Intangible Capital and Competition in Ride Sharing: The Case of Lyft-Motivate Merger

Preliminary Draft

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Abstract

This study focuses on estimating the role of intangible capital on firms' competitiveness. We use Lyft's acquisition of Motivate, the biggest bike sharing company in the U.S. at the time, to evaluate the degree to which intangible capital affects the competition between Lyft and Uber. By acquiring Motivate, Lyft gained more consumer data as we interpret intangible capital, and bikes' presence on the streets potentially helped Lyft build stronger brand salience by rebranding bikes. We estimate the effect of the acquisition on Lyft's ridership by using a triple-difference model, and employing trip-level ride sharing data from New York City before and after the acquisition. We find that the acquisition helped Lyft increase its ridership by around 10%.

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1 Introduction

The effects of mergers and acquisitions (M&A) on competition has been commonly debated in the related literature and several policy discussions. This paper approaches this debate from a different and novel perspective by taking into account the structural transformation in the economy which is shaped by the rise of intangible capital. We investigate the following questions: Do firms leverage intangible capital acquired during M&A transactions to enhance their competitive power? Does intangible capital help the acquirer firm in M&A transactions increase intra-firm spillover? Does intangible capital acquired after mergers have significant impacts on the dynamics of industry competition? We attempt to address these questions by developing a novel and causal empirical framework. We use the case of Lyft's acquisition of Motivate, the biggest bike sharing company in the U.S. at the time, and apply difference-in-difference-in-differences (DDD) model to evaluate the degree to which intangible capital affects the competition between Lyft and Uber.

These questions are important because U.S. economy has been experiencing a technological progress and the transition to a knowledge economy which increases the role of intangible capital assets. The share of intangible capital (e.g. information technology, knowledge, human, and organizational capital, user data, brand equity) in total capital has been rising from 20% during 1970s up to 70% during 2010s (Falato et al. (2020)). We argue that the incentives for U.S. companies towards M&A transactions would be dramatically shaped by the phenomena of increasing intangible capital in the U.S. economy. More explicitly, in contrast to the traditional merger analysis focusing on the role of accumulating and effectively utilizing tangible capital (e.g. plants, properties, equipment and structures) acquired in M&A transactions, we suggest that the acquirer firm would instead target intangible capital of the acquired firm to internalize its economic competencies in the business model because the former firm would try to keep pace with the evolving economy towards knowledge economy.

Intangible capital is composed of several different components and each component would provide distinct benefits to the acquirer firm. In our context, there are three main conceptual channels how intangible capital accumulated through M&As in the ride-sharing industry would bring different advantages for the acquirer. First, given that access to the ride-sharing service is based on the usage of app, M&As providing new app integration would be convenient for the customers, which provides a positive network externality driven app driven intangible capital. Second, M&As would provide the acquirer firm to re-brand its newly acquired products with its original brand name, which results in increasing brand salience in the marketplace. For instance, in our context of the study, Lyft replaced the name of all the bikes with its own brand and hence potentially increased its brand salience in the daily life in NYC. In that way, Lyft bikes which are noticed by bike customers more can also influence their decision when they choose a ride-sharing service in favor of Lyft against Uber. Given the highly similar nature of the service provided by the firms, brand salience constitutes a significant factor in determining the market shares. Third, M&As would provide integrated rich level of user data across different production units which can spill over the efficiency gain within the firm boundary. In our case, Lyft was able to integrate both bike-sharing and ride-sharing apps into the single app which enables the customers to choose any transportation mode Lyft provides. In return, Lyft gains an advantage to operationalize the user data interchangeably between its bike-sharing and ride-sharing services. However, due to data limitations, we are not able to distinguish all these three distinct channels of intangible capital. Hence, our empirical results proxy some potential combination of these three candidate channels and we argue that the acquirer firms internalize at least one of the three channels to enhance their competitive power in the industry. Since the data limitation prevents us to distinctly analyze each of these channels, we need to study an industry which has an underlying nature of business operations combining all of these three channels at the same time. We select ride-sharing industry as a good candidate for such an industry because its intangible capital heavy business nature is likely to benefit all the three channels of intangible capital we have described.

Employing the rich variation in various databases such as bike-sharing and ride-sharing trips, we apply difference-in-difference-in-differences (DDD) model to estimate the causal impact of the acquisition on competition in ride-sharing market. We find that after the acquisition Lyft increases its rides by 10% compared to Uber; even more on weekends.

Related Literature. This paper contributes to several strands of literature. The first strand of the literature is related to the merger evaluation using program evaluation methods. There is an extensive series of papers which study the effects of merger activities for different industries such as gasoline (Hastings (2010), Hosken et al. (2011), Taylor et al. (2010), Simpson and Taylor (2008)), parking (Choné and Linnemer (2012)), hospitals (Vita and Sacher (2001)), Brickley and Van Horn (2002),Tenn (2011), Lewis and Pflum (2017), Cooper et al. (2019)), beer (Frake (2017)), and airlines (Bamberger et al. (2004), Kwoka and Shumilkina (2010)). Our contribution in this strand of the literature is two-fold. First, we analyze the merger evaluation by investigating ride-sharing market as another key industry for which the literature has not focused on yet. Second, we provide a novel methodological contribution by designing an causal approach based on DDD estimation strategy which is rarely implemented in the literature due to the lack of appropriate variation in the data. We use the advantage of having our rich-level of ride-sharing data which provides a sufficiently rich variation and hence enables us to implement DDD estimation strategy.

