Intra-Firm Technology Adoption under Network Effects: Evidence from the Movie Industry

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Abstract

This paper investigates the role of network effects in explaining the *within*-firm rate of technology adoption. I study the conversion of movie distribution and exhibition from 35mm film to digital technology. These industries constitute a hardware-software system with indirect network effects. I specify and estimate a dynamic oligopoly game of digital hardware adoption by movie theaters and digital movies (software) supply by movie distributors. Crucially, theaters' technology-adoption decisions are made at the screen level so diffusion occurs both within and across firms. Counterfactual simulations establish that: (1) at the industry level, diffusion occurs mainly within rather than across firms; (2) differences in technology adoption across firms, which are commonly attributed to scale economies and strategic incentives, are in part due to larger firms' ability to initially adopt the technology at a smaller scale. Therefore, explicitly accounting for intra-firm adoption dynamics is important to better explain aggregate diffusion and firm heterogeneity in technology adoption.

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1 Introduction

Innovations contribute to economic growth only insofar as they are broadly adopted by firms. Understanding the factors affecting firms' adoption decisions is therefore essential to devise effective policies encouraging the spread of new technologies. One such factor are network effects, which have been the object of an extensive empirical literature. This literature focuses mainly on the inter-firm adoption margin by assuming firms make 0–1 adoption decisions or by studying firms' first adoption. By contrast, this paper investigates how network effects drive the intra-firm margin of technology adoption, that is, the rate at which a new technology replaces the old technology *within* a given firm. The objective is to evaluate how the latter margin contributes to industry-wide diffusion and shapes the relationship between market structure and technology adoption.

The importance of analyzing this margin appears at two separate levels. First, if intra-firm diffusion constitutes the main driver of industry diffusion, policy aiming at accelerating adoption should explicitly target inefficiently slow diffusion within firms. Second, differences in adoption across firms that are attributed to scale economies and strategic interactions may, in fact, be better explained when accounting for intra-firm adoption dynamics: In an environment with network effects, capital indivisibilities amplify the positive link between firm size and early adoption.

The study focuses on the conversion of movie distribution and exhibition from 35mm film to digital cinema in France, between 2005 and 2013. Digital cinema consists of distributing motion pictures to theaters over a 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: The two technologies (digital and film) are incompatible.

Digital cinema is well suited for analyzing the role of network effects in intra-firm technology adoption for two reasons. 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 of digital movies—the software—supplied by distributors. Conversely, software availability depends on the hardware installed base.

Second, indirect network effects lead to intra-firm technology diffusion (i.e.,*within* theaters). Indeed, the benefit of replacing a film projector with a digital projector can initially be small because of the limited availability of digital movies. As a consequence, it is only optimal for a given theater to initially convert a small fraction of its capital stock of screens to digital projection. As the industry-wide share of screens equipped with digital projectors grows over time, so does the availability of digital movies. The latter in turn further increases theaters' marginal benefit from adoption, and leads to the process of technological diffusion *within* theaters. According to industry professionals, network effects were a major factor affecting adoption.[1]

This mechanism applies more generally to other industries. A recent and still developing example is the trucking industry's adoption of electric vehicles (hardware), which depends on the availability of charging infrastructures (software).[2] At a given point in time, a trucking firm's rate of adoption of electric vehicles will reflect the overlap between its distribution routes and the network of available charging stations.

The paper leverages three 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 hardware prices, and (3) a time series reporting the share of movies distributed in digital.

To quantify the contribution of the intra-firm margin to aggregate diffusion and the cross-sectional heterogeneity in adoption, I specify a structural model and simulate counterfactuals shutting down this margin. Theaters' technology-adoption choices are modeled as a dynamic oligopoly game, allowing for rich theater and market heterogeneity. Every period, theaters choose the number of screens to equip with the digital projection hardware, given their competitors' adoption decisions, the adoption cost, and the availability of digital movies. In turn, the availability of digital movies depends on the number 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, the paper assumes firms condition their adoption decisions on moments summarizing the industry state, rather than all possible realizations of it: the equilibrium concept employed in this paper follows the *moment-based equilibrium* defined in Ifrach and Weintraub (2017).[3]

Theaters' single-period profits are estimated using the two-step estimator of Bajari, Benkard, and Levin (2007) (hereafter BBL (2007)). By recovering the equilibrium actually played in the data, this approach allows me to deal with equilibrium multiplicity, a prevalent issue in games with network effects. The estimation approach exploits differences

[1] "[...] distributors would provide digital copies of films if the screens they worked with were digital. There was some reluctance by exhibitors to digitize (for many reasons) and one of the reasons given was that there were no digital copies of films." (D. Hancock (IHS Markit), personal communication, September 28^{th}, 2017) "We would start by converting 2-3 screens in the theater, just to be sure that there are enough digital movies to screen, and then later on roll-out to the rest of screens" (J. Mizrahi (Ymagis), personal communication, October 14^{th}, 2017)

[2] See "How Tesla's first truck charging stations will be built" - Reuters 02/01/2018

[3] This framework has been used in recent empirical work by Jeon (2017) and Gerarden (2017).

in adoption behavior across theaters (e.g., differences in adoption times, units of new technology acquired, and adoption costs) to estimate how theaters and market characteristics affect single-period profits.

Using the estimated model, the paper first evaluates the extent to which industry diffusion is driven by intra-firm diffusion. The equilibrium industry diffusion (i.e., variance in adoption times across all screens) is decomposed into an intra-firm and inter-firm margins. To separate the two margins, a counterfactual diffusion path is simulated, restricting every theater' adoption-strategy space to a binary 0–1 adoption decision. In this sense, theaters are restricted to converting their entire capital stock of screens at once, conditional on adoption, thus shutting down the intra-firm margin. Importantly, theaters take the aggregate share of digital movies over time as given in the equilibrium played in the data: this approach, therefore, computes a counterfactual *best-response*.[4] The analysis shows aggregate diffusion (i.e., the dispersion in adoption times across capital units) is mainly explained (69%) by the diffusion within rather than across theaters.

Second, the analysis moves from the industry to the local market level. The estimated model is used to evaluate the role of the intra-firm margin in explaining the observed heterogeneity in adoption rates across firms. Such differences have been historically attributed to two important factors: firm size (economies of scale) and market concentration (strategic incentives).[5] The objective is to isolate the role of the intra-firm margin from the latter two factors. The intra-firm margin plays a role because large theaters are able to initially convert a smaller fraction of their stock of screens than are small theaters. It is optimal to do so due to the presence of indirect network effects: the benefit from adopting depends on the availability of digital movies, and initially, only a small fraction of movies is released in digital. As a result, larger theaters and more concentrated local markets (i.e., markets with fewer theaters, keeping the total stock of screens fixed) introduce the technology faster—all else equal.

The introduction lag, or difference in expected time to first adoption between a small and large theater (resp. between a competitive and concentrated market), is simulated under (1) the equilibrium adoption strategy played in the data and (2) the counterfactual best response outlined above (intra-firm margin shut down)—in a given local market, fixing theaters and market characteristics. By comparing the introduction lags simulated under adoption strategies (1) and (2), one can isolate the role of the intra-firm margin from other

[4]A counterfactual best-response is sufficient to decompose the equilibrium aggregate diffusion rate into an intra-firm and inter-firm margins. While interesting in itself for welfare analysis, computation of counterfactual equilibria is complicated by multiplicity.

[5]Differences can also arise due to heterogeneity in firm characteristics (type of programming, integration etc.) which the model allows and controls for.

factors (scale economies, strategic interactions). For the average urban local market with more than $100,000$ inhabitants, a significant fraction of the introduction lag (30% to 42% for small/large theaters, and 43% to 69% for less/more concentrated market) is due to the intra-firm adoption margin. Therefore, in addition to economies of scale and strategic incentives, intra-firm adoption dynamics are an important factor explaining differences in adoption behavior across firms and shape the relationship between market structure and technology adoption.

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 quantifies the magnitude of indirect network effects via reduced-form analysis. Section 6 develops the dynamic model of technology adoption. Section 7 estimates the industry model. Finally, section 8 presents the counterfactual analysis.

2 Related literature

Previous empirical work estimating the extent of network effects in technology adoption has focused mainly on the inter-firm (or extensive) margin, modelling adoption as a 0–1 decision. This approach is appropriate when adopters are end-consumers with a unit demand for the technological good or when, in the case of firm adoption, the technology is not embodied in capital. Recent examples in the case of consumer goods include video games platforms (Clements and Ohashi (2005), Corts and Lederman (2009), Dubé, Hitsch, and Chintagunta (2010), Lee (2013)), DVD players (Karaca-Mandic (2003)), and home computers (Goolsbee and Klenow (1999)). More recently, Ryan and Tucker (2012) studies the diffusion of videocalling within a multinational firm. In their model, the within-firm rate of adoption is measured by the number of employees using the technology, with each employee making 0–1 adoption decisions; network effects arise within the firm.[6]

In the case of firm adoption, examples include the US Fax market (Economides and Himmelberg (1995)), Automatic Teller Machines (Saloner and Shepard (1995)), electronic switching in the US telecommunication industry (Majumdar and Venkataraman (1998)), and the Automated clearinghouse payment system (Gowrisankaran and Stavins (2004), and Ackerberg and Gowrisankaran (2006)). In contrast to this literature, this paper analyzes

[6]Note that in all the aforementioned papers, except in the cases of home computers and videocalling, network effects are indirect. This type of network effects have been formally modelled by Chou and Shy (1990), and further developed by Church and Gandal (1992). Recent theoretical contributions include Markovich (2008), and Markovich and Moenius (2013).

the extent to which network effects, at the industry level, determine not only whether the technology is adopted, but also how the intra-firm adoption rate is affected.

I also contribute to the literature analyzing the drivers of intra-firm technology adoption. The development of this literature has been limited by the lack of detailed data at the unit of capital level. In order to observe the intra-firm spread of an innovation, each firm has to be observed over long time periods since the date of initial adoption. Intra-firm adoption was first analyzed in Mansfield (1963), who studies railroads' conversion from steam to diesel powered locomotives. In this model, a new technology diffuses within the firm as the risk attached to the payoff from this technology is reduced over time through inter-firm and intra-firm learning. Other empirical studies based on the learning approach include Nabseth and Ray (1974), Romeo (1975), Levin, Levin, and Meisel (1992), and Fuentelsaz, Gomez, and Polo (2003).[7]

Recently, alternatives to the learning model were proposed. In particular, Battisti and Stoneman (2005) propose stock effects as an important driver of the time intensity of intra-firm adoption, using the case of Computer Numerically Controlled Machine tools within firms in the UK engineering and metalworking sectors.[8] Other studies following this approach include Hollenstein (2004) and Hollenstein and Woerter (2008). This strand of the literature relies on cross-sectional survey data and is constrained to estimating the effect of firm- or environment-specific factors on inter- and intra-firm adoption at a given point in time. By contrast, this paper relies on a panel of adoption decisions for all firms active in a given industry, and explicitly models the dynamics of stock effects.

This paper makes a contribution to the literature on market structure and innovation (including 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)). This paper follows this methodological approach and analyzes how market structure, and in particular firm size, can impact the timing of technology adoption specifically via the intra-firm margin.

Finally, 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

[7]A literature on the "depth" of adoption considers the intensity of use of a given stock of new technology. One example is Astebrot's (2004) study of the effect of learning sunk costs. The depth of adoption differs from the intra-firm margin of adoption, in that the stock of new technology adopted is fixed while the extent to which this stock's technological capabilities are exploited varies.

[8]The stock-effect approach argues intra-firm diffusion will not be instantaneous, because the marginal profit gain from increased use of new technology decreases with use. In their case, the decreasing marginal returns from further adoption are implied by a Cobb-Douglas specification of the production function (implying decreasing marginal productivity of capital embodying the new technology).

(Gil (2008)), seasonality (Einav (2007)), strategic entry and exit, and spatial retail competition (Davis (2006a),Davis (2006b), Takahashi (2015), Gil, Houde, and Takahashi (2015)), and the quality-variety trade-off in screening brought about by digital projection (Rao and Hartmann (2015)). In the strand focusing on technology adoption, the closest paper is Gil and Lampe (2014), who analyze Hollywood's conversion to color in the 1940s-1950s. Another related paper in this strand is Waldfogel (2016). The latter paper studies the effect of digital movie production, alternative distribution channels (streaming), and online film criticism on new product releases. The present paper focuses on the digitalization of the movie distribution and exhibition sectors, with theater releases as the main channel of distribution.

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 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 inspects the print, attaches the reels together, and positions them so they can be fed to the screening platter of 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 venue 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 automation cues in the server.

3.1.1 Distributors' supply of digital movies

Digital distribution of movies drastically cuts printing and shipping costs for movie distributors. To print an 80-minute feature film can cost US$1,500 to $2,500 per print. By contrast, a feature-length movie can be stored on an off-the-shelf 300 GB hard drive for $50.[9] 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 Exhibitors' adoption of digital projectors

Digital projection allows exhibitors to cut down on operating costs. Screening film prints is a technical task, requiring mechanical skills that are growing rare. Film projectionists are commonly represented by powerful unions and are therefore expensive.[10] 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. One consequence is that uncertainty about the benefits of the technology and learning, which are usually thought of as important determinants of intra-firm diffusion, are not central to adoption decisions. Digital projection also opens up the possibility of using theaters for "alternative content" such as pop concerts, opera broadcasts, and sports events.

3.1.3 Multi-homing by movie distributors and theaters

Multi-homing in movie distribution consists of the distribution of a given movie on both film and digital supports. It was initially very common: most movies released in digital format were also distributed on film. As the technology diffused, the share of multi-homed movies decreased toward 0.

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

[9] 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.

[10] See 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.

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. 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.[11] 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.[12] 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 making movies. 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.[13]

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. Figure 1 represents the distribution of theaters by size, defined as the number of screens owned by the theater. Half of the theaters are mono-screen. 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.[14] In the early phase of the diffusion

[11] 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.

[12] See Bordwell (2013).

[13] 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.

[14] See Kopp (2016).

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 intra-firm adoption decisions.

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.[15] 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 movie 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 (market size). 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 com-

[15] Based on CNC 2014 annual report.

pared to non-art house theaters. Therefore, art house theaters may differ in their adoption behavior.

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. This information is used to study the role of indirect network effects in driving within-theater adoption of digital.

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.[16] Both sources are public and provide snapshots of the digital-exhibition industry at different time 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 source are detailed in Appendix A.1. Figure 2 represents the 18 observation dates along 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.1.

Two auxilliary 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 demand, 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), (4) the share of movies released in digital (distributed partially or entirely in digital), and (5) in 2015 only, a categorical variable for ticket sales (e.g., "150,000 to 200,000 tickets sold"), number of movies screened, total number of screenings, shares of movies screened that year by type (art house vs. non-art house), and by nationality (US, France, Europe, and other) for each active theater.

The second auxiliary dataset, obtained from the European Audiovisual Observatory, pro-

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

vides time-series information on digital-projector acquisition costs.[17] 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 price MSRP) of digital projectors. The analysis accounts for the VPF subsidies, which cover 50% of the projector price.[18] 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.[19]. The hardware adoption cost is interpolated to obtain estimates at the 13 observation dates. Figure 3 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.[20] Rates of entry and exit are, however, low (around 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. A description of variables used in the analysis is shown in Table 1.

Local market definition and competitors

Local market demand and competition is defined with respect to the urban or rural unit in

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

[18]Although the law mandating VPF subsidies was only enacted in September 2010, it was retro-active. 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.

