleet, maintenance, purchasing procurement, etc. The rental car industry might not possess the technical knowledge of AVs to compete, yet, those potential rivals are lacking of the fleet management experience. Experts (Autonomous Cars Will End the $75 Billion Rental Car Industry as We Know it, 2016) believe, the car rental industry could win the battle based on their existing fleet management knowledge.

What can the car rental industry do to ensure its survival and success in the autonomous future? Over the next decade when the landscape of the car ownership changes and AVs start to dominate the road, the rental car industry may rely on its existing capability of managing and maintaining enormous fleets to win over consumers. One of the fleet management's optimal goals is to ensure demand meets supply at the right time and the right place. An anticipated technique in the future robotaxi (a self-driving taxi or a driverless taxi) market could be the one being applied by the current ridesharing industry, a third party designed ridesharing platform to connect riders and drivers. As transportation providers are not employed by the platform designer, the technique to balance the supply with demand relies on the strategy of 'surge pricing'[1] (Hall et al., 2015; Riquelme et al., 2015), a passive supply-demand-matching strategy which is not designed to expand demand but to enlarge revenue. Unless the wait time of getting a ride can be reduced, the current inventory pooling strategy has its unique value in enhancing future robotaxi's inventory management.

Yet, the car rental industry's demand is hard to accurately forecast due to:

1 the industry's reservation (the demand side) practice such as a non-guaranteed reservation format

2 a widely fluctuated capacity (the supply side) since a fleet can be moved around between locations at a determined cost (Haensel et al., 2012).

Almost every major car rental firm has more than one location in a metropolitan area. For example, Enterprise, Hertz and Avis have 44, 23 and 17 locations respectively in the Seattle area. This scale is where all other potential rivals in robotaxi market cannot compete with. In general, locations are distributed around airport, downtown and suburb (collectively, the aggregate of these three locations is called a pool). As business customers tend to utilise airport locations during weekdays and leisure customers downtown/suburb locations during weekends, it is not uncommon to expect demands at airport locations to spike on weekdays and downtown locations on weekends (Carroll and Grimes, 1995). In larger car rental firms, a group of stations share the same fleet; and, rental stations are usually aggregated into pools (Oliveira et al., 2017). Unlike airlines, hotels or cruise lines, car rental firms can easily shuttle their fleet between locations to meet demands. As demand forecast techniques in revenue management matured (Fiig et al., 2014), pricing decision in the car rental industry is expected to be synchronised with the allocation of inventory; especially, decisions are expected to take into account that inventory is not fixed but flexible. This means costs of the fleet shuttling within a pool need to be considered when applying a dynamic pricing strategy to maximise profits. Unless the cost of shuttling inventory is negligible, the inventory pooling strategy needs to consider that:

1 weekday and weekend rates fluctuate significantly depending on locations

2 inventory pooling is effective when prices between airport and non-airport (namely, downtown/suburb) are inversely correlated.

This investigation intends to explore how the car rental industry balances demand with supply via inventory pooling strategy and attempts to explain whether the current strategy is sustainable in the autonomous future.

The remainder of this investigation is organised as follows. Section 2 is the literature review, Section 3 is the hypotheses development, Section 4 is the data, methods and discussion, Section 5 is the compatibility of the current pooling strategy in the future robotaxi market, and Section 6 is the concluding remarks.

2 Literature review

Extended literature of operations management related to inventory pooling has demonstrated various effects of consolidating common inventory stock on a stochastic demand (Das and Tyagi, 1997; Kurata, 2014; Swinney, 2011). Two major suggestions are found from the inquiry of how to optimise profits by efficiently matching supply with demand. On the demand side, scholarly work (e.g., Graves et al., 1986; Toktay and Wein, 2001), in general, have emphasised that demand forecasting reduces inventory managing costs. On the supply side, the journey started from Maister's (1976) 'square root law' of locations, which states, and has mathematically proved, that when demands are independent and each location has the same proportion of demand, the system-wide average inventory increases proportionally to the square root of the number of locations in which inventory is held. In other words, consolidating locations can be beneficial to the firms. Later, Eppen's (1979) study of newsvendor-type markets illustrated that pooling inventory for different demand sources decreases inventory costs. The intertwined nature between Eppen's pooling effect and Maister's 'square root law' of location consolidations incubated two noticeable lines of work (Williams and Tokar, 2008). One focused on how to integrate inventory control with other logistics activities such as transportation and warehousing (e.g., Tyagi and Das, 1998; Buffa and Reynolds, 1979; Mattsson, 2007) and the other on the inter-firms' collaborative inventory management (e.g., Langley, 1980; Kumar and Chandra, 2002; Cardenas-Barron, 2007). Study on the inventory pooling effect continues to gain attention and expands to the marketing field which is interested in how to gain more customers. For example, Swinney (2011) discussed what type of consumer purchasing behaviours is expected when inventory is intentionally fluctuating. One of the findings was that pooling may benefit the firm when margins are high and demands are negatively correlated. Zhong et al. (2018) explained how integrating the heterogeneous service level requirements of different customers into the pooling model could expand customer base. Kurata (2014) asserted that product availability naturally influences customers' purchasing decisions. When customers are product-availability-conscious, the design of a centralised inventory system needs to avoid a long delivery lead time. To summarise findings from the previous literature, inventory pooling saves costs as it reduces uncertainty and efficiently improves the matching of supply with demand.

Literature related to dynamic pricing is plentiful. Many agreed that dynamic pricing, the demand-side management, increases revenue and profits (McAfee and te Velde, 2007; Sahay, 2007). To ensure that a dynamic pricing produces beneficial results, important parameters and constraints of product distributions need to be identified. First, consumers respond to marginal incentives (Chen and Pearcy, 2010); second, the product has a finite shelf life and the capacity is fixed. Such operational characteristics are possessed by travel and hospitality industries such as airline (Alderighi et al., 2011; Escobari, 2014), hotel (Kimes, 2011; Bayoumi et al., 2013) and sports industry (Drayer et al., 2012; Bouchet et al., 2016). As demand data became easier to obtain, new technologies became widely available to enable the adjustment of price changing at nearly no cost. Those modern technologies of analysing demands and pricing data fast and thoroughly subdued the hurdle of constraints in the area of inventory capacity (Elmaghraby and Keskinocak, 2003). As such, the dynamic pricing started to make inroads into retail and other industries where the sellers have the capability to store inventory (Chen et al., 2016). When the capacity is fixed, the mechanism of 'posted price'[2] is employed to balance supply and demand, instead of 'price discovery'[3] which is more relevant when capacity is more flexible due to inventory pooling (Einav et al., 2018). Further, in the event when more demand than semi-flexible supply, then, 'surge price' (Hall et al., 2015; Riquelme et al., 2015), instead of 'posted price', produces much better results. 'Surge price' not only balances supply and demand, but also extracts more profits. Elmaghraby and Keskinocak (2003) explained how industries that traditionally relied on improving inventory management to increase profits are now eager to look at a better demand side management. Numerous scholarly works have addressed the dynamic pricing under a flexible production capacity (Ceryan et al., 2013; Yang and Zhang, 2014). Basically, scholars have discussed how to set price decisions to match the inventory and maximise profits. Rules of thumb to deal with a flexible capacity are that:

1 prices should be changing periodically instead of continuously over time

2 firms are required to set the desired inventory level before the demand is known (Simchi-Levi et al., 2014).

However, research in the area of the car rental logistic problems is scarce. As car rental revenue heavily involves the efficiently matching of rental location, fleet size, car type, length of rental, and time of rental, a large body of car rental literature focused on solutions of how to match pricing decisions with the capacity based on mathematical modelling (Oliveira et al., 2017). Madden and Russell (2012) studied Dollar Thrifty Auto Group and provided their optimisation model to solve fleet deployment issues as direct data is not observable. Some early works were descriptive and focused on revenue management such as how to control capacity, price and booking requests (Carroll and Grimes, 1995; Geraghty and Johnson, 1997). Since this type of quantitative approach, in terms of how to optimise revenue, has been borrowed from the airline industry (Oliveira et al., 2017), the pioneer of revenue management, certain parameters adapted from the airline industry faced different challenges in the car rental industry. For example, precisely forecasting demand and supply is difficult due to the industry norm of reservation practice and fleet flexibility (Gordon, 2015). Citing this unique characteristic of capacity flexibility, numerous scholars dedicated their work in fleet management problems. As early as 1977, Edelstein and Melnyk (1977) explained how Hertz Cooperation controlled their fleet size or available capacity on a pool basis. Pachon et al. (2003) exemplified three phases of decision-making in fleet control:

1. locations that need to be grouped into one pool
2. the quantity, variety and the deployment of the fleet within each pool
3. mathematical algorithms to solve pool segmentation problems (also see Yang et al., 2009).