The second strand we touch upon is competition in sharing platforms. For instance, Cao et al. (2018) categorize market expansion and market stealing of incumbent firms to study the effects of entry of bike-sharing firms on entry and exit dynamics of the bike-sharing platform. Nikzad (2017) studies the effects of competition on the ride-sharing through equilibrium welfare and wage analysis. Jiang et al. (2018) analyzes the degree of competition and accessibility in ride sharing markets in San Francisco and New York City based on statistical techniques. Our contribution is to consider both ride-sharing and bike-sharing operations to measure how M&As could create market advantage for the acquirer firm depending on the nature of production technology becoming more intangible capital heavy.

Our paper also contributes to the literature which emphasizes the role of intangible capital on firm dynamics. Given that the secular rise of corporate intangible capital over the last five decades (Corrado et al. (2009); Corrado and Hulten (2010); McGrattan and Prescott (2010); Eisfeldt and Papanikolaou (2014); Corrado et al. (2016); McGrattan (2020)), there are several papers which measure the effect of intangible capital on different firm dynamics such as productivity growth (Corrado et al. (2017)) and firm behavior (De Ridder (2019)). Atalay et al. (2014) argue that the use of intangible capital enhances intra-firm spillover and in that regard it is one of the closest papers to our main story. We investigate how the intra-firm spillovers provided by intangible capital affect firms' competitiveness. Our contribution is to emphasize that the motivation of acquirer firms in M&As would be to use the intangible capital accumulated through the transaction as a leverage to enhance competitive advantage. In that regard, to the best of our knowledge, we provide the first attempt to investigate the role of intangible capital in merger evaluation.

Layout. The remainder of the paper is structured as follows. Section 2 discusses some motivating facts on the rise of intangible capital and competition in the ride-sharing industry. Section 3 introduces the rich-level of data we use in our study. Section 4 includes a detailed discussion how we construct a causal empirical method based on DDD and shows the main empirical results. We conclude by discussing some potential future work.

2 Motivating Facts

U.S. economy has been experiencing a technological progress and transition to an intangible capital intensive economy including information technology, knowledge, human, and organizational capital, user data, and brand equity. Figure A1 documents that the share of intangible capital in total capital in the U.S. economy has been rising from 20% during 1970s up to 70% during 2010s. This secular trend is also valid in the ride sharing platforms. For instance, Figure A2 shows that the intangible capital ratio of Lyft and Uber is dramatically high and more importantly their ratio is higher than the average economy-wide intangible ratio during the corresponding years shown in Figure A1.

The natural question would be on how we relate the accumulation of intangible capital to the M&A dynamics in the ride-sharing platforms. We argue that acquirer firms would use the intangible capital accumulated through M&A transactions to leverage its competitive advantage against the rival firms. Hence, the degree of competition in the ride-sharing market would be a key determinant how the accumulation of intangible capital creates an advantage for the acquirer firms. In that regard, we indeed find a stylized fact that there is a fierce competition (especially between Uber and Lyft) in the ride-sharing platform, which is increasing over the last years. Figure A3 shows that even though Uber takes a big portion of the market share, Lyft starts to grab a significant amount of the market share from Uber, which indicates that Lyft tries to gain a competitive advantage over Uber over time. We see that Lyft has more than doubled its market share from 11.5% to almost 25% over last 5 years, whereas Uber lost its market share from 87.5% to around 75% over last 5 years. It indicates that even though the ride-sharing market is very concentrated in the sense that there are only two big operating firms, competition between the two becomes fierce over time.

We now bring another fact which motivates us further to investigate the relationship between intangible capital accumulated through M&A's and the competitive advantage in the marketplace. Figure A4 shows the raw correlation between the number of trips i) Lyft bike vs. Lyft ride, ii) Lyft ride vs. Uber ride and iii) Lyft bike vs. Uber ride in each hour in a day. As expected, we find that the correlation between Lyft and Uber rides is dramatically high all hours in a day, which proxies an increasing competition between the two firms. Moreover, we also see that the correlation between Lyft bikes and Lyft rides increases during rush hours in a day, which would indicate that Lyft would take advantage of its bike operation. This makes sense because bike trips can be potentially a substitute for rides during rush hours. We also see an increasing correlation between Lyft bikes and Uber rides during rush hours, which can be interpreted as people using the option of bike trips as a substitute for rides during rush hours would also spill over the network externality to the rival firms' ride trips, but this is out of our scope in this paper.

3 Data

In this section, the first part introduces the ride sharing and bike sharing data and shows some summary statistics and the variation of each dataset across different taxi zones. The second part discusses the measurement of firm-level intangible capital through which we motivate that sharing platforms have intangible capital heavy businesses.

3.1 Ride Share and Bike Share Data

We use trip-level ride sharing data from New York City, provided by NYC Taxi and Limousine Commission (TLC). The dataset contains 662,519,590 ride sharing trips taken during the period between January 2016 and December 2019 using Lyft or Uber. We can observe when each trip started and ended, pick-up location and the ride sharing firm. For the time period after January 2017 we can also observe the drop-off location. During this time period, we observe more than 453,000 ride sharing trips on average per day. Figure A3 shows the market shares, and Figure A5 shows the trip counts of ride share companies over time.

