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Digitization, Product Variety and Concentration: Evidence from the South Korean Movie Market

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ABSTRACT

Digitization, Product Variety and Concentration:

Evidence from the South Korean Movie Market

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Digitization has led to dramatic cost reductions and reshaped both what and how products are sold. This dissertation examines the impact of digitization on the behavior of market intermediaries that bring together producers and consumers. Our empirical context is the transition from 35mm film to digital cinema technologies in the South Korean movie industry during the period of 2006-16. Using detailed data on theaters' daily scheduling decisions, we focus on changes in two aspects of theaters' assortments decisions: product variety and supply concentration. Our results from various empirical analyses suggest the followings. (1) Overall, digitization helps theaters provide consumers with more variety of movies (increased product variety), but it also leads theaters to disproportionately concentrate the supply of screens towards blockbuster movies (increased concentration). (2) The effects are moderated by two supply-side factors: technology compatibility and capacity constraint. In particular, a limited availability of movies in a compatible format can have a negative impact on product variety for early adopters. Also, the effects

vary across different sizes of theaters. (3) The effects are also moderated by demand. A theoretical model and empirical test demonstrate that the effects varies by demand fluctuations across weekend evening (i.e., peak demand) vs. other time slots. The increase in supply concentration is limited to weekend evening time slots. In other time slots, there is a decrease in supply concentration. Product variety increases in all time slots except for weekend evenings. Overall, this dissertation provide evidence that digitization affect market intermediaries' assortment decisions by enhancing flexibility in distribution, but its impact is moderated by both supply- and demand-side factors.

The rest of the dissertation is organized as follows. In Chapter 1, we briefly review prior studies on digitization, focusing on its impact on product variety and concentration. In Chapter 2, we describe the institutional features of our empirical context, the South Korean movie market, and present a series of exploratory data analyses. In Chapter 3, we develop a theoretical model of theaters' scheduling decisions, which predicts the moderating role of demand. In Chapter 4, we assess the impact of digitization on product variety and supply concentration. We also empirically test the model predictions from Chapter 3. Chapter 5 concludes.

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CHAPTER 1

Digitization, Product Variety and Concentration: A Literature Review

1.1. Introduction

Digitization indicates the digital representation of information. The word "digit" comes from the Latin word for finger, *digitus*, which is associated with discrete counting. In the 1940s, George Robert Stibitz, a mathematician at (then) Bell Telephone Laboratories, used the word "digital" in reference to the electric purses emitted by a machine that fires anti-aircraft guns (Ceruzzi, 2012). Since then the era of storing and transmitting data in digital medium has begun. Among others, magnetic memories, compact discs, hard disk drives, flash memories and solid state drives are examples that have been successfully commercialized. From the perspective of economics, these technologies greatly reduced the marginal costs of storing and replicating information. The costs associated with transporting information were also reduced since digital mediums tend to be portable.

However, it was not until the rise of the Internet in the 1960s when the marginal cost of information transmission went close to zero. The Internet allows computers to communicate with other computers. Built largely on the technology developments funded by US military in the 1960s and 1970s (such as TCP/IP) (Greenstein, 2015), the privatization of the Internet in the 1990s led to its commercialization. For instance, Goldfarb (2006) highlights the role of universities in the early diffusion of the internet. The internet had become soon available not only for wired devices but also for wireless devices. The IBM Simon Personal Communicator, one of the first smartphones, was released for purchase by the public in 1994. The Nokia 9000 Communicator was released in 1996. Both devices provided basic communication features such as fax, short messages and email. The mobile Internet was widely adopted when (then) Apple Computer Inc. released its first iPhone in 2007. According to the World Bank, the percentage of world population using the internet has steadily increased from 0.048% in 1990 to 49.723% in 2017.[1]

Digitization has led to a dramatic reduction in various economic costs and reshaped what and how products are produced, sold and consumed (Greenstein et al., 2013; Goldfarb and Tucker, 2019). For instance, Goldfarb and Tucker (2019) emphasize the role of digitization in reducing five types of economic costs: search costs, replication costs, transportation costs, tracking costs and verification costs. The impact of digital technology on market outcomes are also empirically documented in various domains, which includes the market for books (Waldfogel and Reimers, 2015), healthcare (Athey and Stern, 2002; Miller and Tucker, 2011), movies (Waldfogel, 2016), music (Aguiar and Waldfogel, 2018; Mortimer et al., 2012), and newspapers (Gentzkow, 2007; George and Waldfogel, 2006), among others.

A complementary way to understand digitization is to evaluate its impact on different types of market players: e.g., producers, intermediaries and consumers. On the producer side, for example, digital technologies reduced the production costs of information goods (e.g., books, movies, music and news), which has induced firm entry and increased product variety (e.g., Waldfogel and Reimers, 2015; Waldfogel, 2016; Aguiar and Waldfogel, 2018).

[1]Source: `https://data.worldbank.org/indicator/it.net.user.zs`

On the consumer side, the impact of reduced search costs has been studied from the perspective of prices (Brynjolfsson and Smith, 2000; Brown and Goolsbee, 2002; Zettelmeyer et al., 2006) and product variety (Anderson, 2006; Brynjolfsson et al., 2011), to name a few.

In this chapter, we briefly review prior studies on digitization, focusing on its impact on product variety and concentration. For each topic, we first discuss its importance from the perspective of economics and marketing. Then, we summarize related studies based on their focus on producers, market intermediaries and consumers. We also discuss studies on digitization in the movie industry, which we use as our empirical context in the rest of this dissertation.

1.2. Digitization and Product Variety

A large body of economics and marketing literature has discussed the value of product variety and consumers' variety-seeking behavior. Classical theories argue that increased product variety enables consumers to find products that better match their preferences (Baumol and Ide, 1956; Lancaster, 1990) and fulfill their need for variety-seeking (McAlister, 1982; Simonson, 1990).

To better understand the impact of digitization on product variety, it would be helpful to distinguish the variety of products in different stages of a market: i.e., product variety in production, product variety in distribution and product variety at consumption. This is because there can be various mechanisms through which digitization affects different market players differently. For instance, lower search costs allow consumers to discover niche products (Yang, 2013), which increases product variety in consumption. At the same time, lower replication costs can allow distributors to disproportionately increase the shelf space allotted to popular products (Brynjolfsson et al., 2011), which decreases product variety in distribution. Both search costs and replication costs are reduced with digitization. Below, we begin our discussion with product variety in consumption, which has gained the most attention in literature, followed by product variety in production and distribution.

Product variety in consumption

Digitization has reduced consumer search costs, especially in the online context, which typically allows consumers to better discover the products that better match their preferences (Yang, 2013). The impact of digitization on product variety at the consumption stage is well publicized with the term “the long tail” by Anderson (2006).

There are various digital channels through which consumer search costs can be reduced. Online search engines are likely the most relevant example one can come up with, but there are more. For instance, popularity information (in the form of sales rankings and/or sales quantities) (Tucker and Zhang, 2011) is more conveniently communicated with consumers on digital platforms. Modern recommendation engines can be another example—the collection and digital processing of large-scale consumer data have enabled recommendation algorithms (e.g., collaborative filtering) to more efficiently intervene in consumers’ product discovery and choices (Fleder and Hosanagar, 2009). Lastly, online reviews provide consumers with a type of product information that was not easily revealed previously—the experience/opinion of other consumers (Chevalier and Mayzlin, 2006).

Holding others fixed, lower search costs can result in higher product variety. Due to low search costs, more niche products are likely to enter consumers' consideration sets, some of which will eventually convert to sales, which results in an increased product variety in consumption.[2] A few empirical studies provide evidence on the relationship between information and product variety. Tucker and Zhang (2011) provide evidence that popularity information benefits niche products more than popular products. Yang et al. (2012) document that the valence of online reviews better predict the sales of niche products than that of popular products. Zhang (2018) document a relaxation of sharing restrictions increases the sales of lower-selling music albums by 40%.

Product variety in production

Digitization has reduced the production costs of goods and service, especially for the information goods such as movies, books, and music. Lower production costs can increase product variety in production by justifying the entry cost of marginal products and/or marginal firms that otherwise had not entered. Waldfogel (2016) documents a 250% increase in the variety of U.S. movies produced from 2000 to 2012. A similar increase in product variety is also documented for self-published books and music. Waldfogel and Reimers (2015) document a substantial increase in the number of self-published books since 2006 and discuss the role of e-book market. For the music market, Aguiar and Waldfogel (2018) document the number of new music products released tripled between 2000 and 2008.

[2] On the other hand, lower search costs can also generate more superstar effect (Rosen, 1981). We come back to this point in Section 1.3.

Unlike the case of product variety in consumption (Brynjolfsson and Hitt, 2003), the welfare implications of increased product variety in production can be marginal. The argument is as follows. The increase in product variety in production may be largely driven by the entry of marginal products. By definition, the quality of marginal products could not justify the costs required to enter the market, so the welfare-improving effects by these products are, at most, marginal. In regard to this matter, Aguiar and Waldfogel (2018) point to the role of *ex ante* uncertainty regarding product sales. Since commercial success of new products are, at least partially, unpredictable, lower production costs facilitate more entry of not only *ex post* marginal products but also *ex post* successful products. Therefore, the welfare effects of the digitization-led product variety in production can be greater in a world with uncertainty than in a world with perfect foresight. Aguiar and Waldfogel (2018) refer to the welfare gain from increased product variety due to lower production cost as the "long tail in production," and distinguish from the usual long tail phenomenon in consumption.

Product variety in distribution

Digitization has also significantly reduced distribution costs for market intermediaries (e.g., distributors and retailers). For instance, the marginal cost of disseminating information goods is virtually zero. Even non-information goods have benefited, as digital technology has improved supply chain efficiencies (Rai et al., 2006).

Previous studies seem to have paid relatively less attention to market intermediaries in explaining the impact of digitization on product variety. The lack of attention may arise from the observation that product variety is virtually unlimited in the e-commerce context.

The rise of online retailers in the 1990s (e.g., Amazon) immediately removed the shelf space constraints that the traditional brick-and-mortar stores have dealt with. So, when it comes to online distribution, the question of product variety may seem trivial. However, we argue that the issue of product variety in the distribution stage still remains relevant. First, the reductions in transportation and tracking costs (Goldfarb and Tucker, 2019) and the improved supply chain efficiencies (Rai et al., 2006) point to potential changes in assortment decisions of brick-and-mortar stores. Second, even if product variety is unlimited online, its impact on local markets can be heterogeneous, depending on market conditions. In the regard, Quan and Williams (2018) serve as an example. Using the data of online shoe transactions between 2012 and 2013 and the product availability for a few large brick-and-mortar retailers, the authors demonstrate that accounting for heterogeneity in consumer tastes across markets reduces the welfare effects of increased online variety by 30%.

1.3. Digitization and Concentration

By reducing various economic costs, digital technologies have driven many markets to be more competitive (e.g., Brown and Goolsbee, 2002; Jensen, 2007) and allowed consumers to better find niche products as we discussed in the previous section. Yet, there is a growing concern among policymakers about concentration and competition in today's marketplaces. For instance, top 100 firms generated 46% of US GDP in 2013, which increased sharply from 33% in 1994 (The Economist, 2016a). Reporters point out a handful of companies has taken over the Silicon Valley, while "the region's (admittedly numerous) startups compete to provide the big league with services or, if they are lucky, with their next acquisition" (The Economist, 2016b). Not surprisingly, the issue of competition in the digital economy is repetitively raised at international forums, such as OECD (2012) and G20 (Marin, 2017). In 2018, the Stigler Center at the University of Chicago dedicated its annual Antitrust and Competition conference to the topic of "Digital Platforms and Concentration."

Assessing the effects of digitization on concentration needs for a careful investigation on specificities of focal markets. To illustrate, consider the digitization of the music and the movie industries, as an example. The music industry has gone through the introduction of MP3s and streaming services. Ordanini and Nunes (2016), for instance, report that digitization might have decreased the prevalence of blockbusters. In the abstract, the authors write that "In general, we observe a growing winner-take-all effect for songs until the advent of MP3s in 1998, when this trend abated... The trend reverses itself as the number of songs making the chart increases steadily after the launch of legitimate online music sellers such as iTunes." The movie industry has also gone through its digitization process from 35mm to digital technologies. Hence, if one extrapolates from the music industry to the movie industry, perhaps based on the fact that production and search costs decreased in both industries, one might expect that blockbusters would become less prevalent. However, as shown in Chapter 4 we find that on average blockbusters increased in the movie industry. This raises the question of "why?"

There are several factors that may explain the different effects of digitization between markets for music and movies, such as the relative size of investments (related to entry barrier), the number of suppliers, and market structure. One additional explanation for the difference is the role of market intermediaries in these markets. In the music industry, digitization helped to weaken the incumbents (e.g., retailers such as The Wall, Sam Goody, etc., went bankrupt in the U.S.) and made it easier for consumers to buy music in an unbundled (non-album) form. In contrast, in the movie industry, intermediaries such as theaters have maintained their relevance due to studios' preferences for offering new releases in theaters before making the movie more broadly available via streaming services and DVDs. Consequently, the movie industry's transition to digital has not necessarily been tied to the fall of traditional brick-and-mortar retailers (i.e., theaters). This contrasts with many other markets (e.g., music, software). Instead, the number of cinema screens worldwide has increased continuously, even in the US market, which has been almost fully digitized.[3]

As illustrated, the impact of digitization on concentration is likely context-dependent. Below, we review prior studies on the relationship between digitization and sales concentration, which we view as an important driver of market concentration. We organize the rest of this section into a review of theoretical works and a review of empirical works.

Theory

Theoretical predictions about the impact of digitization on sales concentration are ambiguous. On one hand, given the long tail effects (Anderson, 2006), digitization is predicted to *decrease* concentration as consumers can switch to more niche products. Cachon et al. (2008) show that low consumer search costs potentially lead to broader assortment provided by firms, which can contribute to increased sales of niche products. Yang (2013) also show that low search costs and high search targetability can lower sales concentration.

[3]Source: `www.natoonline.org/data/us-movie-screens/`

One the other hand, digitization is predicted to *increase* sales concentration as low search costs can generate superstar effects (Rosen, 1981). Once consumers learn about the full distribution of vertically differentiated products' qualities, consumers with homogeneous preferences will all choose the best alternative. Fleder and Hosanagar (2009) show that increasing use of online recommendation engines can serve as a mechanism through which digitization drives more consumers to demand popular products.

Bar-Isaac et al. (2012) show that a reduction in search cost may lead to both superstar and long-tail effects if products are vertically and horizontally differentiated. The author argue that, under an limited level of vertical heterogeneity in consumer preferences, there is an equilibrium where highest-quality products are produced and sold to everyone (the superstar effects) and niche products are also produced and sold (the long tail effects). Thus, it implies that the relative level of vertical heterogeneity, compared to that of horizontal heterogeneity determines the effect sizes. Hervas-Drane (2015) also demonstrate that changes in the efficiency of word of mouth can generate both superstar and long tail effects.

Empirics

Previous empirical works report mixed results on the impact of digitization on concentration (e.g., Elberse and Oberholzer-Gee, 2006). One one hand, studies show that digitization can decrease concentration. Tucker and Zhang (2011) show that providing consumers with product popularity information benefits niche products more than popular products. Brynjolfsson et al. (2011) examine a multichannel retailer and provide empirical evidence that product sales are significantly less concentration in the Internet channel. Similarly, Zentner et al. (2013) investigate consumer panel data from a video rental chain and find that consumers are more likely to rent niche titles when they move to online channels. Kumar et al. (2014) report that pay-cable broadcast shifts consumers' DVD purchases toward niche titles, which suggest an information spillover from the broadcast. Collectively, these studies suggest that digitization leads to less sales concentration, primarily by lowering search costs.

On the other hand, studies also show that digitization can increase concentration. For instance, the results of Cai et al. (2009) and Salganik et al. (2006) suggest that, because popularity information serves as a signal of product quality and popularity itself is self-reinforcing, so digitization increases sales concentration. Fleder and Hosanagar (2009) find that the increasing use of online recommendation engines is another mechanism through which digitization drives more consumers to demand popular products. Recently, Tan et al. (2017) find that increased product variety increases concentration in sales of DVDs, as the substitution effect from added variety is greater for niche products than for popular products.

1.4. Digitization and the Movie Industry

The movie industry long been investigated from various perspectives (e.g., Eliashberg et al. (2006) provides a comprehensive review). Among the numerous papers on the movie market, Caoui (2018) is perhaps the most relevant to this dissertation. Using a dataset from French film industry, the author examines the role of network effects in the adoption of digital projectors. Rao and Hartmann (2015) also pay attention to the impact of digital technology in the movie industry. Using a rich dataset from India, the authors investigate a demand-side effect of digital technology by evaluating consumers' relative valuations of screen size and movie variety. They find that more urban and higher-education regions prefer larger screens, whereas other regions prefer greater movie variety. Although its main focus is not on digital technology per se, Wozniak (2013) investigates the interaction between an efficiency gain from the removal of some vertical restraints and digital projection.

CHAPTER 2

Digitization and the Movie Picture Industry (joint with Eric Anderson and Brett Gordon)

2.1. Introduction

Over the course of a decade, digital cameras and projectors almost completely replaced the use of 35mm reels in shooting and distributing a film, which led to a dramatic cost reduction in disseminating and showing movies. For instance, US movie studios spent a total of $716 million for printing and duplicating 192 movie titles in 2002 (Husak, 2004). A physical movie that opened on 3,000 screens (i.e., wide release) incurred roughly $6 million in distribution costs. Expanding beyond wide release (there were roughly 35,000 screens in the 2002 U.S. movie market) would further inflate distribution costs, even without taking into account international releases. With digital films, disseminating movies costs less than 10% of physical distribution (Silver and Alpert, 2003). Nearly all movies in all markets have shifted from physical to digital distribution as of 2018.

Nonetheless, the market maintains many of its traditional features. Movie theaters still have capacity constraints due to the fixed number of screens and seats and compete locally with one another. Later in Chapter 4, this features enable us to better isolate the effect of new technology on firm behavior from other confounding factors, such as changes in theater characteristics, capacity constraints, and/or market structure.

In this chapter, we document the adoption process of digital technology and its consequences in the context of the South Korean movie market. We use detailed data of South Korean theaters' daily scheduling decisions during 2006-16. A key benefit of our dataset is that it covers an almost complete history of digital cinema diffusion at all major theaters in the country, from the beginning to the last stage of screen conversion from 35mm film to digital. The data contain the daily screening schedule of all major theater chains in the country at the theater-screen-show level (e.g., theater chain X at theater Y; screen A; December 24, 2016 - Saturday; 5pm; *La La Land* - Digital), which corresponds to over 550 theaters and 3,400 screens.

The rest of this chapter is structured as follows. We begin with a brief illustration of the transition from the 35mm film to digital cinema technologies in Section 2.2, followed by detailed explanations of our empirical context and the data in Section 2.3. We also describe how we identify the transition timing of screens and how the adoption of digital technologies proceeded in the market. Then, we present a series of empirical associations between digitization and various decisions made by movie distributors and theaters. In particular, we touch upon topics such as distribution breadth and time-to-market in Section 2.4, product variety, supply concentration, inventory management and differentiation in Section 2.5. Lastly, we discuss how such changes have likely affected movie consumption through the lens of sales concentration in Section 2.6. Section 2.7 concludes.

2.2. From 35mm to Digital Cinema

Digital cinema refers to digital distribution and exhibition of movies. Digital technologies have enabled movies to be stored in bits, shipped to theaters either on hard disk drives or through digital transmission, and projected using digital projectors. On June 18, 1999, two screens in Los Angeles and another two in New York screened the Lucas film, *Star Wars: Episode I - The Phantom of Menace*, using Texas Instrument's Digital Light Processing projector technology. It was the first time a fully digital movie was shown to the public (Revkin, 1999; Los Angeles Times, 1999). In February 2000, digital cinema went international. Theaters in London, Manchester, Brussels, Paris, and Tokyo were equipped with digital projectors for *Toy Story 2*.[1] By 2015, almost 90% of screens worldwide were converted to digital (Vivarelli, 2015).

The widespread adoption of digital cinema brought a huge cost benefit to the industry by gradually eliminating physical prints of 35-millimeter reel film and simplifying the delivery of movies. Given that the number of theaters showing a typical wide-release movie ranges from 1,000 to 4,000 and per-print cost varies from $1,500 to $2,500, distribution costs for movies in physical prints ranged from $1.5 million to $10 million. This cost range is a conservative estimate because it does not take into account international wide-release and that some theaters order multiple copies of a single movie to show it on more than one screen simultaneously.

Both distributors and theaters are likely to be benefited from digital distribution of movies. Supplying movies is a sequential process operated by three distinct players: producers, distributors, and exhibitors. Once a studio completes production of a movie, distributors and theaters decide how many copies to ship to each theater. There have been two popular contract schemes in the industry between movie distributors and exhibitors: flat fee-based and sharing-based. The former requires exhibitors to pay a fixed amount

[1]Source: `www.tech-notes.tv/Dig-Cine/Digitalcinema.html` (last access on 11 Jan. 2019).

to acquire the right to show a movie. It was widely used until the industry moves to the sharing-based contracts in the 1950s (Weinstein, 1998, p. 84) or earlier (Hanssen, 2002, p. 380). Sharing-based contracts indicate that distributors and theaters split either the total revenue or the net profit (revenue minus distribution costs). A sharing-based contract can also have a flat fee (Filson et al., 2005, p. 364). Sharing-based contracts can be based on either a flat ratio (e.g., 50:50) or sliding-scale under which the share of distributors is larger (about 70%) than that of theaters in the first week of release, then the share decreases over time. The latter is known to be effective to incentivize theaters to keep movies for longer runs. While we do not have data on contracts, we expect that the specific terms of contracts may vary across different combinations of studio-distributor-theater-movie. In the case, the cost benefit is shared by both distributors and exhibitors.

Digital distribution also eliminated some constraints of physical films. For instance, switching between movies within screen-day was costly as physical labor by projectionists is involved for the 35mm prints. Setting up reels in ways that they would alternate could take two to four hours.[2] With digitization, there is virtually no difference between projecting a single digital file to one screen vs. multiple screens. That is, digitization enhances the flexibility of shelf space (i.e., screens) management by exhibitors.

Despite the cost benefit and improved flexibility in scheduling, the economics of switching to digital cinema were challenging for theaters. The cost of converting a traditional screen to digital ranged between $75,000 and $150,000, with an expected lifetime of 10 years. It is just one third of the expected lifetime of film projectors, while digital projectors costs more for maintenance. To deal with theater owners who did not want to

[2]Source: `https://movies.stackexchange.com/questions/21754/what-format-do-movie-theaters-now-use` (last access on 6 Nov. 2019).

bear the cost, Hollywood studios came up with a new finance model called a Virtual Print Fee (VPF) agreement (Sanders, 2008). Simply put, once a studio and theater enter into a VPF agreement, the studio pays about $800-$1,000 to the theater for each digital distribution of the studio's movies. In this way, studios subsidized theaters, sharing the burden of digital screen conversion.

The first VPF agreements between four major Hollywood studios (Sony Pictures, Disney, Twentieth Century Fox, and Universal) and a technology company, Access Integrated Technology, occurred in 2005. The partnership's goal was to roll out digital cinema technology to 4,000 screens across the US/Canada. The technology company was renamed Cinedigm in April 2018.[3] Five years later, DCIP (Digital Cinema Implementation Partners), which consists of the three largest US theater chains (Regal Entertainment Group, AMC Entertainment and Cinemark) and the major Hollywood studios, announced the completion of $660 million in financing for a digital cinema upgrade for the 14,000 screens the chains manage.[4] In October 2011, Twentieth Century Fox announced the cessation of 35-millimeter prints and institution of VPF payment by 2013 (Belton, 2012).

2.3. Empirical Context and Data

2.3.1. The South Korean Movie Market

We use data from the South Korean movie market from 2006 to 2016. Movies are one of the most popular entertainment products in South Korea — the country boasts the world's highest per capita annual movie attendance (4.22 movies per person in 2015),

[3]Source: `http://investor.cinedigm.com/news-releases/news-release-details/new-sony-pictures-agreement-christieaix-supports-digital-cinema` (last access on 11 Jan. 2019).
[4]Source: `www.dcip.com/press` (last access on 11 Jan. 2019).

followed by Iceland (4.0), Singapore (3.9), and the United States (3.6) (KOFIC, 2016). For U.S. studios, South Korea is the fifth largest international box office market, with an annual size of 1.5 billion US dollars in 2015, and is one of the few countries globally where the box office revenue from domestic movies is comparable to that from imported movies. For instance, the share of domestic movie revenue ranges between 42% and 64% during our observation period.

Two unique features of the South Korean movie market make it attractive for this study. First, theatrical exhibition is the dominant channel for movies in the country during our period of observation. In 2015, South Korean movie theaters earned about 1.5 billion USD, while the revenue from all other channels such as DVDs and online streaming, was only about about 367 million USD. Second, while it can vary across contracts, the revenue-sharing ratio between theaters and distributors is known to be fixed at around 50:50, and the ratio tends not to change over the lifecycle of a movie's run.[5] This simplifies greatly the objective function of distributors and theaters, as profit margins are the same across movies: theaters simply need to maximize the expected total attendance for a given week.

