

Online Appendix

for

Digitization and Flexibility:
Evidence from the South Korean Movie Market

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- (A) A model of theaters' scheduling decisions
- (B) A natural experiment for supply concentration
- (C) Additional figures and tables

A A model of theaters' scheduling decisions

A.1 The model

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

$$\begin{aligned} \max_{\mathbf{a} \in \mathbf{A}} \quad & \pi(\mathbf{a}) = \sum_{j \in J} R_j(a_j) - C(a_j) \\ \text{subject to} \quad & a_j \in \mathbb{Q}_{\geq 0}, \forall j \quad (\text{non-negativity constraint}) \\ & \sum_{j \in J} a_j \leq K \quad (\text{capacity constraint}) \end{aligned} \tag{A.1}$$

The decision variable is $\mathbf{a} = (a_1, \dots, a_J)$ 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).¹

Revenue function We specify the theater's revenue function as follows:

$$R_j(a_j) = [p_j \cdot (1 - \theta_j) + \kappa] \cdot q_j(a_j), \tag{A.2}$$

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.² Then, the revenue function simplifies to $R_j(a_j) = \bar{r} \cdot q_j(a_j)$, where $\bar{r} = p \cdot (1 - \theta) + \kappa$ 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 $q_1(a) > q_2(a) > q_3(a) > \dots > q_J(a)$ 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.

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 scheduling movies within a screen. The scheduling cost represents the marginal and/or fixed cost of labor required to change the movie playing

¹For the sake of parsimonious representation, we abstract away from other important dimensions of scheduling problems, which include theater size, competition, dynamic decisions, and *ex ante* demand uncertainty.

²We consider a flat ratio to simplify the model and, more importantly, it is the case in our empirical context.

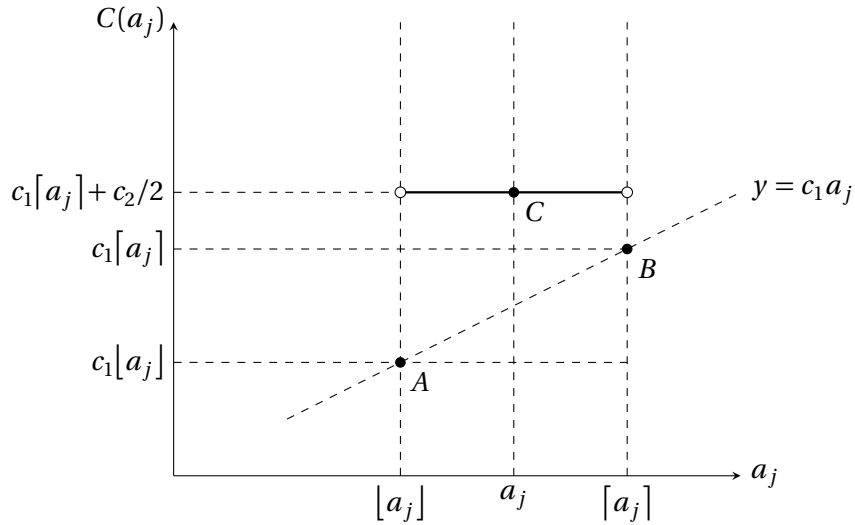
on a screen. To capture both types, we specify the cost function as follows:

$$C(a_j) = c_1 \lceil a_j \rceil + \frac{c_2}{2} \mathbb{I}\{\lceil a_j \rceil - a_j > 0\}, \quad (\text{A.3})$$

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.³ 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 scheduling cost that occurs when theaters switch between movies across slots within a screen. We assume that the theater pays a scheduling 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 A.1 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 scheduling (point C).

Figure A.1: An illustration of cost function



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 theaters to find suboptimal solutions in terms

³The parameter captures both the price actual dollar amount a theater has to pay

⁴To 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.

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.

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) $a_1^* \geq a_2^* \geq \dots \geq a_j^*$ and ii) $\sum_j a_j = K$. To see this, consider that the cost function is common across movies and $q_1(a) > q_2(a) > q_3(a) > \dots > q_j(a)$ 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 \mathbf{a}^* is defined as $PV(\mathbf{a}^*) = \sum_j \mathbb{I}\{a_j > 0\} = k^*$ such that $a_1^*, \dots, a_{k^*}^* > 0$ and $a_{k^*+1}^*, \dots, a_j^* = 0$.*

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

A.2 Model predictions

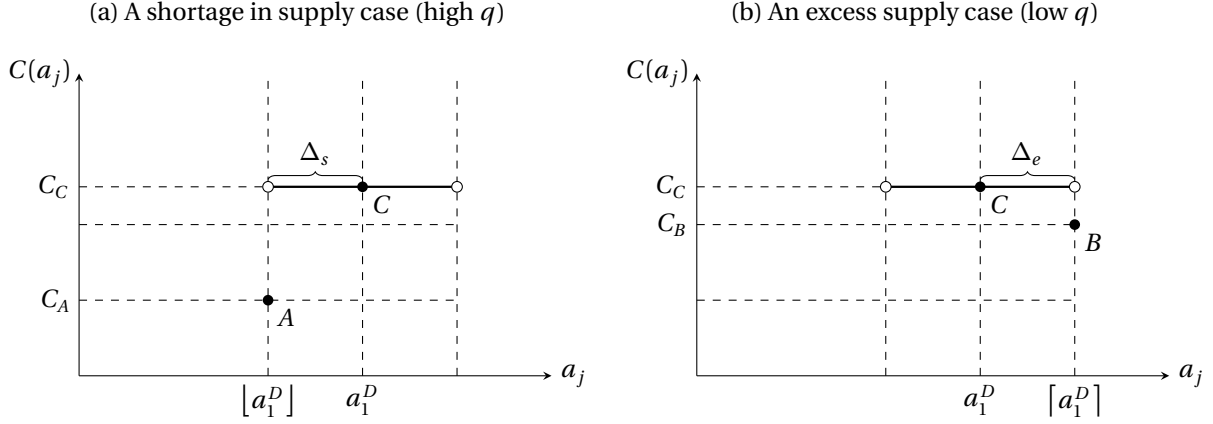
We evaluate the impact of digitization on product variety and supply concentration by showing the existence of boundary conditions in which the relative size of model primitives produce different predictions about the impact of digitization. Specifically, we first assume that digitization drives both acquisition and scheduling costs to zero (i.e., $c_1 \rightarrow 0$ and $c_2 \rightarrow 0$). 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.