The pick-up and drop-off locations are in taxi-zone level, which is a collection of census tracts. It is used by TLC to report the taxi and ride sharing data for de-identification purposes. Although the actual data point has the exact location of the pick-ups and drop-offs, TLC reports only the taxi zone that those locations belong to. For the purposes of this paper, we aggregate the trips by hour of day, date, pick-up location and operator firm. The resulting dataset has the trip counts by the pick-up location for each firm during the period between 2016 and 2019 for each hour of day.

We also use bike sharing data provided by Motivate, the bike share operator in New York City. This dataset contains trip-level bike sharing data from 2013 to 2019. We use this dataset to identify where the active bike stations are located, and figure out which taxi zones have active bike stations. We label a taxi-zone as "with-bike taxi zone" if there is at least one active bike share station in the taxi zone, and "without-bike taxi zone" otherwise. Table A1 shows the number of taxi zones, and the market shares of Uber and Lyft for each category.

Figure A6 is a map of taxi zones, where the colors represent the total ride share trips per square mile originating from each taxi zone. It shows that Manhattan has the highest number of ride share trips per square mile. Figure A7 shows where the with-bike and without-bike taxi zones are. All with-bike zones are either in Manhattan, or in parts of Queens and Brooklyn that are closest to Manhattan.

We observe that day of week and time of day seems to have a strong effect on the number of ride share trips. Figure A8 shows the average ride sharing trips for each hour during each day of week. Therefore, we expect that the acquisition might have differential impacts on trip counts depending on the time of day and day of week.

3.2 Measurement of Intangible Capital

We follow the perpetual inventory method of Peters and Taylor (2017) which is commonly used methodology in the related literature to measure firm-level intangible capital.

According to the approach of Peters and Taylor (2017) (also other studies on measuring intangible capital such as Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2014), Ewens et al. (2019))), intangible assets can be divided into three broad groups: (i) knowledge capital, (ii) human and organizational capital, and (iii) externally acquired intangible capital. We proxy knowledge capital based on the capitalized R&D expenditures and the stock of organization capital estimated by capitalizing selling, general, and administrative (SG&A) expenses. Externally acquired intangible capital (e.g. Goodwill) is included on the balance sheet and hence we do not need to develop a measurement for this component.

We construct the stock of knowledge capital from past R&D expenses using the perpetual inventory method:

$$A_{it} = (1 - \delta_{R\&D})A_{it-1} + R\&D_{it}$$

where A_{it} is the end-of-period stock of knowledge capital, $R\&D_{it}$ is the R&D expenditures for each firm i during the year t, and $\delta_{R\&D} = 15\%$ (Hall et al. (2000)). We assume that starting A_{i0} is zero.

In order to proxy organizational capital, we capitalize Sales, General, and Administrative Expenses (SG&A) which is defined by GAAP as a firm's operating expenses unrelated to the cost of goods sold. Some examples include advertising and marketing expenses and provisions for employee bonuses. We follow the related literature that α fraction of SG&A represents an organizational capital investment.

$$B_{it} = (1 - \delta_{SG\&A})B_{it-1} + \alpha \times SG\&A_{it}$$

where $\delta_{SG\&A} = 20\%$ (Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2014)). To the best of our knowledge, the only estimate of α comes from Hulten and Hao (2008), who estimate $\alpha = 0.3$. We assume that starting B_{i0} is zero.

Finally, we include intangible assets (G_{it}) in the balance sheet to the measured stock of R&D (A_{it}) and organizational capital (B_{it}) and construct a measure of total intangible capital (INT_{it}) for each firm i during year t as follows

$$INT_{it} = G_{it} + A_{it} + B_{it}$$

4 Empirical Analysis

Our goal is to estimate the causal impact of Lyft's acquisition of Motivate on the competition in ride share industry in New York City, using a difference-in-difference-in-differences (DDD) estimator. We use December 2018, the first month after Lyft completed the acquisition of Motivate as the starting point of the treatment. We assume that only the taxi zones where there is at least one bike share station are treated.

4.1 Empirical Model

The unit of observation in the dataset is the number of trips by a particular company for a given hour of a calendar day in a taxi zone. This choice of the unit of observation results in many zeros in the dependent variable. Therefore, we consider a setting where the number of trips follows a Poisson distribution. The conditional mean function for the number of trips is

$$\begin{aligned} E[n_{ithf}|D_{it}] = \exp(hour_h \times wday_w \times & \\ & (\beta_0 + \beta_1 Lyft + \beta_2 Year_t + \beta_3 Zone_i \\ & + \theta_1 Month_t + \theta_2 Holiday \\ & + \delta_0 Lyft \times Year_t + \delta_1 Lyft \times Zone_i + \delta_2 Zone_i \times Year_t \\ & + \delta_3 Lyft * D_{it})) \end{aligned} \tag{1}$$

where n_{ithf} represents the number of ride sharing trips by firm f that starts in zone i during hour h of date t. $wday_w$ is a dummy variable and a function t. In addition,

$Lyft = 1$ if f is Lyft, and $D_{it} = 1$ if $t \geq$ 2018-11-30 and $i \in Z_B$, where $Z_B \equiv \{z \in Z | z \text{ is a with-bike taxi zone}\}$. $Zone_i$ is a dummy variable for taxi zone i which takes 1 if it includes at least one bike station. $\{Year_t, Month_t, Holiday\}$ are year, month and holiday fixed effects, respectively. This specification implies that we estimate a separate treatment effect for each day of week and each hour of day.

