Pro-competitive Bundling Under Credit Frictions
A Story From Indian Cinema[1]

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Abstract:

I document a novel mechanism thorugh which bundling can facilitate entry in markets with information and credit frictions, and measure the extent of procompetitive effects in the Indian movie exhibition industry. In industries characterized by small firms needing a durable input and a consumable to produce, volatile operating profits, credit frictions, and the provider of the consumable being able to observe a portion of operating profits, a bundle of a durable good lease and the metering good / service solves allows implementing a profit share. This eliminates the need for small downstream firms to borrow at high rates and shifts the burden of financing the durable good to large upstream firms facing lower interest rates. Small independent cinemas in India often opt for a bundle containing a lease of digital projection equipment and in-cinema advertising distribution services. I estimate a structural model of cinemas' choice between this bundle that involves no borrowing and other choices that involve borrowing to back out interest rates that best rationalize observed choices. Cinemas predicted to opt for the bundle face interest rates on average 11.30 percentage points higher than large established cinema equipment providers. I simulate counterfactual polices where the bundle is no longer available. When only an outright purchase option is available, 71.56% of cinemas predicted to opt for the bundle become unviable. When an unbundled lease with a fixed monthly fee is available, 55.88% remain unviable.

[1] The data used in this paper were obtained from UFO Moviez pursuant to an antitrust case where I submitted evidence on UFO Moviez's behalf.

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1 Introduction

Bundling – the selling of several goods or services in one package – often invites antitrust scrutiny. Bundling is usually evaluated under the Rule of Reason, where anticompetive effects are weighed against procompetitive effects. The economic literature has, over the years, considered several procompetitive and anticompetitive motivations for bundling.

Anticompetitive theories of bundling usually involve multiproduct firms leveraging market power in one market into another market by bundling their products together. This theory fell out of favour when the Chicago-school single-monopoly-profit theorem held sway. This theorem argued that a monopolist could extract its profits only once, and could not increase its profits by tying. However, it was eventually realized that the single-monopoly-profit theorem rested on unrealistic assumptions, and starting with Aghion and Bolton (1987), a growing literature has provided rigorous grounding for the leveraging theory.[1] Recent work by Zhou (2017) showed that bundling can reduce consumer welfare through relaxing competition and raising prices.[2]

This paper, however, is concerned with procompetitive bundling. There are two strands of this literature. The newer strand emphasizes cost savings from joint production, as in Bakos and Brynjolfsson (1999), and Evans and Salinger (2005). The older and mostly dormant strand emphasizes that bundling can be used as a price discrimination device, which can in turn lead to market expansion. A series of papers following Stigler (1968) emphasized that bundling can increase profits and may increase consumer welfare when consumer valuations are negatively correlated across different products[3] , while others following Bowman (1957) emphasized that when durable goods require after-market consumables bundling the consumables with the durable good effectively acted as a meter allowing the inference of demand for the durable good[4] .

I document a novel procompetitive mechanism of which bundling is a key component that facilitates demand expansion through reducing entry costs. Consider a scenario where a small firm needs a durable good input and at least one consumable to begin production; the supplier of the consumable can observe a significant part of the small firm's operating profits;[5] the firm's operating profits are highly volatile; the durable good is relatively expensive; the firm must finance the up-front purchase through borrowing; and the environment is characterized by credit frictions (small firms access credit at higher interest rates than large firms for the same project). In this scenario, forcing a small firm to purchase the durable good outright would lead to a high borrowing burden, and may deter entry. Even if, following the trade credit literature,[6] the

[1] Aghion and Bolton (1987) did not explicitly consider bundling, instead showing how an incumbent could profitably deter entry through long term contracts under incomplete information. However, long term contracts may be thought of as bundling sales in different periods, and the paper's main insght became one of the mainstays of future work on anticompetitive bundling, including Whinston (1990), Carlton and Waldman (2002), Nalebuff (2004), and Choi and Stefanadis (2001).

[2] Previous work by Matutes and Regibeau (1988), Nalebuff (2000), Armstrong and Vickers (2010) and others argued that this was not usually a concern.

[3] Other important contributions in this strand include Adams and Yellen (1976), Bakos and Brynjolfsson (1999), McAfee et al. (1989), and Schmalensee (1984).

[4] Other important contributions in this strand include Burstein (1960), Oi (1971), and Telser (1979).

[5] This may happen if there is a known relationship between the quantity of the consumables used and the output produced, and production technology is known so that costs are easily estimable.