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

[20]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.

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.[21] In 2010, Metropolitan France contained $2,243$ urban units and about $33,700$ rural units.

For the largest cities (Paris, Lyon, Marseille), the urban unit division is not appropriate, because the resulting local markets are too large. In these cases, the relevant market within each city is the *"arrondissement"* (equivalent to zipcode in the US).[22] 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 small theaters (fewer than three screens).[23] 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.[24] As expected, the stock of screens grows with the market size. A larger fraction of theaters are 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).

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

[22]The subdivision by *arrondissement* is arbitrary, given that theaters are engaged in spatial competition. However, the use of a distance measure instead to define a firm's rivals (in which the relevant market is theater-specific) would make the dynamic model intractable.

[23]These subsidies covered part or all of a theater's adoption costs. This restriction allows the paper to avoid having to model firms' beliefs regarding the distribution of future government and regional subsidies (and subsequent increase in the number of digitalized screens). Although the model does not formally include subsidized firms, their adoption decisions will matter for the aggregate diffusion of digital projectors: their contribution to the network of digital screens is accounted for but assumed to be exogenous to the model.

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

Preliminary analysis of the data shows that the intra-firm margin is quantitatively important at the aggregate level, and that there is substantial heterogeneity in adoption rates by firm size.

Figure 4a shows the number of new digital screens equipped per year. Figure 4b 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 inter-firm adoption, whereas (2) is informative about the degree of intra-firm adoption. Starting in 2008, a large fraction of 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 intra-firm margin. An alternative way of measuring the contribution of intra-firm adoption 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.[25]

With respect to firm heterogeneity in adoption, figure 5 shows the share of digital screens over time for theaters grouped by size. Larger theaters adopt the technology faster (i.e., there is a first-order stochastic shift of the adoption path as firm size decreases). On the one hand, this pattern can be due to size-related factors affecting theater's profits and adoption costs. In particular, theaters of varying size might differ in their characteristics (type of programming, ownership), in their competitive environment, and in profits per screen if economies of scale are important. On the other hand, capital indivisibilities at the screen level can also explain the initial lag in adoption of small theaters: if the share of digital movies is initially small, theaters have an incentive to initially convert a small share of screens to digital. Hence, only the largest theaters are able to adopt at the margin. To distinguish the contribution of capital indivisbilities from other potential factors explaining the delay, a structural model is needed. Before describing the model (section 6), the next section presents reduced-form evidence for the magnitude of network effects in this industry.

5 Reduced-Form Analysis

The anecdotal evidence garnered from industry professionals suggests indirect network effects are at play in the diffusion of digital cinema (see footnote 1). This section provides estimates

[25]This likely underestimates the contribution of the intra-firm margin because the panel stops before the end of the diffusion.

of the magnitude of these network effects. The analysis focuses primarily on hardware adoption, because of the richness of the data there. The results indicate that digital-movie availability is an important variable affecting theaters' digital hardware adoption. This variable will therefore be an important component in the structural model analyzed in the rest of the paper.

As noted in Gowrisankaran and Stavins (2004), network effects (whether direct or indirect) are difficult to identify using only time-series data because the adoption cost is decreasing over time while the network size is increasing over time. Disentangling both effects is challenging.

The effect of digital-movie availability on theaters' adoption of digital projectors is identified here by leveraging differences in movie programming between art house theaters and commercial theaters. The underlying assumption is that art house theaters' adoption of digital projectors would depend on the availability of digital art house movies, whereas commercial theaters' adoption would depend on the availability of digital commercial (non-art house) movies. At a given period t, both types of theaters will face the same hardware adoption cost but different digital-movie availabilities, giving cross-sectional variation in this latter variable.[26]

A theater is defined as an "art house" if at least 80% of the movies it screened in 2015 were art house movies. A theater is defined as a commercial theater if at most 20% of the movies it screened in 2015 were art house movies.[27] This definition is preferable to the use of the "art house" label awarded by the CNC every year (and observed in the data), because thresholds to qualify for the award can be as low as 30% in small urban and rural markets. The preferred definition allows for better identification of theater' type but has the disadvantage that data on the share of art house movies screened by the theater are only available for 2015. The share in 2015 is assumed to reflect the average share of art house movies screened by the theater over the diffusion period $2005-2014$. The validity of this assumption rests on two observations. First, the data show that no changes occured in theaters' CNC-defined art house labels over the sample period. Art house theaters tend to maintain their art house label, whereas commercial theaters do not turn into art house theaters.[28] Second, the share of art house movies released per year remained relatively

[26] Differences in digital-movie availability for art house and commercial movies stems from heterogeneity among distributors. Distributors of commercial movies (e.g., the majority of US studios) started distributing on digital earlier than smaller art house distributors.

[27] The quantitative results (documented below) are robust to both relaxing and restricting the thresholds used to define art house and commercial theaters.

[28] One reason for the stability in art house labels is that art house theaters receive state aid, which acts as an incentive to maintain their programming.

constant between 2005 and 2015.[29] In particular, the conversion to digital did not have an impact on it.

Because the share of art house (resp. commercial) movies released on digital are not directly observed in the data, the reduced-form analysis assumes that the latter variables can be proxied by the share of art house (resp. commercial) screens converted to digital across the industry. Details on how these two variables are constructed are presented in Appendix B. This assumption is valid if the availability of digital movies is driven by the installed base of digital projectors. In addition to the anecdotal evidence stating so, the assumption is buttressed by regressing the share of movies released in digital on the industry share of screens equipped with a digital projector, instrumenting the latter by the hardware-adoption cost, and controlling for year fixed effects. The results indicate the installed base of digital projector has a positive and significant effect on digital-movie availability.[30]

The reduced-form model relates the share of digital screens in theater i to: (1) the industry-wide installed base of (art house or commercial) screens, (2) the adoption cost, (3) firm characteristics (number of screens and seats), and (4) market characteristics (market size, competitors' screens). Denote by S_i the total number of screens in theater i, and by s_{it} the number of digital screens in theater i by period t. The dependent variable is the share of screens converted to digital s_{it}/S_i. The analysis focuses on non-adopters' incentive to adopt, so only the case of *first* adoption is considered; that is, the dependent variable is s_{it}/S_i conditional on $s_{it-1}/S_i = 0$.[31] Capital indivisibilities imply that the dependent variable is discrete and can take values in $s_{it}/S_i \in \{0, \frac{1}{S_i}, \frac{2}{S_i}, ..., 1\}$.

Let $\mathbf{x}_{it}$ be the list of regressors including the aggregate share of digital art house or commercial screens, the adoption cost, theater i's number of screens S_i, number of seats, CNC-defined art house label, competitors' digital screens, and competitors' film screens.

An ordered probit model relating the discrete dependent variable s_{it}/S_i to $\mathbf{x}_{it}$ is estimated by maximum likelihood. The sample is restricted to art house and commercial miniplexes (4–7 screens). The periodic sample with 13 dates is used, and it contains 42 art house theaters and 111 commercial theaters.[32] Table 4 presents the estimates of the ordered probit model under three specifications: (1) is the baseline specification, (2) includes dummies for regions, market size, chain membership, box-office revenue (in 2015), and (3) includes theater-level

[29] According to statistics compiled by the CNC, the share of art house movies released per year fluctuates between 55% and 62% between 2005 and 2015. The average share is 58.7% over the sample period. Over the diffusion period, on average, 25% of US movies released in France are art house, whereas this share for French movies is 68%. See Bilan 2015 at `http://www.cnc.fr/web/fr/bilans/-/ressources/9217573`

[30] A 1% increment in the industry share of digital screens (instrumented by digital projector prices) implies a 1.51% increment in the share of movies released in digital.

[31] Every period, only theaters that have not yet adopted are included in the regression.

[32] Multi and megaplexes (8 screens or more) are excluded because the majority are commercial theaters.

random effects.[33] In all specifications, year fixed effects are included. An ordered logit specification, included in Appendix B, predicts effects of similar magnitude.

The results indicate that the share of digital art house (resp. commercial) screens in the industry has a significant and positive effect on art house (resp. commercial) theaters' own adoption of digital screens. The effect of a 10% increment in the industry share of art house (resp. commercial) digital screens on the probability of adoption is represented in Figure 6a as a function of the initial industry share of art house (resp. commercial) digital screens.[34] An increase in the share of digital screens from 50% to 60% increases the probability of adoption by approximately 10%.

The hardware-adoption cost exerts a negative and significant effect on the probability that a theater adopts. Figure 6b shows that a one-standard-deviation decrease in the adoption cost (corresponding to €6,500) increases the probability of adoption by approximately 55%—when 50% of screens in the industry are digital.

In summary, these results indicate the magnitude of the network effect is significant. A given art house (resp. commercial) theater's likelihood of adoption responds to the share of art house (resp. commercial) movies released in digital, under the assumption that the latter variable can be proxied by the installed base of art house (resp. commercial) digital screens across the industry. The section relies on anecdotal evidence and a time-series regression to support this assumption.

6 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 study the role of the intra-firm margin, by simulating counterfactual adoption paths.

Theaters' technology adoption choices are modelled as a dynamic oligopoly game in the tradition of Ericson and Pakes (1995). The central part of the model specifies how theaters make their technology adoption decisions—both at the inter-firm and intra-firm margins—as a function of their type, the adoption cost, their rivals' adoption decisions, and the availability of technology-specific complementary goods (film or digital movies). Theaters adopt digital projectors for two reasons: (1) to be able to screen movies exclusively released on digital and (2) for cost-reduction purposes. For the distribution market, a reduced-form

[33] Focusing on first adoption might lead to selection of theaters over time. The inclusion of theater random effects alleviates this concern.

[34] Marginal effects are evaluated at the mean and are obtained by summing marginal effects on the probabilities of converting non-zero shares of digital screens $s_{it}/S_i > 0$.

model is used. This part of the model is meant to capture, for a given movie to be released, a distributor's decision regarding on which support to distribute it (film and/or digital), given the technology-specific network size (number of 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.[35]

6.1 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 $\mathbf{x}_{it} \in \mathscr{X}$. Firm state $\mathbf{x}_{it}$ is decomposed into $(\boldsymbol{\tau}_i, s_{it}, \mathbf{z}_{it})$:

- $\boldsymbol{\tau}_i$ 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.

- $\mathbf{z}_{it}$ is a vector containing theater i's competitors' types and digital screens. This vector is at the *local market* level (urban or rural unit in which theater i is located), and differs from the *industry* state, which is at the national level and defined below.

Let the industry state, $\mathbf{y}_t$, be a vector over individual firm states that specifies, for each firm state $\mathbf{x} \in \mathscr{X}$, 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.

[35] All vectors are denoted in bold.

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.[36] This modelling assumption is discussed in more length in section 6.3.

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

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

There is no uncertainty in state transition. A theater's state s_{it} is bounded above by its maximum capacity S_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, and is assumed to follow a finite Markov process, independent of all previously defined quantities:

$$p_t = p_{t-1} + \eta_{t-1} \tag{2}$$

where η_{t-1} is a discrete random variable, i.i.d across periods, with a non-positive support. Denote by $\mathbf{P}(p_{t+1}|p_t)$ the corresponding Markov kernel. This 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. It is publicly observable to all firms.[37]

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

$$p_t + \epsilon_{it} \tag{3}$$

where p_t is the aggregate adoption cost and ϵ_{it} is a theater-specific shock, drawn from a normal distribution $N(0, \sigma^2)$. 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, the relationship between the share of digital movies, and s_t, the number of digital screens, must be specified. This is done by considering distributors' technology-choice problem.

[36] 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.

[37] The exogeneity of the price process can be relaxed. 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 this transition matrix (only time series information used).

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 available exclusively in digital format in period t, and h_t^f denote the share of movies available 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).

The share of multi-homed movies, h_t^m, is not observed in the data (only $h_t^d + h_t^m$ is observed). In anticipation of the estimation section, and to keep the exposition concise, the rest of the model is derived under the "no multi-homing" assumption: $h_t^m = 0$ for all t. As a robustness check, the model is also derived and estimated under the polar "wide multi-homing" assumption, $h_t^d = 0$ for all t. The qualitative findings, included in Appendix C.2, are robust to this assumption.

For the rest of the analysis, define $h_t \equiv h_t^d$ so that $1 - h_t = h_t^f$. The share of digital movies, h_t, is assumed to depend on the share of digital screens in the industry at the beginning of the period.[38] Let

$$h_t = \Gamma(s_t/S) \tag{4}$$

denote distributors' reaction function giving the share of movies released in digital as a function of the industry-wide share of digital screens.[39]

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

$$\Pi(\mathbf{x}_{it}, p_t, h_t, a_{it}, \epsilon_{it}) = \pi(\mathbf{x}_{it}, h_t) - a_{it}(p_t + \epsilon_{it}) \tag{5}$$

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, which are not observed in the data, are specified via reduced-form and estimated. Namely, $\pi(\mathbf{x}_{it}, h_t)$ is obtained by aggregating profits per movie screening across all movies the theater *is able* to screen given its stock of digital and film screens. The technologies being incompatible, a theater can screen a digital movie only if it has a digital screen. A theater lagging in its adoption of digital will have fewer movies to screen over time, because as the network of digital screens grows, an increasing share of movies is only

[38] This approximation is made for tractability. Because distributors share box-office revenue with theaters, and this revenue differs across theaters, distributors might base their decision not only on the aggregate number of digital screens, but also on the identity of the converted theaters.

[39] This simple specification for the relationship determining h_t can be relaxed to account for other exogenous determinants of the share of digital movies. It is imposed due to the limited amount of time-series information necessary to fit the relationship.

available on digital.

It is assumed that, every period, theater i randomly draws a mass $M_i \subset M$ of movies from the mass M released in that period. By the law of large numbers, a share h_t of movies drawn are digital movies. In particular, every theater draws the same share h_t of digital movies per period.[40] Denote by R_i the number of screenings a theater can host if it is able to screen all M_i movies drawn. The number of screenings R_i is exogenous and depends only on the theater's type $\boldsymbol{\tau}_i$.

Let $\pi_d(\mathbf{x}_{it})$ and $\pi_f(\mathbf{x}_{it})$ be the single-period profits *per movie screening* in state $\mathbf{x}_{it}$ from screening a digital or film copy, respectively. Due to cost reductions from digital projection, these profits satisfy: $\pi_f(\mathbf{x}_{it}) \leq \pi_d(\mathbf{x}_{it})$. Operating profits are obtained by aggregating profits *per movie screening* across all screenings, and are given by

$$\pi(\mathbf{x}_{it}, h_t) = R(\boldsymbol{\tau}_i) \times \begin{cases} \frac{s_{it}}{S_i}\pi_d(\mathbf{x}_{it}) + (1-h_t)\pi_f(\mathbf{x}_{it}) & \text{if} \quad \frac{s_{it}}{S_i} \leq h_t \\ h_t\pi_d(\mathbf{x}_{it}) + (1-\frac{s_{it}}{S_i})\pi_f(\mathbf{x}_{it}) & \text{if} \quad \frac{s_{it}}{S_i} \geq h_t \end{cases} \tag{6}$$

where s_{it}/S_i is the share of digital screens in the theater in period t, and h_t is the share of movies released in digital.

Three points should be noted. First, equation (6) implies $\pi(\mathbf{x}_{it}, h_t)$ is strictly concave and piece-wise linear so the single-period marginal benefit from further adoption is decreasing. Ideally, theaters wishes to match the share of digital screens s_{it}/S_i to the share of digital movies released h_t.