There are two sources of new customers for Lyft due to the treatment. The first is that customers switch from Uber to Lyft, denoted as SfU, and the second is the new Lyft customers who would not use ride sharing otherwise, denoted as LNC. The treatment might also affect the number of new Uber customers, denoted as UNC. Table 1 depicts the summary of how our DDD estimator works in a two-by-two setting (Cunningham (2021)). The first difference (D1 column in Table 1) takes the firm (Uber and Lyft) fixed effect out before and after the acquisition date. The second difference (D2 column in Table 1) takes the sector-specific time effect and firm-specific (Uber and Lyft) time effect out. Finally, the third difference (D3 column in Table 1) takes zone-specific time effects out. As a result, we have the remaining estimate of $\delta_3 = 2 * SfU + NLC - UNC$, which we interpret as the causal impact of the acquisition on the relative change in number of Lyft ride trips. We would ideally want to estimate $SfU + NLC$ instead as it is the treatment effect on Lyft. In the current setting, customers who switch from Uber will be double counted as a result of using Uber as the control group, since Uber is affected by the treatment as well. Therefore, the parameter estimate from the DDD estimation will capture SfU twice. Additionally, it will also capture the additional change in Uber ridership due to the change in new customers as a result of the treatment. Therefore, we cannot interpret δ_3 as the treatment effect, since $\delta_3 = 2SfU + NLC - NUC$. Since we have year-zone specific fixed effects, we cannot capture NLC or NUC separately, hence we cannot identify SfU, which makes estimating our target, $SfU + NLC$, not attainable. However, we can still estimate a lower bound for the treatment effect.

Table 1: Summary of the Identification of DDD estimator

Firm	Zone	Period	Outcome	D1	D2	D3
		After	$L + T + L_t + A_t$			
	A		+SfU + NLC	$T + L_t + A_t$		
		Before	L	+ SfU + NLC		
Lyft					$A_t - B_t + SfU + LNC$	
		After	$L + T + L_t + B_t$			
	B			$T + L_t + B_t$		
		Before	L			
						$2 \times SfU$
		After	$U + T + U_t + A_t$			+ NLC - NUC
	A		- SfU + NUC	$T + U_t + A_t$		
		Before	U	- SfU + NUC		
Uber					$A_t - B_t - SfU + NUC$	
		After	$U + T + U_t + B_t$			
	B			$T + U_t + B_t$		
		Before	U			

Assume that $NLC + NUC$, which is the treatment effect on the total number of new ride share customers is non-negative. That is, the acquisition does not make the number of rides smaller. Then,

$$SfU + NLC \geq SfU + \frac{NLC - NUC}{2} = \frac{\delta_3}{2} \tag{2}$$

Hence, dividing the DDD estimate by two would give us a lower bound for the treatment effect estimate. We also correct for the standard error of the DDD estimate accordingly.

4.2 Identification Assumptions

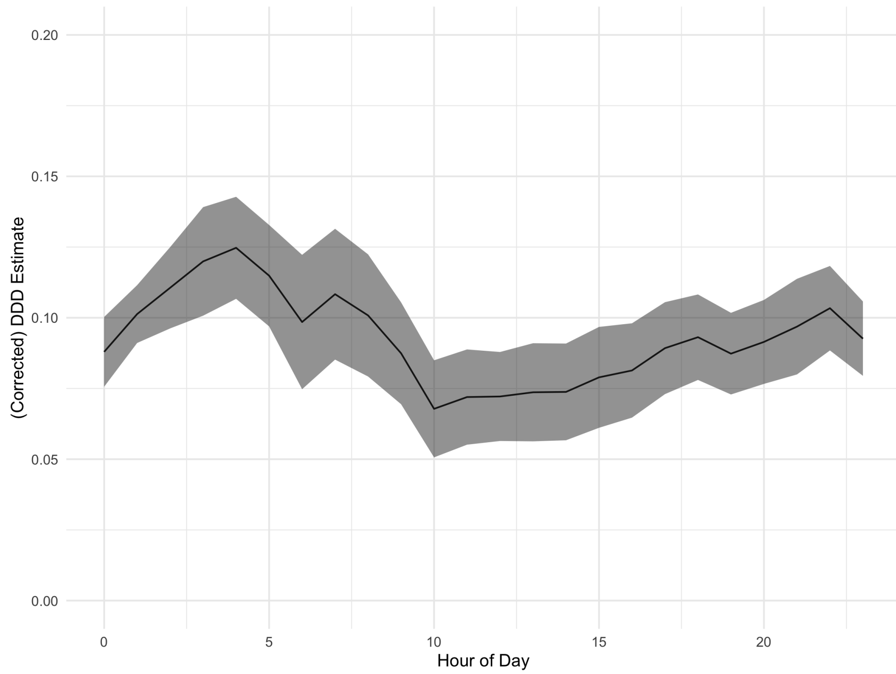
We have several identification assumptions for our DDD estimation. First, we assume that there are only three common trends which are sector, Lyft-specific and Uber-specific time trends. We also assume that there is no extra treatment by Lyft to the with-bike zones after the acquisition. This assumption is crucial because other potential subsequent Lyft policies after the acquisition would interact with the effect of the acquisition per se, which would make our DDD estimate biased. Another assumption we have is that there is no compositional changes in zone demographics before and after the acquisition. One potential concern would be to have a mobility of people sorting on several zone-specific characteristics which can correlate with the underlying determinants why people choose bike trips. We also assume a standard condition that there is no spatial autocorrelation in errors. Another key assumption generally made in the related literature is that we hold Stable Unit Treatment Value Assumption (SUTVA) in the sense that there is no interference and there is only a single treatment effect across units. Other technical assumptions we bring to identify our DDD estimate are that outcomes are additive, treatment occurs only if there is a bike station is within taxi zone boundaries, and finally, treatment is binary.