[6] This literature (Cunat, 2007; Wu et al., 2014) documents that upstream suppliers allowing deffered payments is an imporant source of borrowing for many downstream firms. Trade credit may arise because firms in a business relationship have more information about each other than financial institutions. The procompetitive mechanism I study relies on trade credit, but also

durable good provider were to offer a fixed fee lease and assume the burden of borrowing to finance the cost of the durable good (at lower interest rates than the small firm), the volatility of operating profits downstream may require further borrowing to be able to pay the fixed fee in some periods. By bundling the durable good lease and the consumable, the upstream firm can observe at least some operating profits and fashion the charge as a profit share, reducing or eliminating the borrowing burden downstream. By reducing the inefficiency caused by credit frictions, this arrangement reduces costs. Combined with price discrimination, this increases entry. Bundles of durable input leases and consumables exist in a broad range of industries, including fast food and restaurant franchising, car rental franchising, gym and fitness franchising, automotive service franchising, agriculture, fishing, construction, film production, and renewable energy.

I use data from the Indian movie exhibition industry to estimate the extent of market expansion this mechanism can generate. Accordingly, this paper is also related to the recent empirical literature measuring efficiencies from bundling.[7] and that studying digitization in movie exhibition.[8] As a developing country, India is characterized by considerable credit frictions. The movie exhibition industry in India is fragmented, with the majority of screens being indpendently owned (non-chain). Cinemas also face extremely volatile operating profits. After the switch from analog to digital projection in the early 2010s, cinemas needed Digital Cinema Equipment (DCE), including expensive digital projectors and servers, which need to be imported from the US, in order to operate. While in the West, most cinemas buy their DCE outright, it is common in India for DCE providers to offer independent and smaller chain cinemas a bundle containing a DCE lease and in-cinema advertising services, where the provider operates an ad platform that sells on-screen advertising slots before a movie starts. This bundle's fee structure is sensitive to the screen's operating profits, and eliminates the cinemas' borrowing burden. DCE providers also provide standalone access to their advertising platforms, but do not provide standalone leases.

I build a simple discrete choice structural model of cinemas' choice between three alternatives – opt for the bundle (option B), buy DCE outright and access in-cinema ad services separately from a third party (option A), or do not enter / exit (option O) – to estimate the borrowing costs that would rationalize observed choices. I construct ex-ante expected profits for each option as a function of borrowing costs. A structural model of revenue allows me to construct expected revenues from incomplete observed revenues. Borrowing costs are identified by differential choices between options A and B by cinemas of different sizes, and the fact that all cinemas in my sample entered. My estimates imply that borrowing costs fall with firm size. Further, the smallest cinemas face borrowing rates up to 15 percentage points higher than minimum long term lending rates, which agrees with industry participants' estimates.

I then simulate two counterfactuals. The first counterfactual attempts to measure the extent of the market expansion effect by asking what would happen if all cinemas who opted for the bundle were forced to buy their DCE instead. To do this, using the estimated borrowing rates, I back out operating costs and

requires metering through bundling to give it full effect.

[7] Important contributions include Ho et al. (2012), Crawford and Cullen (2007), Crawford and Yurukoglu (2012), and Crawford et al. (2018).

[8] Caoui (2023) studied how network effects slowed the shift from analog to digital projection in French cinemas.

construct expected profits for these cinemas from option A. I find that 71.56% of the screens which my model predicts as currently opting for the bundle would be rendered unviable. The second counterfactual attempts to measure how much of this effect may be attributed to trade credit and how much to the bundling's metering function. In this counterfactual, I impose unbundling on DCE providers, so that they would be forced to offer a fixed montly fee lease in addition to outright sale, but not a bundle. I assume that cinemas would have to borrow to make up any shortfall whenever the monthly rent is due, and calculate expected profits. This requires simulating revenue paths, which I do using a Markov assumption on observed revenue errors. I find that 55.88% of screens which my model predicts as currently opting for the bundle would remain unviable, indicating that the bundling is key to unlocking efficiency gains. Applying this percentage to all screens, 33.06% of India's screens would be rendered unviable. However, there is significant geographical variation.

Since unbundling is a common remedy imposed by competition authorities, this paper illustrates the dangers of ignoring interactions with market imperfections like credit frictions when evaluating the competitive effects of bundling. More widely, it illustrates how novel business models can develop in an effort to counteract inefficiencies created by market frictions.

2 A Novel Procompetitive Mechanism

Consider a market which satisfies the following conditions. First, firms require a relatively large up-front investment to start operations. This may involve capital goods, or investment in brand-building, for example. The investment needs to be large enough relative to other costs and revenue so as to factor into economic decision making, including regarding entry and exit. Firms also cannot self-finance, and must turn to credit markets. Second, credit frictions exist resulting in small firms facing higher borrowing costs than large firms for the same project.[9] Third, the investment good or service is provided by a provider (or combination of providers) who is larger than at least some firms. Fourth, downstream operating profits are volatile. Fifth, there are information frictions – operating profits are ordinarily unobservable to third parties (or monitoring would be costly). Sixth, there exists a consumable good or service which, when provided to downstream firms, allows the provider to observe or reasonably accurately estimate enough of the operating profit.[10] This may happen in the case of a consumable input that converts into output in (known) fixed proportions with a known cost structure. Alternatively, it may happen with distribution services where marginal costs of production are easily estimable.