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

The left panel of Figure A.2 graphically illustrates the case of shortage in the supply of screens for the top movies. Suppose $\mathbf{a}^D = (a_1^D, \dots, a_j^D)$ is the optimal solution for a theater when $c_1 = c_2 = 0$ (the superscript

Figure A.2: The relative demand and the impact of digitization



D represents digital projection). Consider a situation in which the theater finds $a_1^F = [a_1^D]$ 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 $SC(\mathbf{a}^F) = [a_1^D]/K$ 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

$$\underbrace{c_1 + c_2}_{\text{Cost of flexibility}} > \underbrace{\tilde{r}_1(q_1(a_1^D) - q_1(a_1^F))}_{\text{Gain from residual demand}} + \underbrace{\tilde{r}_J(q_J(a_J^D) - q_J(1))}_{\text{Loss from marginal movie}}, \quad (\text{A.4})$$

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 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. A.4 holds),*

(P1a) *digitization increases movie concentration in theaters, and*

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

⁵The demand condition can be represented as $R_1(a_1^F) - C(a_1^F) + \sum_{j>1} R_1(a_j) - C(a_j) > R_1(a_1^D) - C(a_1^D) + \sum_{j>1} R_1(a_j) - C(a_j)$. Later we show that Equation A.4 can be derived from this inequality.

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

The right panel of Figure A.2 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:

$$\underbrace{c_1 + c_2}_{\text{Cost of flexibility}} > \underbrace{\tilde{r}_1(q_1(a_1^D) - q_1(a_1^F))}_{\text{Loss from excess supply}} + \underbrace{\tilde{r}_j q_j(a_j^D)}_{\text{Gain from increased variety}}. \quad (\text{A.5})$$

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. A.5 holds),*

(P2a) *digitization decreases movie concentration in theaters, and*

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

A.3 Proofs

Condition A.4. 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 $a_1^F = \lceil a_1 \rceil$. 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 $a_j^D = 1 - (a_1^D - \lceil a_1^D \rceil) < 1$. 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

$$\begin{aligned}
R_1(a_1^F) - C(a_1^F) + R_J(1) - C(1) &> R_1(a_1^D) - C(a_1^D) + R_1(a_J^D) - C(a_J^D) \\
\tilde{r}_1 q_1(a_1^F) - c_1 a_1^F + \tilde{r}_J q_J(1) - c_1 &> \tilde{r}_1 q_1(a_1^D) - (c_1 + 1)a_1^F - c_2/2 + \tilde{r}_J q_J(a_J^D) - c_1 - c_2/2 \\
\tilde{r}_1 q_1(a_1^F) + \tilde{r}_J q_J(1) &> \tilde{r}_1 q_1(a_1^D) - c_1 - c_2/2 + \tilde{r}_J q_J(a_J^D) - c_2/2 \\
c_1 + c_2 &> \tilde{r}_1(q_1(a_1^D) - q_1(a_1^F)) + \tilde{r}_J(q_J(a_J^D) - q_J(1))
\end{aligned}$$

□

Condition A.5. 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

$$\begin{aligned}
R_1(a_1^F) - C(a_1^F) &> R_1(a_1^D) - C(a_1^D) + R_1(a_J^D) - C(a_J^D) \\
\tilde{r}_1 q_1(a_1^F) - c_1 a_1^F &> \tilde{r}_1 q_1(a_1^D) - c_1 a_1^F - c_2/2 + \tilde{r}_J q_J(a_J^D) - c_1 - c_2/2 \\
c_1 + c_2 &> \tilde{r}_1(q_1(a_1^D) - q_1(a_1^F)) + \tilde{r}_J q_J(a_J^D)
\end{aligned}$$

□

B A Natural Experiment for Supply Concentration

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. We leverage a natural experiment which 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 B.1. Two major South Korean theater chains implemented the VPF model to roll out digital screens for their own theaters 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.⁶ This creates a natural experiment where the same movies were disseminated in different formats (reel film and digital file) to theaters with 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 theaters until January 2012 and February 2010, respectively. Other theaters, which includes the franchise theaters of the two chains, were supplied with digital files for all movies.⁷

The case of *Harry Potter and Deathly Hallows: Part II* (2011) characterizes the natural experiment

Figure B.1: 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).

⁶It 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.

⁷The financing model was only applicable to company-owned theaters, not to franchise theaters.

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 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.

Empirical specification 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 theaters (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:

$$\log(\text{Concentration}_{j\ell}) = \beta \cdot \text{Treated}_{\ell} \times \text{Target}_j + \mu_j + \nu_{\ell} + \varepsilon_{j\ell}. \quad (\text{B.1})$$

Here, $\text{Concentration}_{j\ell}$ is the opening week slot share of movie j at theater ℓ . Treated_{ℓ} is an indicator variable, which takes the value of one if theater 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 fixed effects, respectively. The two fixed effects capture any effects that are specific to movies and theaters. 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 Table 5, the sign of $\hat{\beta}$ should be negative. The magnitude of $\hat{\beta}$ represents the average percentage 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 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.

