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Estimating the Costs of Standardization: Evidence from the Movie Industry

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Abstract

This paper studies an industry's conversion from the current technology standard to a more efficient one, when network effects are present. If the new technology is incompatible with the installed base, adoption may be inefficiently delayed. I quantify the magnitude of excess inertia in the case of the switch of movie distribution and exhibition 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 19% relative to under coordination; adoption externalities explain 29% of the surplus loss.

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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. However, in the medium to long-run, standardization has costs: 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 excess inertia can arise, attempts to empirically assess it remain scarce. This paper studies a two-sided network's decision to switch from the current technology standard to a more efficient one and estimate the magnitude and sources of excess inertia.

Two sources of inefficiency lead to the adoption of the new technology being too slow. 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 may not reflect the social ones.[2] 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.[3] Appropriate policy intervention should account for the type of inefficiency and the (potentially asymmetric) distribution of excess inertia across firms on the two-sided network.

As an application, I study the conversion of movie distribution and exhibition from the 35mm film standard to digital cinema in France, between 2005 and 2013. Digital cinema consists of distributing motion pictures to theaters over digital support (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.

Digital cinema is well suited for assessing excess inertia in standard adoption. First, the movie distribution-exhibition industries constitute a hardware-software system with (indirect) network effects (Katz and Shapiro (1985)). Adoption of digital projectors—the hardware—by theaters is contingent on the availability and variety of digital movies—the

[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.

[2] When network effects are direct, adoption externalities always arise. When network effects are indirect, such as in hardware-software systems, Church, Gandal, and Krauske (2008) show that, under some conditions, software variety gives rise to (technological) externalities between hardware adopters.

[3] Another potential source of inefficiency, not considered in this paper, is market power in technology provision. Externalities only arise when preferences are heterogeneous, and cannot be solved with joint action without side-payments (subsidies). Coordination failure arises even with identical adopters, and it can be solved without side-payments.

software—supplied by distributors. Conversely, software variety depends on the hardware installed base. Second, 35mm film and digital are incompatible technologies.

Market forces may not have provided sufficient incentives for an efficient switch from 35mm film to digital. First, the adoption of digital projectors by a theater raises distributors' incentive to release movies in digital. This increased number and variety of digital movies is a positive externality on other theaters equipped with digital projectors, which is not internalized by the adopter.[4] Second, uncertainty about other distributors' willingness to release movies in digital can lead to coordination failure, with some distributors inefficiently delaying their digital conversion.[5] 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.[6]

The paper leverages four novel datasets: (1) a panel recording adoption of digital projectors at the theater-screen level, as well as information on local market conditions and theater characteristics, (2) a time series of digital projector prices, (3) a time series reporting the share of movies distributed in digital, and (4) estimates of the average distribution cost curves (printing, shipping and storage cost per movie print) under the film and digital technologies.

To quantify the magnitude of excess inertia among downstream and upstream firms, I specify a dynamic structural model and simulate two counterfactuals. 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 digitally equipped screens in the industry.

Because network effects are at the industry level, with a few hundred theaters adopting, this framework generates a particularly high-dimensional state space. To alleviate the computational burden, I exploit the fact that a single theater's adoption decisions have a negligible impact on aggregate software availability, which allows me to recast its problem as a single-agent dynamic problem. The model is estimated using a conditional choice

[4] A negative externality on non-adopters (due to decreased availability of film movies) is possible. But in practice, multi-homing (i.e., dual distribution on film and digital) blunts this externality.

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

[6] 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.

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 equipping a movie screen with digital technology.

Using the estimated model, the paper simulates two counterfactuals. 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 movies). In this counterfactual, (positive) 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 (downstream excess inertia). 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 upstream excess inertia.[7]

The adoption path under the equilibrium market outcome is delayed compared to the coordination and planner's benchmarks: by 1 to 3.5 years for the time to 10% adoption, and 0.5 to 2.5 years for the time to 90% adoption. Additionally, inefficiencies in adoption reduce surplus by 19% relative to under coordination. Adoption externalities across theaters explain 29% of the surplus loss. The results indicate that, in the switch from 35mm to digital, excess inertia is mainly due to slow adoption in the upstream distribution market. A standard-setting organization would have been a beneficial instrument to coordinate firms on the new technology and avoid delays.

The previous analysis focuses on theaters' surplus due to a lack of data on upstream distributors' profits. However, it is not a priori clear whether upstream distributors benefit under the two benchmarks. In the last section of the paper, I provide evidence that, given estimates of distributors' average distribution cost curves (under film and digital respectively), distributors' surplus also increases under the counterfactual scenarios. The trade-off hinges on the magnitudes of economies of scale in printing, shipping, and storing movie prints (whether in 35mm film or digital) and cost reductions from digital relative to film distribution. The latter dominates the former under the counterfactual adoption paths of

[7] In this sense, upstream excess inertia is obtained as a residual and can arise because of coordination failure and adoption externalities across distributors.

digital screens.

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. Finally, section 7 presents the counterfactual analysis.

2 Related Literature

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 highlighted in Manski (1993,1995). Rysman (2019) discusses this issue in the specific case of network effects and reviews the approaches taken to address it. In the context of direct network effects, recent contributions uses regional or individual-specific exogenous shifters of network size to identify direct 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.

In the case of 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).[8] 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 econometric 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

[8]This type of network effects have been formally modeled by Chou and Shy (1990), and further developed by Church and Gandal (1992). Recent theoretical contributions include Markovich (2008), and Markovich and Moenius (2013). For a review of the literature on network effects, see Farrell and Klemperer (2007).

(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 providing a case study of excess inertia in technology adoption, and by disentangling the sources of surplus loss.

This paper makes a contribution to the literature using dynamic games to study innovation and technology adoption. The recent research on this topic builds dynamic structural models and simulates 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 (2017)). This paper contributes to this literature in two ways. First, the paper evaluates the role of firm heterogeneity and externalities in delaying new technology adoption. 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 an important feature of a wide array of industries.[9]

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 (2008)), seasonality (Einav (2007)), 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 (streaming), and online film criticism on new product releases. Rao and Hartmann (2015) study the quality-variety trade-off in screening brought about by digital projection. Yang, Anderson, and Gordon (2019) evaluate the impact of digital projection on product variety and supply concentration (i.e., number of screens on which the top movie is shown). The present paper contributes to this strand by using the transition from film to digital as an example of a technology standard switch and estimate how the diffusion path differs from the social optimum.

[9] Examples from the intra-firm technology adoption literature include: Mansfield (1963), Nabseth and Ray (1974), Romeo (1975), Levin, Levin, and Meisel (1992), Fuentelsaz, Gomez, and Polo (2003), and Battisti and Stoneman (2005).

3 Industry Background

This section describes the movie-distribution and movie-exhibition industries before and after the advent of digital technology. It presents 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 specified steps in a vertically structured industry. After the movie is shot and produced, distributors print the movie onto 35mm film reels and ship the reels to movie theaters. At the theater, a projectionist prepares the reels and arranges them 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 US, 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 powerful computer known as a "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.

Digital projection automates all the technical tasks that were previously performed by the projectionist. Unskilled staff can control the playback of the content (movie featured, trailers, ads), the projector, sound system, auditorium lighting, and tab curtains through the server.

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.[10] In addition, hard drives can be returned to distributors for reuse. With several hundred movies distributed every year, the US distribution industry saves over $1 billion annually.

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.[11] By contrast, operating a digital projector is a simple task: 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.

A consequence of the “automated” nature of digital projection is that uncertainty and learning, which can be important determinants of technology diffusion, are not central to theaters' adoption decisions.

3.1.3 Multi-homing by movie distributors and theaters

Multi-homing in movie distribution consists of the distribution of 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). Importantly, the decision to multi-home involves a trade-off between economies of scale and cost reduction. On the one hand, there are economies of scale in printing, shipping, and storing movie prints (whether in film or digital). By multi-homing, distributors split their production over two cost functions (film and digital) and forgo some of these economies of scale. On the other hand, there are cost reductions from digital relative to film distribution, which incentive distributors to multi-home.

Multi-homing in movie 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 movie distributors. An agreement was reached with the Virtual Print Fee (VPF) system.

[10] The latter figure of $50 does not include the price of encryption-key generation, transportation, and storage, which add approximately $200–$300. For French/European movies, these figures are around €950 for film print distribution and around €350 for digital print distribution, including shipping, encryption-key generation, and storing.

[11] Film projectionists are commonly represented by powerful unions and are therefore expensive. 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.

The VPF system was born in the US market and was rapidly adopted in the rest of the world. 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 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.[12] 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.[13] The vast majority of movies released over the diffusion period were in 2D.

3.1.6 Welfare implications

Although the paper does not discuss welfare, digital cinema is expected to increase consumer surplus by reducing the cost of bringing movies to the market. A first consequence of such reduction in costs are wider releases with increased access for theaters located in small and rural markets. Second, cost reductions in movie making will lead to new product entry.[14]

3.2 The French distribution and exhibition market

3.2.1 The French exhibition industry

The French exhibition industry is fragmented, with a large fraction of small theaters: 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 (end of the diffusion of digital cinema) 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.[15] In the early phase of the diffusion period (in 2007), these shares were: Gaumont-Pathé (12.1% of screens), CGR (7.1%), and UGC (7.0%). Market shares were relatively stable over the diffusion period. 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.

[12] As noted by Davis (2006a), theaters' ability to set ticket prices is constrained by distributors' incentives. Because the conversion to digital distribution affected mainly the cost of a movie print, which is a *fixed* cost from the point of view of movie tickets, it did not significantly impact ticket pricing. However, by decreasing distribution costs, it increased competition for screens between distributors. The latter may have had a positive impact on theaters' share in box office revenue.

[13] See Bordwell (2013).

[14] Aguiar and Waldfogel (2018) show that if product quality is unpredictable at the time of investment (as is typically the case with cultural products such as movies), new product entry can have large welfare benefits.

[15] See Kopp (2016).

3.2.2 The French distribution industry

The French distribution industry is less concentrated than its US counterpart. In 2014, for example, the four-firm concentration ratio was 35.2% in France and 57.4% in the US. Over the diffusion period 2005–2014, US movies had an average 47% market share (of total box-office revenue), French movies had a 39% market share, and European and other nationalities made up 14% of the box office.[16] An important point to note is that US studios distribute their movies 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 US movies are distributed in France depends primarily on the installed bases of film and digital projectors in France.

3.2.3 The VPF and government subsidies

In the US, the VPF system was the result of bilateral negotiations between distributors and exhibitors. This was initially the case in France as well, until a law was passed on September 2010 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. As in the US, the VPF 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 the hardware-acquisition process in France. 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 less 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. This share depends on the theater location (e.g., small rural area, large city). The label, awarded every year, entitles the theater to government financial support (in the form of a lump-sum subsidy). A priori, operating profits may differ for art house theaters compared to non-art house (or commercial) theaters. Additionally, digital movies availability differs for commercial movies (e.g., US block-busters) compared to art house and independent movies. In particular, art house distributors lagged behind commercial distributors in their switch to digital. Therefore, art house theaters may differ in their adoption behavior.

[16]Based on CNC 2014 annual report.

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.[17] Both sources are public and provide snapshots of the digital-exhibition industry at different periods spanning June 2005 through March 2013, in France. Thirteen dates are obtained from the Cinema Yearbooks, and 5 dates from the Cinego database. At each of the 18 observation dates, the number of digital projectors acquired is known for every active theater. The observation dates and sources are detailed in Appendix A. Figure 1a represents the 18 observation dates along with the industry share of screens equipped with digital projection. As seen in this figure, 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.

Two auxiliary datasets complement the main adoption panel dataset. The first is obtained from the French National Center of Cinematography (CNC hereafter). The CNC dataset provides a rich set of information on theaters' characteristics, local market size, and the share of movies available in digital, between 2005 and 2015. More precisely, this annual dataset contains: (1) lists of all active theaters, (2) the number of screens, the number of seats, the address, the owner's identity (theater 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 share of movies released in digital (distributed partially or entirely in digital).

The second auxiliary dataset, obtained from the European Audiovisual Observatory, provides time-series information on digital-projector acquisition costs.[18] 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 between theaters and manufacturers. This time-series is taken as representative of the "list" price (or manufacturer's suggested retail

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

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

price MSRP) of digital projectors. The analysis accounts for the VPF subsidies, which cover 50% of the projector price.[19] 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.[20] The hardware adoption cost is interpolated to obtain estimates at the 13 observation dates. Figure 1b shows the time series for this variable.

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.[21] 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 France, which were active in 2005 or entered before 2008 equipped with the old technology. Table 1 shows a description of the variables used in the analysis.

