

## Online Platforms' Creative "Disruption" in Organizational Capital – The Accumulated Information of the Firm: The Depreciation of the Value of Data

Wendy C. Y. Li (Moon Economics Institute) wendyli@moonecon.org

Paper prepared for the Conference on The Valuation of Data November 2 – November 3, 2023 Session 2: Methodologies of Data Valuation - I Time: Thursday, November 2, 2023 [11:45AM-1:15PM EST]



# Online Platforms' Creative "Disruption" in Organizational Capital – The Accumulated Information of the Firm

Wendy C. Y. Li Moon Economics Institute

**P. J. Chi** University of California Los Angeles

Citation:

Li, W.C.Y. and P. J. Chi (2023). Online platforms' creative "disruption" in organization capital – the accumulated information of the firm, *Moon Economics Institute Discussion Paper, No. 1.* 

MOON ECONOMICS INSTITUTE https://moonecon.org/



#### **Online Platforms' Creative "Disruption" in Organizational Capital**

## - The Accumulated Information of the Firm

Wendy C.Y. Li (Moon Economics Institute)<sup>1,2</sup> and P.J. Chi (University of California, Los Angeles)

Updated on August 1, 2023

#### Abstract

Online platforms based on troves of data and digital technologies have revolutionized and disrupted the industry sectors. This paper presents a new method, centering on organizational capital, to examine how the entry of an online platform, a new data-driven business innovation, affects an existing firm's value of organizational capital and investment in organizational capital. An online platform's key disruption in its sector is traditional firms' knowledge derived from their relatively limited amounts of data. This disruption can hence be measured by a firm's organizational capital, the accumulated information of the firm. The approach is supported by our finding that the organization capital of dominant online platforms is highly correlated with rising global data flow, the first empirical evidence that successfully links the explosive global data flow to an economic value. Moreover, we also find that when the global data flow increases by five folds, Big Tech's organizational capital stock doubles. The major findings based on the firm-level data of the U.S. hospitality and the transportation industries during the period of 2002 to 2018 are as follows. When an online platform enters the industry, the existing incumbents with a lower degree of digital transformation have a higher depreciation rate of organizational capital. This is the first empirical evidence of the anticipated effect of new business innovations on the depreciation rate of organizational capital. However, there is no immediate impact on the output, the employment, or the total factor productivity of existing incumbents. In the increasing digitally and physically inter-connected world, new online platforms' disruptions in traditional industries will be significant, fast, and on a massive scale. Our paper provides a new methodology to measure online platforms' disruptions in traditional brick-and-mortar firms in a timely manner

<sup>&</sup>lt;sup>1</sup> Corresponding Author: Wendy C.Y. Li, <u>wendyli@moonecon.org</u>

<sup>&</sup>lt;sup>2</sup> We thank Diane Coyle and Steve Lihn for their helpful comments.

<sup>© 2019 - 2023</sup> by Wendy C.Y. Li and P.J. Chi. All rights reserved.

#### 1. Introduction

Online platforms based on artificial intelligence (AI) and troves of data have disrupted the sectors they have entered. An online platform is a data-driven business innovation. The data-driven nature of online platforms' business models enables them to provide data-targeting services in a more time-efficient and cost-effective manner (Li, Nirei, and Yamana, 2019a, b). Online platforms can not only increase their operational scale without facing traditional constraints, but can also collect valuable consumer and non-consumer data to create new innovations, products, and services, which are all crucial for entering adjacent business sectors. That is, online platforms' business models are highly scalable, in both scale and scope. Moreover, as AI is becoming a more affordable and adaptable tool (Marko, 2019), data determine the overall power and accuracy of an algorithm and thus are vital for firm competitiveness. By collecting data from both users and third parties, online platforms have a competitive advantage in data powered by the network effect and the virtuous cycle between data and AI algorithms.

Can the impacts of online platforms be effectively examined by conventional methods? Economists traditionally resort to the Schumpeterian paradigm and use the entry and exit rates of firms to measure the creative destruction of new innovations on competition and innovation. However, most online platforms, especially online sharing platforms, were founded only in the past decade, and their impact may not have propagated to firm entries or exits, making this approach inapplicable before a significant amount of time has passed. Another major difficulty in investigating this topic is the dearth of data from not only the perspective of affected firms but also the perspective of online platforms (Demunter, 2018). As a result, the current literature on the impact of online platforms on competition and innovation is limited to case studies, theoretical studies, conceptual studies, and regional studies. Studies on the measured impacts are focused on

the revenues and service quality of affected firms (Nadler, 2014; Zervas et al., 2014; Wallsten, 2015; Cohen et al., 2016; Brynjolfsson et al., 2018; OECD 2018). It is therefore imperative to find an alternative method that can rapidly identify the impact of online platforms on competition, innovation, and welfare.

Online platforms are new data-driven business models, and business models contain business processes and designs that are the main components of organizational capital. Prescott and Visscher (1980) define organizational capital as the accumulated information of the firm, a firm's knowledge of how to produce, compete, and grow. Lev and Radhakrishnan (2005) gave a clear operational definition of organizational capital: it is firm-embodied and provides firms a sustainable competitive advantage that cannot be completely codified, transferred to other firms, and imitated by other firms. As indicated in the classic information pyramid, data is the base for firms to derive information, knowledge, and then understanding (Coyle and Li, 2020). If we apply this concept to firms, organizational capital captures the essence of the information, knowledge, and understanding that firms derive from data, which in turn guides a firm to produce, compete, and grow.<sup>3</sup> That is, firms derive their firm-specific knowledge from data (e.g., transaction data) and utilize the knowledge to various management functions within the firm. Firms with an advantage in data can better produce, compete, and grow.

To demonstrate the relationship between data and organizational capital, we compare the global data flow<sup>4</sup> with the combined organizational capital of global top online platform

<sup>&</sup>lt;sup>3</sup> In the rest of the paper, we use "knowledge" to refer the combination of "information, knowledge, and understanding" in the information pyramid.

<sup>&</sup>lt;sup>4</sup> Note that the global data flow is defined as the internet traffic and measured by the annual data volume. Because companies use accumulated data to derive the desired information, and most of these data, if not all, are stored in the cloud, the global data flow can represent a meaningful index for the accumulated volume of data that is suitable to compare.

companies.<sup>5</sup> Table 1 shows the seven online platform firms considered: Microsoft, Amazon, Apple, Google, Facebook, Alibaba, and Tencent<sup>6</sup>, which are also among the global top-ten companies. We find that the combined organizational capital stock closely follows the rising trend of the global data flow (Figure 1 (a)). Quantitatively, the growth rates of the two time series are highly correlated, with an R<sup>2</sup> value of 0.775 (Figure 1 (b)). This finding is crucial, especially when all recent studies such as Coyle et al. (2020) and Tomiura et al. (2020) have recognized the conundrum of linking the exponential growth of global data flow to an economic value. It provides new evidence that, in the digital era, dominant online platform companies have been aggressively investing in organizational capital to grasp the great economic opportunities created by the explosive global data growth. Moreover, we also find that when the global data volume increases by five folds, the Big Tech's organizational capital stock, i.e., the value of data, doubles, a relationship we have termed Li's law of value of data (Figure 1 (c)).