Second, network effects are indirect: 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 share of digital screens in the industry through equation (4).

Third, a theater's type (firm and market characteristics) impacts the theater's profits per screen, $\pi(\mathbf{x}_{it}, h_t)/S_i$, via two channels: the number of screenings per screen $R(\boldsymbol{\tau}_i)/S_i$ and the profit per screening $(\pi_d(\mathbf{x}_{it}), \pi_f(\mathbf{x}_{it}))$. The impact of theater size on profits per screen can be non-linear if, for instance, larger theaters have more screenings per screen ($R(\boldsymbol{\tau}_i)/S_i$ increasing in S_i), but profits per screening decrease with theater size ($\pi_d(\mathbf{x}_{it}), \pi_f(\mathbf{x}_{it})$ decreasing in S_i).

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 $\boldsymbol{\omega}_{it} \equiv (\mathbf{x}_{it}, p_t, \mathbf{y}_t, \epsilon_{it})$. Although theater i's single-period profits, $\Pi(.)$, do not directly depend on the industry state $\mathbf{y}_t$, the firm tracks this variable in order to form expectations about the

[40]This assumption reduces significantly the complexity of the model. Relaxing these assumptions would yield firm-specific shares of digital movies $\{h_{it}\}_{i \in I}$. 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 from adoption for smaller theaters.

future evolution of s_t which in turn determines, via equation (4), the (payoff-relevant) share of digital movies h_t.

In this setting, the large number of firms (due to network effects at the industry level) and the dimension of firms' state $\mathscr{X}$ generate a high-dimensional industry state space. 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 $\mathbf{y}_t$ is 1,071,993,300. To alleviate the computational burden, two assumptions are imposed.

First, firms are assumed to condition their adoption decision on moments summarizing the industry state vector $\mathbf{y}_t$, rather than all possible realizations of the vector $\mathbf{y}_t$. Ifrach and Weintraub (2017) proposed an alternative approximation of MPE based on moments of the industry space, which is the approach followed here.[41] More precisely, firms are assumed to condition their adoption decisions on the un-normalized first moment of the distribution of $\{s_{it}\}_{i \in I}$, that is, the total number of digital screens in the industry s_t.

Second, the paper assumes that firms do not keep track of the whole vector of competitors' states $\mathbf{z}_{it}$, but only of competitors' total number of digital screens denoted z_{it}.

In summary, firms are assumed to condition their adoption decisions on the *moment-based state* $\widetilde{\boldsymbol{\omega}}_{it} = (\widetilde{\mathbf{x}}_{it}, p_t, s_t, \epsilon_{it})$, where the moment-based firm state $\widetilde{\mathbf{x}}_{it}$ is defined by $\widetilde{\mathbf{x}}_{it} = (\boldsymbol{\tau}_i, s_{it}, z_{it})$.[42] The analysis focuses on equilibria in pure symmetric *moment-based* strategies, defined as mappings from the current *moment-based* state $\widetilde{\boldsymbol{\omega}}_{it}$ into actions (i.e., number of screens to be converted to digital).

Perceived transition kernel: Define $\widetilde{\boldsymbol{\gamma}}_{it} \equiv (\widetilde{\mathbf{x}}_{it}, p_t, s_t)$, as the moment-based state excluding the private firm-specific shock, so that

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

Similarly define $\boldsymbol{\gamma}_{it} \equiv (\mathbf{x}_{it}, p_t, \mathbf{y}_t)$ as the true underlying state excluding the private firm-specific shock, so that

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

As noted in Ifrach and Weintraub (2017), the moment-based state process $\{\widetilde{\boldsymbol{\gamma}}_{it}, t \geq 0\}$ is in general *not* Markov, even if the true state process $\{\boldsymbol{\gamma}_{it}, t \geq 0\}$ is. By aggregating information via moments, the moments obtained are not necessarily sufficient statistics for next period's

[41] Approximation methods to MPEs were initially proposed in the IO literature on dynamic games with complete information by Weintraub, Benkard, and Van Roy (2008), and subsequently refined in Benkard, Jeziorski, and Weintraub (2015).

[42] This definition differs from Ifrach and Weintraub's (2017) definition of the moment-based industry state in the fact that it does not keep track of *dominant firms' states*, but only of an aggregate moment describing the states of firms.

moments: for instance, given s_t, next-period state s_{t+1} depends on whether the s_t digital screen are owned by small vs. large theaters, art vs. non art house theaters, or located in rural vs. large urban market. In this sense, many underlying industry distributions can yield the same current-period moment s_t, but different next-period moment s_{t+1}. Therefore, one has to construct a Markov approximation of the kernel transition matrix guiding the dynamics of the process $\{\widetilde{\boldsymbol{\gamma}}_{it}, t \geq 0\}$. Assume theater i follows moment-based adoption strategy a' while all other theaters use moment-based adoption strategy a. The objective is to define a kernel $\widehat{\mathbf{P}}_{a',a}$, which is a good approximation of the non-Markov process $\{\widetilde{\boldsymbol{\gamma}}_{it}, t \geq 0\}$. The process described by $\widehat{\mathbf{P}}_{a',a}$ correponds to firm i's perception of the evolution of its own state $\widetilde{\mathbf{x}}_{it} = (\boldsymbol{\tau}_i, s_{it}, z_{it})$, the adoption price p_t, and the industry moment s_t. To keep the exposition concise, the construction of the perceived transition kernel is detailed in Appendix C.1.

Value function and optimal adoption rule: Let $a(\widetilde{\boldsymbol{\gamma}}_{it}, \epsilon_{it})$ be a pure moment-based 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 *moment-based* 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):

$$V(\widetilde{\boldsymbol{\gamma}}_i, \epsilon_i) = \max_{a_i} \big\{ \pi(\widetilde{\mathbf{x}}_i, h) - a_i(p + \epsilon_i) + \beta \sum_{z_i', p', s'} V(\boldsymbol{\tau}_i, s_i + a_i, z_i', p', s') \widehat{\mathbf{P}}_a(z_i', p', s' | \widetilde{\boldsymbol{\gamma}}_i) \big\} \tag{7}$$

where β is the discount factor, $\widehat{\mathbf{P}}_a$ is the perceived transition kernel previously defined, giving the perceived probability of one-period reachable states for competitors' digital screens, the adoption price, and the adoption moment vector s, given firm i's belief a about its competitors' actions. The share of digital movies can be derived using equation (4) as: $h' = \Gamma(s'/S)$. Moreover, $V(\boldsymbol{\tau}_i, , s_i + a_i, z_i', p', s')$ is firm i's *ex-ante* value function, that is, before observing next-period firm-specific shock ϵ_i'. It is given by: $V(\boldsymbol{\tau}_i, s_i + a_i, z_i', p', s') = \int V(\boldsymbol{\tau}_i, s_i + a_i, z_i', p', s', \epsilon_i') dF(\epsilon_i')$.

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

$$W(a_i|\widetilde{\boldsymbol{\gamma}}_i) = \beta \sum_{z_i', p', s'} V(\boldsymbol{\tau}_i, s_i + a_i, z_i', p', s') \widehat{\mathbf{P}}_a(z_i', p', s' | \widetilde{\boldsymbol{\gamma}}_i) \tag{8}$$

Define $\Delta W(k|\widetilde{\boldsymbol{\gamma}}_i) \equiv W(k|\widetilde{\boldsymbol{\gamma}}_i) - W(k-1|\widetilde{\boldsymbol{\gamma}}_i)$ 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}.[43] It can be expressed as

$$a_{it} = \begin{cases} 0 & \text{if} \quad \Delta W(1|\widetilde{\boldsymbol{\gamma}}_{it}) - p_t \leq \epsilon_{it} \\ k & \text{if} \quad \Delta W(k+1|\widetilde{\boldsymbol{\gamma}}_{it}) - p_t < \epsilon_{it} \leq \Delta W(k|\widetilde{\boldsymbol{\gamma}}_{it}) - p_t \\ & \quad \text{and } 1 \leq k < S_i - s_{it} \\ (S_i - s_{it}) & \text{if} \quad \epsilon_{it} < \Delta W(S_i - s_{it}|\widetilde{\boldsymbol{\gamma}}_{it}) - p_t \end{cases} \tag{9}$$

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

$$P(a_{it}|\widetilde{\boldsymbol{\gamma}}_{it}) = \begin{cases} \int_{\Delta W(1|\widetilde{\boldsymbol{\gamma}}_{it}) - p_t}^{\infty} dF(\epsilon_{it}) & \text{if} \quad a_{it} = 0 \\ \int_{\Delta W(k+1|\widetilde{\boldsymbol{\gamma}}_{it}) - p_t}^{\Delta W(k|\widetilde{\boldsymbol{\gamma}}_{it}) - p_t} dF(\epsilon_{it}) & \text{if} \quad a_{it} = k \in \{1, 2, ..., S_i - s_{it} - 1\} \\ \int_{-\infty}^{\Delta W(S_i - s_{it}|\widetilde{\boldsymbol{\gamma}}_{it}) - p_t} dF(\epsilon_{it}) & \text{if} \quad a_{it} = S_i - s_{it} \end{cases} \tag{10}$$

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 (7):

$$V(\widetilde{\boldsymbol{\gamma}}_i) = \pi(\widetilde{\mathbf{x}}_i, h) + \sum_{a_i} P(a_i|\widetilde{\boldsymbol{\gamma}}_i)\big(-a_{it}(p + E[\epsilon_i|\widetilde{\boldsymbol{\gamma}}_i, a_i]) + W(a_i|\widetilde{\boldsymbol{\gamma}}_i)\big) \tag{11}$$

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

6.2 Market equilibrium

In every period, the sequence of events is as follows: First, distributors observe the outstanding number of digital screens s_t in the industry and publicly make their distribution decision

[43] The cut-off rule can be derived by noting the following two points: (1) a_{it} is optimal in state $\widetilde{\boldsymbol{\gamma}}_{it}$ *iff* $W(a_{it}|\widetilde{\boldsymbol{\gamma}}_{it}) - a_{it}(p_t + \epsilon_{it}) \geq W(a'|\widetilde{\boldsymbol{\gamma}}_{it}) - a'(p_t + \epsilon_{it})$ for all $a' \neq a_{it}$, and (2) $\Delta W(k|\widetilde{\boldsymbol{\gamma}}_{it})$ is decreasing in k (W is concave - which stems from the strict concavity of the single-period profit function $\pi(\widetilde{\mathbf{x}}_i, h)$ in $a_{i,t-1}$). Combining (1) and (2) yield the cut-off rule.

(film or digital) for movies released in that period. Second, theaters receive 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 released in digital h_t, their competitors' digital screens, 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 moment-based strategies. In a moment-based equilibrium, each theater's adoption decision is optimal in every (moment-based) 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 a moment-based equilibrium if:

$$V(\widetilde{\boldsymbol{\gamma}}_{it}; \mathbf{a}^*) \geq V(\widetilde{\boldsymbol{\gamma}}_{it}; a_i', \mathbf{a}_{-i}^*) \text{ for all firm states } \widetilde{\boldsymbol{\gamma}}_{it} \text{ and strategies } a_i' \tag{12}$$

where $V(\widetilde{\boldsymbol{\gamma}}_{it}; \mathbf{a}^*)$ is theater i's ex-ante value function at state $\widetilde{\boldsymbol{\gamma}}_{it}$, given that all theaters play strategy $\mathbf{a}^*$, and $V(\widetilde{\boldsymbol{\gamma}}_{it}; a_i', \mathbf{a}^*)$ 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.[44]

6.3 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.

[44] The existence proof in Ifrach and Weintraub (2017) requires the industry state process to be irreductible and aperiodic (and is derived for the long-run perceived kernel, not the short-run kernel used here), so it is not directly applicable to this setting. One can, however, show that at least one degenerate equilibrium (e.g., with no adoption) exists.

7 Estimation

This section discusses the identification and estimation of the structural model presented in section 6. The objective is to recover (1) the single-period profit functions per digital and film movie screening ($\pi_d(\widetilde{\mathbf{x}}_{it}), \pi_f(\widetilde{\mathbf{x}}_{it})$) and (2) the variance of the firm-specific shock. To circumvent computational and equilibrium multiplicity issues, the model is estimated using a two-step CCP-based approach (Bajari, Benkard, and Levin (2007)). Estimation results point to cost reductions from digital projection, heterogeneity in profits per screen across theaters, and the presence of scale economies in operation (profits per screen increasing in theater size).

7.1 Identification

Standard results for the identification of discrete-choice models, as in Magnac and Thesmar (2002) and Bajari, Chernozhukov, et al. (2015), apply to this setting. Variable profits are identified, but fixed-cost components entering operating profits must be normalized to zero. The discount factor β is assumed to be known.

Differences in adoption times (and units of technology acquired) across firms allow the identification of the functions π_d and π_f's dependence on firm state $\widetilde{\mathbf{x}}_{it}$. Because the aggregate adoption cost, which is observed by the econometrician (up to a firm-specific private shock), is decreasing over time, differences in adoption times across firms reveal differences in the paid adoption costs, which translate into differences in firms' single-period profits: for example, firms that adopt earlier must be receiving higher single-period profits than firms that adopt later.

More precisely, to evaluate which elements of the single-period profit functions are identified, note that there are two motives for adopting a digital projector. A firm adopts a digital projector: (1) to gain access to digital movies it would otherwise not be able to screen and (2) for cost-reduction purposes (the profits from screening a digital movie may be higher than the profits from screening a film movie: ($\pi_f(\widetilde{\mathbf{x}}_{it}) \leq \pi_d(\widetilde{\mathbf{x}}_{it})$)).

Adoption for the first motive is informative about $\pi_d(\widetilde{\mathbf{x}}_{it})$. When $h_t > \frac{s_{it}}{S_i}$ (i.e., the share of digital movies released is greater than the share of digital screens owned by theater i), theater i adopts in order to gain access to new digital movies (the fraction $h_t - \frac{s_{it}}{S_i}$ of unscreened digital movies). The marginal benefit from adoption per-movie screening is $\pi_d(\widetilde{\mathbf{x}}_{it})$. The variation in adoption times across different theaters, allows the identification of the function $\pi_d(\widetilde{\mathbf{x}}_{it})$.

Adoption for the second motive is informative about the difference $\pi_d(\widetilde{\mathbf{x}}_{it}) - \pi_f(\widetilde{\mathbf{x}}_{it})$, or the cost-reduction from screening a digital movie relative to a film movie. [45] This difference is identified by exploiting capital indivisibilities. Consider the example in Figure 7. Given h_t and the fact that the theater has not adopted yet, the four-screen theater contemplates the options of converting one screen (left panel) or two screens (right panel). In the first case, the theater forgoes profits of $A \times \pi_d(\widetilde{\mathbf{x}}_{it})$, whereas in the second case, the theater forgoes profits of $B \times \pi_f(\widetilde{\mathbf{x}}_{it})$ (where A and B are masses of movies). Ignoring continuation values, the theater chooses to convert two rather than one screen ($\frac{s_{it}}{S_i} = 1/2$) *iff* $A \times \pi_d(\widetilde{\mathbf{x}}_{it}) - B \times \pi_f(\widetilde{\mathbf{x}}_{it}) \geq p_t$. In cases where this inequality holds (which correspond to cases where theaters over-invest), different adoption times allow identification of the difference $(\pi_d(\widetilde{\mathbf{x}}_{it}) - \pi_f(\widetilde{\mathbf{x}}_{it}))$ (up to the known constants A and B).