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 that form a single unbroken spread of urban development, with no distance between habitations greater than 200 meters, and have a total population greater than 2,000 inhabitants. Communes not belonging to an urban unit are considered rural.[22] 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,

[19]Although the law mandating VPF subsidies was only enacted in September 2010, it was retroactive. Moreover, anecdotal evidence indicates that pre-2010, the majority of projectors were purchased under VPF agreements. The model will assume digital projector-purchases before 2010 benefited from VPF subsidies.

[20]The GDP Implicit Price Deflator for France is used.

[21]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.

[22]Communes correspond to civil townships and incorporated municipalities in the US.

because the resulting local markets are too large. In these cases, the relevant market within each city is the *"arrondissement"* (equivalent to zipcode in the US).[23] 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

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.[24] Table 2 and 3 report cross-sectional summary statistics, and highlight the market and firm heterogeneity captured by the data.

Table 2 shows summary statistics for the 399 theaters with at least four screens. A significant fraction of these theaters, 33%, are art house theaters. The average theater has eight screens, and 1,538 seats. 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 3 reports summary statistics by market type. Paris and its suburbs are controlled for separately because attendance rates are significantly higher in the capital compared to national averages.[25] 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).

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

[23]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."

[24]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 (adoption times and units of technology adopted) 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 assumed to be exogenous in the model.

[25]Moviegoers in Paris visit theaters on average 12 times a year, compared to a national average of $4-5$ times over the diffusion period.

screens converted to digital per year belong to theaters that have already adopted at least one digital screen in previous periods, highlighting the importance of the intensive margin.[26] To closely match this feature of the data in the theoretical section, adoption decisions will be modeled at the screen-level.

Second, adoption by a theater's competitors does not significantly affect its likelihood of adoption. I provide evidence for this in the estimation section 6.3.1. Therefore, strategic interactions in local markets are ruled out in the model.

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 loss due to excess inertia.

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 obtain greater availability/variety 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). For the distribution market, the model captures a distributor's per-period decision regarding on which support to distribute its 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. In equilibrium, theaters convert their screens optimally to digital projection, given their information sets and beliefs about future states, and these beliefs are consistent with theaters' adoption decisions and distributors' optimal choices of distribution format.[27]

[26] An alternative way of measuring the contribution of the intensive margin is to decompose the sample variance in adoption times across all screens in the industry into within-theater and between-theater variances. The former sample variance is 1.28 (corresponding to a standard deviation of 1.13 years), the latter is 1.02 (or a standard deviation of 1.01 years). Therefore, within-theater variance in adoption times explains about 56% of total variance across all screens in the industry. This likely underestimates the contribution of the intra-firm margin because the panel stops before the end of the diffusion.

[27] All vectors are denoted in bold.

5.1 Adoption of digital projectors by theaters

Time is discrete and infinite. A period corresponds to six months.

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

Firm state space: Firm heterogeneity is reflected through firm states. In period t, the individual state of theater $i \in I$ is a vector denoted by $\mathbf{x}_{it} \in \mathcal{X}$.[28] Firm state $\mathbf{x}_{it}$ is decomposed into $(\boldsymbol{\tau}_i, s_{it})$:

- $\boldsymbol{\tau}_i$ is a vector representing theater i's type, which is fixed throughout the game. $\boldsymbol{\tau}_i$ includes firm size S_i (number of screens), local market characteristics (market size, denoted $market_i$, and number of competitors' screens, denoted S_{-i}), art house label $art_i \in \{0, 1\}$, and a chain identifier $chain_i \in \{0, 1, ..., C\}$ (with $chain_i = 0$ if i is not horizontally integrated).

- $s_{it} \in \{0, 1, ..., S_i\}$ represents the number of screens converted to digital by theater i, by the beginning of period t. The remaining $S_i - s_{it}$ screens operate using the film technology.

Let the industry state, $\mathbf{x}_t$, be a vector over individual firm states that specifies, for each firm state $\mathbf{x} \in \mathcal{X}$, the number of firms (across the industry) at $\mathbf{x}$ in period t. Focusing on symmetric and anonymous equilibrium strategies, this definition of the industry state is without loss of generality. Let $S = \sum_{i \in I} S_i$ denote the total number of screens in the industry, and let $s_t = \sum_{i \in I} s_{it}$ denote the total number of digital screens in the industry in period t.

Theaters that are part of the same chain are assumed to make their adoption decisions independently. This assumption is motivated by the fact that modelling adoption at the chain level is computationally burdensome: each chain's state should record firms' states for all theaters part of the chain. The resulting chain state vector is high-dimensional.[29] This modelling assumption is discussed in more length in section 5.3.

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 a state s_{it+1} given by

$$s_{it+1} = s_{it} + a_{it} \quad \text{for} \quad a_{it} \leq S_i - s_{it} \tag{1}$$

[28] An earlier version of the paper includes strategic interactions at the local market level (oligopoly game). Theaters track their competitors' adoption decisions. See online appendix.

[29] The chain adoption state vector for Gaumont-Pathé (70 theaters) has dimension 1,088,430—assuming all theaters have four screens and ignoring theaters' types and rivals states.

There is no uncertainty in state transition. A theater's state s_{it} is bounded above by its maximum capacity S_i.

Aggregate adoption cost: The aggregate adoption cost process, $\{p_t,\ t \geq 0\}$, includes the digital-projector price (net of VPF contributions) and ancillary costs. This process is assumed deterministic and publicly observable to all firms. The process reflects technological advances in the manufacturing of digital projectors, as well as learning-by-doing and scale economies, which exogeneously decreases the hardware adoption cost over time.[30]

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. This theater-specific shock is privately drawn at the beginning of each period and is independent across periods and theaters.

Before defining theaters' single-period profit function, digital movie availability is first discussed.

Availability of digital movies: Every period, a continuum of mass M of movies is released. Movies are short-lived and are screened by theaters for one period. Let h_t^d denote the share of movies released exclusively in digital format in period t, and h_t^f denote the share of movies released exclusively in film in period t. Denote by $h_t^m = 1 - h_t - h_t^f$ the share of multi-homed movies (i.e., distributed on both film and digital).

According to industry professionals, multi-homing was widespread over the diffusion period studied in this paper (2005–2014).[31] To match this feature of the distribution market, I impose the restriction that $h_t^d = 0$, i.e., a given movie is either multi-homed or released exclusively in film.

For the rest of the analysis, define $h_t \equiv h_t^m$ so that $1 - h_t = h_t^f$. The share of multi-homed movies, h_t, is assumed to depend on the installed base of digital screens. Let

$$h_t = \Gamma(\mathbf{x}_t) \tag{3}$$

denote distributors' reaction function giving the share of movies multi-homed as a function of the industry state vector. This mapping is increasing in its arguments. The mapping $\Gamma(.)$ is an endogenous object and is allowed to depend on the adoption equilibrium played by

[30] The process can be assumed to be random. For example, the transition matrix of the process can depend on the stock of digital screens in the industry: $\mathbf{P}(p_{t+1}|p_t, s_t)$. The simpler specification is imposed due to the limited amount of data available to estimate a transition matrix (only time series information used).

[31] This is consistent with the findings of Anderson, Gordon and Yang (2019) for the digitization of the Korean movie industry. They find that the vast majority of distributors multi-homed until 2015.

downstream movie theaters.

Theaters' Single-Period Profit Function: The single-period profit of theater i (net of the adoption cost) in period t, if it adopts a_{it} units of digital hardware, is given by

$$\Pi(\mathbf{x}_{it}, p_t, h_t, a_{it}, \epsilon_{it}) = \pi(\mathbf{x}_{it}, h_t) - a_{it}(p_t + \epsilon_{it}) \tag{4}$$

where $\pi(\mathbf{x}_{it}, h_t)$ are theater i's operating profits (screenings, concessions, advertisements) in period t, which depends on the firm state $\mathbf{x}_{it}$ and the shares of digital movies h_t, and $a_{it}(p_t + \epsilon_{i,t})$ is the total cost of converting a_{it} screens in period t.

Operating profits are decomposed into total profits from digital screens $\pi_d(\mathbf{x}_{it}, h_t)$ and total profits from film screens $\pi_f(\mathbf{x}_{it})$.[32] I introduce a set of minimum shape restrictions that have to be satisfied by these payoffs to be consistent with theaters choosing movies optimally to maximize operating profits (recall that $\mathbf{x}_{it} = (\boldsymbol{\tau}_i, s_{it})$):

Assumption 1. *Let n denote the number of digital screens in theater i, then*

1. $\pi_d(\boldsymbol{\tau}_i, n, h_t) - \pi_d(\boldsymbol{\tau}_i, n-1, h_t)$ *is nonincreasing in n, given h_t. (concavity in n)*
2. $\pi_f(\boldsymbol{\tau}_i, n-1) - \pi_f(\boldsymbol{\tau}_i, n)$ *is nondecreasing in n, given h_t. (concavity in $S_i - n$)*
3. $\pi_d(\boldsymbol{\tau}_i, n, h_t) - \pi_d(\boldsymbol{\tau}_i, n-1, h_t)$ *is nondecreasing in h_t, given n. (Supermodularity)*

The first assumption states that the marginal benefit from an additional digital screen is nonincreasing in the number of digital screens. The second assumption states the same result but for film screens instead (if the number of digital screen is n, the number of film screens is $S_i - n$). Both assumptions illustrate the fact that, when choosing which movies to screen, theaters rank movies by potential box-office revenue and choose to screen movies with the highest box-office potential first (given firm and market characteristics). The third assumption states that the marginal benefit from an additional digital screen increases with the availability of digital movies. Again, if theaters pick movies with the highest potential box-office revenue, then the expected revenue per digital screen is higher when choosing from a larger pool of digital movies (large h_t). Note that the equivalent of this last assumption for film screens is not necessary, because all movies released per period are available on film (either because multi-homed or exclusively released on film).

Assumption 1–3 and equation (3) make clear the positive feedback loop between the hardware and software sides of the market. For a theater, the benefit from adopting a digital projector depends on the share of movies available in digital h_t (technology-specific software), which in turn depends on the installed base of digital screens in the industry.

[32] Note that $\pi_f(\mathbf{x}_{it})$ is independent of h_t because all movies are available on film.

State space: In a Markov Perfect Equilibrium, firms use Markov adoption strategies and condition their adoption decision only on the current vector of state variables $\boldsymbol{\omega}_{it} \equiv (\mathbf{x}_{it}, p_t, \mathbf{x}_t, \epsilon_{it})$. Although theater i's single-period profits, $\Pi(.)$, do not depend directly on the industry state vector $\mathbf{x}_t$, the firm tracks this variable in order to form expectations about the future evolution of the (payoff-relevant) share of multi-homed movies h_t, determined by equation (3).

The analysis focuses on equilibria in pure symmetric Markov strategies, defined as mappings from the current state $\boldsymbol{\omega}_{it}$ into actions a_{it} (i.e., number of screens to be converted to digital). In the rest of the model, define $\boldsymbol{\gamma}_{it} \equiv (\mathbf{x}_{it}, p_t, \mathbf{x}_t)$ as the state excluding the private firm-specific shock, so that

$$\boldsymbol{\omega}_{it} = (\mathbf{x}_{it}, p_t, \mathbf{x}_t, \epsilon_{it}) = (\boldsymbol{\gamma}_{it}, \epsilon_{it})$$

Value function and optimal adoption rule: Let $a(\boldsymbol{\gamma}_{it}, \epsilon_{it})$ be a pure adoption strategy. Firms aim to maximize expected discounted profits, by choosing the number of screens to equip with a digital projector at the current period, taking into account the effect on future operating profits and given their belief about future values of the state vector. The value function of firm i is defined as the solution of the following Bellman equation (where the subscript t is omitted and next-period variables are marked with a prime):

$$\begin{aligned} V(\boldsymbol{\gamma}_i, \epsilon_i) = \max_{a_i} \big\{ &\pi(\mathbf{x}_i, h) - a_i(p + \epsilon_i) \\ &+ \beta \sum_{p', \mathbf{x}'} V(\boldsymbol{\tau}_i, s_i + a_i, p', \mathbf{x}') \mathbf{P}_a(p', \mathbf{x}' | \boldsymbol{\gamma}_i) \big\} \end{aligned} \tag{5}$$

where β is the discount factor, $\mathbf{P}_a$ is the transition kernel, giving the probability of one-period reachable states for the adoption price and industry state vector, given firm i's belief a about other theaters' actions. Moreover, $V(\boldsymbol{\tau}_i, s_i + a_i, p', \mathbf{x}')$ is firm i's *ex-ante* value function, that is, before observing next-period firm-specific shock ϵ_i'. It is given by: $V(\boldsymbol{\tau}_i, s_i + a_i, p', \mathbf{x}') = \int V(\boldsymbol{\tau}_i, s_i + a_i, p', \mathbf{x}', \epsilon_i') dF(\epsilon_i')$.