4.3 Empirical Results

We estimate the causal effect of Lyft's acquisition of Motivate on the competition in ride share industry in New York City using a Poisson GLM estimator. The standard errors are clustered at the firm, zone and firm-zone level, as suggested by Bertrand et al. (2004).

Figure 1 documents the DDD estimate of the regression equation (1) by each hour. After controlling several fixed effects, we see that the coefficient of DDD causal estimate (δ_3) is statistically significant and positive in all hours of the day, i.e. after the acquisition Lyft was able to increase its rides compared to Uber during all hours. Moreover, we see that this positive impact of the acquisition on Lyft rides reaches its peak during the early morning and late evening hours during the day, i.e. Lyft increases its rides by around 10% in early morning and late evening hours compared to Uber. We interpret this result that increasing intensity of using ride-sharing during the rush hours enables Lyft to internalize the effects of the acquisition because increasing brand salience through bikes is more likely to attract customers which use ride sharing more frequent during rush hours within the weekdays.

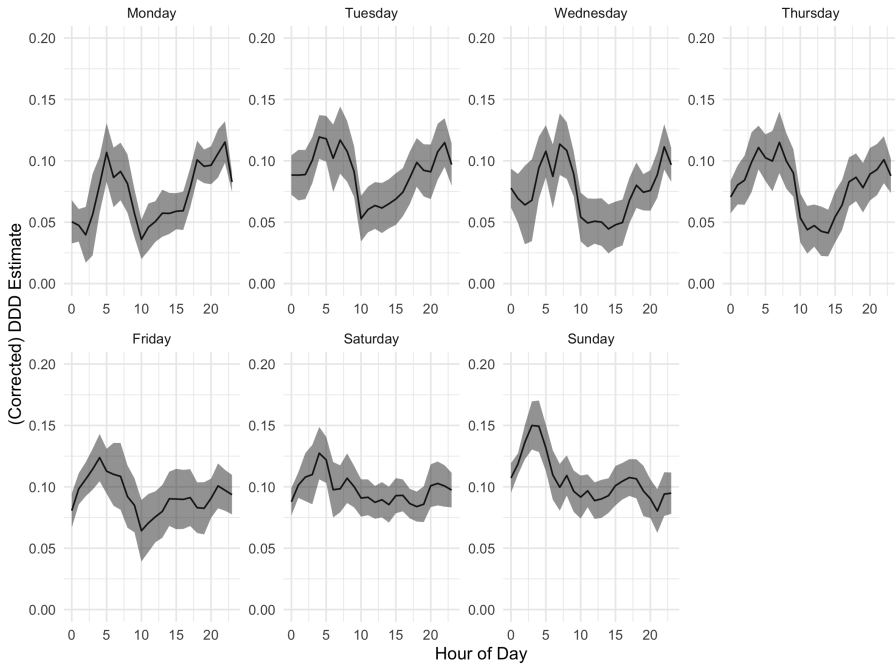
Figure 1: DDD Estimate - By Hour



Note: This figure documents the DDD estimate of the regression equation (1) by each hour, which is divided by two according to the equation (2). Solid lines represent the DDD estimates for each corresponding day-hour pair and dash areas correspond to 95% confidence intervals.

The next step is to investigate whether the causal estimate shows a heterogeneous pattern across hours and days of the week. When we analyze the causal estimates across different hours and days of the week, we observe different patterns between weekdays and weekends. Figure 2 shows that the causal estimate of DDD is statistically and economically significant and positive during all hours and days within the week. Moreover, we find that the positive effect reaches its peak during rush hours on weekdays, whereas the effect is even higher during the weekends along with the evidence that the higher effect during the weekend is almost uniformly distributed across hours. Given that customers are likely to use ride and bike sharing for leisure activities during weekends more compared to during weekdays, the intensity of using ride sharing is more uniformly distributed across hours during weekends, which enhances Lyft's opportunity to benefit its brand salience through bikes for attracting the customers to ride sharing at higher frequency of time during the weekends.

Figure 2: DDD Estimate - By Day and Hour



Note: This figure documents the DDD estimate of the regression equation (1) by each day and hour, which is divided by two according to the equation (2). Solid lines represent the DDD estimates for each corresponding day-hour pair and dash areas correspond to 95% confidence intervals.

5 Conclusion

This study focuses on the role of intangible capital in Mergers and Acquisitions (M&A) evaluation for industry competition by using the ride and bike sharing markets in which intangible capital brings the features of synergy and network externality to the acquirer of the acquisition. We investigate whether acquirer sharing platforms in M&A transactions leverage intangible capital to enhance their competitive advantage. To handle this question, we use the case of bike-sharing platforms and in particular Lyft's acquisition of bike-sharing company. Employing the rich variation in the dataset of bike-sharing and ride-sharing trips, we apply difference-in-difference-in-differences (DDD) model to estimate the causal impact of the acquisition on competition in ride-sharing market. We find that after the acquisition

Lyft increases its rides by 10% compared to Uber; even more on weekends. We interpret this result that intangible capital accumulated through the merger enhances Lyft's opportunity to benefit its brand salience through bikes by attracting their bike customers to ride sharing.