Finally, the variance of the firm-specific shock, $V(\epsilon_{it}) = \sigma^2$, is identified from the variation in adoption times and units of technology adopted between theaters in the same firm state $\widetilde{\mathbf{x}}_i$.

7.2 Estimation

7.2.1 Parameterization:

This section details the model parameterization. A theater's single-period operating profits are constructed as the product of the total number of screenings $R(\tau_i)$ and the expected profit per screening. The total number of screening $R(\boldsymbol{\tau}_i)$ and the profits per movie screening $(\pi_f(\widetilde{\mathbf{x}}_{it}), \pi_d(\widetilde{\mathbf{x}}_{it}))$ are parameterized, and are estimated separately.

The number of screenings $R(\boldsymbol{\tau}_i)$ is estimated outside the model, using data on screenings in 2015 for each active theater in the model. This variable is explained by a reduced-form model that includes theater and market characteristics part of theater type $\boldsymbol{\tau}_i$: theater size S_i, market size $market_i$, number of rival screens S_{-i}, art house status art_i, and interaction between these variables. This specification allows the number of screenings per screen to vary non-linearly with theater size, capturing potential scale economies. The assumption that the 2015-level for the dependent variable is representative of the diffusion period relies on the fact that the annual number of screenings per screen did not vary significantly over the diffusion period.[46]

[45] A direct way of identifying this difference would exploit the presence of multi-homed movies, which are available on both formats, and therefore impact theaters' incentive to adopt only via the cost reduction motive. However, due to data limitation, this identification approach is not possible under the "no-multihoming" assumption ($h_t^m = 0$).

[46] The annual number of screenings per screen for multi/megaplexes (8 screens or more) was on average $1,787$ with a standard deviation of 40 over $2008 - 2015$, whereas for miniplexes, the average number of screenings per screen is $1,346$ with a standard deviation of 30 (based on CNC's "bilan 2015" and the report by the Digital Diffusion Observatory published in September 2016. Both reports are available (in French) at: `http://www.cnc.fr/web/fr/publications`)

For the single-period profit per movie screenings $\pi_d(\widetilde{\mathbf{x}}_{it})$ and $\pi_f(\widetilde{\mathbf{x}}_{it})$, a simple Breshnahan and Reiss (1991)-style reduced form is used:

$$\pi_f(\widetilde{\mathbf{x}}_{it}) = \alpha_0^f + \alpha_1^f S_i + \alpha_2^f \mathbf{1}\{art_i = 1\} + \alpha_3^f S_{-i} + \alpha_4^f z_{it} + \alpha_{market_i}^f + \alpha_{chain_i}^f \quad (13)$$

$$\pi_d(\widetilde{\mathbf{x}}_{it}) = \alpha_0^d + \alpha_1^d S_i + \alpha_2^d \mathbf{1}\{art_i = 1\} + \alpha_3^d S_{-i} + \alpha_4^d z_{it} + \alpha_{market_i}^d + \alpha_{chain_i}^d + \alpha_5^d \frac{s_{it}}{S_i} \quad (14)$$

where S_i is the number of screens in theater i, s_{it} is the number of digital screens in theater i in period t, art_i is an indicator for art house theaters, S_{-i} is the total number of screens owned by theater i's competitors, z_{it} is the total number of digital screens owned by theater i's competitors in period t, and α_{market_i} and α_{chain_i} are dummies for market size and chain identifier.[47]

The cost reduction from screening digital movies compared to film movies is allowed to depend on the share of digital screens in theater i via the term $\alpha_5^d \frac{s_{it}}{S_i}$. The cost reduction is expected to be increasing in theater i's share of digital screens. This specification is imposed because, according to industry professionals, operating both technologies simultaneously within a given theater is relatively costly (e.g., limited ability to re-allocate movies across screens within the theater).

The specifications for $R(\boldsymbol{\tau}_i)$ and $(\pi_d(\widetilde{\mathbf{x}}_{it}), \pi_f(\widetilde{\mathbf{x}}_{it}))$ allow profits per screen to vary non-linearly with theater size via two channels: the number of screenings per screen and profits per screening. This specification will capture potential scale economies, for which empirical evidence is available (Verma (2001)).[48] The variables S_{-i} and z_{it} entering $(\pi_d(\widetilde{\mathbf{x}}_{it}), \pi_f(\widetilde{\mathbf{x}}_{it}))$ capture the effect of strategic interactions between competitors on profits.

The parameters of interest are the vector $\boldsymbol{\alpha} = \left(\{\alpha_i^j\}_{i=0\ldots5}, \alpha_{market=1\ldots6}^j, \alpha_{chain=0\ldots3}^j, j \in \{f, d\}\right)$ entering the profit per digital and film screenings and the variance σ^2 of the firm-specific shock.

7.2.2 Estimation approach:

The paper follows the two-step method of BBL (2007) for two reasons. First, the high dimensionality of the model, due to network effects at the industry-level, renders a full-solution method impractical. Second, as is common in games of technology adoption under network effects, equilibrium multiplicity is severe. The two-step method, which avoids equilibrium computation, helps circumvent the multiplicity issue by directly estimating the equilibrium played in the data.

In a first step, the equilibrium policy rule and transition probabilites are estimated from the data, under the assumption that firms play a moment-based equilibrium, and then equi-

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

[48] Only variable profits are identified, so potential scale economies are not due to fixed costs (concession stands, box-office etc.) but to decreasing average variable cost.

librium value functions are approximated via simulation by using the estimated equilibrium policy functions and transition probabilities. In a second step, the parameters are estimated by imposing the optimality condition stating that the equilibrium value function yields a higher payoff than the value function from non-equilibrium deviations.

First-step estimation:

Movie theaters' adoption-policy function. The first element to estimate is the equilibrium policy function governing theaters' adoption of digital hardware. The policy function is a cut-off rule in the idiosyncratic shock ϵ_{it} given by equation (9). The estimation proceeds by first recovering the conditional choice probabilities (CCP) from the data. Next, the cut-offs forming the equilibrium policy function are obtained from the CCP by inverting equation (10). The conditional choice probabilities $P(a_{it}|\widetilde{\gamma}_{it})$ are estimated using an ordered probit model, and in what follows are assumed to be known.[49]

The cut-offs are recovered by noting that for $a \in \{0, .., S_i - s_{it}\}$,

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

where $\epsilon_{it} \sim N(0, \sigma^2)$ and Φ is the normal cumulative distribution. The cut-offs can be obtained by inverting equation (15):

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

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 $\widetilde{\gamma}_{it}$.

Transition probabilities of the exogeneous hardware price process. To estimate the transition probabilities of the price process $\{p_t, t \geq 0\}$, the variable is first discretized. The number of discrete grid points is 15. Over the diffusion period, the price process was on a downward trend, possibly due to technological advances in hardware manufacturing, learning by doing, and scale economies. Every period, the price is assumed to either move to a lower grid point, or stay at the current state. The initial (and maximum) price at $t = 0$ is set at the actual price level observed in the data: €$84,000$. The minimum price level is set at €$40,000$. The probability that the price transitions to a lower grid point is estimated from the transitions observed in the data.

[49] In the estimation part, the network size effect (share of digitally equipped screens across the industry) is separately identified from the adoption cost *in the policy rule* $P(a_{it}|\widetilde{\gamma}_{it})$ via functional form restriction. Additionally, to simulate the value function at states $\widetilde{\gamma}_{it}$ which are not visited in the data, knowledge of the CCP $P(a_{it}|\widetilde{\gamma}_{it})$ is required, and the two-step estimation method relies on the functional form of the policy function.

Distributors' policy function. As noted in the model, distributors' policy rule regarding the distribution format (film or digital) is aggregated, because the data provides only information on the aggregate share of movies released on digital format h_t.[50] The relationship between the share of digital movies h_t and the aggregate share of digital screens s_t, given by equation (4), is fitted directly from the data.[51]

Value functions. The expected value function at a given state is forward-simulated: a large number of paths starting at the given state are simulated using the estimated policy rules, and the discounted sum of profits obtained from these simulated paths are averaged. The simulated paths, starting from a given state $\{\widetilde{\boldsymbol{\gamma}}_{i0}\}_{i\in I}$, are generated using the following procedure:

1. Initialize the industry at the given state $\{\widetilde{\boldsymbol{\gamma}}_{i0}\}_{i\in I}$.
2. Draw firm specific adoption shocks $\{\epsilon_{i0}\}_{i\in I}$ and corresponding adoption decisions dictated by the estimated policy rule.
3. Calculate the single period profit $\Pi(\widetilde{\boldsymbol{\gamma}}_{i0}, \epsilon_{i0})$ given by equation (5).
4. Update the current state $\{\widetilde{\boldsymbol{\gamma}}_{i0}\}_{i\in I}$ according to the adoption decisions and transition of the exogeneous price process to next period state: $\{\widetilde{\boldsymbol{\gamma}}_{i1}\}_{i\in I}$.
5. Repeat steps 1-4 for T periods.

The equilibrium value function at state $\{\widetilde{\boldsymbol{\gamma}}_{i0}\}_{i\in I}$ is obtained by averaging $L = 500$ simulated paths. The paths have length $T = 40$ periods (or 20 years). The discount factor used is $\beta = 0.975$.[52] An estimate of the equilibrium value function is obtained as

$$\frac{1}{L}\sum_{l=1}^{L}\left\{\sum_{t=0}^{T}\beta^t\Pi^h(\widetilde{\boldsymbol{\gamma}}_{it}, \epsilon_{it}|\{\widetilde{\boldsymbol{\gamma}}_{i0}\}_{i\in I}, \boldsymbol{\alpha}, \sigma)\right\} \tag{17}$$

where $\widetilde{\boldsymbol{\gamma}}_{it} = (\widetilde{\mathbf{x}}_{it}, p_t, s_t)$ and $\Pi^h(\widetilde{\boldsymbol{\gamma}}_{it}, \epsilon_{it}|\{\widetilde{\boldsymbol{\gamma}}_{i0}\}_{i\in I}, \boldsymbol{\alpha}, \sigma)$ is the single period profit in simulation h at period t, when the firm follows the equilibrium adoptions strategy a^*, under the candidate parameters $(\boldsymbol{\alpha}, \sigma)$.[53]

[50] Under the "no multi-homing" assumption, $h_t^m = 0$ for all t.

[51] Note the industry share of digital screens accounts for (subsidized) small theaters and theaters that entered already equipped with digital projection. Their adoption is, however, assumed to follow a deterministic and exogeneous process. Theaters in the model take this process as given.

[52] An alternative value for the discount factor, $\beta = 0.95$, is also considered.

[53] The linearity of the single-profit function in $(\boldsymbol{\alpha}, \sigma)$ is exploited to reduce the computational intensity of the procedure: in the second step, the value function at a given state can be simulated only once, instead of for every candidate parameter vector $(\boldsymbol{\alpha}, \sigma)$.

Second-step estimation: In the second step, the underlying parameters $(\boldsymbol{\alpha}, \sigma)$ are set such that equilibrium condition (12) is satisfied for every firm i, state $\widetilde{\boldsymbol{\gamma}}_i$ and non-equilibrium deviation a'_i. Denote by $\chi = \{i, \widetilde{\boldsymbol{\gamma}}_i, a'_i\}$ a particular equilibrium condition. Under parameter vector $(\boldsymbol{\alpha}, \sigma)$, define

$$g(\chi; \boldsymbol{\alpha}, \sigma) = \widehat{V}(\widetilde{\boldsymbol{\gamma}}_i | a^*_i, a^*_{-i}) - \widehat{V}(\widetilde{\boldsymbol{\gamma}}_i | a'_i, a^*_{-i}) \tag{18}$$

as the difference between the simulated value function at state $\widetilde{\boldsymbol{\gamma}}_i$, when firm i plays the estimated policy rule a^*_i and the deviation a'_i.[54] The equilibrium condition (12) is satisfied if $g(\chi; \boldsymbol{\alpha}, \sigma) \geq 0$. The objective of the second step is to find the parameter vector $(\boldsymbol{\alpha}, \sigma)$ such that this inequality holds for all possible equilibrium conditions indexed by χ. BBL (2007) demonstrate that one can restrict estimation to a sufficiently large subset that covers the space of inequalities. The estimation proceeds by selecting $N_\chi = 3,600$ equilibrium conditions. Deviations from the equilibrium adoption strategy are obtained by adding perturbations to the estimated cut-off points. The selected equilibrium conditions are combined to form the objective function:

$$Q(\boldsymbol{\alpha}, \sigma) = \frac{1}{N_\chi} \sum_{j=1}^{N_\chi} \left(\min\{g(\chi_j; \boldsymbol{\alpha}, \sigma)\}, 0\right)^2 \tag{19}$$

The estimator of the underlying parameters is the solution of

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

This function is not trivially minimized at the zero vector, because the adoption cost $a_{it} \times p_t$ enters in periods when the theater converts some of its screens to digital.

Although BBL (2007) derive the asymptotic formula for the variance-covariance matrix, implementing it remains computationally burdensome (as one needs to compute the cross-partial derivate of Q with respect to $(\boldsymbol{\alpha}, \sigma)$ and the first-stage parameters). Bootstrap sampling is therefore preferred to obtain standard errors. One difficulty with non-parametric bootstrap is the presence of correlation in decisions across local markets, therefore, sampling market-histories with replacement, as is commonly done in dynamic oligopoly games, is not a valid approach. Instead, a parametric boostrap procedure is used.[55]

[54] In the above notation, dependence on the first-step parameters is omitted for ease of notation.

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

7.3 Estimation results

7.3.1 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 10 shows kernel density estimates of the intra-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 D).

A theater's share of screens converted to digital between t and $t + 1$, denoted a_{it}/S_i, is explained by the share of digital movies (or equivalently the aggregate share of digital screens in the industry, through equation (4)), the aggregate adoption cost, 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' digital screens in period t, and competitors' total number of screens. 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 5 presents the estimates of the ordered probit model under the four specifications. As expected, across the four specifications, the share of digital screens in the industry (equivalently the share of digital movies) is positively related to the probability of adoption, whereas the adoption cost is negatively related to the probability of adoption. Larger theaters are more likely to adopt, but the marginal effect is decreasing. Art house theaters are less likely to adopt. The share of a theater's screens already converted to digital is negatively related to further adoption.[56]

Competitors' total number of screens and digital screens do not significantly impact a theater's likelihood of adoption. This estimate indicates that strategic interactions between firms are not a major determinant of adoption.[57] Theaters located in Paris are more likely to adopt than theaters located in the small urban areas with $20,000$ to $100,000$ thousands inhabitants. Among the chain dummies, CGR theaters are more likely to adopt than single theaters or theaters belonging to smaller chains. The rest of the analysis uses specification (4).

To check the goodness of fit, model predictions (from specification (4)) for the share of digital screens are compared to actual shares in the data. Tables 6, 7, and 8 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.[58]

Distributors' reaction function. Figure 9 shows distributors' reaction function (equation (4)) 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.[59] One issue with games of technology adoption under network effects is the way the network is initially seeded with the new technology to break the "chicken or the egg" problem. In the case of France, the problem was resolved by the US studios' initial commitment to distribute movies in digital (in Figure 9, the intercept is non-zero).