<sup>&</sup>lt;sup>5</sup> See Section 2 for the methodology of how to calculate the firm-level organizational capital stock.

<sup>&</sup>lt;sup>6</sup> Cusumano et al. (2020) classify both Microsoft and Apple as online platform companies.

Ranking	Company	Businesses	Market Cap <sup>†</sup>	Organizational Capital* <sup>7</sup> /Market Cap
1	Microsoft	Internet/Online Platform	1,036	15.38%
2	Amazon	<b>Online Platform</b>	936	12.19%
3	Apple	Internet/Online	913	2.08%
		Platform		
4	Google	<b>Online Platform</b>	767	4.33%
5	Facebook	<b>Online Platform</b>	538	2.00%
6	Berkeshire	Financial	505	
	Hathaway			
7	Alibaba	<b>Online Platform</b>	431	1.32%
8	Tencent	<b>Online Platform</b>	403	1.22%
9	Johnson &	Pharmaceutical	372	
	Johnson			
10	Visa	Financial	370	

## Table 1: Global Top Ten Most Valuable Companies

Date: June 18, 2019 (for market cap)

† Unit: US \$1 billion\* Source: this research

<sup>&</sup>lt;sup>7</sup> This column indicates that firms with a higher degree of organizational capital intensity are also more valuable. This is consistent with the main finding in Eisfeldt and Papanikolaou (2013).



Figure 1: Big Tech's Combined Organizational capital vs. Global Data Flow

Data Sources: Global data flow data: Cisco Systems; Combined organizational capital stock: this research.Companies include Microsoft, Amazon, Apple, Google, Facebook, Alibaba, and Tencent.

To our knowledge, no study has examined the impact of the entry of online platforms on the value of organizational capital of existing firms and their investments in organizational capital. Online platforms have a data advantage, not only in volume, but also in richness and variety, and data can easily be recombined and aggregated with other datasets. This new and unique nature of digital data allows an online platform company to utilize data to the scale and scope that far exceed its offline counterparts. Hence, when an online platform enters an industry sector, its key disruption to traditional firms in that sector is firm-specific knowledge derived from their relatively limited amounts of data. It can therefore be anticipated that the disruption can be measured from the perspective of a firm's organizational capital. Conceptually, this new business innovation can reduce the values of traditional firms' existing organizational capital, an impact that can be measured by the depreciation rate of organizational capital (Lev and Radhakrishnan, 2005).

This paper investigates the impact of the entry of an online platform on competition and innovation, from the perspective of the changes in the depreciation rate and the stock of organizational capital, as well as from changes in the investment behaviors of existing incumbents. Specifically, does the introduction of a new business innovation generate a creative "disruption" that makes the conventional business model of existing incumbents outdated or deteriorate faster? Both the resource-based theory and the study by Lev and Radhakrishnan (2005) conceptually predict that the organizational capital of existing incumbents will depreciate faster, but no study has demonstrated the empirical evidence and the magnitude of such a depreciation change. In addition, given the dynamic nature of competition, existing incumbents may be able to adopt digital technologies, and reorient or reinvent their business models to digitally transform themselves to cope with new business innovations in the industry. This raises a question of whether there is a difference in the depreciation pattern between incumbents with digital transformation

and those without. Moreover, Eisfeldt and Papanikolaou (2013) find that firms with a higher degree of organizational capital intensity are also more productive, and that their average market return is 4.6% higher. Therefore, it is worth examining how the entry of online platforms can affect the existing incumbents' investment in organizational capital and their organizational capital stock.

In this paper, we study the impact of online platforms' entry using the U.S. hospitality and transportation industries, two of the few industries that lead the adoption of digitization over the rest of the economy. Our data sources are from Compustat. The data cover the period between 2002 and 2018.

Our key findings are as below. First, when an online platform enters the industry, the existing incumbents with a lower degree of digital transformation have a higher deprecation rate of organizational capital. This is the first empirical evidence of the anticipated effect of new business innovations on the depreciation rate of organizational capital. Second, when online platforms enter the industry, existing incumbents with a higher degree of digital transformation are more organizational capital-intensive, and accumulate a higher stock of organizational capital. However, there is no immediate impact on the output, employment, or total factor productivity of existing incumbents.

The rest of paper proceeds as follows. Section 2 describes the empirical methodology. Section 3 describes the data. Section 4 shows the empirical analysis results. Section 5 concludes.

## 2. Empirical Methodology - Depreciation and Stock of Organizational Capital

Information is an asset to the firm, and the accumulated information in the firm is defined as organizational capital (Prescott and Visscher, 1980). Firms develop and accumulate information, affecting their production technology. The accumulated information is distinct from physical or human capital in the standard growth model (Arrow, 1962; Rosen, 1972; Tomer, 1987; Ericson and Pakes, 1995; Atkeson and Kehoe, 2005). Organizational capital is firm-embodied and provides firms a sustainable competitive advantage that cannot be completely codified, transferred to other firms, and imitated by other firms (Lev and Radhakrishnan, 2005). Following this definition and earlier related studies (Lev and Radhakrishnan, 2005; Eisfeldt and Papanikolaou, 2013; Falato et al., 2013; Li, 2015, 2016a; Peters and Taylor, 2017; Brynjolfsson et al. 2018b; Li et al., 2019), we use the selling, general, and administrative (SG&A) expense as a proxy for a firm's investment in organizational capital. Firms report this expense in their annual income statements, and it includes most of the expenditures that generate organizational capital, such as employee training costs, brand enhancement activities, consulting fees, and the installation and management costs of supply chains.