We have several steps for the future work. First, we aim to estimate the heterogeneous treatment effects in which the causal impact of the acquisition would differ across several demographics such as income, age, education, employment and residential population. Hence, we would potentially investigate which part of the society would help Lyft internalize its intangible capital for the competitive advantage. Second, we plan to design a empirical framework for continuous treatment in which we would extend binary treatment into continuous treatment. The motivation is that the exposure to brand salience and user data can be heterogeneous based on the number of bike stations. Hence, we would use the number of bike trips within zone as a treatment which captures the intensity of treatment.

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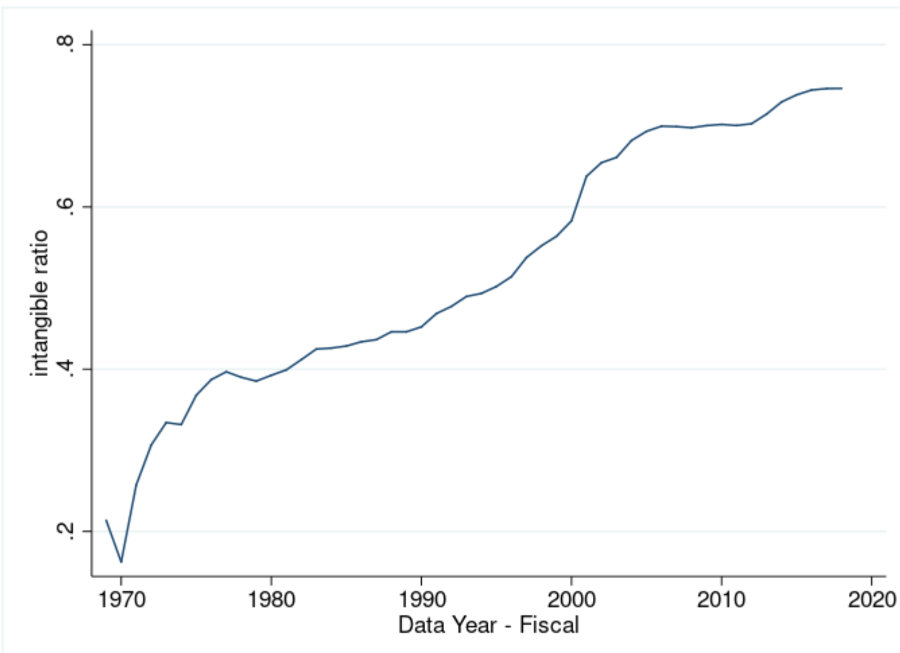
Appendix

Table A1: Share of Ride Trips by Zone Category

Zone Category	Number of taxi zones	Share of Lyft trips	Share of Uber trips
Without Bike	161	0.329	0.352
With Bike	96	0.671	0.648

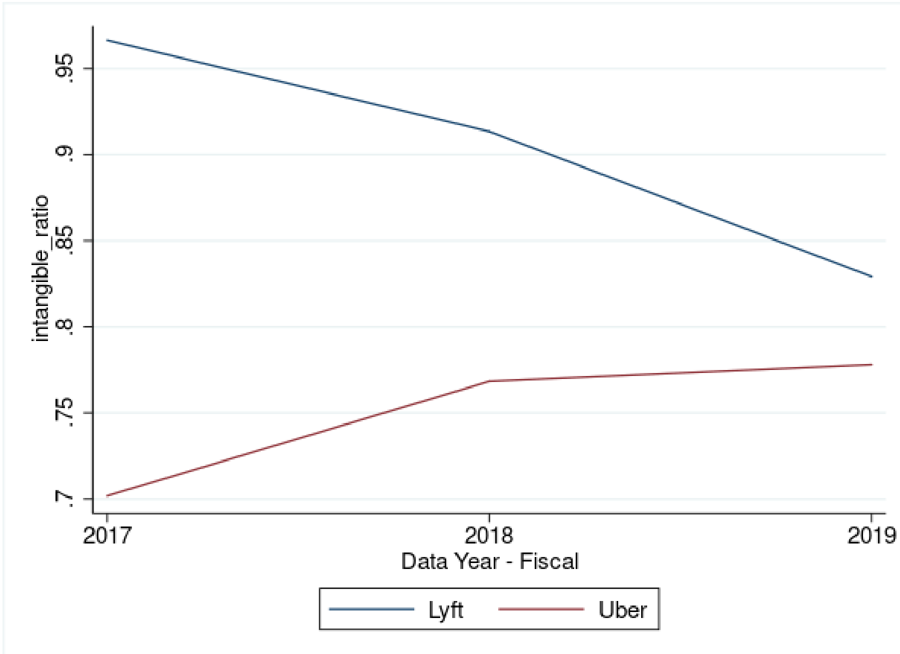
Note: This figure shows the number of taxi zones, and the market shares of Uber and Lyft for each category.