The optimal adoption rule can be expressed as a function of the *choice-specific* value functions. Let $W(a_i|\boldsymbol{\gamma}_i)$ denote the discounted expected value function when firm i converts a_i screens in the current period:

$$W(a_i|\boldsymbol{\gamma}_i) = \beta \sum_{p', \mathbf{x}'} V(\boldsymbol{\tau}_i, s_i + a_i, p', \mathbf{x}') \mathbf{P}_a(p', \mathbf{x}' | \boldsymbol{\gamma}_i) \tag{6}$$

Define $\Delta W(k|\boldsymbol{\gamma}_i) \equiv W(k|\boldsymbol{\gamma}_i) - W(k-1|\boldsymbol{\gamma}_i)$ for $k \in \{1, 2, .., S_i\}$ as the difference in the choice-specific value functions of converting k and $k-1$ screens to digital. 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}. The optimal adoption rule takes the form of a set of cut-offs in ϵ_{it}.[33] It can be expressed as

$$a_{it} = \begin{cases} 0 & \text{if} \quad \Delta W(1|\boldsymbol{\gamma}_{it}) - p_t \leq \epsilon_{it} \\ k & \text{if} \quad \Delta W(k+1|\boldsymbol{\gamma}_{it}) - p_t < \epsilon_{it} \leq \Delta W(k|\boldsymbol{\gamma}_{it}) - p_t \\ & \quad \text{and } 1 \leq k < S_i - s_{it} \\ (S_i - s_{it}) & \text{if} \quad \epsilon_{it} < \Delta W(S_i - s_{it}|\boldsymbol{\gamma}_{it}) - p_t \end{cases} \tag{7}$$

The optimal adoption rule can alternatively be recast in the form of conditional choice probabilities (CCP):

$$P(a_{it}|\boldsymbol{\gamma}_{it}) = \begin{cases} \int_{\Delta W(1|\boldsymbol{\gamma}_{it})-p_t}^{\infty} dF(\epsilon_{it}) & \text{if} \quad a_{it} = 0 \\ \int_{\Delta W(k+1|\boldsymbol{\gamma}_{it})-p_t}^{\Delta W(k|\boldsymbol{\gamma}_{it})-p_t} dF(\epsilon_{it}) & \text{if} \quad a_{it} = k \in \{1, 2, ..., S_i - s_{it} - 1\} \\ \int_{-\infty}^{\Delta W(S_i - s_{it}|\boldsymbol{\gamma}_{it})-p_t} dF(\epsilon_{it}) & \text{if} \quad a_{it} = S_i - s_{it} \end{cases} \tag{8}$$

Finally, the *ex-ante* value function (i.e., before the firm observes the idiosyncratic shock ϵ_{it}) can be derived by taking expectations with respect to ϵ_i in equation (5):

$$V(\boldsymbol{\gamma}_i) = \pi(\mathbf{x}_i, h) + \sum_{a_i} P(a_i|\boldsymbol{\gamma}_i)\big(- a_{it}(p + E[\epsilon_i|\boldsymbol{\gamma}_i, a_i]) + W(a_i|\boldsymbol{\gamma}_i)\big) \tag{9}$$

The last equation expresses the ex-ante value function V, as a function of the choice-specific value function W and probabilities $P(a_i|\boldsymbol{\gamma}_i)$. The latter are both functions of the ex-ante value function. An equilibrium ex-ante value function is a fixed-point of this mapping.

5.2 Market equilibrium

In every period, the sequence of events is as follows: First, distributors observe the installed base of digital screens (i.e., the industry state vector $\mathbf{x}_t$) and publicly make their distribution decision (film or multi-homing) for movies released in that period. Second, theaters receive

[33] The cut-off rule can be derived by noting the following two points: (1) a_{it} is optimal in state $\boldsymbol{\gamma}_{it}$ *iff* $W(a_{it}|\boldsymbol{\gamma}_{it}) - a_{it}(p_t + \epsilon_{it}) \geq W(a'|\boldsymbol{\gamma}_{it}) - a'(p_t + \epsilon_{it})$ for all $a' \neq a_{it}$, and (2) $\Delta W(k|\boldsymbol{\gamma}_{it})$ is nonincreasing in k (which stems from assumption 1–3). Combining (1) and (2) yield the cut-off rule.

a private draw ϵ_{it} from the distribution of hardware costs, and decide whether to convert any screens to digital, given the share of movies multi-homed h_t and their private adoption cost. Third, theaters receive operating profits and pay the adoption cost. The state variables evolve as the adoption decisions are completed and new values of the exogenous variables are realized.

The analysis focuses on equilibrium in pure symmetric Markov Perfect strategies. In a Markov Perfect equilibrium, 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 $\mathbf{a}^*$ is an equilibrium if:

$$V(\boldsymbol{\gamma}_{it}; \mathbf{a}^*) \geq V(\boldsymbol{\gamma}_{it}; a'_i, \mathbf{a}^*_{-i}) \text{ for all firm states } \boldsymbol{\gamma}_{it} \text{ and strategies } a'_i \tag{10}$$

where $V(\boldsymbol{\gamma}_{it}; \mathbf{a}^*)$ is theater i's ex-ante value function at state $\boldsymbol{\gamma}_{it}$, given that all theaters play strategy $\mathbf{a}^*$, and $V(\boldsymbol{\gamma}_{it}; a'_i, \mathbf{a}^*)$ is theater i's ex-ante value function when the theater unilaterally deviates to strategy a'_i. Given the large number of theaters, the mapping $\Gamma(.)$ is assumed to be the same under strategy profiles $\mathbf{a}^*$ and $(a'_i, \mathbf{a}^*_{-i})$ (it is not affected by unilateral deviations). Due to network effects, the game has multiple equilibria, some of which can be found numerically.[34]

5.3 Remarks

The assumption that theaters make their adoption decisions independently, even within chains, is violated if theater chains coordinate adoption decisions across theaters. Two incentives to do so are: (1) to benefit from lower per-unit adoption cost when placing large orders of projectors and (2) to tip the industry by significantly increasing the share of digital screens in the industry. To alleviate concern (1), the model controls for chain effects in the profits from operating (firm type $\boldsymbol{\tau}_i$ include an indicator for the three largest theater chains). Regarding the second motive, the largest chain (Gaumont-Pathé) controlled 12.1% of screens and had a market share (box-office revenue) of approximately 20%: given its relatively small capital stock of screens, its ability to tip the market toward digital appears limited.

6 Estimation

This section discusses the identification and estimation of the structural model presented in section 5. The objective is to recover firms' operating profits $\pi(\mathbf{x}_{it}, h_t)$. Estimation results

[34] One can show that at least one degenerate equilibrium (e.g., with no adoption) exists.

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 analyze uncovers the main dimension of hetereogeneity in profits from digital across theaters.

6.1 Identification

Standard results for the identification of discrete-choice models, as in Rust (1994), Magnac and Thesmar (2002), and Bajari, Chernozhukov, et al. (2015), apply to this setting. Assuming that (β, F) are known, the single-period payoff is not identified without further restrictions. I use fonctional form restrictions and a normalization.

First, as equation (4) shows, the single-period payoff is linear in the adoption cost p_t and the action a_{it}. This restriction is arguably well-informed given the structure of the problem. Second, I normalize total operating profits when theater has not converted any screen to 0. Indeed, we have (recalling that $\mathbf{x}_{it} = (\boldsymbol{\tau}_i, s_{it})$)

$$\begin{aligned} \pi(\mathbf{x}_{it}, h_t) &= \pi_d(\mathbf{x}_{it}, h_t) + \pi_f(\mathbf{x}_{it}) \\ &= \sum_{n=1}^{s_{it}} \left[(\pi_d(\boldsymbol{\tau}_i, n, h_t) - \pi_d(\boldsymbol{\tau}_i, n-1, h_t)) - (\pi_f(\boldsymbol{\tau}_i, n-1) - \pi_f(\boldsymbol{\tau}_i, n)) \right] + \pi_f(\boldsymbol{\tau}_i, 0) \end{aligned} \tag{11}$$

The term $\pi_f(\boldsymbol{\tau}_i, 0)$ corresponds to total operating profits when theater i has no digital screens. It is independent of theater i's adoption behavior and is therefore a fixed component of operating profits. Only the cost reduction from converting screen $n \in \{1, ..., S_i\}$ (term in the sum) can be identified from knowledge of the CCP. In the rest of the paper, $\pi_f(\boldsymbol{\tau}_i, 0)$ is set to 0, and I focus on profits from a digital screen relative to a film screen. This restriction is relatively innocuous given that the main object of interest will be the counterfactual change in surplus due to the cost reduction from digital adoption. In the rest of the analysis, persistent firm and market characteristics $(\boldsymbol{\tau}_i)$ are exogeneous.

6.2 Estimation

6.2.1 Parameterization

This section details the model parameterization. Operating profits are obtained by summing profits per digital screen (relative to a film screen) over the s_{it} digital screens converted by theater i by time t. Importantly, profits per digital screen vary across screens (Assumption

1-1) and increase with the availability of digital movies (Assumption 1-3).

To capture this dependence parsimoniously, I assume that there are two possible levels of profit per digital screen: (1) a baseline level $\pi_d(\boldsymbol{\tau}_i)$ corresponding to the cost-reduction from converting a screen to digital keeping revenue constant; and (2) a decayed level $\widetilde{\pi}_d(\boldsymbol{\tau}_i, h_t) \equiv \pi_d(\boldsymbol{\tau}_i) - \delta(\boldsymbol{\tau}_i, h_t)$ equal to the baseline profits less a decay. From Assumption 1-3, $\delta(\boldsymbol{\tau}_i, h_t)$ is nonincreasing in h_t. Additionally, I assume that a fraction $\min\{\frac{s_{it}}{S_i}, h_t\}$ of screens yields profits $\pi_d(\boldsymbol{\tau}_i)$ per screen, whereas the remaining $\max\{0, \frac{s_{it}}{S_i} - h_t\}$ yield profits $\widetilde{\pi}_d(\boldsymbol{\tau}_i, h_t)$. Theater i's operating profits in state $(\mathbf{x}_{it}, h_t)$ are therefore given by

$$\pi(\mathbf{x}_{it}, h_t) = \begin{cases} s_{it}\pi_d(\boldsymbol{\tau}_i) & \text{if} \quad \frac{s_{it}}{S_i} \leq h_t \\ S_i\left(h_t\pi_d(\boldsymbol{\tau}_i) + (\frac{s_{it}}{S_i} - h_t)\widetilde{\pi}_d(\boldsymbol{\tau}_i, h_t)\right) & \text{if} \quad \frac{s_{it}}{S_i} \geq h_t \end{cases} \tag{12}$$

Figure 3 illustrates this representation of operating profits in the case of a 5-screen theater when $h_t = 0.5$. The left-hand side figure shows a general form of profits per digital screen, whereas the right-hand side represents the functional form restriction imposed. As h_t increases, the decay decreases and profits from the fraction $\max\{0, \frac{s_{it}}{S_i} - h_t\}$ of digital screens increase from $\widetilde{\pi}_d(\boldsymbol{\tau}_i, h_t)$ to $\pi_d(\boldsymbol{\tau}_i)$.

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

$$\pi_d(\boldsymbol{\tau}_i) = \alpha_0 + \alpha_1 S_i + \alpha_2 \mathbf{1}\{art_i = 1\} + \alpha_3 S_{-i} + \alpha_{market_i} + \alpha_{chain_i} \tag{13}$$

$$\delta(\boldsymbol{\tau}_i, h_t) = \delta_0 + \delta_1 S_i + \delta_2 h_t + \delta_3 h_t \times S_i + \delta_4 h_t \times \mathbf{1}\{art_i = 1\} \tag{14}$$

where S_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.[35] Equation (13) specifies how profits per digital screen depends on firm and market characteristics. Equation (14) specifies the decay in profits. The decay depends on theater size, availability of digital movies, art house status, and interactions. 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.[36] Finally, I control for the interaction of h_t with a theater's art house status to capture the fact that availability of art house digital movies lagged behind that of commercial digital movies. Without this control, the model will translate slower adoption of art house theaters into lower profits ($\alpha_2 < 0$), whereas in fact, art house theaters delay their adoption because fewer art house movies are available in digital compared to commercial

[35]See Table 1 for the different categories of market size.

[36]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.

movies.

