Estimating the Costs of Standardization: Evidence from the Movie Industry

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Abstract

This paper studies the decentralized adoption of a technology standard when network effects are present. If the new standard is incompatible with the current installed base, adoption may be inefficiently delayed. I quantify the magnitude of "excess inertia" in the switch of the movie distribution and exhibition industries from 35mm film to digital. I specify and estimate a dynamic game of digital hardware adoption by theaters and digital movies supply by distributors. Counterfactual simulations establish that excess inertia reduces surplus by 16% relative to the first-best adoption path; network externalities explain 41% of the surplus loss. Targeted adoption subsidies or a mandate on digital distribution help bridge this welfare gap.

Keywords: dynamic games, network effects, technology adoption, movie industry
JEL Classification: C73, L15, O33, L82

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1 Introduction

Technology standards play a central role in networked industries.[1] When the value of a technology increases with the number of users, firms have an incentive to coordinate on a single technology—the standard—to exploit the benefits of a larger network and ensure interoperability of complementary products. However, once coordinated on a standard, the industry may become reluctant to switch to new and superior technologies if they are incompatible with the installed base. Can standardization prevent the efficient adoption of new technologies? While the theoretical literature (Farrell and Saloner (1985, 1986)) has shown that inefficient delay (i.e., excess inertia) can arise, attempts to empirically assess it remain scarce. This paper studies the diffusion of a new technology standard in the movie industry and estimates the magnitude of excess inertia.

Two sources of inefficiency can delay the adoption of the new technology. First, network effects may give rise to adoption externalities: the marginal adopter benefits other adopters (and may hurt non-adopters) so that the private costs and benefits do not reflect the social ones. Second, incomplete information about other firms' willingness to adopt induces coordination failure: firms are unwilling to risk switching without being followed, which creates delays in adoption.

As an application, I study the conversion of movie distribution and exhibition from the 35mm film standard to digital cinema between 2005 and 2013 in France, the largest European market by number of screens and theaters. Digital cinema consists of distributing motion pictures to theaters over digital supports (internet or hard drives) as opposed to the historical use of 35mm film reels. To screen digital movies, theaters must equip their screens with digital video projectors instead of film projectors.

This technological switch is well suited for assessing excess inertia in standard adoption. Indeed, the movie distribution-exhibition industries constitute a hardware-software system with (indirect) network effects (Katz and Shapiro (1985)).[2] Because film and digital are incompatible technologies, adoption of digital projectors—the hardware—by theaters is contingent on the availability and variety of digital movies—the software—supplied by distributors. Conversely, software variety depends on the hardware installed base.

Market forces may not have provided sufficient incentives for an efficient switch from

[1] Examples include AC in electric power distribution, FedACH for wire transfers in banking, USB for data transmission, MP3 and 3.5mm jack for music distribution, NTSC for color TV transmission, and 4G LTE in broadband networks for mobile devices. The European Commission has identified five priority domains (5G, cloud, cybersecurity, big data and the internet of things) where ICT standardisation is most urgent. Applications that would benefit from standardization in these domains include e-health, intelligent transport systems, and smart energy (European Commission (2016)).

[2] See also Chou and Shy (1990), Church and Gandal (1992), Church, Gandal, and Krauske (2008).

35mm film to digital. On the exhibition side, the adoption of digital projectors by a theater raises distributors' incentive to release movies in digital. This increased availability of digital movies is a positive externality on other theaters, which is not internalized by the adopter. On the distribution side, uncertainty about other distributors' willingness to release movies in digital can lead to coordination failure, with some distributors inefficiently delaying their digital conversion.[3] Indeed, it is optimal for a distributor to release a given movie in digital only if sufficiently many theaters are equipped to screen it. The fraction of equipped theaters will be high if sufficiently many distributors are releasing digital movies. This chicken-and-egg problem can make a unilateral switch to digital suboptimal.[4]

The paper leverages novel datasets on adoption of digital projectors at the theater-screen level, theater characteristics, digital conversion costs, digital movie availability, and average distribution costs (printing, shipping and storage cost per movie print) under the film and digital technologies.

To test whether the diffusion of digital was inefficiently delayed, I specify a dynamic structural model of the movie exhibition and distribution sectors. Theaters' technology-adoption choices are modeled as a dynamic game played at the level of the French movie industry, allowing for rich theater and market heterogeneity (e.g., type of programming, chain affiliation, market size, number of rival's screens, etc.). Every period, theaters choose the number of screens to equip with digital projectors, given the adoption cost and availability of digital movies. In turn, the availability of digital movies depends on the installed base of digital screens in the industry.

Because network effects are at the industry level, with hundreds of theaters adopting, this framework generates a particularly high-dimensional state space. To alleviate the computational burden, I define a nonstationary oblivious equilibrium (Weintraub, Benkard, Jeziorski, and Van Roy (2008)) of the game exploiting the fact that a single theater is non-atomic and plays against the *expected* distribution of the industry state. The model is estimated using a conditional choice probability-based method (Hotz and Miller (1993), Hotz, Miller, Sanders, and Smith (1994)) combined with matrix inversion to obtain choice-specific value functions (Aguirregabiria and Mira (2007), Pesendorfer and Schmidt-Dengler (2008)). The estimation approach exploits differences in adoption behavior across theaters (e.g., differences in adoption times, units of new technology acquired, and adoption costs) to estimate how exogenous theaters and market characteristics affect the single-period profits from converting a screen

[3]Distributors' willingness to switch depends on costs that vary widely across heterogeneous distributors (large U.S. studios vs. small French distributor) and are private information.

[4]In general, these two sources of inefficiency may arise both for upstream distributors and downstream theaters. The focus on externalities among downstream theaters is motivated by the data and the institutional framework.

to digital.

Using the estimated model, the paper quantifies the delay in adoption and explores various policy remedies via counterfactual analysis. First, in the planner's benchmark, I solve for the adoption path chosen by a planner maximizing aggregate theater profits, taking as given upstream distributors' equilibrium reaction function (fraction of movies released in digital given the installed base of digital screens). In this counterfactual, adoption externalities across theaters are internalized, leading to a steeper adoption path. Differences in theaters' surplus between the market outcome and the planner's benchmark are attributed to adoption externalities across theaters. Second, in the coordination benchmark, I assume that the planner mandates coordination on digital distribution upstream starting in 2005 and maximizes aggregate theater profits. Differences in theater' surplus between the coordination and the planner's benchmarks are attributed to coordination failure upstream.

The adoption path under the equilibrium market outcome is delayed compared to the coordination and planner's benchmarks: by 0.8 to 3 years for the time to 10% adoption, and 0.3 to 0.5 years for the time to 90% adoption. Additionally, inefficient delays in adoption reduce surplus by 16% relative to the first-best path (coordination benchmark). Adoption externalities across theaters explain 41% of the surplus loss.

Broad-based adoption subsidies and subsidies targeting small theaters are effective at internalizing these adoption externalities. Under a 25% adoption subsidy, both policies achieve industry profits on par with the planner's benchmark. Nonetheless, the results indicate that coordinating distributors to make their movies available in digital would be more effective than subsidizing theater adoption. In general, whether a planner should target the software or the hardware side in a two-sided market is an empirical question that is industry-specific: e.g., it depends on the magnitude of indirect network externalities from hardware to software (and from software to hardware) and the magnitude of the cost reductions on each side.

The methodology and empirical findings are relevant for understanding the determinants of technology adoption and, ultimately, productivity growth in other hardware-software industries with many firms. Recent examples include: the switch from USB-A/B to USB-C in the consumer electronics industry, where computer and smartphone (hardware) manufacturers' adoption depends on the availability of USB-C compatible software (i.e., peripherals and accessories such as monitors, webcams, audio system, controllers, TVs, keyboards, mouses, and printers); or the switch from chip card to contactless technology in the debit/credit card market, where issuance of contactless cards by financial institutions (hardware side) is predicated on merchants (software side) acceptance and adoption of contactless point-of-sale terminals.

The rest of the paper is organized as follows. The next section reviews the literature and highlights the main points of departure from it. Section 3 presents the movie distribution and movie exhibition industries, describes the technology and highlights the specificities of the French market. Section 4 describes the data and gives preliminary descriptive statistics. Section 5 develops the dynamic structural model of technology adoption. Section 6 shows the identification and estimation of the industry model. Section 7 presents the counterfactual analysis. Section 8 concludes.

Tables and figures are located after the main text.

2 Related Literature

This paper is related to the literature studying the emergence of technology standards, and in particular, the benefits of standard-setting organizations (SSOs) relative to decentralized markets. Recent work includes Rysman and Simcoe (2008), Farrell and Simcoe (2012), and Simcoe (2012). This paper differs from this literature by shifting the focus from delays occurring during an SSO's deliberation process to the subsequent delays in the decentralized diffusion of the standard elected by the SSO. Given that reaching consensus on the technical specifications of a standard does not guarantee immediate adoption, this paper complements the literature by emphasizing delays in post-consensus adoption.[5]

Previous empirical work on technology adoption under network effects has primarily focused on the identification and estimation of network effects. Identification is, in general, not straightforward due to the reflection problem (Manski (1993)). Rysman (2019) discusses this issue in the case of network effects and reviews the approaches taken to address it. In the context of direct network effects, recent contributions use regional or individual-specific exogenous shifters of network size to identify network effects: Gowrisankaran and Stavins (2004) study ACH adoption by banks, Tucker (2008) studies video-messaging adoption by a bank's employees, Goolsbee and Klenow (1999) study adoption of home computers.

For technologies with indirect network effects, the literature relies on instruments that shift adoption on one side of the market (e.g., software market) to identify the degree of indirect network effects on the other side of the market (e.g., hardware market). Recent examples include: video games platforms (Clements and Ohashi (2005), Corts and Lederman (2009), Dubé, Hitsch, and Chintagunta (2010)), compact disks titles-players (Gandal, Kende, and Rob (2000)), DVD titles-players (Karaca-Mandic (2003), Gowrisankaran, Park, and Rysman (2014)). In addition to the endogeneity problem, the latter paper highlights other econo-

[5] In the case of digital cinema, deliberation by the Society of Motion Picture and Television Engineers took place between 2000 and 2004. I focus on the diffusion of the standard elected, between 2005 and 2014.

metric issues arising with time series data: hierarchical variation and spurious correlation. Because the data structure in this paper is likely to give rise to the same econometric issues, I build on their approach in the estimation section.

A few papers within this literature go beyond the estimation of network effects and discuss welfare implications. Ohashi (2003) studies the war between VHS and Betamax in the VCR market and quantifies the value of compatibility between the two technologies. Rysman (2004) studies the Yellow Pages market and analyzes the trade-off between market power and internalization of network effects. Augereau, Greenstein, and Rysman (2006) discuss the potential role of ISPs differentiation in the initial failure to coordinate on a standard for 56K modems. Ackerberg and Gowrisankaran (2006) examine the welfare implications of customer and bank subsidies in ACH adoption. Ryan and Tucker (2012) study video-calling adoption within a multi-national firm and simulate counterfactual diffusion paths under alternative network seeding policies. Lee (2013) studies the welfare impact of exclusivity contracts between software providers and hardware platforms in the video game industry. The present paper contributes to this literature by investigating whether equilibrium standard adoption in network industries would differ from the social optimum, and if so, by identifying the role of adoption externalities in the surplus loss.

This paper makes a contribution to the literature using dynamic games to study innovation and technology adoption. Recent research analyzes the effect of competition on innovation (e.g., Goettler and Gordon (2011), Igami (2017), Igami and Uetake (2017)) or technology adoption (Schmidt-Dengler (2006), Macher, Miller, and Osborne (2021)). This paper contributes to this literature in two ways. First, I apply the dynamic oligopoly framework to tackle a novel question: i.e., the efficiency of the technology diffusion path in a network industry. Recent advances in the estimation of dynamic games allow high-dimensional strategic interdependence (adoption externalities) between firms at the industry level. Second, this paper highlights the importance of measuring and modeling adoption within the firm (e.g., at the unit of capital level). Indeed, multi-homing (i.e, the simultaneous use of two technologies across a firm's capital stock) is a common feature of a wide array of industries (Mansfield (1963), Battisti and Stoneman (2005)).

This paper contributes to the empirical literature studying the movie industry. This literature has considered many facets of the industry: the effect of vertical integration (Gil (2009), Andrew Hanssen (2010)), seasonality (Einav (2007)), release dates (Einav (2010)), strategic entry and exit, and spatial retail competition (Davis (2006a), Davis (2006b), Takahashi (2015), Gil, Houde, and Takahashi (2015)). Recent contributions have studied digitization in the movie industry. Waldfogel (2016) studies the effect of digital movie production, alternative distribution channels, and online film criticism on new releases. Rao and Hartmann

(2015) study the quality-variety trade-off in screening brought about by digital projection. Yang, Anderson, and Gordon (2020) evaluate the impact of digital projection on product variety and supply concentration. Whereas the last two papers analyze how theater-level screening choices change post-digital adoption, I focus on theaters' dynamic decision to adopt, which is primarily driven by labor costs savings and digital software availability.

3 Industry Background

This section describes the movie-distribution and movie-exhibition industries before and after the advent of digital technology. It presents the costs and benefits of digital cinema from the perspective of distributors and exhibitors and discusses the effect of digital cinema on movie ticket prices and quality. Finally, this section highlights the specificities of the French distribution and exhibition markets and important stylized facts.

3.1 From 35mm film to digital

For most of the 20th century, movies reached viewers after going through a series of steps in a vertically structured industry. After the movie is shot and edited, distributors print the movie onto 35mm film reels and ship the reels to movie theaters. At the theater, a projectionist arranges the reels so they can be fed to a film projector. When the movie's run is over, the print is broken back down into shipping reels and either sent to the next theater or returned to the distributor.

On January 19, 2000, the Society of Motion Picture and Television Engineers, in the U.S., initiated the first standards group dedicated to developing digital cinema. The technology would entail (1) movie distribution on a digital support (via the internet or hard drives), instead of the historical uses of film reels and (2) movie projection via digital projection hardware instead of the film-projection technology.

To screen a digital movie, theaters must equip their screens with digital projectors. Four manufacturers supply digital cinema projectors worldwide: Sony, Barco, Christie, and NEC. The average list price of a digital projector (in 2010 euros) was €$88,000$ in 2005, €$50,000$ in 2010, and €$40,000$ by 2012. In addition to the digital projector, a digital cinema requires a dedicated computer, the "server." A digital movie is supplied to the theater as a digital file called a Digital Cinema Package (DCP). The DCP is copied onto the internal hard drives of the server, usually via a USB port.

3.1.1 Supply of digital movies by distributors

Digital distribution of movies drastically cuts printing and shipping costs for movie distributors. The cost of an 80-minute feature film print is on average between US$1,500 and $2,500. By contrast, a feature-length movie can be stored on an off-the-shelf 300 GB hard drive for $50.[6] In addition, hard drives can be returned to distributors for reuse. With several hundred movies distributed every year, the distribution industry saves over $1 billion annually.

Importantly, the distribution format (digital or film print) is independent of the support on which the movies is shot (i.e., with a film or digital camera). Indeed, editing and post-production have been done digitally since the mid-1990s and digital cameras have been the main medium for shooting since the early 2000s.

3.1.2 Adoption of digital projectors by exhibitors

Digital projection allows exhibitors to cut down on operating costs. Screening film prints is a technical task, requiring mechanical skills that are increasingly rare and costly.[7] By contrast, digital projection automates all the tasks that were previously performed by the projectionist. Untrained staff can easily compose a playlist and launch a projection as on a regular computer. Digital projection also opens up the possibility of using theaters for "alternative content" such as pop concerts, opera broadcasts, and sports events.

3.1.3 Multi-homing by movie distributors and theaters

Multi-homing in distribution consists in distributing a given movie on both film and digital supports. According to industry professionals, multi-homing was widespread over the diffusion period studied in this paper (2005–2014).

Multi-homing in exhibition refers to equipping a given screen with both a digital and film projector. This type of multi-homing was rare for practical reasons (limited space in screening booth, heavy and sensitive projection equipment), and because theaters laid off their projectionists following the adoption of digital projection.

3.1.4 The Virtual Print Fee system

A large fraction of the cost savings from digital cinema is realized by distributors. For this reason, theaters have been reluctant to switch without a cost-sharing arrangement with distributors. An agreement was reached with the Virtual Print Fee (VPF) system. Under this system, the distributor pays a fee per digital movie to help finance the digital hardware acquired by the theater. The VPF contract would typically cover 50% of the hardware

[6] Encryption-key generation, transportation, and storage, add approximately $200–$300. For French/European movies, these figures are around 950€ for film print distribution and around 350€.

[7] Film projectionists are commonly represented by powerful unions. See the interview in l'Obs 07/14/2010 (in French) "Frédéric, projectionniste chez UGC pour 1800 euros par mois" The collective bargaining agreements set the minimum monthly salary to €1,500 over the period of interest.

adoption cost; the rest has to be paid for by the exhibitor.

3.1.5 Impact on ticket prices and movie quality; and the role of 3D

Excluding 3D movies, the film-digital quality differential was small enough not to warrant any impact on ticket prices. Although 3D movies, and in particular *Avatar* (released in the winter 2009, grossing $2.7 billion worldwide), were initially a major selling point for digital projection, exhibitors quickly realized it was not expanding the audience as promised (Bordwell (2013)). The vast majority of movies released over the diffusion period were in 2D.