The key to calculating the stock of organization capital is its depreciation rate, but past studies have only assumed its value rather than truly estimated it. For example, Eisfeldt and Papanikolaou (2013) adopted the conventionally assumed R&D depreciation rate of 15% as the depreciation rate of organizational capital for all industries, all firms, and all times. Falato et al. (2013), Peters and Taylor (2017), and Brynjolfsson et al. (2018b) followed the same practice, except that they assumed the depreciation rate to be 20% instead.<sup>8</sup> There are three major problems with applying

<sup>&</sup>lt;sup>8</sup> Brynjolfsson et al. (2018b) used the stock of organizational capital measured by Peters and Taylor (2017), who used 20% as the depreciation rate for organizational capital, and cited Falato et al. (2013) as the source. However, Falato et al. (2013) did not estimate this rate by themselves – they claimed that it came from a study by Lev and

the R&D depreciation rate as the depreciation rate of organizational capital and using a single fixed depreciation rate across the board. First, the depreciation rate should and does vary by the type of intangible capital (Li, 2015, 2016a; Li and Hall, 2018). Second, the driving forces of the depreciation of intangible capital are obsolescence and competition, both of which reflect the innovation and competition environment of the individual industry (Hall, 2005). This dissimilarity has been evidenced by the clear variations in the country-specific, industry-level depreciation rates of R&D assets (Li, 2016b; Li and Hall, 2018). Even within the same industry, the depreciation rate can vary over time, since the pace of technological progress and the degree of market competition do not stay the same indefinitely. Third, the depreciation rate of organizational capital indicates the level of the appropriateness of a firm's organizational capital (Lev and Radhakrishnan, 2005; Li, 2015, 2016a; Li and Hall, 2018), which should differ among firms. A higher depreciation rate indicates that the firm can appropriate less return from its investment in organizational capital. As shown by Li (2015), market leaders in the U.S. high-tech industries generally have a lower depreciation rate of organizational capital than their followers. This is consistent with the argument in the resource-based theory: the sustained competitive advantage of a firm lies primarily in the application of valuable tangible or intangible resources that are neither perfectly imitable nor substitutable without great effort (Barney, 1991).

In sum, the old approach of using a fixed depreciation rate for all firms and at all times cannot reflect the impact of new business innovations on the organizational capital of existing firms. This problem is especially serious in the digital era. When online platforms enter industry sectors, online platforms' key disruption to traditional firms in the same sector is their firm-specific

Radhakrishnan (2004), but did not list the work in the References section. It should be noted that Lev and Radhakrishnan published a paper in 2005, where they assumed the service life of R&D assets as five years for all firms and used the straight-line amortization method, leading to an R&D depreciation rate at 20% per year. This is an assumption rather than estimation.

knowledge that guides them how to produce, compete, and grow. As indicated earlier, organizational capital can measure the firm-specific knowledge, and the new business innovations of online platforms can reduce the values of traditional firms' existing organizational capital, an impact that can be measured by the depreciation rate of organizational capital (Lev and Radhakrishnan, 2005).

In this research, we make a substantial improvement in the construction of firm-level organization capital by measuring the depreciation rate of organization capital for each firm. We follow the method developed by Li and Hall (2018) (see Appendix A), which is a forward-looking profit model only requiring firm-level data on sales and investments in intangible capital to identify the firm-level depreciation rates of such intangible capital. In addition, we follow the methodology in Hall (1993) that has been adopted by other studies (Eisfeldt and Papanikolaou, 2013; Falato et al., 2013; Li, 2015, 2016a; Peters and Taylor, 2017; Brynjolfsson et al. 2018b; Li et al., 2019) and use the perpetual inventory method to construct the firm-level stock of organizational capital and calculate the associated growth.<sup>9</sup>

<sup>&</sup>lt;sup>9</sup> Note that Lev and Radhakrishnan (2005) adopted a production residual approach to measure firm-level organizational capital. However, because the production residual may contain other types of intangibles, the approach may overestimate the size of organizational capital (Bresnahan, 2005).

#### 3. Data

Following earlier studies, we use the selling, general, and administrative (SG&A) expense as a proxy for a firm's investment in organizational capital. Specifically, we examine the data for key firms in the hospitality and transportation industries in the U.S. where public data are available. Our SG&A data are from firms' public income statements, and cover the years of 2002 to 2018.

Our data cover 8 U.S. existing incumbents. For the transportation industry, we study two public companies, Hertz and Avis. For the hospitality industry, we study existing incumbents, including Hyatt, Starwood, and Marriott,<sup>10</sup> and three existing online platform companies, Expedia, Booking Holdings<sup>11</sup>, and TripAdvisor, which initially had different business models from that of Airbnb. The choice of the companies is based on data availability, and we cover most major players in the two industries as much as possible.

Our analysis for the U.S. transportation industry covers two leading rental car incumbents: Avis Budget Group Inc. and Hertz Global Holdings, Inc. Although rental car companies and Uber belong to the same transportation industry using passenger cars, it is not obvious whether they are substitutes for each other. Generally speaking, Uber caters to shorter-term transportation demand, but there may be market segments overlapping with those for rental cars. As Uber aims to expand its current online ridesharing platform as a super app that offers comprehensive transportation services to consumers, the market overlap may increase in the future.

Both rental car companies initially created car-sharing services to deal with rising car-sharing demand and the entry of online ridesharing platforms. Hertz launched a global

<sup>&</sup>lt;sup>10</sup> Starwood was acquired by Marriott International in September 2016.

<sup>&</sup>lt;sup>11</sup> The Priceline Group changed its name to Booking Holdings in 2018.

car-sharing service in 2008, which offers rental car service by the hour. In 2013, Avis acquired Zipcar, which also offers on-demand car sharing services based on an online subscription business model—members may have to pay a membership fee in addition to a reservation charge. Currently, Zipcar has 1 million members, 75% of them in the U.S. The rental term is generally shorter than typical rental car service length, but may be longer than that provided by a taxi or Uber. As the demand growth for car-sharing services slowed down but the demand for ridesharing services grew rapidly, Hertz and Avis successively partnered with both Uber and Lyft. Hertz partnered with Uber and Lyft in 2016, by renting cars to ridesharing drivers. The average rental length is two to three months, much longer than the typical term in its core business. The partnership business not only increases the utilization of its rental vehicles, but also takes advantage of the rising demand in ridesharing services. Later, Avis also partnered with Lyft in 2018, and Uber in 2019, but operated at a scale around 15% of Hertz's, in terms of the number of the rental vehicles (Forman, 2019).

## 4. Empirical Analysis

#### 4.1 Organizational Capital: Depreciation and Stock

In this section, we examine the impact of online platforms on existing incumbents from the perspective of organizational capital. Table 1 shows the firms included in this study and the estimated depreciation rates of organizational capital following the Li and Hall 2018 model described in Appendix A. Also listed is the degree of digitalization of each firm in each industry category. For example, compared with three existing online travel platform companies, traditional incumbents like Hyatt and Marriott have a lower degree of digitalization.

#### **Table 2: Depreciation Rates of Organizational Capital**

Firms	δ_OC [%]	Degree of Digitalization	
	US Hospitality Firms		
Hvatt	36%	Lower	
Marriott	46%	Lower	
Starwood	33%	Lower	
	U.S. Online Travel Platform Com	panies	
Expedia	8%	Higher	
Booking	19%	Higher	
TripAdvisor	17%	Higher	
	US Rental Car Companies		
Hertz	14%	Teamed up with Uber and Lyft in 2016	
Avis	36%	Teamed up with Uber in 2018 and Lyft in 2019, at around 10% of Hertz's scale	

#### for Key U.S. Firms in the Hospitality and Transportation Industries

Source: this research.