Consider first the inefficiency inherent in such a market from the perspective of small firms. They must borrow to finance the up-front investment at higher rates than available to larger established firms, and in some cases borrowing costs may be too large to make the firm viable where it would have been had the firm

[9] I discuss possible reasons for such credit frictions in Section 3 below.

[10] This is similar to the set-up in the metering literature, where the provision of the consumable allows the observation of demand for the durable good.

had access to lower rates. The inefficiency is driven by credit frictions.

Consider now a scenario where, following the trade credit literature, the upstream provider of the investment good or service offers the option to lease in an effort to reduce the borrowing burden of downstream firms. The upstream provider must now finance the cost of the investment, but at lower rates than those available to smaller downstream firms, potentially reducing inefficiencies arising from credit frictions. However, the information friction still applies, and the upstream firm cannot tailor its charge according to downstream firms' operating profits. Consider what happens when it charges a fixed per-period fee. Since operating profits are volatile, it is possible that accumulated operating profits in some periods may not be enough to cover the fee due, requiring short-term borrowing. This may lead to a more inefficient outcome than the base case – even though the investment good or service is financed at lower rates, downstream firms may need additional financing, and the total interest burden between upstream and downstream firms might be higher.

Consider now a scenario where the upstream provdier of the investment good or service bundles a lease with the good or service which allows it to observe at least some part of downstream operating profits. The borrowing burden for downstream firms can now be eliminated by tailoring the charge for the bundle as a profit share. This leads to two potential procompetitive efficiencies – first, entry may increase because the upstream firm can now price discriminate; and second, shifting the borrowing burden from firms which face high borrowing costs to those which face low borrowing costs. The second efficiency arises even when upstream firms do not have market power and increases entry through reduced borrowing costs.

This mechanism applies regardless of the reasons for the interest rate differential across firms of different sizes for the same project. The standard theoretical explanation for differential interest rates is different risk profiles. In this case, the upstream investment good or service provider being able to access credit at lower interest rates for the same project may be indicative of it performing a risk pooling function. The consequent efficiency gain is then reducing default risk. Section 3.1 details frictions other than differing risk profiles that might increase interest rates for small firms. If these reasons are more prevalent, then the consequent efficienty gain is reducing frictions.

Bundles of equipment leases and consumables exist in a wide range of industries that satisfy the conditions for this mechanism to operate. Fast food and restaurant franchisors often provide franchisees bundles containing machine leases, maintenance contracts, point of service systems, and consumables. Car rental franchisors often provide franchisees bundles containing vehicle leasing, servicing contracts, insurance, and fleet tracking systems. Gym and fitness franchors often provide franchisees bundles containing gym equipment leases, servicing contracts, and member management systems. Automotive servicing franchisors often provide franchisees bundles of equipment leases, and consumables like oils, parts, and tyres. Farming equipment manufacturers often bundle farm equipment leases with consumables like seeds, fertilizers, and pesticides. Fishing vessel manufacturers often bundle vessel and equipment leases with servicing contracts, licences and quotas, market access, sales support and consumables like fuel, bait and ice. Construction equipment manufacturers often bundle equipment leases with insurance coverage, fuel, and consumables like oils and filters. Film equipment producers often bundle camera and lighting equipment leases with studio and set rental, distribution, and marketing support. Solar panel manufacturers often offer a lease bundled with energy storage and monitoring equipment. Sections 3 and 4 show why the mechanism applies to this paper's empirical application.

3 Institutional Background

This paper's empirical application is situated in the Indian movie exhibition industry. A large portion of India's screens are independently owned and not a part of large cinema chains. DCE (projectors and servers) is more expensive than the old analog equipment, and small cinemas operate in a climate of significant credit frictions. DCE providers offer outright purchase, or a bundle containing a DCE lease and in-cinema advertising services (i.e. they sell in-cinema advertising slots).[11] In this section, I first describe credit frictions in India, then offer background on the Indian movie exhibition industry and the unique business model followed by UFO Moviez and its competitors.

3.1 Credit Frictions in India

Micro, Small and Medium Enterprises (MSMEs) face higher borrowing rates than large firms. The standard explanation is that small firms being riskier.