3.2 The French distribution and exhibition market

3.2.1 The French exhibition industry

The French exhibition industry is fragmented: half of theaters are mono-screen, and an additional 15% are two-screen theaters. The largest theater chains by share of total screens in 2014 are Gaumont-Pathé (13.6% of screens), CGR (7.8%), and UGC (7.5%). These three chains make up 50.1% of total box office revenue (Kopp (2016)). The French exhibition industry experienced small entry and exit rates over the diffusion period (around 1.5% per year). As a result, the majority of digital projectors acquired were replacing old film projectors, enabling the analysis of the industry's choice between the old and new technology standard.

3.2.2 The French distribution industry

Between 2005 and 2014, U.S. movies had an average 47% market share (of total box-office revenue in France), French movies had a 39% market share, and European and other nationalities made up 14% of the box office.[8] Importantly, U.S. studios distribute their movies in France via national subsidiaries (e.g., Universal France or Warner Bros. France). Subsidiaries tailor their advertising and distribution campaigns to the national market they operate in. Therefore, the support—film or digital—over which U.S. movies are distributed in France depends in part on the installed bases of film and digital projectors in France.

3.2.3 The VPF and government subsidies

The VPF system was initially the result of bilateral negotiations between distributors and exhibitors. In September 2010, a law was passed making VPF contributions mandatory: any distributor willing to distribute digital copies of its movie must pay a fixed fee to the theater booking the digital copy. The VPF contributions would go toward covering 50% of the digital projector cost, the rest being paid by the exhibitor.

Government and regional subsidies to small theaters were another important feature of

[8] Calculations based on the CNC 2014 annual report.

the hardware-acquisition process. Many small "continuation" theaters, which receive movies only two or three weeks after their national release, did not generate enough VPF to be able to acquire the digital-projection hardware. The government, along with the regions, stepped in to help these theaters finance their digital conversion. These aids were allocated to theaters that owned fewer than three screens and were not part of a chain controlling 50 screens or more.

3.2.4 Art house theaters

French theaters can acquire the "art house" label if they screen a minimum share of independent and art house movies. The label, awarded every year, entitles the theater to government financial support (in the form of a lump-sum subsidy). A priori, art house theaters may differ in their adoption behavior from commercial (i.e., non-art house) theaters if there are significant differences in operating profits.

4 Data and Descriptive Statistics

This section describes the data and presents descriptive statistics. The data contain information on theaters' digital-adoption decisions, theater characteristics, adoption costs, and availability of digital movies over time.

The main dataset is a panel describing digital adoptions by theaters. This dataset was collected from two sources: the European Cinema Yearbooks published by Media Salles, and an online database maintained by Cinego, a private digital platform.[9] Both sources are public and provide snapshots of the digital-exhibition industry at different periods spanning June 2005 through March 2013, in France. At each of the 18 observation dates, the number of digital projectors acquired is known for every active theater. Figure 1a represents the 18 observation dates along with the industry share of screens equipped with digital projection. The panel is aperiodic (starting in 2008) and stops before the diffusion is complete in 2014. Five periods are dropped to ensure a relative periodicity in the sample (6 months). Details about this procedure can be found in Appendix A.

Three auxiliary datasets complement the main adoption panel dataset. The first is obtained from the French National Center of Cinematography (CNC hereafter). This dataset, covering the period 2005-2015, contains (1) lists of all active theaters, (2) the number of screens, the number of seats, the address, the owner's identity (chain, individual), and art house status for each active theater, (3) market population (categorical) at the urban/rural unit level (defined below), and (4) the annual share of movies released in digital (distributed

[9] Raw data available at: `http://www.mediasalles.it/yearbook.htm` and `https://cinego.net/basedessalles` (via the Internet Archive)

partially or entirely in digital) in France.

The second auxiliary dataset, obtained from the European Audiovisual Observatory, provides time-series information on digital-projector acquisition costs.[10] Namely, the time-series for the hardware adoption cost is constructed by adding (1) the price of a digital projector (net of VPF contributions) to (2) ancillary costs. The time-series for digital-projector prices is based on a survey of projector manufacturers. Actual prices paid by specific theaters are not public due to nondisclosure agreements. This time-series is taken as representative of the "list" price of digital projectors. The analysis accounts for the VPF subsidies, which cover 50% of the projector price. Ancillary costs include the price of other equipment (the server and the digital sound processor), Theater Management software, and labor costs (installation). Estimates of ancillary costs were collected by the European Audiovisual Observatory, but are only available for 2010. In the analysis, these ancillary costs are assumed to have stayed constant over the sample period. This assumption seems reasonable for labor costs. According to the Observatory, price declines for the server and digital sound processor are more limited than for the digital projector. The hardware-adoption cost is adjusted to 2010 constant euros. The hardware adoption cost is interpolated to obtain estimates at the 13 observation dates. Figure 1b shows the time series for this variable.

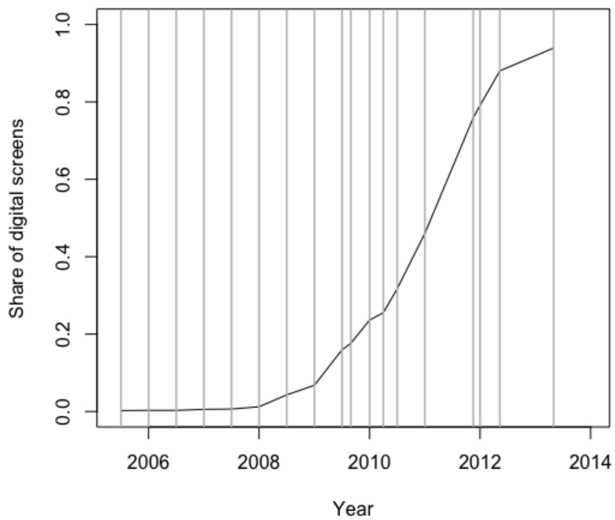
Third, data on the number of movies released in digital in the U.S. between 2005 and 2015 is obtained from the Internet Movie Database (IMDb). For each movie release, the website reports technical specifications including the "printed film format" over which the movie was distributed (e.g., 35mm, digital). This information is collected for all U.S. movie releases over the period of interest.

The analysis is conducted on the data after the following preparation. Itinerant theaters, which account for 5% of active theaters, are dropped. Because the focus is on firms' decision to convert existing capital from film to digital, theaters that enter during the diffusion period already equipped with digital projectors are excluded from the model. Their contribution to the overall installed base of digital screens is, however, accounted for and taken as exogenous. Firms exiting before conversion to digital are also excluded.[11] Rates of entry and exit are, however, low (between 1 and 1.5% of firms enter or exit every year). Theaters in French overseas territories are excluded. The final sample includes $1,671$ theaters, located in $1,169$ markets (urban or rural units, defined below), and observed over 13 dates between June 2005 and April 2012. The sample covers 87% of all non-itinerant theaters located in Metropolitan

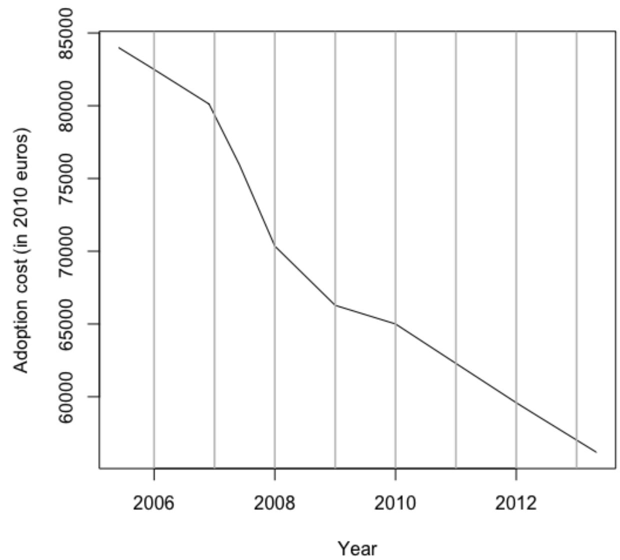
[10]See "The European Digital Cinema Report - Understanding digital cinema roll-out" (Council of Europe, 2012)

[11]The inability to convert is, however, not a significant cause for exit because the CNC and regional governments subsidized digital adoption for the smallest and less financially sound theaters.

Figure 1: Data and descriptive statistics



(a) Observation times for the diffusion of digital projectors



(b) Hardware adoption cost (2010 €)

France, which were active in 2005 or entered before 2008 equipped with the old technology.

Local market definition and competitors

Local market demand and competition are defined based on the urban or rural unit in which the theater is located. An urban unit is defined by the INSEE, the French National Statistics Office, for the measurement of contiguously built-up areas. It is a "commune" alone or a grouping of communes forming a single unbroken spread of urban development, with no distance between habitations greater than 200 meters, and a total population greater than 2,000 inhabitants. Communes not belonging to an urban unit are considered rural.[12] In 2010, Metropolitan France contained $2,243$ urban units and about $33,700$ rural units.

For the largest cities (Paris, Lyon, Marseille), the urban unit division is not appropriate, because the resulting local markets are unreasonably large. In these cases, the relevant market within each city is the *"arrondissement"* (equivalent to zipcode in the U.S.).[13] In the rest of the paper, a theater's competition is measured using the number of competing screens in the same local market.

Descriptive statistics

[12]Communes correspond to civil townships and incorporated municipalities in the U.S.

[13]The subdivision by *arrondissement* is arbitrary, given that theaters are engaged in spatial competition. As a robustness check, a theater's competition can also be measured using distance bands around the theater location. With a distance band of 5 miles, this alternative definition gives similar values for the variable "number of competitors' screens."

The analysis focuses on theaters with at least four screens, due to the prevalence of government and regional subsidies for theaters with three screens or fewer.[14] Tables 1 and 2 report cross-sectional summary statistics, and highlight the market and firm heterogeneity captured by the data for the 399 theaters with at least four screens.

Table 1 reports summary statistics by market size. Paris and its suburbs are controlled for separately because attendance rates are significantly higher in the capital compared to national averages. As expected, the stock of screens grows with the market size. A larger fraction of theaters is art house in rural areas because the CNC's threshold requirements to qualify are lower for relatively less dense areas. Theater size increases on average with market size (except for Paris, where the scarcity of space limits theater size).

Table 2 describes theater characteristics. A significant fraction of theaters, 33%, are art house theaters. The average theater has eight screens. Thirty-five percent of theaters are part of the three largest theaters chains: Gaumont-Pathé, CGR, and UGC. In total, 53.4% of theaters are miniplexes (4-7 screens), and 46.6% are multiplexes/megaplexes (8 screens or more).

Table 1: Summary statistics by market size (theaters with at least 4 screens)

Geographic location	Theaters	Markets	Theater size (mean)	Art house (share)	Screens per market (mean)	Screens per market (st.dev)
Urban unit - >100k inhab	174	101	9.17	0.21	15.79	8.43
Urban unit - 20 to 100k inhab	126	116	7.02	0.56	7.63	2.99
Urban unit - <20k inhab and rural	17	17	6.65	0.65	6.65	3.55
Paris	37	15	7.19	0.14	17.73	9.57
Paris - inner suburbs	18	18	9.22	0.28	9.22	4.98
Paris - outer suburbs	27	26	7.93	0.19	8.23	4.32
National	399	293	8.12	0.34	11.05	7.26

Preliminary analysis of the data uncovers two important points. First, theaters tend to gradually roll-out digital technology over their stock of screens. Figure 2a shows the number of new digital screens equipped per year. Figure 2b decomposes this number into: (1) screens installed by new adopters (theaters with no digital screens in $t-1$), and (2) screens installed by theaters with some digital screens by $t-1$. (1) is informative about the degree of adoption at the extensive margin, whereas (2) is informative about the degree of adoption at the intensive margin (within-theater). Starting in 2008, a large fraction of screens converted to digital per year belong to theaters that have already adopted at least

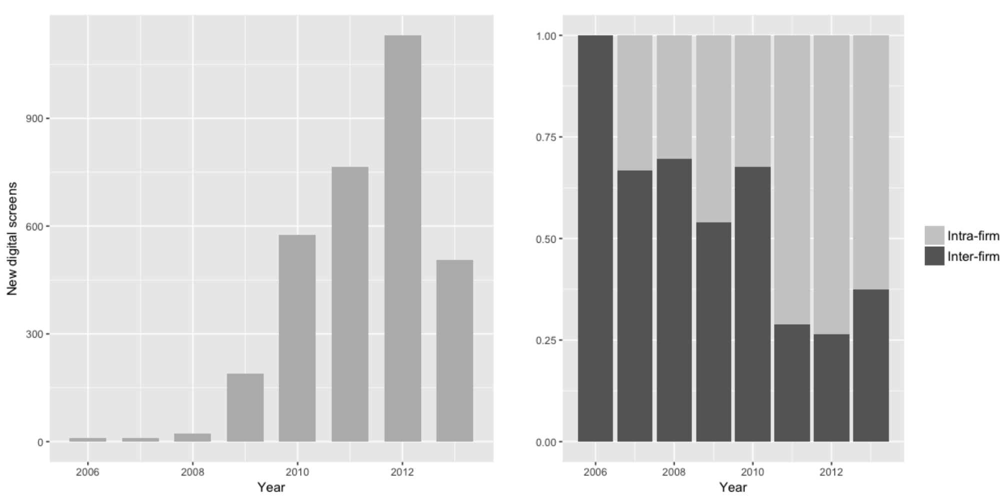
[14] These subsidies covered part or all of a theater's adoption costs. They were allocated according to a government-determined (or regional) timeline. Therefore, subsidized theaters' adoption behavior does not stem from an optimization problem and is not informative about underlying benefits from adoption. Although the model does not formally include subsidized firms, their adoption decisions contribute to the installed base of digital projectors but remain small due their limited share of box office revenue.

Table 2: Summary statistics (theaters with at least 4 screens)

	Minimum	Mean	Maximum	St. Deviation
Theaters characteristics				
Number of screens	4	8.12	23	3.74
Art house label	0	0.34	1	0.47
Number of rival screens	0	8.70	44	11.27
Theaters size				
Miniplexes (4-7 screens)	0	0.53	1	0.50
Multi- and Megaplexes (8 screens or more)	0	0.47	1	0.50
Theaters chains (indicator)				
UGC	0	0.08	1	0.28
Gaumont-Pathé	0	0.17	1	0.37
CGR	0	0.10	1	0.30
Cost of digital conversion (per screen, 2010 €)	$56,000$	$69,862$	$84,000$	$10,166$

one digital screen in previous periods, highlighting the importance of the intensive margin.

Figure 2: Within-theater adoption



(a) *New digital screens* (b) *Decomposition: Inter/Intra-firm*

Note: "Inter-firm" corresponds to screens installed by new adopters (no digital screens by $t-1$). "Intra-firm" corresponds to screens installed by theaters with some digital screens by $t-1$. Subsidized theaters (3 screens or fewer) are excluded.

If digital movie availability is limited, one would expect theaters to convert only a fraction of their screen in a given period. To closely match this feature of the data in the theoretical section, adoption decisions will be modeled at the screen-level. In Appendix B, I provide reduced-form evidence that the gradual adoption of digital screens is partly driven by increasing availability of digital movies.

Second, adoption by a theater's competitors does not significantly affect its likelihood of adoption. Table 3 shows the result of an ordered probit model in which the fraction of screens converted by a theater during the past 6 months is regressed on firm and market characteristics. A polynomial in time is included to capture aggregate time shocks (e.g., adoption cost, availability of digital movies, etc.). Once I control for market characteristics that may create correlation between firms in the same local market, adoption by a theater's competitors does not significantly affect its adoption decision. The likelihood-ratio test of specification (3) against a specification including competitors' digital screen adoption fails to reject the null of no effect at the 5% confidence level. To reflect this feature of the data, the industry model will include strategic interactions only at the industry level (via network effects) but not at the local market level.[15]

5 Industry Model

This section presents the dynamic structural model. The model will be subsequently used to guide the estimation and recovery of theaters' operating profits under the film and digital technologies. These profits are required to quantify, via simulation of counterfactuals, the amount of surplus lost due to excess inertia and the effect of policy remedies (e.g., adoption subsidies).

Theaters' technology adoption choices are modeled as a dynamic game played at the level of the French movie industry. Digital projectors are durables, so the model must incorporate the fact that theaters can delay their adoption to a future date to benefit from lower prices and greater availability of complementary goods (i.e., digital movies).

The central part of the model specifies how theaters make their technology adoption decisions—at the screen-level—as a function of their firm and market-level characteristics, the adoption cost, and the availability of technology-specific complementary goods (film or digital movies). Theaters have an incentive to convert to digital projection due to cost-reductions (primarily labor cost savings). Although the analysis focuses on the exhibition sector, the model captures via a reduced-form distributors' per-period decision regarding on which support to distribute movies (film and/or digital), given the technology-specific installed bases (screens equipped with film/digital projectors).

Finally, an equilibrium of the distribution-exhibition industries is specified. I start by

[15] The lack of strategic interactions can be explained by the fact that digital conversion does not create a differentiation advantage because movies were multi-homed. Moreover, despite lower costs under digital, anecdotal evidence indicates that theaters did not reduce ticket prices after switching to digital because of distributors' resistance (Davis (2006b)).