Table 2 shows that in the hospitality and transportation industries, the physical asset-heavy and less digitalized incumbents generally have higher depreciation rates of organizational capital. For example, compared with traditional incumbents such as Marriott and Hyatt, U.S. online travel

platform companies, including Expedia, Booking, and TripAdvisor<sup>12</sup>, all have smaller depreciation rates of organizational capital. As for the two U.S. rental car companies, Hertz teamed up with Uber and Lyft to tap the advantage of the rising ridesharing demand at least two years earlier and at a much larger scale than its rival Avis. Hertz also has a smaller depreciation rate of organizational capital between the two companies.

Online platforms are data-driven business models, and business models contain business processes and designs that are the main components of organizational capital. When a new system or process is introduced in the industry, the resource-based theory (Barnet, 1991) and the study by Lev and Radhakrishnan (2005) predict that the old type of organizational capital obsoletes at a faster rate, or equivalently, suffers an increased depreciation rate. Here we verify these theoretical expectations by examining how the depreciation rate of organizational capital for each of the firms listed in Table 2 is affected by the entry of a new online platform. Table 3 summarizes the changes of the firm-level depreciation rate of organizational capital associated with the entry of Airbnb and Uber.

The results in Table 3 present the following impacts of online platforms. First, as theoretically expected, after Airbnb's entry in 2014, traditional U.S. incumbents with mid-end and high-end hotel chains suffered higher depreciation rates of organizational capital. <sup>13</sup> The increase in traditional incumbents' depreciation rates of organizational capital captures the negative disruption by Airbnb's entry.

<sup>&</sup>lt;sup>12</sup> Note that TripAdvisor has a different underlying business model from that of Expedia and Booking. Unlike Expedia and Booking, Expedia diverts consumers to Expedia and Booking for reservations of hotels, rental cars, or other services.

<sup>&</sup>lt;sup>13</sup> Note that Zervas et al. (2014) found no impact of Airbnb's entry on the sales of traditional incumbents with midend and high-end hotel chains.

Firms	Entry Event	Entry Date	δ_OC
Marriott	Series D, Airbnb	5/22/2014	Increase
Starwood	Series D, Airbnb	5/22/2014	Increase
Hyatt	Series D, Airbnb	5/22/2014	Increase
Expedia	Series D, Airbnb	5/22/2014	Increase
Booking	Series D, Airbnb	5/22/2014	Decrease
TripAdvisor	Series D, Airbnb	5/22/2014	Decrease
Avis	Purchasing Zipcar	1/2/2013	Decrease
Hertz 1	Series C, Uber	8/22/2013	Decrease
Hertz 2	Deal with Uber/Lyft	6/30/2016	Decrease

 Table 3: Changes in Depreciation Rates of Organizational Capital

Source: this research

Second, the impact of Airbnb's entry on the three existing online travel platform companies is indefinite. Compared to traditional hotel chains, existing online travel platform companies are more diversified in the coverage of services, including airline tickets, rental cars, and lodging. In the lodging service, they offer complementary services to traditional hotels. The existence of Expedia and Booking -- two established and successful online sharing platform companies -- did not deter the entry of Airbnb in 2008. Soon after Airbnb became a player, the two online travel platform companies quickly adjusted their data-driven business models and expanded their business into the service of private rooms and properties. The main revenue source of TripAdvisor is the advertising service for companies such as Expedia and Booking. As more online travel platforms offer a one-stop shop by including more services such as tourism information to travelers, TripAdvisor may face a higher degree of competition.

Third, in the U.S. transportation industries, we find an expected directional change in the depreciation rate of organizational capital when firms partnered with online platforms and/or carsharing service providers. For example, after Uber's entry, Hertz partnered with Uber and Lyft in 2016, by providing rental cars to Uber and Lyft drivers. We find that the estimated depreciation of Hertz's organizational capital decreased. In addition, Avis purchased Zipcar in 2013. After entering the car-sharing market through Zipcar, Avis's depreciation rate of organizational capital went down. Moreover, Hertz began to partner with Uber and Lyft in 2016, to tap the benefit of the rising ridesharing demand. Hertz's depreciation rate of organizational capital went down after this partnership. These results imply that traditional incumbents can maintain their competitiveness by digitally transforming themselves and providing services complementary to online platforms.

Our next step is to examine the impact of the entry of online platforms on the size and growth of firms' organizational capital. As mentioned earlier, in the digital era, when an online platform enters an industry sector, its key disruption to traditional firms in that sector is their firm-specific knowledge that guides them how to produce, compete, and grow. Organizational capital can measure the firm-specific knowledge, and the entry of new online platforms can reduce the value of traditional firms' existing organizational capital. Figures 2 to 7 show the annual organizational capital stock, the growth rates of investment in organizational capital, and the growth rates of organizational capital of key firms for which data are available in this study.



Figure 2: Annual Organizational Capital Stock for Key U.S. Hospitality Firms



Figure 3: Growth Rates of Organizational Capital Investment and Stock for Key U.S. Hospitality Firms

In Figures 2 and 3, we compare three traditional incumbents and three existing online platform companies in the U.S. hospitality industry in terms of the size and growth of organizational capital and the growth of investment in organizational capital. The comparison shows several important facts: first, we see that after 2004, Expedia Inc., a company spun off from Microsoft in 1999, that earned a revenue of only 35.5% of Starwood's in 2005, has a larger stock of organizational capital than Starwood and Marriott. This phenomenon is also shown in Booking: after the financial crisis, when its revenue was only 49.8% of Starwood's in 2009, Booking overtook Starwood in organizational capital stock and has been catching up with Expedia in recent years. The gap in the organizational capital stock between traditional incumbents such as Marriott and Starwood, and online platforms such as Expedia and Booking, has been widening since 2012.

In 2012, the world entered a new era of AI, and big data became a crucial input for the innovation and production of digital goods and services.<sup>14</sup> As AI becomes less expensive, data are vital for firm competitiveness, not only in innovation but also in efficiency. Online travel platforms have a competitive advantage in data, and their organizational capital is big data-driven. As shown in Table 2, compared with traditional incumbents, online platform companies have smaller depreciation rates of organizational capital. Additionally, they had higher growth rates of investment in organizational capital and of organizational capital stock most of the time, and traditional incumbents performed relatively poorly, as indicated in Figure 3. For example, Starwood had a negative growth rate of investment in organizational capital during the financial crisis and essentially a zero growth of investment in organizational capital in the 2010s, and was later acquired by Marriot International Corporation in 2016. In sum, compared with traditional

<sup>&</sup>lt;sup>14</sup> Lee (2018) points out that the turning point for neutral network (or rebranded as deep learning) came in 2012, a year that the AI's breakthrough "truly [brings] AI's power to bear on a range of real-world problems," and kickstarted "the massive potential of the field to decipher human speech, identify fraud, make lending decisions, help robots 'see', and even drive a car."

incumbents with a lower degree of digitalization, existing online platform companies are accumulating a larger stock of organizational capital due to the lower depreciation rates of organizational capital and the higher growth rates of investment in organizational capital.