Fleet utilisation and its impacts on revenue optimisation can be found in the work of Oliveira et al. (2017), which explains why managing fleet flexibility within a pool, instead of a fixed capacity at a station level, produces better financial outcomes. The operational practice of adjusting fleet size at a determined cost by moving cars between rental stations within a pool can be found in the literature of revenue and operations management related to the car rental industry (Carroll and Grimes, 1995; Fink and Reiners, 2006; Pachon et al., 2006; Haensel et al., 2012; You and Hsieh, 2014).

Literature in the area of robotaxi fleet management is at its early development stage. First, by definition, robotaxi can be treated as a type of sharing a fleet of AVs. As such, cost of a trip, profit per mile or per trip (Firnkorn and Mueller, 2011; Bischoff and Maciejewski, 2016; Boesch et al., 2018; Stocker and Shaheen, 2018; Nunes and Hernandez, 2019) serves better estimates for future choices of the travel mode. As the industry is at the early adoption stage, there are insufficient real operational data to reach a consensus, in terms of the cost of usages. Some asserted that the usage of robotaxi is more expensive than that of the CDVs such as a robotaxi trip would cost between \$1.58 to \$6.01 on a per-mile basis vs. the \$0.72 cost of owning a car (Nunes and Hernandez, 2019); some (Burns et al., 2013) provided simulation results to prove the cost of robotaxi would be ten times lower than that of CDVs. Second, in the operation side, the area of fleet size, variations and relocation strategies is the main focus. Numerous study revolved on these issues. For example, Vosooghi et al. (2019) applied a multi-agent activity-based simulation and studied the Rouen-Normandie metropolitan in France. Their conclusions indicated that several factors such as the demographic structure of the metropolitan and the preferences of AV's variation impact robotaxi fleet sizing. A study of the travel mode by shared autonomous vehicles (SAVs) in Austin, Texas, conducted by Fagnant and Kochelman (2018) revealed that vehicle-miles travelled by SAVs exceed person-trip miles demanded due to anticipatory relocations of empty vehicles between trip calls. Further, the population density influences service level (Bischoff and Maciejewski, 2016) which means the usage of AVs in the city centre is more efficient compared to the suburban area. Finally, unlike the service mode of CDVs' vehicles-awaiting-customers, the shorter wait time (quicker pickups) would attract more revenue for robotaxi mode of customers-awaiting-vehicles. This type of the operation may require the right choice of dispatching algorithm (Hoerl et al., 2018) instead of physical locations.

3 Hypotheses development

By definition, the concept of inventory pooling applies to the strategy that a firm attempts to match supply with demand by managing a common inventory stock to serve multiple markets in a timely manner. As such, the technique involves inventory sharing within a pool (spatial dimension) in a timely (temporal dimension) fashion. The mechanism of capacity adjustment through pricing decisions and its relationship with the discrete demand (explained in the previous section) leads to the following four hypotheses related to the relationship with the demand between spatial and temporal dimension:

1 As indicated in Section 2 (literature review), to ensure that a dynamic pricing produces beneficial results, consumers have to respond to marginal incentives (Chen and Pearcy, 2010). This is one of the reasons why firms segment customers according to customers' price sensitivity (Stole, 2007; Cho et al., 2018; Aryal et al., 2018) to optimise the profit. For example, airlines would offer different types of fare, each with different restrictions and price levels for a seat on the same flight (Botimer and Belobaba, 1999). In general, business travelers do not normally stay over a Saturday night at the destination and airlines would impose a higher fare for this type of travellers (Stavins, 1996, Cheng et al., 2015). As such, the car rental industry also segments the market into weekday business market vs. weekend leisure market and would offer higher price during weekday and lower price during weekend (Khan et al., 2009). Integrating these variations on price sensitivity influenced by weekday or weekend between business and leisure markets, we expect players would set its location price based on the difference between days of the week. Thus:

   Hypothesis 1 Day of the week (i.e., whether it is a weekday or weekend) affects the location pricing strategy.

2 Fleet utilisation is extremely critical in the rental car industry's operational costs. The optimal goal is not to have any idle fleet, and, the design of the network should aim at having 100% of the fleet occupied 100% of the time. As such, follow Oliveira et al.'s (2017) fleet and revenue management framework, the ultimate purpose of a pool design should be how to efficiently and effectively utilise all fleet within a pool among locations. In addition, as indicated in Section 2, Maister's (1976) square root law of locations indicates the system-wide average inventory increases proportionally to the square root of the number of locations in which inventory is held. Since a pool consists of airport, downtown and suburb in the rental car

industry, we would expect the pricing strategy should exhibit certain positive or negative correlation among locations within a pool. Thus:

Hypothesis 2 The correlation between the location pricing strategy of airport and that of downtown is negative.

Hypothesis 3 The correlation between the location pricing strategy of airport and that of suburb is negative.

Hypothesis 4 The correlation between the location pricing strategy of downtown and that of suburb is positive.

4 Data, methods and discussion

There are two sections of data analysis. The first section (Section 4) is related to the car rental industry's pooling strategy (CDVs' strategy) and the second section (Section 6) related to the AVs' strategy. The intended subjects to be investigated for the first section are the four largest car rental firms in the US car rental market, either by fleet size, number of locations or revenue. They are:

1 Enterprise Holdings including Alamo, Enterprise and National car rental (hereafter Enterprise)

2 The Hertz Corporation including Dollar and Thrifty car rental (hereafter Hertz)

3 Avis Budget Group including Payless (hereafter Avis)

4 Advantage Rent-a-Car (hereafter Advantage).

Total market share by revenue of these four firms in 2017 was 96.08% of the US car rental market according to Statista, an online statistics portal, headquartered in Hamburg, Germany. Among these firms, Enterprise has 6,400 rental locations, Hertz has 4,000, Avis has 3,100 and Advantage has 76 rental locations. The data in this investigation are directly quoted from Enterprise, Hertz, Avis and Advantage (i.e., excluding those firms under their corporate umbrella). The ten largest US airports examined in this study are based on the list provided by Airline Origin and Destination Survey (DB1B) from Bureau of Transportation Statistics: Atlanta (ATL), Los Angeles (LAX), Chicago (ORD), Dallas (DFW), New York (JFK), Denver (DEN), San Francisco (SFO), Las Vegas (LAS), Seattle (SEA) and Charlotte (CLT). To prepare the analysis of how car rental firms apply pricing strategy to meet demand, data of some exogenous factors which might impact rental rate associated with these ten largest US airports are listed in Table 1.

Data source for the daily rental rate is from Galileo, one of the three largest global distribution systems (GDSs), used by professional travel agents. A total of 9,200 real time observations were collected based on daily rate on a standard or midsize car from three different locations within each city: airport, downtown and suburb. As Advantage does not have downtown or suburban locations in almost any of these ten cities (other than Las Vegas downtown) and no presence at Seattle airport, the data collected from Advantage were mostly excluded in the main test and used only for the comparison between all airports' pricing. A total of 8,208 observations were used to analyse the correlations of daily rental rates among airports, downtown and suburban locations within a same pool. As the data are from real time observations and not from simulations or partial selective dates within the studied periods, the analysis tends to be somewhat descriptive oriented vs. statistical inferences.

Sample data on daily rate of a midsize car were collected from 3 January to 29 May 2018 for the listed rental rate between 1 July and 30 September 2018. The car rental firms' revenue management involves many variables (endogenous factors) such as location, car size, time-of-the-day arrival and length of rental (Anderson et al., 2004; Li and Pang, 2017), and each one of them impacts the rental price. All firms have a single airport for most cities (except for certain metropolitan areas) but numerous downtown and suburban locations. For example, Hertz has nine downtown and 57 suburban locations in the San Francisco metropolitan area. To make this investigation manageable, one location from downtown and one from suburb were selected for each firm/pool. All prices are based on the daily rate, 24 hours rental time, between the arrival time of 12:01 pm and returning at 12:00 noon the next day. In the car rental industry, a weekend rental starts at 12:01 pm Thursdays and ends at 12:00 noon on Mondays. Weekday rental rate starts at 12:01 pm on Mondays and ends at 12:00 noon on Thursdays. If a metropolitan area has more than one airport, the airport with the largest volume in terms of passenger traffic is selected (e.g., LAX airport in Los Angeles and ORD airport in Chicago).

4.1 Methods and results

Table 2 presents Pearson and Spearman correlations between price, day of the week (weekday or weekend), location (airport/downtown/suburb), and car rental firm (Enterprise/Hertz/Avis). Consistent with Hypothesis 1, the highly significant and negative correlations between the price and the dummy variable for weekend suggest that the price is significantly lower (higher) during weekends (weekdays). In addition, the result also shows that the price is:

1 higher (lower) for airports and downtowns (suburbs)

2 lower for Enterprise, the largest player, and higher for Hertz and Avis, the smaller players.