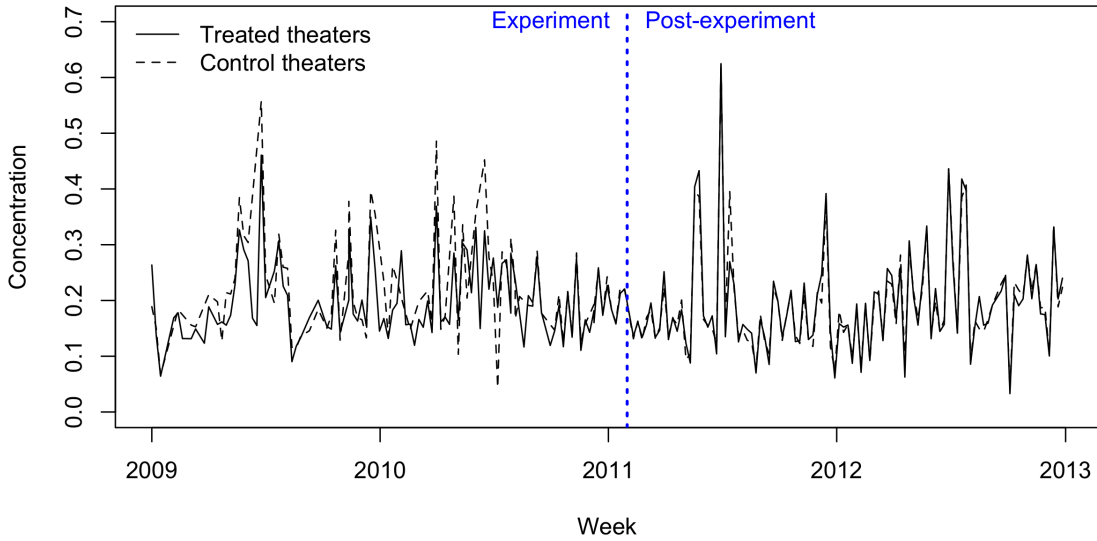
Estimating sample For estimation, we use the movies that (i) were released during our observation period, (ii) were shown in film at treatment theaters and in digital at control theaters, and (iii) had the highest screen share among movies released on the same day. Of the 288 movies, 18 movies were

Table B.1: Treated vs. control theaters

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

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

Figure B.2: 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.

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 B.1). Nonetheless, the trends in supply concentration at the two sets of theaters appear to be parallel after VPF contracts are in effect at all theaters (see Figure B.2).

Table B.2: Estimation results of the natural experiment

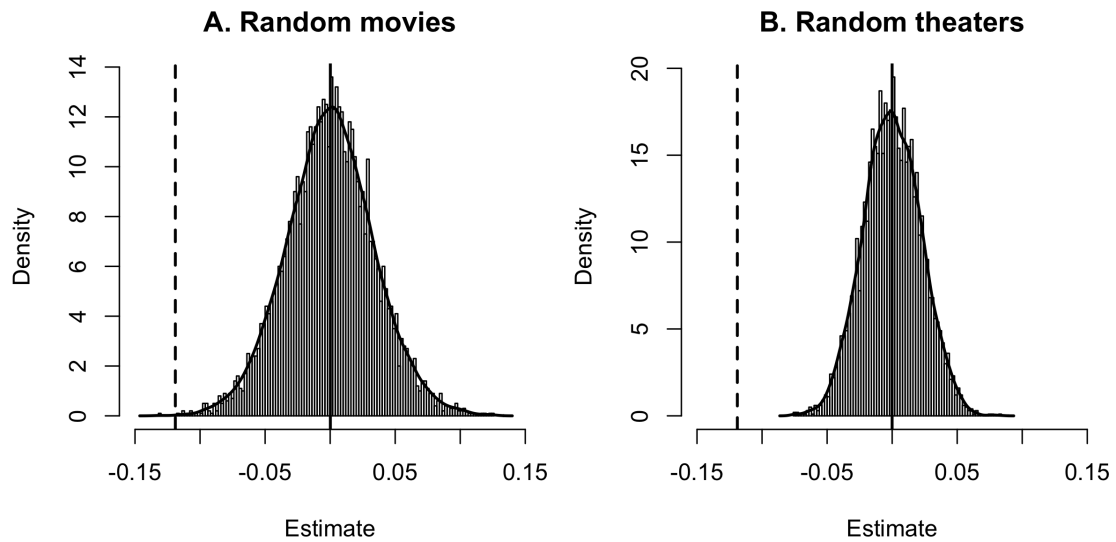
	<i>DV: Supply concentration (at theater-level)</i>	
	(1) w/ control movies	(2) (2) w/o control movies
Treated \times Target		
$\hat{\beta}^{2011-16}$	-0.119***	
SE	(0.028)	
Treated		
$\hat{\beta}^{2011-16}$		-0.126***
SE		(0.031)
Movie FE	Yes	Yes
Theater FE	Yes	No
N	35,357	1,230
R^2	0.802	0.678
Adj.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

Note: Columns report estimated β in Equation B.1. Standard errors are clustered by theaters; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Results Table B.2 reports the estimation results of Equation B.1. 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 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 B.2 suggests that digitization supply movie concentration in the sample theaters.

Robustness: placebo tests As a robustness check for our findings regarding supply concentration in Table B.2, we conduct two different placebo tests. First, we randomly draw a set of movies and assign them as target movies and estimate Equation B.1, while fixing the split between treated and control theaters. Second, while fixing the target movies, we randomly assign theaters 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 B.3 in the Online Appendix shows the distribution of estimates. The graph shows that an estimate of -0.119 from Table B.2, Equation B.1 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.

Figure B.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 from column (1) in Table B.2.