Table 3: Adoption policy function

	Dependent variable: Share of screens converted a_{it}/S_i							
	(1)		(2)		(3)		(4)	
	Estimate	s.e	Estimate	s.e	Estimate	s.e	Estimate	s.e
Time	0.664	0.065	0.665	0.065	0.691	0.067	-0.243	0.056
Time squared	-0.021	0.003	-0.021	0.003	-0.020	0.003	0.032	0.004
Time x Art house	-0.211	0.147	-0.217	0.147	-0.291	0.147	0.129	0.009
Time squared x Art house	0.016	0.007	0.016	0.007	0.019	0.007	-0.007	0.001
Own screens	0.091	0.031	0.086	0.032	0.069	0.034	-0.219	0.043
Own screens squared	-0.003	0.001	-0.003	0.001	-0.001	0.002	-0.010	0.002
Art house	0.194	0.792	0.202	0.791	0.612	0.787	0.001	0.143
Competitors' screens (film and digital)	-0.003	0.002	-0.005	0.003	-0.001	0.003	0.012	0.006
Own share of d-screens	-1.360	0.111	-1.380	0.112	-1.666	0.118	-0.028	0.039
Market dummies								
Paris - outer suburbs			-0.239	0.170	-0.108	0.172	-0.005	0.126
Urban unit - 20k-100k inhabitants			-0.086	0.142	-0.091	0.144	-0.004	0.124
Urban unit - >100k inhabitants			-0.078	0.148	-0.097	0.149	-0.010	0.118
Paris - inner suburbs			-0.345	0.189	-0.174	0.191	-0.005	0.069
Paris			-0.017	0.172	0.186	0.174	-0.004	0.079
Chain dummies								
Gaumont-Pathe					-0.151	0.080	-0.001	0.135
CGR					0.328	0.094	-0.000	0.066
UGC					-0.914	0.133	-0.007	0.046
Interactions: own screens × other variables							✓	
Observations	4,788		4,788		4,788		4,788	
- log Likelihood	2,186		2,182		2,144		2,276	
AIC	4,391		4,394		4,323		4,613	

Note: Specification (1) is the baseline specification. Specification (2) augments the baseline by including market dummies to control for market size. Specification (3) includes both market dummies and theater-chain dummies for the three major French theater chains (Gaumont-Pathé, CGR, and UGC). Specification (4) also controls for interactions between theater size S_i and all other variables. For market dummies, the omitted category is urban unit with fewer than 20k inhabitants and rural units. For the chain dummies, the omitted category is single firm and small chains.

characterizing a Markov Perfect equilibrium of the game. Next, and in anticipation of the estimation and computation sections, I impose simplifying assumptions to deal with the high-dimensionality of the state space. These assumptions are shown to be consistent with the (nonstationary) oblivious equilibrium concept of Weintraub, Benkard, Jeziorski, and Van Roy (2008).

All vectors are denoted in bold.

5.1 Adoption of digital projectors by theaters

Time is discrete and infinite, $t = 1, 2, \ldots, \infty$. A period corresponds to six months.

Firms: A firm is a movie theater. There are N firms indexed by $i \in \mathbf{N} = \{1, ..., N\}$. This set is fixed throughout the game: no entry and exit occur.

Firm types: Denote by $\boldsymbol{\tau}$ the vector representing a theater's type, which is fixed throughout the game. A firm's type includes the theater size (number of screens), local market characteristics (market size and the total number of competitors' screens), art house label, and a chain identifier.[16] Denote by $\mathcal{T}$ the set of possible types. For type $\boldsymbol{\tau} \in \mathcal{T}$, let $N_{\boldsymbol{\tau}}$ and $S_{\boldsymbol{\tau}}$ denote the total number and size of theaters of type $\boldsymbol{\tau}$ (satisfying $\sum_{\boldsymbol{\tau} \in \mathcal{T}} N_{\boldsymbol{\tau}} = N$). The type of theater i is denoted $\boldsymbol{\tau}(i)$.

Firm state space: In period t, the state of theater $i \in \mathbf{N}$, publicly observed by all firms, is the number of screens converted to digital by t, denoted $s_{it} \in \mathcal{S}_{\boldsymbol{\tau}(i)} \equiv \{0, 1, ..., S_{\boldsymbol{\tau}(i)}\}$. The remaining $S_{\boldsymbol{\tau}(i)} - s_{it}$ screens operate using the film technology.

Let $\mathbf{x}_{it} = (\boldsymbol{\tau}(i), s_{it})$. The variables $\mathbf{x}_{it}$ and $(\boldsymbol{\tau}(i), s_{it})$ are used interchangeably. The industry state is the vector of all players' public state variables in time t and is denoted by

$$\mathbf{x}_t = ((\boldsymbol{\tau}(1), s_{1t}), \ldots, (\boldsymbol{\tau}(N), s_{Nt}))$$

Denote by $S = \sum_{i \in \mathbf{N}} S_{\boldsymbol{\tau}(i)}$ the total number of screens in the industry, and $s_t = \sum_{i \in \mathbf{N}} s_{it}$ the total number of digital screens in the industry in period t.

Theaters part of the same chain are assumed to make their adoption decisions independently. This assumption is imposed to keep the estimation computationally tractable.[17]

Transition dynamics: A theater can increase its number of digital screens, s_{it}, by paying an adoption cost. If firm i converts a_{it} screens to digital in period t, the firm transitions to

[16] Theater size, measured by the number of screens, is stable over time for all theaters.

[17] Each chain's state should record firms' states for all theaters part of the chain, resulting in high-dimensional chain states. For instance, Gaumont-Pathé (70 theaters) has a chain state with dimension 1,088,430—assuming all theaters have four screens and ignoring theaters' types. Appendix D.4 discusses the validity and implication of this assumption in more detail.

a state $s_{i,t+1}$ given by

$$s_{i,t+1} = s_{it} + a_{it} \quad \text{for} \;\; a_{it} \leq S_{\boldsymbol{\tau}(i)} - s_{it} \tag{1}$$

There is no uncertainty in state transition. A theater's state s_{it} is bounded above by its maximum capacity $S_{\boldsymbol{\tau}(i)}$.

Aggregate adoption cost: The aggregate adoption cost process, $\{p_t\}_{t\geq 1}$, includes the digital-projector price (net of VPF contributions) and ancillary costs. This process is publicly observable to all firms and assumed to evolve exogenously and deterministically. The process reflects technological advances in the manufacturing of digital projectors, as well as learning-by-doing and scale economies, which exogenously decrease the hardware adoption cost over time.

Firm-specific adoption cost: The per-screen adoption cost for theater i in period t is the sum of two components:

$$p_t + \epsilon_{it} \tag{2}$$

where p_t is the aggregate adoption cost and ϵ_{it} is a theater-specific shock, drawn from a distribution with c.d.f F at the start of period t. This theater-specific shock is privately observed at the beginning of each period and is independent across periods and theaters.

Availability of digital movies: Movies are screened by theaters for one period. According to industry professionals, multi-homing was widespread over the diffusion period studied in this paper (2005–2014).[18] To match this feature of the distribution market, I impose the restriction that a given movie is either multi-homed (i.e., distributed on both film and digital) or released exclusively on film.

For the rest of the analysis, define h_t as the share of movies available in digital (hereafter, simply "the share of digital movies"). This share is a function of the industry state $\mathbf{x}_t$ as well as an exogenous shifter, the share of digital movies released in the U.S denoted $h_{US,t}$.[19] Let

$$h_t = \Gamma(\mathbf{x}_t, h_{US,t}) \tag{3}$$

denote distributors' reaction function giving the share of digital movies as a function of the industry state vector and the state variable $h_{US,t}$. The latter variable is publicly observable to all firms and assumed to evolve exogenously.

Theaters' Single-Period Profit Function: The single-period profit of theater i in period

[18] This is consistent with the findings of Yang, Anderson, and Gordon (2020) for the digitization of the Korean movie industry. They find that the vast majority of distributors multi-homed until 2015.

[19] The dependence of h_t on the whole vector of firm states $\mathbf{x}_t$ is without loss of generality. In practice, however, this vector is high-dimensional and simplifying restriction are imposed in Section 5.2.

t, if it converts a_{it} units, is given by

$$\Pi_i(a_{it}, \mathbf{x}_t, p_t, h_{US,t}, \epsilon_{it}) = \pi_{\boldsymbol{\tau}(i)}(s_{it}, h_t) - a_{it}(p_t + \epsilon_{it}) \tag{4}$$

where $\pi_{\boldsymbol{\tau}(i)}(s_{it}, h_t)$ are theater i's operating profits (screenings, concessions, advertisements) in period t, which depends on the firm type and state $\mathbf{x}_{it} = (\boldsymbol{\tau}(i), s_{it})$ and the shares of digital movies h_t, and $a_{it}(p_t + \epsilon_{it})$ is the total cost of converting a_{it} screens in period t. There is a positive feedback loop between the hardware and software sides of the market, if $\pi_{\boldsymbol{\tau}(i)}(s_{it}, h_t)$ is increasing in h_t. For a theater, the benefit from adoption depends on the share of digital movies h_t, which in turn depends on the installed base of digital screens in the industry (Equation (3)).

Let the difference in single-period profits from choosing action a versus a' be denoted

$$\begin{aligned} \Delta\Pi_i(a, a', \mathbf{x}_t, p_t, h_{US,t}, \epsilon_{it}) &= \Pi_i(a, \mathbf{x}_t, p_t, h_{US,t}, \epsilon_{it}) - \Pi_i(a', \mathbf{x}_t, p_t, h_{US,t}, \epsilon_{it}) \\ &= -(a - a')(p_t + \epsilon_{it}) \end{aligned} \tag{5}$$

The single-period profit function satisfies the following "decreasing difference" restriction

$$\Delta\Pi_i(a, a', \mathbf{x}_t, p_t, h_{US,t}, \epsilon_i) < \Delta\Pi_i(a, a', \mathbf{x}_t, p_t, h_{US,t}, \epsilon'_i) \text{ for any } a > a' \text{ and } \epsilon_i > \epsilon'_i. \tag{DD}$$

From Equation (4), the incremental return $\Delta\Pi_i$ equals the incremental cost of converting a versus a' screens to digital. This incremental cost is the product of the number of additional screens $a - a'$ and the per-screen cost $p_t + \epsilon_{it}$. Restriction (DD) states that the incremental cost (in absolute value) is increasing in the per-screen cost or equivalently in ϵ_{it}. The restriction will guarantee that theaters use monotone strategies in ϵ_{it}: intuitively, theaters which draw a lower adoption cost per screen will tend to convert more screens, all else equal.

State space: In a Markov Perfect Equilibrium (MPE), firms use Markov adoption strategies and condition their adoption decision only on the current vector of state variables $\boldsymbol{y}_t \equiv (\mathbf{x}_t, p_t, h_{US,t})$ and firm-specific shock ϵ_{it}. In particular, firms track $\mathbf{x}_t$ to form expectations about the future evolution of the (payoff-relevant) share of digital movies h_t.

A pure Markov strategy is a mapping from the current state and shock $(\boldsymbol{y}_t, \epsilon_{it})$ into an action $a_{it} \in A_i$.[20] An action profile $\mathbf{a}_t$ denotes the vector of joint actions in period t, $\mathbf{a}_t = (a_{1t}, \ldots, a_{Nt}) \in A = \Pi_{i=1}^N A_i$. The notation $\mathbf{a}_{-i,t} = (a_{1t}, \ldots, a_{Nt}) \setminus a_{it} \in A_{-i}$ refers to the actions by theaters other than i.

Value function and optimal adoption rule: Let $\sigma_i(\mathbf{a}|\boldsymbol{y})$ denote theater i's conditional

[20] The action space A_i is in fact state-specific, because the space of admissible actions is bounded above by $S_{\boldsymbol{\tau}(i)} - s_{it}$. I omit this dependence in the notation for clarity of exposition.

ex-ante (i.e., before the realization of ϵ_i) belief that action profile $\mathbf{a}$ will be played in state $\boldsymbol{y}$. The ex-ante value function (where the subscript t is omitted and next-period variables are marked with a prime) is given by

$$V_i(\boldsymbol{y};\sigma_i) = \sum_{\mathbf{a}\in A} \sigma_i(\mathbf{a}|\boldsymbol{y}) \left[\pi_{\boldsymbol{\tau}(i)}(s_i, h) - a_i p + \beta \sum_{\boldsymbol{y}'} G(\boldsymbol{y}'|\boldsymbol{y},\mathbf{a}) V_i(\boldsymbol{y}';\sigma_i)\right] \\ - \sum_{a_i=0}^{S_{\boldsymbol{\tau}(i)}-s_i} \sigma_i(a_i|\boldsymbol{y}) a_i \mathbb{E}[\epsilon_i|a_i,\boldsymbol{y}] \tag{6}$$

where β is the discount factor, $G(\boldsymbol{y}'|\boldsymbol{y},\mathbf{a})$ is the probability that state $\boldsymbol{y}'$ is reached when the current action profile and state are $(\mathbf{a},\boldsymbol{y})$, and h is determined by equation (3). The next-period industry state $\mathbf{x}'$ (in $\boldsymbol{y}' = (\mathbf{x}', p', h'_{US})$) is a deterministic function of $(\mathbf{x},\mathbf{a})$ because, for every firm j,

$$s'_j = s_j + a_j$$

Uncertainty about $\boldsymbol{y}'$ is encapsulated in firm i's beliefs about other firms' adoption decisions in $\sigma_i(\mathbf{a}|\boldsymbol{y})$.

The optimal adoption rule can be expressed as a function of the *choice-specific* value functions. Let $W_i(a_i|\boldsymbol{y};\sigma_i)$ denote the discounted expected value function of theater i, net of current period payoff, when converting a_i screens in state $\boldsymbol{y}$ with beliefs σ_i:

$$W_i(a_i|\boldsymbol{y};\sigma_i) = \beta \sum_{\mathbf{a_{-i}}\in A_{-i}} \sigma_i(\mathbf{a}_{-i}|\boldsymbol{y}) G(\boldsymbol{y}'|\boldsymbol{y}, a_i, \mathbf{a}_{-i}) V_i(\boldsymbol{y}';\sigma_i). \tag{7}$$

Define $\Delta W_i(a,a'|\boldsymbol{y};\sigma_i) \equiv W_i(a|\boldsymbol{y};\sigma_i) - W_i(a'|\boldsymbol{y};\sigma_i)$ for $(a,a') \in \{0,1,2,..,S_{\boldsymbol{\tau}(i)} - s_{it}\}$ as the difference in the choice-specific value functions of converting a and a' screens to digital in state $\boldsymbol{y}$ with beliefs σ_i. Firm i's optimal adoption rule is derived by noting that, in deciding the number of screens to convert to digital technology, the firm compares the choice-specific value functions *net* of the adoption cost. The adoption cost, in turn, depends on the current list price p_t, and firm i's idiosyncratic shock ϵ_{it}.

Player i's set of best responses in state $(\boldsymbol{y},\epsilon_i)$ and under beliefs σ_i is defined as

$$\mathrm{BR}_i(\boldsymbol{y},\epsilon_i;\sigma_i) = \{a_i \in A_i : W_i(a_i|\boldsymbol{y};\sigma_i) - a_i(p+\epsilon_i) \geq W_i(a'|\boldsymbol{y};\sigma_i) - a'(p+\epsilon_i) \text{ for all } a' \in A_i\} \tag{8}$$

where operating profits $\pi_{\boldsymbol{\tau}(i)}(s_i,h)$ cancel out because they do not depend on the action taken in the current period. Srisuma (2013) shows that, if the single-period payoffs satisfy restriction (DD), $\mathrm{BR}_i(\boldsymbol{y},\epsilon_i;\sigma_i)$ is a singleton set almost surely. Additionally, for any given beliefs, each player's best response is a nonincreasing pure strategy almost surely, that is,

$$a(\boldsymbol{y}, \epsilon_i; \sigma_i) \leq a(\boldsymbol{y}, \epsilon_i'; \sigma_i) \text{ for all } \epsilon_i > \epsilon_i'$$

With a discrete action space, the optimal adoption rule, given beliefs σ_i, takes the form of a set of cut-offs in ϵ_i. Additionally, for any beliefs, the lowest and highest actions ($a = 0$ or $a = S_{\boldsymbol{\tau}(i)} - s_{it}$) are always played with positive probability because the shock ϵ_{it} takes value on the real line whereas the choice-specific value functions is uniformly bounded above—due to bounded profits and expected adoption cost (last term in Equation (6)).

5.2 Market equilibrium

A MPE in pure strategies is first defined. In a MPE, each theater's adoption decision is optimal in every state, given its beliefs about future states, and those beliefs are consistent with the adoption decisions of other theaters. The adoption strategy profile $\mathbf{a} = (a_1, \dots, a_N)$ and beliefs $\boldsymbol{\sigma} = (\sigma_1, \dots, \sigma_N)$ form a Markov Perfect equilibrium if:
(i) for all i, a_i is a best response to $\mathbf{a}_{-i}$ given the beliefs σ_i at all states $\boldsymbol{y}$ (*optimality*).
(ii) for all i, the beliefs σ_i are consistent with the strategies $\mathbf{a}$ (*belief consistency*).

Under restriction (DD), Srisuma (2013) provides existence results for a pure strategy MPE in which equilibrium strategies are monotone in ϵ_i. Moreover, defining the corresponding conditional choice probabilities (CCP) as

$$F_i(a|\boldsymbol{y}) = P\left(a(\boldsymbol{y}, \epsilon_i; \sigma_i) \leq a|\boldsymbol{y}\right)$$

the latter paper shows that a necessary and sufficient condition for a MPE is that the vector of CCP $\{F_i(a|\boldsymbol{y})\}_{i,\boldsymbol{y}}$ is a fixed point of the best-response probability mapping (an extension of the equilibrium characterization results of Pesendorfer and Schmidt-Dengler (2008) (Proposition 1) and Aguirregabiria and Mira (2007) (Representation Lemma) to the class of ordered choice games).

Estimation and computation of a MPE present computational difficulties due to the high dimensionality of the state space $\mathbf{x}_t$. In this particular setting, $N = 399$ and each theater has at least 5 possible states ($S_{\boldsymbol{\tau}(i)} \geq 4$). In anticipation, I reduce the dimensionality of the state space by imposing behavioral restrictions and defining an alternative equilibrium concept.