Table 3 presents Pearson and Spearman correlations of prices between locations. First, the correlation between airport and downtown pricing is positive, which is contrary to Hypothesis 2. Next, the correlation between airport and suburb pricing is negative, consistent with Hypothesis 3. Lastly, the correlation between downtown and suburb pricing is positive, consistent with Hypothesis 4.

Overall, other than Hypothesis 2, the results of this empirical test agree with the prevalent concept that to effectively execute inventory pooling strategy, the component market demands should be negatively correlated (Swinney, 2011). Does this mean that inventory pooling is not likely to happen between airport and downtown locations? These mixed results lead to the following exploration, by incorporating some exogenous factors (from Table 1) which impact how firms set their rental pricing, in searching how to apply location pricing to complement capacity adjustment so shuttling activities can be minimised.

Table 1 Exogenous factors and daily rental rates of the top ten airports

	Airport passenger volume	*Per capita income*	*Population*	*Median housing price*	*Ratio of visitors vs. population*	*Ridesharing usage**	*Number of rental locations*	*Daily rental rate*	*Uber per mile cost*
ATL	8.44578	63,831	5,949,950	210,000	8.5715	0.00135	175	48.27	0.81
LAX	3.10217	67,014	13,291,490	634,000	3.5587	0.0018	246	49.34	0.81
ORD	4.06297	67,143	9,498,720	215,000	5.6955	0.00275	197	52.07	0.95
DFW	4.22588	65,000	7,539,710	195,000	3.0107	0.0009	177	65.01	0.91
JFK	1.49199	73,108	19,979,480	410,000	2.9881	0.00461	274	109.28	1.75
DEN	10.07126	73,107	2,932,420	383,000	10.8102	0.00175	88	70.39	1.00
SFO	5.68773	98,710	4,729,480	860,000	5.3917	0.00377	184	74.19	1.21
LAS	10.46947	53,159	2,231,650	266,000	19.2234	0.0008	72	55.16	0.96
SEA	5.74690	80,257	3,939,360	430,000	10.3824	0.0016	88	70.95	1.35
CLT	8.56731	60,708	2,569,210	204,000	10.4312	0.00075	77	53.24	0.81

Notes: *Ridesharing usage is based on the percentage passenger per 100,000 population.
**Ratio of visitors vs. population = total number of visitors/population.
***Data collected from Census.gov and Statista.com based on 2017's statistics.

Table 2 Correlations between price, day of the week, location and company

			V1	*V2*	*V3*	*V4*	*V5*	*V6*	*V7*	*V8*
V1	*PRICE*	Corr.		–0.062	0.232	0.057	–0.290	–0.189	0.081	0.108
		Sig.		< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001
V2	*WEEKEND*	Corr.	–0.063		0.005	–0.003	–0.002	0.005	–0.011	0.005
		Sig.	< .0001		0.657	0.779	0.869	0.637	0.333	0.623
V3	*AIRPORT*	Corr.	0.340	0.005		–0.502	–0.502	–0.003	0.006	–0.003
		Sig.	< .0001	0.657		< .0001	< .0001	0.752	0.570	0.803
V4	*DOWNTOWN*	Corr.	–0.019	–0.003	–0.502		–0.497	0.001	–0.002	0.001
		Sig.	0.088	0.779	< .0001		< .0001	0.920	0.827	0.907
V5	*SUBURB*	Corr.	–0.323	–0.002	–0.502	–0.497		0.002	–0.004	0.001
		Sig.	< .0001	0.869	< .0001	< .0001		0.829	0.725	0.894
V6	*ENT*	Corr.	–0.254	0.005	–0.003	0.001	0.002		–0.498	–0.505
		Sig.	< .0001	0.637	0.752	0.920	0.829		< .0001	< .0001
V7	*HERTZ*	Corr.	0.161	–0.011	0.006	–0.002	–0.004	–0.498		–0.498
		Sig.	< .0001	0.333	0.570	0.827	0.725	< .0001		< .0001
V8	*AVIS*	Corr.	0.093	0.005	–0.003	0.001	0.001	–0.505	–0.498	
		Sig.	< .0001	0.623	0.803	0.907	0.894	< .0001	< .0001	

Notes: Table 2 reports Pearson (Spearman) correlations between daily car rental price, day of the week, location, and company in the upper (lower) diagonal. *PRICE* = daily car rental price, *WEEKEND* = 1 for weekends, = 0 for weekdays, *AIRPORT* = 1 for airports, = 0 for other locations, *DOWNTOWN* = 1 for downtowns, = 0 for other locations, *SUBURB* = 1 for suburbs, = 0 for other locations, *ENT* = 1 for Enterprise, = 0 other companies, *HERTZ* = 1 for Hertz, = 0 other companies and *AVIS* = 1 for Avis, = 0 other companies.

Table 3 Correlations of prices between locations

			V1	*V2*	*V3*
V1	*AIRPORT_PRICE*	Corr.		0.187	–0.035
		Sig.		< .0001	0.067
V2	*DOWNTOWN_PRICE*	Corr.	0.220		0.215
		Sig.	< .0001		< .0001
V3	*SUBURB_PRICE*	Corr.	–0.064	0.394	
		Sig.	0.001	< .0001	

Notes: Table 3 reports Pearson (Spearman) correlations of prices between locations within the same city/company in the upper (lower) diagonal. *AIRPORT_PRICE* = daily car rental price at the airport location for the city/company, *DOWNTOWN_PRICE* = daily car rental price at the downtown location for the city/company and *SUBURB_PRICE* = daily car rental price at the suburb location for the city/company.

4.2 Pricing strategy and locations

Table 4 is the output of correlations between day of the week and location by firms and pools.

Out of ten metropolitans (or ten pools), the majority of airport's daily rental rates of weekends are lower than those of weekdays (consistent with Hypothesis 1). Yet, all three rivals at Seattle airport unanimously set their price with no fluctuation between weekdays and weekends. For example, when applying independent sample t-test by using Hertz airport's weekday and weekend's daily rental rate to compare the differences, the report (see Table 5) shows there was no significant difference in the daily rental rates for weekday ($M = 71.53$, $SD = 26.92$) and weekend ($M = 68.79$, $SD = 20.80$), conditions: $t(90) = 0.55$, $p = 0.580$. As such, an inverse correlated pricing strategy among its three locations, airport, downtown and suburb, is not found. Apparently, pooling activities are excluded in cities like the Seattle pool. Firms are expected to shuttle unneeded inventory during weekends from airport to their downtown or suburban locations within the same pool to meet demands (Swinney, 2011). However, this can only happen when there is a discrete demand between weekdays and weekends. The average daily rental price at Seattle pool (see Table 1) is the third highest in the nation (behind that of New York and San Francisco). Seattle is also the only city without Advantage Rent-a-Car's rivalry. In addition, its per capita income is the second highest among ten metropolitans. Results of the Pearson correlation indicated that there was a significant positive association between income and daily rental rate, [$r(10) = 0.690$, $p = 0.027$].

Out of 36 pairs from the above comparisons, only Hertz offers discrete pricing between its airport and suburb locations. Hertz at Denver airport even shows a significant positive correlation with day of the week. However, its weekend shows otherwise and weekday shows no correlation. This simply implies that the Denver pool is more inclined toward a weekend or leisure market. From Table 1, ratio of visitors vs. population, Denver is the second highest among all ten metropolitans. When a city's car rental market has a strong leisure consumption, then the location may only show discrete demands during weekends. This applies to New York (Enterprise and Avis) and Las Vegas (Hertz) as well.