The parameters of interest are the vector $\boldsymbol{\alpha} = (\{\alpha_i\}_{i=0\ldots3}, \alpha_{market=1\ldots6}, \alpha_{chain=0\ldots3}, \{\delta_i\}_{i=0\ldots4})$ 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 $\mathcal{N}(0, \sigma^2)$.

6.2.2 Estimation approach

Two issues make the estimation of the dynamic game complicated. First, the large number of firms (due to network effects at the industry level) and the dimension of firms' state $\mathcal{X}$ generate a high-dimensional industry state space.[37] Second, as is common in games of technology adoption under network effects, there are multiple equilibria.

Although two-step methods (such as Bajari, Benkard, and Levin (2007), Pesendorfer and Schmidt-Dengler (2008), Aguirregabiria and Mira (2007), and Pakes, Ostrovsky, and Berry (2007)) can be used to address both issues, they remain computationally burdensome (for standard errors computation). Because strategic interactions are ruled out at the local market level, the approach taken here is to recast the dynamic game as a single-agent dynamic discrete-choice problem for each theater. The underlying assumption is that a single theater's adoption behavior has a negligible impact on the process $\{h_t\}_{t\geq0}$.[38] This process is assumed to be exogeneous and deterministic from the point of view of a single theater. In the rest of the analysis, I replace the industry state $\mathbf{x}_t$ (in the vector $\boldsymbol{\gamma}_{it}$) by h_t. Denote by L_i the dimension of firm i's state space $\{\boldsymbol{\gamma}_{it}\}$.

The estimation approach follows the CCP-based method proposed in Hotz and Miller (1993) and Hotz, Miller, et al. (1994). In a first step, the CCP giving the equilibrium policy rule are estimated from the data. Next, using the CCP, I obtain the 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 (or equivalently, between predicted and actual differences in choice-specific value functions).

First-step estimation:

Movie theaters' adoption-policy function. The estimation proceeds by first recovering the conditional choice probabilities (CCP) governing theaters' equilibrium adoption of digital hardware. The CCP $P(a_{it}|\boldsymbol{\gamma}_{it})$ are estimated using an ordered probit model, and in what follows are assumed to be known.

[37] 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.

[38] Note that in approximation methods to MPE, such as Ifrach and Weintraub (2017), a similar assumption is imposed: firms' ignore their effect on the transition of the industry state moment.

As pointed out by Gowrisankaran, Park, and Rysman (2014), a simple regression of theaters' adoption on digital movie availability h_t and adoption cost p_t will run into several econometric issues. The effect of h_t is not identified without further restrictions (simultaneity problem in the system of equations determining the effect of software availability on hardware adoption, and hardware adoption on software availability). Additionally, due to the hierarchical structure of the data (a_{it} varies in the cross-section and times series, while (h_t, p_t) vary only in the time series) the effect of h_t and p_t are only estimated in the time series—a small sample problem. To sidestep these two issues, I instead include time dummies η_t in the regressors. The latter are estimated consistently (in the cross-section) and capture the combined effects of digital movie availability, adoption cost, and aggregate time shocks.[39]

The Hotz-Miller inversion gives a one-to-one mapping between the differences in choice-specific value functions and the CCP (equation (8)). Note that for $a \in \{0, .., S_i - s_{it}\}$,

$$P(a_{it} \leq a|\boldsymbol{\gamma}_{it}) = \int_{\Delta W(a+1|\boldsymbol{\gamma}_{it})-p_t}^{\infty} dF(\epsilon_{it}) = 1 - \Phi\left(\frac{\Delta W(a+1|\boldsymbol{\gamma}_{it}) - p_t}{\sigma}\right) \tag{15}$$

where $\epsilon_{it} \sim \mathcal{N}(0, \sigma^2)$ and Φ is the normal cumulative distribution. Differences in choice-specific value functions can be obtained by inverting equation (15):

$$\frac{\Delta W(a+1|\boldsymbol{\gamma}_{it}) - p_t}{\sigma} = \Phi^{-1}(1 - P(a_{it} \leq a|\boldsymbol{\gamma}_{it})) \tag{16}$$

If the firm idiosyncratic shock ϵ_{it} equals this (normalized) cut-off, firm i is indifferent between adopting a and $a+1$ digital screens, in state $\boldsymbol{\gamma}_{it}$. Using equation (16), I can construct estimates $\widehat{\Delta W}(a+1|\boldsymbol{\gamma}_{it})$ from knowledge of the CCP $\widehat{P}(a_{it} \leq a|\boldsymbol{\gamma}_{it})$.

Value functions. Given a candidate parameter vector and knowledge of the CCP, the expected value function solves a system of linear equations.[40] To see this, equation (9) can be rewritten:

[39] By following this approach, I can only predict adoption behavior *on-path*, i.e., for the equilibrium realization of the process $\{h_t, p_t\}_{t \geq 0}$. As noted in Bajari, Benkard, and Levin (2007), the inability to predict behavior in states not observed in the data may have important consequences on profit estimates relevant off-path. However, in my setting, no parameter of interest is determined off-path.

[40] This is noted by Aguirregabiria and Mira (2007) and Pesendorfer and Schmidt-Dengler (2008).

$$
\begin{aligned}
V(\boldsymbol{\gamma}_i) &= \sum_{a_i} P(a_i|\boldsymbol{\gamma}_i)\big(\pi(\mathbf{x}_i, h) - a_{it}(p + E[\epsilon_i|\boldsymbol{\gamma}_i, a_i]) + W(a_i|\boldsymbol{\gamma}_i)\big) \\
&= \sum_{a_i} P(a_i|\boldsymbol{\gamma}_i)\big(\pi(\mathbf{x}_i, h) - a_{it}(p + E[\epsilon_i|\boldsymbol{\gamma}_i, a_i])\big) + \beta \sum_{a_i, \boldsymbol{\gamma}'_i} P(a_i|\boldsymbol{\gamma}_i) P(\boldsymbol{\gamma}'_i|\boldsymbol{\gamma}_i, a_i) V(\boldsymbol{\gamma}'_i)
\end{aligned}
\tag{17}
$$

In matrix notation, the expected value function as a function of a candidate parameter $\boldsymbol{\alpha}$ can be written (omitting the subscript i):

$$
\begin{aligned}
\mathbf{V}(\boldsymbol{\alpha}) &= \sum_{a} \mathbf{P}(a)\big(\boldsymbol{\Pi}(\boldsymbol{\alpha}) - a_i(\mathbf{p} + \mathbf{e}(a))\big) + \beta \cdot \mathbf{F} \cdot \mathbf{V}(\boldsymbol{\alpha}) \\
&= (\mathbf{I} - \beta \cdot \mathbf{F})^{-1} \left\{ \sum_{a} \mathbf{P}(a)\big(\boldsymbol{\Pi}(\boldsymbol{\alpha}) - a_i(\mathbf{p} + \mathbf{e}(a))\big) \right\}
\end{aligned}
\tag{18}
$$

where $\mathbf{V}(\boldsymbol{\alpha})$ is the $L_i \times 1$ dimensional vector of ex-ante value functions, $\mathbf{I}$ is the $L_i \times L_i$ identity matrix, $\mathbf{F}$ is an $L_i \times L_i$ matrix with (k, l)-element equal to $P(\boldsymbol{\gamma}'_i = k|\boldsymbol{\gamma}_i = l)$, $\mathbf{P}(a)$ is an $L_i \times 1$ vector of CCP with k^{th}-element equal to $P(a_i = a|\boldsymbol{\gamma}_i = k)$, $\boldsymbol{\Pi}(\boldsymbol{\alpha})$ is an $L_i \times 1$ vector of single-period profits $\pi(\mathbf{x}_{it}, h_t)$, $\mathbf{p}$ is an $L_i \times 1$ block vector of adoption costs, and $\mathbf{e}(a)$ is an $L_i \times 1$ vector with k^{th}-element equal to $E[\epsilon_i|\boldsymbol{\gamma}_i = k, a]$.[41]

Let $\widetilde{\mathbf{V}}(\boldsymbol{\alpha})$ be the solution of this system of linear equations, for a given candidate parameter $\boldsymbol{\alpha}$ and estimated CCP $\widehat{P}(a_i|\boldsymbol{\gamma}_i)$. The choice-specific value functions $\widetilde{W}(a_i|\boldsymbol{\gamma}_i; \boldsymbol{\alpha})$, and corresponding predicted CCP $\widetilde{P}(a_i|\boldsymbol{\gamma}_i; \boldsymbol{\alpha})$ can be derived using equations (6) and (16).

Second-step estimation:

In the second step, the underlying parameters $\boldsymbol{\alpha}$ are set such that the predicted CCP $\widetilde{P}(a_i|\boldsymbol{\gamma}_i; \boldsymbol{\alpha})$ match the actual CCP $\widehat{P}(a_i|\boldsymbol{\gamma}_i)$ for every firm i and state $\boldsymbol{\gamma}_i$. Equivalently, one can match the differences in choice-specific value functions $\Delta\widetilde{W}(a_i|\boldsymbol{\gamma}_i; \boldsymbol{\alpha})$ and $\Delta\widehat{W}(a_i|\boldsymbol{\gamma}_i)$.[42] The objective function is

$$
Q(\boldsymbol{\alpha}) = ||\Delta\widetilde{W}(a_i|\boldsymbol{\gamma}_{it}; \boldsymbol{\alpha}) - \Delta\widehat{W}(a_i|\boldsymbol{\gamma}_{it})||_2 = \sqrt{\sum_{i, \boldsymbol{\gamma}_i, a_i} \Big(\Delta\widetilde{W}(a_i|\boldsymbol{\gamma}_{it}; \boldsymbol{\alpha}) - \Delta\widehat{W}(a_i|\boldsymbol{\gamma}_{it})\Big)^2}
$$

[41] The discount factor used is $\beta = 0.95$.

[42] 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 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.[43]

6.3 Estimation results

6.3.1 First-step estimates

Theaters' adoption-policy function. The conditional choice probabilities 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 $s_{it}/S_i \in \{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\}$, whereas multi- and megaplexes (theaters with 8 screens or more) are assumed to adopt on the space $s_{it}/S_i \in \{0, \frac{1}{8}, \frac{2}{8}, ..., \frac{7}{8}, 1\}$. Figure 4 shows kernel density estimates of the within-firm adoption rates for miniplexes (panel (a)) and multi/megaplexes (panel (b)), conditional on partial adoption ($s_{it}/S_i > 0$ and $s_{it}/S_i < 1$). For miniplexes, the density has three identifiable modes. The previous assumption restricting the strategy space to the set $\{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\}$ appears non-restrictive. For multi/megaplexes, the density shows a mode around 0.2. The grid chosen, $\{0, \frac{1}{8}, \frac{2}{8}, ..., \frac{7}{8}, 1\}$, is sufficiently fine given the estimated density of s_{it}/S_i.

Because theaters cannot divest and roll back the old technology, a firm cannot transition to lower states. For instance, a four-screen theater with $s_{it}/S_i = 3/4$ can only transition to $s_{it+1}/S_i \in \{3/4, 1\}$. 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 B).

A theater's share of screens converted to digital between t and $t+1$, denoted a_{it}/S_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

[43] (1) draw a bootstrap sample of firms (initial industry state), (2) *simulate* the diffusion process across all firms in the bootstrap sample using the (parametric) first-stage estimated CCP, and (3) estimate the model following the two-step procedure using the simulated data. Repeat the three steps N_b times.

of screens, a polynomial in time, and its interaction with the theater's art house status.[44] The polynomial in time captures the effect of digital movie availability, adoption cost, and aggregate time shocks, which all vary in the time series. The interaction of time and art house status captures any aggregate shocks that are specific to art house theaters (e.g., lags in *art house* digital movie availability). 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_i and all other variables.

Table 4 presents the estimates of the ordered probit model under the four specifications. As expected, across the four specifications, the time effects are increasing. This trend reflects decreasing adoption costs and increasing digital movie availability. Larger theaters are more likely to adopt, but the marginal effect is decreasing. Art house status affects the likelihood of adoption only through its interaction with time. This indicates that the main driver of differences in adoption behavior between art house and commercial theaters are differences in digital movie availability rather than inherent differences in the cost-reductions from digital. The share of a theater's screens already converted to digital is negatively related to further adoption.[45]

Competitors' total number of screens does not significantly impact a theater's likelihood of adoption. Moreover, I verify that strategic interactions between firms are not a major determinant of adoption: the likelihood-ratio test of specification (3) and (4) against a specification controlling for competitors' digital screens adoption fails to reject the null that the coefficient on competitors' adoptions is zero at the 5% confidence level. 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 B.2 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.

[44] Due to time gaps in the panel (see Appendix A), time dummies cannot be used.

[45] This finding is expected because, given a share of digital movies, theaters that are lagging in terms of adoption (low s_{it}/S_i) have a greater incentive to adopt.