As shown in Table 2.1, the market has grown with digital cinema in both supply and demand. From 2006 to 2016, there was a greater supply of theaters, screens, and both domestic and foreign movies. More than 100 theaters entered the market during the period, which added about 700 screens nationwide (137% growth). The increase in movie

[5]The ratio varies over time across chains for imported movies. Specifically, it was known that distributors of foreign movies had received 60% of revenue from Seoul-based theaters until 2013, when theaters announced to change the ratio to 50:50 (CJ CGV) or 55:45 (Lotte Cinema). One can expect that the difference in ratio reduces the effect size of digitization on supply concentration if the top movies are more likely to be foreign.

supply is even more noticeable. The number of newly released domestic movies nearly tripled from 108 in 2006 to 302 in 2016. For foreign movies, while a total of 237 movies were imported and released in the market in 2006, the number rose to 1,218 in 2016. However, not all new movies were widely released. While the number of wide releases increased (from 80 to 95 for domestic movies and from 98 to 237 for foreign movies), their share decreased. For instance, 80 domestic movies out of 108 (74%) were widely released in 2006, but the share dropped to 31% by 2016. The same is true for foreign movies: 41% of imported movies were widely released in 2006, but the share declined to around 20% in 2016. Demand for movies has also been growing, as reflected in an increase in total revenue and per-capita admissions.

2.3.2. Datasets

We collected two datasets on showtimes and box-office sales from an online database system operated by the Korean Film Council (`www.kobis.or.kr`) using a web scrapper from January to March 2017. We obtained two datasets, *showtime* and *box-office*, during the period from 2006 to 2016. The period covers the beginning-, interim-, and post-digital distribution phases of the market.

Showtime dataset. The showtime dataset contains the daily screening schedule of all major theater chains at the theater-screen-show level. We observe the dates of the first and last showing of a movie at each theater, the number of screens (or shows) allocated to the movie, and the screening format (film or digital) of every showing.

Figure 2.1 reports trends in the showtime dataset. Definition of each variable is as follows: VARIETY is the number of different movies screened; CONCENTRATION is

Table 2.1: Overview of the South Korean movie market

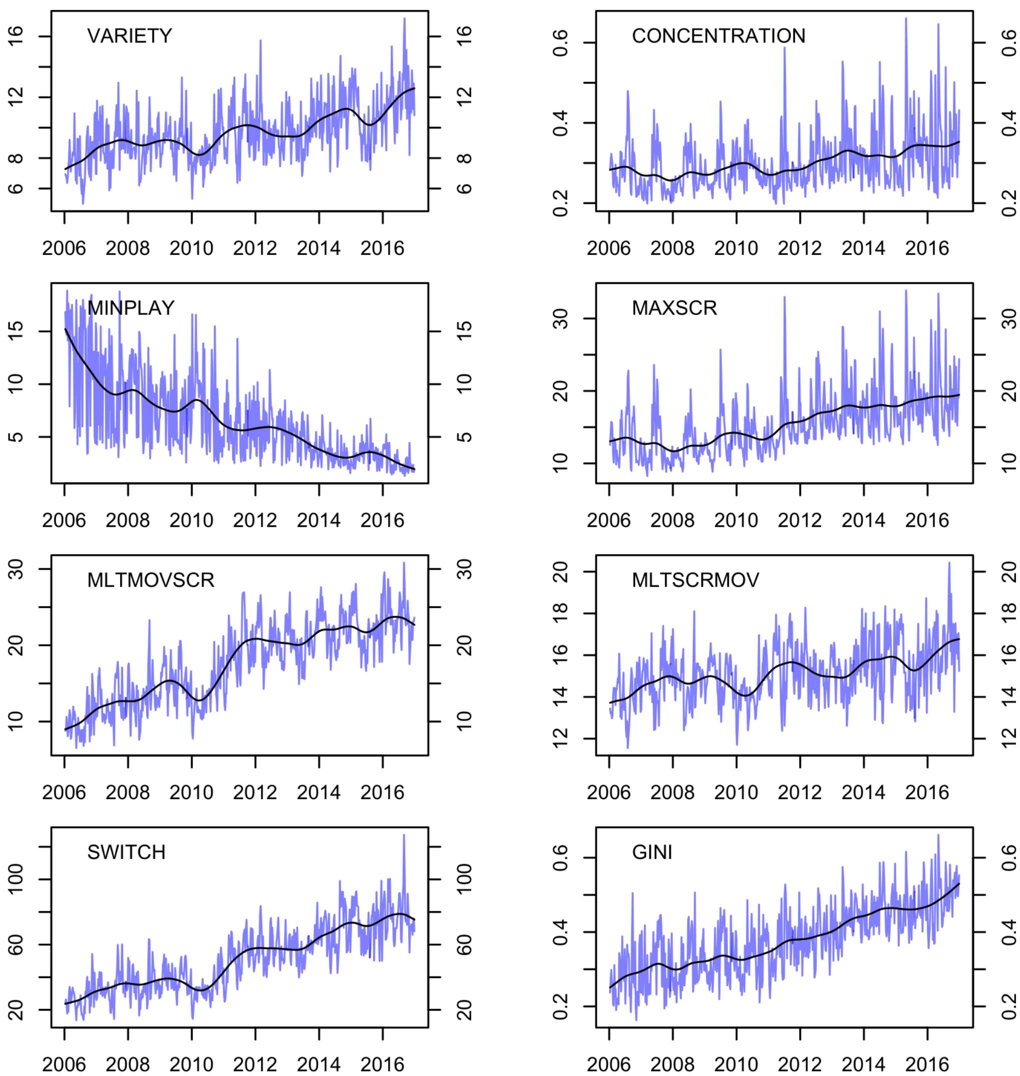
Year	Theaters[a]	Screens[b]	Releases[c]		Wide Releases[f]		Total Revenue[g]		Admissions
			D[d]	F[e]	D[d]	F[e]	Box-office	Other[h]	(per capita)
2006	321	1,880	108	237	80	98	1,034	372	3.13
2007	314	1,975	112	281	72	112	1,081	300	3.22
2008	309	2,004	108	272	62	132	1,029	232	3.04
2009	305	2,055	118	243	58	135	1,108	90	3.15
2010	301	2,003	140	286	62	132	1,150	109	2.92
2011	292	1,974	150	289	63	135	1,169	161	3.15
2012	314	2,081	175	456	72	131	1,347	200	3.83
2013	333	2,184	183	722	70	162	1,418	245	4.17
2014	356	2,281	217	878	83	208	1,501	268	4.19
2015	388	2,424	232	944	84	212	1,538	300	4.22
2016	417	2,575	302	1,218	95	237	1,547	367	4.20

Note: [a]number of theaters; [b]number of total screens; [c]number of released movie titles officially reported by Korean Film Council; [d]domestic movies; [e]foreign movies; [f]number released movies with at least 50 opening screens; [g]revenues are in million USD using exchange rate of .000089; [h]all other revenue sources other than box-office and export (e.g., DVD, TV, streaming, etc.). The column "Wide Releases" is based on our own data exploration. All other data are from Korean Film Council's annual white papers. The increasing discrepancy between the numbers of all releases and wide releases (especially for foreign movies) suggests that the market has accommodated more variety of movie release types.

the maximum screen share of a movie; MINPLAY is the minimum number of slots for a movie; MAXSCR is the maximum number of screens for a movie; MLTMOVSCR is the number of screens that showed multiple movies; MLTSCRMOV is the number of movies on multiple screens; and GINI is Gini coefficient of play counts. The black solid lines are smooth splines.

As shown in the plots, theaters' reaction to digital distribution stands out from the trends. In the main text, we discussed in depth about VARIETY and CONCENTRATION. Figure suggests that digitization-driven cost reduction also leads theaters to more

Figure 2.1: Trends in the showtime dataset



flexibly manage their screens, which decreases the minimum number of shows for a movie (MINPLAY) to one and increasing the maximum number of screens a single title has (MAXSCR). Moreover, there are more screen that show multiple movies (MLTMOVSCR) and more movies that are allocated to multiple screens (MLTSCRMOV) within a week. This has been possible because there is increasing number of switch between titles at a screen (SWITCH). It is immediate that the Gini index has increased given the changes in other variables.

Box-office dataset. The box-office data contain *national* attendance figures for all movies released during the observation period.[6] This dataset includes basic attributes of movies, such as producer, distributor, director, country of origin, film ratings, and genre. We restrict our attention to 2,527 movies that were wide-released with at least 50 opening screens across the country between 2006 and 2016. Table 2.2 reports the summary statistics of the box-office dataset. The difference between mean and median values of all variables suggests the skewness of the distributions. While top movies enjoyed over 17 million total attendance, over 1,800 screens, and 6 months of in-release days, median movies just had about 0.2 million viewers, 200 screens, and a month on screen. Comparing the statistics of movies released in 2006 and in 2015 reveals some interesting patterns, which can be summarized as increased sales concentration. We will discuss the patterns in depth in Section 2.6.

2.3.3. The Adoption Process

Our main focus is how theaters respond to digitization-driven technological change with regard to their scheduling decisions. For this, we need to know when each screen was converted and understand how theaters decided to convert. Using the showtime dataset, we infer the timing of a screen's transition to new technology from the date on which the screen first showed a digital-format movie. For multiplex theaters (i.e., theaters with multiple screens), each screen has a unique transition date. Thus, we have data on the

[6] Despite significant effort, we have been unable to obtain more detailed demand data, such as ticket sales at the theater-movie-time level.

Table 2.2: Summary statistics of box-office data

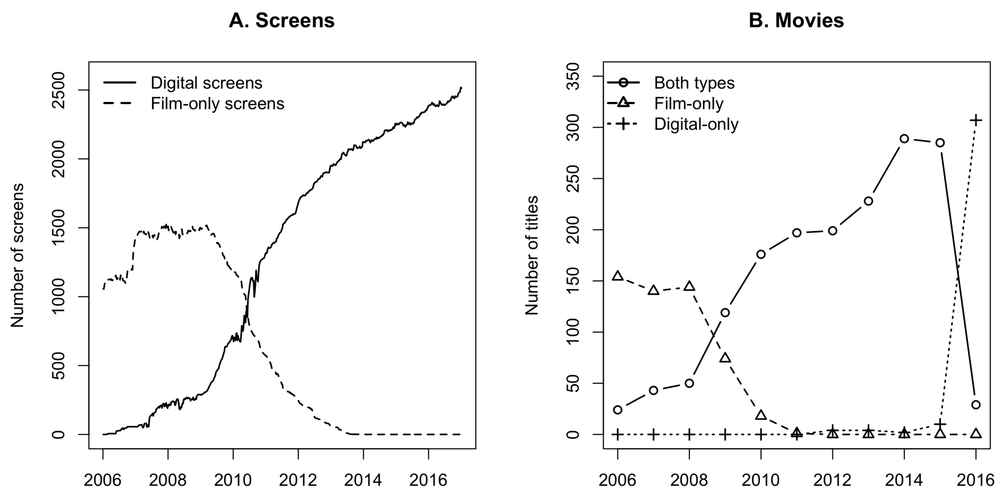
	Mean	SD	Min	Median	Max
Movies 2006-2015					
Total attendance	777,023	1,569,806	1,544	205,479	17,588,621
Opening screens	287	221	50	226	1,843
In-release days	35	20	7	30	181
Movies released in 2006					
Total attendance	746,331	1,263,349	10,166	343,425	10,777,895
Opening screens	186	102	54	164	618
In-release days	32	15	14	28	98
Movies released in 2015					
Total attendance	700,452	1,726,411	1,875	82,646	13,386,168
Opening screens	348	292	50	272	1,843
In-release days	33	19	7	28	102

date on which the transition from 35mm film to digital was completed for each Korean market screen and theater. In below, we describe the adoption process of digital cinema technologies.

Digital cinema technologies quickly dominated the market, led by the diffusion of digital screens and increased supply of digital movies. Figure 2.2A illustrates the diffusion process of digital screens in the market. As shown, the number of digital screens increased steadily. At the same time, the number of film-only screens quickly decreased from about 1,500 in mid-2009 to zero in 2013. The term "film-only screens" indicates that some digital screens have both digital and traditional film projectors, and thus can show both movie types.

Next, Figure 2.2B shows the supply of movies by format. Changes in the number of movies released in both film and digital suggest that studios and distributors did not choose one format over the other, but provided theaters with both types of movies until

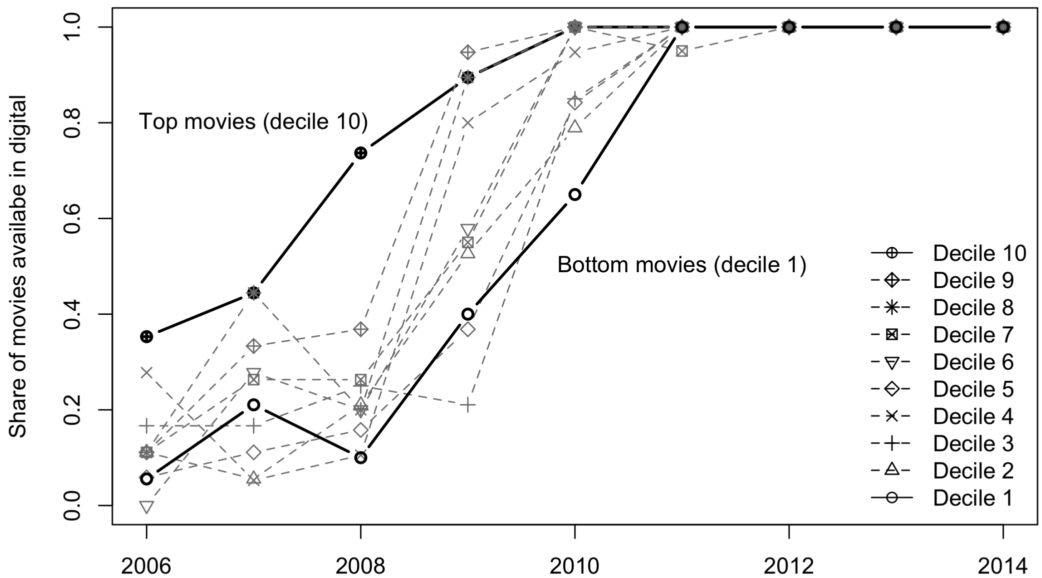
Figure 2.2: Supply of digital screens and movies over time



2015. In 2016, fewer than 50 movies were available in film format. Popular movies went to digital first. About half of the most popular movies (the top 10% of movies in terms of attendance) were available in digital in 2006, whereas none of the bottom-10% movies were in digital (see Figure 2.3). This implies that the decision to go digital is closely related to the cost-benefit ratio. Theaters tend to demand a greater number of copies of high-popularity movies than low-popularity movies in order to disseminate them to a greater number of screens.

The diffusion of digital screens was driven not only by the opening of new theaters, but also by the conversion of traditional film screens. In 2006, the two largest theater chains in the country, CJ CGV and LOTTE Cinema established D-Cinema Korea Co., Ltd., and began to convert their screens by adopting the US market's VPF financing model. The third largest chain, MEGABOX, independently started to convert its screens to digital. The market share of the three chains exceeded 60% in 2006 and 90% in 2016.

Figure 2.3: Movie format choice by popularity



Note: Figure reports the share of movies of different formats by their popularity over time. We decile-group movies based on total attendance, where decile 10 includes the most popular movies in a given year, and decile 1 includes the least popular movies. In 2006, for instance, about 35% of top movies were available in digital, while less than 10% of the least popular movies were available in digital. Between 2006 and 2011, during which most of the movies went to digital, top movies tend to account for the highest share of digital movies than other groups.

Figure 2.4 illustrates the conversion process of the three chains at theaters that opened before 2006. Each row represents one theater of a corresponding chain; each dot indicates the conversion date of a film screen to digital. The upper panel reports chain-owned theaters, and the lower panel reports franchised theaters. Figure 2.4 reveals two aspects of the conversion process. First, sometimes screens converted simultaneously across theaters, but many screens were also converted sequentially within a theater. Second, chains converted their own theaters (upper panel) earlier than franchised theaters (lower panel). As shown in the figure, most CGV-owned screens were converted by 2010, whereas those at CGV-franchise theaters were converted in 2010 or later. It appears that the ownership structure of a theater plays a role in the timing of screen conversion.

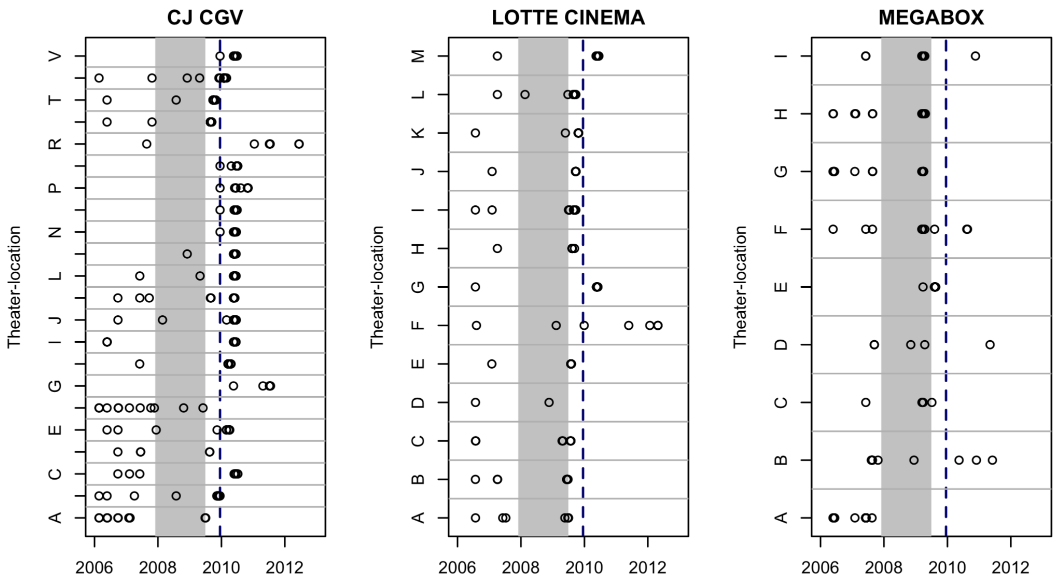
To better understand the variation in conversion timing, we spoke with an industry expert with over 30 years of experience in cinema technology. He described at least three relevant explanations for the variation in Figure 2.4; each could produce plausibly exogenous variation in conversion timing. First, the Great Recession likely delayed the diffusion of digital screens due to its impact on financial lending institutions, which provided the necessary capital to implement the conversions. This source of variation appears consistent with the relative lack of conversions shown in the shaded area in each plot of Figure 2.4. Second, James Cameron's *Avatar* (2009 film), a well-known digital conversion accelerator in the U.S. market, had a similar effect in South Korea.[7] We can see in Figure 2.4 that many screens of LOTTE Cinema and MEGABOX were converted just before the release of *Avatar* in South Korea. Third, there are only four digital projector manufacturers worldwide, two of which likely supplied all the equipment to South Korean theaters. When demand for digital projectors was high (e.g., several months before the release of *Avatar*), it was likely difficult for non-US theaters to secure as many digital projectors as they wanted in a timely manner. This explains the high conversion volume of CJ CGV screens in the months after *Avatar*'s release.

Thus, problems accessing capital in the recession and a limited number of projector manufacturers provide two sources of supply-side variation in screen conversion timing; the success of *Avatar* provides an industry-wide demand shock.

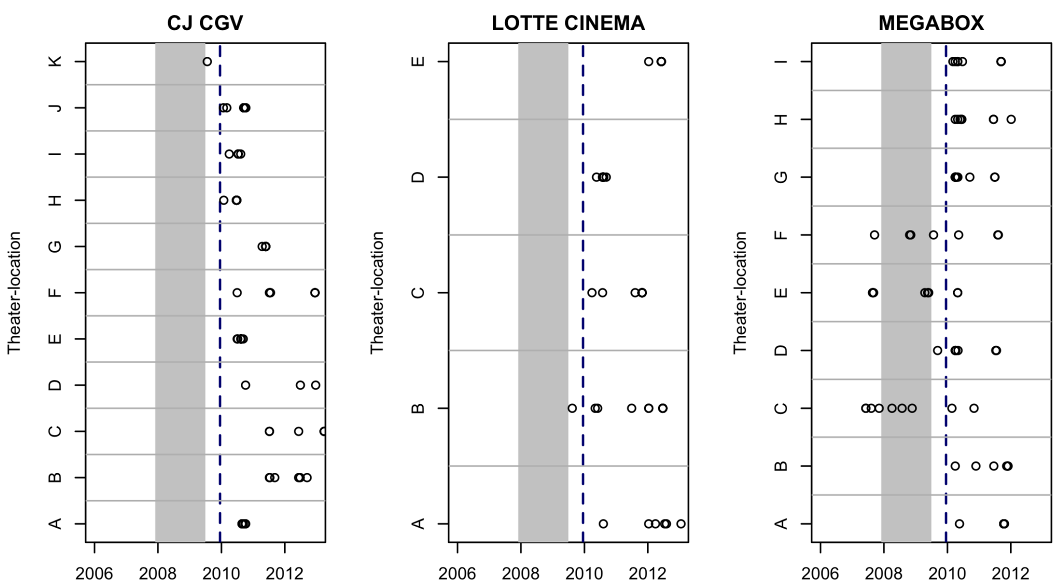
[7]Source: `www.deadline.com/2012/02/cinemas-digital-takeover-the-decline-and-fall-of-film-as-we-have-known-it-208772/` (last access on 11 Jan. 2019).

Figure 2.4: Variation in digital conversion timing

A. Chain-owned theaters



B. Franchise theaters



Note: Figure reports the rollout process of digital screens for the top three theater chains in the market. Each row represents a theater of the corresponding chain, and each dot indicates a conversion of film screen to digital. The grey area and the vertical dashed line indicate the period of the Great Recession and the release date of James Cameron's *Avatar* (2009 film), respectively. Only theaters that opened before 2006 are shown.

We further present two regressions in Table 2.3 and 2.4 to examine theater chains' choices to convert particular screens within a theater. In Table 2.3, we report three theater-level regressions where the dependent variable is the number of days between 2006-01-01 and a theater's first conversion of a screen to digital. The results show that ownership type (chain-owned first), theater size (larger theaters first), chain identity, and geographic location all help explain conversion timing.

How deliberate were chains' choices to convert particular screens within a theater? Given that the most popular movies went to digital first, one could suspect that larger screens were converted first, to accommodate greater associated demand. However, Table 2.4 shows that screen size is not associated with how early a screen is converted within a theater. It reports four separate screen-level regressions where the dependent variable is the number of days between conversion of a screen and the first conversion at a theater. Columns (3) and (4) include the theater-level fixed effects to absorb any time-invariant characteristics of the specific theater, e.g., newer theaters or those in particular geographic locations being more likely to convert. The results suggest that there is no significant correlation between screen size and conversion timing for a given theater.

Overall, we conclude that there are both systematic and random components in the chains' conversion timing decisions. The existence of the random component is crucial in identifying the causal impact of digitization on theaters' scheduling decisions in Chapter 4.

Table 2.3: Determinants of conversion timing at the theater-level

	Unit of observation : theater		
	(1)	(2)	(3)
Franchise	256.466***	479.079***	432.678***
	(79.465)	(82.684)	(84.823)
Size	−91.270***	−56.984***	−57.409***
	(11.762)	(13.235)	(13.237)
Chain FE	No	Yes	Yes
City FE	No	No	Yes
N	316	316	316
R^2	0.175	0.276	0.332
Adj. R^2	0.170	0.264	0.287

Note: Theater size is measured by the number of screens. Standard errors are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table 2.4: Determinants of conversion timing at the screen-level

	Unit of observation : screen			
	(1)	(2)	(3)	(4)
Seats	−0.288	−0.721	−0.160	−0.348
	(0.198)	(0.608)	(0.177)	(0.527)
Seats (squared)		0.001		0.0004
		(0.001)		(0.001)
Theater FE	No	No	Yes	Yes
N	1,128	1,128	1,128	1,128
R^2	0.002	0.002	0.632	0.632
Adj. R^2	0.001	0.001	0.509	0.508

Note: Screen size is measured by the number of seats. We used theaters for which the number of screens did not change within the observation period. Standard errors are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

2.4. Digitization and Movie Distribution

In this section, we describe the associations between digitization and two aspects of movie distribution: distribution breadth and time-to-market.