C Additional Figures and Tables

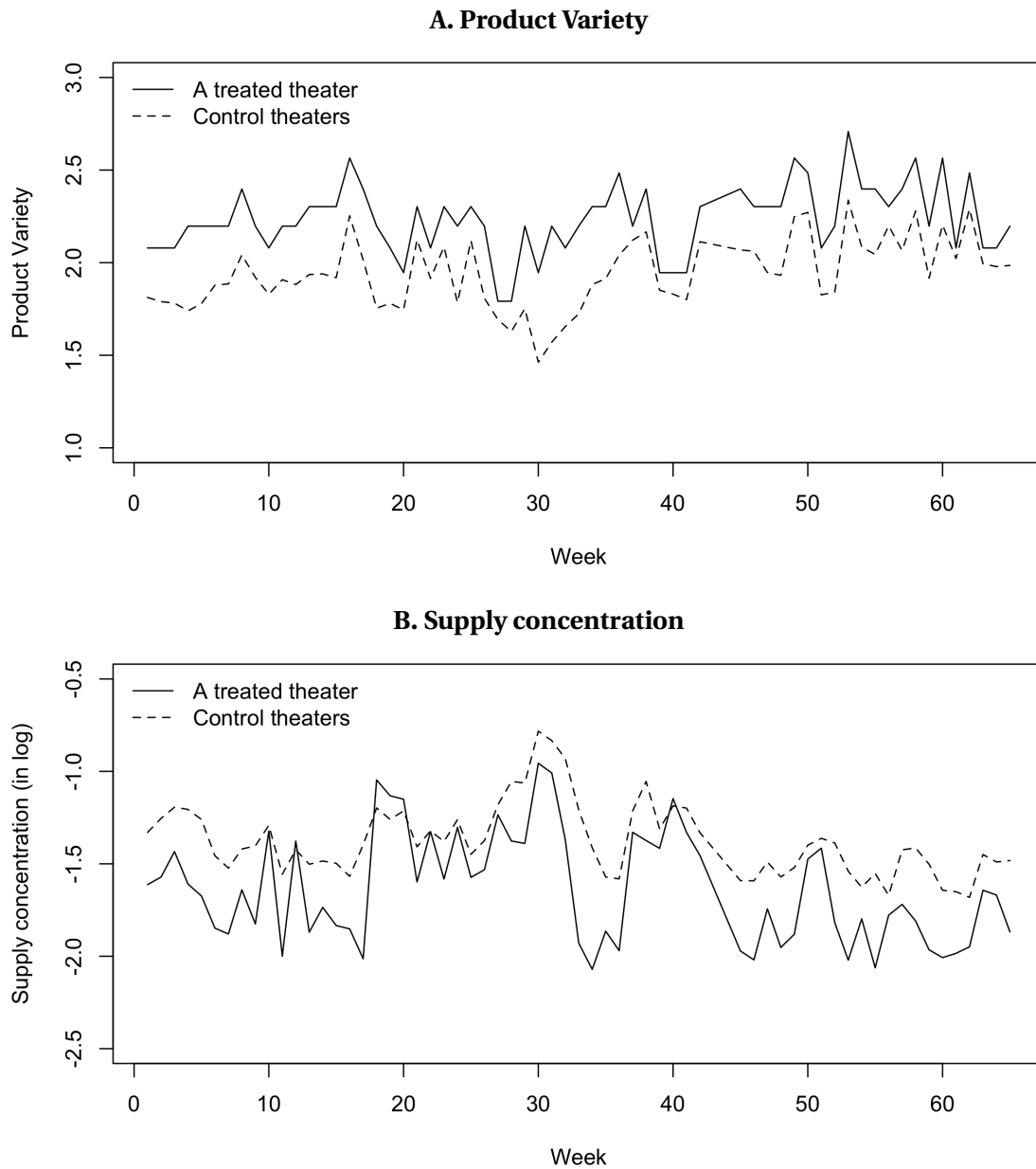
Table C.1: Supply concentration: an alternative measure

<i>DV: screen share (in log, at theater-week level)</i>						
	(1)	(2)	(3)	(4)		
	Pooled	Between	Within: long comparison	Within: short comparison		
<i>All data</i>						
Digital	0.477*** (0.021)	0.316*** (0.048)	0.161*** (0.017)	0.093*** (0.014)		
R ²	0.176	0.350	0.795	0.833		
Adj. R ²	0.176	0.347	0.794	0.829		
<i>By time period</i>						
Digital: 2006-10	0.315*** (0.037)	0.345*** (0.049)	0.178*** (0.020)	0.085*** (0.015)		
Digital: 2011-16	0.495*** (0.068)	0.254*** (0.075)	0.123*** (0.021)	0.114*** (0.033)		
R ²	0.183	0.350	0.795	0.833		
Adj. R ²	0.183	0.348	0.794	0.829		
Year-Week FE	No	Yes	Yes	Yes		
Theater FE	No	No	Yes	No		
Theater-Year FE	No	No	No	Yes		
N	157,308	157,308	157,308	157,308		

<i>DV: screen share (in log, at theater-week level)</i>						
	Model (3)			Model (4)		
	Within: long comparison			Within: short comparison		
	Screens: 1-4	Screens: 5-7	Screens: 8+	Screens: 1-4	Screens: 5-7	Screens: 8+
Digital: 2006-10	0.064* (0.038)	0.218*** (0.024)	0.182*** (0.023)	-0.021 (0.037)	0.139*** (0.029)	0.111*** (0.014)
Digital: 2011-16	-0.040 (0.035)	0.250*** (0.024)	0.159*** (0.022)	-0.019 (0.053)	0.188*** (0.050)	0.200*** (0.035)
Year-Week FE	Yes			Yes		
Theater FE	Yes			No		
Theater-Year FE	No			Yes		
N	157,308			157,308		
R ²	0.800			0.833		
Adj.R ²	0.799			0.829		

Note: Tables report estimated β in Equation 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 theaters and are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Figure C.1: 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 C.2: Product variety: parallel trending theaters only

<i>DV: product variety (in log, at theater-week level)</i>				
	(1) Pooled	(2) Between	(3) Within: long comparison	(4) Within: short comparison
<i>All data</i>				
Digital	0.147*** (0.027)	-0.041 (0.068)	-0.150*** (0.023)	-0.098*** (0.013)
R ²	0.022	0.205	0.805	0.840
Adj. R ²	0.022	0.201	0.803	0.836
<i>By time period</i>				
Digital: 2006-10	-0.012 (0.054)	-0.108 (0.075)	-0.205*** (0.027)	-0.134*** (0.012)
Digital: 2011-16	0.192*** (0.067)	0.192** (0.076)	0.041* (0.023)	0.029 (0.030)
R ²	0.030	0.208	0.806	0.840
Adj. R ²	0.030	0.203	0.805	0.836
Year-Week FE	No	Yes	Yes	Yes
Theater FE	No	No	Yes	No
Theater-Year FE	No	No	No	Yes
N	104,034	104,034	104,034	104,034