Assumption 1. *Theaters use oblivious strategies where they condition their adoption decisions only on their own type and state* $\mathbf{x}_{it}$ *and the time period* t*. Theaters take the evolution of the aggregate state variables* $(\mathbf{x}_t, h_t, p_t, h_{US,t})$ *as deterministic.*

The equilibrium concept used is the nonstationary oblivious equilibrium (NOE) of Weintraub, Benkard, Jeziorski, and Van Roy (2008). This equilibrium concept is used to approximate the short-run dynamics of an industry starting from a given initial industry state.[21] If there is a large number of firms and no aggregate shocks, the industry state starting from an initial state approximately follows a deterministic path. Each firm can make close-to-optimal decisions based on its own type and state $\mathbf{x}_{it} = (\boldsymbol{\tau}(i), s_{it})$ and by knowing the deterministic path followed by the industry state ($\mathbf{x}_t$ or, equivalently, the payoff-relevant state h_t).

The NOE concept is particularly well suited to model equilibrium outcomes in the digital conversion of the movie industry: there is a large number of small firms and screens so that converting a single screen to digital has a negligible impact on the aggregate state of the industry and the availability of digital movies h_t. Moreover, it is reasonable to assume that theaters do not track the whole industry state vector $\mathbf{x}_t$, but rather, form beliefs about the evolution of h_t. With a large number of firms, the process $\{h_t\}_{t\geq 1}$ is close to deterministic.

Next, I define nonstationary oblivious strategies, beliefs, and value functions.

Nonstationary oblivious strategies. In a NOE, each firm's decisions depend only on the firm's own type and state $\mathbf{x}_{it} = (\boldsymbol{\tau}(i), s_{it})$ and the time period.[22] In this sense, strategies are type-symmetric. A nonstationary oblivious strategy is a sequence $\mathbf{a}^{no} = \{a_1^{no}, a_2^{no}, \dots\}$, where for each period t, theater i takes action $a_t^{no}(\mathbf{x}_{it}, \epsilon_{it})$. This type of strategy differs from a (stationary) Markov strategy $a_i(\boldsymbol{y}_t, \epsilon_{it})$ which is a function of the current vector of state variables $\boldsymbol{y}_t = (\mathbf{x}_t, p_t, h_{US,t})$ (in particular, the whole industry state $\mathbf{x}_t$) but does not depend on time.

Nonstationary oblivious beliefs. Theaters make their adoption decision assuming that the industry state evolves deterministically: in particular, the industry state at time t is the *expected* industry state after t time periods of evolution given the other firms' strategy and starting from the initial industry state. Under this assumption, the industry state is a function of time. For a common nonstationary oblivious strategy $\mathbf{a}^{no}$ played by all theaters, and given the initial industry state $\mathbf{x}_1$, I define the deterministic process of digital movie availability $\{\overline{h}_t\}_{t\geq 1}$ as

$$\overline{h}_t = \mathbb{E}_{\mathbf{x}_t}[h_t|\mathbf{x}_1] \tag{9}$$

where the expectation is taken with respect to the industry state $\mathbf{x}_t$ generated by strategy $\mathbf{a}^{no}$ and, as before, h_t is determined by Equation (3). I make the dependence of the process

[21] NOE differs from the stationary oblivious equilibrium of Weintraub, Benkard, and Van Roy (2008), which is suited to approximate the long-run steady state dynamics of an industry.

[22] A firm's type $\boldsymbol{\tau}(i)$ includes the total number of rivals' screen (irrespective of their projection technology), which is exogenous and fixed throughout the game (no entry or exit occurs).

$\{\overline{h}_t\}_{t\geq 1}$ on the strategy $\mathbf{a}^{no}$ explicit by denoting it $\left\{\overline{h}_t(\mathbf{a}^{no})\right\}_{t\geq 1}$.[23]

Nonstationary oblivious value functions. For a pair of nonstationary oblivious strategies $(\tilde{\mathbf{a}}^{no}, \mathbf{a}^{no})$, I define an ex-ante nonstationary oblivious value function for period t (that is before ϵ_{it} is realized), if firm i follows strategy $\tilde{\mathbf{a}}^{no}$ whereas all other firms use strategy $\mathbf{a}^{no}$, as

$$\widetilde{V}_{\boldsymbol{\tau}(i),t}(s_{it}|\tilde{\mathbf{a}}^{no}, \mathbf{a}^{no}) = \mathbb{E}_{\epsilon_{it}}\left[\pi_{\boldsymbol{\tau}(i)}(s_{it}, \overline{h}_t(\mathbf{a}^{no})) - \tilde{a}_t^{no}(\mathbf{x}_{it}, \epsilon_{it})\left(p_t + \epsilon_{it}\right) + \beta \widetilde{V}_{\boldsymbol{\tau}(i),t+1}(s_{i,t+1}|\tilde{\mathbf{a}}^{no}, \mathbf{a}^{no})\right] \tag{10}$$

where $s_{i,t+1} = s_{it} + \tilde{a}_t^{no}(\mathbf{x}_{it}, \epsilon_{it})$. This value function corresponds to the expected net present value of a type-$\boldsymbol{\tau}(i)$ theater that is at state s_{it} at time t and follows nonstationary oblivious strategy $\tilde{\mathbf{a}}^{no}$, under the assumption that, for all $t \geq 1$, the availability of digital movies is $\overline{h}_t(\mathbf{a}^{no})$ at time t. Note that the nonstationary oblivious value function remains a function of the competitors' strategy $\mathbf{a}^{no}$ through the expected availability of digital movies $\overline{h}_t(\mathbf{a}^{no})$, even if the firm's state trajectory ($\{s_{it}\}_{t\geq 1}$) only depends on the firm's own strategy $\tilde{\mathbf{a}}^{no}$. I abuse notation by using $\widetilde{V}_{\boldsymbol{\tau}(i),t}(s_{it}|\mathbf{a}^{no}) \equiv \widetilde{V}_{\boldsymbol{\tau}(i),t}(s_{it}|\mathbf{a}^{no}, \mathbf{a}^{no})$ to refer to the nonstationary oblivious value function when firm i follows the same strategy $\mathbf{a}^{no}$ as its competitors.

Nonstationary oblivious equilibrium. An nonstationary oblivious equilibrium consists of a strategy $\mathbf{a}^{no}$ that satisfies

$$\sup_{\tilde{\mathbf{a}}^{no}} \widetilde{V}_{\boldsymbol{\tau}(i),t}(s_{it}|\tilde{\mathbf{a}}^{no}, \mathbf{a}^{no}) = \widetilde{V}_{\boldsymbol{\tau}(i),t}(s_{it}|\mathbf{a}^{no}) \text{ for all } i \in \mathbf{N}, \text{ state } s_{it} \in \mathcal{S}_{\boldsymbol{\tau}(i)} \text{ and periods } t \tag{11}$$

The belief consistency requirement in a nonstationary oblivious equilibrium is "weaker" than for a Markov Perfect equilibrium. In the latter, belief consistency requires that each firm optimizes given beliefs (about state transitions) generated by its competitiors' equilibrium strategies. In the former equilibrium concept, belief consistency only requires that each firm optimizes given the deterministic path of expected aggregate states generated by its competitors' equilibrium strategies. Importantly, firm i ignores: (1) its impact on the process $\{\overline{h}_t\}_{t\geq 1}$ (given competitors' equilibrium strategies) and (2) the feedback of its own action on other competitors. The actual stochastic process $\{h_t\}_{t\geq 1}$ will in general not coincide with the deterministic process $\{\overline{h}_t\}_{t\geq 1}$, but converges to it as the number of firms grows to infinity (keeping the number of firm types fixed).

Weintraub, Benkard, Jeziorski, and Van Roy (2008) provide existence results for NOE that converge to a stationary strategy as t goes to infinity. That is, they consider nonsta-

[23] Weintraub, Benkard, Jeziorski, and Van Roy (2008) use an alternative but equivalent representation of the industry state. The industry state can be expressed as the distribution (or number of firms) in each possible state. This representation is without loss of generality when focusing on anonymous and (type-)symmetric equilibrium strategies because the identity i of the firm does not matter (Doraszelski and Satterthwaite (2010)).

tionary oblivious strategies $\mathbf{a}^{no} = \{a_1^{no}, a_2^{no}, \dots\}$, such that

$$\lim_{t\to\infty} a_t^{no}(\mathbf{x}_i, \epsilon_i) = a^{no}(\mathbf{x}_i, \epsilon_i) \text{ for all } (\mathbf{x}_i, \epsilon_i)$$

for some stationary oblivious strategy $a^{no}(\mathbf{x}_i, \epsilon_i)$. In this particular setting, it is natural to focus on outcomes generated by strategies that become stationary as t goes to infinity, that is, where the movie industry converges to a stationary state: indeed, with unbounded shocks ϵ_{it}, all theaters eventually convert and their strategy converges to a singleton $\lim_{t\to\infty} a_t^{no}(\boldsymbol{\tau}(i), s_i, \epsilon_i) = 0$. I return to this property in the estimation section as it allows me to focus on a finite horizon.

To ease navigation, Table 4 shows a complete list of the state variables presented in the industry model.

Table 4: List of state variables

	Description	Observed?
Exogenous state variables		
$\boldsymbol{\tau}(i)$	Firm i's type (screens $S_{\boldsymbol{\tau}(i)}$, market characteristics, art house, chain)	Observed
$S_{\boldsymbol{\tau}(i)}$	Firm i's total number of screens	Observed
p_t	Per-screen adoption cost	Observed
ϵ_{it}	Firm-specific private adoption shock	No
$h_{t,US}$	Share of movies released in digital in t in the U.S.	Observed
$\pi_{\boldsymbol{\tau}(i)}(s_{it}, h_t)$	Firm i's single-period payoff function	Estimated
Endogenous state variables		
a_{it}	Number of screens converted in t	Observed
s_{it}	Number of screens at the start of period t	Observed
$\mathbf{x}_{it}$	$(\boldsymbol{\tau}(i), s_{it})$	Observed
$\mathbf{x}_t$	$(\mathbf{x}_{1t}, \dots, \mathbf{x}_{it}, \dots, \mathbf{x}_{It})$	Observed
h_t	Share of movies released in digital in t in France	Observed
$\overline{h}_t(\mathbf{a}^{no})$	Nonstationary oblivious belief about h_t ($\mathbb{E}_{\mathbf{x}_t}[h_t\|\mathbf{x}_1]$) given strategy profile $\mathbf{a}^{no}$	No

6 Estimation and Identification

This section presents the identification and estimation of the structural model presented in section 5. The objective is to recover firms' operating profits $\pi_{\boldsymbol{\tau}(i)}(s_{it}, h_t)$. Estimation results indicate that there is a significant reduction in costs with the conversion to digital. These cost-reductions are consistent with labor cost savings and the magnitude of projectionnists' wages. Finally, the analysis uncovers the main dimensions of hetereogeneity in profits from digital across theaters.

6.1 Estimation approach

Given that the behavioral restrictions and the NOE concept are motivated by issues related to estimation, I start by discussing estimation assuming that the parameter of interest are identified, and show identification of the model in the following section.

Two issues make the estimation of a MPE in the dynamic game of Section 5.1 complicated. First is the curse of dimensionality: the large number of firms (due to network effects at the industry level) and the dimension of firms' states generate a high-dimensional industry state space.[24] Second, as is common in games of technology adoption under network effects, there are potentially multiple equilibria.

Although recent approaches for dynamic game estimation (Aguirregabiria and Mira (2007), Bajari, Benkard, and Levin (2007), Pesendorfer and Schmidt-Dengler (2008), and Pakes, Ostrovsky, and Berry (2007)) can be used to address the multiplicity issue, the estimation and computation of counterfactuals will still be infeasible due to the dimensionality of the state space. The model is, therefore, estimated under the assumption that the data is generated by a nonstationary oblivious equilibrum (that becomes stationary as time progresses) as introduced in Section 5.2.

Assumption 2. *The data is generated by a nonstationary oblivious equilibrium* $\mathbf{a}^{no}$ *in which strategies are nonincreasing in* ϵ_i *and become stationary as time progresses. In the long-run steady state, all theaters have converted to digital (*$s_{it} = S_{\boldsymbol{\tau}(i)}$*), adoption strategies are stationary (in fact constant,* $a_t^{no} = 0$*), all movies are available in digital (*$\overline{h}_t = 1$*), and single-period profits are constant and given by* $\pi_{\boldsymbol{\tau}(i)}(S_{\boldsymbol{\tau}(i)}, \overline{h}_t = 1)$*.*

Assumption 2 allows me to restrict attention to the finite vector of choice-probabilities corresponding to the NOE played in the data, for $t = 1, \ldots, \overline{T}$, that is,

$$\{P_t(a_{it}^{no}|\mathbf{x}_{it})\} \text{ for all } t = 1, \ldots, \overline{T} \text{ and } \mathbf{x}_{it} = (\boldsymbol{\tau}(i), s_{it})$$

In the industry model, the shock ϵ_{it} has full support on the real line and single-period profits are bounded, therefore, a firm can always choose $a_{it} = 0$ with positive probability. In practice, $\overline{T}$ is chosen large enough so that, given the realization of the equilibrium $\mathbf{a}^{no}$

[24] For instance, ignoring firm heterogeneity and assuming all 399 firms are four-screen theaters (so $s_{it} \in \{0, 1, 2, 3, 4\}$), the total number of possible industry states $\mathbf{x}_t$ is 1,071,993,300.

played in the data—in which, by 2015 the industry was entirely converted to digital—the industry-wide adoption steady state has been reached by $\overline{T}$ with probability arbitrarily close to one. In what follows, $\overline{T}$ is set to 30 periods (i.e., 15 years) and the probability that the steady state is reached (over $1,000$ simulations of the industry trajectory) is 97%.

The estimation approach follows the CCP-based method proposed in Hotz and Miller (1993) and Hotz, Miller, Sanders, and Smith (1994) for single-agent dynamic problems, and Pesendorfer and Schmidt-Dengler (2008) for dynamic games (see Srisuma (2013) for an extension to games with ordered choices). This estimation approach relies on the *necessary* condition for an equilibrium: i.e., choice probabilities are a fixed point of the best-response probability mapping. In a first step, the nonstationary oblivious CCP giving the equilibrium policy rule are estimated from the data. Next, using the CCP, I obtain the nonstationary oblivious choice-specific value functions for each candidate parameter. In this step, I avoid forward-simulation by using the matrix inversion method suggested by Aguirregabiria and Mira (2007) and Pesendorfer and Schmidt-Dengler (2008). In the last step, I estimate the parameter of interest by minimizing the distance between the predicted CCP and the actual CCP.

In dynamic games with unordered choices (such as the ones studied in Pesendorfer and Schmidt-Dengler (2008)), unbounded shocks guarantee that all actions are chosen with positive probability: the Hotz-Miller inversion approach provides a one-to-one mapping between choice probabilities and all differences in choice-specific value functions. This is not always the case in games with ordered choices. Under monotonicity of equilibrium strategies, the inversion approach must account for the fact that choice probabilities can only be mapped to differences in choice-specific value functions *between actions played with positive probability.*

First-step estimation:

Movie theaters' adoption-policy function. The estimation proceeds by first recovering the nonstationary oblivious CCP governing theaters' equilibrium adoption of digital projectors. The CCP $P_t(a_{it}^{no}|\mathbf{x}_{it})$, which are a function of time, and the type and state of firm i, are estimated using an ordered probit model, and in what follows are assumed to be known. Denote $\widehat{P}_t(a_{it}^{no}|\mathbf{x}_{it})$ estimates of the nonstationary oblivious CCP.

Monotonicity of equilibrium adoption strategies can be used to characterize the mapping from CCP to differences in choice-specific value function. Denote the set of actions played with positive probability in period t and state $\mathbf{x}_{it}$ by

$$Supp(\mathbf{x}_{it}, t) = \{a_i \in A_i : P_t(a_i|\mathbf{x}_{it}) > 0\} \subseteq A_i$$

Let the elements of $Supp(\mathbf{x}_{it}, t)$ be ranked in increasing order and indexed by k. Denote by a_k the k^{th} largest element of $Supp(\mathbf{x}_{it}, t)$. Invoking the monotonicity of strategies, the indifference condition between action a_k and a_{k+1} can be expressed as

$$\begin{aligned} W_t(a_k|\mathbf{x}_{it}) - a_k(p_t + \bar{\epsilon}_{i,k}) &= W_t(a_{k+1}|\mathbf{x}_{it}) - a_{k+1}(p_t + \bar{\epsilon}_{i,k}) \\ \Leftrightarrow \bar{\epsilon}_{i,k} &= \frac{\Delta W_t(a_{k+1}, a_k|\mathbf{x}_{it})}{a_{k+1} - a_k} - p_t \end{aligned} \tag{12}$$

where $\Delta W_t(a_{k+1}, a_k|\mathbf{x}_{it})$ is the difference in the oblivious choice-specific value functions of converting a_{k+1} and a_k screens to digital in state $(t, \mathbf{x}_{it})$. Equation (12) expresses the cut-offs characterizing the equilibrium adoption strategy as a function of differences in the choice-specific value function. These cut-offs can be used to map CCP to differences in the choice-specific value function

$$P_t(a_{it}^{no} \leq a_k|\mathbf{x}_{it}) = 1 - F(\bar{\epsilon}_{i,k}) = 1 - F\left(\frac{\Delta W_t(a_{k+1}, a_k|\mathbf{x}_{it})}{a_{k+1} - a_k} - p_t\right) \tag{13}$$

Differences in choice-specific value functions can be obtained from knowledge of the CCP, by inverting equation (13):

$$\frac{\Delta W_t(a_{k+1}, a_k|\mathbf{x}_{it})}{a_{k+1} - a_k} - p_t = F^{-1}\left(1 - P_t(a_{it}^{no} \leq a_k|\mathbf{x}_{it})\right) \tag{14}$$

Using equation (14), I can construct estimates of $\widehat{\Delta W_t}(a_{k+1}, a_k|\mathbf{x}_{it})$ from knowledge of the CCP $\widehat{P}_t(a_{it}^{no} \leq a_k|\mathbf{x}_{it})$ estimates for all $a_k \in Supp(\mathbf{x}_{it}, t)$.