6.3.2 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 (12), 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 the baseline profits $\pi_d(\boldsymbol{\tau}_i)$ 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. Note that, 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 costs of operating, and by definition $\pi_d(\boldsymbol{\tau}_i)$ are profits per digital screen relative to a film screen *keeping revenue constant* (i.e., gross of the decay).

The decay function is decreasing in the availability of digital movies (or equivalently in time because h_t is a deterministic function of time). As h_t converges to one, a theater's choice set of digital movies increases so profits per digital screen increase. Theater size doesn't significantly impact the decay. One would expect the decay to be larger for large theaters, fixing digital movie availability, because larger theaters need more digital movies. Finally, the interaction with art house status is positive, consistent with digital movie availability lagging for art house movies compared to commercial movies.

Profits per digital screen relative to film implied by the structural estimates have the correct order of magnitude. Figure 5 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 €$2,445$ and €$7,810$, with a mean of €$5,346$ and median of €$5,183$. 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 the magnitude of excess inertia in the transition from 35mm film to digital cinema. 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' equilibrium 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, a third of which is accounted for by externalities among downstream theaters. The last subsection analyzes distributors' costs of multi-homing and provide evidence that they benefit under the two counterfactual scenarios.

7.1 Planner's benchmark

By converting its screens to digital, a theater raises distributors' incentive to release movies in digital. This increased number and variety of digital movies is a positive externality on other theaters equipped with digital projectors.[46] Additionally, by increasing digital movie availability, non-adopters' option value from digital technology also increases. Such increased profits and option values are not internalized by the adopter, and 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

$$\max_{\{\mathbf{a}_t\}_{t\geq 0}} E\left[\sum_{i\in I}\sum_{t=0}^{\infty} \beta^t \Pi(\mathbf{x}_{it}, p_t, h_t, a_{it}, \epsilon_{it})\right] \quad \text{s.t.} \quad h_t = \Gamma(\mathbf{x}_t) \tag{19}$$

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 $\mathbf{x}_0$ is fixed to $s_{i0} = 0$ for all i.[47]

Problem (19) 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 assume that distributors' reaction function (equation (3)) is a function of the aggregate share of digital screen in the industry $\frac{s_t}{S}$ rather than the whole industry state vector $\mathbf{x}_t$. This assumption helps reduce the dimension of the state space. Figure 6 shows $h_t = \Gamma(\frac{s_t}{S})$ as fitted from the data. This relation gives the share of digital movies per period as a function of the share of digital screens in the industry.

[46] Without multi-homing, there would be a negative externality on non-adopters, as the fraction of movies released in 35mm film would decrease.

[47] Note that h_t and t were used inter-changeably in $\pi_d(\boldsymbol{\tau}_i)$, because in the estimation part, the process $\{h_t\}$ is a deterministic function of t. Denote it $f(t)$. In solving the planner's benchmark, I compute the time period corresponding to the counterfactual process $\{h_t\}$, using $f^{-1}(h_t)$.

Second, I note that the object of interest is the maximized value of the planner's objective function (discounted sum of industry profits) and 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 $\{\mathbf{a}_t = a_{1t}, ..., a_{It}\}_{t\geq 0}$. To do so, I generate a large number of random industry adoption paths and select the path that maximizes the objective function in problem (19). The simulated paths are generated by adding perturbations to the equilibrium cut-offs in each theater's CCP. For a given vector of perturbations $\{\xi_i\}_{i\in I}$, the simulated path is obtained using the following procedure.

1. Initialize the industry at $\mathbf{x}_0$ such that $s_{i0} = 0$ for all i.
2. Draw firm specific adoption shocks $\{\epsilon_{i0}\}_{i\in I}$ and corresponding adoption decisions dictated by each firm's perturbed CCP.
3. Calculate single-period industry profits $\sum_{i\in I} \Pi(\mathbf{x}_{i0}, p_0, h_0, a_{i0}, \epsilon_{i0})$
4. Update the current state $\{\boldsymbol{\gamma}_{i0}\}_{i\in I}$ according to the adoption decisions and transition of the exogeneous price process to next period state: $\{\boldsymbol{\gamma}_{i1}\}_{i\in I}$. In particular, $h_1 = \Gamma(\frac{s_1}{S})$.
5. Repeat steps 1-4 for T periods.

Given a vector of perturbations $\{\xi_i\}_{i\in I}$, the objective function is obtained by averaging L simulated paths. The paths have length $T = 40$ periods (or 20 years).[48] An estimate of the objective function is obtained as

$$\frac{1}{L}\sum_{l=1}^{L}\left\{\sum_{i\in I}\sum_{t=0}^{\infty}\beta^t \Pi^l(\mathbf{x}_{it}, p_t, h_t, a_{it}, \epsilon_{it})\right\} \tag{20}$$

where $\Pi^l(\mathbf{x}_{it}, p_t, h_t, a_{it}, \epsilon_{it})$ is the single-period profit of firm i in simulation l at period t, when the firm follows the adoption strategy obtained by adding the perturbation ξ_i to its equilibrium CCP. In practice, I draw $K = 15,000$ perturbation vectors and compute the objective function for each vector $\{\xi_i\}_{i\in I}$. I select the perturbation vector that yields the highest value of the estimated objective function (20). Let $\{\mathbf{a}_t^P\}_{t\geq 0}$ be the planner's policy rule corresponding to the optimal perturbation vector.

[48] In the equilibrium market outcome, firms have an incentive to free-ride on other firms' adoption, so the speed of digital conversion is slower than what the profit-maximizing industry planner would choose. Therefore, if $T = \inf\{t \geq 0 : s_{it} = S_i, \forall i \in I\}$ is the first period by which the industry has fully switched to digital in the non-cooperative market equilibrium, then the planner will have switched the industry to digital by T. In practice, $T = 20$.

Figure 7a shows an example of simulated industry adoption paths. Each simulated path corresponds to a perturbation vector $\{\xi_i\}_{i\in I}$.[49] Figure 7b plots the effect of 500 additional perturbation draws on the maximum value of the estimated objective function (expression (20)) as a function of the total number of perturbation draws. Beyond $10,000$ perturbation draws, the incremental improvement in the maximized objective function is less than $2,000$ € (i.e. less than 0.002% of aggregate industry profits).

As a robustness check, the social planner's dynamic problem (19) is explicitly solved after reducing the dimension of the state and strategy spaces. The results are presented in Appendix C. The optimum policy rule obtained yields an industry diffusion path that is consistent with $\{\mathbf{a}_t^P\}_{t\geq 0}$.

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 maximize aggregate theater profits. In other words, $h_t = 1, \forall t$. I assume that 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

$$\max_{\{\mathbf{a}_t\}_{t\geq 0}} E\left[\sum_{i\in I}\sum_{t=0}^{\infty}\beta^t \Pi(\mathbf{x}_{it}, p_t, h_t = 1, a_{it}, \epsilon_{it})\right] \tag{21}$$

where the expectation is taken with respect to the sequence of theaters' idiosyncratic shocks. The initial industry state $\mathbf{x}_0$ is fixed to $s_{i0} = 0$ 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 $h_t = 1, \forall t$.

Each single-agent decision problem is an optimal stopping problem. Indeed, when multi-homing is manded for all movies-periods, 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 $\{p_t\}_{t\geq 0}$ and exogeneous theater characteristics are the factors driving the diffusion process.

Let $\{\mathbf{a}_t^C\}_{t\geq 0}$ be the solution of problem (21).

[49] And one particular sequence of theaters' idiosyncratic shocks. More precisely, for each firm i, I transform the equilibrium cut-offs κ in firms CCP (estimated by ordered probit) into $\kappa + \xi_i$ where ξ_i is drawn from $\mathcal{N}(X, Y)$ where $X \sim \mathcal{N}(-1.5, 2)$ and $Y \sim \mathcal{U}[0.5, 2]$.

7.3 Counterfactual Results

Figure 8a and 8b show the diffusion paths under the non-cooperative market outcome and the two benchmarks for digital screens (left) and digital movies (right).[50] As expected, the diffusion of digital is faster under the two counterfactual scenarios: by 1 to 3.5 years for the time to 10% adoption, and 0.5 to 2.5 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. Let $\{\mathbf{a}_t^M\}_{t\geq 0}$ be the vector of adoption decisions in the non-cooperative market outcome. For given sequences of adoption decisions $\{\mathbf{a}_t\}_{t\geq 0}$ and digital movie availability $\{h_t\}_{t\geq 0}$, define the aggregate theater surplus (net of adoption costs) as

$$TS(\{\mathbf{a}_t\}_{t\geq 0}, \{h_t\}_{t\geq 0}) = E\left[\sum_{i\in I}\sum_{t=0}^{\infty}\beta^t \Pi(\mathbf{x}_{it}, p_t, h_t, a_{it}, \epsilon_{it})\right] \quad \text{where} \quad \mathbf{x}_{it} = (\boldsymbol{\tau}_i, \sum_{t\geq 0} a_{it}) \quad (22)$$

Denote aggregate theater surplus under the non-cooperative market outcome, planner's benchmark, and coordination benchmark by TS^M, TS^P, and TS^C, given adoption decisions $\{\mathbf{a}_t^M\}_{t\geq 0}$, $\{\mathbf{a}_t^P\}_{t\geq 0}$, and $\{\mathbf{a}_t^C\}_{t\geq 0}$ and corresponding sequences of digital movies availability $\{h_t\}_{t\geq 0}$.

Table 6 shows industry profits under the three scenarios. Recall that 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, denoted (TS^M, TS^P, TS^C) (are 86.11 million euros under the market outcome, 92.03 million euros under the planner's benchmark, and 106.21 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.[51] Overall, excess inertia causes theaters' surplus to be 19% lower than under full coordination. Adoption externalities across downstream firms explain 29% of this surplus loss.

[50] In all three scenarios, I compute the average over the sequence of firm idiosyncratic adoption shocks.

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

7.4 Distributors' surplus

The previous section focuses on theaters' surplus. Does distributors' surplus increase under the two benchmarks? A priori, it is not clear: multi-homing is more prevalent and may be costlier than 35mm film. This section argues that, given estimates of average distribution costs under film and digital, distributors also benefit under the two benchmarks.

To make the exposition clear, note that conversion to digital distribution affects only printing, shipping and storage costs of movie copies (PSS). Other costs incurred by distributors (e.g., advertising space purchase, advertising content creation, promotional events) remain constant.

Multi-homing may be costlier than film distribution because of economies of scale in PSS. When multi-homing, distributors split their production over two cost functions (film and digital), and in doing so, lose some of the scale economies. Denote by $C_f(Q)$ (resp. $C_d(Q)$) the total PSS costs of Q film copies (resp. Q digital copies); and $AC_f(Q)$ (resp. $AC_d(Q)$) the corresponding decreasing average cost curves. Digital distribution is more efficient so $C_d(Q) < C_f(Q)$. For a distributor releasing Q copies of a movie, multi-homing (with a fraction κ of digital copies and $(1-\kappa)$ of film copies) is costlier than film distribution if

$$C_f(Q) \leq C_d(\kappa Q) + C_f((1-\kappa)Q)$$

or equivalently

$$AC_f(Q) \leq \kappa AC_d(\kappa Q) + (1-\kappa)AC_f((1-\kappa)Q)$$

Whether the previous inequalities hold depends on the value of κ and the degrees of scale economies in film and digital.

To compare distributors' costs under the market outcome and benchmarks, I collect data on average PSS costs per copy for film and digital, from the CNC. The CNC publishes a yearly report on the French movie distribution industry.[52] The reports contain a breakdown of total (industry-level) distribution costs into PSS costs, advertising space purchase, advertising content creation, and promotional costs. In particular, this information is available by number of copies (categorical variable). Table 7 shows average costs per copy for film and digital by total number of copies. The data confirms that digital distribution is about 80% less costly than film distribution and that the average cost per copy is decreasing in the number of copies. Shortcomings of the data are that it covers only French distributors, and for the "100-200 copies" category, costs per copy on film seem to increase.

[52]The 2017 report, for instance, can be accessed at: `https://www.cnc.fr/cinema/etudes-et-rapports/etudes-prospectives/les-couts-de-distribution-des-films-dinitiative-francaise-en-2017_959089`.

I use the data in Table 7 to compute the discounted sum of distribution costs for a distributor releasing one movie per period on Q copies

$$C(Q) = Q \times \sum_{t=0}^{\infty} \beta^t \left\{ h_t \left(\frac{s_t}{S} AC_d(\frac{s_t}{S}Q) + (1 - \frac{s_t}{S})AC_f((1 - \frac{s_t}{S})Q) \right) + (1 - h_t)AC_f(Q) \right\}$$

under the market outcome, planner's benchmark, and coordination benchmark. When multi-homing, I assume that $\kappa = \frac{s_t}{S}$.