<i>DV: product variety (in log, at theater-week level)</i>						
	Model (3) Within: long comparison			Model (4) Within: short comparison		
	Screens: 1-4	Screens: 5-7	Screens: 8+	Screens: 1-4	Screens: 5-7	Screens: 8+
Digital: 2006-10	-0.297** (0.118)	-0.136*** (0.029)	-0.212*** (0.024)	-0.067 (0.047)	-0.120*** (0.015)	-0.144*** (0.016)
Digital: 2011-16	0.123 (0.079)	0.044* (0.025)	0.027 (0.025)	0.135 (0.187)	0.061*** (0.022)	-0.019 (0.048)
Year-Week FE	Yes			Yes		
Theater FE	Yes			No		
Theater-Year FE	No			Yes		
N	104,034			104,034		
R ²	0.807			0.840		
Adj.R ²	0.805			0.836		

Note: Tables report estimated β in Equation 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 theaters and are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table C.3: Supply concentration: parallel trending theaters only

<i>DV: supply concentration (in log, at theater-week level)</i>				
	(1)	(2)	(3)	(4)
	Pooled	Between	Within: long comparison	Within: short comparison
<i>All data</i>				
Digital	0.229*** (0.019)	0.131*** (0.045)	0.136*** (0.016)	0.098*** (0.013)
R ²	0.063	0.527	0.764	0.792
Adj. R ²	0.063	0.524	0.762	0.786
<i>By time period</i>				
Digital: 2006-10	0.126*** (0.035)	0.158*** (0.049)	0.158*** (0.018)	0.116*** (0.014)
Digital: 2011-16	0.309*** (0.065)	0.011 (0.055)	0.038 (0.023)	0.005 (0.035)
R ²	0.068	0.528	0.765	0.792
Adj. R ²	0.068	0.525	0.762	0.786
Year-Week FE	No	Yes	Yes	Yes
Theater FE	No	No	Yes	No
Theater-Year FE	No	No	No	Yes
N	97,055	97,055	97,055	97,055

<i>DV: supply concentration (in log, at theater-week level)</i>						
	Model (3)			Model (4)		
	Within: long comparison			Within: short comparison		
	Screens: 1-4	Screens: 5-7	Screens: 8+	Screens: 1-4	Screens: 5-7	Screens: 8+
Digital: 2006-10	0.176 (0.151)	0.167*** (0.019)	0.130*** (0.014)	-0.403*** (0.083)	0.147*** (0.023)	0.111*** (0.015)
Digital: 2011-16	-0.113 (0.117)	0.062** (0.026)	0.050* (0.026)	-0.170 (0.157)	-0.002 (0.043)	0.063 (0.041)
Year-Week FE	Yes			Yes		
Theater FE	Yes			No		
Theater-Year FE	No			Yes		
N	97,055			97,055		
R ²	0.766			0.792		
Adj.R ²	0.763			0.786		

Note: Tables report estimated β in Equation 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 theaters and are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table C.4: Supply concentration by dayparts: daypart specific concentration

	<i>DV: supply concentration (in log, at theater-week-daypart level)</i>					
	2006-10			2011-16		
	(1) Screens: 1-4	(2) 5-7	(3) 8+	(4) Screens: 1-4	(5) 5-7	(6) 8+
<i>MTW daytime</i> [†]						
Digital	-0.010 (0.027)	0.102*** (0.019)	0.110*** (0.016)	-0.062** (0.028)	-0.034 (0.032)	0.008 (0.027)
<i>MTW evening</i>						
Digital	0.010 (0.031)	0.170*** (0.022)	0.170*** (0.016)	0.025 (0.031)	0.067** (0.029)	0.056* (0.030)
<i>Thursday-Friday</i>						
Digital	-0.011 (0.025)	0.111*** (0.019)	0.123*** (0.016)	-0.042 (0.027)	0.031 (0.031)	0.059** (0.026)
<i>Weekend daytime</i>						
Digital	-0.019 (0.022)	0.078*** (0.019)	0.105*** (0.016)	-0.028 (0.032)	0.034 (0.033)	0.086*** (0.030)
<i>Weekend evening</i>						
Digital	0.007 (0.028)	0.154*** (0.022)	0.170*** (0.018)	0.044 (0.037)	0.133*** (0.030)	0.124*** (0.031)
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Theater-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Theater-Daypart FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	52,111	99,972	149,398	129,702	157,979	214,120
<i>R</i> ²	0.658	0.548	0.660	0.612	0.692	0.741
Adj. <i>R</i> ²	0.652	0.542	0.656	0.607	0.689	0.738

Note: Columns report estimated β in Equation 2 for supply concentration by time period and theater size. Supply concentration is defined in each specific daypart. Standard errors are clustered by theaters and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

[†]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).

Table C.5: Product variety by dayparts for Model 3

	<i>DV: product variety (in log, at theater-week-daypart level)</i>					
	2006-10			2011-16		
	(1) Screens: 1-4	(2) 5-7	(3) 8+	(4) Screens: 1-4	(5) 5-7	(6) 8+
<i>MTW daytime</i> [†]						
Digital	-0.044 (0.037)	-0.160*** (0.025)	-0.100*** (0.022)	0.196** (0.093)	0.135*** (0.026)	0.064 (0.041)
<i>MTW evening</i>						
Digital	-0.059 (0.037)	-0.183*** (0.025)	-0.128*** (0.023)	0.030 (0.063)	-0.039 (0.028)	-0.081* (0.049)
<i>Thursday-Friday</i>						
Digital	-0.047 (0.033)	-0.159*** (0.025)	-0.116*** (0.023)	0.167* (0.091)	0.072*** (0.024)	0.041 (0.039)
<i>Weekend daytime</i>						
Digital	-0.046 (0.035)	-0.130*** (0.025)	-0.083*** (0.022)	0.125* (0.071)	0.056** (0.026)	-0.039 (0.046)
<i>Weekend evening</i>						
Digital	-0.076** (0.032)	-0.192*** (0.024)	-0.151*** (0.023)	-0.023 (0.059)	-0.105*** (0.026)	-0.158*** (0.052)
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Theater-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Theater-Daypart FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	52,111	99,972	149,399	129,703	157,979	214,120
<i>R</i> ²	0.677	0.543	0.623	0.676	0.571	0.641
Adj. <i>R</i> ²	0.672	0.538	0.620	0.673	0.567	0.638

Note: Columns report estimated β in Equation 2 for product variety by time period and theater size. Standard errors are clustered by theaters and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

[†]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).