Value functions. Given a candidate parameter vector and knowledge of the CCP, the expected oblivious value function solves a system of linear equations. For each firm type and state $\mathbf{x}_{it} = (\boldsymbol{\tau}(i), s_{it})$ and period $t = 1, \ldots, \overline{T}$,

$$\begin{aligned} \widetilde{V}_{\boldsymbol{\tau}(i),t}(s_{it}|\mathbf{a}^{no}) = &\sum_{a_{it}=0}^{S_{\boldsymbol{\tau}(i)}-s_{it}} P_t(a_{it}^{no}|\mathbf{x}_{it}) \left[\pi_{\boldsymbol{\tau}(i)}(s_{it}, \overline{h}_t(\mathbf{a}^{no})) - a_{it}^{no}(p_t + \mathbb{E}[\epsilon_i|a_{it}^{no}, \mathbf{x}_{it}])\right] \\ &+ \beta \sum_{a_{it}=0}^{S_{\boldsymbol{\tau}(i)}-s_{it}} P_t(a_{it}^{no}|\mathbf{x}_{it}) \widetilde{V}_{\boldsymbol{\tau}(i),t+1}(s_{i,t+1}|\mathbf{a}^{no}) \end{aligned} \tag{15}$$

where $s_{i,t+1} = s_{it} + a_{it}^{no}$.

In period $t = \overline{T}$, the industry enters its long-run steady state where $\overline{h}_t = 1$ and $s_{it} = S_{\boldsymbol{\tau}(i)}$ for all i and $t > \overline{T}$. All firms that have not fully converted yet are restricted to do so, that is, $P_{\overline{T}}(S_{\boldsymbol{\tau}(i)} - s_{it}|\mathbf{x}_{i,\overline{T}}) = 1$ for all $\mathbf{x}_{i,\overline{T}}$. (as discussed above, $\overline{T}$ is chosen large enough so that firms have completed their conversion by this period with probability close to one). For $t > \overline{T}$, the value function is constant and equal to:

$$\widetilde{V}_{\boldsymbol{\tau}(i),\overline{T}+1}(S_{\boldsymbol{\tau}(i)}|\mathbf{a}^{no}) = \pi_{\boldsymbol{\tau}(i)}(S_{\boldsymbol{\tau}(i)}, \overline{h}=1) + \beta \widetilde{V}_{\boldsymbol{\tau}(i),\overline{T}+1}(S_{\boldsymbol{\tau}(i)}|\mathbf{a}^{no}) = \sum_{l=0}^{\infty} \beta^l \pi_{\boldsymbol{\tau}(i)}(S_{\boldsymbol{\tau}(i)}, \overline{h}=1)$$

Denote by L the cardinality of the set of possible type-state combination $\mathbf{x}_{it} = (\boldsymbol{\tau}(i), s_{it})$. L equals $\sum_{\boldsymbol{\tau}\in\mathcal{T}} (S_{\boldsymbol{\tau}}+1)$ because the number of digital screens in a type-$\boldsymbol{\tau}$ theater is an element of the set $\mathcal{S}_{\boldsymbol{\tau}} = \{0, 1, ..., S_{\boldsymbol{\tau}}\}$. Collecting the equilibrium ex-ante value functions $\widetilde{V}_{\boldsymbol{\tau}(i),t}(s_{it}|\mathbf{a}^{no})$ for all $t = 1, \ldots, \overline{T}$, all types $\boldsymbol{\tau} \in \mathcal{T}$, and states $s \in \mathcal{S}_{\boldsymbol{\tau}}$ in matrix notation, the expected value function as a function of a candidate structural parameter $\boldsymbol{\alpha}$ can be written

$$\begin{aligned} \widetilde{\mathbf{V}}(\boldsymbol{\alpha}) &= \sum_a \mathbf{P}(a)\big(\mathbf{\Pi}(\boldsymbol{\alpha}) - a(\mathbf{p} + \mathbf{e}(a)\big) + \beta \cdot \mathbf{F} \cdot \widetilde{\mathbf{V}}(\boldsymbol{\alpha}) \\ &= (\mathbf{I} - \beta \cdot \mathbf{F})^{-1} \left\{ \sum_a \mathbf{P}(a)\big(\mathbf{\Pi}(\boldsymbol{\alpha}) - a(\mathbf{p} + \mathbf{e}(a))\big) \right\} \end{aligned} \tag{16}$$

where $\widetilde{\mathbf{V}}(\boldsymbol{\alpha})$ is the $(L \cdot \overline{T}) \times 1$ dimensional vector of ex-ante value functions, $\mathbf{I}$ is the $(L \cdot \overline{T})$-dimensional identity matrix, $\mathbf{F}$ is the $(L \cdot \overline{T}) \times (L \cdot \overline{T})$ dimensional matrix consisting of a type-$\boldsymbol{\tau}$ theater's conditional choice probabilities $\{P_t(a|\boldsymbol{\tau}, s)\}_{a=0}^{S_{\boldsymbol{\tau}}-s}$ in row $(\boldsymbol{\tau}, s, t)$ and columns $\{(\boldsymbol{\tau}, s+a, t+1)\}_{a=0}^{S_{\boldsymbol{\tau}}-s}$ and zeros in the remaining columns; For $t = \overline{T}$, all rows $\{(\boldsymbol{\tau}, s, \overline{T})\}_{\boldsymbol{\tau},s}$ transition to the absorbing state $(\boldsymbol{\tau}, S_{\boldsymbol{\tau}}, \overline{T})$ with probability one. $\mathbf{P}(a)$ is an $(L \cdot \overline{T}) \times (L \cdot \overline{T})$-dimensional matrix of CCP with diagonal elements equal to $P_t(a|\boldsymbol{\tau}, s)$ and off-diagonal elements equal to zero, $\mathbf{\Pi}(\boldsymbol{\alpha})$ is an $(L \cdot \overline{T}) \times 1$ vector of single-period profits with row $(\boldsymbol{\tau}, s, t)$ containing $\pi_{\boldsymbol{\tau}}(s, \overline{h}_t)$, $\mathbf{p}$ is an $(L \cdot \overline{T}) \times 1$ block vector of adoption costs with row $(\boldsymbol{\tau}, s, t)$ containing p_t, and $\mathbf{e}(a)$ is an $(L \cdot \overline{T}) \times 1$ vector with row $(\boldsymbol{\tau}, s, t)$ equal to $\mathbb{E}[\epsilon_i|a, (\boldsymbol{\tau}, s)]$. The matrix $(\mathbf{I} - \beta \cdot \mathbf{F})$ is invertible because it is a strictly diagonally dominant matrix $(1 > \beta \sum_{a=0}^{S_{\boldsymbol{\tau}}-s} P_t(a|\boldsymbol{\tau}, s))$.

Let $\widetilde{\mathbf{V}}(\boldsymbol{\alpha}) = \{\widetilde{V}_{\boldsymbol{\tau},t}(s; \boldsymbol{\alpha})\}_{\boldsymbol{\tau}\in\mathcal{T}, s\in\mathcal{S}_{\boldsymbol{\tau}}, t=1,\ldots,\overline{T}}$ be the solution of system (16), for a given candidate parameter $\boldsymbol{\alpha}$ and the actual equilibrium CCP vector played in the data. The predicted nonstationary oblivious choice-specific value functions $\widetilde{W}_t(a|\mathbf{x}_{it}; \boldsymbol{\alpha})$, and predicted CCP $\widetilde{P}_t(a_{it}|\mathbf{x}_{it}; \boldsymbol{\alpha})$ can be derived as follows

$$\widetilde{W}_t(a|\mathbf{x}_{it}; \boldsymbol{\alpha}) = \beta \widetilde{V}_{\boldsymbol{\tau}(i),t+1}(s_{i,t+1}; \boldsymbol{\alpha}) \quad \text{where } \mathbf{x}_{it} = (\boldsymbol{\tau}(i), s_{it}) \text{ and } s_{i,t+1} = s_{it} + a \tag{17}$$

$$\widetilde{P}_t(a_{it}^{no} \le a_k|\mathbf{x}_{it}; \boldsymbol{\alpha}) = 1 - F\left(\frac{\Delta\widetilde{W}_t(a_{k+1}, a_k|\mathbf{x}_{it}; \boldsymbol{\alpha})}{a_{k+1} - a_k} - p_t\right) \text{ for all } a_k \in Supp(\mathbf{x}_{it}, t) \tag{18}$$

Second-step estimation:
In the second step, the underlying parameters $\boldsymbol{\alpha}$ are set such that the predicted CCP $\widetilde{P}_t(a_{it}^{no} \leq a_k|\boldsymbol{\tau}(i), s_{it}; \boldsymbol{\alpha})$ match estimates of the actual equilibrium CCP $\widehat{P}_t(a_{it}^{no} \leq a_k|\boldsymbol{\tau}(i), s_{it})$ (obtained in step 1) for every firm type $\boldsymbol{\tau} \in \mathcal{T}$, state $s \in \mathcal{S}_{\boldsymbol{\tau}}$, period $t = 1, \ldots, \overline{T}$, and action $a_k \in Supp(\mathbf{x}_{it}, t)$. Equivalently, one can match the differences in choice-specific value functions, which are a monotone transformation of the CCP. I follow this second approach.[25] The objective function is

$$
\begin{aligned}
Q(\boldsymbol{\alpha}) &= ||\Delta\widetilde{W}_t(a_{k+1}, a_k|\boldsymbol{\tau}, s; \boldsymbol{\alpha}) - \widehat{\Delta W_t}(a_{k+1}, a_k|\boldsymbol{\tau}, s)||_2 \\
&= \sqrt{\sum_{\boldsymbol{\tau},s,t,k} \left(\Delta\widetilde{W}_t(a_{k+1}, a_k|\boldsymbol{\tau}, s; \boldsymbol{\alpha}) - \widehat{\Delta W_t}(a_{k+1}, a_k|\boldsymbol{\tau}, s)\right)^2}
\end{aligned}
\tag{19}
$$

The estimator of the underlying parameters is the solution of

$$
\min_{\boldsymbol{\alpha}} Q(\boldsymbol{\alpha})
$$

Standard errors are obtained by bootstrap sampling. One difficulty with non-parametric bootstrap is the presence of correlation in decisions across local markets and firms, therefore, sampling market-histories (or firm-histories) with replacement, as is commonly done in dynamic oligopoly games, is not a valid approach. Instead, a parametric boostrap procedure is used. This approach is detailed in Appendix C.2.

6.2 Identification

This section examines the identification of the industry model. In a NOE, firms take the evolution of the industry state as exogenous and deterministic. This path would be indeed deterministic with infinitely many firms playing an equilibrium nonstationary oblivious strategy $\mathbf{a}^{no}$. In this section, I assume that the econometrician observes a single infinite population of firms (fixing the set of firm types) playing strategy $\mathbf{a}^{no}$ over a finite horizon of length $\overline{T}$. This approach differs from the common identification approach for MPE in dynamic oligopoly games which relies on a cross-section of market-paths and requires, under multiplicity of equilibria, that the same equilibrium is played in all markets. By using only a single market, the paper sidesteps the multiplicity issue by identifying the parameters of interest from observation of many firms of the same type.

[25]Matching differences in the choice-specific value functions is preferred here because the objective function is quadratic in the parameter, and the gradient can be easily derived.

The conditional choice probabilities $P_t(a|\boldsymbol{\tau}, s)$ are identified from the data for every firm type $\boldsymbol{\tau} \in \mathcal{T}$, firm state $s \in \{0, 1, \ldots, S_{\boldsymbol{\tau}} - 1\}$, action $a \in \{1, \ldots, S_{\boldsymbol{\tau}} - s\}$, and period $t = 1, \ldots, \overline{T} - 1$. The corresponding differences in the choice-specific value functions $\Delta W_t(a', a|\boldsymbol{\tau}, s)$ are identified for actions played with non-zero probability (Equation (14)). As is standard in the literature on identification of dynamic decision problems (Rust (1994), Magnac and Thesmar (2002), and Bajari, Chernozhukov, Hong, and Nekipelov (2015)), the discount factor and the distribution of firm shocks (β, F) are assumed to be known.

The unknown elements are the (nonstationary) oblivious single-period profits which are a function of the firm type and state $(\boldsymbol{\tau}(i), s_{it})$, action a_{it}, and time t. Adoption costs are assumed to enter linearly into single-period profits under the restriction

$$\pi_{\boldsymbol{\tau}(i)}(s_{it}, \overline{h}_t) - a_{it}(p_t + \epsilon_{it})$$

which fixes the dependence of profits on firm adoption decision a_{it}. This restriction is arguably well-informed given the structure of the problem. The structural parameters to identify are, therefore, the set of single-period profits gross of the adoption cost

$$\boldsymbol{\alpha} \equiv \boldsymbol{\Pi} = \{\pi_{\boldsymbol{\tau}}(s, \overline{h}_t)\}_{\boldsymbol{\tau} \in \mathcal{T}, s \in \mathcal{S}_{\boldsymbol{\tau}}}$$

for every firm type $\boldsymbol{\tau} \in \mathcal{T}$, state $s \in \mathcal{S}_{\boldsymbol{\tau}}$, and period $t = 1, \ldots, \overline{T}$. The number of unknown parameters is

$$(L \times \overline{T}) = \sum_{\boldsymbol{\tau} \in \mathcal{T}} (S_{\boldsymbol{\tau}} + 1) \times \overline{T}$$

The necessary conditions for optimality can be expressed as

$$\Delta W_t(a_{k+1}, a_k|\boldsymbol{\tau}, s) = \Delta \widetilde{W}_t(a_{k+1}, a_k|\boldsymbol{\tau}, s; \boldsymbol{\Pi}), \text{ for } \boldsymbol{\tau} \in \mathcal{T}, s \in \{0, 1, \ldots, S_{\boldsymbol{\tau}} - 1\}, t \leq \overline{T} - 1 \tag{20}$$

where $(a_{k+1}, a_k) \in Supp(\boldsymbol{\tau}, s, t)$, and $\Delta \widetilde{W}_t(a_{k+1}, a_k|\boldsymbol{\tau}, s; \boldsymbol{\Pi})$ can be derived by Equation (17). Importantly, there are no equilibrium conditions for $s = S_{\boldsymbol{\tau}}$ (the theater has completed its conversion) or $t = \overline{T}$ (the steady state is reached and all firms are restricted to convert their remaining screens).

Because actions 0 and $S_{\boldsymbol{\tau}(\boldsymbol{i})} - s_{it}$ are always played with positive probability, Equation (20) implies *at least* $(L - \overline{\tau}) \cdot (\overline{T} - 1)$ identifying restrictions (where $\overline{\tau}$ is the cardinality of type space $\mathcal{T}$). The next lemma shows that if action $a = 1$ is played with positive probability, some of the optimality conditions are linearly dependent: intuitively, the optimality condition for any pair of actions a_k and a_{k+1} can always be rewritten as a linear combination of optimality conditions involving actions 1 and 0. In this case, there are in fact *exactly* $(L - \overline{\tau}) \cdot (\overline{T} - 1)$

identifying restrictions.

Lemma 1. *If action $a = 1$ is played with positive probability, the necessary optimality conditions (20) form a system of $(L - \overline{\tau}) \cdot (\overline{T} - 1)$ linearly independent equations in the $(L \times \overline{T})$ unknown parameters $\mathbf{\Pi}$.*

The proof is included in Appendix C.1. Combining Equations (16) and (17) for actions $a_k = 0$ and $a_{k+1} = 1$, one obtains a system of linear equations in the unknown parameter $\mathbf{\Pi}$

$$\mathbf{Y} = \mathbf{X} \cdot \mathbf{\Pi} \tag{21}$$

where $\mathbf{Y}$ and $\mathbf{X}$ are a $((L - \overline{\tau}) \cdot (\overline{T} - 1)) \times 1$-dimensional and $((L - \overline{\tau}) \cdot (\overline{T} - 1)) \times (L \times \overline{T})$-dimensional matrices which are function of the (known) CCP, prices, discount factor β, and distribution of the firm-specific shock F. I augment this system of equations with two sets of restrictions.[26]

Assumption 3. *The following payoff normalizations are imposed. Single-period profits under the film technology are set to zero: $\pi_{\boldsymbol{\tau}}(s = 0, \overline{h}_t) = 0$ for every type $\boldsymbol{\tau} \in \mathcal{T}$ and period $t = 1, \dots, \overline{T}$. Single-period profits when there are no digital movies (i.e., $\overline{h}_1 = 0$) are set to zero: $\pi_{\boldsymbol{\tau}}(s, \overline{h}_1 = 0) = 0$ for every type $\boldsymbol{\tau} \in \mathcal{T}$ and firm state $s \in \{0, 1, \dots, S_{\boldsymbol{\tau}}\}$.*

Assumption 3 imposes a total of $L + \overline{\tau} \times (\overline{T} - 1)$ restrictions. Augmenting system (21) with these restrictions yields a system of $(L \times \overline{T})$ in $(L \times \overline{T})$ equations in as many unknowns. $\mathbf{\Pi}$ is exactly identified under a full rank condition. If action $a = 1$ is not played, then there are more restrictions than unknowns and $\mathbf{\Pi}$ is over-identified (under the normalizations of Assumption 3).