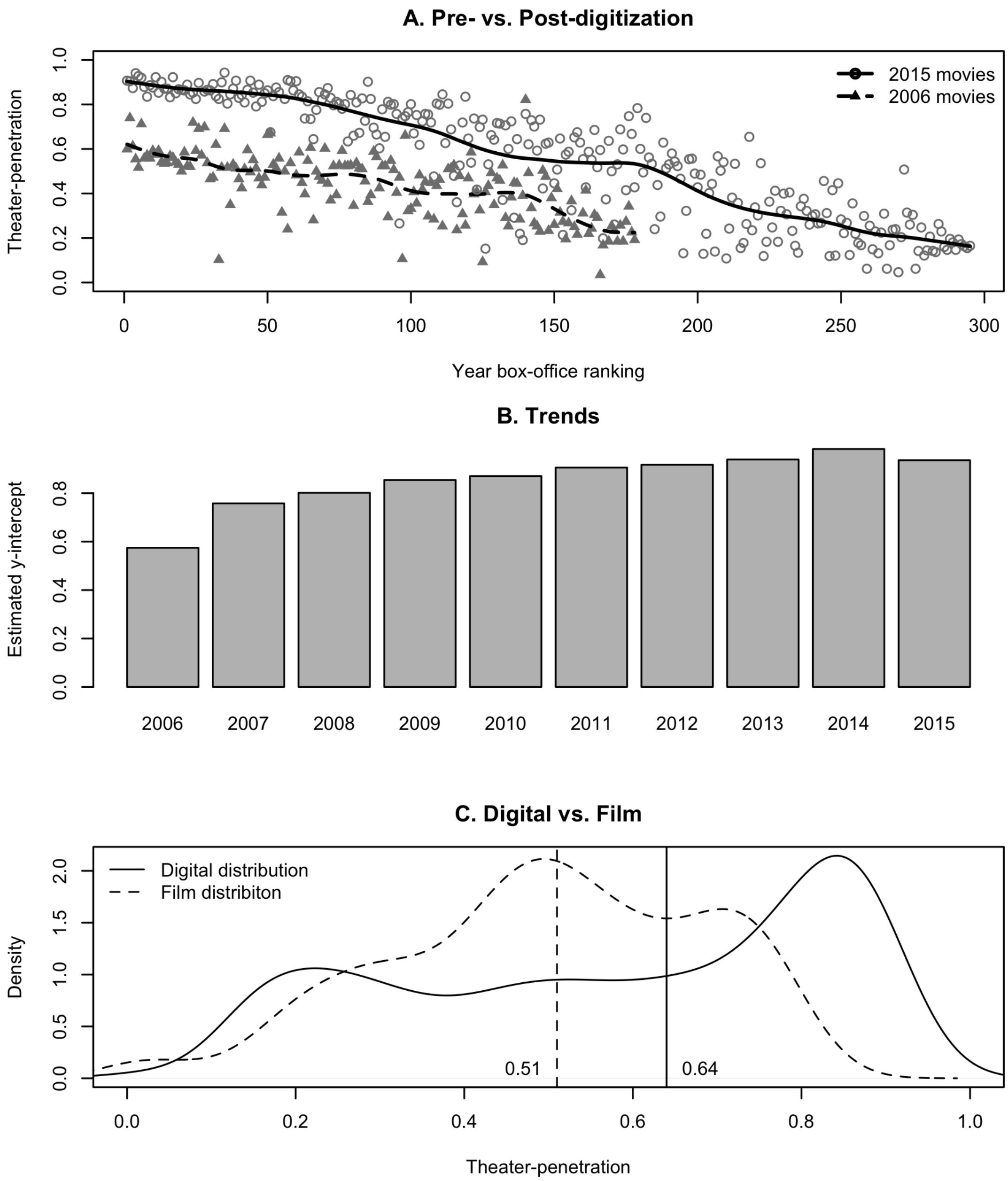
2.4.1. Distribution breadth

Figure 2.5 reports the change in distribution breadth of movies.[8] In the upper panel, we compare the distribution of movies' theater-penetration in 2006 (pre-digitization) and 2015 (post-digitization). A total of 178 movies were released in 2006 (triangles), and 296 movies in 2015 (circles). The x-axis indicates a movie's box-office ranking. Two important patterns emerge. First, it is clear that the distribution has shifted outward. For instance, the top movies in 2006 were shown in 60-75% of theaters nationwide, while the top movies in 2015 were shown in about 90% of theaters. The increased theater-penetration is consistent across movies from rank 1 to rank 178, or the total number of movies in 2006. Second, some of the relatively unpopular movies in 2015 were shown at a smaller portion of theaters than were those in 2006. The majority of movies, except for several outliers in 2006, were shown in at least 20% of theaters in the market. In 2015, 41 movies were shown in less than 20% of theaters. This suggests that the increased variety of movies is due to the entry of marginal products, which would have not been supplied by distributors or picked by theaters without the large reduction in distribution costs.

Two additional plots in the panels below provide more insights about the relationship between digitization and distribution breadth. The middle panel shows that the distribution of theater-penetration of movies continuously shifted outward over time. It reports

[8]We operationalize the distribution breadth of a movie as the share of theaters that show the movie (i.e., theater-penetration).

Figure 2.5: Trends in distribution breadth



Note: Theater-penetration for a movie is defined as the share of theaters that show the movie among all the theaters in the country. Solid and dashed lines in the first panel are smooth splines. Vertical lines in the last panel represent the median of each distribution.

how y-intercept estimates, obtained from regressing the theater-penetration of movies for each year on their yearly box-office rankings (linear and quadratic terms), change. Next, the bottom panel compares the distribution of theater-penetration of movies by distribution format. The solid line represents the estimated kernel density of the distribution of penetration rate for the movies that were digitally distributed. The dashed line is for film-based movies. The key difference between the two distributions lies in their shapes. The shape of the distribution for digital movies is more bimodal, whereas that for film movies is more centered around the median value. In addition, the tails of the distribution for digital movies are fatter on both sides. These patterns again suggest that digitization increased the distribution breadth for movies.

2.4.2. Time-to-market

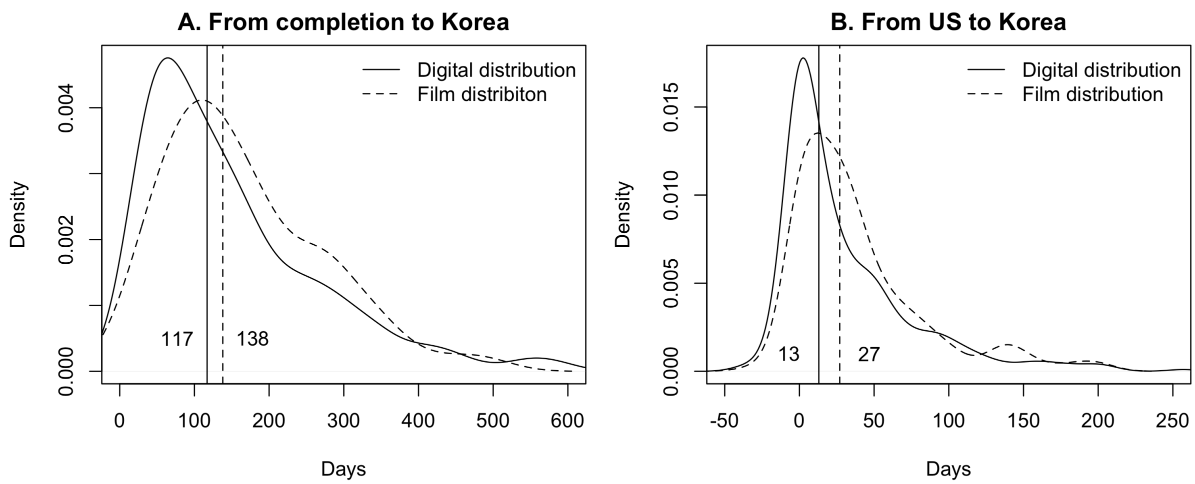
Digitization is likely to decrease time-to-market,[9] as disseminating movies digitally is faster and cheaper than film distribution. Lower replication costs and enhanced efficiency in scheduling for digital movies make them less likely to sit in studios' inventory, waiting for theaters to pick them up. In addition, threats from digital piracy incentivize studios and theaters to reduce delays in release across markets.

In order to check empirically whether data support our expectation, we use an additional dataset from IMDb.[10] IMDb provides detailed information about the timeline of a movie's production status, and its release dates across countries. For instance, we can observe that the production of the movie *Moonlight* (2016) was completed on July 21, 2016,

[9] We operationalize a movie's time-to-market as the length of time between the end of production and theatrical release.

[10] The Internet Movie Database: `https://pro-labs.imdb.com` (last access on 11 Jan. 2019).

Figure 2.6: Trends in time-to-market



Note: Figure shows the distribution of the length of delay in release window for digital and film movies. The values in the right panel can be negative, which means that a US movie was released in South Korea first. Vertical lines represent the median of each distribution.

and it was released in the US on November 18, 2016, and in South Korea on February 22, 2017. It took 120 days for the movie to be wide-released in its home country, and another 96 days to be released in South Korea. We are interested in knowing whether the time length between release dates in two countries is shorter for digital movies. Hence, we collected the completion and release dates for US movies released in South Korea within the observation period. Completion date information was available for a total of 333 movies, and release date information (for both the US and South Korea) was available for 548 movies.

Figure 2.6 shows the distribution of the length of delay in release window for digital and film-based movies. The left panel compares the time between completion and release in the US by distribution format (solid line: digital; dashed line: film). Both distributions are right-skewed, but the mode of the solid line is shifted more to the left, which suggests that digitally distributed movies had shorter delays in general. The median value of the distribution for digital movies is 117 days, while that for film movies is 138 days. The right panel compares the time between release in the US and release in South Korea by movie format. Again, the distribution for digitally distributed movies shows a shorter delay between release dates in the two markets. The median value for digital movies is 13 days, and that for film movies is 27 days. Overall, the patterns suggest that digitization decreases the time from production of products to sale.

2.5. Digitization and Movie Exhibition

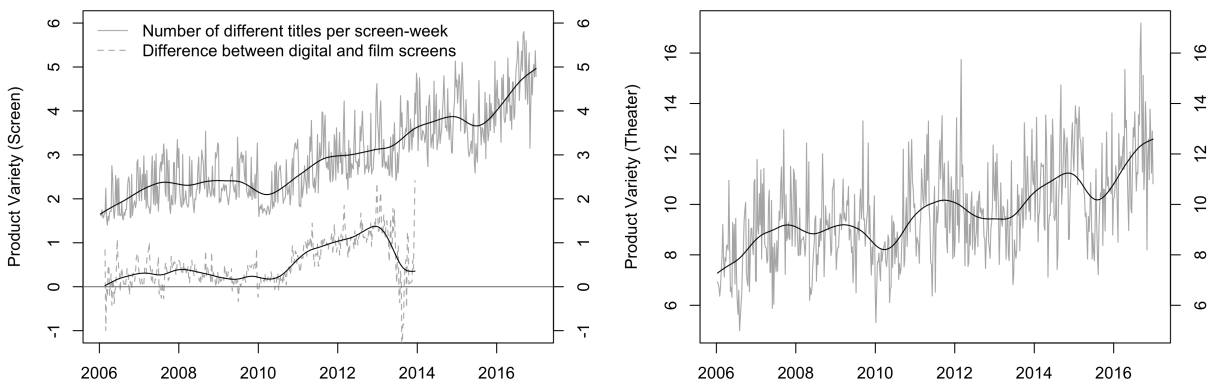
In this section, we describe the associations between digitization and four aspects of movie exhibition: product variety, supply concentration, inventory management and differentiation.

2.5.1. Product variety

Figure 2.7 shows trends in product variety.[11] As shown in the solid gray line, the average number of titles a single screen shows per week more than doubled during the observation period, from 1.9 in 2006 to 4.6 in 2016. As shown in the right panel, variety at theater-level also increased from 7.8 in 2006 to 12 in 2016. Note that the screen-level variety multiplied by the average number of screens is not equal to the theater-level variety, because a title may be screened on more than one screen. This indicates that the variety of movies available to an ordinary moviegoer increased by more than 50% over the 11 years in our observation period. The dashed line in the left panel of Figure 2.7, which is the difference in the number of unique titles between digital-enabled and film-only screens, suggests that

[11] We operationalize product variety as the number of different movies shown at a theater in a given week. While we use the number of different movie titles as our measure of product variety, there can be other ways to define product variety in a horizontally differentiated product space, such as genre.

Figure 2.7: Trends in product variety



Note: Solid black lines are smooth splines. The difference is negative at the beginning and the end of the line, where data are noisier due to smaller screen numbers. There are fewer than 10 digital-enabled screens in the first 20 weeks of 2006, and fewer than 10 film-only screens in the last 20 weeks, before they disappeared altogether.

digital-enabled screens drove the increase in variety. Overall, the difference tends to be positive, which suggests that digitization increases variety.

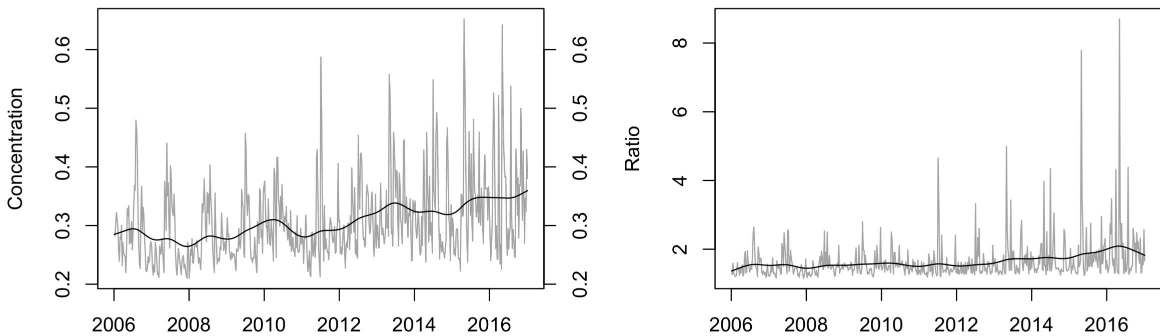
2.5.2. Supply concentration

Figure 2.8 reports an upward trend in supply concentration.[12] On average, 29% of total show times were allocated to the movies with the largest number of screens in 2006, and the share increased to 38% in 2016.In the left panel of Figure 2.8, the increased variability of concentration in supply is noticeable, compared to a relatively gradual increase in the average concentration. Changes in the frequency and height of spikes show that the variability of concentration in supply increased greatly.

These changes are more visible when we use a slightly different measure of concentration. In the right panel of Figure 2.8, we report concentration in supply measured by the

[12]We operationalize supply concentration as the maximum share of slots allocated to one movie at a theater. Note that this is a conservative measures of supply concentration. Others such as Gini index or the ratio between the highest and lowest number of slots would exaggerate concentration without taking into account of the entry of marginal movies.

Figure 2.8: Trends in supply concentration



Note: Solid lines are smooth splines. The left panel shows the trend in movie concentration, as the mean screen share of the biggest movie in a given week. The screen share of a movie is the number of slots allocated to the movie divided by total slots. The right panel reports the mean ratio between movies with the highest and second highest screen share.

ratio between the highest and second highest number of slots assigned to a single movie in a given week. For instance, if the most screened movie was shown ten times and the second most screened movie was shown five times, the concentration ratio is two. Changes in the concentration ratio over time are striking. The maximum ratio was smaller than three until 2011, but it was greater than eight in 2016, which indicates the top movie in 2016 was shown eight times more than any other movie in the market.

Together, these metrics show that the top movies are more dominant in both an absolute and relative sense. First, the top movies are garnering a greater share of screens. In addition, the second-most-screened movies are losing share of screens, which explains the increased concentration ratio.

2.5.3. Inventory management

The upper panel of Figure 2.9 reports the distribution of screen allocation (y-axis) by the number of days after release (x-axis) up to 40 days. Each line represents a percentile of the distribution over time. The left panel reports the case of movies released in 2006, in which almost none of the movies were digitally screened (pre-digitization). The right panel is the same plot but based on movies released in 2015 (post-digitization).

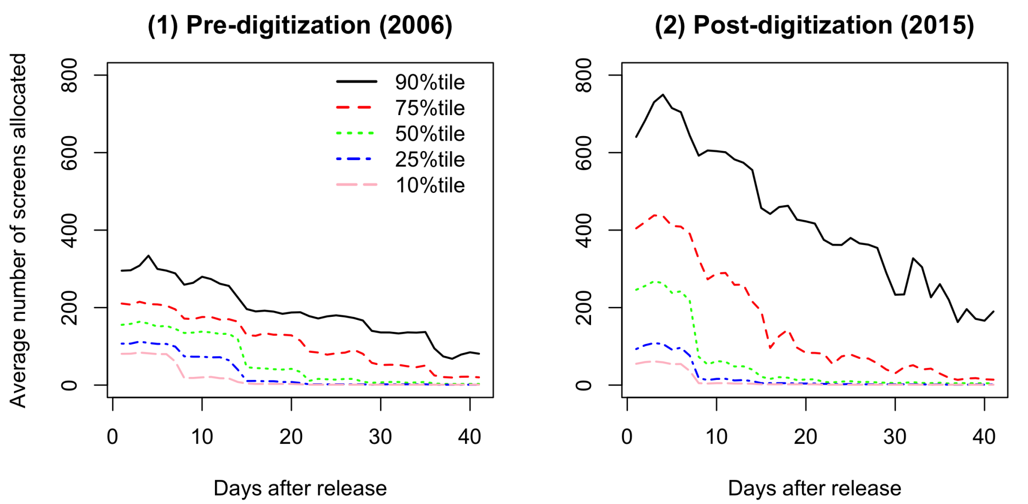
The figure highlights two things that changed between the two time periods, which are consistent with the squeezed middle story. First, with more screens supplied (shown in Figure 2.2), movies in year 2015 are allotted with relatively more screens when first released. The relative location of y-intercepts across the two figures show this. For instance, movies above the middle of the distribution (i.e., over fiftieth percentile) enjoyed far more screens in 2015 than they did in 2006. Movies in the ninetieth percentile movies were shown in about 300 screens in 2006, but the number of screens allocated to those movies more than doubled to about 650 in 2015. However, the increase is quite modest for movies in fiftieth percentile and it is almost invisible for those below fiftieth percentile. This change makes the movies in the middle to be squeezed by increased share of the top and niche movies.

Such change in opposing directions emerges again when we look at the rate at which the number of screens decreases to zero. While even mid- and low-popular movies were shown at least for two to three weeks in 2006 (top-left panel), it now takes less than two weeks before such movies are dragged down from screens (top-right panel).

The bottom panel provides more comprehensive picture of the changes in the length of in-release periods. Its left panel shows the cumulative mass function of in-release days for 2006 (blue line) and 2015 (red line) movies. Here, in-release days of a movie is defined as the number of days elapsed since its release until no theaters in the market allocate screens to it, which does not include re-releases. As shown in the left panel, 2015 movies

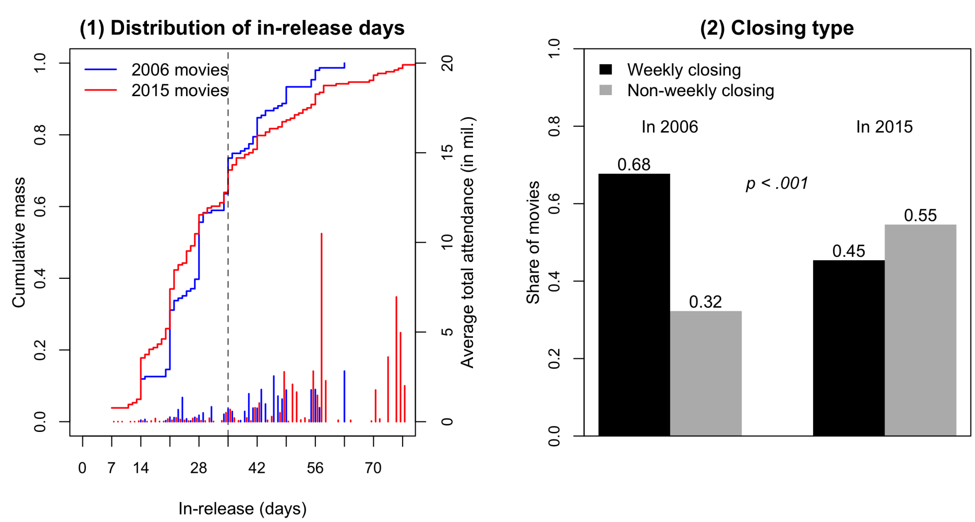
Figure 2.9: Trends in inventory management

A. Distribution of screen numbers over time



Note: Figure reports the distribution of screen allocation (y-axis) by the number of days after release (x-axis) up to 40 days. Each line represents a percentile of the distribution over time.

B. Distribution of in-release days and closing types



Note: Figure compares the distribution of in-release days of movies. Only movies released on Thursday are used (87% and 74% in 2006 and 2015, respectively). Weekly closing refers to the case where a movie closed with in-release days of multiples of seven. The left panel shows the cumulative mass function of in-release days for 2006 (blue line) and 2015 (red line) movies. Here, in-release days of a movie is defined as the number of days elapsed since its release until no theaters in the market allocate screens to it (not including re-releases).

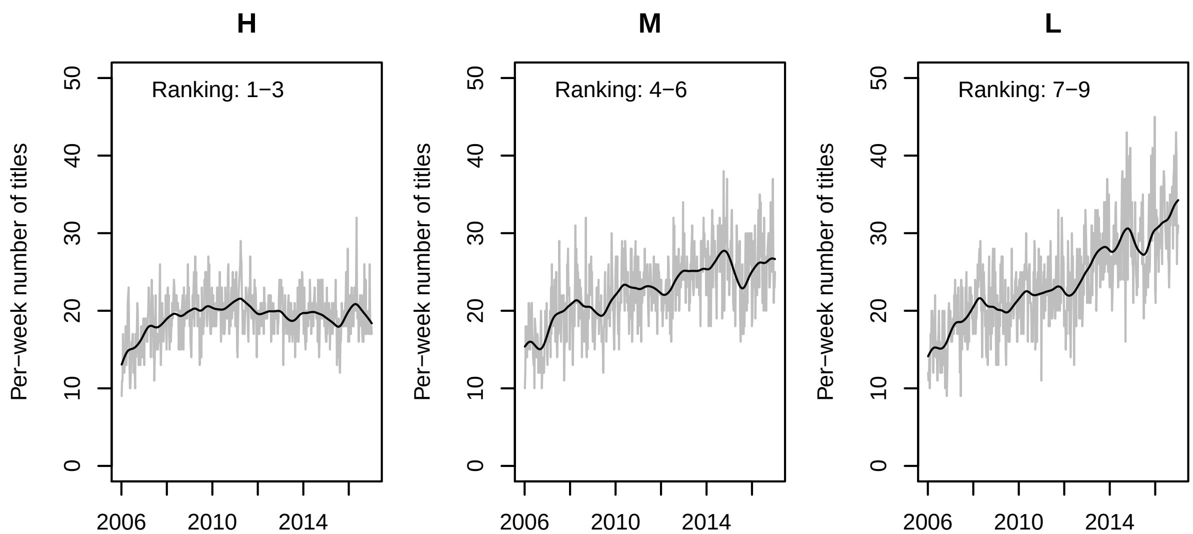
are more dispersed in terms of in-release days. That is, the number of movies that were shown for a shorter period and movies that were shown for a longer period was larger in 2015 than in 2006. The right panel compares the closing type of movies of the two periods. Weekly closing refers to the case where a movie closed with in-release days of multiples of seven (e.g., first show on Thursday and last show on Wednesday). The data shows that the share of weekly closing movies dropped from 68% in 2006 to 45% in 2015. These observations imply that theaters are getting more flexible in adjusting movie titles across weeks by reacting to realized demand, which can accelerate the process of 'the rich get richer, the poor get poorer.'

2.5.4. Differentiation

Figure 2.10 reports the trends in differentiation. The figure reports the number of unique titles chosen by 92 static panel of theaters over time by movies' rankings. Rankings are determined at each theater by the number of showings allotted to movies. For instance, if a theater showing two movies in a given week showed the first movie ten times and the second movie twice, the first movie is rank 1 and the second movie is rank 2.

As shown in Figure 2.10, theaters have differentiated by choosing different L (and some M) movies while staying relatively similar in choosing H movies. There can be two explanations. First, increased supply of (marginal) movies allows theaters to more differentiate. Second, increased flexibility in inventory management (Section 2.5.3) allows theaters to more differentiate. In either case, by reducing costs for movie production and distribution, digitization has likely contributed to the shift in the level of differentiation in product choice.

Figure 2.10: Trends in differentiation

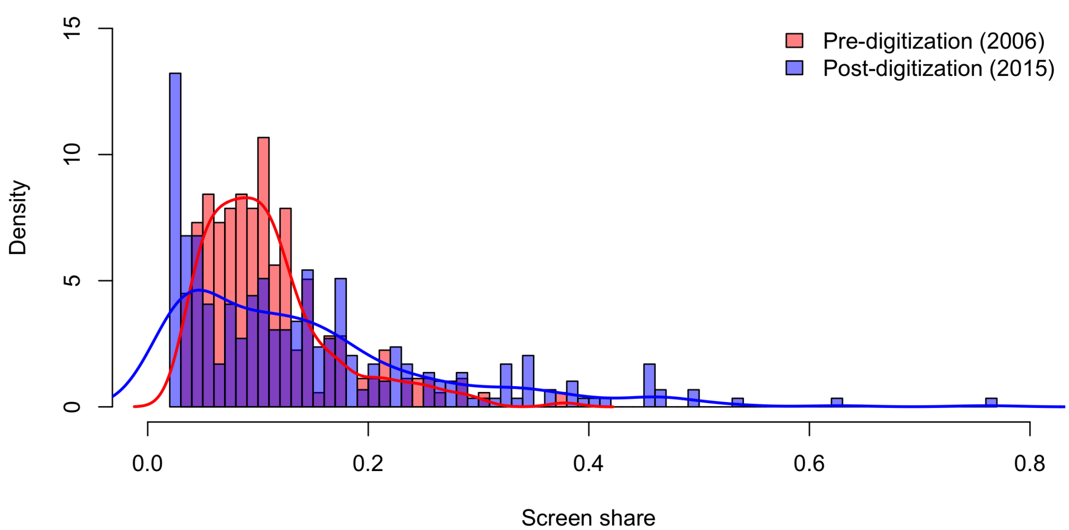


We group rankings into three groups (ranking 1-3, ranking 4-6 and ranking 7-9) and track the number of unique titles within each group across all theaters over time. One way to view the three groups is that they represent the expected popularity of movies. H (ranking 1-3) is the most popular movies, L (ranking 4-9) is the least popular movies, and M (ranking 4-9) is in the middle. The number of unique titles indicates the level of differentiation. The more theaters differentiate by showing different titles, the higher the number should be. On the contrary, the less theaters differentiate by showing the same titles, the lower the number should be.