7.3.2 Second-step estimates

This section presents estimation results for the total number of screenings $R(\boldsymbol{\tau}_i)$ and profits per movie screening $(\pi_f(\widetilde{\mathbf{x}}_{it}), \pi_d(\widetilde{\mathbf{x}}_{it}))$. These components are combined, as in equation (6),

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

[57] The likelihood-ratio test of specification (3) and (4) against a specification without competitors' screens and digital screens fails to reject the null that both coefficients are zero at the 5% confidence level.

[58] 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.

[59] Under the no-multihoming assumption, h_t^m equals 0 for all t.

to obtain theaters' single-period operating profits.

First, estimates for the total number of screenings are presented in Table 9. Specification (1) includes firm size S_i and market size $market_i$ (and their interaction) as explanatory variables. Specification (2) augments the model with the art house variable. Specification (3) also includes the number of competing screens S_{-i}.

As expected, the annual number of screenings per theater is increasing in theater size, and in market size. Theaters located in Paris and other urban units with more than 100,000 inhabitants host more screenings. Art house theaters also host more screenings, all else equal. The effect of the number of competing screens is not significant. Finally, the negative intercept in all specification indicates potential non-linearities in the effect of size: the number of screenings per screen is increasing in the theater size.[60]

Next, estimates of the parameters entering the single-period profits *per movie screening* and the variance of adoption costs are presented in Table 10. The coefficients entering $\pi_f(\widetilde{\mathbf{x}}_{it}$ and $\pi_d(\widetilde{\mathbf{x}}_{it})$ are restricted to be equal $\alpha_i^f = \alpha_i^d$. Profits per screening are decreasing in theater size and are lower for art house theaters, although estimates are not precise. In light of the previous results regarding the total number of screenings, this finding indicates that the utilization rate (i.e., the share of seats occupied per screening) does not vary significantly with theater size. Theater size positively affects profits per screen mainly through its effect on the number of screenings per screen. Fixing market size, profits are decreasing in the number of competing screens, whereas competitors' digital screens do not affect profits (effect of the opposite sign of competitors' screens).

The market dummies are not significant. These estimate indicate that market size mainly affects the number of screenings but not profits per screening. This is the case if the utilization rate (i.e., share of seats occupied per screening) does not vary with market size. Next, cost reductions from digital projection are positive and significant as indicated by the coefficient on "own-share of digital screens." Finally, the standard deviation of adoption costs is €$2,995$, and is relatively smaller than the adoption cost, which is between €$40,000$ and €$84,000$. The estimate for the standard deviation of the adoption costs is close to the average price decrease per period, €3,308, indicating that the dispersion in adoption times for otherwise identical firms is close to one period.

Profits levels implied by the structural model have the correct order of magnitude. The distribution of annual profits per screen across theaters, predicted by the model, is presented in Figures 10a (before the diffusion of digital cinema) and 10b (at the end of the diffusion).

[60] For example, the annual number of screenings per screen for a monopolist non-art house theater in an urban unit with 20,000–100,000 inhabitants is 1,012 for a 4-screen theater, 1,648 for an 8-screen theater, and 1,860 for a 12-screen theater.

Annual profits per screen are approximately between €10,680 and €26,130 before diffusion, and between €14,620 and €33,900 after diffusion. These results are contrasted with estimates using theater chains' income statements, obtained for the years 2014 to 2016 (i.e., after the diffusion period). The chains' annual total profits are divided by the total number of screens. Estimates range between €22,000 and €30,000. Therefore, profits levels implied by the structural model are economically plausible and reasonable.

Finally, combining estimates for the total number of screenings with profits per screening, the model predicts economies of scale in operation. Figures 11a and 11b show predicted annual profits per screen as a function of theater size and market size. Other firm characteristics are set to: monopolist, non art house, and not horizontally integrated. The combined effect of theater size on the number of screenings per screen and profits per screening implies that profits per screen are increasing in theater size. The marginal effect is decreasing. An increase from 5 to 10 screens increases profits per screen from €15,000 to €19,000 (to €23,000 in Paris), before the conversion to digital.

8 Counterfactual simulations

This section uses the calibrated model to conduct counterfactual simulations and examine the role of the intra-firm margin at the industry and local market levels. First, the intra-firm margin is found to significantly contribute to industry-level diffusion: both the introduction time and the overall dispersion in adoption times across screens depend on within-theater adoption rates. Second, the relationship between local market structure (in terms of theater size and market concentration) and technology adoption is impacted by theaters' ability to adopt at the margin (intra-firm margin effect), controlling for the role of other factors (economies of scale and strategic interactions).[61]

8.1 Intra-firm margin and aggregate diffusion

The first simulation exercise decomposes the diffusion of digital projection over the industry capital stock (screens) into an inter-firm margin (diffusion across firms) and an intra-firm margin (diffusion within firms). Additionally, the counterfactual simulation is used to evaluate the impact of the intra-firm margin on the introduction time, that is, the expected time to first adoption. The analysis indicates both aspects of aggregate diffusion—duration and introduction time—are significantly impacted by the intra-firm margin, pointing to the

[61]This paper does not discuss social welfare. A discussion of potential welfare benefits of digital cinema, in particular via new product offerings, is presented in section 3.

importance of this margin of adoption in understanding industry diffusion.

A firm's equilibrium adoption behavior is decomposed into an inter-firm (or extensive) margin, in which the firm decides whether to begin using the technology, and an intra-firm (or intensive) margin, in which the firm decides what fraction of its capital stock to convert. Whereas firms' equilibrium behavior reflects both margins, the extensive margin can be isolated by simulating firms' adoption behavior restricting the strategy space from $s_{it} \in \{0, 1, ..., S_i\}$ to $s_{it} \in \{0, S_i\}$. In this counterfactual, firms are restricted to convert their whole capital stock at once, conditional on adoption. In this sense, the intra-firm (or intensive) margin is shut down. Because the objective is to decompose the firm's *equilibrium* adoption behavior, only a counterfactual *best response* (to the equilibrium played in the data) is necessary—that is, fixing the price process $\{p_t, t \geq 0\}$ and the share of digital movies $\{h_t, t \geq 0\}$ over time to their values in the equilibrium played in the data. The best response is computed using the value function iteration algorithm of Pakes and McGuire (1994).[62]

Figure 12 presents the diffusion curves (industry-wide share of screens equipped with a digital projector over time) under the equilibrium adoption strategy (inter/intra-firm), and the counterfactual adoption best response (inter-firm only). The simulation shows that the introduction time, or expected time to first adoption, is delayed from June 2007 to January 2011. In the counterfactual case, the diffusion is complete by June 2013, whereas in the equilibrium case, diffusion is completed by June 2015. These findings imply that the inter-firm margin, or dispersion in adoption times across firms, explains 31% of the aggregate diffusion (or dispersion in adoption times across units of capital). In other words, 69% of the dispersion in adoption across screens is due to dispersion in adoption within firms.

The introduction lag—defined as the difference in introduction times—between the equilibrium and counterfactual diffusion paths is 1,297 days and corresponds to 44% of the equilibrium diffusion duration. The introduction time is significantly impacted by firms' ability to gradually convert their capital of screens to the new digital technology. This finding is expected as firms delay their adoption until sufficiently many movies are released in digital, because they are constrained to make a binary adoption decision.[63] While the previous result concerns introduction times at the industry level, the next section focuses on introduction times at the local market level (urban and rural unit).

[62] Note that, while a counterfactual *equilibrium*—in which the share of digital movies is endogenously determined—is of separate interest, obtaining such equilibrium is complicated by equilibrium multiplicity due to network effects.

[63] Fixing the counterfactual share of digital movies h_t and the adoption cost p_t as in the data is crucial for the introduction lag computed. If, for instance, firms expected h_t to reach 1 in 2008, the counterfactual introduction time would be earlier than 2008.

8.2 Introduction lag and market structure

This section analyzes the role of the intra-firm adoption margin in explaining differences in adoption times across firms. Such differences have been historically attributed to two important factors: firm size (economies of scale) and market concentration (strategic incentives).[64] This section distinguishes the effect of the intra-firm margin from the latter two factors, and shows that this margin accounts for an important share of the differences in adoption times across firms.

8.2.1 Firm size

The adoption data indicates large theaters converted faster than small theaters to digital projection. For example, by 2010, 24% of all miniplex theaters (4–7 screens) had at least one digital screen, against 64% of all multi/megaplex theaters (8–23 screens).[65] Fixing theater and local market characteristics, the presence of scale economies can in part explain the delay in adoption of a small theater relative to a large theater. If profits per digital screen increase with theater size, large theaters will adopt earlier than small theaters. This subsection argues that, in addition to the aforementioned factor, the intra-firm margin plays an important role in explaining this delay: large theaters introduce the technology faster because they are able to convert a smaller fraction of their capital stock. It is optimal to do so due to the presence of indirect network effects: the benefit from adopting depends on the availability of digital movies, and initially, only a small fraction of movies is released in digital.

To separate the contribution of the intra-firm margin from that of scale economies, the introduction time—defined as the expected time to first adoption—is simulated in a given local market (set to an urban unit with more than $100,000$ inhabitants), with one monopolist theater owning S_i screens, under (1) the equilibrium adoption strategy (equilibrium played in the data) and (2) the counterfactual best response with no intra-firm margin. Theater characteristics are set to non-art house, not part of a theater chain.

Denote by $T^E_{S_i,m}$ the introduction time in this local market with a monopolist theater with size S_i, under the equilibrium adoption strategy. Similarly, define $T^C_{S_i,m}$ as the introduction time in the same local market with a monopolist theater with size S_i, under the counterfactual best-response strategy. As in the previous section, the theater is best responding to the equilibrium played in the data. In particular, the hardware price and the share of digital movies follow the same processes as in the equilibrium played in the data. By varying the monopolist's size S_i, differences in introduction times between small and large firms, $T^E_{S_i=small,m} - T^E_{S_i=large,m}$ and $T^C_{S_i=small,m} - T^C_{S_i=large,m}$, are obtained.

In the counterfactual with no intra-firm margin, differences in introduction times across

[64] See Hall and Khan (2002).

[65] See Tables 7 and 8.

theaters with varying size ($T^C_{S_i=small,m} - T^C_{S_i=large,m}$) will reflect differences in period profits stemming from economies of scale. In the equilibrium, these differences in introduction times ($T^E_{S_i=small,m} - T^E_{S_i=large,m}$) will reflect both scale economies as well as the intra-firm margin effect. The results are shown in Table 11.[66] The reference firm is a four-screen theater ($small = 4$), and introduction lags are computed relative to larger theaters ($S_i \in \{8, 10, 12\}$). The introduction lag in the equilibrium case is between 398 and 532 days, whereas the introduction lag in the counterfactual case is between 278 and 304 days. The results indicate the intra-firm margin accounts for 30% to 42% of the introduction lag. The remainder is due to scale economies.

8.2.2 Market concentration

The previous exercise focuses on the difference in introduction times between a small and large monopolist theater, controlling for theater and market characteristics. This subsection performs the same decomposition exercise, varying local market concentration instead of theater size. That is, the total capital stock of screens in the local market is kept fixed, while varying the number of (equally-sized) theaters competing in this local market. Differences in introduction times between local markets with different levels of market concentration will stem from scale economies (as the average theater size increases with market concentration), strategic interactions (as a theater's adoption decision depends on its rivals' film and digital screens), and the intra-firm margin effect outlined in the previous subsection. The objective is to evaluate the contribution of the latter to differences in introduction times between local market with different levels of concentration.

Introduction times are computed under (1) the equilibrium adoption strategy (equilibrium played in the data) and (2) the counterfactual best response with no intra-firm margin. Theater characteristics are set to non-art house, not part of a theater chain. The total stock of screens is set to 24 screens. The market size is set to "urban unit with more than 100,000 inhabitants."

Denote by $T^E_{n,m}$ the introduction time in this local market with n equally sized theaters, under the equilibrium adoption strategy (equilibrium played in the data). Similarly, define $T^C_{n,m}$ as the introduction time in this local market with n equally sized theaters, under the counterfactual best-response strategy, with no intra-firm margin. By varying the number of theaters in the market, n, differences in introduction times between markets with different level of concentration are obtained: $T^E_{n_1,m} - T^E_{n_2,m}$ and $T^C_{n_1,m} - T^C_{n_2,m}$, with $n_1 > n_2$.

The number of competitors in the market, n, takes values in $\{1, 2, 3, 6\}$. The refer-

[66] The percentiles of $T^E_{4,m} - T^E_{S_i,m}$ and $T^C_{4,m} - T^C_{S_i,m}$ are obtained by using all bootstrap estimates (for the policy rule and the structural parameters) to simulate these introduction lags, and derive their empirical distribution.

ence market is the less concentrated market with six four-screen theaters ($n_1 = 6$), and is compared to more concentrated markets: monopoly, duopoly, and three-firm oligopoly ($n_2 \in \{1, 2, 3\}$). The introduction time is simulated for all markets, and differences (or introduction lags) are shown in Table 12.[67] The introduction lag under the equilibrium adoption strategy is between 205 and 256 days, whereas the introduction lag under the counterfactual is between 78 and 116 days. These results indicate that the intra-firm margin accounts for 43% to 69% of the introduction lag between the reference market ($n_1 = 6$) and more concentrated markets ($n_2 \in \{1, 2, 3\}$). The rest of the lag is explained by economies of scale (as average theater size decreases with n) and strategic interactions between theaters.

9 Conclusion

This paper investigates the role of network effects in intra-firm technology adoption. The within-firm share of capital equipped with the new technology increases with the availability of complementary software. In turn, software availability increases as the hardware technology diffuses across and within firms. The study focused on the digitalization of the movie distribution and exhibition industries because they offer an ideal setting for studying this mechanism.

The analysis shows that when software availability matters for adoption, the intra-firm margin explains a significant share of the aggregate diffusion phenomenon: in terms of dispersion in equilibrium adoption times, as well as time to first adoption. Second, because firms with varying size differ in their ability to gradually roll out the technology, intra-firm adoption dynamics and the presence of capital indivisibilities amplify the positive relationship between firm size and early adoption; i.e., they explain a significant share of the delay in adoption of smaller firms.

Two implications can be derived. First, the results underline the fact that designing policies (e.g., technology subsidies) that encourage faster technological diffusion within firm may be as important as designing policies that encourage faster diffusion across firms. Second, in a network industry or hardware-software system, new technologies are adopted earlier if individual firms are larger, because they are able to adopt at the margin. This sheds new light on potential effects of antitrust and merger control on firms' ability to adopt innovations.

The current study could be extended in several directions, one important is noted. An avenue of research would be to analyze the role of vertical relations between the software and hardware industries (here, distribution and exhibition) and the effect of such vertical relations on firms' incentives to adopt. These vertical relations are particularly relevant if

[67]The percentiles are obtained as in Table 11.

the payoff from adopting is asymmetric between the software and hardware markets and involves transaction costs.