Finally, note that $\pi_{\boldsymbol{\tau}}(s, \overline{h}_t)$ is only identified over the support of the deterministic path $\{\overline{h}_t\}_{t=1,\dots,\overline{T}}$. Therefore, for every firm type $\boldsymbol{\tau} \in \mathcal{T}$ and firm state $s \in \{0, 1, \dots, S_{\boldsymbol{\tau}}\}$, at most $\overline{T}$ restrictions are available to identify the dependence of $\pi_{\boldsymbol{\tau}}(s, h_t)$ on h_t.[27] In the next section, I impose parametric restrictions that reduce the dimensionality of the parameter space $\mathbf{\Pi}$ and allows identification of the effect of h_t on profits.

[26] The first normalization I impose is similar to the usual "outside good" action normalization found in the literature, where the single-period payoff of a reference action is set to zero. In my case, the single-period payoff of choosing action $a = 0$ is set to zero when $s = 0$.

[27] If the econometrician has access to a cross-section of markets (with infinite number of firms), e.g., different countries, multiplicity of equilibria can help with the identification of the effect of h_t. Different deterministic paths for $\overline{h}_t$ would be observed across markets and one can use the time series and cross-sectional variation in $\overline{h}_t$ to identify the effect of h_t.

6.3 Parameterization

This section details the model parameterization. Operating profits are obtained by summing profits per digital screen (relative to film) over the s_{it} digital screens converted by theater i and time t. Profits from film screens are normalized to zero.

The parameterization aims to capture two features of the model: (i) the heterogeneity in profits per digital screen across theaters and markets and (ii) the positive dependence of these profits on the share of movies available in digital h_t. In particular, when h_t is low (early phase of diffusion), theaters have a limited choice of digital movies and optimally convert only a fraction of their screens to digital: the marginal benefit from converting an additional screen to digital is decreasing.

To capture this dependence parsimoniously, I define, for each theater, two levels of profits per digital screen: $\pi_d(\boldsymbol{\tau})$ corresponds to the baseline profits if all movies were available in digital ($h_t = 1$) and $\widetilde{\pi}_d(\boldsymbol{\tau}, h_t)$ are profits per digital screen if the fraction of digital movies is h_t (with $h_t < 1$).

When h_t is less than one, theater i has a limited choice of digital movies, therefore, its profits from a digital screen ($\widetilde{\pi}_d(\boldsymbol{\tau}, h_t)$) will be lower than if all movies were available in digital ($\pi_d(\boldsymbol{\tau})$). Denote by $\delta(\boldsymbol{\tau}, h_t) \equiv \pi_d(\boldsymbol{\tau}) - \widetilde{\pi}_d(\boldsymbol{\tau}, h_t)$, the profit loss (or decay) from limited availability of digital movies. As h_t converges to one, $\delta(\boldsymbol{\tau}, h_t)$ is expected to decrease.

In summing profits across digital screen, the following functional form is assumed: a fraction $\min\{\frac{s_{it}}{S_{\boldsymbol{\tau}(i)}}, h_t\}$ of screens yields profits $\pi_d(\boldsymbol{\tau})$ per screen, whereas the remaining $\max\{0, \frac{s_{it}}{S_{\boldsymbol{\tau}(i)}} - h_t\}$ yield profits $\widetilde{\pi}_d(\boldsymbol{\tau}, h_t) = \pi_d(\boldsymbol{\tau}) - \delta(\boldsymbol{\tau}, h_t)$. Theater i's operating profits in state $(\mathbf{x}_{it}, h_t)$ are therefore given by

$$\pi_{\boldsymbol{\tau}}(s_i, h_t) = \begin{cases} s_i \pi_d(\boldsymbol{\tau}) & \text{if} \quad \frac{s_i}{S_{\boldsymbol{\tau}(i)}} \leq h_t \\ S_{\boldsymbol{\tau}(i)} \left(\frac{s_i}{S_{\boldsymbol{\tau}(i)}} \pi_d(\boldsymbol{\tau}) - (\frac{s_i}{S_{\boldsymbol{\tau}(i)}} - h_t) \delta(\boldsymbol{\tau}, h_t) \right) & \text{if} \quad \frac{s_i}{S_{\boldsymbol{\tau}(i)}} \geq h_t \end{cases} \tag{22}$$

This specification captures decreasing marginal benefits from an additional digital screen. For instance, a 5−screen theater with adoption rate $\frac{s_{it}}{S_{\boldsymbol{\tau}(i)}} = h_t = 0.4$ receives profits per digital screen equal to $\pi_d(\boldsymbol{\tau})$. If the firm were to convert its third screen to digital, the marginal benefit would be $\widetilde{\pi}_d(\boldsymbol{\tau}, h_t) < \pi_d(\boldsymbol{\tau})$.

The effect of a marginal increase in h_t on profits (i.e., the "network benefit") for a theater that has fully converted ($\frac{s_{it}}{S_{\boldsymbol{\tau}(i)}} = 1$) is given by

$$S_{\boldsymbol{\tau}(i)} \left(\pi_d(\boldsymbol{\tau}) - \widetilde{\pi}_d(\boldsymbol{\tau}, h_t) + (1 - h_t) \frac{\partial \widetilde{\pi}_d(\boldsymbol{\tau}, h_t)}{\partial h_t} \right) > 0$$

The term $\pi_d(\boldsymbol{\tau}) - \widetilde{\pi}_d(\boldsymbol{\tau}, h_t)$ corresponds to the change in profits for the marginal screen, whereas $(1-h_t)\frac{\partial\tilde{\pi}_d(\boldsymbol{\tau},h_t)}{\partial h_t}$ corresponds to the change in profits for the supra-marginal screens (a share $\frac{s_{it}}{S_{\boldsymbol{\tau}(i)}} - h_t = 1-h_t$ of screens). Profits for infra-marginal screens (a share h_t) are not affected since constant and equal to $\pi_d(\boldsymbol{\tau})$.

For the profits per digital screen $\pi_d(\boldsymbol{\tau})$ and decay $\delta(\boldsymbol{\tau}, h_t)$, a reduced form is used:

$$\pi_d(\boldsymbol{\tau}) = \alpha_0 + \alpha_1 S_{\boldsymbol{\tau}(i)} + \alpha_2 art_i + \alpha_3 S_{-i} + \alpha_{market_i} + \alpha_{chain_i} \tag{23}$$

$$\delta(\boldsymbol{\tau}, h_t) = \delta_0 + \delta_1 S_{\boldsymbol{\tau}(i)} + \delta_2 h_t \tag{24}$$

where $S_{\boldsymbol{\tau}(i)}$ is the number of screens in theater i, art_i is an indicator for art house theaters, S_{-i} is the total number of screens owned by theater i's competitors, and α_{market_i} and α_{chain_i} are dummies for market size and chain identifier. Equation (23) specifies how profits per digital screen depends on firm and market characteristics. Equation (24) specifies the decay in profits. The decay depends on theater size and availability of digital movies. The decay is expected to decrease with digital movie availability. Because larger theaters screen more movies, the decay is expected to increase with theater size for a given level of h_t.[28]

The parameters of interest are the vector

$$\boldsymbol{\alpha} = (\{\alpha_k\}_{k=0,\dots,3}, \alpha_{market=1,\dots,6}, \alpha_{chain=1,\dots,3}, \{\delta_k\}_{k=0,\dots,2})$$

entering the profit per digital screen and decay. All parameters are dynamic in the sense that they must be inferred from firms' dynamic decision process. The distribution F of the firm-specific shock ϵ_{it} is set to $\mathcal{N}(0,\sigma^2)$. The discount factor used is $\beta = 0.95$. Robustness checks are conducted in Appendix D.4.

6.4 Endogeneity of digital movie availability

The model is estimated under the assumption that a nonstationary oblivious equilibrium generates the data (Assumption 2). In equilibrium, firms take the evolution of digital movie availability as deterministic, following the process $\{\overline{h}_t(\mathbf{a}^{no})\}_{t=1,\dots,\overline{T}}$ (Equation (9)).

If the mapping $\Gamma(\cdot)$ were known, $\overline{h}_t(\mathbf{a}^{no})$ could be computed by simple matrix multiplication from the knowledge of the equilibrium CCP and the initial industry state $\mathbf{x}_1$. Estimating $\Gamma(\cdot)$ precisely is, however, infeasible due to the high-dimensionality of $\mathbf{x}_t$ and the short panel nature of the data (the asymptotics are in T). Instead, I exploit the actual process $\{h_t\}_{t=1,\dots,\overline{T}}$ observed in the data as an estimator for $\{\overline{h}_t(\mathbf{a}^{no})\}_{t=1,\dots,\overline{T}}$: indeed, h_t converges to $\overline{h}_t(\mathbf{a}^{no})$ as the number of firms grows to infinity (the asymptotics are in N).

[28] Smaller theaters might be able to delay their conversion longer because they screen fewer movies overall. Ignoring this mechanism would affect the estimation results by predicting lower profits for smaller theaters.

The actual process $\{h_t\}_{t=1,\dots,\overline{T}}$ observed in the data is determined endogenously by the realized adoption of digital screens. To estimate the parameter δ_2 characterizing the effect of h_t on the decay in single-period profits, I follow an approach similar to Gowrisankaran, Park, and Rysman (2014). First, I include a set of time dummies for $t = 1, \dots, \overline{T}$ in place of h_t in equation (24). Second, I regress the time dummy coefficients on h_t, and instrument the latter variable by digital movie availability in the U.S. $h_{US,t}$. This identification strategy exploits the fact that whether a U.S.-produced movie is released in digital in France at time t is at least partly a function of whether the movie was released in digital in the U.S. However, digital release decisions in the U.S. were arguably not affected by the installed base of screens in France (Appendix B discusses the validity of this instrument in more detail).[29] This two-step approach addresses the issue of hierarchical variation in a similar way as Donald and Lang (2007) for the treatment effect literature.

The estimation approach differs from that of Gowrisankaran, Park, and Rysman (2014) in two respects: in their paper, the time dummy coefficients capture the present discounted value of the expected stream of future benefits from the complementary goods market, whereas, in the current paper, these coefficients enter the (static) single-period profits of theaters and, therefore, do not include the future benefits from digital movie availability; second, their paper assumes a general auto-regressive structure (in particular with one lag) on the time coefficients, allowing for "accumulated capital" of complementary goods. By contrast, the current paper assumes that movies are short-lived from the perspective of theaters. This assumption seems reasonable with a period of 6 months and a focus on miniplexes and multiplexes which rules out smaller "continuation" theaters.

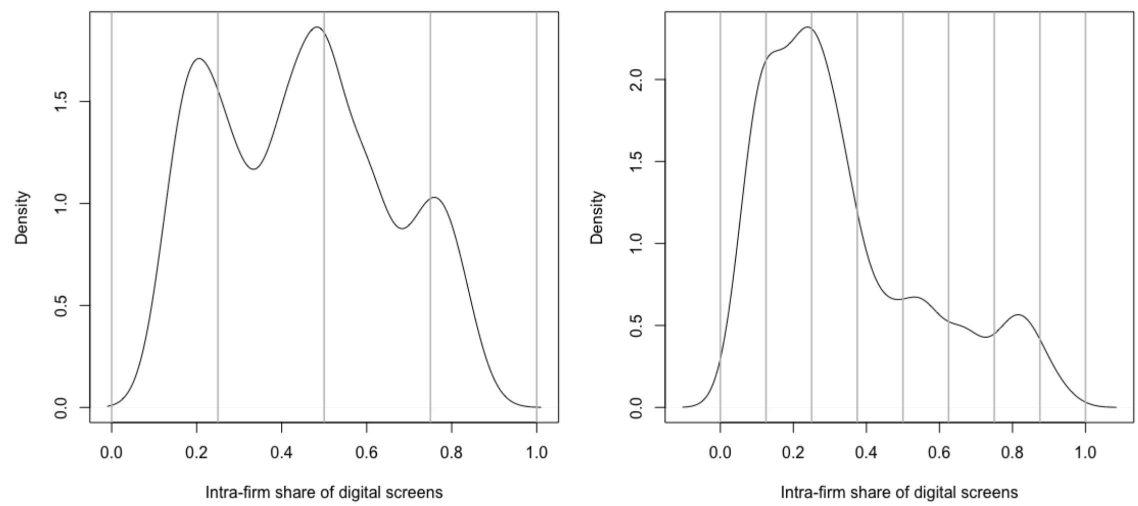
6.5 Estimation results

6.5.1 First-step estimates

Theaters' adoption-policy function. The nonstationary oblivious CCP are estimated using a flexible reduced form, via an ordered probit model. To further control the size of the state space, theaters' strategy space (the number of screens that can be converted) is restricted to lie on a grid. More precisely, miniplexes (theaters with 4 to 7 screens) are assumed to adopt on the space $s_{it}/S_{\boldsymbol{\tau}(i)} \in \{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\}$, whereas multi- and megaplexes (theaters with 8 screens or more) are assumed to adopt on the space $s_{it}/S_{\boldsymbol{\tau}(i)} \in \{0, \frac{1}{8}, \frac{2}{8}, ..., \frac{7}{8}, 1\}$. Figure 3

[29] This instrument would be less valid if aggregate shocks (affecting all firms in France and the U.S.) are important. Given the data available, there is less concern for unobserved aggregate shocks to the adoption cost. In addition, under the payoff normalization imposed, the difference between profits from a digital and film screen is estimated. As a result, aggregate shocks to box-office revenue (which are independent of the screening format) are differenced out.

Figure 3: Density estimate of the intra-firm rate of adoption by firm size



(a) Miniplexes (4-7 screens) (b) Multi/Megaplexes (8 screens or more)

Notes: Both density estimates correspond to the distribution of $s_{it}/S_{\boldsymbol{\tau}(i)}$ *conditional on* $s_{it}/S_{\boldsymbol{\tau}(i)} > 0$ *and* $s_{it}/S_{\boldsymbol{\tau}(i)} < 1$

shows kernel density estimates of the within-firm adoption rates for miniplexes (panel (a)) and multi/megaplexes (panel (b)), conditional on partial adoption.[30] For miniplexes, the density has three identifiable modes. Additionally, 93.1% of observations are within 5% of a grid point in $\{\frac{1}{4}, \frac{1}{2}, \frac{3}{4}\}$. For multi- and megaplexes, 96.2% of observations are within 5% of a grid point in $\{\frac{1}{8}, \frac{2}{8}, ..., \frac{7}{8}\}$. Overall, the coarsening of the state space reduces its dimensionality without imposing too strong a restriction on firms' admissible states.

Because theaters cannot divest and roll back the film technology, a firm cannot transition to lower states. For instance, a four-screen theater with $s_{it}/S_{\boldsymbol{\tau}(i)} = 3/4$ can only transition to $s_{it+1}/S_{\boldsymbol{\tau}(i)} \in \{3/4, 1\}$. In this sense, next period's possible states depend on the firm's adoption rate in the current period. This dependence is accounted for in constructing the likelihood (see Appendix C.3).

In a nonstationary oblivious equilibrium, theaters' adoption decision are a function of the firm state $\mathbf{x}_{it} = (\boldsymbol{\tau}(i), s_{it})$ and time. A theater's share of screens converted to digital between t and $t+1$, denoted $a_{it}/S_{\boldsymbol{\tau}(i)}$, is explained by the number of screens in the theater (and its square), the share of digital screens in the theater in period t, whether the theater is an art house, competitors' total number of screens, a polynomial in time, and its interaction with the theater's art house status. The polynomial in time captures the effect of the deterministic—

[30] A gaussian kernel is used and the bandwidth is selected using the biased cross-validation approach of Scott and Terrell (1987).

under nonstationary oblivious beliefs—processes $\{\overline{h}_t, p_t, h_{US,t}\}$, which all vary in the time series. A second specification augments the model by including market dummies to control for market size. A third specification includes both market dummies and theater-chain dummies for the three major French theater chains (Gaumont-Pathé, CGR, and UGC). Finally, a fourth specification also controls for interactions between theater size $S_{\boldsymbol{\tau}(i)}$ and all other variables.

Table 3 presents the estimates of the ordered probit model under the four specifications. In specification (4), where all variables are interacted with $S_{\boldsymbol{\tau}(i)}$, interaction terms are omitted. Marginal effects are, however, similar to the first three specifications.

As expected, across the four specifications, the time effects are positive. This trend reflects decreasing adoption costs and increasing digital movie availability. Larger theaters are more likely to adopt, but the marginal effect is decreasing. The share of a theater's screens already converted to digital is negatively related to further adoption. This finding is expected because, given a share of digital movies, theaters lagging in their adoption (low $s_{it}/S_{\boldsymbol{\tau}(i)}$) have a greater incentive to adopt.

Competitors' total number of screens does not significantly impact a theater's likelihood of adoption. Theaters located in Paris are more likely to adopt than theaters located in the small urban areas with fewer than $20,000$ inhabitants and rural areas, although the effect is not significant. Among the chain dummies, CGR theaters are more likely to adopt than single theaters or theaters belonging to smaller chains.

Appendix C.4 compares model predictions for the share of digital screens to actual shares in the data. Overall, and given the limitations imposed by the parametric specification of the policy function, the model captures the main trends in the data well. The rest of the analysis uses specification (3) based on the AIC.

6.5.2 Second-step estimates

This section presents estimation results for the profit per digital screen (the baseline $\pi_d(\boldsymbol{\tau}(i))$ and decay $\delta(\boldsymbol{\tau}(i), h_t)$). These components are combined, in equation (22), to obtain theaters' single-period operating profits.