2.5.5. Movies in the middle

Figure 2.11 reports the distribution of movies' screen shares, defined as the maximum number of screens allocated to a movie divided by the total screens available in the market. Solid lines are kernel density estimates. The distribution in the post-digitization period (year 2015) is more skewed to right and has a longer right tail compared to the pre-digitization period (year 2006). This figure suggests that one consequence of the increase in both product variety and concentration is that the movies in the middle have been "squeezed" by an increase in screen share of both the top and niche movies. Such products have become observationally equivalent to low-popularity products, as relatively fewer movies have achieved modest levels of distribution with digitization. Concurrently, such products might have become less frequent, as studios have come to view blockbusters and low-budget movies as more favorable products to invest.

Figure 2.11: Movies in the middle are squeezed



2.6. Digitization and Movie Consumption

In this section, we discuss how digitization has likely affected the consumption of movies through the lens of sales concentration.

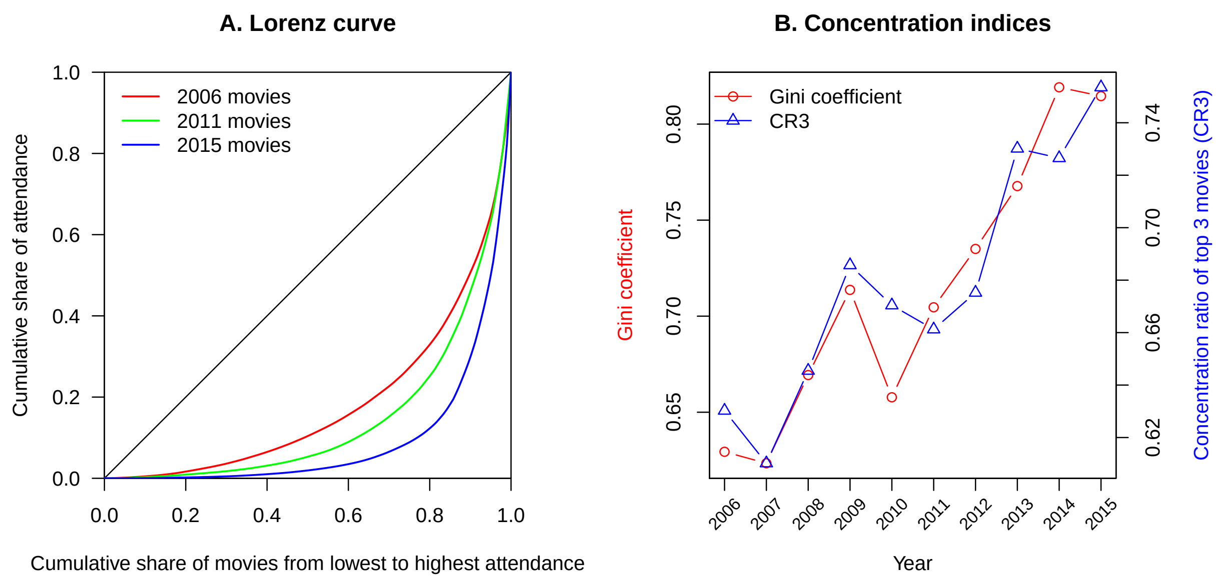
2.6.1. Sales concentration

High-risk, high-return is among the phrases that describe the motion picture industry, inducing returns to be highly concentrated to few select products. One question is how digitization is associated with sales concentration—i.e., does digitization drive sales to be more (or less) concentrated?

Figure 2.12 shows that the market has been more concentrated in consumption along our observation period. In the left panel, the Lorenz curve for each year summarizes the degree of concentration in the consumption (total attendance) of movies released in a given year. The Gini coefficients the ratio of the area between the 45-degree line and the observed Lorenz curve to the area of the triangle below the 45-degree line. The higher the coefficient, the more unequal the distribution is. In the right panel, the concentration ratio reports the average share of top three movies in attendance in each week. Both indicators clearly show that few number of movies are taking larger share of total returns over time.

One explanation for the increased sales concentration is that, due to the digitization-driven cost reductions, the ways in which movies are supplied are shaped in favor of more concentration in consumption. Indeed, various aspects of supply-side adjustments to digitization we document in Section 2.4 and 2.5 seem to be relevant. This includes increased distribution breadth, increased supply concentration and more differentiation

Figure 2.12: Trends in sales concentration

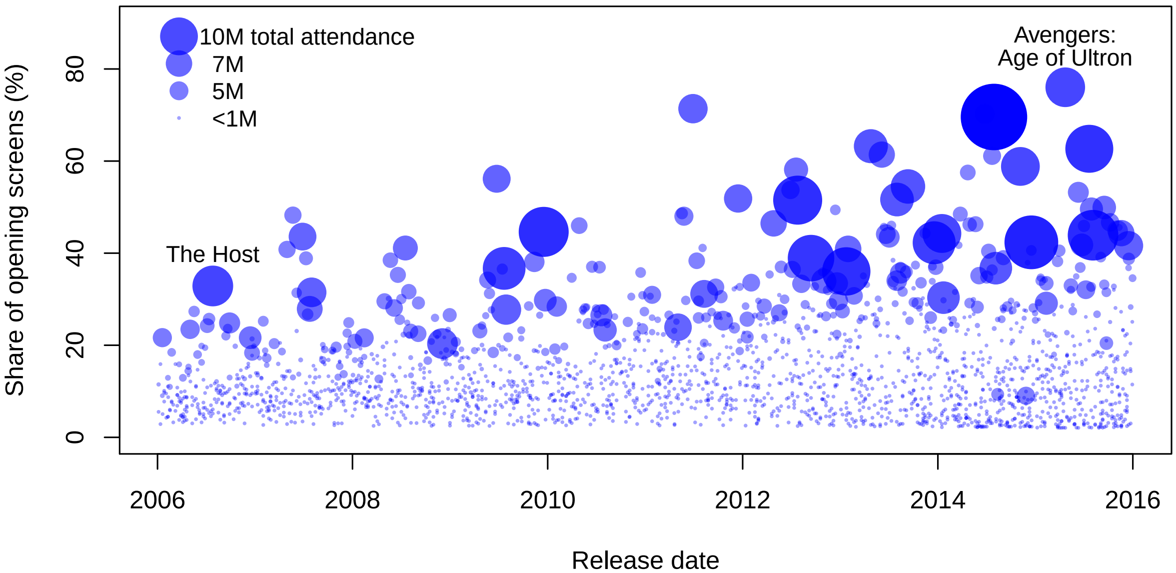


with less popular movies, at least. Of course, there can be alternative explanations as well. For instance, the distribution of movies' popularity may have been more skewed; consumers' preferences may have evolved in a particular way; and/or the increased entry of marginal movies have simply inflated the concentration measure. These are all plausible explanations that can justify what we see in Figure 2.12 and we do not aim to refute these explanations. Instead, we present in the subsequent sections some descriptive evidence which suggest that supply-side factors have played a role, among others, in inducing sales to be more concentrated.

2.6.2. Links to supply-side decisions

First, Figure 2.13 shows the evolution of theaters' business model and its impact on commercial success of movie titles. Here, each circle represents a unique movie title and its size corresponds to the total attendance of the movie. Movies are positioned by release

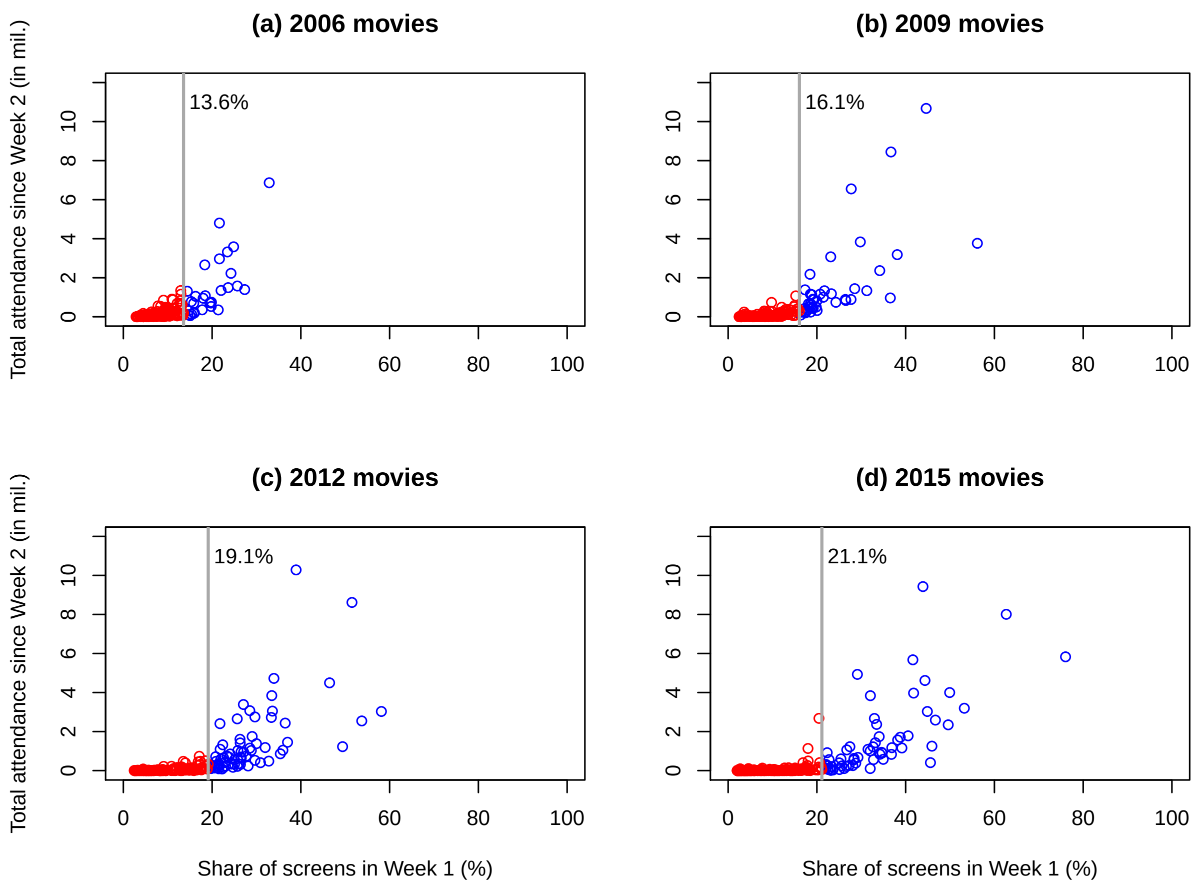
Figure 2.13: Trends in movies' opening screen share and attendance



date (x-axis) and the share of opening screens (y-axis). A movie's opening screen is defined as the total number of screens allocated to the movie within the first seven days of its release.

There are two noticeable patterns revealed in the plot. First, the range of opening screen share is expanding and it creates greater inequality among movies in screen allocation. For instance, while no other movies occupied more screens than The Host with 32.9% in 2006, the maximum number of screens allocated to a single movie escalated to 76.0% for Avengers: Age of Ultron in 2015. It is an astonishing number: an ordinary moviegoer will find during the week of its release that about eight out of ten screens are dominated by the movie. The remaining three were left for a brutal com- petition among a handful number of small-medium size movies. Second, there has been more frequent appearance of mega hits. Although the 2016 blockbuster ended up having slightly less total attendance (10.5 million) than the 2006 blockbuster (10.8 million), it is quite obvious

Figure 2.14: Discontinuity in returns



Note: Four scatter plots, each of which represents movies from a specific year, report the relationship between movies' national share of screens in Week 1 (x-axis) and the total attendance, number of moviegoers, after Week 2 in million (y-axis). In each panel, movies are clustered and color-coded using the k-means analysis with two centers. The gray lines represent the cutoff values in x-axis of two clusters.

that we can spot bigger circles more frequently as we move our attention from left to the right side of the figure

Second, Figure 2.14 highlights that there is a discontinuity in the relation between initial screen allocation and eventual returns. The four scatter plots, each of which represents movies from a specific year, report the relationship between movies' national share of screens in Week 1 (x-axis) and the total attendance, number of moviegoers, after Week

2 in million (y-axis). In each panel, movies are clustered and color-coded using the k-means analysis with two centers. The gray lines represent the cutoff values in x-axis of two clusters. It suggests that there is a significant increase in the slope that relates x and y at the point of discontinuity. In other words, movies with more opening screens are more likely to have greater return in general, and it is a way more likely to be so when the opening screen numbers exceed a certain point of discontinuity. Interestingly, it seems like the inflexion point has shifted to the right over time. In 2006, procuring at least 13.6% of screens (or 255 screens) in opening week would have been something distributors must accomplish to aim a great success of a movie. The opportunities have been increasingly narrowing down—it requires 21.1% of screens (or 512 screens) in 2015 while the size of return at the point of discontinuity is even smaller than before.

2.7. Discussion

In this chapter, we use two datasets from the South Korean movie market to investigate the associations between digitization and various aspects of decisions made by distributors and exhibitors. A series of exploratory analyses suggest that digitization likely (1) increased distribution breadth of movies, (2) decreased time-to-market, (3) increased the variety of movies, (4) increased concentration in screen supply, (5) provided more flexibility in inventory management for theaters, and (6) helped theaters to differentiated more in choosing relatively less popular movies. The data also suggest that the consumption of movies is more concentrated on top-selling movies, which is associated with the supply-side adjustments to digitization.

It is important to note that all we present in this chapter is correlational, not causal. In the subsequent chapters, we tackle the issue of causality, focusing on two aspects of theaters' scheduling decisions: product variety and supply concentration.

CHAPTER 3

A Model of Theaters' Scheduling Decisions (joint with Eric Anderson and Brett Gordon)

3.1. Introduction

In this chapter, we develop a theoretical model of theaters' scheduling decisions and the effects of digitization with two goals: (1) to convey the key intuitions about the mechanism through which digitization affects product variety and supply concentration and (2) to demonstrate that the impact of digitization is moderated by the relative demand for the top movies.

Our model suggests two ways in which digitization can affect product variety and supply concentration. First, digitization reduced the marginal cost of creating and distributing movies, which eliminated a constraint of physical films. With digitization, a theater can screen any number of movies simultaneously on any number of screens without being constrained by the number of physical copies on hand. This could make it easier for a theater to skew showings toward a single movie and/or to incorporate niche movies that play on only a few screens. Second, digitization also reduced the costs associated with switching between movies within a screen, which once required the physical labor of a projectionist with 35mm films (Mondello, 2017). Again, this can facilitate additional showings of movies on other screens and help support niche movies. In sum, digitization allows theaters to more flexibly manage their screens by greatly reducing, if not eliminating, costs and eliminating the constraint of physical films.

Our model predicts that the effects of digitization on product variety and supply concentration are directionally different, depending on the relative demand for the top movies to the supply of screens. A key intuition is that supply is lumpy, or discrete, due to the costs associated with screening movies in the 35mm film format. To see this, imagine a theater with three screens. Each screen has four time-slots, so the theater has a total of twelve slots that can show a movie. Suppose the theater faces demand for five showings (time-slots) for a movie but because of costs, it only acquires one copy and shows the movie four times on one screen. We refer to this case as a "shortage" in the supply of screens for the movie, since the demand for the fifth time slot is unfulfilled. If the costs go to zero under digitization, the theater would show the movie five times (vs. four times with film). In this case, digitization increases supply concentration from 4/12 to 5/12. At the same time, digitization may decrease product variety, as the movie takes a slot that might have been allotted to a niche movie. Alternatively, there can be an "excess" supply of screens for the movie. Now imagine that the theater faces demand for seven showings for a movie. The theater acquires two copies of the movie and shows the film eight times on two screens, which indicates more supply of screens than demand. It is not worth acquiring another niche movie for the one residual slot (acquisition cost) and it is also not worth changing the movie (switching cost). With digitization, the theater shows the movie just seven times (vs. eight times with film) and allots the eighth slot to other movies. As a result, digitization decreases supply concentration from 8/12 to 7/12.

Note that the excess supply may be used to bring in a niche movie, which would increase product variety.

The rest of this chapter is structured as follows. We first discuss the model intuition using a toy model in Section 3.2, and then formalize the intuition in Section 3.3. In Section 3.4, we present model predictions about the impact of digitization on product variety and concentration. Section 3.5 concludes.

3.2. A Toy Model

Consider a theater that owns two screens $\{A, B\}$ and solves a single-period scheduling problem. Each screen has three time-slots $\{1, 2, 3\}$, so that each period the theater has a total of six slots that can show a movie that we label $\{A1, A2, A3, B1, B2, B3\}$. We assume each slot has the same fixed capacity of S (i.e., number of seats). Three movies $\{H, M, L\}$ with deterministic and perfectly predictable demand $\{q_H, q_M, q_L\}$ are available to the theater.

Then, we consider three types of operating costs for the theater: fixed cost, marginal cost, and switching cost. First, fixed cost, C_F, refers to the cost of acquiring a copy of a movie for the first time. Second, marginal cost, ρC_F, is the cost of acquiring an additional copy of the same movie, where $\rho \in [0, 1)$ represents the economies of scale. Third, a theater incurs a switching cost, C_S, when the theater switches between movies across slots within a screen. For instance, the theater has to pay C_S if screen A shows a different movie in $A1$ and $A2$ but pays no switching cost if the same movie is shown in $A1$ and $A2$. In practice, C_S captures change costs from additional labor.

Below, we present two different conditions of the relative demand for the top movie (H) under which the model predicts directionally opposing impacts of digitization on product variety and supply concentration.

3.2.1. Case 1: A shortage in the supply of screens for the top movie

We consider a market where H represents a blockbuster for which a single screen alone cannot serve the demand, whereas M and L are movies with relatively low commercial appeal. To capture this environment, we assume $3S < q_H < 4S$ and $S < q_L < q_M < 2S$.[1] Define the residual demand of movies as $q_H^R = q_H - 3S$, $q_M^R = q_M - S$, and $q_L^R = q_L - S$, where it is assumed that $q_L^R < q_M^R < q_H^R$. To simplify, we normalize ticket prices to one. We assume $C_F < 3S$. That is, the revenue from selling all seats of a screen ($3S$) is greater than the cost of purchasing a copy of a movie (C_F).

Given these assumptions, a theater always purchases a copy of H and shows it in all three slots of a screen, say A. After eliminating dominated strategies, the theater has four choice alternatives for $\{B1, B2, B3\}$: MMM, MML, HMM, and HML. For instance, MMM indicates the theater pays C_F to acquire a copy of movie M and allocates it to all three slots of screen B. The payoff for the theater from screen B is then $q_M - C_F$, or equivalently $S + q_M^R - C_F$. The movie variety resulting from the choice of MMM is 2, H on screen A and M on screen B, and concentration is 50% (both H and M have three out of six slots). In contrast, a strategy HML on screen B leads to variety of 3 (i.e., all 3 movies are shown) and concentration of 67% (four showings of H in six slots). Table

[1] These demand conditions are chosen to demonstrate the existence of a boundary condition under which our model predicts a particular directional change in theaters' scheduling decisions with digitization.

Table 3.1: Choice alternatives for high q_H case

	Screen A	Screen B	Total payoff	Payoff at zero costs	Variety	Concentration
(i)	HHH	MMM	$4S + q_M^R - 2C_F$	$4S + q_M^R$	2	50%
(ii)	HHH	MML	$5S + q_M^R - 3C_F - C_S$	$5S + q_M^R$	3	50%
(iii)	HHH	HMM	$4S + q_H^R + q_M^R - 2C_F - \rho C_F - C_S$	$4S + q_H^R + q_M^R$	2	67%
(iv)	HHH	HML	$5S + q_H^R - 3C_F - \rho C_F - 2C_S$	$5S + q_H^R$	3	67%

Table 3.2: Choice alternatives for low q_H case

	Screen A	Screen B	Total payoff	Payoff at zero costs	Variety	Concentration
(i)	HHH	MMM	$3S + q_H^R + q_M^R - 2C_F$	$3S + q_H^R + q_M^R$	2	50%
(ii)	HHH	MML	$4S + q_H^R + q_M^R - 3C_F - C_S$	$4S + q_H^R + q_M^R$	3	50%
(iii)	HHL	MML	$4S + q_M^R + q_L^R - 3C_F - \rho C_F - 2C_S$	$4S + q_M^R + q_L^R$	3	40%

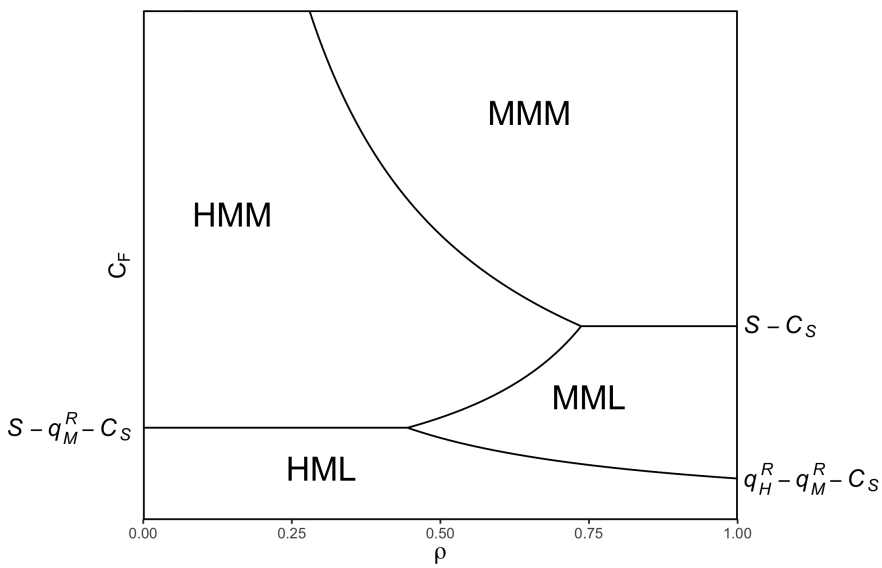
Table 3.3: Choice alternatives for two-period case

Period 1	Period 2	Total payoff	Payoff at zero costs	Variety	Concentration
(HHH, MMM)	(HHH, MMM)	$7S + q_H^R + q_M^R - 2C_F$	$7S + q_H^R + q_M^R$	2	50%
(HHH, MMM)	(HHH, LLL)	$9S + q_H^R + q_L^R - 3C_F$	$9S + q_H^R + q_L^R$	2	50%
(HHH, MMM)	(HHH, MLL)	$9S + q_H^R + q_M^R - 3C_F - C_S$	$9S + q_H^R + q_M^R$	3	50%
(HHH, MML)	(HHL, MML)	$9S + q_H^R + q_M^R + q_L^R - 3C_F - \rho C_F - 3C_S$	$9S + q_H^R + q_M^R + q_L^R$	3	42%

3.1 provides the full description for the four choice alternatives that are not dominated by other alternatives.

The optimal choice for the theater, which depends on the size of costs, C_F, ρ, and C_S, relative to the size of demand and capacity, is shown graphically in Figure 3.1. Each optimal choice results in a different product variety, defined as the number of distinct movies shown at the theater, and concentration in supply, defined as the percentage of slots allocated to the most popular movie. When the costs are sufficiently high, the optimal choice for the theater is (i) MMM, which results in variety of two and concentration of three. We assume that digitization reduces all three types of costs and has multiple effects. First, observe that the optimal choice switches from (i) MMM to (ii) MML as the fixed cost decreases. A lower fixed cost of acquiring a movie enables low-volume movies a higher chance to be shown, which increases variety from two to three. Second, observe that the optimal choice switches from (i) MMM or (ii) MML to (iii) HMM as the marginal cost goes down along with the fixed cost. A lower marginal cost of an additional movie showing allows high-volume movies another chance to be shown, which increases concentration in supply from 50% to 67%. Note that in the case of (ii) MML to (iii) HMM, L is crowded out by H, which results in a decreased variety from three to two. Lastly, (iv) HML is optimal when the two costs are sufficiently low and both variety and concentration increase. Reduction of switching cost causes the three intercepts to move up, which expands the region where HML is the optimal choice to expand.