Table 4 Correlations between day of the week and location by firm and city

	Car firm	*Enterprise*			*Hertz*			*Avis*		
	Location	*D/week*	*Airport*	*D/town*	*D/week*	*Airport*	*D/town*	*D/week*	*Airport*	*D/town*
ATL	Airport	–.624**			–.343**			–.845**		
	D/town	.293**	–.204		–.796**	.290**		0.083	–0.770	
	Suburb	0.170	–.044	.839**	–.804**	.481**	.858**	0.083	–0.770	1.000**
LAX	Airport	–.455**			–.246*			–.702**		
	D/town	–.137	.401**		–.693**	0.042		–0.155	.282**	
	Suburb	.292**	–0.009	0.079	0.156	–0.139	–.070	–0.155	.282**	1.000**
ORD	Airport	–.577**			–.829**			–.805**		
	D/town	0.019	0.125		–.364**	.309**		–0.005	0.104	
	Suburb	–0.083	0.160	.435**	.610**	–.696**	–.218*	–.345**	.584**	.381**
DFW	Airport	–.444**			–.636**			–.621**		
	D/town	–.423**	–0.194		–.667**	.872**		–.289**	.210*	
	Suburb	–0.131	–0.102	0.142	0.055	–.405**	–.284**	–0.280	–0.025	0.167
JFK	Airport	0.085			–.356**			0.016		
	D/town	.359**	.215*		.474**	–0.138		–0.102	0.103	
	Suburb	.240*	0.188	0.103	.707**	–.253*	.449**	–0.155	–0.086	0.015
DEN	Airport	–0.100			.671**			–.724**		
	D/town	–0.118	0.154		–0.108	0.135		–0.136	0.158	
	Suburb	–0.106	.622**	0.048	.260*	–.548**	–0.205	–0.034	–0.172	0.111
SFO	Airport	–.219*			–.601**			–.697**		
	D/town	.486**	–0.081		–.461**	.861**		–.754**	.761**	
	Suburb	–0.109	0.060	–0.500	–.860**	.769**	.684**	.703**	–.526**	–.752**
LAS	Airport	–.363**			–0.140			–.423**		
	D/town	–0.035	–0.077		.330**	0.023		–0.155	.227*	
	Suburb	.326**	–.419**	0.036	–0.005	.570**	0.030	.451**	–.287**	0.064
SEA	Airport	–0.105			–0.037			0.115		
	D/town	.352**	–.447		–.299**	0.136		–.327**	–0.035	
	Suburb	–0.041	.606**	.215*	–0.145	.598**	.392**	–.243*	.349**	–.348**
CLT	Airport	–.869**			–.448**			–.382**		
	D/town	.249*	–.238*		.435**	–.234*		–0.012	–.677**	
	Suburb	0.054	–0.160	.343**	.281**	0.034	.248*	0.148	–.606**	.876**

Notes: **Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

Table 4 Correlations between day of the week and location by firm and city (continued)

	Car firm	*Enterprise (Weekend)*			*Hertz (Weekend)*			*Avis (Weekend)*		
	Location	*D/week*	*Airport*	*D/town*	*D/week*	*Airport*	*D/town*	*D/week*	*Airport*	*D/town*
ATL	Airport	–0.241			–0.125			–.755**		
	D/town	.331*	–.354**		–.896**	0.094		–0.181	0.051	
	Suburb	0.181	–0.125	0.166	–.944**	.317*	.911**	–0.181	0.051	1.000**
LAX	Airport	–0.221			–0.222			–.566**		
	D/town	0.052	.515**		–.673**	–0.078		0.181	–.302*	
	Suburb	.304*	0.216	0.125	–.272*	–0.056	0.078	0.181	–.302*	1.000**
ORD	Airport	.277*			–.687**			–.622**		
	D/town	0.049	0.171		–0.170	0.101		0.030	0.140	
	Suburb	–0.197	0.084	.457**	.300*	–.627**	–0.058	–0.034	.485**	.474**
DFW	Airport	.716**			–.277*			–.349*		
	D/town	–.510**	–.616**		–.301*	.757**		–0.153	0.101	
	Suburb	–0.209	–0.151	0.174	.352**	–.496**	–.466**	–0.037	0.003	0.123
JFK	Airport	–0.265			–0.200			–0.001		
	D/town	–0.270	.550**		.599**	–0.026		0.181	0.107	
	Suburb	0.248	0.188	0.107	.894**	–0.140	.436**	0.181	0.107	1.000**
DEN	Airport	0.236			–.409**			–.646**		
	D/town	0.115	0.126		–0.030	0.082		–0.079	0.107	
	Suburb	–0.093	.604**	0.015	.179	–.456**	–0.101	0.037	–0.153	0.027
SFO	Airport	0.241			–0.217			–.677**		
	D/town	.412**	0.135		0.019	.864**		–.760**	.883**	
	Suburb	0.056	0.009	0.009	–.775**	.674**	.504**	.896**	–.506**	–.604**
LAS	Airport	–.286*			–0.084			–.384**		
	D/town	0.152	0.148		–0.059	0.104		0.181	–.272*	
	Suburb	.450**	–.320*	0.002	0.020	.575**	0.130	–0.070	–0.164	–0.131
SEA	Airport	–0.246			0.063			0.031		
	D/town	0.210	–0.151		–0.008	0.234		–0.268	0.224	
	Suburb	0.009	.556**	0.185	–0.122	.518**	.477**	–0.165	.378**	–.310*
CLT	Airport	–.766**			–0.100			–0.264		
	D/town	0.214	–0.157		.458**	–0.019		–0.072	–.752**	
	Suburb	–0.014	–0.207	.286*	0.057	0.225	.524**	0.035	–.736**	.907**

Notes: **Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

Table 4 Correlations between day of the week and location by firm and city (continued)

	Car firm	*Enterprise (Weekdays)*			*Hertz (Weekdays)*			*Avis (Weekdays)*		
	Location	*D/week*	*Airport*	*D/town*	*D/week*	*Airport*	*D/town*	*D/week*	*Airport*	*D/town*
ATL	Airport	0.058			0.010			0.015		
	D/town	0.045	0.209		0.199	0.086		0.000	0.060	
	Suburb	0.000	0.270	.900**	–.010	.371*	–0.070	0.000	0.060	1.000**
LAX	Airport	0.019			0.174			0.043		
	D/town	–0.071	0.034		0.100	–0.222		–0.199	–0.308	
	Suburb	–0.299	–0.086	0.111	0.124	–0.274	.683**	–0.199	–0.308	1.000**
ORD	Airport	–0.006			–0.067			0.199		
	D/town	–0.271	.573**		0.039	–0.140		0.070	0.105	
	Suburb	0.030	.695**	.403*	0.237	–0.179	0.062	0.197	–0.036	0.104
DFW	Airport	–0.259			0.183			–0.199		
	D/town	–0.199	–0.080		.320*	.737**		–0.065	–0.217	
	Suburb	0.000	–.350*	.562**	–0.095	–.674**	–.437**	0.000	–.469**	0.308
JFK	Airport	–0.072			–0.199			–0.008		
	D/town	0.087	–0.061		–0.144	.946**		0.171	0.176	
	Suburb	–0.199	.479**	0.134	0.054	–0.067	0.180	0.199	–0.126	0.037
DEN	Airport	–0.252			–0.055			0.051		
	D/town	–0.219	0.162		0.091	–0.007		0.022	–0.032	
	Suburb	0.047	.655**	0.064	–0.116	–.616**	–.321*	–0.023	–.410*	0.245
SFO	Airport	0.151			–.352*			0.000		
	D/town	–0.119	–0.138		0.000	.388*		–0.051	0.165	
	Suburb	0.199	0.034	.337*	–0.199	0.117	0.175	0.000	–0.002	–.931**
LAS	Airport	0.351			0.004			–0.014		
	D/town	–0.137	–0.343		0.232	0.202		–0.225	0.061	
	Suburb	–0.268	–.529**	0.157	0.163	.573**	0.023	–0.225	0.061	1.000**
SEA	Airport	–0.055			–0.022			–0.065		
	D/town	0.080	–.800**		–0.053	–0.139		–0.020	–.466**	
	Suburb	0.056	.669**	–.705**	–0.036	.734**	0.014	0.000	.499**	–.962**
CLT	Airport	–0.024			–0.080			0.043		
	D/town	0.006	–0.125		–0.103	–0.257		0.064	–.730**	
	Suburb	0.061	–0.173	.438**	0.230	0.106	–0.248	0.048	–.470**	.875**

Notes: **Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

Table 5 Independent sample t-test between Seattle Hertz's weekday and weekend fare

Group statistics

	WKD0WKN1	*N*	*Mean*	*Std. deviation*	*Std. error mean*
SEATTLFare	0	39	71.5331	26.92756	4.31186
	1	53	68.7696	20.80278	2.85748

Independent samples test

		Levene's test for equality of variances		*t-test for equality of means*					*95% confidence interval of the difference*	
		F	*Sig.*	*t*	*df*	*Sig. (2-tailed)*	*Mean difference*	*Std. error difference*	*Lower*	*Upper*
SEATTLFare	Equal variances assumed	12.921	.001	.555	90	.580	2.76345	4.97547	–7.12119	12.64809
	Equal variances not assumed			.534	68.984	.595	2.76345	5.17275	–7.55594	13.08285

The complementary correlation counts from three rivals are 2, 5 and 6, respectively (if weekend only: 3, 4 and 7; if weekday only: 4, 4 and 7) with Enterprise being the lowest and Avis the highest by testing the correlation on airport vs. downtown, airport vs. suburb and downtown vs. suburb within the same pool among ten metropolitans. Smaller rivals are required to use pooling strategy more frequently to increase the availability of inventory to fend off bigger rivals' threat, as to compete for market share, inventory availability is critical.