In the U.S. car rental industry, Hertz is one of the frontrunners and has a more stabilized growth rate of organizational capital stock. In 2010, its organizational capital stock surpassed that of Avis (see Figure 4), one of its main competitors, due to Avis's lesser amount of investment in organizational capital and higher deprecation rate of organizational capital. After 2010, Avis increased its investment in organizational capital and has been matching Hertz in the growth rate of organizational capital stock since the company acquired Zipcar in 2013 (see Figure 5).



Figure 4: Annual Organizational Capital Stock for Key U.S. Rental Car Firms



Figure 5: Growth Rates of Organizational Capital Investment and Stocks for Key U.S. Rental Car Firms

#### 4.2 Firm-level Employment, Output, and Total Factor Productivity (TFP)

Our empirical analysis in the previous section shows that we can capture online platforms' disruption in traditional incumbents' existing knowledge from the perspective of organizational capital. In this section, we examine the impact of the entry of new online platforms on existing incumbents from the traditional perspective of outputs, employment, and total factor productivity (TFP).

Figure 6 plots the historic numbers of employees for the same U.S. firms discussed previously. In the U.S. rental car industry, the employment numbers for both Avis and Hertz began a rising trend of at least four years shortly after Uber's entry in March 2009. In the U.S. hospitality industry, an important time of reference is the start of Airbnb in August 2008. Despite the data gaps in the traditional hotel chains, we find that the employment numbers for Marriott, Hyatt, and Starwood either increased or stayed steady after Airbnb's entry. The numbers for the three existing online travel platforms (Expedia, Booking, and TripAdvisor), on the other hand, show clear growth. In sum, the data for the above U.S. industries do not show any negative impact of online sharing platforms on the employment of existing incumbents.

Figure 7 plots the time series of sales for the firms in the same industries. In the U.S. transportation industry, after Uber's entry, neither Hertz nor Avis experienced a decline in sales. In the U.S. hospitality industry, after Airbnb's entry, the sales data for traditional hotel chains show mostly slight steady increases. On the other hand, existing online travel platforms like Booking and Expedia enjoyed substantial growths after Airbnb's entry. In sum, we do not see any negative impact of online platforms on the sales or outputs of existing incumbents.

Figures 8 and 9 present the TFPs for the same U.S. firms. We use Imrohoroglu and Tuzel's (2015) approach to estimate firm-level TFPs. In the U.S. hospitality industry, the TFPs of

traditional incumbents surprisingly exhibit an overall positive trend after Airbnb's entry. Moreover, the TFPs for three online travel platforms (Expedia, Booking, and TripAdvisor) do not show a coherently negative impact following the entry of Airbnb. Compared with traditional incumbents, existing online travel platforms can more easily adjust and incorporate new services introduced by new online platforms. For example, after Airbnb's entry, Booking expanded its services into the sharing service of private rooms and properties. Booking.com is extremely profitable and has grown rapidly with an average gross profit rate of 99.34% in the past three years. In fact, Booking.com has a cost competitive advantage over Airbnb in finding the supply of private rooms and properties in European markets. As for the two U.S. rental car companies, Avis and Hertz, we cannot find a coherent TFP pattern after Uber's entry (Figure 9). Therefore, based on the data available for these firms, we do not find any coherent negative impact of online sharing platforms on the TFPs of existing incumbents.

In sum, by analyzing firm data, we find that after an online platform's entry, there is no consistent negative effect on the firm-level outputs, employment, and TFPs. This empirical finding is not unexpected because it takes time for productivity to change, a change that can immediately affect employment and the output.



Figure 6: Historic Numbers of Employees

Data Sources: 10K Reports



Figure 7: Sales

Data Sources: 10K reports



Figure 8: TFP for U.S. Hotels and Online Travel Platforms

Data Sources: 10K reports and this research



Figure 9: TFP for the U.S. Transportation Companies

Data Sources: 10K reports and this research

## 6. Conclusion

Online platforms are new business innovations based on digital technologies and troves of data, and they have disrupted the industry sectors they entered. As shown in this research, traditional economic measurement approaches, including outputs, employment, and TFP, cannot detect online platforms' disruption process in time successfully, especially when most online sharing platforms were founded only in past decade. In this research, we propose a new way to examine the creative disruption of online platforms from the perspectives of the organizational capital of existing incumbents and their investment behaviors in organizational capital. An online platform's key disruption to traditional firms in their respective sectors is firm-specific knowledge derived from their relatively limited amounts of data. The disruption can be assessed by the change in a firm's organizational capital. Our approach echoes recent studies on the history of technologies and the modern productivity paradox of great innovations, which indicate that organizational capital is a key to answering the question of why productivity is trending downward while we remain in the middle of a digital revolution (Velu, 2019; Brynjolfsson et al., 2018; David, 1990; Devine, 1983).

Our results based on the U.S. transportation and hospitality industries where online platforms have entered show that existing incumbents with a higher degree of digital transformation are more organizational capital-intensive and accumulate a larger stock of organizational capital. We do not see an immediate impact on the firm-level output or employment, or any coherent impacts on the firm-level total factor productivity. Instead, the effect of the entry of an online platform operates through the depreciation of organizational capital. Existing incumbents with a lower degree of digital transformation have a higher deprecation rate of organizational capital. As a result, they experience a negative impact on organizational capital.

Our research findings indicate that when an online platform enters an industry, an existing incumbent with a higher degree of digital transformation can better maintain its organizational capital, which is its accumulated knowledge of how to produce, compete, and grow. One of our examples shows that, even though online travel sharing platforms like Booking and Expedia garnered significant amounts of user data and enjoyed powerful network effects, these existing companies did not deter the entry of Airbnb, which found a niche market and created digital services to utilize idle assets and serve the unmet demand. Airbnb's new business innovation inspired Booking and Expedia to broaden their businesses by introducing similar services. In fact, after the entry of Airbnb, Booking's organizational capital depreciated more slowly, and its business continued rapid growth with an average gross profit margin of over 99% in the past three years. In contrast, traditional, non-online platform incumbents like Marriott and Hyatt suffered a higher depreciation in their organizational capital, which was less data-driven and lower digitalized.