Figure 3.1: Optimal choice depending on the size of costs



3.2.2. Case 2: An excess supply of screens for the top movie

We now consider different model primitives where the demand for blockbuster (i.e., movie H) can be fully served if the theater shows the movie in a screen for a given time period. In this case, there can be an excess supply of screens even after the demand for H is met, but a theater may decide to keep showing H due to the costs associated with switching to other movies (C_F, ρC_F, and C_S). When the costs decrease with digitization, a theater will allocate the excess supply of screens to other movies, such as M and L.

To show this, we assume that $2S < q_H < 3S$ instead of $3S < q_H < 4S$, while maintaining the same demand conditions for other two movies, i.e., $S < q_L < q_M < 2S$. In addition, we define the residual demand of movies similarly as before: $q_H^R = q_H - 2S$, $q_M^R = q_M - S$, $q_L^R = q_L - S$, and $q_H^R < q_L^R < q_M^R$. Under this new demand condition, it is no longer optimal for the theater to show H in all three slots of a screen. If costs are sufficiently low, a theater would better off to allocate two slots to H and the remaining one to another.

Table 3.2 provides the full description of the choice alternatives after eliminating those dominated by other alternatives. Depending on the relative size of the three costs, one of the three alternatives can be optimal for the theater. We highlight the first (i) and the last row (iii) of the table: the former is likely to be optimal when costs are high while the latter is likely to be optimal when costs approach to zero. Unlike the previous case, we see that the supply concentration can decrease from 50% to 40% with the digitization-driven cost reductions (iii).

3.2.3. A Two-period Case

We consider a two-period version of the model. Suppose that it is optimal for the theater to show H in a screen and M in another screen in a single-period case when costs are high. Would it be still optimal if the theater also operates in the day after? The answer depends on the total demand for each movie over the two periods. If the total demand simply doubles from a single- to two-period case, the single-period optimal solution will be still optimal in two-period case. For instance, if the demand for H is $3S$ and $6S$ in a single- and two-period case, respectively, it would be optimal for the theater to show H in a screen in each period.

The case becomes less obvious when the total demand is not an integer multiplication of a screen capacity for a day, which is $3S$ in the model. Suppose the total demand for movie H is $5S$, which is not an integer multiplication of $3S$. The theater would want to allocate total $1.67(\approx 5/3)$ screens to H over the two periods, but, again, it is additionally costly to serve a *fraction* of demand due to the costs we have discussed. By trading off the costs and potential revenue from the residual demand, theater should decide (1) whether to serve the residual demand for H, and, if so, (2) whether to utilize the excess supply after serving them.

We provide a simple analysis of the case using the same model. We assume that the acquisition costs (C_F and ρC_F) are not recurring — i.e., the theater can acquire a move at C_F and show it in a screen in both periods. However, C_s is proportional to the number of switchings made during two periods. Demand conditions are $2S < q_L < 3S < q_M < 4S < q_H < 5S$.

In Table 3.3, we present four choice alternatives that we can expect the theater would choose. Again, we highlight the first and last rows of the table. In the first row, the theater chooses to show H and M in a screen in each period. Total $3S$ of demand for each movie is served in period 1, and the remaining is served in period 2. Since $q_M < 4S < q_H < 5S$, there are an excess supply arises from both screens. When costs are sufficiently high, the theater would give up utilizing the excess supply, which makes a total payoff of $7S + q_H^R + q_M^R - 2C_F$. However, as shown in the last column, the theater would be willing to order L and flexibly switching between movies within a screen and a period, which yields higher payoff when costs are low. As a result, supply concentration goes down from 50% to 42%.

3.2.4. Discussion

Using a simple setup, we have shown that there are two demand conditions where the digitization-driven cost reductions result in different directional changes in product variety and concentration. The key intuition is that digitization reduces both acquisition and switching costs incurred at theaters, and that profit-maximizing theaters respond to the cost shock strategically by taking into account the demand conditions. We formalize the intuition using a mathematical model in the next section.

3.3. The Model

A profit-maximizing theater decides the optimal allocation of screens to J movies by solving the following optimization problem:

$$\begin{aligned} \max_{\mathbf{a} \in \mathbf{A}} \quad & \pi(\mathbf{a}) = \sum_{j \in J} R_j(a_j) - C(a_j) \\ \text{subject to} \quad & a_j \in \mathbb{Q}_{\geq 0},\ \forall j \quad \text{(non-negativity constraint)} \\ & \sum_{j \in J} a_j \leq K \quad \text{(capacity constraint)} \end{aligned} \tag{3.1}$$

The decision variable is $\mathbf{a} = (a_1, ..., a_J)$ where each element represents the number of screens the theater allots to each movie. Both revenue, R_j, and cost, C_j, are a function of screen allocation. Note that a_j can take a value of either zero or a positive rational number. For instance, $a_j = 0$ indicates that the theater does not show movie j and $a_j = 0.5$ indicates that j is shown in a screen but only for a half-day. K is the capacity of the theater (i.e., total number of screens).[2]

[2]For the sake of parsimonious representation, we abstract away from other important dimensions of scheduling problems, which include competition, dynamic decisions, and *ex ante* demand uncertainty.

3.3.1. Revenue function

We specify the theater's revenue function as follows:

$$R_j(a_j) = [p_j \cdot (1 - \theta_j) + \kappa] \cdot q_j(a_j), \tag{3.2}$$

where p_j is ticket price, θ_j is the fraction of revenue the theater pays to distributors, κ is average concession profit per moviegoer. $q_j(a_j)$ is ticket sales, which is assumed to increase in a_j at a diminishing return ($\partial q_j/\partial a_j \geq 0$ and $\partial^2 q_j/\partial a_j^2 \leq 0$). We assume that the ticket price and revenue sharing ratio are invariant across movies.[3] Then, the revenue function simplifies to $R_j(a_j) = \tilde{r} \cdot q_j(a_j)$, where $\tilde{r} = p \cdot (1-\theta) + \kappa$ is common across movies.

We take into account the heterogeneity in movies' commercial appeal to consumers. To capture this environment, without loss of generality, we assume that $q_1(a) > q_2(a) > q_3(a) > ... > q_J(a)$ for any value of a. In particular, we consider that $j = 1$ represents the top movie, where $q_1(\cdot)$ is sufficiently greater than the demand for any other movies available in the market.

3.3.2. Cost function

We consider two types of costs associated with showing movie j in a_j screens: the cost of acquiring a copy (or copies) of a movie and the cost of switching movies within a screen. The switching cost represents the marginal cost of labor required to change the movie playing on a screen. The theater does not incur the switching cost if it only shows one

[3]We consider a flat ratio to simplify the model and, more importantly, it is the case in our empirical context.

movie on a given screen. To capture both types, we specify the cost function as follows:

$$C(a_j) = c_1 \lceil a_j \rceil + \frac{c_2}{2} \mathbb{I} \left\{ \lceil a_j \rceil - a_j > 0 \right\}, \tag{3.3}$$

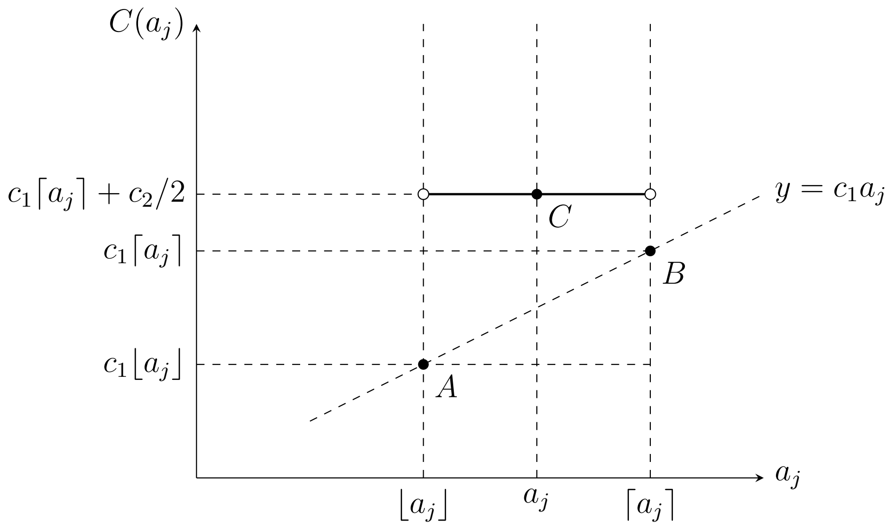
where $\lceil a_j \rceil$ is the ceiling, or the smallest integer that is greater than or equal to a_j (similarly, we define $\lfloor a_j \rfloor$ as the floor, or the greatest integer that is smaller than or equal to a_j). c_1 and c_2 are nonnegative cost parameters. The first term captures the acquisition cost of movies. For instance, if the theater wants to show movie j in three screens simultaneously, it has to pay a cost of $3c_1$.[4] The second term captures a switching cost that occurs when theaters switch between movies across slots within a screen. We assume that the theater pays a one-time switching cost ($c_2/2$) when it allots a fraction of a screen to a movie. So, a theater has to pay c_2 if a screen shows two different movies, whereas this cost is zero if a single title is shown on the screen. Note that $\lceil a_j \rceil - a_j > 0$ is true only if a_j is a non-integer value.

Figure 3.2 provides a graphical illustration of the cost function. Suppose that a theater considers three options for the number of screen it allots to a movie: $\lfloor a_j \rfloor$, a_j, and $\lceil a_j \rceil$. Showing a movie in $\lfloor a_j \rfloor$ screens costs $c_1 \lfloor a_j \rfloor$ as point A in the figure indicates. Similarly, showing a movie in $\lceil a_j \rceil$ screens costs $c_1 \lceil a_j \rceil$ (point B in the figure). Lastly, if the theater shows a movie in a_j screens, which can be a non-integer rational number, it has to pay $c_1 \lceil a_j \rceil$ for the cost of acquisition and $c_2/2$ for the cost of switching (point C).

The key intuition embedded in our cost function is that the cost of flexibility, such as when a theater allocates more than one movie to a single screen, exists in scheduling problems. Depending on the relative magnitude of parameters, the cost may induce

[4]To capture a form of quantity discount, we can change this term to be nonlinear (e.g., quadratic). This does not change the model's predictions.

Figure 3.2: An illustration of cost function



theaters to find suboptimal solutions in terms of revenue (e.g., A or B) more profitable than the optimal solution under zero cost environment (C). In the later part of this section, we show that the distribution costs is a core mechanism through which digitization can reshape product assortment.

3.3.3. Optimal scheduling decision

Given the concavity of the revenue function, combined with the form of the cost function, there exists a solution for the theater's maximization problem. Denote the optimal solution as $\mathbf{a}^*$, which satisfies two properties: i) $a_1^* \geq a_2^* \geq ... \geq a_J^*$ and ii) $\sum_j a_j = K$. To see this, consider that the cost function is common across movies and $q_1(a) > q_2(a) > q_3(a) > ... > q_J(a)$ for any value of a, which suggests that i) holds. Since we are not considering the fixed cost of operating a screen, theaters always want to fully utilize all the screens, which suggests that ii) holds.

For a given $\mathbf{a}^*$, we define two functions that characterize the optimal scheduling decision.

Definition 1 (Product variety)**.** *The product variety for a given* $\boldsymbol{a}^*$ *is defined as* $PV(\boldsymbol{a}^*) = \sum_j \mathbb{I}\{a_j > 0\} = k^*$ *such that* $a_1^*, ..., a_{k^*}^* > 0$ *and* $a_{k^*+1}^*, ..., a_J^* = 0$*.*

Definition 2 (Supply concentration)**.** *The supply concentration for a given* $\boldsymbol{a}^*$ *is defined as* $SC(\boldsymbol{a}^*) = \max_j\{a_j^*/K\} = a_1^*/K$*.*

3.4. Model Predictions

We evaluate the impact of digitization on product variety and supply concentration by showing the existence of boundary conditions in which the relative size of model primitives produce different predictions about the impact of digitization. Specifically, we first assume that digitization drives both acquisition and switching costs to zero (i.e., $c_1 \to 0$ and $c_2 \to 0$). Next, we compare optimal solutions with or without digital projection technology in a comparative statics manner. In doing so, we focus on two types of movies: the top movie ($j = 1$) and the marginal movie ($j = k^*$).

As previously discussed, we consider two different conditions of the relative demand for the top movies under which the model predicts directionally opposing impacts of digitization on product variety and supply concentration. If there is a *shortage* in the supply of screens for the top movie (i.e., demand for the movie was under-served), then digitization can allow theaters to serve the residual demand for the movie, which increases supply concentration and potentially decreases product variety. On the other hand, if there is an *excess* supply of screens for the top movie (i.e., demand for the movie was over-served), then digitization can allow theaters to utilize the excess supply for other movies, which decreases supply concentration and potentially increases product variety. We formalize the two conditions in the below.

3.4.1. Case 1: A shortage in the supply of screens for the top movie

The left panel of Figure 3.3 graphically illustrates the case of shortage in the supply of screens for the top movies. Suppose $\mathbf{a}^D = (a_1^D, ..., a_J^D)$ is the optimal solution for a theater when $c_1 = c_2 = 0$ (the superscript D represents digital projection). Consider a situation in which the theater finds $a_1^F = \lfloor a_1^D \rfloor$ optimal if c_1 and c_2 are strictly greater than zero (the superscript F represents film projection). $\Delta_s = a_j^D - a_j^F$ represents the level of shortage in the supply of screens for the top movies. In this case, digitization *increases* supply concentration from $SC(\mathbf{a}^F) = \lfloor a_1^D \rfloor / K$ to $SC(\mathbf{a}^D) = a_1^D / K$.

When is this likely the case? To see this, consider the following inequality that can be derived from the setup:[5]

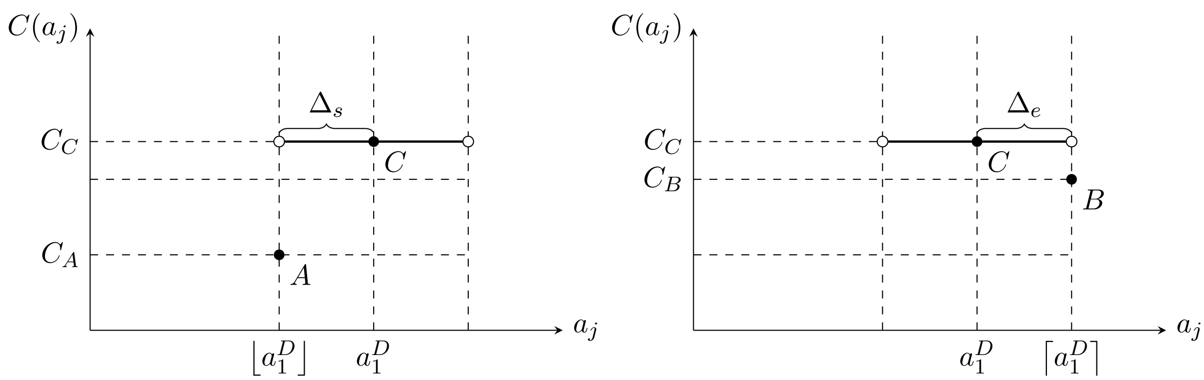
$$\underbrace{c_1 + c_2}_{\text{Cost of flexibility}} > \underbrace{\tilde{r}_1(q_1(a_1^D) - q_1(a_1^F))}_{\text{Gain from residual demand}} + \underbrace{\tilde{r}_J(q_J(a_J^D) - q_J(1))}_{\text{Loss from marginal movie}}, \tag{3.4}$$

where the LHS represents the cost of flexibility, which incurs when splitting a screen for two movies. The two terms in the RHS represent the gain from serving the residual demand of the top movie and the loss from allotting fewer screens to marginal movies. By construction, the first term is greater than zero, whereas the second term is smaller than zero. The sum of the two terms together constitutes the efficiency gains of digital projection. The inequality indicates that if the cost of flexibility (LHS) is not justified by

[5]The demand condition can be represented as $R_1(a_1^F) - C(a_1^F) + \sum_{j>1} R_1(a_j) - C(a_j) > R_1(a_1^D) - C(a_1^D) + \sum_{j>1} R_1(a_j) - C(a_j)$. In Section 3.5, we prove that Equation 3.4 can be derived from this inequality.

Figure 3.3: The relative demand and the impact of digitization

(a) A shortage in supply case (high q) (b) An excess supply case (low q)



the efficiency gains (RHS), a theater would rather give up on trying to serve the residual demand of the top movie that can arise from a shortage in the supply of screens (i.e., Δ_s). In this case, digitization can decrease product variety if additional showings of the top movies crowds out marginal movies. Hence, the model produce the following predictions:

Prediction 1: *If there is a shortage in the supply of screens for the top movie (i.e., if Eq. 3.4 holds),*

(P1a) digitization increases movie concentration in theaters, and

(P1b) digitization weakly decreases the variety of movies offered by theaters.

3.4.2. Case 2: An excess supply of screens for the top movie

The right panel of Figure 3.3 illustrates the case of an excess supply of screens for the top movie. Analogous to the previous case, we consider a situation where a_1^D is optimal with digital projection and $a_j^F = \lceil a_1^D \rceil$ is optimal with film projection. $\Delta_e = a_j^F - a_j^D$ represents the level of an excess supply of screens for the top movie. Under this condition, digitization *decreases* supply concentration from $SC(\mathbf{a}^F) = \lceil a_1^D \rceil / K$ to $SC(\mathbf{a}^D) = a_1^D / K$.

The condition can be represented as the following:

$$\underbrace{c_1 + c_2}_{\text{Cost of flexibility}} > \underbrace{\tilde{r}_1(q_1(a_1^D) - q_1(a_1^F))}_{\text{Loss from excess supply}} + \underbrace{\tilde{r}_J q_J(a_J^D)}_{\text{Gain from increased variety}} . \tag{3.5}$$

The inequality compares the cost of flexibility (LHS) and the total benefit (RHS), where the two terms on the RHS represent the loss from not utilizing an excess supply (smaller than zero) and the gain from an increased variety (greater than zero), respectively. If the cost of flexibility (LHS) is greater than the total benefit, a theater would not utilize the excess demand that can arise from screen allotted to the top movie (i.e., Δ_e). With digitization, the theater would adjust screens for the top movie from a_j^F to a_j^D. If the excess supply is used to bring in more marginal movies, then product variety can increase. Hence, the model produce the following predictions:

Prediction 2: *If there is an excess supply of screens for the top movie (i.e., if Eq. 3.5 holds),*

(P2a) digitization decreases movie concentration in theaters, and

(P2b) digitization weakly increases the variety of movies offered by theaters.

3.5. Discussion

In this chapter, we have shown that digitization reduces both acquisition and switching costs incurred at theaters, and that profit-maximizing theaters strategically respond to the cost shock by taking into account the demand conditions. Using both a toy model and a mathematical model, we analyzed the impact of digitization on product variety and supply concentration. The model predicts that the effects of digitization on product variety and supply concentration are directionally different, depending on the relative demand for the top movies to the supply of screens. If there is a *shortage* in the supply of screens for the top movie (i.e., demand for the movie was under-served), then digitization can allow theaters to serve the residual demand for the movie, which increases supply concentration and potentially decreases product variety. On the other hand, if there is an *excess* supply of screens for the top movie (i.e., demand for the movie was over-served), then digitization can allow theaters to utilize the excess supply for other movies, which decreases supply concentration and potentially increases product variety. We empirically test the model predictions in the next chapter.

Appendix

Proof of condition 1. We show that there exists a set of model primitives that satisfy the following inequality:

$$R_1(a_1^F) - C(a_1^F) + \sum_{j>1} R_1(a_j) - C(a_j) > R_1(a_1^D) - C(a_1^D) + \sum_{j>1} R_1(a_j) - C(a_j),$$

where $a_1^F = \lfloor a_1 \rfloor$.

We consider the case where a_j^F and a_j^D for other movies ($j > 1$) are identical except for $j = J$. For the least popular movie, $a_J^F = 1$ and $a_J^D = 1 - (a_1^D - \lfloor a_1^D \rfloor) < 1$. The intuition is that, with film technology, a theater allots an entire screen to the least popular movie, whereas the theater with digital technology *splits* the screen for a blockbuster and the marginal movie.

Under this condition, the revenue and costs for movies in the middle cancel out, which yields

$$R_1(a_1^F) - C(a_1^F) + R_J(1) - C(1) > R_1(a_1^D) - C(a_1^D) + R_1(a_J^D) - C(a_J^D)$$

$$\tilde{r}_1 q_1(a_1^F) - c_1 a_1^F + \tilde{r}_J q_J(1) - c_1 > \tilde{r}_1 q_1(a_1^D) - (c_1 + 1)a_1^F - c_2/2 + \tilde{r}_J q_J(a_J^D) - c_1 - c_2/2$$

$$\tilde{r}_1 q_1(a_1^F) + \tilde{r}_J q_J(1) > \tilde{r}_1 q_1(a_1^D) - c_1 - c_2/2 + \tilde{r}_J q_J(a_J^D) - c_2/2$$

$$c_1 + c_2 > \tilde{r}_1(q_1(a_1^D) - q_1(a_1^F)) + \tilde{r}_J(q_J(a_J^D) - q_J(1))$$

□

Proof of condition 2. We show that there exists a set of model primitives that satisfy the following inequality:

$$R_1(a_1^F) - C(a_1^F) + \sum_{j>1} R_1(a_j) - C(a_j) > R_1(a_1^D) - C(a_1^D) + \sum_{j>1} R_1(a_j) - C(a_j),$$

where $a_1^F = \lceil a_1 \rceil$.

Similar to the previous proof, we consider the case where a_j^F and a_j^D for other movies $(j > 1)$ are identical except for $j = J$. For the least popular movie, $a_J^F = 0$ and $a_J^D = 1 - (\lceil a_1^D \rceil - a_1^D) < 1$. The intuition is that, with film technology, a theater allots an additional screen to the blockbuster, whereas the theater with digital technology *splits* the screen for a blockbuster and the marginal movie.

Under this condition, the revenue and costs for movies in the middle cancel out, which yields

$$R_1(a_1^F) - C(a_1^F) > R_1(a_1^D) - C(a_1^D) + R_1(a_J^D) - C(a_J^D)$$

$$\tilde{r}_1 q_1(a_1^F) - c_1 a_1^F > \tilde{r}_1 q_1(a_1^D) - c_1 a_1^F - c_2/2 + \tilde{r}_J q_J(a_J^D) - c_1 - c_2/2$$

$$c_1 + c_2 > \tilde{r}_1(q_1(a_1^D) - q_1(a_1^F)) + \tilde{r}_J q_J(a_J^D)$$

$\square$

CHAPTER 4

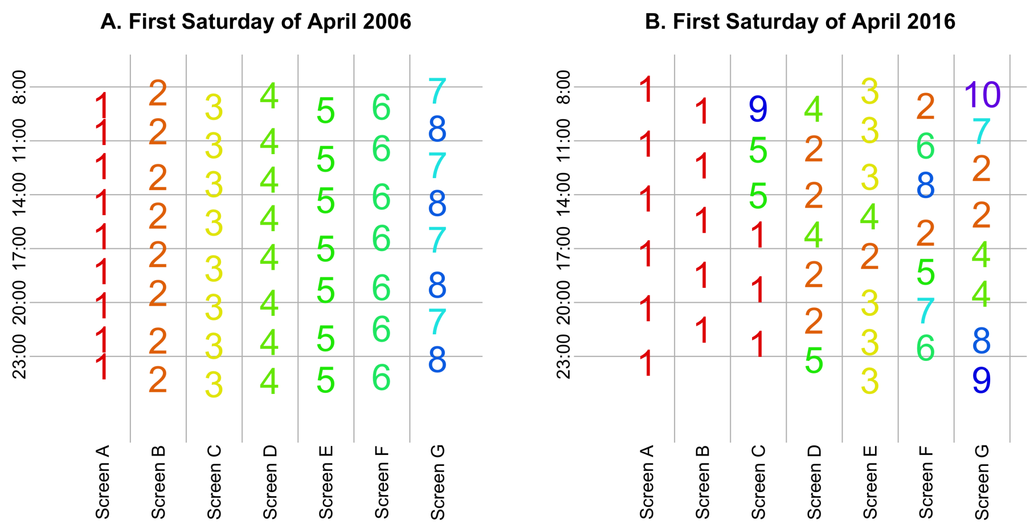
Assessing the Impact of Digitization (joint with Eric Anderson and Brett Gordon)

4.1. Introduction

In this chapter, we assess the causal impact of digitization on theaters' assortment decisions, using the South Korean movie dataset we described in Chapter 2. In particular, we focus on two aspects of assortment decisions: *product variety* and *supply concentration*. To illustrate, Figure 4.1 presents the actual scheduling decisions at a Seoul-based cinema on the first Saturday of April 2006 (all film-based movies) and the first Saturday of April in 2016 (all digital movies). Each number represents a movie shown during a particular screening slot. Movies are ranked according to the number of screenings — i.e., 1 indicates the top movie in each panel. Comparing the two plots reveals two important changes. First, *product variety*—which we define as the number of unique movies shown either at a theater or a screen—increases. At the theater-level it increases from 8 to 10 and at the screen-level it increases from 1 to 3 in screen C, for instance. Second, the *supply concentration*—the maximum share of slots allocated to one movie at a theater—increases from 16% (9 out of 55 total screenings) in 2006 to 30% (14 out of 47) in 2016.