Figure A1: Intangible Capital Ratio



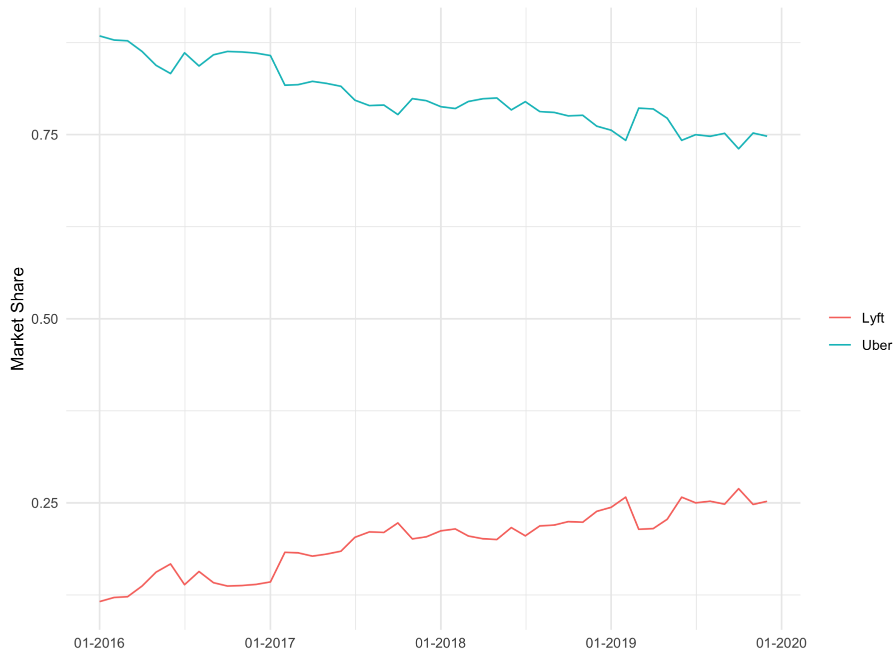
Note: This figure shows the yearly simple average of intangible ratio in the Compustat dataset. Intangible ratio is defined as $\frac{\text{Intangible capital stock}}{\text{Intangible capital stock + Tangible capital stock}}$. Intangible capital stock is constructed based on the perpetual inventory method of Peters and Taylor (2017). Tangible capital stock is the total net plant,property and equipment.

Figure A2: Lyft & Uber Intangible Capital Ratio



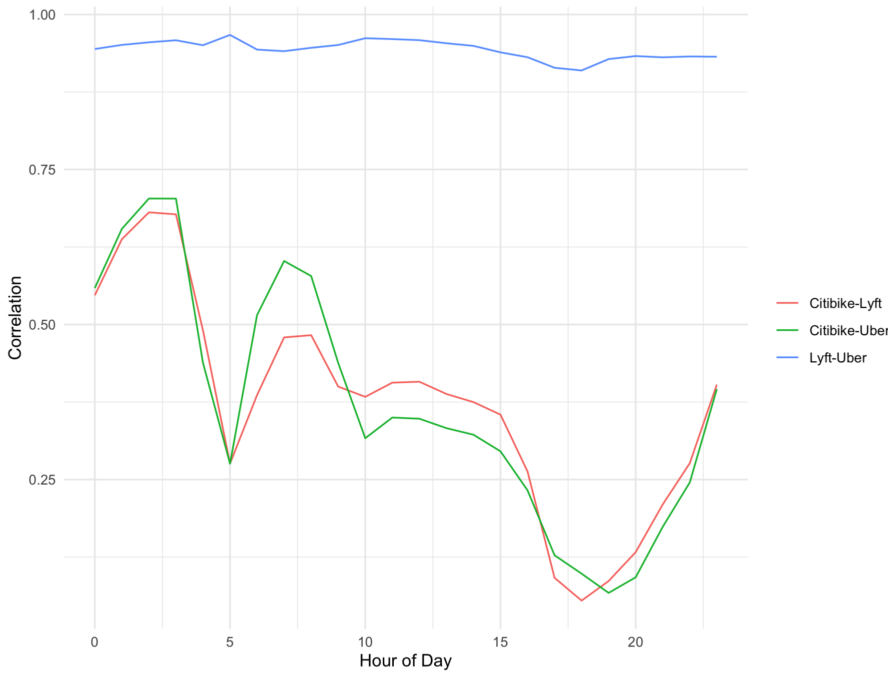
Note: This figure shows the annual intangible capital ratio of Lyft and Uber where intangible capital ratio is defined as $\frac{\text{Intangible capital stock}}{\text{Intangible capital stock + Tangible capital stock}}$. Intangible capital stock is constructed based on the perpetual inventory method of Peters and Taylor (2017). Tangible capital stock is the total net plant,property and equipment.

Figure A3: Market Shares



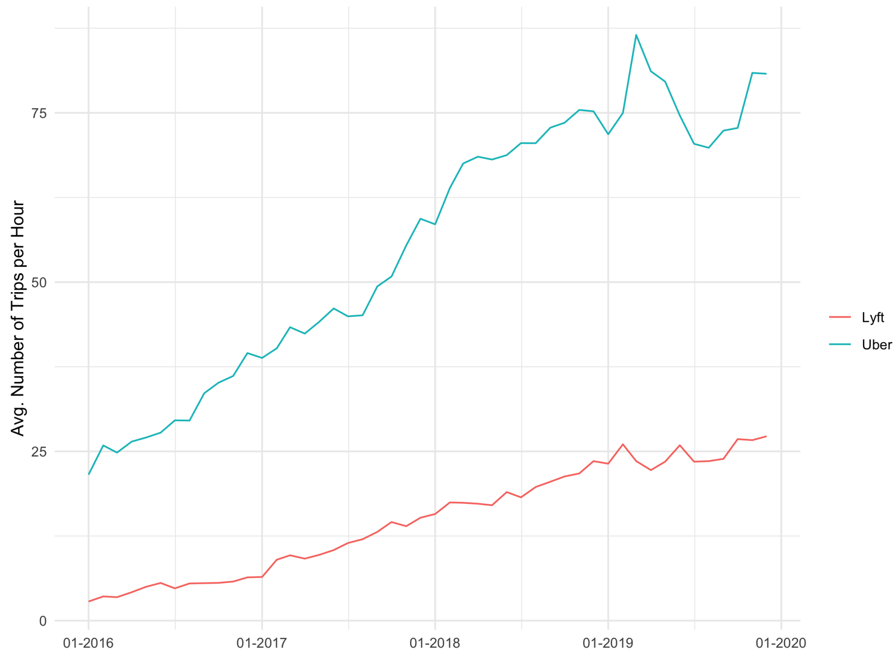
Note: This figure shows the market shares of Uber and Lyft in ride-sharing over time.