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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 d-screens	competitors' digital screens by time t
	competitors f-screens	competitors' film screens by time t
	box-office*	number of tickets sold (annual - categorical)
	art house movies*	share of art house movies
	screenings*	total number of screenings
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. * variables only available for* 2015

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: 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: Share of screens converted s_{it}/S_i conditional on $s_{i(t-1)}/S_i = 0$ (ordered probit)

	Share of screens converted s_{it}/S_i conditional on $s_{i(t-1)} = 0$					
	(1)		(2)		(3)	
	Estimate	s.e	Estimate	s.e	Estimate	s.e
Industry share of d-screens	2.392**	1.219	2.896**	1.263	2.425**	1.131
Adoption cost	-2.557**	1.002	-2.623**	1.043	-2.714**	1.018
Own screens	0.053	0.055	0.062	0.059		
Seats	-0.085	1.176	-0.288	1.302		
Art house	0.024	0.130	0.021	0.138		
Competitor d-screens	0.013	0.010	0.012	0.011	0.013	0.010
Competitor f-screens	-0.004	0.004	-0.005	0.004	-0.004	0.004
Year FE	Yes		Yes		Yes	
Region FE	No		Yes		No	
Market size FE	No		Yes		No	
Chain FE	No		Yes		No	
Box-office FE	No		Yes		No	
Theater RE	No		No		Yes	
Observations	1,563		1,563		1,562	
-log Likelihood	391.292		373.626		384.251	
AIC	816.584		805.251		798.502	

Note: ***$p < 0.01$;**$p < 0.05$; *$p < 0.1$. *d-screen = screen equipped with a digital projector. f-screen = screens equipped with a film projector. For market dummies, the omitted category is "urban unit with 20 to 100 thousands inhabitants." For the chain dummies, the omitted category is "single firm and small chains."*

Table 5: 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
Industry share of d-screens	0.775	0.156	0.796	0.158	1.013	0.164	1.939	0.384
Adoption cost	-1.313	0.023	-1.317	0.025	-1.382	0.025	-1.514	0.038
Own screens	0.088	0.030	0.084	0.031	0.068	0.032	0.102	0.044
Own screens sqrd	-0.003	0.001	-0.003	0.001	-0.001	0.001	-0.005	0.002
Art house	-0.114	0.066	-0.130	0.069	-0.156	0.069	-0.321	0.218
Competitors' d-screens	0.001	0.009	0.000	0.009	-0.003	0.009	-0.003	0.009
Competitors screens	-0.002	0.003	-0.005	0.003	-0.001	0.003	0.016	0.008
Own share of d-screens	-1.422	0.113	-1.443	0.113	-1.699	0.118	-1.361	0.300
Market dummies								
Urban unit - <20k inhab and rural			0.102	0.139	0.104	0.140	-0.335	0.343
Urban unit - >100k inhab			0.024	0.073	0.009	0.071	-0.965	0.243
Paris - inner suburbs			-0.237	0.139	-0.064	0.140	-0.718	0.354
Paris - outer suburbs			-0.133	0.114	-0.000	0.060	-0.692	0.296
Paris			0.092	0.114	0.293	0.116	-0.568	0.308
Chain dummies								
Gaumont-Pathé					-0.146	0.079	0.211	0.254
CGR					0.309	0.093	-1.028	0.386
UGC					-0.891	0.129	-1.238	0.378
Interactions: own screens × other variables							X	
Observations	4,788		4,788		4,788		4,788	
- log Likelihood	2,222.981		2,220.041		2,182.751		2,150.577	
AIC	4,461.962		4,466.082		4,397.502		4,357.154	

Note: For market dummies, the omitted category is "urban unit with 20 to 100 thousands inhabitants." For the chain dummies, the omitted category is "single firm and small chains."

Table 6: 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.

Table 7: 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 6, but the reference group is miniplexes instead of all firms. The predicted rates are obtained by averaging 500 *simulation paths.*

Table 8: 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 6, but the reference group is multi/megaplexes instead of all firms. The predicted rates are obtained by averaging 500 *simulation paths.*

Table 9: Annual number of screenings as function of theater type

	Dependent variable: number of screenings		
	(1)	(2)	(3)
Own screens	2,285*** (102)	2,547*** (129)	2,570*** (130)
Paris - outer suburbs	1,206 (1,346)	2,645* (1,415)	2,747* (1,411)
Urban unit - ≤ 20k inhab and rural	469 (1,733)	960 (1,726)	1,114 (1,723)
Urban unit - ≥ 100k inhab	2,989*** (914)	4,253*** (983)	3,926*** (1,089)
Paris - inner suburbs	1,855 (1,575)	2,778* (1,581)	2,889* (1,577)
Paris	−1,512 (1,219)	−11 (1,315)	−456 (1,456)
Art house		2,986*** (1,008)	3,002*** (1,005)
Competitors' screens			48 (36)
Own screens × Paris - outer suburbs	33 (158)	−216 (173)	−237 (173)
Own screens × urban unit - ≤ 20k inhab and rural	83 (249)	−69 (250)	−97 (250)
Own screens × urban unit - ≥ 100k inhab	−268** (114)	−501*** (132)	−450*** (138)
Own screens × Paris - inner suburbs	−5 (167)	−217 (177)	−236 (176)
Own screens × Paris	797*** (156)	546*** (172)	609*** (179)
Own screens × art house		−520*** (154)	−531*** (154)
Own screens × competitors' screens			−8* (4)
Constant	−5,093*** (753)	−6,691*** (962)	−6,796*** (962)
Observations	399	399	399
R^2	0.909	0.911	0.912
Adjusted R^2	0.906	0.908	0.909
Residual Std. Error	2,726.2 (df = 387)	2,692.6 (df = 385)	2,683.9 (df = 383)
F Statistic	349.7*** (df = 11; 387)	304.3*** (df = 13; 385)	265.7 *** (df = 15; 383)

Note: ***$p < 0.01$;**$p < 0.05$; *$p < 0.1$. *For market dummies, the omitted category is "urban unit with 20 to 100 thousands inhabitants."*

Table 10: Structural parameter estimates (in 2010 euros)

	Estimate	s.e
Profits per movie screening: $\pi_f(\widetilde{\mathbf{x}}_{it})$		
Constant	12.274	1.885
Own screens	-0.043	0.057
Art house	-0.657	0.827
Competitors screens	-0.015	0.053
Competitors' d-screens	0.015	0.074
Market dummies		
Urban unit - >100k inhab	-0.340	0.840
Urban unit - <20k inhab and rural	0.166	1.275
Paris - inner suburbs	-0.923	0.833
Paris - outer suburbs	-0.629	0.865
Paris	-0.779	1.098
Chain dummies		
Gaumont-Pathé	-0.778	0.823
CGR	3.310	2.241
UGC	-2.295	0.909
Profits per digital movie screening:		
own share of d-screens	2.420	1.054
Adoption cost		
Firm shock: standard deviation σ	$2,995$	$1,441$

Note: Standard errors are calculated using $N_b = 600$ bootstrap samples.

Table 11: Introduction lag (in days) by firm size

	Equilibrium: $T^E_{4,m} - T^E_{S_i,m}$ intra and inter-firm margins			Counterfactual: $T^C_{4,m} - T^C_{S_i,m}$ inter-firm margin		
Firm size	Mean	5th	95th	Mean	5th	95th
$S_i = 8$	398.3	314.2	480.4	278.3	141.9	404.8
$S_i = 10$	468.0	383.9	557.8	294.3	146.3	416.8
$S_i = 12$	532.9	434.9	633.4	304.8	150.4	427.5

Note: Summary statistics of the introduction lag between the reference firm ($S_i = 4$) and larger firms, are presented. The introduction lags are computed by averaging 500 sample paths for each firm. The means of $T^E_{4,m}$ and $T^C_{4,m}$ correspond to March 2011 and September 2012 respectively.

Table 12: Introduction lag (in days) by number of firms

	Equilibrium: $T^E_{6,m} - T^E_{n_2,m}$ intra and inter-firm margins			Counterfactual: $T^C_{6,m} - T^C_{n_2,m}$ inter-firm margin		
Market	Mean	5th	95th	Mean	5th	95th
$n_2 = 3$	205.5	136.6	269.5	116.7	64.5	184.2
$n_2 = 2$	210.7	106.7	298.1	113.1	50.3	189.7
$n_2 = 1$	256.2	-14.7	528.2	78.5	5.0	160.8

Note: Summary statistics of the introduction lag between the reference market ($n_1 = 6$) and more concentrated markets, are presented. The introduction lags are computed by averaging 500 sample paths for each market. The means of $T^E_{6,m}$ and $T^C_{6,m}$ correspond to August 2009 and February 2012 respectively.

Figures

Figure 1: Distribution of theaters by size (number of screens)

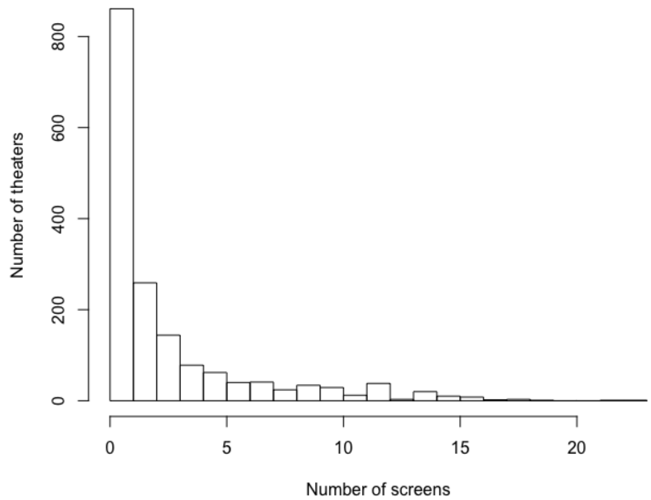


Figure 2: Observation times (vertical lines) for the diffusion of digital projectors

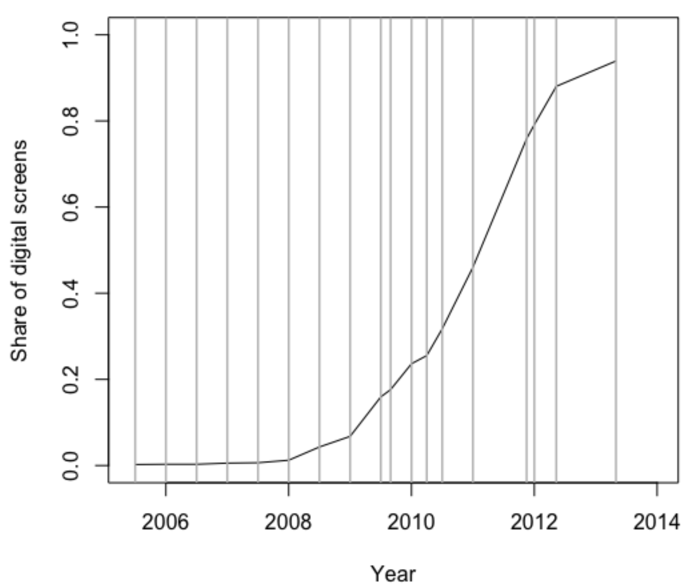


Figure 3: Hardware adoption cost

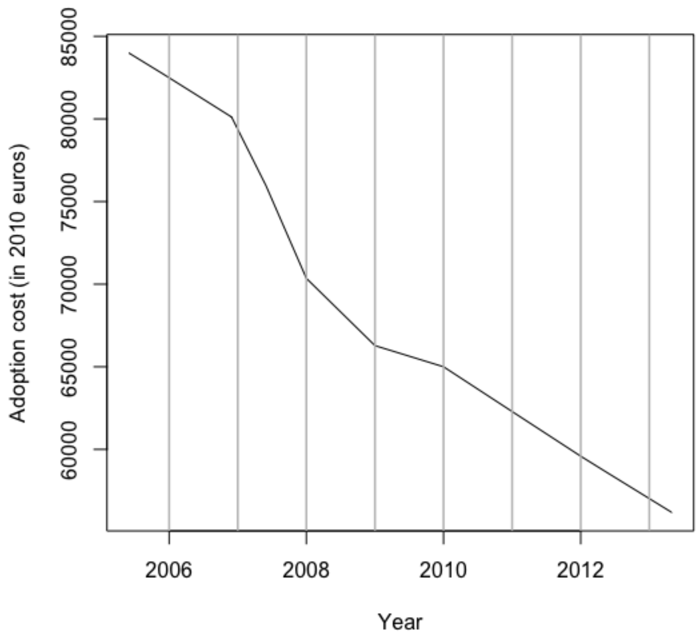
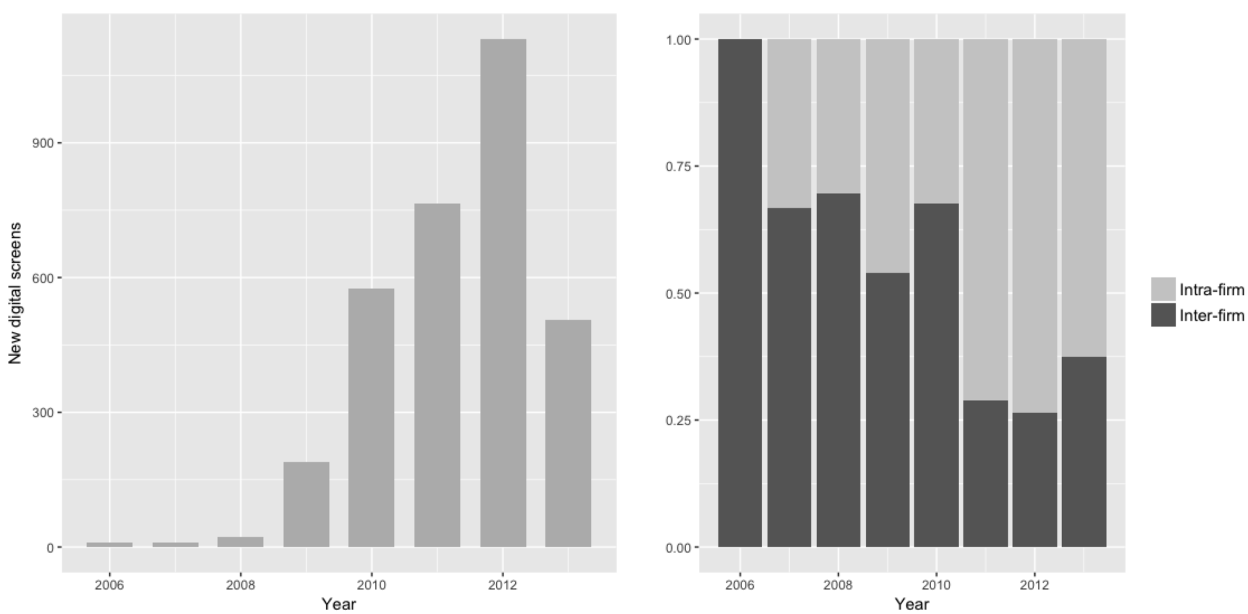


Figure 4



(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 5: Aggregate share of digital screens by theater size