Moreover, this research brings important conceptual and measurement advances in the research of intangible capital (e.g., the value of data), especially when intangible capital is becoming increasingly important in the economy. First, we find that the combined organization capital of dominant online platforms is highly correlated with the rising global data flow, the first piece of empirical evidence that successfully links the explosive global data flow to an economic value. This finding is crucial, especially when all recent studies have recognized the conundrum of linking the exponential growth of global data flow to an economic value. Second, our finding clearly supports both the conceptual breakthrough by Prescott and Vissher (1980) that organizational capital is the accumulated information of the firm, and the approach by Lev and Radhakrishnan (2005) that the investment of organizational capital can be measured by a firm's SG&A expenditure. Third, we further extend the conceptual development in organizational capital

research by applying the classical information pyramid to the concept of organizational capital. We argue and demonstrate that organizational capital measures the essence of firm-specific knowledge derived from data, the value of data. We also find that when the global data volume increases by five folds, the Big Tech's organizational capital stock, i.e., the value of data, doubles, a relationship we have termed Li's law of value of data. Fourth, this is the first study that has estimated the firm-level depreciation rate of organizational capital and demonstrated that it can be a good indicator to measure the impact of new business innovations on the organizational capital of existing, traditional brick-and-mortar firms.

Lastly, this study can help derive many implications about the economy under digital transformation by online platforms today and in upcoming years. In the creative disruption process caused by online platforms, traditional "brick-and-mortar" incumbents can maintain their competitiveness by digitally transforming themselves and providing services complementary to online platforms. As the world is entering the era of 5G, IoT, and AIoT, these advanced digital infrastructure and technologies are stimulating firms to create new business innovations that can lead to further disruptions to traditional industries, not only in the service sector, but also in the manufacturing sector. Moreover, the recent COVID-19 pandemic has accelerated the pace of digital disruption in almost every sector of the daily lives in the U.S. and some other countries, including education, healthcare, and food. Before the pandemic, the U.S. healthcare spending accounted for 17.8% of GDP in 2019, when the telehealth service represented only 0.063% of the amount. At that time, industry experts estimated that the telehealth service would grow about 25% annually (IBISWorld, 2020). This growth rate is expected to become higher now due to the socialdistancing restriction and infection concerns related to COVID-19. Online telehealth platforms, as is Booking.com for the travel industry, provide a marketplace facilitating the exchange between

patients and third parties like hospitals and individual health service providers and doctors. Given the gigantic size of the U.S. healthcare sector, the scale of the disruption can be huge. In the dining and grocery sectors, online platforms like Uber Eats and Instacart provide a marketplace facilitating the exchange between consumers and third parties such as chain restaurants, independent restaurants, and other food service providers. That is, in the increasing digitally and physically inter-connected world, new online platforms' disruptions in traditional industries are going to be significant, fast, and on a massive scale. Our paper provides a new methodology to measure online platforms' disruptions in traditional brick-and-mortar firms in a timely manner.

## References

- Acemoglu, D., Makhdoumi, A., Malekian, A., & Ozdaglar, A. 2019. "Can We Have Too Much Data?" VOX CEPR Portal column article, November 18<sup>th</sup>.
- Ahmad, N. and Schreyer, P. 2016, "Measuring GDP in a Digitalised Economy", *OECD Statistics Working Papers*, 2016/07, OECD Publishing, Paris.
- Arrow, K.J. 1962. The Economic Implications of Learning by Doing, *Review of Economic Studies*, 29(3): 155-73.
- Atkeson, A., & Patrick., J. 2005. Modeling and Measuring Organizational capital, *Journal of Political Economy*, 113, pp: 1026-1053.
- Botsman, R., & Rodgers, R. 2010. What's Mine is Yours. 2011 Edition. USA: HarperBusiness.
- Bresnahan, T.F. 2005. Comments on Lev, B., & Radhakrishnan, S. 2005. The valuation of organization capital. In *Measuring Capital in a New Economy*, Corrado, C., Haltiwanger, J., Sichel, D. (eds). Chicago: National Bureau of Economic Research and University of Chicago Press: Chicago, IL; 99–109.
- Brodersen, K.H., Gallusser, F., Koehler, J., Remy, N., and Scott, S.L. 2015. Inferring Causal impact using Bayesian structural time-series models. *Annals of Applied Statistics*, 9, pp: 247-274.
- Brynjolfsson, E., Collis, A., Diewert, W.E., Eggers, F., & Fox, K.J. 2018. The Digital Economy, GDP and Consumer Welfare: Theory and Evidence, *the Sixth IMF Statistical Forum proceeding papers*, November, Washington, DC.
- Brynjolfsson, E., Rock, D., & Syverson, C. 2018a. Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. In *Economics of Artificial Intelligence*, University of Chicago Press.

- Brynjolfsson, E., Rock, D., & Syverson, C. 2018b. The Productivity J-Curve: How Intangibles Complement General Purpose Technologies, National Bureau of Economic Research Working Paper No. 25148, October.
- Carlin, B., Chowdhry, B., & Garmaise, M. 2011. Investment in Organizational capital, Working Paper, Anderson Graduate School of Management, UCLA.
- Chipman, I. 2018. Susan Athey: Why Business Leaders Shouldn't Have Blind Faith in AI,
   Stanford Graduate School of Business column article, May 23<sup>rd</sup>.
   <a href="https://www.gsb.stanford.edu/insights/susan-athey-why-business-leaders-shouldnt-have-blind-faith-ai">https://www.gsb.stanford.edu/insights/susan-athey-why-business-leaders-shouldnt-have-blind-faith-ai</a>
- Cohen, P., Hahn, R., Hall, J. Sevitt, S., & Metcalfe, R. 2016. Using Big Data to Estimate Consumer Surplus: the Case of Uber, National Bureau of Economic Research Working Paper No. 22627.
- Coyle, D., Diepeveen, S., Wdowin, J., Kay, L., & Tennison , J. 2020. The Value of Data: Policy Implications, February,
   <u>https://www.bennettinstitute.cam.ac.uk/media/uploads/files/Value\_of\_data\_Policy\_Impli</u> cations Report 26 Feb\_ok4noWn.pdf
- Coyle, D., Li, W.C.Y. 2020. The Data Economy: Market Size and Global Trade, the 2021 ASSA/SGE Sessions Proceeding Paper.
- Cusumano, M.A., Yoffie, D.B., & Gawer, A. 2020. The Future of Platforms, MIT Sloan Review, February 11, https://sloanreview.mit.edu/article/the-future-of-platforms/
- David, B.P.A. 1990. The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox, *The American Economic Review*, 80 (2): 355-361.

Demunter, C. 2018. "Towards a Taxonomy of Platforms in the Collaborative Economy:

Outcomes of a Workshop on Measuring the Collaborative Economy", presented at the 2018 OECD Workshop on Online Platforms, Cloud Computing and Related Products, 6 September.