Figure A4: Correlation of Number Trips Across Firms - By Hour



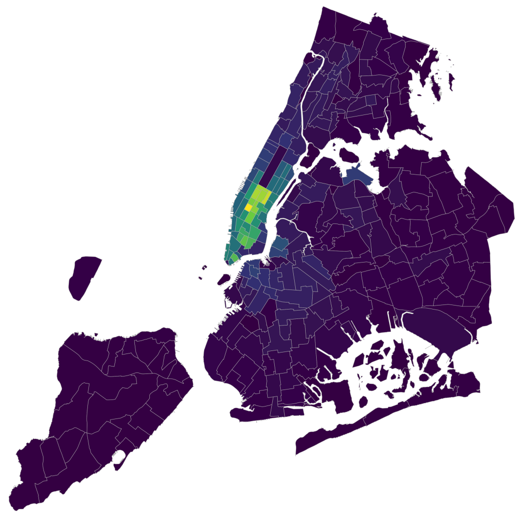
Note: This figure shows the raw correlation between the number of trips i) Lyft bike vs. Lyft ride, ii) Lyft ride vs. Uber ride and iii) Lyft bike vs. Uber ride in each hour in a day.

Figure A5: Average Number of Trips Per Hour



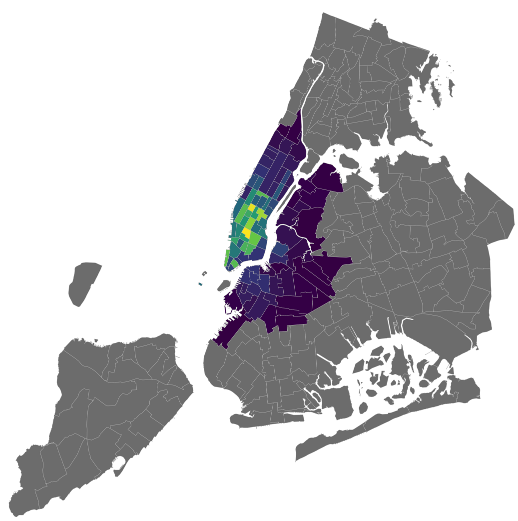
Note: This figure shows the average number of trips per hour for Citi Bike, Lyft and Uber.

Figure A6: Ride-share Heatmap, New York City



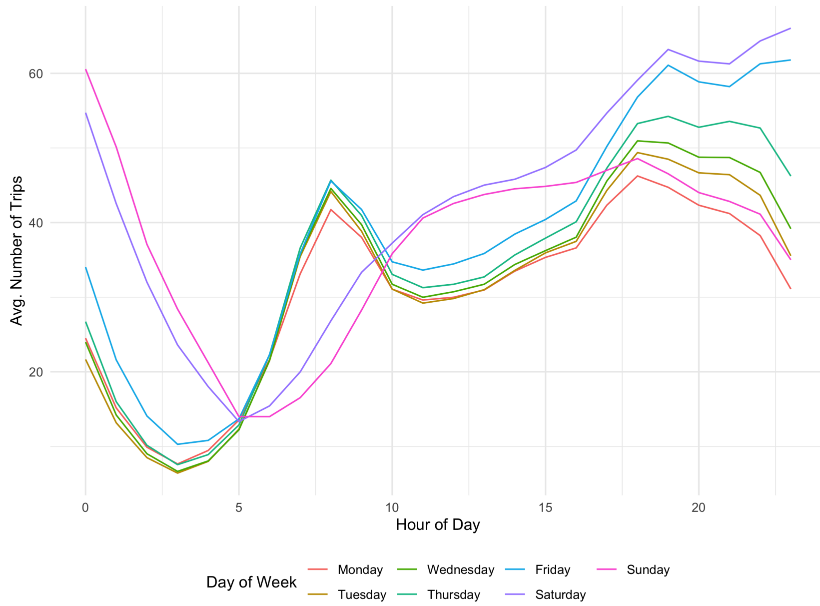
Note: This figures shows a map of taxi zones, where the colors represent the total ride share trips per square mile originating from each taxi zone. Lighter colors represent higher total ride share trips.

Figure A7: Bike-share Heatmap, New York City



Note: This figures shows where the with-bike and without-bike taxi zones are. Grey colors denotes the without-bike taxi zones. Lighter colors within the with-bike zones represent higher total bike share trips.

Figure A8: Average Number of Ride-sharing Trips - By Day and Hour



Note: This figures shows the average ride-sharing trips for each hour during each day of week.