Figure 9 plots the average total cost $C(Q)/Q$ for various values of Q. The results indicate that distribution costs are lower under the two benchmarks compared to the market outcome for a typical range of Q: the cost-reduction from digital more than compensate for the loss in scale due to multi-homing.

8 Conclusion

This paper studies the dynamic trade-off faced by a standardized industry. An industry with network effects benefits from coordinating on a single technology, the "standard," to exploit network benefits. However, once bound together by the benefits of the standard, firms may become reluctant to switch to new and better technologies as they become available. As an application, the paper focuses on the French movie industry's conversion from the 35mm film standard to digital between 2005 and 2013.

I construct a dynamic game of digital hardware adoption by theaters and digital movie supply by distributors. Using data on theaters' adoption decisions and the rich cross-sectional variation in theater and market characteristics, I estimate theaters' payoff from converting their screens to digital. The estimated model is used to quantify the magnitude of excess inertia in the transition to digital. I simulate two counterfactuals: in the first, a planner maximizes aggregate theater profits taking as given upstream distributors reaction function; in the second, the planner mandates coordination on digital distribution upstream and maximizes aggregate 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 non-cooperative market outcome relative to under coordination. Additionally, two-thirds 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.

The results suggest that policy intervention in network industries can be beneficial, in particular, to coordinate firms' adoption of new technologies. Moreover, the most effective instrument (between adoption subsidies or standard-setting committees) depends on the source of inefficiency and the side of the market that exhibits excess inertia. In the case of digital cinema, the analysis indicates that inertia lies mainly in the upstream distribution market.

The current study can be extended in several directions; an important one is noted. The assumption that the digital manufacturing sector is competitive ("non-sponsored" technology) could be relaxed. A monopoly or oligopoly in digital manufacturing may help align the market outcome with the optimal diffusion path. For example, penetration pricing internalizes network effects across periods (between early and late adopters), and contingent contracts can be used to solve the coordination problem. However, due to market power, the overall effect on theaters and distributors' surplus is ambiguous.[53]

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).

Aguiar, L. and J. Waldfogel (2018). "Quality Predictability and the Welfare Benefits from New Products: Evidence from the Digitization of Recorded Music". *Journal of Political Economy* 126.2, pp. 492–524 (cit. on p. 8).

Aguirregabiria, V. and P. Mira (2007). "Sequential Estimation of Dynamic Discrete Games". *Econometrica* 75.1, pp. 1–53 (cit. on pp. 3, 22, 23).

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 pp. 22, 23).

Bajari, P., V. Chernozhukov, et al. (2015). "Identification and Efficient Semiparametric Estimation of a Dynamic Discrete Game" (cit. on p. 20).

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).

[53] In the case of the Yellow Pages market, Rysman (2004) finds that a more competitive industry is preferable from a welfare standpoint.

Chou, C.-f. and O. Shy (1990). "Network Effect without Network Externalities". *International Journal of Industrial Organization* 8.2, p. 259 (cit. on p. 4).
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. 4).
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 pp. 5, 8).
— (2006b). "Spatial competition in retail markets: Movie Theaters". *Rand Journal of Economics* 37.4, pp. 964–982 (cit. on p. 5).
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).
Farrell, J. and P. Klemperer (2007). "Chapter 31 Coordination and Lock-In: Competition with Switching Costs and Network Effects". *Handbook of Industrial Organization* 3.06, pp. 1967–2072. arXiv: `arXiv:1011.1669v3` (cit. on p. 4).
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).
Fuentelsaz, I., J. Gomez, and Y. Polo (2003). "Intrafirm Diffusion of Technologies: An Empirical Application". *Research Policy* 32, pp. 533–551 (cit. on p. 5).
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. (2008). "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, 23).

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, et al. (1994). "A Simulation Estimator for Dynamic Models of Discrete Choice". *The Review of Economic Studies* 61.2, pp. 265–289 (cit. on p. 22).

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. 3, 22).

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. 22).

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).

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).

Levin, S. G., S. L. Levin, and J. B. Meisel (1992). "Market Structure , Uncertainty , and Intrafirm Diffusion : The Case of Optical Scanners in Grocery Stores". *The Review of Economics and Statistics* 74.2, pp. 345–350 (cit. on p. 5).

Macher, J., N. H. Miller, and M. Osborne (2017). "Finding Mr. Schumpeter: An Empirical Study of Competition and Technology Adoption" (cit. on p. 5).

Magnac, T. and D. Thesmar (2002). "Identifying Dynamic Discrete Decision Processes". *Econometrica* 70.2, pp. 801–816 (cit. on p. 20).

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).

Nabseth, L. and G. F. Ray (1974). “The Diffusion of new industrial processes: an international study.” *Cambridge: University Press* (cit. on p. 5).

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. 4).

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. 22).

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. 3, 22, 23).

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).

Romeo, A. A. (1975). “Interindustry and Interfirm Differences in the Rate of Diffusion of an Innovation”. *The Review of Economics and Statistics* 57.3, pp. 311–319 (cit. on p. 5).

Rust, J. (1994). “Structural Estimation Decision Processes”. *Chapter 51* 1, pp. 3139–3139 (cit. on p. 20).

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 pp. 4, 34).

— (2019). “The reflection problem in network effect estimation”. *Journal of Economics & Management Strategy* 28.1, pp. 153–158. eprint: `https://onlinelibrary.wiley.com/doi/pdf/10.1111/jems.12301` (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).

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. eprint: `https://doi.org/10.1287/mnsc.1080.0897` (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).

Yang, J., E. Anderson, and B. R. Gordon (2019). “Digitization and Distribution: The Ends Against the Middle”. *SSRN Electronic Journal* (cit. on p. 5).

Tables

Table 1: List of variables

Type	Variable	Description
Movie theater	digital screens: s_{it}	number of screens converted to digital by time t
	screens : S_i	total number of screens
	seats	average number of seats per screen
	art house	equals 1 if art house theater
	chain	identifier of movie theater chain
	competitors screens	number of rivals' screens in local market
Market demand	region	identifier for the 22 administrative regions
	market size	identifier for: Paris, Paris inner suburbs ("petite couronne") Paris outer suburbs ("grande couronne"), urban unit with more than 100 thousands inhabitants, urban unit with 20 to 100 thousands inhabitants, urban unit with less than 20 thousands inhabitants and rural
Digital projector	adoption cost: p_t	list prices for 2K digital projectors (including VPF subsidies and ancillary costs) in 2010 euros
Movie distribution	digital movies h_t	share of movies released in digital format

Note: The first three categories in market size (Paris and suburbs) are colinear with the regional dummy for "Ile-de-France", the latter is therefore excluded.

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

Variable	Minimum	Mean	Maximum	Std. Deviation
Theater characteristics				
Screens	4	8.118	23	3.736
Seats	112	1,538	7,408	961
Art House	0	0.336	1	0.473
# Competitors (theaters)	0	3.118	14	3.414
Theater size (indicators)				
Miniplexe (4-7 screens)	0	0.534	1	0.499
Multi/Megaplexe (8 screens or more)	0	0.466	1	0.499
Theater chains (indicators)				
UGC	0	0.083	1	0.276
Gaumont-Pathé	0	0.168	1	0.374
CGR	0	0.103	1	0.304
Per screen cost of digital conversion (in 2010 euros)	56,176	68,366	84,000	8,800

Table 3: Summary statistics by market size (theaters with at least 4 screens)

	Theaters	Markets	Theater size (mean)	Art house (share)	Screens per market (mean)	Screens per market (sd)
Urban unit - >100k inhab	174	101	9.167	0.213	15.792	8.431
Urban unit - 20 to 100k inhab	126	116	7.024	0.563	7.629	2.986
Urban unit - <20k inhab and rural	17	17	6.647	0.647	6.647	3.552
Paris	37	15	7.189	0.135	17.733	9.565
Paris - inner suburbs	18	18	9.222	0.278	9.222	4.977
Paris - outer suburbs	27	26	7.926	0.185	8.231	4.320
National	399	293	8.117	0.337	11.055	7.262

Table 4: 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 × Art house	-0.211	0.147	-0.217	0.147	-0.291	0.147	0.129	0.009
Time squared × 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	-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	0.087
UGC					-0.914	0.133	-0.007	0.046
Interactions: own screens × other variables							X	
Observations	4,788		4,788		4,788		4,788	
- log Likelihood	2,186		2,182		2,144		2,276	
AIC	4,390		4,393		4,322		4,613	

Note: 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."

Table 5: Structural parameter estimates (in 2010 €)

	Estimate	s.e
Profit per digital screen: $\pi_d(\boldsymbol{\tau}_i)$		
Constant	$3,763.63$	745.03
Own screens	136.19	59.04
Art house	$2,124.22$	$1,321.19$
Competitors' screens	-2.02	5.16
Market dummies		
Paris - outer suburbs	-265.24	299.23
Urban unit - 20k-100k inhabitants	-239.39	274.75
Urban unit - >100k inhabitants	-223.95	285.20
Paris - inner suburbs	-414.96	341.85
Paris	234.80	339.67
Chain dummies		
Gaumont-Pathe	-215.02	151.96
CGR	698.24	211.96
UGC	$-1,598.39$	422.78
Decay function:		
Constant	$8,321.21$	$2,322.58$
Own screens	-53.30	85.73
Time	-590.94	244.08
Time x Own screens	12.86	8.57
Time x Art house	239.84	126.99

Note: Standard errors are calculated using $N_b = 600$ *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* $10,000$ *€.*

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

	Market outcome	Planner benchmark	Coordination benchmark
Gross Industry Profits	177.41	219.95	235.66
Adoption costs	91.29	127.92	129.43
Net Industry Profits	86.11	92.03	106.23
Change in Net Profits	0	5.92	20.12
Change in Net Profits (in %)	0	6.90	23.40

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

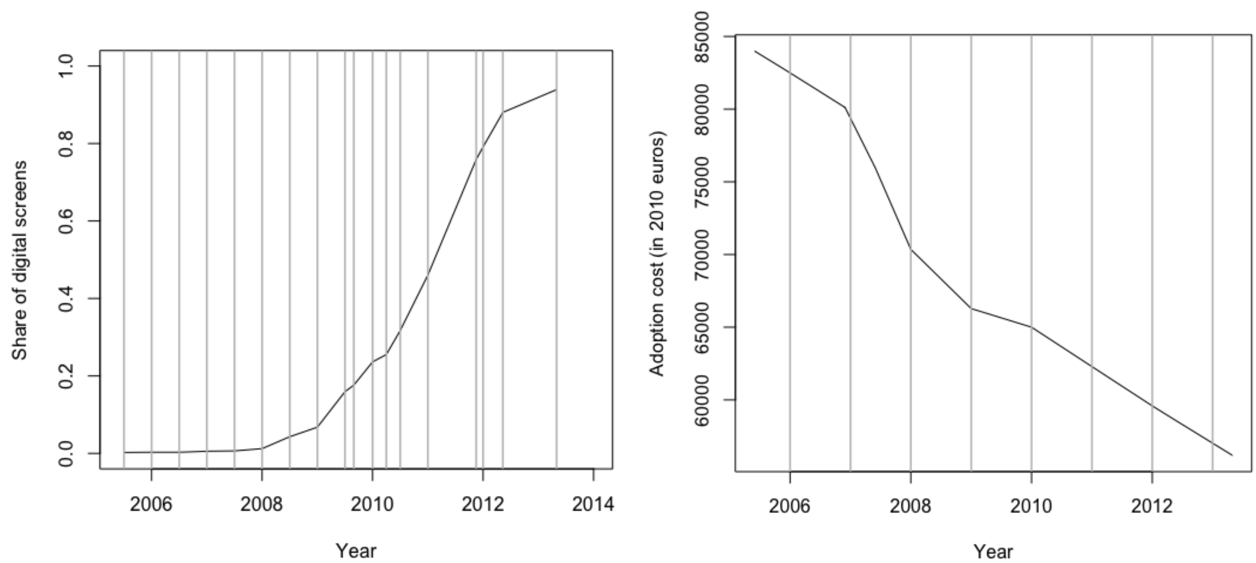
Table 7: Average printing, shipping, storage cost per copy, by total number of copies (in thousands, 2010 €)

	Film		Digital	
Copies	LB	UB	LB	UB
<10 copies	1.14	2.28	0.50	1.00
10-50 copies	0.88	2.19	0.13	0.64
50-100 copies	0.79	1.58	0.13	0.26
100-200 copies	1.01	2.02	0.12	0.23
200-400 copies	0.59	1.17	0.09	0.18
>400 copies	0.57	1.13	0.08	0.15