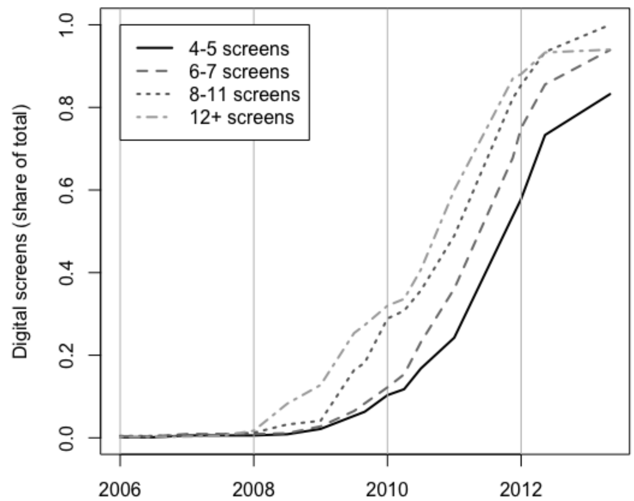
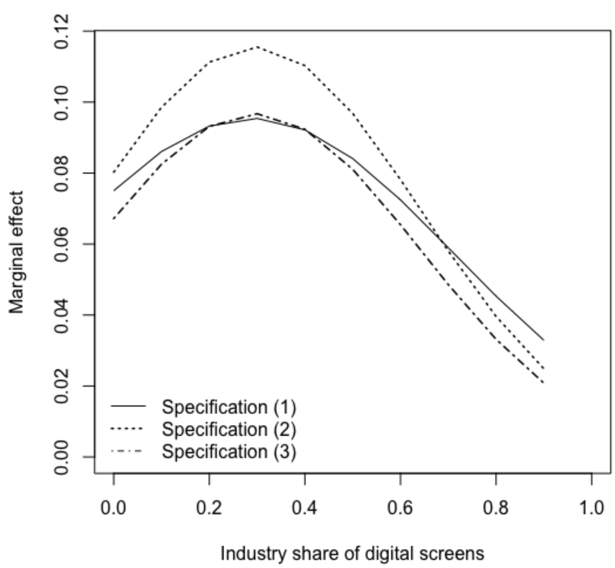
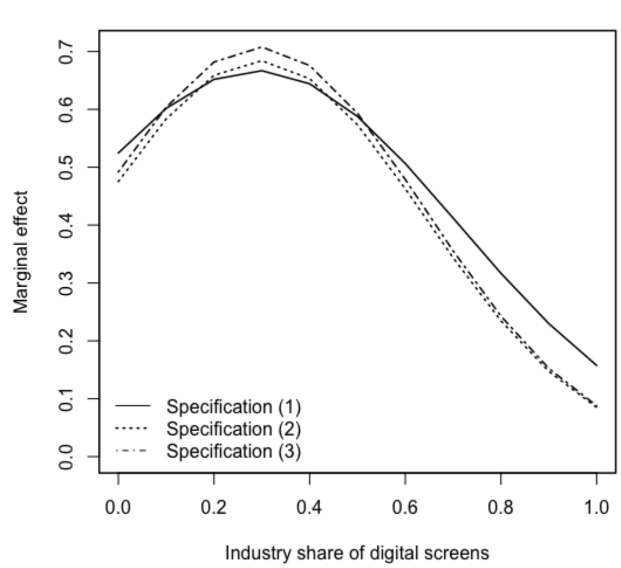


Figure 6: Effects of the industry share of digital screens and adoption cost on the probability of adoption



(a) Effect of an increase in the share of digital screens



(b) Effect of a decrease in the adoption cost

Notes: Panel (a) shows the effect of a 10% *increment in the industry share of digital screen, on the probability of adoption, evaluated at the mean, as a function of the initial industry share of digital screens. Panel (b) shows the effect of a one standard deviation decrease in the adoption cost on the probability of adoption evaluated at the mean as a function of the industry share of digital screens.*

Figure 7: Identification of $\pi_d(\widetilde{\mathbf{x}}_{it}) - \pi_f(\widetilde{\mathbf{x}}_{it})$

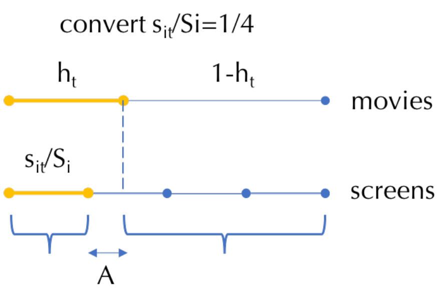
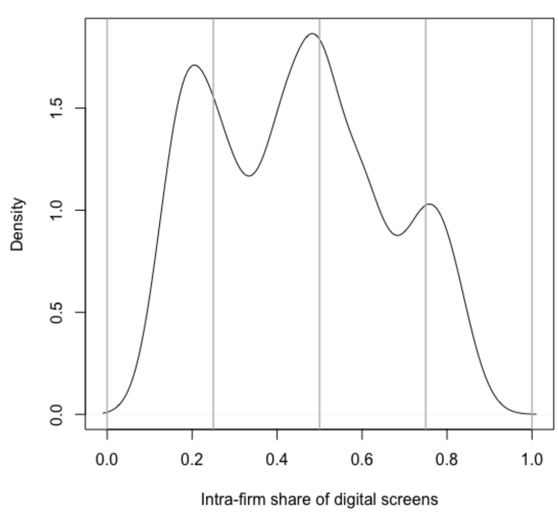
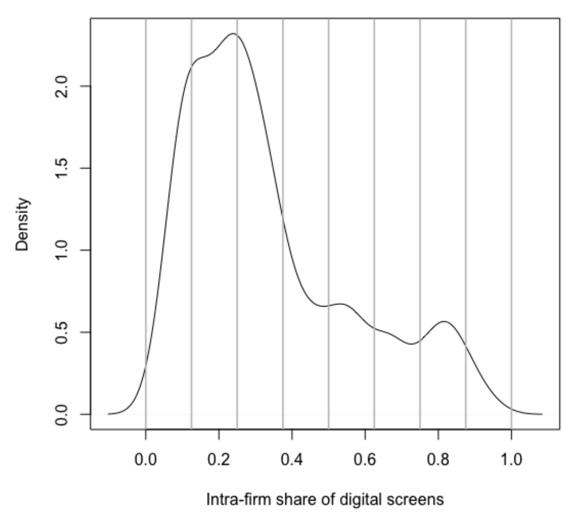


Figure 8: Density estimate of the intra-firm rate of adoption by firm size



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

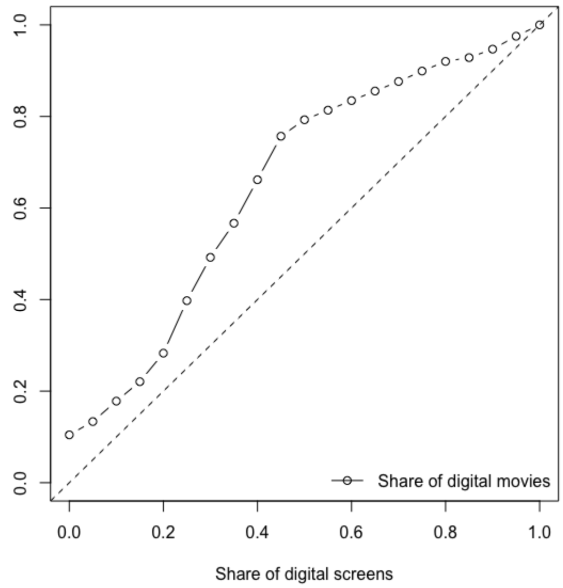


Figure 10: Predicted distribution of annual profits per screen (in euros) across theaters: (a) Before the diffusion of digital cinema, (b) after the diffusion of digital cinema

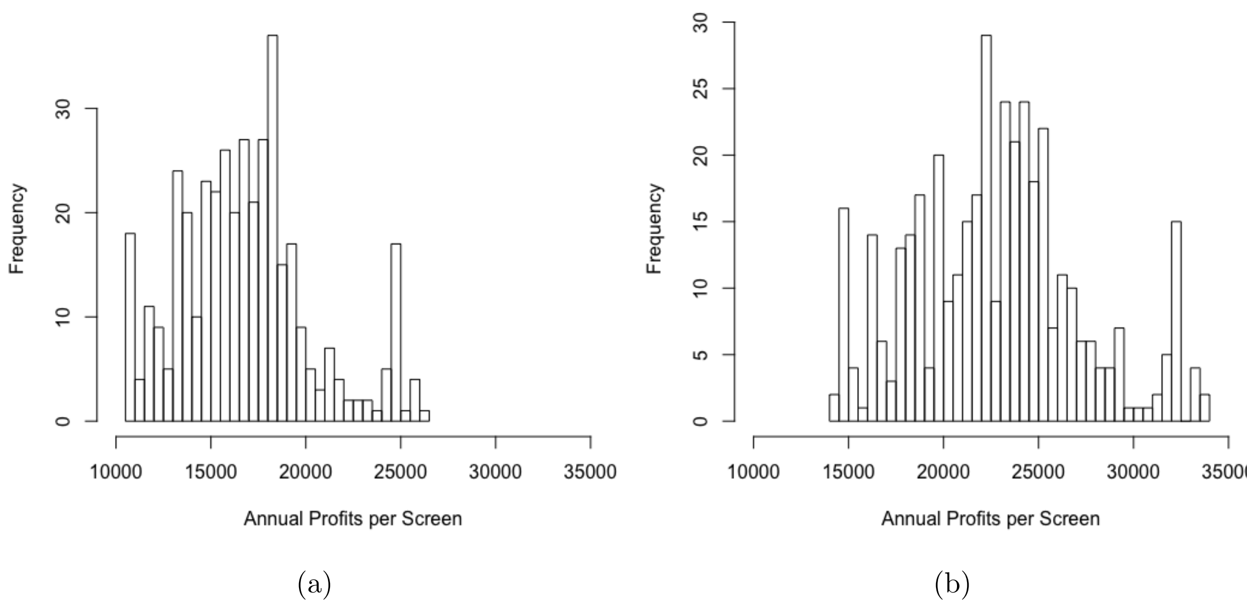
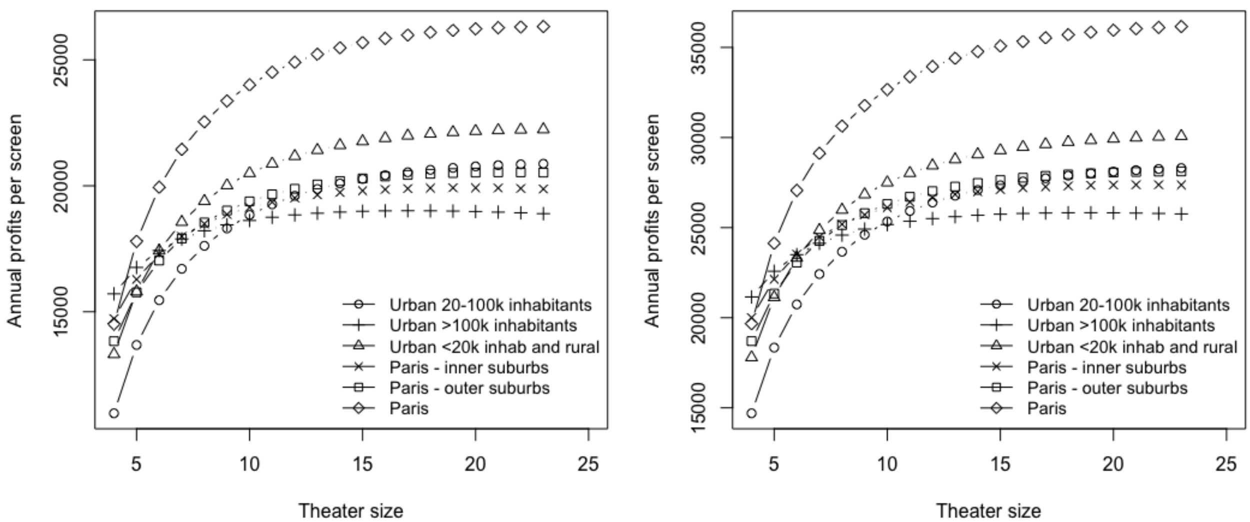


Figure 11: Predicted annual profits per screen as a function of firm size

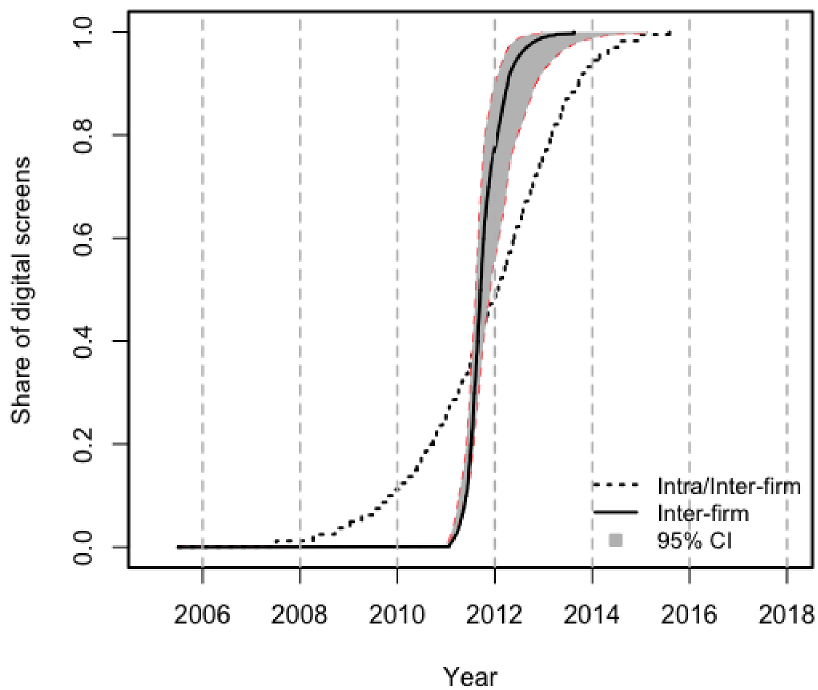


(a) Before the diffusion

(b) After the diffusion

Notes: Predicted profits are calculated fixing other characteristics to: monopolist, non art house theater, not horizontally integrated.

Figure 12: Aggregate adoption rate with and without the intra-firm adoption margin



Note: The diffusion curves are obtained by generating 500 *sample paths with a length of* 20 *years. The sample average of these paths are reported. The* 95% *confidence interval is obtained by using the structural parameters corresponding to* 5*th and* 95*th percentiles of the distribution of time to full adoption.*

A Data

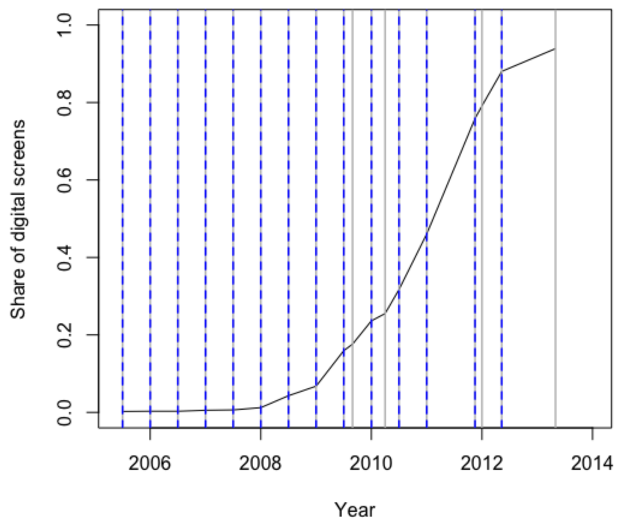
A.1 Panel of digital projector acquisitions

Table 13 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 13.

Table 13: 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	

Figure 13: Share of digitally equipped screens and observation times



B Reduced-form analysis

This section details the construction of the variable "share of digital screens" for the art house and commercial networks. Denote by p_i the share of art house movies screened by theater i in 2015. Recall that art house theaters are defined as theaters with $p_i \geq 0.8$, while commercial theaters are defined as theaters with $p_i \leq 0.2$. The share of art house digital screens in period t is defined by:

$$\frac{s_{t,a}}{S_a} = \frac{\sum_{i \in I} p_i s_{it}}{\sum_{i \in I} p_i S_i} \tag{20}$$

Similarly the share of commercial digital screens is defined by:

$$\frac{s_{t,c}}{S_c} = \frac{\sum_{i \in I} (1 - p_i) s_{it}}{\sum_{i \in I} (1 - p_i) S_i} \tag{21}$$

note that in both cases the share is computed with respect to the total number of art house (resp. commercial) screens, not the total number of screens. This is because the analysis focuses on specialized art house theaters ($p_i \geq 0.8$) and commercial theaters ($p_i \leq 0.2$).