4.2.1 Airport vs. non-airport (downtown/suburb)

One third of the nations' 30 airport outlets appears to follow a significant negative correlation with its non-airport locations (Hypothesis 3) (downtown/suburb treated as one pair – only Avis' Charlotte pool has a complementary relationship between airport, downtown and suburb simultaneously) although airport and downtown is not negatively correlated when data of downtown and suburb (downtown and suburb is not a pair) was separated (see the analysis on Hypothesis 2). Charlotte is the smallest and Las Vegas is the third smallest airports by passenger volume. Fleet shuttling is relatively easier in small metropolitan areas due to the warehousing distance effects (Mattsson, 2007; Ramaa et al., 2012). In addition, Charlotte's ridesharing usage percentage (see Table 1) is also the lowest among ten metropolitans (Las Vegas is the second lowest). Results of the Pearson correlation indicated that there was a significant positive association between the ridesharing usage percentage and the daily rental rate, [$r(10) = 0.735$, $p = 0.015$]. This positive correlation may explain why:

1 in New York, only one player's (Hertz) airport and suburb has a complementary relationship as New York has the highest ridesharing usage percentage

2 all three players' airport vs. non-airport in Charlotte has a complementary relationship.

The reason of being so is that ridesharing firms have crushed not only the public ground transportation system but also the car rental industry (Auto Rental News, 2017). When demand for car rental becomes weaker due to a strong ridesharing usage, the inventory pooling becomes unnecessary which indirectly impacts the daily rental rate.

4.2.2 Weekdays and weekends effect on airport vs. downtown/suburb

When examining the pricing strategy between locations separately for weekdays and weekends, results fluctuate to some degree. There are two categories:

1 airport vs. downtown

2 airport vs. suburb.

For airport vs. downtown, the only outcome with a complementary relationship, regardless weekends or weekdays, is Charlotte. When using only weekend data, four complementary relationships (Enterprise in Atlanta and Dallas and Avis in Los Angeles and Las Vegas) are added and two (Enterprise and Hertz in Charlotte) are dropped out. When using only weekday data, Seattle for Enterprise and Avis is added to the list and Charlotte for Enterprise and Hertz are dropped out. For airport vs. downtown, when using only weekend data, five complementary relationships (Hertz in Chicago, Dallas and Denver and Avis in Los Angeles and San Francisco) are added. When using only weekday data, two complementary relationships (Avis in Dallas and Denver) are added.

These alternations imply location pricing decisions are particularly influenced by discrete demands during weekends, between airport and downtown as well as between airport and suburb. Recall that from Table 1, other than Denver pool, Atlanta, Chicago, Dallas, Los Angeles and San Francisco are not strong leisure oriented metropolitans (ranking 5, 6, 9, 8 and 7, respectively); as such, weekdays' pricing is strongly business oriented. The end result is a strong weekend discrete demand. A reason that Denver is on the list is because Hertz at Denver has only total of 28 locations and its operation (comparing all number of locations) is ranked 7th among all metropolitans within Hertz's family. A smaller operation requires shuttling activities more and often. This is why a weak discrete demand appeared during weekdays within a pool except four outlets (between airport and downtown's Seattle by Enterprise and Avis; between airport and suburb's Dallas and Denver). Charlotte's pool does not have a clear weekend or weekday influence, but overall, days of the week impact airport and downtown pricing decisions. The direction of how firms share their inventory, or discrete demands between locations within the same pool, can be detected from these alternations. For example, Enterprise's Dallas airport location only shares the fleet with downtown during weekends but not weekdays; and, Avis at Las Vegas airport location only shares the fleet with downtown on weekends.

Apparently, complementary demands do not necessarily just happen only during weekends. It could happen during weekdays too. When a city is categorised as a business destination (vs. leisure), a complementary pricing is expected between its airport and non-airport (downtown/suburb) locations for the whole week; except, there will be a stronger weekend influence than that of weekdays. If it is a leisure destination, then the result is expected to be the other way around. Hertz has the most noticeable price discrimination within the same pool among all three players. Their negative correlation between airport and non-airport locations happens in five metropolitan areas (Chicago, Dallas, New York, Denver and Charlotte). Avis has three (downtown and suburb together treated as non-airport location vs. airport) and Enterprise has two. However, two metropolitan areas, Atlanta and Los Angeles, do not show any evidence of rental station's price discrimination within each pool. These two pools happen to have not only the busiest and the second busiest airport, respectively, in the nation, but also offer the lowest and the second lowest average daily rental rate. In addition, the ridesharing usage percentage ranks 7th and 4th. Busy airports supply relatively more of rental customers; the lower average daily rental rate increases the desire of rental and lower ridesharing usage percentage means higher rental car usage. After factoring all those factors, a possible explanation of no discrete pricing may indicate that costs of fleet shuttling between rental stations outweigh benefits of fleet parking on lots (i.e., stationary inventory is cheaper than migratory inventory). Constant fleet shuttling adds unnecessary burden to their repetitive operation; especially, advanced forecasting techniques are readily available and reliable (Fiig et al., 2014).

Table 6 Independent sample t-test between cities based on size

Group statistics

	Large0Small1	*N*	*Mean*	*Std. deviation*	*Std. error mean*
UberCitySize	.00	30	1.0477	.24281	.04433
	Small	30	.9703	.13780	.02516

Independent samples test

		Levene's test for equality of variances		*t*	*df*	*Sig. (2-tailed)*	*t-test for equality of means*		*95% confidence interval of the difference*	
		F	*Sig.*				*Mean difference*	*Std. error difference*	*Lower*	*Upper*
UberCitySize	Equal variances assumed	3.721	.059	1.517	58	.135	.07733	.05097	–.02470	.17937
	Equal variances not assumed			1.517	45.926	.136	.07733	.05097	–.02527	.17994

4.3 Downtown vs. suburb

Most business travellers utilise airport location for their car rental needs; thus, downtown and suburban locations are more geared toward the leisure market. As such, non-complementary pricing decisions between downtown and suburb should be expected (Hypothesis 4). That is, demands of downtown and suburban locations should be positively correlated. Out of 30 pairs of downtown vs. suburb's pricing strategy, only four pairs with a complementary relationship (demands are negatively correlated and they are Hertz's Chicago and Dallas; Avis's San Francisco and Seattle. No such outcome from Enterprise). If we compare how firms set their daily rental rates by using Avis San Francisco (the one shows pooling relationship with its suburb) and Avis New York downtown's rates (the one shows no pooling relationship with its suburb), the results indicated there was a significant difference on pricing for San Francisco ($M = 81.12$, $SD = 16.39$) and New York ($M = 196.75$, $SD = 12.17$), conditions: $t(182)$, $p < 0.001$. Combining downtown and suburban locations together, Hertz's Chicago has 57 and Dallas has 35 locations; Enterprise has 98 locations each. Avis' Denver has 30 locations and Seattle has 16 locations; Enterprise has 81 in San Francisco and 43 in Seattle. A larger fleet size (assuming the more locations, the larger fleet size) requires less fleet shuttling; thus, a positive correlation between the two locations can play a better supporting role to reinforce airport locations weekday vs. weekend rental rate fluctuations. A smaller rival needs to increase inventory availability by pooling, more than what its larger counterparts do.

4.3.1 Positive correlation of downtown vs. suburb impacts on airport pricing

When using only weekdays or weekends data, New York is the only metropolitan with no complementary relationship between airport and non-airport locations; and no price fluctuation during weekdays and weekends at airport. New York has the highest average daily rental rate, highest Uber cost of 'ride per mile' and ridesharing usage percentage (see Section 4.2.1.) among all ten pools. In addition, its population, number of rental locations also is the highest among all ten pools. Price discrimination may not serve its purpose of profits maximisation. When conventional weekend demands of leisure customer drive up the rental price, all locations within the pool tend to keep daily rental price constant (e.g., Avis quoted a constant daily rate of $195.00 for the entire 92 days with no obvious weekday and weekend fluctuation).

Interestingly, if the computation only employs weekdays data, then complementary or non-complementary correlation does not exist between days of the week and airport, downtown or suburb among all 30 outlets, other than Hertz's Dallas with a non-complementary and San Francisco with a complementary correlation. A common formula for weekends and weekdays pricing between locations for most rivals is to maintain downtown and suburb location's rates compatible and keep them nearly constant; except, rivals will adjust airport location's rates to reflect the nature of complementary demands between business and leisure customer. Other than airport location's volatile fluctuations of the average daily rate, the other locations' rates are nearly unchanged. As such, days of the week do not impact any pricing decisions of airport, downtown and suburb in any of the nation's ten busiest airports during weekdays. Apparently, the fluctuation of weekend demands is important to location pooling effect. If demands are constant such as no discrete demands between business and leisure customer during weekdays, then inventory pooling becomes burdensome as costs of inventory holding (stationary inventory) will outweigh benefits from fleet shuttling (migratory inventory).