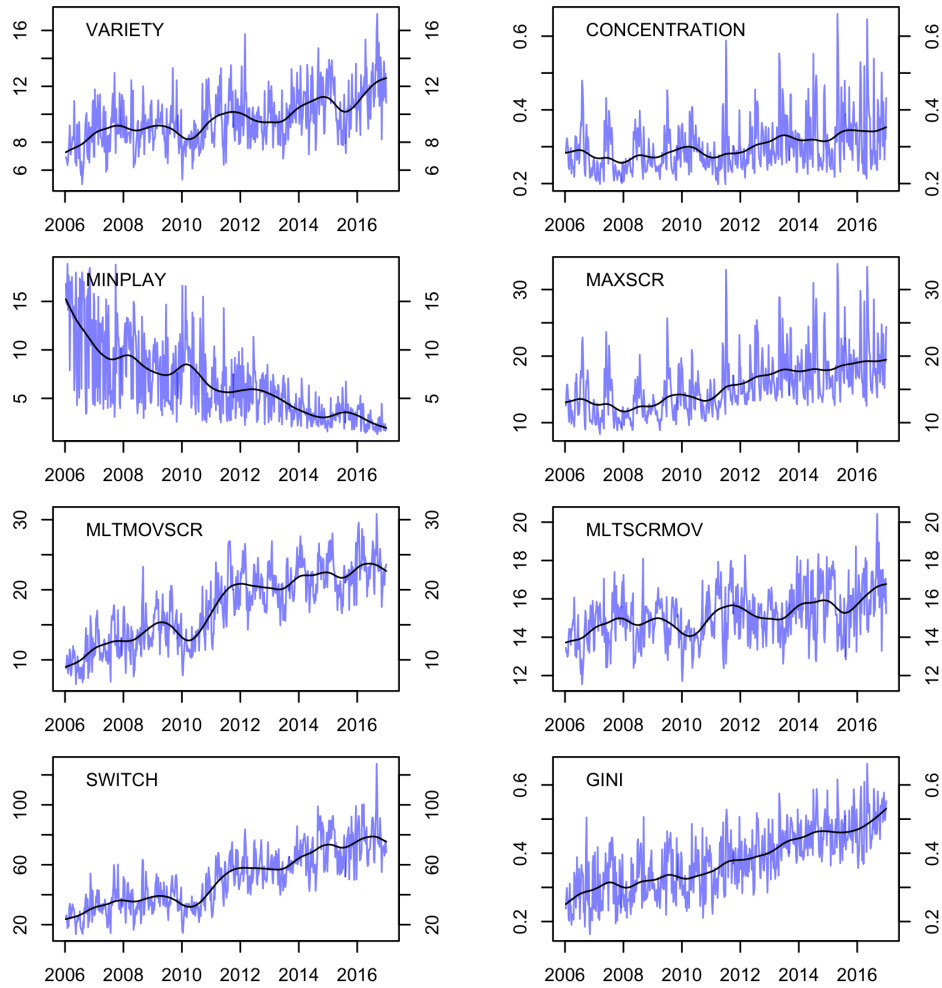
Table C.6: Supply concentration by dayparts for Model 3

	<i>DV: supply concentration (in log, at theater-week-daypart level)</i>					
	2006-10			2011-16		
	(1) Screens: 1-4	(2) 5-7	(3) 8+	(4) Screens: 1-4	(5) 5-7	(6) 8+
<i>MTW daytime</i> [†]						
Digital	0.020 (0.025)	0.127*** (0.025)	0.081*** (0.020)	-0.096* (0.056)	-0.055* (0.030)	-0.004 (0.033)
<i>MTW evening</i>						
Digital	0.022 (0.029)	0.195*** (0.026)	0.140*** (0.020)	-0.027 (0.054)	0.052** (0.023)	0.054 (0.035)
<i>Thursday-Friday</i>						
Digital	0.028 (0.025)	0.140*** (0.024)	0.099*** (0.020)	-0.075 (0.063)	-0.005 (0.029)	0.033 (0.033)
<i>Weekend daytime</i>						
Digital	-0.003 (0.027)	0.085*** (0.025)	0.049** (0.020)	-0.089 (0.055)	0.0002 (0.032)	0.086** (0.038)
<i>Weekend evening</i>						
Digital	0.037 (0.024)	0.177*** (0.024)	0.134*** (0.022)	0.006 (0.059)	0.121*** (0.027)	0.129*** (0.033)
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Theater-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Theater-Daypart FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	50,751	99,931	149,339	124,068	157,884	214,082
<i>R</i> ²	0.491	0.332	0.498	0.437	0.568	0.647
Adj. <i>R</i> ²	0.484	0.325	0.494	0.431	0.565	0.645

Note: Columns report estimated β in Equation 2 for supply concentration by time period and theater size. Supply concentration in each daypart is defined with respect to the movie that was mostly shown in a given theater-week. Standard errors are clustered by theaters and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

[†]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).

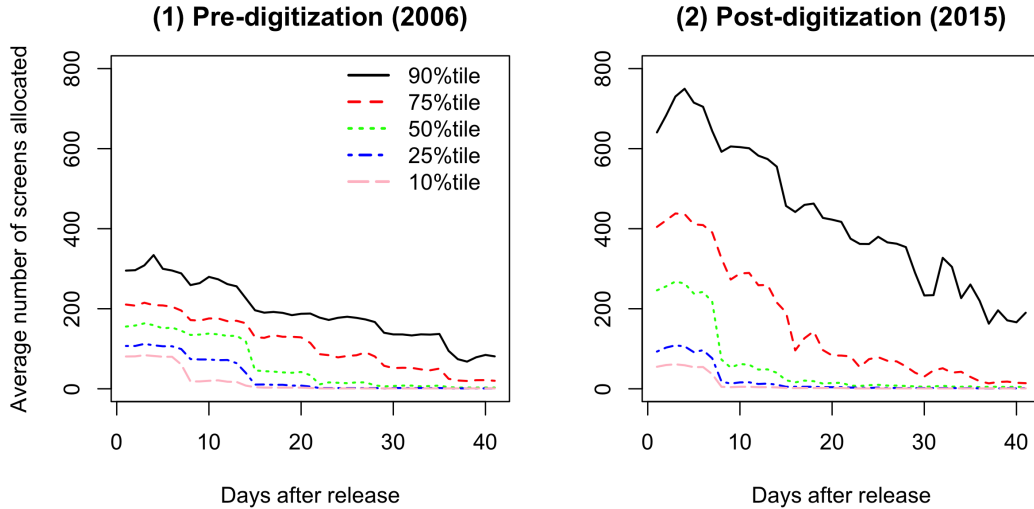
Figure C.2: Flexibility in within-week movie scheduling



Note: Figure reports trends in theaters' weekly movie scheduling decisions. Definition of each variable is as follows: VARIETY is the number of different movies screened; CONCENTRATION is 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 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.