- Devine, W. 1983. From Shafts to Wires: Historical Perspective on Electrification, Journal of Economic History, 43 (2): 355. Retrieved from <u>http://www.j-bradford-</u> delong.net/teaching\_folder/Econ\_210c\_spring\_2002/Readings/Devine.pdf
- Eisfeldt A., & Papanikolaou, D. 2013. Organizational capital and the Cross-Section of Expected Returns, *Journal of Finance*, 4, August, pp: 1365-1406.
- Ericson, R., & Pakes, A. 1995. Markov-perfect Industry Dynamics: A Framework for Empirical Work, *Review of Economic Studies*, 61(1): 53-82.
- Falato, A., Kadyrzhanova, D., & Sim, J. 2013. Rising Intangible Capital, Shrinking Debt Capacity, and the US Corporate Savings Glut, *FEDS Working Paper No. 2013-67*, November 6th.
- Forman, L. 2019. Car-Rental Companies Are Worth Another Ride, *the Wall Street Journal*, September 27<sup>th</sup>.
- Hall, B.H. 1993. The Stock Market's Valuation of R&D Investment during the 1980's, *The American Economic Review*, 83(2), Papers and Proceedings of the Hundred and Fifth Annual Meeting of the American Economic Association, May, pp: 259-264.
- Hall, B.H. 2005. Measuring the Returns to R&D: The Depreciation Problem, Annales

d'Economie et de Statistique Nº 79/80, special issue in memory of Zvi Griliches,

July/December. Also available as *National Bureau of Economic Research Working Paper* No. 13473, October, 2007.

- Hall, R. 2000. Reorganization, *Carnegie-Rochester Conference Series on Public Policy*, 52, pp: 1-22.
- Hathaway, I., & Muro, M. 2017. Ridesharing Hits Hyper-growth,

https://www.brookings.edu/blog/the-avenue/2017/06/01/ridesharing-hits-hyper-growth/

Hayashi, F. 1982. Tobin's Marginal q and Average a: A Neoclassical Reinterpretation, *Econometrica*, 50, pp: 213-224.

IBISWorld, 2020. Telehealth Services in the U.S. Market Size 2005-2025, <u>https://www.ibisworld.com/industry-statistics/market-size/telehealth-services-united-</u> states/

İmrohoroğlu A., & Tüzel, S. 2014. Firm-level Productivity, Risk, and Return, Management Science, 60(8), pp: 2073-2090.

ITIF Panel Discussion on Accelerating Data-Driven Drug Development. 2019. September 18th.

- Jones, I.J., & Tonetti, C. 2019. Nonrivalry and the Economics of Data, NBER working paper.
- Kaplan, J. 2015. Humans Need Not Apply: A Guide to Wealth and Work in the Age of Artificial Intelligence. Yale University Press.
- Lee, K.F. 2018. *AI Superpowers: China, Silicon Valley, and the New World Order*. Houghton Mifflin Harcourt. September 25<sup>th</sup>.
- Lev, B., & Radhakrishnan, S. 2005. The valuation of organization capital. In *Measuring Capital in a New Economy*, Corrado, C., Haltiwanger, J., Sichel, D. (eds). Chicago: National Bureau of Economic Research and University of Chicago Press: Chicago, IL; 73–99.
- Levinsohn, J., & Petrin, A. 2003. Estimating production functions using inputs to control for unobservables, *the Review of Economic Studies*, 70, pp: 317–342.

Li, W.C.Y. 2015. Organization Capital, R&D Assets, and Offshore Outsourcing. 2015

ASSA/SGE Sessions Proceeding Paper.

- Li, W.C.Y. 2016a. Offshore Outsourcing and U.S. Innovation Capacity, Working Paper, U.S. Bureau of Economic Analysis. Presented in *the 2016 National Bureau of Economic Research Summer Institute/CRIW Workshop*, July.
- Li, W.C.Y. 2016b. New Technology Indicator for Technological Progress, Working Paper, U.S. Bureau of Economic Analysis. Presented at *the 34<sup>th</sup> IARIW General Conference* at Dresden, Germany.
- Li, W.C.Y., & Hall, B. H. 2018. Depreciation of Business R&D Capital, *Review of Income and Wealth*, https://doi.org/10.1111/roiw.12380.
- Li, W.C.Y., Nirei, M., & Yamana, K. 2019a. Value of Data: There's No Such Thing as a Free Lunch in the Digital Economy, *VOX CEPR Policy Portal* column article, July 23th.
- Li, W.C.Y., Nirei, M., & Yamana, K. 2019b. Value of Data: There's No Such Thing as a Free Lunch in the Digital Economy, RIETI discussion paper 19-E-022 or BEA working paper, February.
- Li, W.Y. 2019. "Help You Take Flights, Deliver McDonald Meals: Direct Observation of Uber Flying Car Conference," *Business Weekly*, 1649, June, pp: 30-31.
- Lustig, H., Syverson, C., & Nieuwerburgh, S. 2011. Technological Change and the Growing Inequality in Managerial Compensation, *Journal of Financial Economics*, 99, pp: 601-627.
- Marko, K. 2019. Is AI An Agent of Big Tech Hegemony or Multi-disciplinary Research and Innovation? *Diginomica*, October 4<sup>th</sup>.

https://diginomica.com/ai-agent-big-tech-hegemony-or-multi-disciplinary-research-andinnovation

- Matzler, K., Veider, V., & Kathan, W. 2015. Adapting to the Sharing Economy, *MIT Sloan Management Review*, 56.2, pp:71-77.
- McKinsey Global Institute. 2002. Learning to Love Recession, *the McKinsey Quarterly*, 2, pp: 4-5.
- Morton, F.S., Bouvier, P., Ezrachi, A., Juliien, B., Kimmelman, G., Melamed, A.D., & Morgenster,J. 2019. Report on the Study of Digital Platforms, Chicago Stigler Center for the Study of the Economy and the State, May.
- Murgia, M. NHS Trusts Sign First Deals with Google: Contracts with Five Trusts to Share Patient Data Are Part of Transfer of DeepMind Health, *Financial Times*, September 19<sup>th</sup>.
- Nadler, S. S. N., 2014. The Sharing Economy: What Is It and What Is It Going? Working Paper, Massachusetts Institute of Technology.
- Nikkei Asian Review, 2018. Car-sharing Drives up Profit for Japan Market Leader Park24, May 23<sup>rd</sup>. <u>https://asia.nikkei.com/Business/Companies/Car-sharing-drives-up-profit-for-Japan-market-leader-Park24</u>
- Olley, G. S., & Pakes. A. 1996. The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64: 1263–1297.
- Omarova, S., & Steele, G. 2019. There's A Lot We Still Don't Know About Libra, *the New York Times*, November, 4<sup>th</sup>. <u>https://www.nytimes.com/2019/11/04/opinion/facebook-libra-</u> cryptocurrency.html
- Peters, R.H., and Taylor, L. 2017. Intangible Capital and the Investment-q Relation, *Journal of Financial Economics*, 123 (2): 251-72.