Results derived from the analysis in Section 4 can be summarised as follows: Hypotheses 1, 3 and 4 are accepted; except, Hypothesis 4 is rejected. In addition, several factors appear to be influential in pooling:

1 if a city is geared to a strong leisure consumption, then discrete demands are less likely to happen

2 pooling activities are more critical for small firms

3 firms competing in a relatively smaller airport such as Charlotte, utilising downtown's inventory for pooling is beneficial

4 a weekend discrete demand has a much stronger impact on inventory pooling effectiveness

5 inventory pooling becomes less effective if airports passenger volume is relatively high enough such as that of Atlanta and Los Angeles

6 firms equipped with a large fleet size require less inventory pooling activity

7 a constant exorbitant daily rental rate weakens the effectiveness of inventory pooling.

When synthesising these factors, a noticeable pattern can be detected, that the more readily availability of inventory, the less necessity of pooling activities. These findings coincide with the work related to the inventory availability literature such as Yin et al. (2013) and Kurata (2014). Further, since pricing is a primary differentiator for the leisure market but less sensitive to the business market (Cho et al., 2018; Williams, 2018), a weekend discrete demand is expected to have a stronger impact on inventory pooling effectiveness.

5 Compatibility of the current pooling strategy in the future robotaxi market

The car rental industry and ridesharing industry differs in numerous areas such as product, business model, inventory management or pricing strategy. The rise of robotaxi creates an opportunity for the car rental industry to compete in the autonomous future. The average car rental rate is highly correlated to Uber's cost of the 'ride per mile' [data from Table 1: $r(10) = 0.938$, $p < 0.0001$]. This indicates both the car rental and ridesharing industry agreed, at the current price point, demand and supply is matched at its optimal. Assuming the business model and price point of the future robotaxi market is similar to those of today's ridesharing, will the car rental industry's pooling model fit in the autonomous future? This section analyses the ridesharing industry's pricing strategy based on those determinants impacting inventory pooling listed in Section 4. The second section of the data has two sets: one is cities served by both Uber and Lyft and one is the cost of the 'ride per mile' (hereafter 'ride cost') in each city. Cities chosen are:

1 the largest 60 airports listed by DOT (dividing into the largest 30 vs. the rest 30 to detect whether airport size impacts the ride cost

2 30 cities characterised as leisure vs. 30 as business destinations by TripAdvisor, a public traded firm who reviews travel and restaurants.

The purpose is to detect whether the characteristic of a city impacts the ride cost. Cost of the 'ride per mile' is directly quoted from Uber and Lyft's website.

An independent-samples-t-test (see Table 6) was conducted to compare how airport size impacts the ride cost. There was no significant difference in the ride cost between large (M = 1.05, SD = 0.24) and small airports (M = 0.97, SD = 0.14) when using Uber's data. Condition: t(1.51), p = 0.135. The similar results were produced by using Lyft's data: (M = 0.2, SD = 0.19) vs. (M = 0.93, SD = 0.14); condition: t(–0.221), p = 0.826. These results suggest that airport size does not have any effect on the ride cost. To test whether firm size affects the ride cost, a paired-samples-test was conducted to compare Uber (the larger firm) and Lyft's (the smaller one) ride cost. There was no significant difference in the ride cost between Uber's (M = 1.11, SD = 0.35) and Lyft's leisure cities (M = 1.07, SD = 0.38); condition: t(1.02), p = 0.32. But, mixed results were produced for business cities: Uber (M = 1.02, SD = 0.20) vs. Lyft (M = 0.91, SD = 0.18); condition; t(3.72), p = 0.001. These results suggest that firm size does not have impact on leisure but only on business destinations' ride cost. These mixed results (no impact on Uber but on Lyft) also happened to city's characteristic impacting the ride cost. An independent-samples-t-test results showed Uber does not segment its ride cost based on the characteristic of the city: leisure (M = 1.12, SD = 0.35) vs. business (M = 1.02, SD = 0.21); condition: t(1.35), p = 0.182. However, Lyft has a different strategy in pricing based on the city's characteristic: leisure (M = 1.08, SD = 0.38) vs. business (M = 0.92, SD = 1.77); condition: t(2.16), p = 0.002. Apparently, a smaller firm (Lyft) has to be agile and flexible in the price setting strategy, just like what smaller car rental firms have to be in the car rental industry.

Artificial intelligence utilised in driverless vehicles is inevitable. AVs' early adoption may begin in the 2020s or 2030s and become common, affordable in the 2040s to 2060s (Litman, 2014). In the short run, the proposed inventory pooling model may be sustainable to a certain degree based on the following observations:

1 As indicated earlier (Section 2) the ridesharing operation requires the right choice of dispatching algorithm (Hoerl et al., 2018) instead of physical locations; i.e., temporal solution is more critical than spatial solution. As such, inventory pooling activities are less critical. Other than common accurate pricing strategy and forecasting skill, the car rental industry has to rely on appropriate warehousing locations, a type of vehicles-awaiting-customers' service mode, to compete. Effective warehousing locations are critical and efficient pooling technique will make the car rental industry more competitive in terms of the reduction of waiting time. As such, location fleet size serves its purpose to meet demand.

2 The 'surge pricing' strategy employed by ridesharing platforms focuses on equilibrating demand with available supply. The goal is to solve instantaneous imbalances between the available supply and unforeseen demand, not much in expanding demand but enlarging the revenue instead. The car rental industry could circumvent such imbalance with its scale of warehousing availability. Using

Table 1's data, we learned per capita income in a metropolitan impacts the daily rental rate which indirectly affects how the car rental industry applies it onto the segmentation. Since segmentation appears to be somewhat (a mixed result between two ridesharing firms) influential in ridesharing business model, relying on the pooling strategy enhances the car rental industry's capability to meet demand without irritating its customers and preventing more rivals from entering.

3 The metropolitan's characteristics (leisure vs. business) impact how ridesharing industry sets its price point. Although the ridesharing's service mode of 'customers-awaiting-vehicles' prioritises shortening waiting time and enlarging revenue at the same time, the car rental industry can apply customer segmentation strategy to reduce the possibility of demand imbalances.

4 Firm size could possibly impact how ridesharing industry sets its price pending on the characteristic of the city and the segmentation of customers. This is an overlapping area of the pricing strategy between the two industries.

Integrating aforementioned comparisons, the transferability of the proposed inventory pooling model from CDVs to AVs is listed in Table 7.

Table 7 Transferability of determinants' influence intensity from CDVs to robotaxi market

Determinants of pooling	*Transferability from CDVs to robotaxi market*
Leisure oriented	Neutral*
Rental firm size	Neutral
Airport size	Weak**
Weekend discrete demand	Neutral
Location fleet size	Strong***
Higher rental rate****	Strong
Lower rental rate	Strong

Notes *Neutral: impact on ride cost has mixed results between Uber and Lyft; weekend discrete demand constitutes the difference between leisure and business market. Impact on ride cost between leisure and business has mixed results.
**Weak: no impact on ride cost.
***Strong: not tested by Uber and Lyft's data but fleet size is essential for vehicles-awaiting-customers strategy.
****Rental rate: rental rate is highly correlated between two industries.

6 Concluding remarks

Most service industries such as hotels or airlines are applying revenue management techniques to optimise their revenue through customer segmentations and matching the product availability with price. Although this practice applies a price discrimination to meet anticipated consumer demand, it could also mean, there will be no possible revenue when no available inventory since the capacity is fixed. A rental car firm can satisfy the demand from an existing inventory or with a car from the same pool. Extended literature related to revenue management may have instructed us that in order to ensure a dynamic pricing produces beneficial results, customers have to respond to marginal incentives and the capacity is fixed. Several research have tackled the revenue optimisation issues in the car rental industry due to the industry's unique character of capacity flexibility. Yet, the majority of them focused on fleet management or utilisation problems such as what locations should be grouped into one pool. The current research manages to apply results of data analysis to identify factors influence inventory pooling. The proposed pooling model also indicates how to effectively and efficiently utilise the existing fleet within a pool.

The rise of AVs not only poses a threat also creates a new opportunity to the car rental industry. Practitioners should understand the car rental industry may not possess the technical knowledge of AVs to compete, yet, the car rental industry's fleet management experience may win the battle since all of their potential competitors are lacking of this type of experience. Practitioners may consider to rely on appropriate warehousing locations, a type of vehicles-awaiting-customers' service mode to compete against the current ridesharing industry's customers-awaiting-vehicles' service mode.