Note: Estimate for French distributors. Inputed from aggregate PSS costs divided by # of movies per category. For Film, use costs from 2007/2008*; for digital use costs from* 2015 *to* 2017*.*

Figures

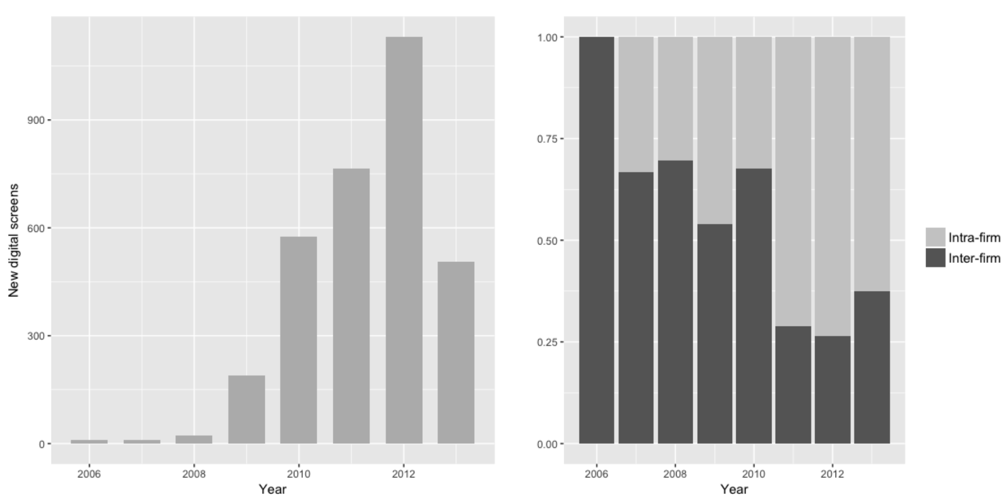
Figure 1: Data and descriptive statistics



(a) Observation times for the diffusion of digital projectors

(b) Hardware adoption cost (2010 €)

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) excluded.*

Figure 3: Parameterization of single-period profits

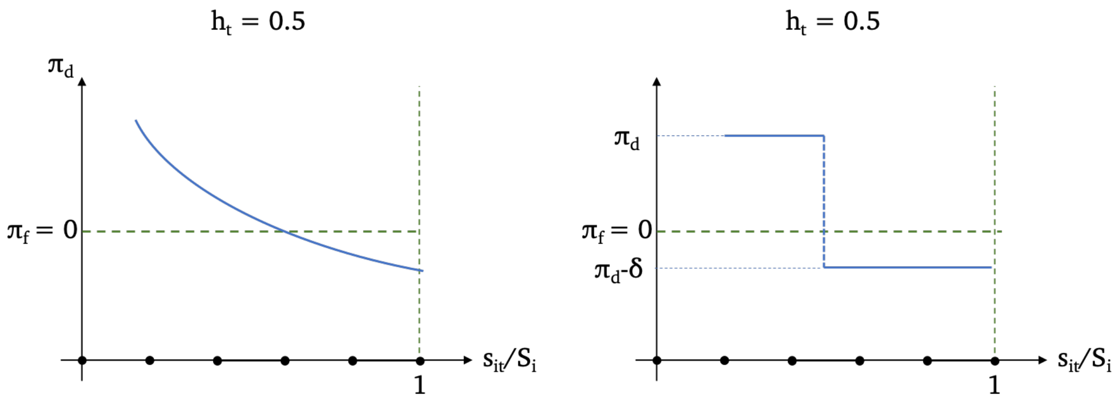
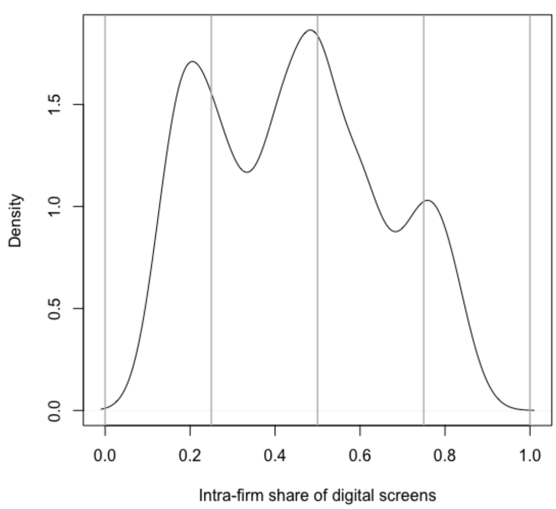
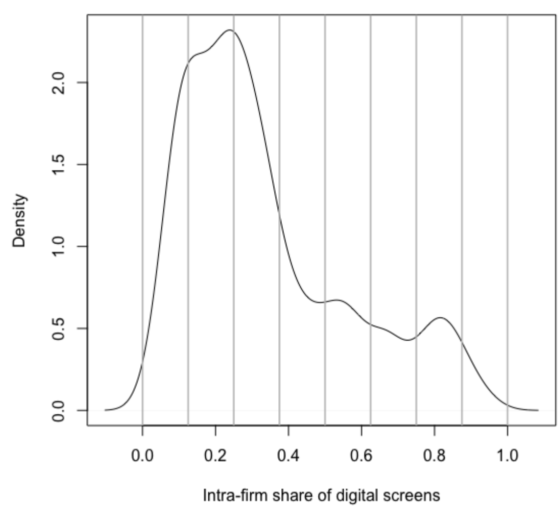


Figure 4: Density estimate of the intra-firm rate of adoption by firm size



(a) Miniplexes (4-7 screens)



(b) Multi/Megaplexes (8 screens or more)

Notes: Both density estimates correspond to the distribution of s_{it}/S_i *conditional on* $s_{it}/S_i > 0$ *and* $s_{it}/S_i < 1$

Figure 5: Histogram of $\pi_d(\boldsymbol{\tau}_i)$ (in 2010 €)

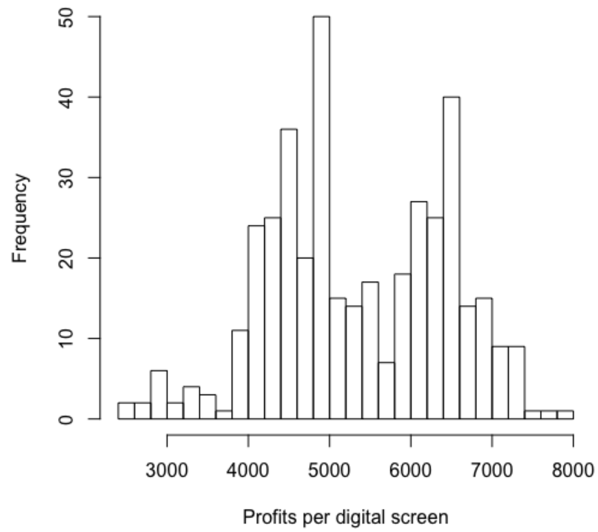


Figure 6: Share of movies available in digital h_t as a function of share of digital screens s_t/S

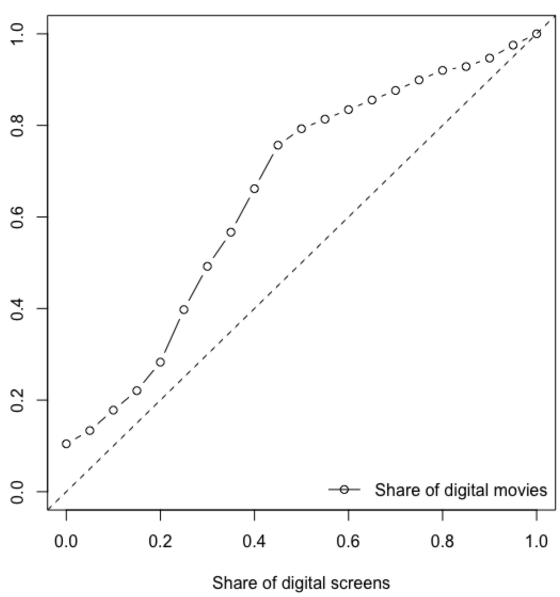
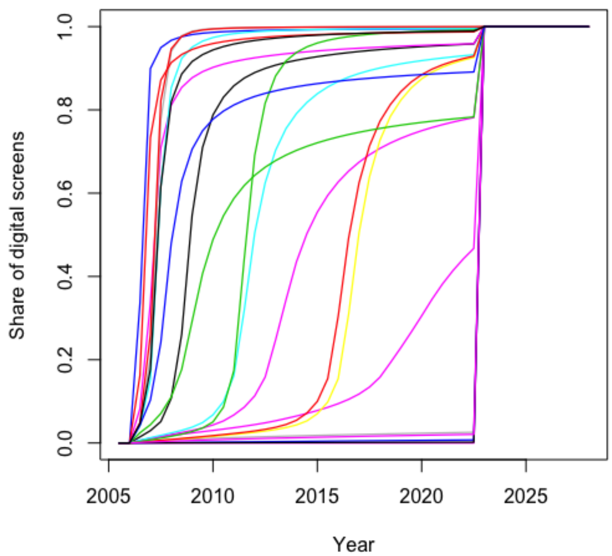
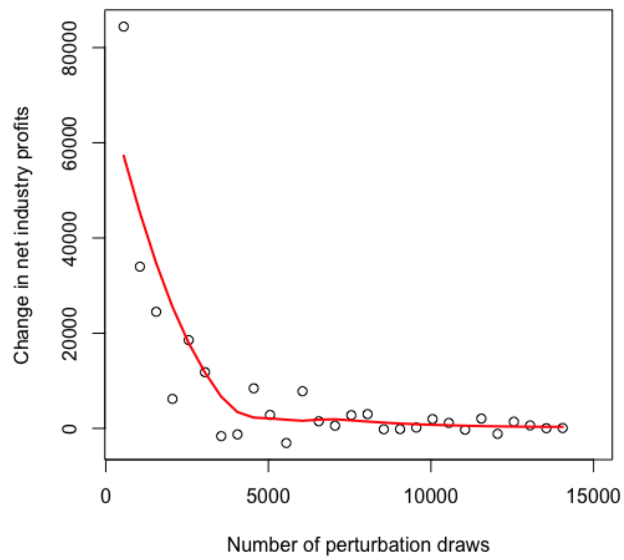


Figure 7: Planner's benchmark

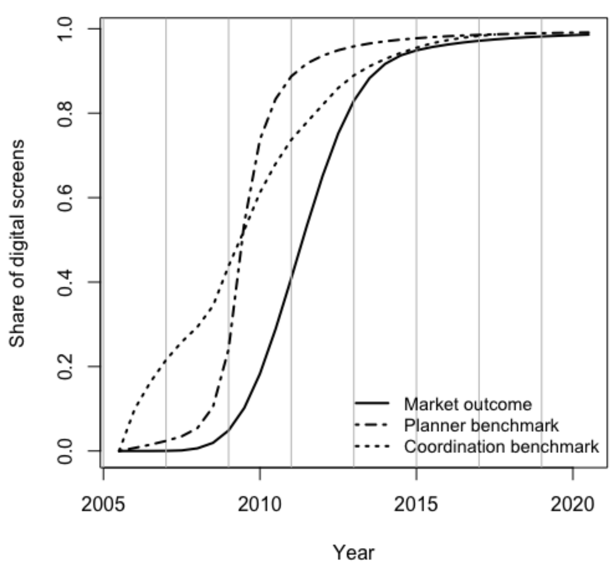


(a) Simulated industry paths (20 perturbation draws)

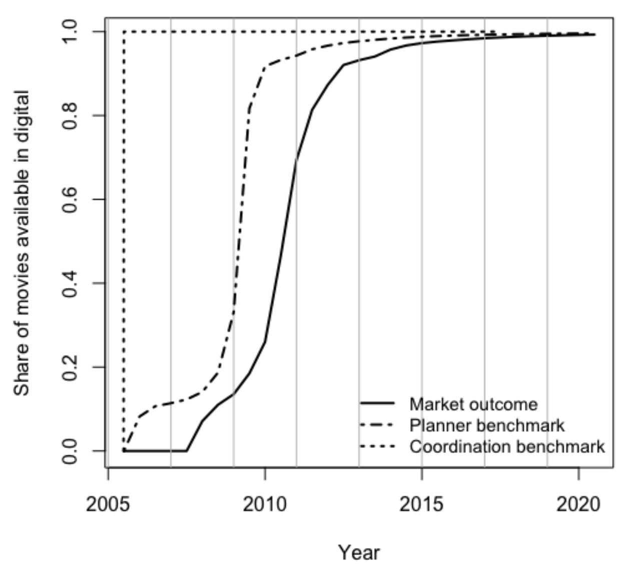


(b) Effect of 500 additional perturbation draws on maximized industry profits

Figure 8: Diffusion paths under the three scenarios

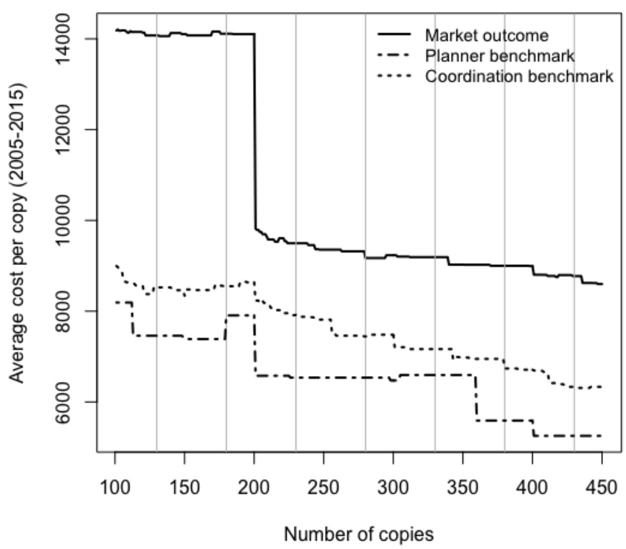


(a) Digital screens



(b) Digital movies

Figure 9: Average cost per copy by number of copies



Note: Film LB and Digital UB used.