Motivated by this example, we proceed to formally assess the impact of digitization on product variety and supply concentration. Measuring the causal impact of digitization,

Figure 4.1: An example of actual screening schedule



Note: Figure compares the screen schedule of the same theater in 2006 (pre-digital distribution) and 2016 (post-digital distribution). Each number within a panel represents a movie shown during a particular screening slot, and movies are ranked according to the number of screenings at that theater on that date.

however, is challenging because a theater's decision to convert a screen to digital is non-random; this decision may be correlated with unobservable factors, such as local consumer preferences and movie availability, that affect the theater's movie-scheduling decisions (see Section 2.3.3). Ignoring these unobservable confounding factors would likely produce biased estimates of the impact of digitization.

We attempt to overcome this challenge through multiple empirical strategies. As our main analysis, we leverage the panel structure of our data and employ a two-way fixed effects regression model. The model allows us to control for quantify the *correlational* associations between digitization and assortment decisions, while controlling for time trends and theater characteristics. We carefully discuss the assumptions under which the estimates can be interpreted as causal. We find that, overall, digitization increases both product variety and supply concentration, whereas the effects are moderated by two supply-side factors: technology compatibility and capacity constraint. Results from alternative estimation strategies, which include an event-study specification and a natural experiment, demonstrate the effects are robust.

Next, we empirically test the model predictions in Chapter 3 about the moderating role of demand. To this end, we exploit variation in the level of demand for movies across different day parts of the week (i.e., within-week demand variation), given an institutional feature that weekend evenings represent periods of peak demand for movies. We find that the data support our model predictions.

The rest of this chapter is structured as follows. We first discuss our main empirical analysis in Section 4.2. We present the estimation results in Section 4.3 and robustness checks in Section 4.4. In Section 4.5, we test the moderating role of demand on the impact of digitization on product variety and supply concentration. In Section 4.6, we conclude with a discussion on alternative explanations.

4.2. Empirical Strategy

Our main empirical strategy relies on within-theater, across-time variation in digital conversion timing. For a given theater ℓ in week t, we construct the variable $\text{Variety}_{\ell t} > 0$, the number of different titles shown, and $\text{Concentration}_{\ell t} \in (0, 1]$, the screen share of the top movie. The independent variable is $\text{Digital}_{\ell t} \in [0, 1]$, which represents the proportion of digital screens among all screens at theater ℓ in week t. For instance, if a six-screen theater has converted three of its screens as of week t, then $\text{Digital}_{\ell t} = 0.5$. Further, $\text{Digital}_{\ell t} = 0$ if none of the screens has converted, and $\text{Digital}_{\ell t} = 1$ if all screens have converted to digital.

4.2.1. Model specification

By leveraging the panel structure of our data, we formulate a two-way fixed effects regression equation as below:

$$\ln(Y_{\ell t}) = \beta \cdot \text{Digital}_{\ell \tilde{t}} + \alpha_{\ell \tilde{t}} + \tau_t + \varepsilon_{\ell t}. \tag{4.1}$$

Here, the outcome variable $Y_{\ell t}$ is either $\text{Variety}_{\ell t}$ or $\text{Concentration}_{\ell t}$. We specify a log-linear relationship between $Y_{\ell t}$ and $\text{Digital}_{\ell t}$. Our choice of this specification is motivated by the observation that our unit-of-analysis (theater) differs in size and the theater-size is correlated with baseline product variety and supply concentration. With the log-linear specification, our parameter of interest (β) captures the percentage change in $Y_{\ell t}$ rather than a level shift. Two subsequent terms are theater-year fixed effect ($\alpha_{\ell \tilde{t}}$; $\tilde{t}$ indicating the year of week t) and year-week fixed effect (τ_t), respectively. $\varepsilon_{\ell t}$ is an error term.

In the next section, we present estimates from Equation 4.1 and from three restricted versions. First, with no fixed effects ($\alpha_{\ell \tilde{t}} = \tau_t = 0$), we obtain a *pooled* estimator that compares the average $\ln(Y_{\ell t})$ between digital vs. non-digital theater-weeks across all periods. All weeks before a theater's digital adoption are non-digital theater-weeks, whereas the weeks after digital adoption are digital theater-weeks. Second, with only a year-week fixed effect ($\alpha_{\ell \tilde{t}} = 0$), the result is a *between* estimator that makes similar comparisons to the pooled estimator but while averaging out any market-wide time-varying confounds. These confounds include both supply-side factors (e.g., the quantity and composition of available movies) and demand-side factors (e.g., changes in the average moviegoers' preferences), as well as other market environments that are common to all theaters.

Third, with both year-week (τ_t) and theater fixed effects (α_ℓ, instead of $\alpha_{\ell\tilde{t}}$), a *within* estimator computes the average difference in $\ln(Y_{\ell t})$ before and after digital adoption at each theater, while averaging out a common time trend. This specification further averages out time-invariant theater-specific confounds such as theater size and quality and local demand characteristics. Fourth, with year-week and theater-*year* fixed effects, the *within* estimator focuses on the variation at each theater only using the data from the year of digital adoption. In other words, this estimator relies on a short window to compare outcomes before and after digital adoption, whereas the previous within estimator relies on a longer window. This specification further controls for any "slow-moving" changes in all theater-year specific unobservables, such as the exact design and layout of a particular theater, local consumer movie preferences and competitive landscape.

Under certain conditions, the estimates obtained using Equation 4.1, with year-week and theater-year fixed effects, may be interpreted as the causal effect of digital adoption. We discuss these conditions through the lens of two distinct identifying assumptions: a conditional independence assumption and a parallel trends assumption. For each assumption, we discuss its requirements and assess its credibility.

4.2.2. Identification: a conditional independence assumption

The classical potential outcome framework has established that the causal effect of a treatment can be measured when treatment assignment and treatment outcomes are independent conditional on observables (e.g., Roy, 1951; Rubin, 1974). This is often referred to as the conditional independence assumption. In order for the assumption to hold in our context, the timing of adoption should be independent of outcomes conditional on the two fixed effects (i.e., $\text{Digital}_{\ell t} \perp \varepsilon_{\ell t} \mid \alpha_{\ell,\tilde{t}}, \tau_t$). Next we discuss the credibility of this assumption in our context by considering three potential threats.

First, theaters' weekly assortment decision might be tied closely to fluctuations in the supply of movies and/or changes in the average moviegoer's preferences over time. This can introduce a systematic bias in our estimate because we always take a difference between time periods. The year-week fixed effect τ_t, addresses this concern by capturing common time-varying variation. Second, there might be time-invariant theater characteristics that are observed by theater-owners but not by us. For instance, theater owners are likely to prioritize the rollout of new technology based on expected return. Theater fixed effects absorb any time-invariant factors such as this. As previously discussed, we further allow the theater fixed effects to vary across years to capture any slow-moving changes in all theater-specific unobservables.[1] As shown in Tables 4.1 and 4.3, there are substantial changes in the magnitude of estimates with the inclusion of these fixed effects, which suggest that the fixed effects control for such confounds.

Lastly, there could be unobserved theater-*week*-specific shocks that affect both digital conversion and assortment decisions. The shocks might be even serially correlated. In this case, there is no means of bypassing the problem with our data with the specification in Equation 4.1. However, converting a screen to digital is a time-consuming process,

[1]Developing an understanding of the data-generating process, i.e., how did theaters decide to adopt, increased our confidence in our analysis. We obtained such an understanding through a conversation with an industry expert with over 30 years of cinema industry experience and who played a significant role in the transition from film to digital cinema. In particular, according to the expert, theaters implemented relatively simple conversion decisions and faced some supply-side restrictions in the availability of digital projectors. Theaters were unable to exert significant control on the precise timing of specific screen conversions. This conversation informed our empirical analysis of theaters' conversion decisions (see Section **??**). Consistent with the expert's explanations, we find that a significant portion of the variation in theaters' conversion decisions can be explained using relatively simple controls.

requiring deciding, planning, and implementing. If the process takes longer than several weeks, any unobserved transient theater-week-specific shocks would less likely to pose a threat to our identifying assumption. This is more likely true for chain-theaters, which represent a large portion of our data, because the rollout plan is made at the enterprise-level, and factors influencing weekly-level variety are less likely to affect the decision process. Note that our argument is analogous to the discussion in Rossi (2014) on why mass promotions are unlikely to generate price endogeneity in household scanner data.

4.2.3. Identification: a parallel trends assumption

Equation 4.1 can be viewed as a difference-in-differences (DID) specification where the timing of treatment varies across a unit-of-analysis (a theater). One DID cohort compares the set of units treated in the same period (the treatment group) relative to other units that have yet to be treated or have already treated (the control group). Thus, the data represent a sequence of DID cohorts. The interpretation of β in Equation 4.1 corresponds to a weighted average of treatment effects across all DID cohorts.[2] This type of DID estimator requires stronger identification assumptions than a typical DID based on a single cohort with one treatment event. While the specific set of assumptions differ across studies, the key identifying assumption is that outcomes follow parallel trends between every treatment-control group pair (e.g., Goodman-Bacon, 2018; Callaway and

[2]Recent studies have characterized the properties of this estimator (e.g., Abraham and Sun, 2018; Athey and Imbens, 2018; Goodman-Bacon, 2018; Han, 2018; Hull, 2018; Strezhnev, 2018; Callaway and Sant'Anna, 2019; de Chaisemartin and d'Haultfoeuille, 2019). The estimator is referred to as a DID with multiple time periods (Callaway and Sant'Anna, 2019), a two-way fixed effects DID (Goodman-Bacon, 2018) or a staggered adoption design (Athey and Imbens, 2018).

Sant'Anna, 2019). Under this pairwise parallel trends assumption, the conditional independence assumption is unnecessary. For instance, Athey and Imbens (2018) argue that a random adoption assumption with exclusion restrictions implies pairwise parallel trends. In that sense, the pairwise parallel trends assumption can be viewed as weaker than the conditional independence assumption.

Although formally testing the parallel trends assumption is infeasible, we can attempt to assess its credibility. To this end, we compute the pairwise correlation for each treated theater and its control theaters (i.e., all other theaters that had not adopted at the time the treated theater adopted) with respect to product variety or supply concentration in pre-treatment periods (see Figure 4.6 in the Online Appendix for a visual illustration). The median correlation across treated theaters is 0.774 for product variety and 0.747 for supply concentration, which suggests that the pre-trends are, on average, highly correlated between treated and control theaters. Later, we check the robustness of our results to the selection of sample theaters that account for the pairwise parallel trend assumption.

A caveat in considering Equation 4.1 as a DID estimator requires further discussion. As discussed in prior studies (e.g., Goodman-Bacon, 2018; Callaway and Sant'Anna, 2019), a negative weighting problem can occur when treatment effects are not stable over time within units. This arises due to early treated units serving as controls for later treated units, and the negative weighting can introduce a bias in the weighted average across DID cohorts. The theater-year fixed effects in Equation 4.1 partially address the concern because we restrict the comparison within the year a digital adoption actually occurred (a short difference), while excluding the preceding and subsequent years in the difference (a long difference). In Section 4.4, we present a robustness check using an event study specification in which we compare the changes in assortment decisions in narrower windows (e.g., 1 week).

4.2.4. Discussion

By leveraging the panel structure of our data, we formulated a two-way fixed effects regression equation in Equation 4.1. The model allows us to measure the differences in theaters' assortment decisions before and after digital adoption, while controlling for various confounds that are either time specific or theater-year specific. Nonetheless, the observational nature of our data suggests the potential existence of other uncontrollable confounds (e.g., unobservable theater-week specific shocks). Such observations motivate us to carefully layout two identification assumptions under which the estimate can be interpreted as causal. First, we discussed how one could view the two sets of fixed effects in Equation 4.1 may be sufficient to treat the adoption timing as quasi-random, which leads to causal interpretation of β. Second, we demonstrated that our specification can be viewed as a generalized form of DID estimator and discussed required identification assumptions. Overall, we believe our estimate of β measures meaningful changes in theaters' assortment decisions, which can be interpreted as causal if one is willing to buy either of the identifying assumptions or, at least, as correlational with a sensible control of immediate confounds.

4.3. Estimation Results

In this section, we report the estimation results of Equation 4.1 for product variety in Section 4.3.1 and for supply concentration in Section 4.3.2. In each subsection, we first show how digital adoption is associated with each of the assortment decisions in the entire sample (i.e., all theaters in 2006-16). Guided by institutional knowledge and our own data exploration, we assess the impact of digitization using two partitions of the data: by time period and by theater-size. For time period, we split the sample into an early (2006-10) and a late period (2011-16) to account for changes in the availability of movies in a digital format. The data shows that 2011 is the first year when all the movies released in the market were digitally available (see Figure 2.3 in Section 2.3.3).

For theater-size, we split theaters into three groups based on the number of screens: small (1-4 screens), medium (5-7 screens), and large (8+ screens). The cutoff values are the 33% and 66% percentile values in the distribution of theater size. This grouping is based on our intuition that the effects of digitization may differ across theaters with different sizes. As an example, consider a single-screen theater and a multiplex with eight screens. Suppose both theaters showed one movie per screen with the 35mm film technology. Digitization can provide such theaters with enhanced flexibility in scheduling, but concentration can never go up at the single-screen theater because it had already been providing the maximum level of concentration.

4.3.1. Results on product variety

The upper panel of Table 4.1 reports the estimation results using the entire sample. There are four columns with different specifications of fixed effects. The first column is for the pooled regression where no fixed effect is included. The estimate reports that theaters fully equipped with digital screens showed 17.9% more movies than non-digital theaters during our observation period. In the second and the subsequent columns we include the week fixed effect. As reported in column (2), the effect size substantially decreases to 2.2% when we added time fixed effect and it is no longer statistically significant. The estimate even becomes negative with theater fixed effect or with theater-year fixed effects as reported in columns (3) and (4), respectively. None of the two estimates are statistically significant.

Partitioning the data into two time periods provides an explanation for the null effects we find from the entire sample. In the bottom panel of Table 4.1, we report the effects of digital adoption on product variety separately for an early period (2006-10) and a late period (2011-16). We find that digitization is decreased (increased) product variety in the early (late) period, which provides an explanation for the null effect we find from the entire sample. The question is why the effects of digitization on product variety different across the two time periods. As discussed, the two time periods represent different levels of movie availability in digital format. In the early period, not all movies were available in digital, whereas all movies were available in digital in the late period. More importantly, the rate at which movies become available in digital was correlated with popularity. As shown in Figure 2.3, popular movies went to digital first. For instance, 35% of the most popular movies were available in digital in 2006. The number went up to 100% by 2010. During the same time period, the digital availability went up from 6% in 2006 to 65% in 2010 for the least popular movies. This observation leads us to conclude that early adopters might have had difficulties in acquiring niche digital movies to show, which is

Table 4.1: Estimation results: product variety by time period

	DV: product variety (in log, at theater-week level)			
	(1) Pooled	(2) Between	(3) Within	(4) Within
	All data			
Digital	0.179***	0.022	−0.031	−0.011
	(0.026)	(0.062)	(0.037)	(0.034)
R^2	0.023	0.139	0.806	0.857
Adj. R^2	0.023	0.136	0.804	0.853
	By time period			
Digital: 2006-10	−0.078	−0.151**	−0.123***	−0.055*
	(0.061)	(0.076)	(0.034)	(0.030)
Digital: 2011-16	0.378***	0.344***	0.150***	0.091***
	(0.074)	(0.083)	(0.026)	(0.016)
R^2	0.039	0.149	0.808	0.857
Adj. R^2	0.039	0.146	0.807	0.853
Year-week FE	No	Yes	Yes	Yes
Theater FE	No	No	Yes	No
Theater-Year FE	No	No	No	Yes
N	157,083	157,083	157,083	157,083

Note: Columns report estimated β in Equation 4.1 for product variety. Standard errors are clustered by theater chains and are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

likely the primary source of an increase in product variety. In other words, Table 4.1 suggests that *technology compatibility* issue played a moderating role between digitization and product variety in the early period.

In terms of magnitude, the inclusion of fixed effects generally reduces the effect size. Focusing on the late period, the pooled specification in column (1) reports a 37.8% more product variety with digital adoption, which slightly decreases to 34.4% with the between specification in column (2). Including theater fixed effects reduces the effect size from 34.4% in column (2) to 15.0% in column (3). The effect further decreases to 9.1% when we move from a long difference (within theater) in column (3) to a short difference (within theater-year) in column (4). We view these patterns as evidence that there are time- and theater-(year)-specific confounds, which are captured by the two fixed effects in Equation 4.1.

Table 4.2 provides a further breakdown of the results by theater-size. For simplicity, we only report the results with week- and theater-year fixed effects (column (4) in Table 4.1). Two interesting patterns are found. First, digital adoption increases product variety at small theaters (screens 1-4) even in the early period, which suggests that compatibility issue only affected larger theaters. Second, in the late period, the effect of digital adoption on product variety is the smallest at large theaters (screens 8+). One explanation for the finding is that the product variety at large theaters tend to be sufficiently high, so digital adoption has relatively little effect.

Collectively, the results in Tables 4.1 and 4.2 suggest the following. First, digitization generally increases product variety unless the issue of technology compatibility is present. Second, a limited availability of movies in a compatible format can have a negative impact on product variety for early adopters. Third, the increase in product variety is largely driven by small and medium-sized theaters bringing more niche movies to screens. This indicates that the effects of digitization are moderated by *capacity constraints*, faced by theaters of different sizes.

Table 4.2: Estimation results: product variety by theater-size

	DV: product variety (in log, at theater-week level)		
	(1) Screens: 1-4	(2) Screens: 5-8	(3) Screens: 8+
Digital: 2006-10	0.037^{**}	-0.112^{***}	-0.092^{***}
	(0.015)	(0.027)	(0.018)
Digital: 2011-16	0.077^{***}	0.118^{*}	0.068^{***}
	(0.023)	(0.064)	(0.018)
Year-week FE	Yes	Yes	Yes
Theater-Year FE	Yes	Yes	Yes
N	32,970	51,351	72,762
R^2	0.759	0.745	0.794
Adj. R^2	0.749	0.737	0.788

Note: Columns report estimated β in Equation 4.1 for product variety. Standard errors are clustered by theater chains and are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

4.3.2. Results on supply concentration

Tables 4.3 and 4.4 report the estimation results on supply concentration, following the same structure as we did for product variety. In the upper panel of Table 4.3, we find that digital adoption is positively associated with supply concentration. The degree of association is as high as 20.4% with statistical significance in column (1) and is as low as 3.3% with no statistical significance in column (4).

When we partition the data in the bottom panel of Table 4.3, the associations remain positive with even greater statistical precision in the early period. For instance, the within estimators in column (3) and (4) reports a 11.1% and a 5.2% increase in concentration with digitization, respectively. The standard errors are also smaller than the results from the entire period. These patterns make intuitive sense. With the issue of technology compatibility, the impact of digitization on product variety was limited in the early period;

Table 4.3: Estimation results: supply concentration by time period

	DV: supply concentration (in log, at theater-week level)			
	(1) Pooled	(2) Between	(3) Within	(4) Within
	All data			
Digital	0.204***	0.135***	0.054*	0.033
	(0.024)	(0.040)	(0.031)	(0.032)
R^2	0.046	0.342	0.728	0.783
Adj. R^2	0.046	0.339	0.726	0.778
	By time period			
Digital: 2006-10	0.199***	0.233***	0.111***	0.052*
	(0.047)	(0.055)	(0.024)	(0.030)
Digital: 2011-16	0.136	−0.048	−0.057**	−0.012
	(0.092)	(0.075)	(0.028)	(0.036)
R^2	0.047	0.347	0.729	0.783
Adj. R^2	0.047	0.344	0.727	0.778
Year-week FE	No	Yes	Yes	Yes
Theater FE	No	No	Yes	No
Theater-Year FE	No	No	No	Yes
N	157,083	157,083	157,083	157,083

Note: Columns report estimated β in Equation 4.1 for supply concentration. Standard errors are clustered by theater chains and are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

popular movies were relatively free from the compatibility issue; so digital adoption could disproportionately benefit theaters to increase the screen supply to popular movies in the early periods.

However, the results for the late period are somewhat puzzling. The estimates are neither as statistically significant as what we see in the early period nor consistent across the four specifications. A breakdown of the results by theater-size provides an answer to

Table 4.4: Estimation results: supply concentration by theater-size

	DV: supply concentration (in log, at theater-week level)		
	(1) Screens: 1-4	(2) Screens: 5-8	(3) Screens: 8+
Digital: 2006-10	-0.011	0.103***	0.105***
	(0.024)	(0.007)	(0.023)
Digital: 2011-16	-0.059**	0.021	0.029**
	(0.023)	(0.049)	(0.012)
Year-week FE	Yes	Yes	Yes
Theater-Year FE	Yes	Yes	Yes
N	32,970	51,351	72,762
R^2	0.702	0.763	0.802
Adj. R^2	0.689	0.755	0.796

Note: Columns report estimated β in Equation 4.1 for supply concentration. Standard errors are clustered by theater chains and are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

the puzzle. We report the results from within estimator with short difference in Table 4.4. We find that the effect of digital adoption on supply concentration is consistently negative across two time periods at small theaters (screens 1-4), whereas the effects are generally positive for larger theaters (screens 5-7 or 8+). For larger theaters, the effects are greater in the early period, which is consistent with the compatibility story. This explains the net effect across all sizes of theaters being noisy as we see in the late period in Table 4.3.

Overall, the results in Tables 4.3 and 4.4 suggest the followings. First, digitization is positively associated with supply concentration at medium-sized and large theaters, which supply most of the screens in the market in recent years. Second, the effect of digitization on supply concentration can be negative at small theaters. Together, these results once again suggest the moderating role of capacity constraints.

4.4. Robustness

In this section, we demonstrate the robustness of our results using two different estimators (an event-study analysis and a natural experiment), a different outcome measure (an alternative measure of supply concentration) and a restriction on the estimating sample (parallel trending theaters).

4.4.1. Event-study specification

As a robustness check, we employ a different identification strategy, an event-study specification. Here, we compare the assortment decisions in the pre- and post-adoption period in a series of narrower time windows. Changing the time window can be viewed as a relaxation of the common trend assumption. Based on our discussions with an industry expert, supply-side restrictions on the availability of digital equipment make it unlikely that a theater could time a screen's conversion to coincide with events within such narrow windows. However, an obvious downside of event-study estimator is the lack of control theaters, which can be more vulnerable to unobserved theater-week specific shocks than the DID estimator. We first replicate the results in the previous section and report the results in Table 4.5. For product variety, we report the results by time periods, whereas the results are shown by theater-size for supply concentration. For the adoption of is first digital screen at each theater, we use the five preceding weeks as the pre-adoption period and one to five weeks as the post-adoption period. That is, we only widen the window in one direction, which allows us to learn how the effect behaves at different periods after adoption. We find that the effects are consistent with what we find in the previous section in terms of its directions across different partitions of the data.

Table 4.5: Event-study specification estimation results

	(1) 1 week	(2) 2 weeks	(3) 3 weeks	(4) 4 weeks	(5) 5 weeks
	DV: Product Variety (in log, at theater-week level)				
$\hat{\beta}^{2006-10}$	−0.036	−0.015*	−0.009	−0.007	−0.013
SE	(0.028)	(0.008)	(0.013)	(0.009)	(0.012)
$\hat{\beta}^{2011-16}$	0.058	0.059**	0.082***	0.122***	0.124***
SE	(0.060)	(0.030)	(0.021)	(0.019)	(0.021)
R^2	0.857	0.846	0.841	0.832	0.820
Adj. R^2	0.799	0.801	0.804	0.800	0.791
	DV: Supply Concentration (in log, at theater-week level)				
$\hat{\beta}^{1-4}$	−0.010	−0.010**	−0.019***	−0.034**	−0.050***
SE	(0.018)	(0.005)	(0.007)	(0.014)	(0.007)
$\hat{\beta}^{5-7}$	0.183***	0.139***	0.087**	0.082**	0.081*
SE	(0.041)	(0.045)	(0.042)	(0.040)	(0.044)
$\hat{\beta}^{8+}$	0.157***	0.101*	0.076	0.089*	0.089**
SE	(0.060)	(0.055)	(0.048)	(0.046)	(0.042)
R^2	0.755	0.738	0.726	0.699	0.680
Adj. R^2	0.656	0.662	0.663	0.642	0.629
Theater FE	Yes	Yes	Yes	Yes	Yes
N	1,683	2,155	2,625	3,093	3,562

Note: The table reports the results of event-study specification at theater-level. The estimates reports the mean difference between pre- and post-adoption in product variety and supply concentration across treated theaters. Standard errors are clustered by theater chains; *p<0.1; **p<0.05; ***p<0.01.

The event-study specification also allows us to exploit the within-theater, across-screen variation. That is, we can compare the change in product variety in a short window around the week of digital adoption at each screen.[3] The upper panel of Table 4.6 reports the

[3]Note that this approach is not applicable to supply concentration as it is measured at theater-level.