The mixed results with no unified pattern of complementary relationship between locations reveal some unforeseen determinants which might indirectly influence the activity of inventory shuttling. As such, for future studies examining additional factors affecting inventory pooling decision, we propose a logit regression as an inventory pooling model reflecting possible determinants of pooling activity:

$$\begin{aligned} POOL = {} & \beta_0 WEEKEND + \beta_2 PCORR + \beta_3 LEISURE + \beta_4 SIZE_F + \beta_5 SIZE_A \\ & + \beta_6 VOLM_A + \beta_7 FLEET_L + \beta_8 FLEET_S + \beta_9 PRICE_H + \beta_{10} PRICE_L \end{aligned}$$

where $POOL$ = 1 if inventory pooling is needed between two locations within a city, = 0 otherwise; $WEEKEND$ = 1 for weekends, = 0 for weekdays; $PCORR$ = 1 if historical price correlation between the two locations is negative, = 0 otherwise; $LEISURE$ = 1 if the city is characterised as leisure-oriented, = 0 otherwise; $SIZE_F$ = a proxy for size of the rental car company, e.g., sales revenue, number of total locations covered ($SIZE_F$ can be replaced with firm fixed effects), $SIZE_A$ = size of the city's airport; $VOLM_A$ = the city's airport traffic volume; $FLEET_L$ = the larger fleet size of the two locations; $FLEET_S$ = the smaller fleet size of the two locations; $PRICE_H$ = the higher daily car rental rate of the two locations; and $PRICE_L$ = the lower daily car rental rate of the two locations. As this theoretical model is based at least partially on exploration rather than specific hypotheses, we do not predict the sign of each coefficient. Also, the validity of the model requires further efforts of mathematical modelling to enforce its capability to predict pooling behaviour and explanatory capability of different components' effects.

Although we attempt to predict whether the existing capabilities are transferable into the future robotaxi market. This exploration concludes with a proposed pooling model factoring in possible determinants. However, this model is simply based on an educational exploration. The validity requires further efforts of mathematical modelling to enforce its capability to predict pooling behaviour and explanatory capability of different components' effects.

The other aspect of inventory pooling involves product pooling. The average variation of car types is 15 at each station which posts the complicated nature of capacity management in the car rental industry. While collecting data for all 15 different products from each location may not seem viable, this infancy step of utilising one type of inventory in the investigation, may induce more scholars' attention into research on this industry. In addition, data availability has been one of the critical constraints to the proliferation of car rental literature. Although the best judgement, in terms of data selection, has been carefully factored into this investigation process, the 9,200 observations selected may not reflect the accuracy of the entire industry's competition environment. However, they can nevertheless provide valuable insights. Location selection is a challenging task. Most firms have multiple downtown or suburban locations and the total number of US locations for all three firms studied exceeds 13,500. In the near future, a study focusing on one single metropolitan area, such as San Francisco pool's 177 locations, may be considered, so a better inventory pooling model can be formulated.

References

Alderighi, M., Cento, A. and Piga, C.A. (2011) 'A case study of pricing strategies in European airline markets: the London-Amsterdam route', *Journal of Air Transport Management*, Vol. 17, No. 6, pp.369–373.

Anderson, C., Rasmussen, H. and Davison, M. (2004) 'Revenue management: a real options approach', *Naval Research Logistics*, Vol. 51, No. 5, pp.686–703.

Aryal, G., Murry, C. and Williams, J.W. (2018) *Price Discrimination in International Airline Markets*, Working Paper, Stanford University, CA.

Auto Rental News (2017) *2017 U.S. Car Rental Market* [online] https://www.autorentalnews.com/fc_resources/PDF/arnfb18-market.pdf (accessed 22 April 2020).

Autonomous Cars Will End the $75 Billion Rental Car Industry as We Know it (2016) [online] https://www.inc.com/alex-moazed/autonomous-cars-will-end-the-75-billion-rental-car-industry-as-we-know-it.html (accessed 22 April 2020).

Bayoumi, A.E-M., Saleh, M., Atiya, A. and Habib, H. (2013) 'Dynamic pricing for hotel revenue management using price multipliers', *Journal of Revenue & Pricing Management*, Vol. 12, No. 3, pp.271–285.

Besbes, O., Castro, F. and Lobel, I. (2018) *Surge Pricing and its Spatial Supply Response*, Working Paper, Columbia Business School, New York.

Bischoff, J. and Maciejewski, M. (2016) 'Autonomous taxicabs in Berlin – a spatiotemporal analysis of service performance', *Transportation Research Procedia*, Vol. 19, pp.176–186.

Boesch, P.M., Becker, F., Becker, H. and Axhausen, K.Y. (2018) 'Cost-based analysis of autonomous mobility services', *Transport Policy*, Vol. 64, pp.76–91.

Botimer, T.C. and Belobaba, P.P. (1999) 'Airline pricing and fare product differentiation: a new theoretical framework', *Journal of the Operational Research Society*, Vol. 50, No. 11, pp.1085–1097.

Bouchet, A., Troilo, M. and Walkup, B.R. (2016) 'Dynamic pricing usage in sports for revenue management', *Managerial Finance*, Vol. 42, No. 9, pp.913–921.

Buffa, F.P. and Reynolds, J.I. (1979) 'A graphical total cost model for inventory-transport decisions', *Journal of Business Logistics*, Vol. 1, No. 2, pp.120–143.

Burns, L., Jordan, W. and Scarborough, B. (2013) *Transforming Personal Mobility*, The Earth Institute, Columbia University, New York.

Cardenas-Barron, L.E. (2007) 'Optimizing inventory decisions in a multi-stage multi-customer supply chain: a note', *Transportation Research Part E*, Vol. 43, No. 5, pp.647–654.

Carroll, W.J. and Grimes, R.C. (1995) 'Evolutionary change in product management: experiences in the car rental industry', *Interfaces*, Vol. 25, No. 5, pp.84–104.

Ceryan, O., Sahin, O. and Duenyas, I. (2013) 'Dynamic pricing of substitutable products in the presence of capacity flexibility', *Manufacturing and Service Operations Management*, Vol. 15, No. 1, pp.86–101.

Chen, L., Mislove, A. and Wilson, C. (2016) 'An empirical analysis of algorithmic pricing on Amazon marketplace', in *Proceedings of the 25th International World Wide Web Conference*.

Chen, Y.M. and Pearcy, J. (2010) 'Dynamic pricing: when to entice brand switching and when to reward consumer loyalty', *The RAND Journal of Economics*, Vol. 41, No. 4, pp.674–685.

Cheng, K.N., Chen, H.P. and Lee, J.Z-H. (2015) 'Competition behavior in service frequency for US airlines', *Service Business*, Vol. 9, No. 1, pp.1–16.

Cho, S.J., Lee, G., Rust, J. and Yu, M.K. (2018) *Optimal Dynamic Hotel Pricing*, Working Paper, Georgetown University, Washington DC.

Das, C. and Tyagi, R. (1997) 'Role of inventory and transportation costs in determining the optimal degree of centralization', *Transportation Research Part E: Logistics and Transportation Review*, Vol. 33, No. 3, pp.171–179.

Drayer, J., Shapiro, S.L. and Lee, S.K. (2012) 'Dynamic ticket pricing in sport: an agenda for research and practice', *Sport Marketing Quarterly*, Vol. 21, No. 3, pp.184–194.

Edelstein, M. and Melnyk, M. (1977) 'The pool control system', *Interfaces*, Vol. 8, No. 1, pp.21–36.

Einav, L., Farronato, C., Levin, J. and Sundaresan, N. (2018) 'Auctions versus posted prices in online markets', *Journal of Political Economy*, Vol. 126, No. 1, pp.178–215.

Elmaghraby, W. and Keskinocak, P. (2003) 'Dynamic pricing in the presence of inventory considerations: research overview, current practices, and future directions', *Management Science*, Vol. 49, No. 10, pp.1287–1309.

Eppen, G.D. (1979) 'Effects of centralization on expected costs in a multi-location newsboy problem', *Management Science*, Vol. 25, No. 5, pp.498–450.

Escobari, D. (2014) 'Estimating dynamic demand for airlines', *Economics Letters*, Vol. 124, No. 1, pp.26–29.

Fagnant, D.J. and Kochelman, K.M. (2018) 'Dynamic ridesharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas', *Journal of Transportation*, Vol. 45, No. 1, pp.143–158.

Fiig, T., Haerdling, R., Poelt, S. and Hopperstad, C. (2014) 'Demand forecasting and measuring forecast accuracy in general fare structures', *Journal of Revenue and Pricing Management*, Vol. 13, No. 6, pp.413–439.