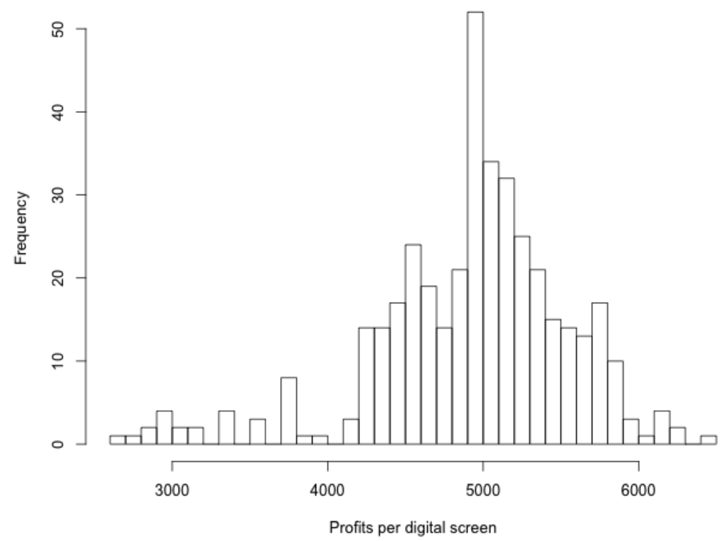
Table 5 shows estimates of the parameters entering the single-period profits per digital screen relative to a film screen. First, there is heterogeneity in profits across theaters. Profits per screen are increasing in theater size. This is the case if there are scale economies in operating a theater, and these economies of scale are larger under digital technology than under 35mm film. Art house status, market size, and competitors' screens do not significantly affect profits per digital screen. This is expected because these variables affect only revenues not the cost of operating, whereas $\pi_d(\boldsymbol{\tau}(i))$ reflects the cost-reduction from converting a screen to digital.

Table 5: Structural parameter estimates (in 2010 €)

	Estimate	s.e
Profit per digital screen: $\pi_d(\boldsymbol{\tau}_i)$		
Constant	$4,024.86$	959.18
Own screens	112.00	51.17
Art house	638.23	696.07
Competitors' screens	-2.16	5.42
Market dummies		
Paris - outer suburbs	-219.65	278.49
Urban unit - 20k-100k inhabitants	-150.87	223.03
Urban unit - >100k inhabitants	-177.61	230.50
Paris - inner suburbs	-325.05	310.92
Paris	246.76	295.56
Chain dummies		
Gaumont-Pathé	-229.05	146.82
CGR	622.02	166.90
UGC	-1,650.32	430.57
Decay function: $\delta(\boldsymbol{\tau}_i, h_t)$		
Constant	$3,920.84$	$1,096.80$
Own screens	17.03	42.71
Digital movies (%)	-2,196.62	444.29

Note: Standard errors are calculated using $N_b = 500$ *bootstrap samples. For market dummies, the omitted category is urban unit with fewer than 20k inhabitants and rural units. For the chain dummies, the omitted category is single firm and small chains. The standard deviation of firm shocks* σ *is set to* $10,000$ *€.*

Figure 4: Histogram of $\pi_d(\boldsymbol{\tau}(i))$ (in 2010 €)



The decay function is decreasing in the availability of digital movies h_t. As h_t increases, a theater's choice set of digital movies increases so profits per digital screen increase. Theater size does not significantly impact the decay. One would expect the decay to be larger for large theaters, fixing digital movie availability, because larger theaters screen more movies.

Profits per digital screen relative to film implied by the structural estimates have the correct order of magnitude. Figure 4 shows the distribution of single-period profits per digital screen across theaters (over a period of 6 months) predicted by the model. Profits per digital screen are between €2,603 and €6,423, with a mean of €4,928 and median of €4,986. These results are contrasted with estimates of projectionist's wages. Collective bargaining agreements set a projectionist's minimum monthly salary at €1,500 over the period of interest, or €9,000 over a period of 6 months. The latter figure is an upper bound on cost-reductions per screen because projectionists are replaced with lower-wage workers. Therefore, profits levels implied by the structural model are economically plausible.

7 Counterfactual Analysis

This section uses the estimated model to quantify, via counterfactual simulations, the delays in adoption and the effect of policy remedies. Two counterfactual adoption paths are simulated for the industry: in the first benchmark, a social planner maximizes aggregate theater profits taking as given upstream distributors' reaction function; in the second benchmark, the social planner mandates coordination on digital distribution for all movie–periods, and maximizes aggregate theater profits. Results point to a sizeable surplus loss, 41% of which is due to externalities among downstream theaters. The last subsection analyzes the role of broad-based and targeted subsidies in reducing this welfare gap.

7.1 Planner's benchmark

By converting to digital, theaters raise distributors' incentive to release movies in digital. This increased number and variety of digital movies is a positive externality on other theaters not internalized by the adopter. As a result, industry profits are not maximized under the non-cooperative market outcome.

In this benchmark, the social planner chooses a sequence of adoption decisions for each theater $\{\mathbf{a}_t = a_{1t}, ..., a_{It}\}_{t\geq 0}$ to maximize the discounted sum of aggregate theater profits

$$\max_{\{\mathbf{a}_t\}_{t\geq 1}} \mathbb{E}\left[\sum_{i\in I}\sum_{t=1}^{\infty} \beta^{t-1}\Pi(a_{it}, \mathbf{x}_t, p_t, h_{US,t}, \epsilon_{it})\right] \quad \text{s.t.} \quad h_t = \Gamma(\mathbf{x}_t, h_{US,t}) \tag{25}$$

where the expectation is taken with respect to the sequence of theaters' idiosyncratic shocks and the planner takes distributors' equilibrium best response Γ as given. The initial industry state $\mathbf{x}_1$ is fixed to $s_{i1} = 0$ for all i.

The Planner's problem (25) is computationnally hard to solve because of the large number of players in the industry: the industry state space is high-dimensional, and an industry adoption policy rule is, in general, a function of the realization of the full vector of adoption shocks $\{\epsilon_{it}\}_{i\in I} \in \mathbb{R}^I$, making the policy-rule space high-dimensional as well.

I deal with these computational issues in two steps. First, I replace the high-dimensional industry state vector $\mathbf{x}_t$ with its first moment (the aggregate share of digital screens in the industry s_t/S) and parameterize distributors' reaction function (Equation (3)) as a function of the aggregate share of digital screens in the industry and the share of digital movies in the U.S. This approximation helps reduce the dimension of the state space and Γ mapping.[31] I use the following reduced-form specification

$$h_t = \left(\frac{s_t}{S}\right)^{\eta_s} h_{US,t}^{\eta_h} \tag{26}$$

The parameters (η_s, η_h) are calibrated using the short-panel of aggregate variables in the

[31] Replacing the industry state by moments has been proposed as an approximation method to MPE by Ifrach and Weintraub (2017). This assumption is restrictive in that the social planner uses only a fraction of the data available (i.e., $\frac{s_t}{S}$ instead of $\mathbf{x}_t$)).

data. The robustness of the results is also evaluated under alternative choices for (η_s, η_h).

Second, I leverage the fact that the object of interest is the maximized value of the planner's objective function (discounted sum of industry profits), not the social planner's policy rule per se. Therefore, instead of solving the planner's full dynamic decision problem, I search for the maximum value of the objective function over the space of feasible industry adoption paths $\{\mathbf{a}_t = a_{1t}, ..., a_{It}\}_{t\geq 1}$. To do so, I generate a large number of random industry adoption paths and select the path that maximizes the objective function in problem (25). Details about this procedure are included in Appendix D.1. Let $\{\mathbf{a}_t^P\}_{t\geq 1}$ be the planner's optimal adoption path.

As a robustness check, the social planner's dynamic problem (25) is explicitly solved after reducing the dimension of the state and strategy spaces. The results are presented in Appendix D.2. The optimum policy rule obtained yields an industry diffusion path that is consistent with $\{\mathbf{a}_t^P\}_{t\geq 1}$.

7.2 Coordination benchmark

To quantify the magnitude of excess inertia in the upstream distribution market, I assume that the planner mandates multi-homing for all movies from the first period on and maximizes aggregate theater profits. In other words, $h_t = 1, \forall t$. The social planner chooses a sequence of adoption decisions for each theater $\{\mathbf{a}_t = a_{1t}, ..., a_{It}\}_{t\geq 1}$ to maximize the discounted sum of aggregate theater profits

$$\max_{\{\mathbf{a}_t\}_{t\geq 1}} \mathbb{E}\left[\sum_{i\in I}\sum_{t=1}^{\infty} \beta^{t-1}\Pi(a_{it}, p_t, \epsilon_{it})\right] \quad \text{s.t.} \quad h_t = 1 \tag{27}$$

where the expectation is taken with respect to the sequence of theaters' idiosyncratic shocks and I omit the dependence of single-period profits on $(\mathbf{x}_t, h_{US,t})$ because h_t is set to one. The initial industry state $\mathbf{x}_1$ is fixed to $s_{i1} = 0$ for all i. Because the value of h_t is fixed, network effects (in hardware adoption) are shut-down, and the problem is equivalent to profits maximization by each theater: I solve a single-agent dynamic decision problem for each theater i, given $h_t = 1, \forall t$. In this sense, the coordination benchmark can be interpreted as the counterfactual market equilibrium under a mandate on multi-homing upstream.

Each single-agent decision problem is an optimal stopping problem. Indeed, when $h_t = 1$, the marginal benefit from converting a screen to digital is constant across screens. As a consequence, theaters make a $0 - 1$ adoption decision. Decreasing adoption costs $\{p_t\}_{t\geq 1}$ and exogenous theater characteristics are the factors driving the diffusion process. Starting from $\overline{T}$, each problem is solved by backward induction.

Let $\{\mathbf{a}_t^C\}_{t\geq 1}$ be the solution of problem (27). Without accounting for distributors' profits, the coordination benchmark defined above is not necessarily optimal. Indeed, mandating multi-homing may raise distributors' costs due to a loss of scale economies. I investigate this issue in Appendix D.3 and find that the cost-reduction from digital distribution more than compensates for the loss in scale due to multi-homing. Distributors' profits are higher under the coordination benchmark than under the market outcome (holding box office revenue constant). The coordination benchmark, therefore, will provide a lower bound on the welfare loss due to coordination failure upstream.

7.3 Quantifying the delay in adoption

Figure 5 (top) shows the expected diffusion paths under the non-cooperative market outcome and the two benchmarks for digital screens (left) and digital movies (right). In the planner's benchmark, I use the parameters estimates $(\widehat{\eta}_s, \widehat{\eta}_h) = (0.52, 0.21)$ obtained through calibration (by ordinary least squares, Equation (26)).[32]

The diffusion of digital is faster under the two counterfactual scenarios: by 0.8 to 3 years for the time to 10% adoption, and 0.3 to 0.5 years for the time to 90% adoption. Additionally, the diffusion path is steeper in the planner's benchmark relative to the coordination benchmark because, in the former, digital movie availability is endogenously determined by the installed base of digital screen. The planner must build up the installed base of digital screen to incentivize distributors to switch.

Next, I compare theaters' aggregate profits under the three scenarios. Profits are computed as the discounted sum of operating profits net of adoption costs for all theaters, given adoption decisions and digital movie availability. Denote aggregate theater surplus under the non-cooperative market outcome, planner's benchmark, and coordination benchmark by TS^M, TS^P, and TS^C.

Table 6 shows industry profits under the three scenarios. Profits from film are normalized to zero, so these figures are relative to the status-quo with no conversion to digital. Industry profits net of adoption costs are 76.18 million euros under the market outcome, 82.25 million euros under the planner's benchmark, and 90.65 million euros under the coordination benchmark. The difference $TS^P - TS^M$ is attributed to downstream excess inertia (specifically, adoption externalities across theaters), and $TS^C - TS^P$ to excess inertia among upstream distributors.[33] Overall, excess inertia causes theaters' surplus to be 16% lower than under full coordination. Adoption externalities across downstream firms explain 41%

[32] I evaluate the sensitivity of the results with respect to these parameters in Appendix D.4.

[33] Upstream excess inertia is estimated as a residual and can arise because of coordination failure and adoption externalities across distributors.

of this surplus loss.

Table 6: Theaters' surplus under the three scenarios (in millions, 2010 €)

	Market outcome	Planner benchmark	Coordination benchmark
Gross Industry Profits	167.54	193.75	209.52
Adoption costs	91.36	111.49	118.88
Net Industry Profits	76.18	82.25	90.65
Change in Net Profits	0	6.07	14.46
Change in Net Profits (in %)	0	7.97	18.98

Note: Profits from film are normalized to 0*: all profits are relative to the status-quo with no adoption.*

7.4 Policy remedies

Having characterized the delay in adoption relative to the two efficient benchmarks, this section evaluates the effect of various policy remedies aiming at accelerating adoption. In particular, I consider broad-based and targeted subsidies to adoption costs. For each policy, a counterfactual NOE is computed, the industry adoption path is simulated, and aggregate profits are computed. Details about the algorithm used to solve for a NOE are presented in Appendix D.6.

Broad-based (or blanket) subsidies are implemented by assuming that the adoption cost incurred by theaters in period t is $(1-\gamma)p_t$ where $\gamma \in (0,1)$.[34] Figure 5 (middle) shows the diffusion paths under various broad-based subsidies ($\gamma \in \{0, 0.25, 0.5, 0.75\}$), for digital screens (left) and digital movies (right). Larger subsidies encourage faster diffusion as expected. Table 7 presents industry profits and total adoption costs (i.e., gross of the subsidy) corresponding to these counterfactual policies. A subsidy of $\gamma = 0.25$ increases net industry profits by 7.93% relative to the market outcome and reaches a level close to the planner's benchmark. Higher levels of the subsidy are detrimental (net industry profits are between 7.4% and 21% lower), however, because they induce too fast a diffusion leading to excessively large adoption costs relative to the return of digital conversion.

To evaluate the distributive impact of these broad-based subsidies, I compute the mean per-screen subsidy by theater size when $\gamma = 0.25$. Multiplexes (8 screens of more) receive a

[34] Aguirregabiria and Suzuki (2014) and Norets and Tang (2014) show that counterfactual behavior is identified when single-period payoffs change additively by pre-specified amounts—even if payoffs are normalized. The subsidy policy falls into the category of pre-specified additive changes to single-period payoffs (independent of the structural parameters) and counterfactuals are identified based on the results of Aguirregabiria and Suzuki (2014) (Proposition 3).

Figure 5: Counterfactual diffusion paths under the efficient benchmarks (top), blanket subsidies (middle), and subsidies targeting miniplexes (bottom)

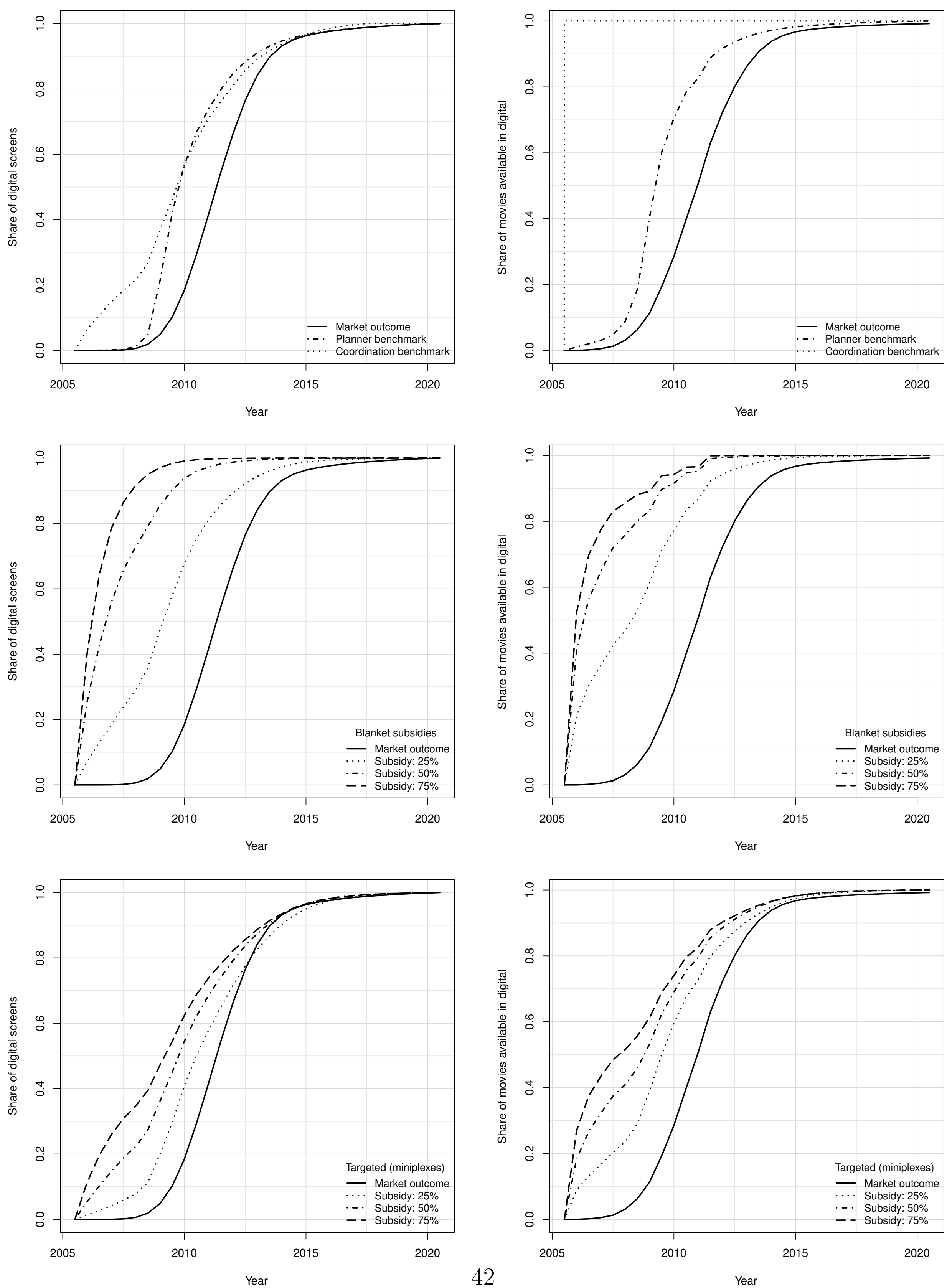


Table 7: Theaters' surplus under counterfactual blanket subsidies (in millions, 2010 €)

	Market outcome	Blanket subsidies $\gamma = 0.25$	$\gamma = 0.50$	$\gamma = 0.75$
Gross Industry Profits	167.54	217.95	262.06	280.74
Adoption costs	91.36	135.73	191.5	220.55
Net Industry Profits	76.18	82.22	70.56	60.19
Change in Net Profits	0	6.04	-5.63	-15.99
Change in Net Profits (in %)	0	7.93	-7.38	-20.99

Note: Profits from film are normalized to 0*: all profits are relative to the status-quo with no adoption.* γp_t *corresponds to the subsidy level incurred by the social planner and* $(1-\gamma)p_t$ *is incurred by the theater. "Adoption costs" include costs to theaters and the social planner.*

5.3% higher subsidy per screen than miniplexes. An 8-screen theater receives on average a 8.2% higher subsidy per screen than a 4-screen theater, and a 23-screen theater receives a 26.3% higher subsidy per screen than a 4-screen theater. These results are consistent with the fact that larger firms incur higher adoption costs (per screen) because they are early adopters: they have higher returns from converting to digital and, due to capital indivisibilities, they can adopt gradually and initially convert a smaller fraction of their screens (when h_t is low).