Table 4.6: Event-study at screen-level estimation results: product variety

	(1) 1 week	(2) 2 weeks	(3) 3 weeks	(4) 4 weeks	(5) 5 weeks
	DV: Product Variety (at screen-level)				
$\hat{\beta}^{2011-16}$	0.175***	0.181***	0.180***	0.203***	0.214***
SE*	(0.034)	(0.028)	(0.025)	(0.024)	(0.022)
$\Delta\%^\dagger$	8.64%	8.89%	8.86%	9.99%	10.55%
R^2	0.456	0.426	0.411	0.408	0.403
Adj. R^2	0.328	0.316	0.315	0.325	0.329
	DV: Number of Switches (at screen-level)				
$\hat{\beta}^{2011-16}$	1.935***	2.215***	2.337***	2.570***	2.685***
SE	(0.463)	(0.378)	(0.336)	(0.331)	(0.316)
$\Delta\%$	44.59%	51.05%	53.87%	59.22%	61.87%
R^2	0.452	0.427	0.406	0.399	0.386
Adj. R^2	0.323	0.317	0.310	0.315	0.310
Theater-Screen FE	Yes	Yes	Yes	Yes	Yes
N	2,646	3,141	3,628	4,118	4,607

*SE: clustered standard errors by theater; *p<0.1; **p<0.05; ***p<0.01.
$^\dagger\Delta\%$: magnitude of estimate in terms of the percentage change from the baseline product variety.

estimation results for the adoptions made in 2011-16. We find the differences in product variety between pre- and post-adoption are statistically significant and the effect size is about 8.6-10.6%. The estimates are robust against the choice of window size, from one week to five weeks after adoption. The results suggest that the effect of digitization is *on impact*: theaters reacted immediately to the new technology.

In the lower panel of Table 4.6, we report another result using the same empirical strategy. We construct an outcome variable, Switch, which measures per screen-week frequency of switches across movies within a screen-day. That is, if a theater shows movie

A in a screen only during the daytime slots and switches to movie B for the evening slots throughout a week, then Switch = 7. We compare the changes in Switch between pre- and post-adoption. We find more switches made by theaters in screens with digital projectors. The effect size tends to greater than that for product variety and it increases in window size. This suggests that digital adoption allows movie theaters flexibly switch between movies with digital projectors, even without increasing product variety. Collectively, Table 4.6 provides us a reassurance about the impact of digitization on product variety as we identify the effect using a different empirical strategy.

4.4.2. A natural experiment

An ideal way to establish the causality between digitization and supply concentration is to conduct an experiment where the top movie is disseminated to two similar groups of theaters, one in 35mm film and another in digital. Our natural experiment provides a setting that is similar in spirit to the ideal experiment.

The natural experiment is generated by the delayed VPF agreement between a subset of Hollywood studios and local theater-chains, as illustrated in Figure 4.2. Two major South Korean theater chains implemented the VPF model to roll out digital screens for their own theater-locations in 2006. However, the VPF agreements between the two chains and two Hollywood studios (Warner Bros Korea and Sony Pictures Releasing Buena Vista Film) were not made immediately.[4] This creates a natural experiment where the same movies were disseminated in different formats (reel film and digital file) to theaters with

[4] It is less likely that this is a result of distributors prioritizing a certain type of chains over another in supplying digital movies. The two Korean chains were the top and second-to-top in terms of market share.

Figure 4.2: A difference-in-differences design using delayed VPF agreement

	Treated theaters (CGV-owned, LOTTE-owned)	**Control theaters** (CGV-franchise, LOTTE-franchise, Other chains)
Target movies (Distributed by Warner Bros, Sony Pictures)	Film distribution due to delayed VPF agreement (A)	Digital distribution (B)
Other movies (Distributed by other studios)	Digital distribution (C)	Digital distribution (D)

Note: The treatment effect of interest is measured by (A-B)-(C-D).

digital-enabled screens. In particular, the Warner Bros and Sony Pictures Releasing Buena Vista Film movies were distributed only in film to the two theater chains' own locations until January 2012 and February 2010, respectively. Other theaters, which includes the franchise locations of the two chains, were supplied with digital files for all movies.[5]

The case of *Harry Potter and Deathly Hallows: Part II* (2011) characterizes the natural experiment well. The movie was distributed by Warner Brothers and released in July 13, 2011 in the South Korean market. At the time of release, the VPF agreement between Warner Brothers and the two Korean theater chains had not yet been made. As a result, the movie was disseminated in physical reel film to the theaters operated directly by the

[5]The financing model was only applicable to company-owned theater-locations, not to franchise locations.

two chains (and to theaters without digital screens). For the remaining theaters, the movie was shown on digital screens. The movie's opening week screen share was about 32.8% at the theaters that showed the movie in digital. In the same week, theaters that showed the same movie using reel film due to the delayed VPF agreement allocated 30.0% of their screen slots to it.

We test whether the difference between the two groups of theaters is statistically significant and generalizable to other movies that went through a similar dissemination process. We construct a 2x2 difference-in-differences type research design, where there are two types of theater-locations (with vs. without VPF agreements with the two studios) and two types of movies (distributed by the two studios vs. by other studios). Then we assess the impact of digital distribution on supply concentration by estimating the following equation:

$$\ln(\text{Concentration}_{j\ell}) = \beta \cdot \text{Treated}_\ell \times \text{Target}_j + \mu_j + \nu_\ell + \varepsilon_{j\ell}. \tag{4.2}$$

Here, $\text{Concentration}_{j\ell}$ is the opening week slot share of movie j at theater-location ℓ. Treated_ℓ is an indicator variable, which takes the value of one if theater-location ℓ is among the theaters that did not have VPF agreements with the two studios, or zero otherwise. Target_j is also an indicator variable that equals one if movie j is distributed by the two studios, or zero otherwise. μ_j and ν_ℓ are a vector of movie fixed effects and theater-location fixed effects, respectively. The two fixed effects capture any effects that are specific to movies and theater-locations. Our main parameter of interest is β, which measures the impact of disseminating and showing movies in non-digital format on supply concentration. To be consistent with what we report in the previous section, the sign of $\hat{\beta}$

should be negative. The magnitude of $\hat{\beta}$ represents the average percentage-point increase in supply concentration for the theaters in the estimating sample.

The identifying assumption is analogous to the common trend assumption of any difference-in-differences design: the average difference in the supply concentration of the treated and control theaters would be the same if the target movies were disseminated to all the theaters in digital. Validating the assumption requires the split of treated and control groups to be orthogonal to the outcome variable. We claim that the selection of theaters that experienced a delay in VPF agreement is conditionally independent of the concentration measure and therefore, is a valid instrument. Similar to the case of Equation 4.1, any effect from time-invariant movie characteristics and theater characteristics are absorbed by the two fixed effects. Any time-specific shocks that are common to all theaters are less of a concern because we compare the two groups of theaters for the same time period for each movie.

For estimation, we use the movies that (i) were released during our observation period, (ii) were shown in film at treatment theaters and in digital at control theaters, and (iii) had the highest screen share among movies released on the same day. Of the 288 movies, 18 movies were distributed by the two studios before their VPF agreements were made. We restricted our attention to multiplex theaters with at least five screens, and drop the theater-movie observations in which a movie was shown in both film and digital formats. Estimating sample does not include theaters without digital screening capabilities. Treated theaters are relatively larger than control theaters in terms of screen and seat numbers (see Table 4.9 in Appendix). Nonetheless, the trends in supply concentration

Table 4.7: Estimation results of the natural experiment

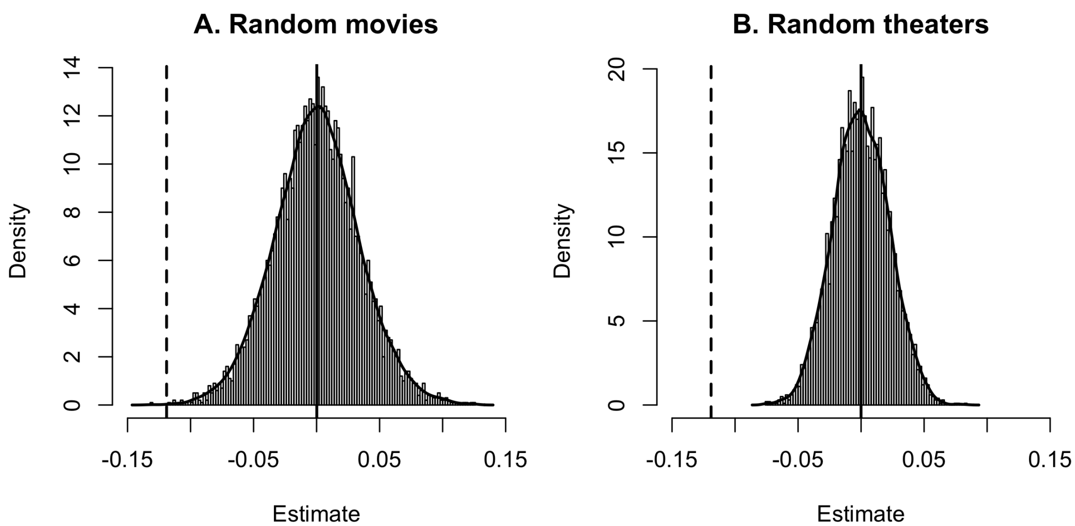
	DV: Supply concentration (at theater-level)	
	(1) w/ control movies	(2) (2) w/o control movies
Treated × Target		
$\hat{\beta}^{2011-16}$	-0.119^{***}	
SE	(0.028)	
Treated		
$\hat{\beta}^{2011-16}$		-0.126^{***}
SE		(0.031)
Movie FE	Yes	Yes
Theater FE	Yes	No
N	35,357	1,230
R^2	0.802	0.678
Adj. R^2	0.799	0.673

Note: Columns report estimated β in Equation 4.2. Standard errors are clustered by theaters; *p<0.1; **p<0.05; ***p<0.01.

at the two sets of theaters appear to be parallel after VPF contracts are in effect at all theaters (see Figure 4.7 in Appendix).

Table 4.7 reports the estimation results of Equation 4.2. The parameter estimate reported in column (1) shows that the treated theaters allocated 11.9% fewer showings for the target movies than the theaters in the control group. This is approximately an 0.025 decrease from the baseline supply concentration of 0.21 of the control theaters for target movies. In column (2) we report the parameter estimate without having control movies, based on the difference in outcomes between treated and non-treated theaters only for target movies. The estimate is slightly greater (in absolute value) than that in

Figure 4.3: Distribution of placebo effects on supply concentration



Note: Figures report the kernel density for the distribution of 5,000 placebo estimates using randomly selected movie titles (left) or theaters (right). In each panel, the black solid line is a kernel density for the distribution of placebo estimates of the effect of digitization on supply concentration. The solid vertical lines are the mean of each distribution, where the dashed line is the true estimate ($-.035$) from column (3) in Table 4.7.

column (1), which demonstrates the importance of controlling for the average concentration level between two groups using the difference-in-differences approach. In sum, Table 4.7 suggests that digitization supply movie concentration in the sample theaters.

As a robustness check for our findings regarding supply concentration in Table 4.7, we conduct two different placebo tests. First, we randomly draw a set of movies and assign them as target movies and estimate Equation 4.2, while fixing the split between treated and control theater-location. Second, while fixing the target movies, we randomly assign theater-locations to the treated or control group and estimate the same equation. In each case, we draw the same number of true target or treated theaters. We repeat the procedure 5,000 times. Figure 4.3 shows the distribution of estimates. The graph shows that an estimate of $-.033$ from Table 4.7, Equation 4.2 is extremely unlikely to have arisen by chance. The mean of these placebo test models is indistinguishable from zero and our true estimate lies in the tail of the distributions.

4.4.3. Alternative measure of supply concentration

Suppose the top movie was shown in 1.5 screens (e.g., one screen for all day and another for just morning) in the pre-digitization era, and now it is shown in 2 screens. Our definition of supply concentration would report an increase supply concentration from 1.5 to 2. However, one could argue that this is not a benefit of digitization because the theater simply showed the same movie more in the same screen in the same day. To address the concern, we estimate Equation 4.1 using a different measure of supply concentration: screen share. We define screen share as the maximum number of screens allotted to a movie divided by the total number of screens at a theater-location. The logic behind the analysis is that this definition treats 1.5 and 2 screens equally, as both require two screens. It only increases if a move is shown on an additional screen or more. We report the results in Table 4.11 in Appendix. The results remain qualitatively unchanged to what we report in the previous section. This suggests that the increase in supply concentration is accompanied with theaters allotting new screens to the top movies rather than more showings in the same screens.

4.4.4. Parallel trending theaters

One of our identification assumptions we discussed in Section 4.2 is pairwise parallel trends across treated and control theaters. As a robustness check, we re-estimate Equation 4.1 by excluding the treated theaters with the pairwise correlation with its corresponding control theaters in the pre-adoption period is less than the sample median. The sample median indicates the median value of the pairwise correlations across all treated theaters. We find the results are qualitatively unchanged (see Table 4.12 and 4.13 in Appendix).

4.5. Testing the Moderating Role of Demand

What we have demonstrated in the previous section is that digitization, overall, increases both product variety and supply concentration. We also find that the effects are moderated by two supply-side factors: technology compatibility and capacity constraints. One may think the effects are not surprising since digital technology allows theaters to increase capacity utilization by reducing costs. In this section, we demonstrate that the effects of digitization are more subtle and also moderated by demand. To this end, we test the model predictions from Chapter 3 by leveraging natural variation in the overall demand for movies across weekdays and weekends.

4.5.1. Summary of model predictions

In Chapter 3, we model a profit-maximizing theater deciding the optimal allocation of screens to movies by solving an optimization problem. The problem's objective function consists of linearly separable revenue and cost functions, both of which depend on the theater's choice of screen allocation. A key intuition in our theoretical model is that supply is lumpy, or discrete, due to the costs associated with screening movies in the 35mm film format. But digitization drives the costs to zero, which allows the theater to serve the actual demand level of movies by supplying any number of screens.

The model predicts that the effects of digitization on product variety and supply concentration are directionally different, depending on the relative demand for the top movies to the supply of screens. If there is a *shortage* in the supply of screens for the top movie (i.e., demand for the movie was under-served), then digitization can allow theaters to serve the residual demand for the movie, which increases supply concentration and potentially decreases product variety. On the other hand, if there is an *excess* supply of screens for the top movie (i.e., demand for the movie was over-served), then digitization can allow theaters to utilize the excess supply for other movies, which decreases supply concentration and potentially increases product variety. In sum, our theoretical model produces the following predictions:

Prediction 1: If there is a shortage in the supply of screens for the top movie,

(P1a) digitization increases movie concentration in theaters, and

(P1b) digitization weakly decreases the variety of movies offered by theaters.

Prediction 2: If there is an excess supply of screens for the top movie,

(P2a) digitization decreases movie concentration in theaters, and

(P2b) digitization weakly increases the variety of movies offered by theaters.

4.5.2. A test for the moderating role of demand

We test the moderating role of relative demand by investigating the heterogeneous impact of digitization across different day parts of the week (e.g., weekdays vs weekend). Our choice of day parts as a test is based on a simple intuition. Moviegoing is a time-consuming leisure activity, and the volume and composition of potential consumers naturally varies across different parts of the week. Hence, we can reasonably expect that there is more demand for the movies on weekends than weekdays as more consumers have more leisure time to possibly allocate towards such an activity.[6]

This observation leads us to assume that, in the era of 35mm film, theaters looked to their expected demand on weekend evenings to inform their film inventory decisions. This implies that the number of film copies a theater would order for the top movies is closer to the level that can serve the peak demand of weekend evenings compared to that of weekdays. As a result of this, during the weekdays theaters will hold in inventory more copies of the top movies than they would otherwise prefer, such that the movies are likely in excess supply on weekdays. In addition, if a theater plans for both weekdays and weekend by compromising between the two levels of demand, then it may not fully serve the peak-period demand for the top movies on weekend. Therefore, we treat weekdays as the case of excess supply, for which digitization is predicted to decrease supply concentration and increase product variety. Similarly, we treat weekend evenings as the case of a shortage in supply. In this case, digitization is predicted to increase supply concentration and decrease product variety.

4.5.3. Empirical specification

To test our predictions, we separately estimate the impact of digitization in different day parts of the week. First, we split a week into five mutually exclusive, collectively exhaustive day parts. The five day parts are (1) MTW daytime: Monday to Wednesday all before 5 PM, (2) MTW evening: Monday to Wednesday all after 5 PM, (3) Thursday-Friday:

[6]During our observation period, the average ticket sales on Friday, Saturday and Sunday is about 2.02 times higher than that of other weekdays.

all Thursday and Friday before 5 PM, (4) Weekend daytime: Saturday before 5PM and Sunday before 5 PM, and (5) Weekend evening: Friday to Sunday all after 5PM. Second, we focus on 2011-16 where all movies were available in digital and multiplex theaters (i.e., theaters with at least five screens). Third, for a given day part at a theater location, we construct the two dependent variables, product variety and supply concentration, as we did in the previous sections. Since the observation unit is a theater location rather than a screen, product variety is defined as the number of movie titles shown at each theater location in a day part.

Denote each dependent variable as $Y_{\ell dt}$, where ℓ stands for theater location, d for day parts, and t for week. We estimate the following regression:

$$\ln(Y_{\ell dt}) = \mu_{\ell\tilde{t}} + \tau_t + \delta_{\ell d} + \sum_d \beta_d \text{Digital}_{\ell t} + \varepsilon_{\ell dt}, \tag{4.3}$$

where $\mu_{\ell\tilde{t}}$ is theater-year fixed effects and τ_t is year-week fixed effects. The two sets of fixed effects control for theater-specific characteristics and time trend as similarly as in Equation 4.1. $\delta_{\ell d}$ is theater-day part fixed effect. $\text{Digital}_{\ell t}$ is the proportion of digital screens among all screens at theater ℓ in week t. The parameter of our interest is β_d, which captures the effect of digital showings on the two dependent variables.

4.5.4. Estimation results

Table 4.8 reports the estimation results of Equation 4.3. While the effects of digitization varies across day parts in both direction and magnitude, we focus on the first and the last day parts: MTW daytime and Weekend evening. For the two day parts, we can detect an asymmetric pattern in the effects of digital showing on the two dependent variables.

That is, digital adoption is positively related with product variety in MTW daytime slots (+19.0%), whereas the association is negative in the Weekend evening slot (−4.8%). On the other hand, digital showing is negatively associated with supply concentration in MTW daytime slots (−6.5%), but the association is positive in the Weekend evening slot (+8.4%).

The estimates are consistent with the predictions. Once a theater adopts digital projection technology, it shows the top movies fewer times than pre-adoption on weekdays, which supports P1a. The variety of movies offered by theaters on weekdays increased, which supports P1b. On weekend evening, theaters allot more screens to the top movies than pre-adoption, which supports P2a. The product variety on weekend evening has modestly decreased, which supports P2b.

4.5.5. Additional analyses

Two additional analyses with alternative moderators also suggest that the effects of digitization are likely to depend on the relative demand. First, the effect size on supply concentration is greater in peak-demand weeks in a year than regular weeks, whereas it is greater in regular weeks for product variety (see the first two columns of Table 4.14 in Appendix).[7] This suggests that there might have been more shortage in the supply of screens for the top movies during the period, compared to regular-demand period. Intuitively, this is likely the case given that studios tend to release their most commercially appealing movies during peak-demand periods. Second, the impact of digitization is more

[7]Following Yang and Kim (2014), we define a week as peak-demand period if it falls into one of the five high-demand periods for movies in the country: Lunar New Year, early May, summer vacation, Chuseok, and Christmas. Yang and Kim (2014) used the same dataset as in this dissertation.

Table 4.8: Estimation results across day parts

	Dependent Variable (in log, at theater-week-day part-level)	
	(1) Product Variety	(2) Supply Concentration
MTW daytime†		
$\hat{\beta}_d^{2011-16}$	0.190^{***}	-0.065^{***}
SE	(0.023)	(0.022)
MTW evening		
$\hat{\beta}_d^{2011-16}$	0.034	0.011
SE	(0.022)	(0.022)
Thursday-Friday		
$\hat{\beta}_d^{2011-16}$	0.139^{***}	-0.002
SE	(0.023)	(0.021)
Weekend daytime		
$\hat{\beta}_d^{2011-16}$	0.093^{***}	0.010
SE	(0.024)	(0.023)
Weekend evening		
$\hat{\beta}_d^{2011-16}$	-0.048^{**}	0.084^{***}
SE	(0.023)	(0.022)
Theater-Year FE	Yes	Yes
Week FE	Yes	Yes
Theater-Day part FE	Yes	Yes
N	372,099	372,099
R^2	0.696	0.721
Adj. R^2	0.693	0.719

Note: Columns report estimated β in Equation 4.3 for each of the two dependent variables. Standard errors are clustered by theaters; *p<0.1; **p<0.05; ***p<0.01.

†MTW daytime (Monday to Wednesday all before 5 PM), MTW evening (Monday to Wednesday all after 5 PM), Thursday-Friday (Thursday all day and Friday before 5 PM), Weekend daytime (Saturday before 5PM and Sunday before 5 PM), and Weekend evening (Friday to Sunday all after 5PM).

clearly pronounced in the capital of the country, Seoul, compared to other regions (see the last two columns of Table 4.14 in Appendix). This suggests that the top movies were less sufficiently supplied in the city than in other parts of the country. We conjecture that this might be due to the city's considerably high population density and theaters being relatively more differentiated—perhaps in reaction to more intense competition, lower travel costs, and/or more diverse tastes for movies.[8] This may also explain a greater effect size of digitization on product variety in Seoul.

4.6. Discussion

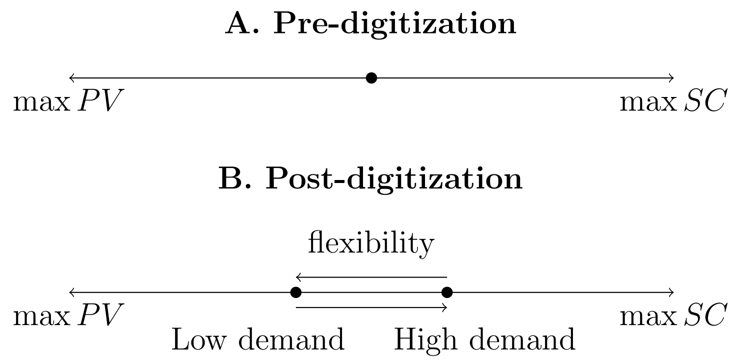
Overall, we find that, while its effects are heterogeneous, digitization increases both product variety and supply concentration. We also find that the effects are not only moderated by supply-side factors, such as technology compatibility and capacity constraints, but also by demand.

One way to view product variety and supply concentration is that the two metrics represent two different marketing strategies. A retailer facing shelf space constraints may offer greater variety of products by reducing the space allotted to popular products. If the retailer gives more space to top-selling brands or products, it may hurt the space allotted to niche products, and potentially decrease product variety.

To illustrate, a retailer' assortment decision can be represented as a point on a continuum where the two extremes represent either maximum product variety or maximum supply concentration. For instance, a theater can either show N different movies in N slots available or show just one move in all N slots. Then, a retailer' assortment decision

[8]About 42,000 people per square mile live in the city as of 2018. Compare this with 27,000 in NYC, 15,500 in Busan (the second most populous city after Seoul), and 1,313 in South Korea.

Figure 4.4: An illustration of the impact of digitization



can be represented as a point on a continuum where the two extremes represent either maximum product variety or maximum supply concentration. For instance, a theater can either show N different movies in N slots available ($\max PV$) or show just one move in all N slots ($\max SC$).

Suppose there is a point on the continuum that represents the market-level assortment decision in the era of pre-digitization (as illustrated in Figure 4.4:A). What this dissertation asks is how the point moves when the digitization-driven cost shock hits the market. In other words, does digitization push the point to greater product variety or to greater supply concentration? What we find in this chapter is that digitization can increase both product variety and supply concentration, suggesting that the point moves to both directions. Section 4.5 answers to the question of "how?" We show that digitization enhances flexibility in scheduling, which allows theaters to respond to demand by switching between the two strategies at lower costs (as illustrated in Figure 4.4:B). Specifically, theaters provide great variety when demand is low (weekdays), whereas they switch to greater concentration when demand is high (weekend evenings).

Alternative Explanations

Throughout the chapter, we provide evidence that digitization affects theaters' assortment decisions by reducing costs and elimination the constraint of physical films. Nonetheless, digitization is not the only explanation for the changes in product variety and supply concentration. Below we discuss factors that might have induced theaters to increase product variety and/or concentration, even without the reduction in distribution costs. We review each of such concerns and discuss (1) how our empirical strategies and findings in the previous sections address the concern and/or (2) if the data and institutional facts support the explanation. In sum, we conclude that the reduction in distribution costs has had its own impact on product variety and concentration, potentially in addition to the effects from other factors.

Increased supply of movies. One could argue that the increase in movie variety in theaters is due to more movies being supplied to the market.[9] This is a supply-side explanation for an increase in product variety ("the long-tail in production" by Aguiar and Waldfogel, 2018). We recognize that both supply- and demand-side side forces have likely play roles in increasing product variety. However, one of our analyses in Section 4.3 demonstrates that the changes in product variety can be seen even within quite narrow windows around digital adoption. Since the supply and demand for movies are unlikely to change drastically within a week or two, we argue that digitization has an effect on product variety by acting on the distribution stage.