A Data

Table 8 presents the observation dates for the panel of digital projector adoption by data sources. The table also shows the periodic subsample selected. The periods selected are such that there is a previous observation period 6 months earlier (in some exeption it is 5 or 7 months). For instance, "May 2012" is selected because the industry is observed on November 2011. The observation periods selected are represented in blue in Figure 10.

Table 8: Observation times by data source

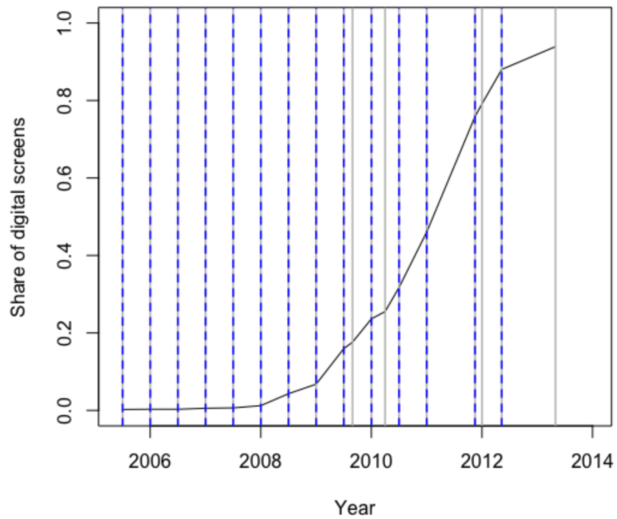
Date	Source	Periodic sample
July 2005	Media Salles	X
January 2006	Media Salles	X
July 2006	Media Salles	X
January 2007	Media Salles	X
July 2007	Media Salles	X
January 2008	Media Salles	X
July 2008	Media Salles	X
January 2009	Media Salles	X
July 2009	Media Salles	X
September 2009	Cinego	
Jarnuary 2010	Media Salles	X
April 2010	Cinego	
July 2010	Media Salles	X
January 2011	Media Salles	X
November 2011	Cinego	
January 2012	Media Salles	
May 2012	Cinego	X
June 2013	Cinego	

B Estimation

B.1 First-step: adoption policy rule

First step estimates for the adoption policy rule are obtained by estimating an ordered probit model. Denote by P_{ij} the probability that theater i transitions to state j. Possible states are $\{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\}$ in the case of miniplexes ($4-7$ screens), and $\{0, \frac{1}{8}, \frac{2}{8}, ..., \frac{7}{8}, 1\}$ in the case of multi/megaplexes (8 screens or more). In constructing the likelihood, one has to account for the fact that theaters cannnot divest the new technology, and therefore cannot transition

Figure 10: Share of digitally equipped screens and observation times



to lower states: the dependent variable s_{it}/S_i satisfies $s_{it} \geq s_{i(t-1)}$. The log likelihood is constructed as follows:

$$lnL = \sum_{i:4 \leq S_i < 8} \sum_{j=s_{i(t-1)}/S_i}^{1} d_{ij} lnP_{ij} + \sum_{i:8 \leq S_i} \sum_{j=s_{i(t-1)}/S_i}^{1} d_{ij} lnP_{ij} \tag{23}$$

where d_{ij} is an indicator for firm i transitioning to state j.

B.2 First step: goodness of fit

To check the goodness of fit of the first-step adoption policy, model predictions for the share of digital screens are compared to actual shares in the data. Tables 9, 10, and 11 present the comparison for all firms, miniplexes only, and multi/megaplexes, respectively. In each table, the aggregate share of digital screens, the share of adopters (theaters with at least one digital screen), and the average within-theater share of digital screens (among adopters) are shown from 2006 to 2013. Overall, given the limitations imposed by the parametric specification of the policy function, the model captures the main trends in the aggregate, inter-firm, and intra-firm diffusion rates, for all firms and by firm size (miniplexes vs. multi/megaplexes). Note that the aggregate share of digital screens was constantly lower for miniplexes than for multi/megaplexes, as reflected in the predictions as well. Additionally, the intra-firm rates' evolution over time is smoother in the prediction than in the data.[54]

Table 9: Predictions using the adoption policy function - All firms

	Aggregate		Inter-firm		Intra-firm	
Year	Data	Prediction	Data	Prediction	Data	Prediction
2006	0.003	0.000	0.021	0.001	0.127	0.161
2007	0.006	0.001	0.028	0.005	0.210	0.215
2008	0.043	0.010	0.056	0.028	0.182	0.256
2009	0.159	0.093	0.122	0.197	0.420	0.359
2010	0.236	0.270	0.431	0.498	0.459	0.470
2011	0.460	0.483	0.684	0.724	0.583	0.596
2012	0.791	0.709	0.841	0.878	0.880	0.761
2013	0.939	0.922	0.934	0.931	0.985	0.934

Note: The column labelled "Aggregate" corresponds to the share of digital screens across all firms in the industry. The column labelled "Inter-firm" corresponds to the share of theaters with at least one digital screen. The column labelled "Intra-firm" corresponds to the within-theater average share of digital screens among theaters with at least one digital screen. The predicted rates are obtained by averaging 500 *simulation paths.*

C Computation: full-solution approach for the planner's benchmark

This section presents the full-solution approach to the planner's problem (19). The planner's benchmark is solved by backward induction starting from T. To address the high-dimensionality problem, I maintain the moment assumption $h_t = \Gamma(\frac{s_t}{S})$ as in section 7.1. Additionally, the planner's adoption strategy space is coarsened by assuming group-symmetric strategies: I assign theaters to N groups based on profits $\pi_d(\boldsymbol{\tau}_i)$ and the planner chooses the same adoption decision (same adoption rate) for theaters within the same group.

These assumptions reduce the dimensionality of the state space tracked by the planner (excluding theaters' idiosyncratic shocks). However, within-group adoption strategies may in general still be a function of the realization of the vector of idiosyncratic shocks, a high-dimensional vector. I deal with this issue by noting that adoption decisions depend only on

[54] In particular, for miniplexes, the intra-firm rate jumps to 41% as early as 2007, whereas the model predicts a slow increase between 2006 and 2009 to reach 40%. The prediction is also smoother in the case of multi/megaplexes, with an increase in the actual intra-firm rates from 13.5% in 2008 to 41.5% in 2009, whereas the model predicts a smoother transition.

Table 10: Predictions using the adoption policy function - Miniplexes (4-7 screens)

	Aggregate		Inter-firm		Intra-firm	
Year	Data	Prediction	Data	Prediction	Data	Prediction
2006	0.002	0.000	0.008	0.000	0.267	0.229
2007	0.007	0.000	0.017	0.002	0.415	0.293
2008	0.007	0.003	0.017	0.007	0.415	0.338
2009	0.024	0.042	0.054	0.093	0.435	0.400
2010	0.112	0.165	0.243	0.317	0.443	0.463
2011	0.294	0.348	0.498	0.584	0.569	0.549
2012	0.653	0.597	0.745	0.798	0.857	0.702
2013	0.879	0.872	0.891	0.885	0.975	0.906

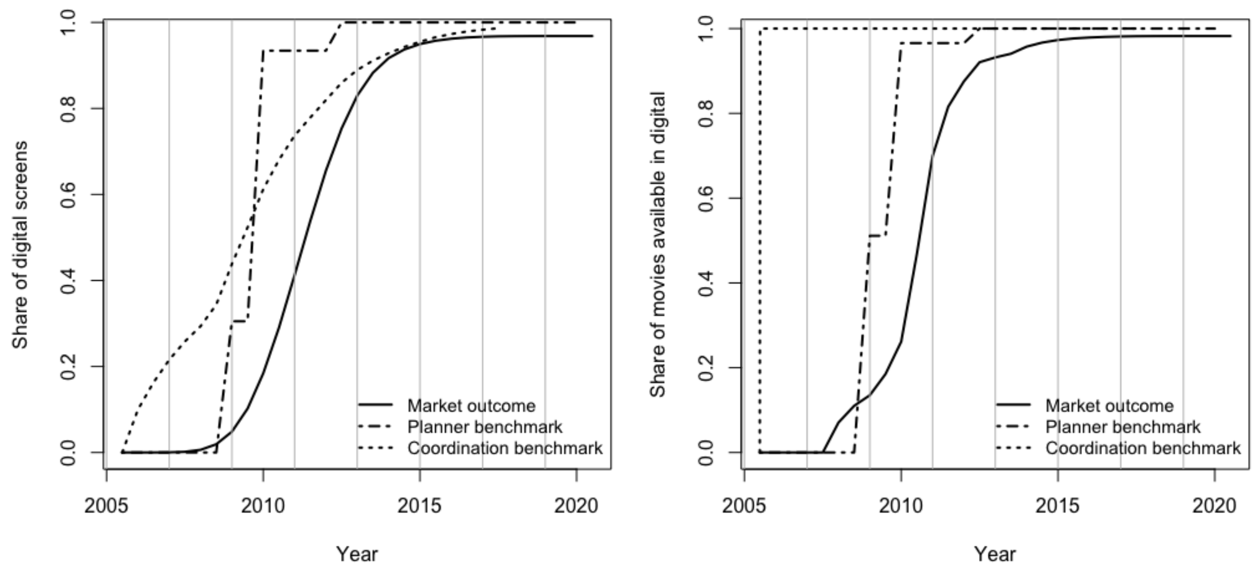
Note: The columns are defined in the same way as in Table 9, but the reference group is miniplexes instead of all firms. The predicted rates are obtained by averaging 500 *simulation paths.*

Table 11: Predictions using the adoption policy function - Multi/Megaplexes (8-23 screens)

	Aggregate		Inter-firm		Intra-firm	
Year	Data	Prediction	Data	Prediction	Data	Prediction
2006	0.003	0.000	0.037	0.001	0.087	0.156
2007	0.005	0.002	0.043	0.010	0.107	0.206
2008	0.015	0.013	0.106	0.056	0.135	0.240
2009	0.092	0.113	0.207	0.332	0.415	0.344
2010	0.307	0.320	0.670	0.707	0.466	0.475
2011	0.554	0.554	0.920	0.914	0.593	0.637
2012	0.870	0.775	0.963	0.978	0.903	0.825
2013	0.973	0.950	0.989	0.987	0.997	0.966

Note: The columns are defined in the same way as in Table 9, but the reference group is multi/megaplexes instead of all firms. The predicted rates are obtained by averaging 500 *simulation paths.*

Figure 11: Diffusion paths under the three scenarios (full-solution approach)



(a) Digital screens

(b) Digital movies

the *average adoption cost* across theaters within a group, i.e. (for N_k theaters in group k):

$$p_t + \frac{1}{N_k} \sum_{i \in I} \epsilon_{it}$$

Appealing to the law of large numbers, the second term is close to zero. By this argument, I can approximate the planner's problem as a non-stochastic problem.[55]

The solution of problem (19) is found by varying N from 1 to 10 groups (5 for miniplexes and 5 for multiplexes). Figures 11a and 11b show the results for $N = 10$. The optimal diffusion path under the planner's benchmark is relatively close to the optimal path found by simulation (Figure 8a).

[55]More precisely, it is a weighted average $\frac{\sum a_{it}\epsilon_{it}}{\sum a_{it}}$, since the number of screens converted differ across theaters of different sizes.