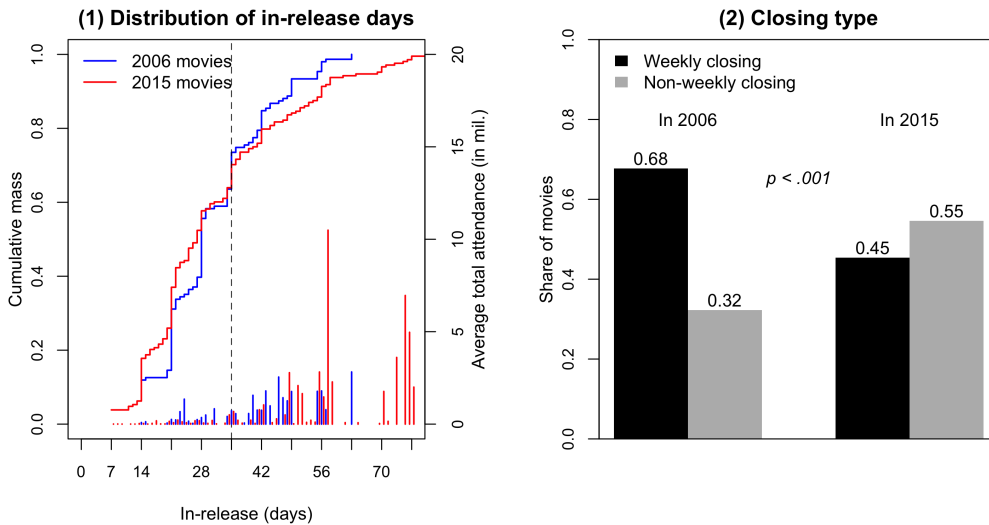
Figure C.3: Flexibility in across-week movie scheduling

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).

Table C.7: Event-study specification estimation results: at theater-level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	-5 weeks	-4 weeks	-3 weeks	-2 weeks	-1 week	0 week	1 week	2 weeks	3 weeks	4 weeks	5 weeks
<i>DV: product variety (in log, at theater-week level)</i>											
Digital: 2006-10	-0.020 (0.015)	-0.040** (0.017)	-0.040** (0.019)	-0.047** (0.020)	-0.057*** (0.022)	-0.004 (0.021)	-0.036* (0.022)	-0.015 (0.017)	-0.009 (0.015)	-0.007 (0.014)	-0.013 (0.013)
Digital: 2011-16	-0.087** (0.037)	-0.050 (0.032)	-0.039 (0.036)	-0.088** (0.045)	-0.133** (0.061)	0.058 (0.043)	0.058 (0.064)	0.059 (0.043)	0.082** (0.039)	0.122*** (0.035)	0.124*** (0.032)
R ²	0.815	0.817	0.821	0.830	0.841	0.868	0.858	0.847	0.842	0.833	0.821
Adj. R ²	0.792	0.792	0.794	0.799	0.807	0.813	0.800	0.802	0.805	0.802	0.793
<i>DV: supply concentration (in log, at theater-week level)</i>											
Digital: screens 1-4	0.029 (0.033)	0.039 (0.033)	0.032 (0.036)	0.014 (0.051)	-0.021 (0.049)	-0.002 (0.054)	0.011 (0.064)	0.013 (0.058)	0.011 (0.050)	-0.008 (0.043)	-0.025 (0.038)
Digital: screens 5-7	-0.012 (0.024)	-0.010 (0.027)	0.008 (0.029)	0.030 (0.028)	0.049 (0.032)	0.149*** (0.050)	0.203*** (0.047)	0.169*** (0.037)	0.119*** (0.031)	0.118*** (0.031)	0.114*** (0.031)
Digital: screens 8+	0.007 (0.027)	0.018 (0.032)	0.020 (0.031)	0.025 (0.027)	0.066** (0.031)	0.049 (0.035)	0.162*** (0.040)	0.105*** (0.034)	0.079*** (0.028)	0.088*** (0.026)	0.088*** (0.025)
R ²	0.742	0.744	0.750	0.769	0.780	0.804	0.792	0.779	0.770	0.745	0.730
Adj. R ²	0.711	0.709	0.711	0.728	0.732	0.722	0.707	0.714	0.717	0.697	0.687
Theater FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,365	2,135	1,902	1,669	1,439	1,700	1,684	2,157	2,628	3,097	3,567