[9] While we do not have data on *supplied* product variety as opposed to *scheduled* product variety, we can reasonably expect that there have been more movies supplied to the market since digitization has also reduced the costs for production and import/export of movies.

Quality of top-selling movies. If top-selling movies are relatively more appealing to moviegoers nowadays compared to the past, one could argue that this explains the increase in movie concentration. However, our empirical analyses directly address this concern in at least two ways. First, the use of time fixed effects (Section 4.3.1 and 4.3.2) controls for aggregate changes in movie demand. Second, we make a comparison while holding fixed the set of movies (Section 4.4.2).

Heterogeneous screen size. Consider a theater that has multiple screens and the number of seats in each screen differs across screens. Normally, we expect theaters to show the top movies in screens with many seats to capitalize on the movies' (expected) popularity. However, an alternative strategy might be allotting a movie more frequently to smaller screens. This allows the theater to offer more screen times to consumers while keeping fixed the total supply of seats for the movie. If this is the case, the previous result cannot be immediately interpreted as digitization increasing the concentration of supply. Instead, the interpretation should be that digitization helps theaters to compete more flexibly for the demand for top movies, which does not necessarily mean an increase in supply concentration.

To check the plausibility of this explanation, we make use of an auxiliary dataset collected from the same data source in February 2017. The dataset reports each screen's number of seats as of February 2017. We use the information to evaluate the relationship between screen supply and seat supply in December 2016. Note that we restrict our analysis to this relatively contiguous time period because of the possibility that theaters had added, split, swapped, or merged screens within a location in a more distant past.

The data does not seem to support the alternative explanation, as shown in Figure 4.8 in Appendix. The figure reports the relative screen size of movies (y-axis) by movie rank (x-axis) in 302 sample theaters with at least five screens in December 2016. Movie rank is determined by the number of showings (more showings lead to higher rank). Seat supply index ranges between 0 and 1, where the value of 1 for a movie indicates that the movie is only shown at the screen with maximum seat capacity in a given theater. Specifically, for each movie shown at a theater, we take average of the number of seats for all showings of the movie across screens with different seat numbers. We divide the per-showing seat number by the largest screen size of the theater so that this normalized average screen size ranges between 0 and 1. A number close to 1 indicates that the movie was shown mostly in the largest screen at a given theater. The points represent the mean value across the sample theaters and the error bars represent one standard deviation.

Figure 4.8 in Appendix shows that movies that are scheduled more frequently are also allotted to screens with more seats. This suggests that digitization is likely to increase supply concentration not only in terms of the number of showings, but also in terms of the total supply of seats.

Inter-temporal substitution of screen supply. Theaters typically show a movie over multiple weeks, which suggests an alternative explanation for the results on concentration. The intuition is as follows. Consider the two cases where a theater shows a movie either in two screens over four weeks or in four screens over two weeks. In both cases, the theater supplies the same amount of screen time (eight screens) to the movie. Likewise, digitization may help theaters to better concentrate their screen time to a movie in early weeks (e.g., week 1), while decreasing concentration in later weeks and/or shortening the run length of movies. If this is the case, although digitization can increase *weekly* concentration, the market-level concentration can remain unchanged across movies in the long run.

We check this possibility by leveraging the natural experiment in Section 4.4.2. Using the same dataset, we estimate the impact of digitization on two additional outcomes: movies' run length and total concentration. First, the run length of a movie is the number of weeks a movie was shown in theaters. If there is inter-temporal substitution of screen supply, the run length of movies should be shorter for theaters that showed digital movies. We find that there is no statistical difference between the two groups of theaters (see the first column of Table 4.10 in Appendix). Second, total concentration is the sum of weekly concentration over a movie's run. If digitization does not change the *total* screen time allotted to movies, we should obtain a null effect of digitization on this outcome. However, we find that total concentration is greater at the theaters that showed digital movies, which is inconsistent with inter-temporal substitution (the second column of Table 4.10 in Appendix).

Screen quota. Movie theaters in South Korea are required to allocate at least 73 screen-days to domestic films for all screens.[10] A screen-day is counted only if a screen shows only Korean movie(s) for the entire day. A concern can arise if this screen quota policy has somehow affected the changes in product variety and supply concentration. We argue that this is less of a concern for two reasons. First, the relatively high share of domestic movie revenue (between 42% and 64%) suggests that the screen quota (73 days or 20% of a year) is less likely to bind in theaters' programming decisions. Second, there was no

[10]See `https://en.wikipedia.org/wiki/Screen_quotas#In_South_Korea`.

change in the policy design for screen quotas during our observation period,[11] while our empirical analyses are based on comparisons between screens or theaters with different technologies. This implies that, even if there are some effects of the screen quotas that are baked into the data generating process for assortment decisions, such quota effects should be removed in the course of our analysis.

Nevertheless, digitization may have helped theaters to better react to demand while complying with the policy because switching between movies within a screen-day is cheaper with digital projection. For instance, theaters can now show two different domestic titles in a screen-day (as opposed to one per each) while better utilizing the remaining screens for other (foreign) movies. Such scenarios are consistent with the mechanism we highlight in this dissertation — digitization enhances flexibility in allocating screens to movies and movie theaters utilize the flexibility to better cope with different demand conditions.

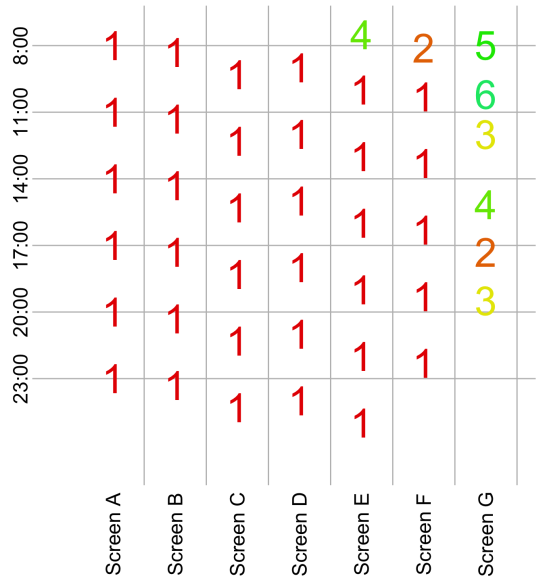
Vertical contracts. The implementation of the VPF (Virtual Print Fee) contract we discussed in Section 4.4.2 may have been confounded with the increase in product variety. Distributors subsidize theaters to screen their movies in digital, which could simply play a role of monetary incentives and increase product variety. To address this concern, we replicate the results on product variety in Tables 4.1, 4.5 and 4.6 using data on independent theaters (not the three major chain theaters) only. Because there was no VPF contracts signed between studios/distributors and independent theater owners, we should find no changes in product variety if monetary incentives explain all the variation. We report the results in Tables 4.15, 4.16 and 4.17 in Appendix. While we lose some statistical precision

[11] In 2006, the government reduced the minimum number of screening days from 146 to 73 days, which had been maintained during our observation period (2006-16).

to some extent due to the reduction in sample size, we find qualitatively the same results. The results suggest that the VPF played little or no effect on product variety via monetary incentives.

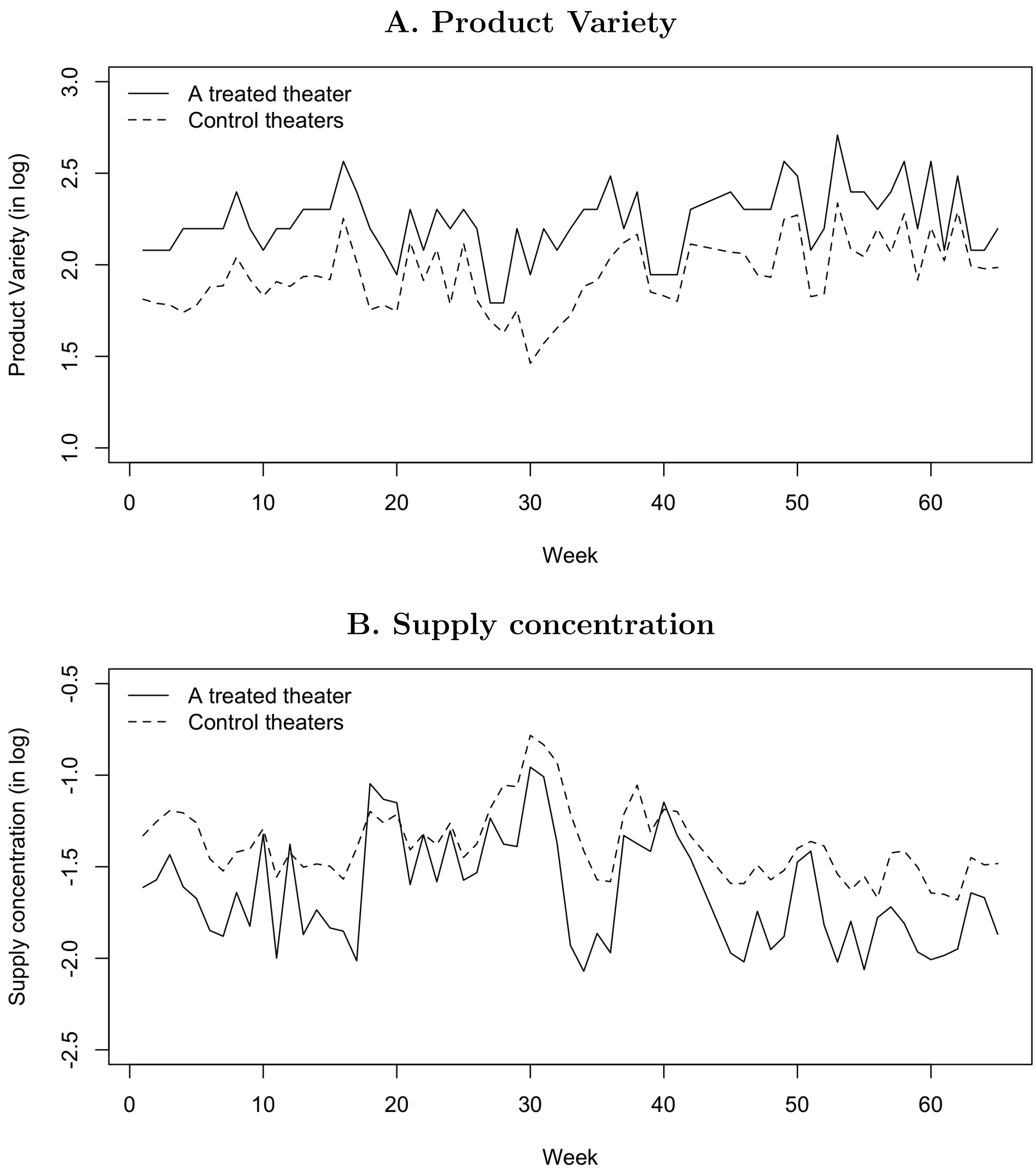
Appendix

Figure 4.5: Movies in the middle are squeezed



Note: The figure reports the scheduling at the same theater in Figure 4.1 on Saturday April 28, 2018. Movie 1 is *Avengers: Infinity War* but the theater still managed to show six different titles in total.

Figure 4.6: An illustration of pre-trends in product variety and supply concentration



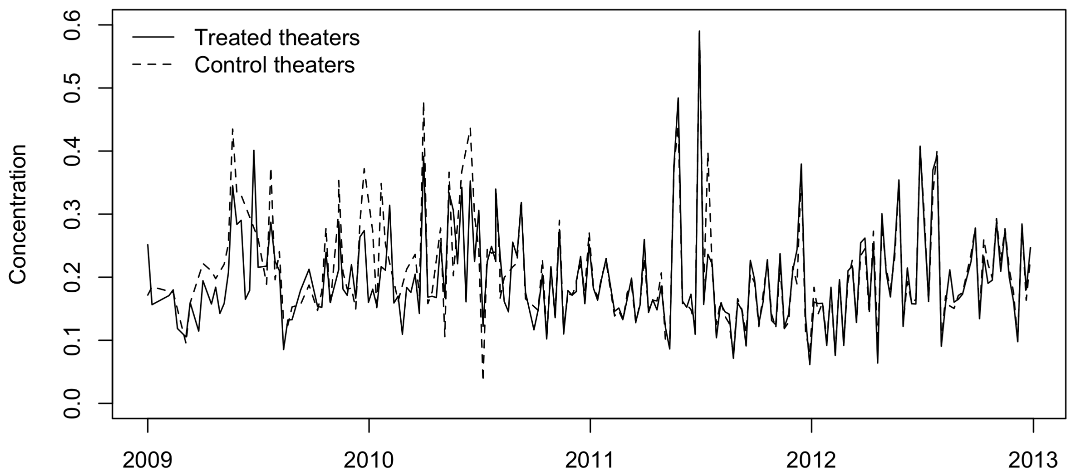
Note: Figure compares pre-trends in product variety and supply concentration between one treated theater and its control theaters. The treated theater was converted in week 66 and we display its pre-trend (weeks 1-65) in solid lines. The dashed lines represent the average pre-trend of all control theaters (i.e., all other theaters that had not adopted at the time the treated theater adopted). The pairwise correlation between the two time-series are 0.829 and 0.798, respectively.

Table 4.9: Treated vs. control theaters

	Treated	Control	Difference
Number of screens	8.121	7.621	0.500**
	(1.779)	(1.850)	(0.023)
Number of seats	1438	1228	210***
	(459)	(458)	(<.01)
Chain-affiliated (0/1)	1.000	0.804	0.196***
	(0)	(.398)	(<.001)
In Seoul (0/1)	0.210	0.183	0.027
	(.210)	(.388)	(.581)

Note: in parentheses are either standard deviations or p-values from t test; *p<0.1; **p<0.05; ***p<0.01.

Figure 4.7: Trends in concentration between treated and control theaters



Note: Figure compares trends in supply concentration, measured by the mean of top movie's screen share across theaters, between treated and control theaters.

Figure 4.8: Screen supply vs. seat supply

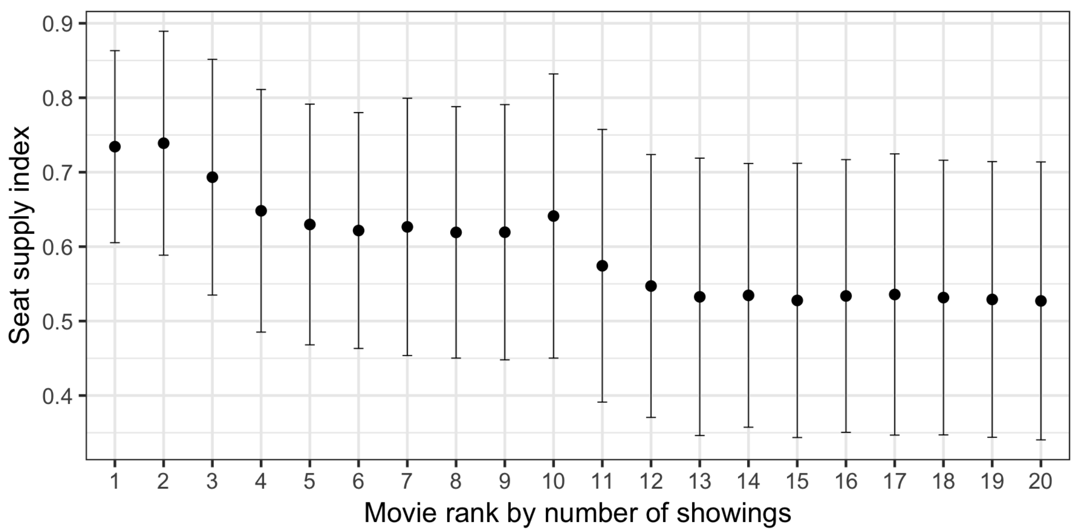


Table 4.10: Additional estimation results from the natural experiment

	(1) Run length (weeks)	(2) Total concentration
Target × treated	−0.018	-0.073^{***}
	(0.084)	(0.020)
Movie FE	Yes	Yes
Theater FE	Yes	Yes
Observations	29,807	29,807
R^2	0.845	0.895
Adjusted R^2	0.842	0.893

Note: The table reports two additional estimation results from the natural experiment. The same dataset as in Table 4.7 is used. The clustered standard errors at the theater-level are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table 4.11: Supply concentration: an alternative measure

	DV: screen share (in log, at theater-week level)	
	Early period (2006-10)	Late period (2011-16)
	By theater-size	
β^{1-4}	-0.036	-0.053
SE	(0.044)	(0.048)
β^{5-7}	0.149***	0.153
SE	(0.015)	(0.094)
β^{8+}	0.108***	0.171**
SE	(0.011)	(0.073)
Week FE	Yes	Yes
Theater-Year FE	Yes	Yes
N	59,188	97,895
R^2	0.804	0.806
Adj. R^2	0.799	0.801

Note: Columns report estimated β in Equation 4.1 for an alternative measure of supply concentration: screen share, which is the maximum number of screens allotted to a movie divided by the total number of screens at a theater. Standard errors are clustered by theater chains; *p<0.1; **p<0.05; ***p<0.01.

Table 4.12: Estimation results: product variety by time period, parallel trending theaters

	DV: product variety (in log, at theater-week level)			
	(1) Pooled	(2) Between	(3) Within	(4) Within
$\hat{\beta}^{2006-10}$	−0.046	−0.128***	−0.177***	−0.094***
SE	(0.031)	(0.022)	(0.030)	(0.026)
$\hat{\beta}^{2011-16}$	0.352***	0.346***	0.137***	0.112***
SE	(0.059)	(0.045)	(0.047)	(0.036)
R^2	0.032	0.182	0.794	0.843
Adj. R^2	0.032	0.178	0.792	0.838
N	116,158	116,158	116,158	116,158
Week FE	No	Yes	Yes	Yes
Theater FE	No	No	Yes	No
Theater-Year FE	No	No	No	Yes

Note: Columns report estimated β in Equation 4.1 for product variety. We exclude the treated theaters with the pairwise correlation with its corresponding control theaters in the pre-adoption period is less than the sample median. The sample median indicates the median value of the pairwise correlations across all treated theaters. Standard errors are clustered by theater chains; *p<0.1; **p<0.05; ***p<0.01.

Table 4.13: Estimation results: supply concentration by theater-size, parallel trending theaters

	DV: supply concentration (in log, at theater-week level)	
	Early period (2006-10)	Late period (2011-16)
	By theater-size	
β^{1-4}	-0.072^{*}	-0.148^{***}
SE	(0.041)	(0.037)
β^{5-7}	0.132^{***}	0.014
SE	(0.025)	(0.046)
β^{8+}	0.114^{***}	0.068
SE	(0.022)	(0.051)
Week FE	Yes	Yes
Theater-Year FE	Yes	Yes
N	40,562	75,596
R^2	0.763	0.778
Adj. R^2	0.756	0.772

Note: Columns report estimated β in Equation 4.1 for supply concentration. We exclude the treated theaters with the pairwise correlation with its corresponding control theaters in the pre-adoption period is less than the sample median. The sample median indicates the median value of the pairwise correlations across all treated theaters. Standard errors are clustered by theater chains; *p<0.1; **p<0.05; ***p<0.01.

Table 4.14: Additional evidence of the moderating role of demand

	DV: in log, at theater-week level			
	Variety	Concentration	Variety	Concentration
	(1)	(2)	(3)	(4)
Regular- vs. Peak-season				
$\hat{\beta}^{Peak}$	0.075***	0.104***		
SE	(0.026)	(0.009)		
$\hat{\beta}^{Regular}$	0.096***	0.071***		
SE	(0.013)	(0.013)		
Seoul vs. Other region				
$\hat{\beta}^{Seoul}$			0.233***	0.131***
SE			(0.053)	(0.020)
$\hat{\beta}^{Other}$			0.078***	0.066***
SE			(0.012)	(0.009)
Week FE	Yes	Yes	Yes	Yes
Theater-Year FE	Yes	Yes	Yes	Yes
Observations	97,895	124,113	97,895	124,113
R^2	0.853	0.783	0.853	0.783
Adjusted R^2	0.849	0.777	0.849	0.777

Note: Columns report estimated β in Equation 4.1 for each of the two dependent variables. For product variety, we use data between 2011 and 2016. For supply concentration, we use theaters with five or more screens. For the first two columns, we split weeks of a year into peak- or regular-demand period. Following Yang and Kim (2014), we define a week as peak-demand period if it falls into one of the five high-demand periods for movies in the country: Lunar New Year, early May, summer vacation, Chuseok, and Christmas. For the last two columns, we split theaters into two groups based on their geographic location: Seoul vs. other regions. Standard errors are clustered by theater chains; *p<0.1; **p<0.05; ***p<0.01.

Table 4.15: Estimation results: product variety by time period, independent theaters

	DV: product variety (in log, at theater-week level)			
	(1) Pooled	(2) Between	(3) Within	(4) Within
$\hat{\beta}^{2006-10}$	-0.482^{***}	-0.579^{***}	-0.033	0.032
SE	(0.144)	(0.157)	(0.060)	(0.049)
$\hat{\beta}^{2011-16}$	0.118	0.013	0.179^{**}	0.089^{**}
SE	(0.138)	(0.191)	(0.078)	(0.042)
Week FE	No	Yes	Yes	Yes
Theater FE	No	No	Yes	No
Theater-Year FE	No	No	No	Yes
N	28,842	28,842	28,842	28,842
R^2	0.030	0.079	0.756	0.823
Adj. R^2	0.030	0.060	0.749	0.815

Note: Columns report estimated β in Equation 4.1 for product variety. Standard errors are clustered by theater; *p<0.1; **p<0.05; ***p<0.01.

Table 4.16: Event-study specification estimation results, independent theaters

	DV: Product Variety (in log, at theater-week level)				
	(1) 1 week	(2) 2 weeks	(3) 3 weeks	(4) 4 weeks	(5) 5 weeks
$\hat{\beta}^{2006-10}$	−0.081	−0.020	0.020	0.008	−0.001
SE	(0.057)	(0.045)	(0.040)	(0.035)	(0.033)
$\hat{\beta}^{2011-16}$	0.096	0.071*	0.070*	0.117***	0.121***
SE	(0.065)	(0.041)	(0.039)	(0.038)	(0.035)
Theater FE	Yes	Yes	Yes	Yes	Yes
N	383	487	588	689	793
R^2	0.879	0.877	0.874	0.871	0.859
Adj. R^2	0.828	0.839	0.844	0.845	0.835

Note: The table reports the results of event-study specification at theater-level. The estimates reports the mean difference between pre- and post-adoption in product variety across treated theaters. Standard errors are clustered by theater; *p<0.1; **p<0.05; ***p<0.01.

Table 4.17: Event-study specification estimation results: at screen-level, independent theaters

	(1) 1 week	(2) 2 weeks	(3) 3 weeks	(4) 4 weeks	(5) 5 weeks
	DV: Product Variety (at screen-level)				
$\hat{\beta}$	0.432	0.472*	0.347*	0.398***	0.422***
SE⋆	(0.288)	(0.250)	(0.184)	(0.125)	(0.103)
Δ%†	21.07%	22.79%	16.31%	19.26%	20.67%
R^2	0.825	0.492	0.477	0.508	0.532
Adj. R^2	0.559	0.274	0.350	0.425	0.471
	DV: Number of Switches (at screen-level)				
$\hat{\beta}$	1.473	1.400	1.598**	1.952***	1.955***
SE	(1.090)	(0.888)	(0.752)	(0.600)	(0.556)
Δ%	38.47%	38.58%	45.61%	58.61%	57.4%
R^2	0.744	0.656	0.615	0.579	0.575
Adj. R^2	0.355	0.508	0.521	0.507	0.520
Theater-Screen FE	Yes	Yes	Yes	Yes	Yes
N	185	384	589	794	1,004

⋆SE: clustered standard errors by theater; *p<0.1; **p<0.05; ***p<0.01.
†Δ%: magnitude of estimate in terms of the percentage change from the average product variety.

CHAPTER 5

Concluding Remarks

In this dissertation, we study the transition from 35mm film to digital projection of movies in South Korea to empirically evaluate the impact of digitization on product assortment. Overall, we find that, while its effects are heterogeneous, digitization increases both product variety and supply concentration. We also find that the effects are not only moderated by supply-side factors, such as technology compatibility and capacity constraints, but also by demand. Our findings suggest digitization of movies creates flexibility in scheduling, which allows theaters to better respond to demand.

We caution that the empirical analyses of this dissertation are based on observational data. While we attempted to recover the causal effects of digitization using various empirical analyses, the observational nature of our data and the institutions pose threats to our identification strategy. Future research will benefit from searching for context in which the effect of digitization can be identified with more credible and/or fewer assumptions. We further caution that our empirical findings may be specific to our empirical context—and hence, may not generalize to markets in other countries and/or to the South Korean market in the future. Future research is needed to replicate these findings in other markets. Furthermore, this dissertation invites more studies on behaviors of market intermediaries in the digital economy. Quantifying the degree of heterogeneity in firm profitability and/or consumer welfare would provide a richer understanding of the impact of digitization. Another potential avenue for future research is to consider the investment decisions of market intermediaries in the process of technological changes. It would be valuable to examine how theaters (or intermediaries in other contexts) have leveraged investments on digitization as a tool for competitive and differentiation strategies, as well as its consequential impact on market outcomes such as product assortment, entry/exit, and market structure.

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