Next, I consider the effect of subsidies targeting miniplexes. Figure 5 (bottom) shows the diffusion paths under targeted subsidies to miniplexes ($\gamma \in \{0, 0.25, 0.5, 0.75\}$) and Table 8 presents the corresponding industry profits and adoption costs. Interestingly, a targeted subsidy of $\gamma = 0.25$ increases industry profits by 7.65%, an outcome that is relatively close to the corresponding broad-based subsidy but at a much lower (65%) cost to the Planner (only miniplexes are subsidized). This result indicates that the welfare gap due to externalities assessed in the previous section can be bridged by targeting smaller theaters delaying their adoption.

Appendix D.5 investigates alternative targeted subsidies, i.e., to the first unit adopted, and finds that they are not as effective as the two policies presented above.

8 Conclusion

Industries with network effects tend to coordinate on a single technology, the standard, to exploit the benefits of a larger network. However, once bound together by the benefits of the standard, firms may become reluctant to switch to better technologies as they become available. In particular, adoption externalities create a wedge between the private and social benefits from adoption. This paper studies empirically whether a new technology standard

Table 8: Theaters' surplus under counterfactual targeted subsidies (in millions, 2010 €)

	Market outcome	Subsidies to miniplexes $\gamma = 0.25$	$\gamma = 0.50$	$\gamma = 0.75$
Gross Industry Profits	167.54	184.52	201.01	212.07
Adoption costs	91.36	102.51	122.03	138.55
Net Industry Profits	76.18	82.01	78.97	73.52
Change in Net Profits	0	5.83	2.79	-2.66
Change in Net Profits (in %)	0	7.65	3.66	-3.49

Note: Profits from film are normalized to 0*: all profits are relative to the status-quo with no adoption.* γp_t *corresponds to the subsidy level incurred by the social planner and* $(1-\gamma)p_t$ *is incurred by the theater. "Adoption costs" include costs to theaters and the social planner.*

can diffuse efficiently in a decentralized market. I exploit rich firm level data in the French movie industry to assess the magnitude of excess inertia in the switch from 35mm to the digital cinema standard.

To do so, I specify a dynamic game of digital hardware adoption by theaters and digital movie supply by distributors. Using data on theaters' adoption decisions and the cross-sectional variation in theater and market characteristics, I estimate theaters' payoff from converting their screens to digital. The delay in adoption is assessed through counterfactuals: first, I consider a planner maximizing theater profits taking as given distributors reaction function; second, the planner mandates coordination on digital distribution upstream and maximizes theater profits.

The counterfactuals show that market forces did not provide enough incentives for an efficient switch from 35mm to digital. Industry profits are lower under the market outcome relative to under coordination. Additionally, 59% of the surplus loss can be ascribed to excess inertia in the upstream distribution market, whereas the rest is due to adoption externalities in the downstream exhibition market.

Finally, the role of policy remedies is considered: e.g., adoption subsidies aligning the private and social benefits of adoption. The results indicate that broad-based and targeted subsidies (to small theaters) can be beneficial. Nonetheless, in the case of digital cinema, the counterfactual analysis suggests that coordinating upstream distributors (through a mandate on digital distribution) is more effective than subsidizing theater adoption. Recent interventions in other industries indicate that policy-makers have been taking a more active role in coordinating standard adoption in hardware-software markets: a particularly topical industry are consumer electronics, where E.U. states have been considering mandating USB-C charging ports on all smartphone manufacturers (European Commission (2021)).

References

Ackerberg, D. A. and G. Gowrisankaran (2006). "Quantifying equilibrium network externalities in the ACH banking industry". *The RAND Journal of Economics* 37.3, pp. 738–761 (cit. on p. 5).

Aguirregabiria, V. and P. Mira (2007). "Sequential Estimation of Dynamic Discrete Games". *Econometrica* 75.1, pp. 1–53 (cit. on pp. 2, 20, 24, 25).

Aguirregabiria, V. and J. Suzuki (2014). "Identification and counterfactuals in dynamic models of market entry and exit". *Quantitative Marketing and Economics* 12.3, pp. 267–304 (cit. on p. 41).

Andrew Hanssen, F. (2010). "Vertical integration during the hollywood studio era". *Journal of Law and Economics* 53.3, pp. 519–543 (cit. on p. 5).

Augereau, A., S. Greenstein, and M. Rysman (2006). "Coordination versus Differentiation in a Standards War: 56K Modems". *The RAND Journal of Economics* 37.4, pp. 887–909 (cit. on p. 5).

Bajari, P., L. Benkard, and J. Levin (2007). "Estimating dynamic models of imperfect competition". *Econometrica* 75.5, pp. 1331–1370 (cit. on p. 24).

Bajari, P., V. Chernozhukov, H. Hong, and D. Nekipelov (2015). "Identification and Efficient Semiparametric Estimation of a Dynamic Discrete Game" (cit. on p. 29).

Battisti, G. and P. Stoneman (2005). "The intra-firm diffusion of new process technologies". *International Journal of Industrial Organization* 23.1-2, pp. 1–22 (cit. on p. 5).

Bordwell, D. (2013). *Pandora's Digital Box: Films, Files, and the Future of Movies.* Irvington Way Institute Press (cit. on p. 8).

Chou, C.-f. and O. Shy (1990). "Network Effect without Network Externalities". *International Journal of Industrial Organization* 8.2, p. 259 (cit. on p. 1).

Church, J. and N. Gandal (1992). "Network Effects, Software Provision, and Standardization". *The Journal of Industrial Economics* 40.1, pp. 85–103 (cit. on p. 1).

Church, J., N. Gandal, and D. Krauske (2008). "Indirect Network Effects and Adoption Externalities". *Review of Network Economics* 7.3, pp. 337–358 (cit. on p. 1).

Clements, M. T. and H. Ohashi (2005). "Indirect Network Effects and the Product Cycle: Video Games in the U.S., 1994-2002". *The Journal of Industrial Economics* 53.4, pp. 515–542 (cit. on p. 4).

Corts, K. S. and M. Lederman (2009). "Software exclusivity and the scope of indirect network effects in the U.S. home video game market". *International Journal of Industrial Organization* 27.2, pp. 121–136 (cit. on p. 4).

Davis, P. (2006a). “Measuring the Business Stealing , Cannibalization and Market Expansion Effects of Entry in the U . S . Motion Picture Exhibition Market”. *The Journal of Industrial Economics* 54.3, pp. 293–321 (cit. on p. 5).

— (2006b). “Spatial competition in retail markets: Movie Theaters”. *Rand Journal of Economics* 37.4, pp. 964–982 (cit. on pp. 5, 14).

Donald, S. G. and K. Lang (2007). “Inference with Difference-in-Differences and Other Panel Data”. *The Review of Economics and Statistics* 89.2, pp. 221–233 (cit. on p. 33).

Doraszelski, U. and M. Satterthwaite (2010). “Computable Markov-perfect industry dynamics”. *RAND Journal of Economics* 41.2, pp. 215–243 (cit. on p. 22).

Dubé, G. J. Hitsch, and Chintagunta (2010). “Tipping and Concentration in Markets with Indirect Network Effects”. *Marketing Science* 29.2, pp. 216–249 (cit. on p. 4).

Einav, L. (2007). “Seasonality in the U. S. motion picture industry”. *The RAND Journal of Economics* 38.1, pp. 127–145 (cit. on p. 5).

— (2010). “Not all rivals look alike: Estimating an equilibrium model of the release date timing game”. *Economic Inquiry* 48.2, pp. 369–390 (cit. on p. 5).

European Commission (2016). “The Joint Initiative on Standardisation under the Single Market Strategy” (cit. on p. 1).

— (2021). “Pulling the plug on consumer frustration and e-waste: Commission proposes a common charger for electronic devices [Press Release, September 23, 2021]” (cit. on p. 44).

Farrell, J. and G. Saloner (1985). “Standardization, Compatibility, and Innovation”. *The RAND Journal of Economics* 16.1, pp. 70–83 (cit. on p. 1).

— (1986). “Installed Base and Compatibility: Innovation, Product Preannouncements, and Predation”. *The American Economic Review* 76.5, pp. 940–955 (cit. on p. 1).

Farrell, J. and T. Simcoe (2012). “Choosing the rules for consensus standardization”. *RAND Journal of Economics* 43.2, pp. 235–252 (cit. on p. 4).

Gandal, N., M. Kende, and R. Rob (2000). “The Dynamics of Technological Adoption in Hardware / Software Systems: The Case of Compact Disc Players”. *The RAND Journal of Economics* 31.1, pp. 43–61 (cit. on p. 4).

Gil, R. (2009). “Revenue Sharing Distortions and Vertical Integration in the Movie Industry”. *The Journal of Law, Economics, & Organization* 25.2 (cit. on p. 5).

Gil, R., Houde, and Y. Takahashi (2015). “Preemptive Entry and Technology Diffusion in the Market for Drive-in Theaters” (cit. on p. 5).

Goettler, R. L. and B. R. Gordon (2011). “Does AMD Spur Intel to Innovate More?” *Journal of Political Economy* 119.6, pp. 1141–1200 (cit. on p. 5).

Goolsbee, A. and P. J. Klenow (1999). “Evidence on Learning and Network Externalities in the Diffusion of Home Computers” (cit. on p. 4).

Gowrisankaran, G., M. Park, and M. Rysman (2014). “Measuring Network Effects in a Dynamic Environment” (cit. on pp. 4, 33).

Gowrisankaran, G. and J. Stavins (2004). “Network Externalities and Technology Adoption: Lessons from Electronic Payments”. *The RAND Journal of Economics* 35.2, p. 260. arXiv: `arXiv:1011.1669v3` (cit. on p. 4).

Hotz, V. J., R. A. Miller, S. Sanders, and J. Smith (1994). “A Simulation Estimator for Dynamic Models of Discrete Choice”. *The Review of Economic Studies* 61.2, pp. 265–289 (cit. on p. 25).

Hotz, V. J. and R. A. Miller (1993). “Conditional Choice Probabilities and the Estimation of Dynamic Models”. *The Review of Economic Studies* 60.3, p. 497 (cit. on pp. 2, 25).

Ifrach, B. and G. Weintraub (2017). “A framework for dynamic oligopoly in concentrated industries”. *Review of Economic Studies* 84.3, pp. 1106–1150 (cit. on p. 38).

Igami, M. (2017). “Estimating the Innovator’s Dilemma: Structural Analysis of Creative Destruction in the Hard Disk Drive Industry, 1981–1998”. *Journal of Political Economy* 125.3, pp. 798–847 (cit. on p. 5).

Igami, M. and K. Uetake (2017). “Mergers, Innovation, and Entry-Exit Dynamics: The Consolidation of the Hard Disk Drive Industry, 1996-2015” (cit. on p. 5).

Karaca-Mandic, P. (2003). “Network Effects in Technology Adoption: The Case of DVD Players” (cit. on p. 4).

Katz, M. L. and C. Shapiro (1985). “Network Externalities, Competition, and Compatibility”. *American Economic Review* 75, pp. 424–440 (cit. on p. 1).

Kopp, P. (2016). *Le cinéma à l’épreuve des phénomènes de concentration* (cit. on p. 8).

Lee, R. S. (2013). “Vertical Integration and Exclusivity in Two-Sided Markets”. *American Economic Review* 103.7, pp. 2960–3000 (cit. on p. 5).

Macher, J., N. H. Miller, and M. Osborne (2021). “Finding Mr. Schumpeter: Technology Adoption in the Cement Industry”. *RAND Journal of Economics* 52(1), pp. 78–99 (cit. on p. 5).

Magnac, T. and D. Thesmar (2002). “Identifying Dynamic Discrete Decision Processes”. *Econometrica* 70.2, pp. 801–816 (cit. on p. 29).

Mansfield, E. (1963). “Intrafirm Rates of Diffusion of an Innovation”. *The Review of Economics and Statistics* 45.4, pp. 348–359 (cit. on p. 5).

Manski, C. F. (1993). “Identification of Endogenous Social Effects: The Reflection Problem”. *The Review of Economic Studies* 60.3, p. 531. arXiv: `arXiv:1011.1669v3` (cit. on p. 4).

Norets, A. and X. Tang (2014). “Semiparametric inference in dynamic binary choice models”. *Review of Economic Studies* 81.3, pp. 1229–1262 (cit. on p. 41).

Ohashi, H. (2003). “The Role of Network Effects in the US VCR Market, 1978–1986”. *Journal of Economics & Management Strategy* 12.4, pp. 447–494 (cit. on p. 5).

Pakes, A., M. Ostrovsky, and S. Berry (2007). “Simple estimators for the parameters of discrete dynamic games”. *RAND Journal of Economics* 38.2, pp. 373–399 (cit. on p. 24).

Pesendorfer, M. and P. Schmidt-Dengler (2008). “Asymptotic least squares estimators for dynamic games”. *Review of Economic Studies* 75.3, pp. 901–928 (cit. on pp. 2, 20, 24, 25).

Rao, A. and W. R. Hartmann (2015). “Quality vs. Variety: Trading Larger Screens for More Shows in the Era of Digital Cinema”. *Quantitative Marketing and Economics* (cit. on p. 5).

Rust, J. (1994). “Structural Estimation Decision Processes”. *Handbook of Econometrics* Chapter 51, pp. 3139–3139 (cit. on p. 29).

Ryan, S. P. and C. Tucker (2012). “Heterogeneity and the dynamics of technology adoption”. *Quantitative Marketing and Economics* 10.1, pp. 63–109 (cit. on p. 5).

Rysman, M. (2004). “Competition Between Networks: A Study of the Market for Yellow Pages”. *Review of Economics and Statistics* 71.2, pp. 483–512 (cit. on p. 5).

— (2019). “The reflection problem in network effect estimation”. *Journal of Economics & Management Strategy* 28.1, pp. 153–158 (cit. on p. 4).

Rysman, M. and T. Simcoe (2008). “Patents and the performance of voluntary standard-setting organizations”. *Management Science* 54.11, pp. 1920–1934 (cit. on p. 4).

Schmidt-Dengler, P. (Dec. 2006). *The Timing of New Technology Adoption: The Case of MRI*. 2006 Meeting Papers 3. Society for Economic Dynamics (cit. on p. 5).

Scott, D. W. and G. R. Terrell (1987). “Biased and unbiased cross-validation in density estimation”. *Journal of the American Statistical Association* 82.400, pp. 1131–1146 (cit. on p. 34).

Simcoe, T. (2012). “Standard Setting Committees: Consensus Governance for Shared Technology Platforms”. *The American Economic Review* 102.1, pp. 305–336 (cit. on p. 4).

Srisuma, S. (2013). “Minimum distance estimators for dynamic games”. *Quantitative Economics* 4.3, pp. 549–583 (cit. on pp. 19, 20, 25).

Takahashi, Y. (2015). “Estimating a war of attrition: The case of the US movie theater industry”. *American Economic Review*, pp. 2204–2241 (cit. on p. 5).

Tucker, C. (2008). “Identifying Formal and Informal Influence in Technology Adoption with Network Externalities”. *Management Science* 54.12, pp. 2024–2038 (cit. on p. 4).

Waldfogel, J. (2016). “Cinematic Explosion: New Products, Unpredictabilty and Realized Quality in the Digital Era”. *Journal of Industrial Economics* 64.4, pp. 755–772 (cit. on p. 5).

Weintraub, G., C. L. Benkard, P. Jeziorski, and B. Van Roy (2008). “Nonstationary Oblivious Equilibrium”. *Manuscript, Columbia* (cit. on pp. 2, 16, 21, 22).

Weintraub, G., L. Benkard, and B. Van Roy (2008). “Markov Perfect Industry Dynamics With Many Firms”. *Econometrica* 76.6, pp. 1375–1411 (cit. on p. 21).

Yang, J., E. Anderson, and B. R. Gordon (2020). “Digitization and Flexibility: Evidence from the South Korean Movie Market”. *SSRN Electronic Journal* (cit. on pp. 6, 17).