- Prescott, E., & Visscher, M. 1980. Organization Capital, *Journal of Political Economy*, 88, pp: 446-461.
- Roberts, A. 2017. Car-Sharing Companies Hit Speed Bumps as Demand Slows, Ride-Hailing Grows, *the Wall Street Journal*, July 14<sup>th</sup>.
- Rosen, S. 1972. Learning by Experience as Joint Production, *Quarterly Journal of Economics*, 86(3): 366-82.
- Scott, S. L., & Varian, H. R. 2014a. Bayesian variable selection for nowcasting economic time series. Economic Analysis of the Digital Economy.
- Scott, S. L., & Varian, H. R. 2014b. Predicting the present with Bayesian structural time series. International Journal of Mathematical Modelling and Numerical Optimisation.
- The Economist. 2019. Big Tech Takes Aim at the Low-profit Retail-banking Industry: Silicon Valley Giants Are After Your Data, Not Your Money," November 21<sup>st</sup>. <u>https://www.economist.com/finance-and-economics/2019/11/21/big-tech-takes-aim-at-the-low-profit-retail-banking-industry</u>
- Tomer, J.F. 1987. Organizational Capital: The Path to Higher Productivity and Wellbeing. New York: Praeger.
- Tomiura, E., Ito, B., & Kang, B. 2020. Cross-border Data Transfers under New Regulations: Findings from A Survey of Japanese Firms, VOX CEPR Policy Portal column article, March 14th.
- Varian, H. R. 2014. Big Data: New Tricks for Econometrics. Journal of Economic Perspectives.
- Velu, C. 2019. Management Information for Business Model Innovation: Unpacking theProductivity Paradox, in Handbook on Digital Innovations, Eds, Nambisan, S; Lyytinen,K and Yoo, Y., Edward Elgar Publishers.

- Wakefield, J. 2019. Google Given Green Light for Toronto Smart City, *BBC News*, October 31<sup>st</sup>, https://www.bbc.com/news/technology-50234146
- Wallsten, S. 2015. The Competitive Effects of the Sharing Economy: How is Uber Changing Taxis? Technology Policy Institute Working Paper.
- Zervas, G., Proserpio, D., & Byers, J. 2014. The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry, Boston University School of Management Research Paper Series, No. 2013-16.

#### **Appendix A: Depreciation Model of Organizational Capital**

We adopt the principles of the Li and Hall (2018) model to estimate the depreciation rate of organizational capital (OC) in this study. Developed for estimating the depreciation rate of business R&D capital, the Li and Hall model assumes that R&D capital depreciates because its contribution to a firm's profit declines over time, and that the main driving forces for the decline are the pace of technological progress or innovations and the degree of industry competition (Hall, 2005). The framework of the Li and Hall model can be applied to other types of intangible capital when quality data for sales and the investment of intangible capital are available. Below is a brief description of the depreciation model of OC used in this study.

A profit-maximizing firm will invest in OC, such that the expected marginal benefit equals the marginal cost. That is, in each period t, a firm will choose an amount of OC investment to maximize the net present value of the expected returns to OC investment:

$$\max_{R_t} E_t[\pi_t] = -R_t + E_t \left[ \sum_{j=0}^{\infty} \frac{q_{t+j+d} I(R_t) (1-\delta)^j}{(1+r)^{j+d}} \right]$$
(1)

where  $R_t$  is the OC investment amount in period t,  $q_t$  is the sales in period t,  $I(R_t)$  is the profit rate due to OC investment,  $\delta$  is the OC depreciation rate, and r is the cost of capital. The parameter dis the gestation lag and is assumed to be an integer, which is no less than 0. OC investment in period t will contribute to the profits in later periods but at a geometrically declining rate. The sales q for periods later than t is assumed to grow at a constant growth rate, g. That is,  $q_{t+j} = q_t (1+g)^j$ 

To resolve the issue that the prices of most OC assets are generally unobservable, the model defines I(R) as a concave function:

$$I(R) = I_{\Omega} \left( 1 - \exp\left[\frac{-R}{\theta}\right] \right)$$
(2)

with I''(R) < 0,  $I'(R) = \frac{I_{\Omega}}{\theta} \exp(\frac{-R}{\theta}) > 0$ ,  $I'(0) = \frac{I_{\Omega}}{\theta}$ , and  $\lim_{R \to \infty} I(R) = I_{\Omega}$ . This functional form has few parameters, but nevertheless shows the desired concavity with respect to *R*. The function *I* includes a parameter  $\theta$ , that defines the investment scale for increases in OC and acts as a deflator to capture the increasing trend of OC investment. The value of  $\theta$  can vary from firm to firm, allowing a different OC investment scale for each firm.

Using the concave function for the profitability of OC, the OC investment model becomes the following:

$$E_{t}[\pi_{t}] = -R_{t} + E_{t} \left[ \sum_{j=0}^{\infty} \frac{q_{t+j+d} I(R_{t}) (1-\delta)^{j}}{(1+r)^{j+d}} \right]$$

$$= -R_{t} + I_{\Omega} \left[ 1 - \exp\left(-\frac{R_{t}}{\theta_{t}}\right) \right] \sum_{j=0}^{\infty} \frac{E_{t}[q_{t+j+d}] (1-\delta)^{j}}{(1+r)^{j+d}}$$
(3)

Note that *d*, *r*, and  $\delta$  are known to the firm at time *t*. Because  $\theta$  varies over time, it is modeled as  $\theta_t \equiv \theta_0 (1+G)^t$ , where *G* is the growth rate of  $\theta_t$ . The value of G is estimated by fitting the data for OC investment to the equation,  $R_t = R_0 (1+G)^t$ . With these expressions of growth rates, Equation (3) becomes:

$$\pi_{t} = -R_{t} + I_{\Omega} \left[ 1 - \exp\left(-\frac{R_{t}}{\theta_{0}(1+G)^{t}}\right) \right] \frac{q_{t}(1+g)^{d}}{\left(1+r\right)^{d-1}\left(r+\delta-g+g\delta\right)}$$
(4)

Note that because of the assumptions of constant growth in sales and OC, there is no longer any role for uncertainty in this equation, and therefore no error term. Assuming profit maximization, the optimal choice of  $R_t$  implies the following first order condition:

$$\frac{\partial \pi_t}{\partial R_t} = \frac{(1+G)^t}{I_\Omega} \theta_0 exp \left[ \frac{R_t}{\theta_0 (1+G)^t} \right] + \frac{q_t (1+g)^d}{(1+r)^{d-1} (r+\delta-g+g\delta)} = 0 \quad (5)$$

For estimation, we add a disturbance to this equation (reflecting the fact that it will not hold identically for all firms in all years), and then estimate  $\theta_0$  and the depreciation rate  $\delta$ .