Table 14 shows the reduced-form regression under the logit specification for the error term. The effect of a 10% increase in the industry share of digital screens in shown in Figure

14. The predicted magnitude of network effect is $10\% - 14\%$ at a 50% share of digital screens. The results are similar to the predictions under the probit specification.

Table 14: Share of screens converted s_{it}/S_i conditional on $s_{i(t-1)}/S_i = 0$ (ordered logit)

	Share of screens converted s_{it}/S_i conditional on $s_{i(t-1)} = 0$					
	(1)		(2)		(3)	
	Estimate	s.e	Estimate	s.e	Estimate	s.e
Industry share of d-screens	4.174	2.276	4.878	2.383	5.596	3.545
Adoption cost	-6.160	2.302	-6.437	2.361	-6.873	2.646
Own screens	0.142	0.107	0.170	0.110		
Seats	0.301	2.396	0.346	2.633		
Art house	0.133	0.257	0.130	0.273		
Competitor d-screens	0.024	0.019	0.024	0.020	0.029	0.024
Competitor f-screens	-0.007	0.008	-0.011	0.009	-0.008	0.010
Year FE	Yes		Yes		Yes	
Region FE	No		Yes		No	
market size FE	No		Yes		No	
Chain FE	No		Yes		No	
Box-office FE	No		Yes		No	
Theater RE	No		No		Yes	
Observations	$1,563$		$1,563$		$1,562$	
-log Likelihood	392.490		373.389		385.241	
AIC	818.980		804.777		800.482	

*Note: *** 0.1% ; * 10%. D-screen = screen equipped with a digital projector. f-screen = screens equipped with a film projector. For market dummies, the omitted category is " urban unit - 20 to 100k inhabitants". For the chain dummies, the omitted category is "single firm and small chains".*

C Industry Model

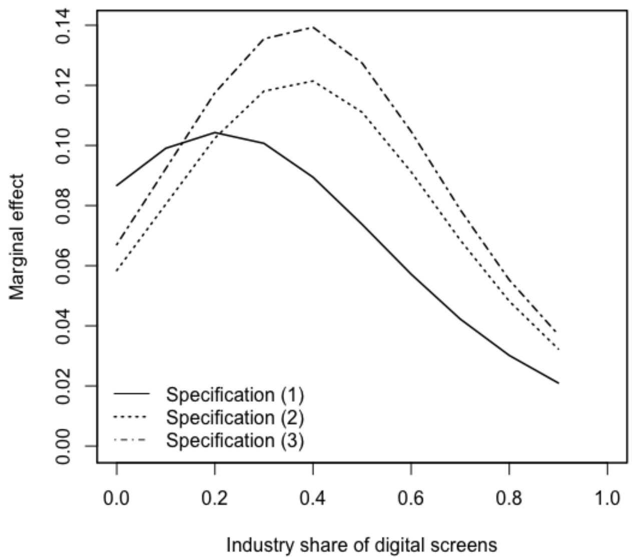
C.1 Perceived transition kernel

Let $\widehat{\mathbf{P}}_{a',a}$ be defined as follows (where the subscript t is omitted and next-period variables are marked with a prime):

$$\widehat{\mathbf{P}}_{a',a}(\widetilde{\mathbf{x}}'_i, p', s'|\widetilde{\mathbf{x}}_i, p, s) = \widehat{\mathbf{P}}_{a',a}(\widetilde{\mathbf{x}}'_i, p'|\widetilde{\mathbf{x}}_i, p, s)\widehat{\mathbf{P}}_{a,a}(s'|p, s) \tag{22}$$

The first sub-kernel $\widehat{\mathbf{P}}_{a',a}(\widetilde{\mathbf{x}}'_i, p'|\widetilde{\mathbf{x}}_i, p, s)$ gives firm i's assessment of its next-period state

Figure 14: Effects of the industry share of digital screens and adoption cost on the probability of adoption



Note: The effect of a 10% *increment in the industry share of digital screen, on the probability of adoption, evaluated at the mean, as a function of the initial industry share of digital screens is represented.*

(including competitors' total number of digital screens) and the exogenous price process. The second sub-kernel $\widehat{\mathbf{P}}_{a,a}(s'|p,s)$ gives firm i's assessment of next-period industry moment. Note this definition of the perceived kernel $\widehat{\mathbf{P}}_{a',a}(\widetilde{\mathbf{x}}_i', p', s'|\widetilde{\mathbf{x}}_i, p, s)$ implicitly assumes that firm i ignores its own impact on the evolution of the industry moment: $\widetilde{\mathbf{x}}_i'$ and s' are independent conditional on $(\widetilde{\mathbf{x}}_i, p, s)$. This assumption is realistic if the number of firms is very large, and therefore a single firm has a negligible impact on the aggregate industry state (and corresponding moment).

The perceived transition kernel for the moment s, $\widehat{\mathbf{P}}_{a,a}(s'|p,s)$, is first defined. The analysis focuses on short-run dynamics (i.e., the diffusion phenomenon) rather than the (adoption) steady state reached by the industry. The perceived kernel is meant to capture the short-run dynamics of the industry moment starting from the initial industry state $(\mathbf{y}_0, p_0)$. It is defined to coincide with the average observed transitions from the current moment-based state (s,p) to the next, the average being taken over many finite and short trajectories that start from the initial state of the industry. The perceived kernel corresponds to the observed frequencies of these transitions under adoption strategy a. Following Ifrach and Weintraub (2017) (Appendix A), $\widehat{\mathbf{P}}_{a,a}(s'|p,s)$ is defined as follows:

$$\widehat{\mathbf{P}}_{a,a}(s'|p,s) = \frac{1}{L}\sum_{l=1}^{L}\frac{\sum_{t=1}^{T}\mathbf{1}\{(p_t^l,s_t^l)=(p,s),s_{t+1}^l=s'\}}{\sum_{t=1}^{T}\mathbf{1}\{(p_t^l,s_t^l)=(p,s)\}} \tag{23}$$

where T is fixed to the time horizon of interest (in this case, 20 years covering the diffusion duration, or 40 periods), and $\{(p_t^l,s_t^l),T\geq t\geq 0)\}_{l=0}^{L}$ is a random sample of size L drawn from the distribution of the process $\{(p_t,s_t),t\geq 0)\}$ generated by the adoption strategy a, and initiated at the true initial industry state and exogeneous price $(\mathbf{y}_0,p_0)$.

The sub-kernel $\widehat{\mathbf{P}}_{a',a}(\widetilde{\mathbf{x}}_i',p'|\widetilde{\mathbf{x}}_i,p,s)$ can be further expressed as

$$\widehat{\mathbf{P}}_{a',a}(\widetilde{\mathbf{x}}_i',p'|\widetilde{\mathbf{x}}_i,p,s) = \mathbf{P}_{a',a}(\boldsymbol{\tau}_i,s_i'|\widetilde{\mathbf{x}}_i,p,s)\widehat{\mathbf{P}}_{a',a}(z_i'|\widetilde{\mathbf{x}}_i,p,s)\mathbf{P}(p'|p) \tag{24}$$

where $\mathbf{P}_{a',a}(\boldsymbol{\tau}_i,s_i'|\widetilde{\mathbf{x}}_i,p,s)$ is firm i's assessment of its next-period state, $\widehat{\mathbf{P}}_{a',a}(z_i'|\widetilde{\mathbf{x}}_i,p,s)$ is firm i's assessment of competitors' next-period digital screens, and $\mathbf{P}(p'|p)$ is the exogenous hardware price process. Equation (24) makes explicit three elements: (1) because firms use moment-based strategies, firm i's assessment of its next-period state is correct (so $(\widetilde{\mathbf{x}}_i,p,s)$ is sufficient to determine the transition probabilities of s_i, given the strategy profile (a',a)); (2) competitors' aggregate state (total number of digital screens) is approximated because only the first moment is tracked (3) the hardware price process is exogenous. The perceived kernel for competitors' next-period number of digital screens is defined similarly to the industry moment sub-kernel, to coincide with the average observed transitions over many finite and short trajectories starting from the initial industry state $(\mathbf{y}_0,p_0)$:

$$\widehat{\mathbf{P}}_{a',a}(z_i'|\widetilde{\mathbf{x}}_i,p,s) = \frac{1}{L}\sum_{l=1}^{L}\frac{\sum_{t=1}^{T}\mathbf{1}\{(z_i^l)=z_i',(\widetilde{\mathbf{x}}_i^l,p^l,s^l)=(\widetilde{\mathbf{x}}_i,p,s)\}}{\sum_{t=1}^{T}\mathbf{1}\{(\widetilde{\mathbf{x}}_i^l,p^l,s^l)=(\widetilde{\mathbf{x}}_i,p,s)\}} \tag{25}$$

where T is defined as in equation (23), and $\{(z_{it}^l,p_t^l,s_t^l,\widetilde{\mathbf{x}}_{it}^l),T\geq t\geq 0)\}_{l=0}^{L}$ is a random sample of size L drawn from the distribution of the process $\{(z_{it},p_t,s_t,\widetilde{\mathbf{x}}_{it}),t\geq 0)\}$ generated by the adoption strategies (a',a) and initiated at the true initial industry state and exogenous price $(\mathbf{y}_0,p_0)$.

Equations (23) and (25) are used to define the perceived kernel for all states *visited* over the L simulation runs. The perceived kernels are defined arbitrarily outside this set. In particular, for non-visited states, the paper uses "status-quo" perceptions, as in Ifrach and Weintraub (2017), assuming the current state of the variable remains the same in the next period.

C.2 Multi-homing

This appendix presents the estimation and counterfactual results under the "wide multi-homing" assumption. This assumption stands as the polar case to the "no multi-homing" assumption detailed in the main text. Setting $h_t^d = 0$ for all t, and defining $h_t \equiv h_t^m$ (so that $1 - h_t = h_t^f$), the single-period operating profits under "wide multi-homing" are given by:

$$\pi(\widetilde{\mathbf{x}}_{it}, h_t) = R(\boldsymbol{\tau}_i) \times \begin{cases} \frac{s_{it}}{S_i}\pi_d(\widetilde{\mathbf{x}}_{it}) + (1 - \frac{s_{it}}{S_i})\pi_f(\widetilde{\mathbf{x}}_{it}) & \text{if} \quad \frac{s_{it}}{S_i} \leq h_t \\ h_t\pi_d(\widetilde{\mathbf{x}}_{it}) + (1 - \frac{s_{it}}{S_i})\pi_f(\widetilde{\mathbf{x}}_{it}) & \text{if} \quad \frac{s_{it}}{S_i} \geq h_t \end{cases} \tag{26}$$

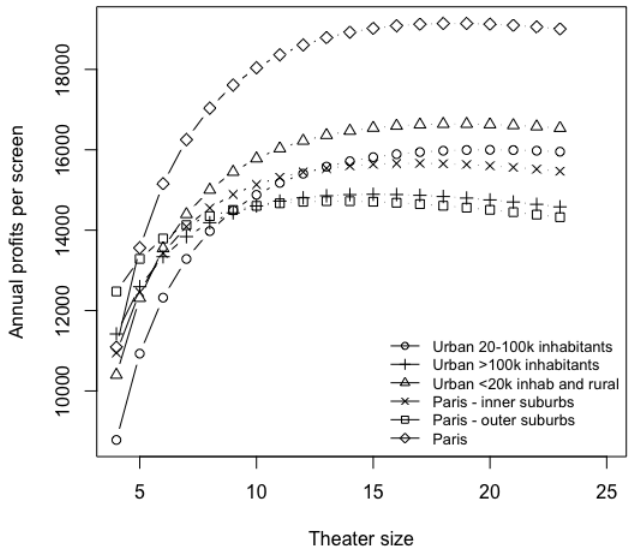
Under "wide multi-homing", theaters adopt the digital projection technology solely for cost-reduction purposes. Therefore, only the difference between profits from a digital and a film screening $(\pi_d(\widetilde{\mathbf{x}}_{it}) - \pi_f(\widetilde{\mathbf{x}}_{it}))$ can be identified from theaters' adoption times and units of technology adopted. Profits per film screening $\pi_f(\widetilde{\mathbf{x}}_{it})$ are normalized to zero.

The model predicts profits per screen $\pi_d(\widetilde{\mathbf{x}}_{it})/S_i$ (or equivalently cost-reductions per screen) between €7,917 and €19,890. Figure 15 shows predicted profits per screen as a function of theater size and market size. Profits per screen are increasing in theater size, with a decreasing marginal effect. As in the "no multi-homing" case, estimates point to the presence of economies of scale in operation. The counterfactual exercise of section 8.1 is conducted using the estimated model. Figure 16 presents the diffusion paths under the equilibrium played in the data and the counterfactual best-response (with no intra-firm margin). The qualitative results are similar to the ones obtained under "no multi-homing". The results are robust to the multi-homing assumption imposed because they are driven by heterogeneity in profits across theaters (which stem from differences in adoption times and units adopted across theaters), not by the absolute level of profits. The assumption on h_t only affects the absolute level of profits.

D Estimation: Adoption policy rule (1st step)

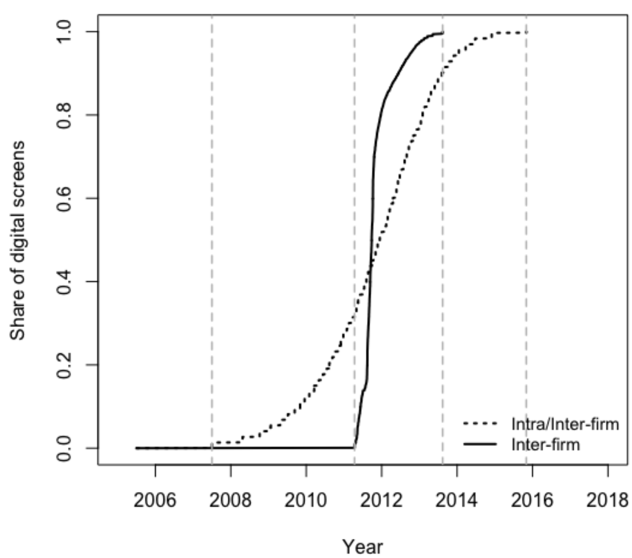
First step estimates for the adoption policy rule are obtained by estimating an ordered probit model. Denote by P_{ij} the probability that theater i transitions to state j. Possible states are $\{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\}$ in the case of miniplexes $(4-7$ screens), and $\{0, \frac{1}{8}, \frac{2}{8}, ..., \frac{7}{8}, 1\}$ 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 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:

Figure 15: Predicted annual profits per screen as a function of firm size



Note: Predicted profits are calculated fixing other characteristics to: monopolist, non art house theater, not horizontally integrated

Figure 16: Aggregate adoption rate with and without the intra-firm adoption margin



Note: The diffusion curves are obtained by generating 500 *sample paths with a length of* 20 *years. The sample average of these paths are reported.*

$$lnL = \sum_{i:4 \leq S_i < 8} \sum_{j=s_{i(t-1)}/S_i}^{1} d_{ij} lnP_{ij} + \sum_{i:8 \leq S_i} \sum_{j=s_{i(t-1)}/S_i}^{1} d_{ij} lnP_{ij} \tag{27}$$

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