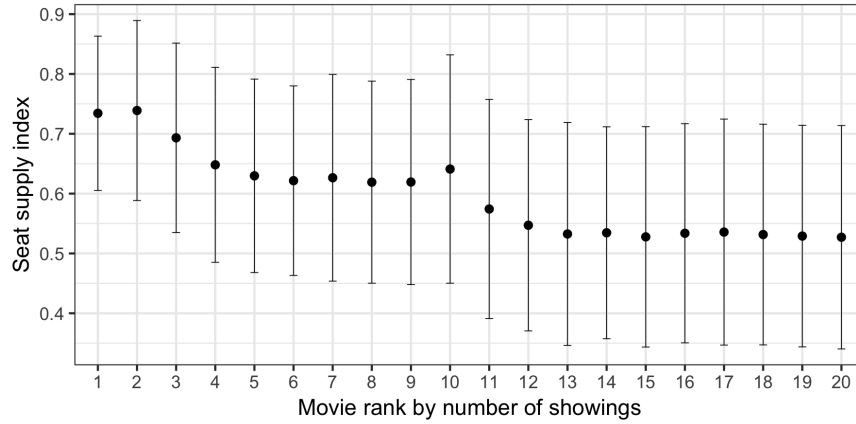
Note: The table reports the results of event-study specification at theater-level. Columns (1)-(5): the estimates report the pre-trends in product variety and supply concentration. We compute the mean difference in product variety or supply concentration between the period of n -weeks before adoption and the five preceding weeks. Columns (6)-(8): the estimates reports the mean difference between pre- and post-adoption in product variety and supply concentration across treated theaters. We use five preceding weeks before adoption as the pre-period and n weeks after adoption as post-period. Standard errors are clustered by theaters and are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.8: Event-study specification estimation results: at screen-level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	-5 weeks	-4 weeks	-3 weeks	-2 weeks	-1 week	0 week	1 week	2 weeks	3 weeks	4 weeks	5 weeks
<i>DV: product variety (in log, at screen-level)</i>											
Digital: 2006-10	0.021 (0.015)	0.009 (0.014)	-0.004 (0.015)	-0.023 (0.016)	-0.024 (0.020)	0.146*** (0.021)	-0.002 (0.021)	0.001 (0.017)	0.022 (0.016)	0.032** (0.016)	0.037** (0.016)
Digital: 2011-16	0.010 (0.021)	0.055*** (0.021)	0.054** (0.023)	0.018 (0.024)	-0.001 (0.028)	0.260*** (0.030)	0.174*** (0.033)	0.182*** (0.028)	0.181*** (0.025)	0.204*** (0.024)	0.216*** (0.022)
R ²	0.434	0.447	0.463	0.479	0.496	0.495	0.496	0.466	0.443	0.427	0.417
Adj. R ²	0.364	0.370	0.377	0.382	0.382	0.379	0.379	0.364	0.352	0.346	0.344
<i>DV: number of switches (at screen-level)</i>											
Digital: 2006-10	-0.227 (0.181)	0.005 (0.196)	0.053 (0.200)	0.155 (0.228)	0.198 (0.299)	0.630** (0.284)	0.045 (0.274)	0.199 (0.242)	0.078 (0.212)	0.230 (0.203)	0.350* (0.191)
Digital: 2011-16	-0.258 (0.256)	0.026 (0.262)	0.134 (0.279)	0.104 (0.309)	0.631* (0.383)	1.453*** (0.381)	1.912*** (0.458)	2.209*** (0.375)	2.335*** (0.334)	2.569*** (0.328)	2.691*** (0.314)
R ²	0.414	0.425	0.434	0.453	0.472	0.457	0.461	0.436	0.414	0.405	0.396
Adj. R ²	0.342	0.344	0.344	0.351	0.354	0.333	0.337	0.328	0.319	0.321	0.320
Theater-Screen FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,744	14,126	12,522	10,910	9,304	9,456	9,366	11,010	12,633	14,239	15,822

Notes: The upper panel reports the changes in product variety after digital transition of a screen. In the lower panel, we report the changes in the number of switches between movies. Specifically, we construct an outcome variable, Switch, which measures per screen-week frequency of switches between 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. Columns (1)-(5): the estimates report the pre-trends in product variety and Switch. We compute the mean difference in product variety or Switch between the period of *n*-weeks before adoption and the five preceding weeks. Columns (6)-(11): the estimates reports the mean difference between pre- and post-adoption in product variety and Switch across treated theater-screens. We use five preceding weeks before adoption as the pre-period and *n* weeks after adoption as post-period. Standard errors are clustered standard errors by theaters are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Figure C.4: Screen supply vs. seat supply



Note: 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.

Table C.9: Additional estimation results of the natural experiment

	(1)	(2)
	Run length (weeks) (at theater-level)	Total concentration (at theater-level)
Target × treated	−0.080 (0.060)	−0.076*** (0.018)
Movie FE	Yes	Yes
Theater FE	Yes	Yes
Observations	35,357	35,357
R ²	0.841	0.899
Adjusted R ²	0.838	0.897

Note: The table reports two additional estimation results from the natural experiment. The same dataset as in Table B.2 is used. The clustered standard errors at the theater-level are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table C.10: Product variety: VPF-unrelated theaters only

<i>DV: product variety (in log, at theater-week level)</i>				
	(1) Pooled	(2) Between	(3) Within: long comparison	(4) Within: short comparison
<i>All data</i>				
Digital	0.111*** (0.037)	-0.158 (0.118)	0.007 (0.034)	0.015 (0.017)
R ²	0.009	0.106	0.789	0.848
Adj. R ²	0.009	0.099	0.786	0.844
<i>By time period</i>				
Digital: 2006-10	-0.319*** (0.106)	-0.469*** (0.120)	-0.086** (0.037)	-0.010 (0.025)
Digital: 2011-16	0.266*** (0.076)	0.242** (0.115)	0.111*** (0.038)	0.041 (0.027)
R ²	0.038	0.128	0.790	0.848
Adj. R ²	0.038	0.121	0.788	0.844
Year-Week FE	No	Yes	Yes	Yes
Theater FE	No	No	Yes	No
Theater-Year FE	No	No	No	Yes
N	78,191	78,191	78,191	78,191

<i>DV: product variety (in log, at theater-week level)</i>						
	Model (3) Within: long comparison			Model (4) Within: short comparison		
	Screens: 1-4	Screens: 5-7	Screens: 8+	Screens: 1-4	Screens: 5-7	Screens: 8+
Digital: 2006-10	0.021 (0.050)	-0.046 (0.038)	-0.060 (0.049)	0.060 (0.046)	-0.033 (0.029)	-0.086*** (0.027)
Digital: 2011-16	0.276*** (0.058)	0.012 (0.036)	-0.030 (0.042)	0.104*** (0.037)	0.055 (0.042)	-0.083 (0.051)
Year-Week FE	Yes			Yes		
Theater FE	Yes			No		
Theater-Year FE	No			Yes		
N	78,191			78,191		
R ²	0.797			0.848		
Adj.R ²	0.795			0.844		

Note: Columns report estimated β in Equation 1 for product variety. Standard errors are clustered by theater and are reported in parentheses; *p<0.1; **p<0.05; ***p<0.01.