Fink, A. and Reiners, T (2006) 'Modeling and solving the short-term car rental logistics problem', *Transportation Research Part E*, Vol. 42, No. 4, pp.272–292.

Firnkorn, J. and Mueller, M. (2011) 'Selling mobility instead of cars: New business strategies of automakers and the impact of private vehicle holding', *Journal of Business Strategy and the Environment*, Vol. 21, No. 4, pp.264–280.

Geraghty, M.K. and Johnson, E. (1997) 'Revenue management saves national car rental', *Interfaces*, Vol. 27, No. 1, pp.107–127.

Gordon, R.F. (2015) 'Why it is difficult to apply revenue management techniques to the car rental business and what can be done about it', *Faculty Works: Mathematics & Computer Studies*, Vol. 1, Molly College, New York.

Graves, S., Meal, H.C., Dasu, S. and Qiu, Y. (1986) 'Two-stage production planning in a dynamic environment', in Axsater, S., Schneeweiss, C. and Silver, E. (Eds.): *Multi-stage Production Planning and Control*, pp.9–43, Springer-Verlag, Berlin, Germany.

Haensel, A., Mederer, M. and Schmidt, H. (2012) 'Revenue management in the car rental industry: a stochastic programming approach', *Journal of Revenue and Pricing Management*, Vol. 11, No. 1, pp.99–108.

Hall, J., Horton, J. and Knoepfle, D. (2019) *Pricing Efficiently in Designed Markets: The Case of Uber*, Working Paper, Stern School of Business, NYU.

Hall, J., Kendrick, C. and Nosko, C. (2015) *The Effects of Uber's Surge Pricing: A Case Study*, Working Paper, University of Chicago Booth School of Business.

Hoerl, S., Ruch, C., Becker, F., Frazzoli, E. and Axhausen, K.W. (2018) 'Fleet control algorithms for automated mobility: a simulation assessment for Zurich', in *97th Annual Meeting of the Transportation Research Board*, Washington DC, January.

Khan, R., Singh, V. and Zhu, T. (2009) *Price Discrimination and Competition in the Auto Rental Industry*, unpublished manuscript.

Kimes, S.E. (2011) 'The future of hotel revenue management', *Journal of Revenue and Pricing Management*, Vol. 10, No. 1, pp.62–72.

Kumar, S. and Chandra, C. (2002) 'Managing multi-item common vendor inventory system with random demands', *International Journal of Physical Distribution & Logistics Management*, Vol. 32, No. 3, pp.188–203.

Kurata, H. (2014) 'How does inventory pooling work when product availability influences customers' purchasing decisions?', *International Journal of Production Research*, Vol. 52, No. 22, pp.6739–6759.

Langley Jr., C.J. (1980) 'The inclusion of transportation costs in inventory models: some considerations', *Journal of Business Logistics*, Vol. 2, No. 1, pp.106–125.

Li, D. and Pang, Z. (2017) 'Dynamic booking control for car rental revenue management: a decomposition approach', *European Journal of Operational Research*, Vol. 256, No. 3, pp.850–867.

Litman, T. (2014) *Autonomous Vehicle Implementation Predictions*, Victoria Transport Policy Institute [online] http://leempo.com/wp-content/uploads/2017/03/M09.pdf (accessed 11 June 2020).

Madden, T. and Russell, R.A. (2012) 'Modelling the rental car pricing and relocation problem', *International Journal of Revenue Management*, Vol. 6, Nos. 3/4, pp.246–257.

Maister, D.H. (1976) 'Centralization of inventories and the "square root law"', *International Journal of Physical Distribution*, Vol. 6, No. 3, pp.124–134.

Mattsson, S.A. (2007) 'Inventory control in environments with short lead times', *International Journal of Physical Distribution & Logistics Management*, Vol. 37, No. 2, pp.115–130.

McAfee, R.P. and te Velde, V. (2007) 'Dynamic pricing in the airline industry', in Hendershott, T.J. (Ed.): *Economics and Information System*, *Handbooks in Information Systems*, Vol. 1, Elsevier Science, New York, NY.

Nunes, A. and Hernandez, K. (2019) *Autonomous Vehicles and Public Health: High Cost or High Opportunity Cost?*, Working Paper, MIT.

Oliveira, B.B., Carravilla, M.A. and Oliveira, J.F. (2017) 'Fleet and revenue management in car rental companies: a literature review and an integrated conceptual framework', *Omega*, Vol. 71, No. C, pp.11–26.

Pachon, J., Iakovou, E. and Ip, C. (2006) 'Vehicle fleet planning in the car rental industry', *Journal of Revenue and Pricing Management*, Vol. 5, No. 3, pp.221–236.

Pachon, J.E., Iakovou, E., Ip, C. and Aboudi, R. (2003) 'A synthesis of tactical fleet planning models for the car rental industry', *Journal of ILE Transportations*, Vol. 35, No. 9, pp.907–916.

Ramaa, A., Subramanya, K.N. and Rangaswamy, T.M. (2012) 'Impact of warehouse management system in a supply chain', *International Journal of Computer Applications*, Vol. 54, No. 1, pp.14–20.

Riquelme, C., Banerjee, S. and Johari, R. (2015) *Pricing in Ride-share Platforms: A Queueing-theoretic Approach*, Working Paper, Stanford University, Stanford, CA.

Sahay, A. (2007) 'How to reap higher profits with dynamic pricing', *MIT Sloan Management Review*, Vol. 48, No. 4, pp.53–60.

Simchi-Levi, D., Chen, X. and Bramel, J. (2014) 'Integration of inventory and pricing', in *The Logic of Logistics. Springer Series in Operations Research and Financial Engineering*, pp.177–209, Springer, New York, NY.

Stavins, J. (1996) 'Price discrimination in the airline market: the effect of market concentration', *Review of Economics and Statistics*, Vol. 83, No. 1, pp.200–202.

Stocker, A. and Shaheen, S. (2018) 'Shared automated mobility: early exploration and potential impacts', in Meyer, G. and Beiker, S. (Eds.): *Road Vehicle Automation 4. Lecture Notes in Mobility*, Springer, Cham.

Stole, L. (2007) 'Price discrimination and competition', in. Armstrong, M. and Porter, R.H. (Eds.): *Handbook of Industrial Organization*, Vol. 3, No. 1, pp.2221–2299, Elsevier Science, Amsterdam.

Swinney, R. (2011) *Inventory Pooling with Strategic Consumers: Operational and Behavioral Benefits*, Working Paper, Duke University, Durham, NC.

Toktay, L.B. and Wein, L.W. (2001) 'Analysis of a forecasting-production-inventory system with stationary demand', *Management Science*, Vol. 47, No. 9, pp.1268–1281.

Tyagi, R. and Das, C. (1998) 'Extension of the square root law for safety stock to demands with unequal variances', *Journal of Business Logistics*, Vol. 19, No. 2, pp.197–203.

Vosooghi, R., Kamel, J., Puchinger, J., Leblond, V. and Jankovic, M. (2019) 'Robot-taxi service fleet sizing: assessing the impact of user trust and willingness to use', in *Transportation Research Board 98th Annual Meeting*, Washington DC.

Williams, B.D. and Tokar, T. (2008) 'A review of inventory management research in major journals', *The International Journal of Logistics Management*, Vol. 19, No. 2, pp.212–232.

Williams, K.R. (2018) *Dynamic Airline Pricing and Seat Availability*, Cowles Foundation Discussion Paper No. 3003U, Yale University.

Yang, N. and Zhang, R.Y. (2014) 'Dynamic pricing and inventory management under inventor-dependent demand', *Operations Research*, Vol. 62, No. 5, pp.1077–1094.

Yang, Y., Jin, W.Z. and Hao, X.N. (2009) 'Dynamic pool segmentation model and algorithm in the car rental industry', *Journal of Computers*, Vol. 4, No. 12, pp.1202–1208.

Yin, Y., Pei, E. and Ranchhod, A. (2013) 'The shopping experience of older supermarket consumers', *Journal of Enterprise Information Management*, Vol. 26, No. 4, pp.444–471.

You, P.S. and Hsieh, Y.C. (2014) 'A study on the vehicle size and transfer policy for car rental problems', *Transportation Research Part E: Logistics and Transportation Review*, Vol. 64, pp.110–121.

Zhong, Y.G., Zheng, Z.C., Chou, M.C. and Teo, C.P. (2018) 'Dynamic inventory pooling policies to deliver differentiated service', *Management Science*, Vol. 64, No. 4, pp.1555–1573.

Notes

1 Surge pricing: a practice of charging more for a service during high demand periods (also see Besbes et al., 2018).

2 Posted price: a published price that a firm will sell a service for (also see Hall et al., 2019).

3 Price discovery: a proper price where supply and demand meet (also see Hall et al., 2019).