However, a wealth of literature documents MSMEs face extra difficulties because they are less diversified, have weaker financial structures, and find it difficult to provide high-quality collateral or ensure transparency with respect to their creditworthiness.[12] The constraints are stronger in developing economies, as the market imperfections that create them are exacerbated.[13] These constraints may lead to higher interest rates from the formal credit sector, or the inability to secure loans from the formal sector and the consequent pursuit of loans from informal sources at even higher rates.

There is evidence of a large credit gap in India, where market imperfections prevent the formal credit sector from fulfiling viable demand from MSMEs. Banerjee and Duflo (2014) took advantage of two policy changes which made some small Indian firms temporarily eligible for priority lending to study the marginal return to credit for these firms. They found a gross marginal rate of return of 89% (not accounting for interest payments). That these firms could not borrow from non-bank sources which offered credit at between 30% and 60% to comparable firms at the time signals the presence of credit constraints. Tandon et al. (2019) estimated that in 2017 (in the middle of period this paper's data are from), India's MSME sector[14] accessed

[11] This would characterize the situation as one of tying – a special case of bundling where consumers must purchase one product (in this case in-cinema advertising services) in order to access another (DCE). However, tying is a special case of bundling, so I use the latter term throughout the paper to avoid confusion.

[12] Beck (2013); Rahaman (2011); and Nguyen et al. (2019).

[13] Kuntchev et al. (2013); Schiffer and Weder (2001); and Bouri et al. (2011).

[14] Up to 2020, the Indian government defined MSMEs based on thier investment equipment. In the services sector the thresholds were up to INR 1 mn for micro enterprises, INR 1-20 mn for small enterprises, and INR 20-50 mn for medium enterprises.

INR 69.3 tn (USD 1.1 tn) of credit, of which only INR 10.9 tn (USD 168 bn; 16%) came from formal sources. Of the remainder, which was served by sources like family, friends and informal sector moneylenders, they estimated that the formal sector could have viably financed INR 25.8 tn (USD 397 bn), 91% of which would have gone to micro and small enterprises.

There are several factors behind MSMEs in India having difficulty accessing formal credit (Tandon et al., 2019, Ch 3). Small Indian businesses often cannot meet stringent documentation protocols to qualify as loan applicants. Indian businesses are also notorious for discrepencies between reported financial data and reality. Before the recent shift to digital payments and the new GST regime, cash payments were the norm, and there were incentives to not record or to understate the volume of cash transactions to evade tax. Some small businesses also lack the manpower and expertise to accurately account for a large number of small offline transactions. Small business owners also find it hard to put up adequate immovable collateral that meet the stringent criteria required by formal institutions. Their reliance on informal loans means that credit bureaus cannot evaluate their creditworthiness. On the supply side too, institutions face higher transactions costs and lower loan sizes for MSME loans. Recovering unpaid loans is especially cumbersome. In 2020-22, India had only about 1.5 judges per 100,000 people, compared to the EU average of 18, leading to a massive backlog of cases that can take decades to resolve. Banks also have limited operations especially outside the large metropolitan areas, and do not have the expertise to adequately assess, understand and appraise MSME businesses. Indian credit evaluation standards also place too much emphasis on collateral and not enough on the ability to repay a loan.

Thus, many MSMEs are forced to access credit through informal sources like moneylenders. Limited available evidence points to moneylenders charging much higher annual rates than the formal sector, even upwards of 100%.[15]

3.2 The Indian Movie Exhibition Industry

Between 2016 and 2020, India averaged around 9,500 cinema screens. While the share of multiplexes has been increasing, the vast majority of screens in India are single screens, numbering 7,031 in 2016 and 6,327 in 2020. Moreover, the vast majority of screens are independently owned and not part of corporate chains. India's biggest chain, PVR-INOX, owned 1,424 screens in 2019, followed by Carnival Cinemas (450), Cinepolis India (381) and Miraj (125). Chain cinemas are concentrated in metropolitan areas. Outside of large metropolitan areas, the landscape is thus fractured with a heavy representation from small businesses.

Cinemas in India raise revenue through several streams. The most important is box office revenue, typically accounting for about 45% of gross revenues. Of gross ticket receipts, 12-18% is tax, and a substantial portion goes to distributors under revenue sharing agreements. Food and beverage sales are also substantial, also typically contributing 40-45% to gross revenues. A third source is in-cinema advertising – advertisements

[15] See for instance, Hoffmann et al. (2021) and Reserve Bank of India (2004). Most studies look at lending to households, which involve much smaller ticket sizes. I expect rates to be even higher for the ticket sizes required to invest in expensive capital goods like in this paper's application.

shown on screen before a movie plays – typically contributing about 5% to gross revenues. A fourth important and unique source is Virtual Print Fee (VPF), explained below, also typically contributing about 5% to gross revenues. Other revenues, including from physical advertising space and parking fees, are negligible.

The empirical application in this paper uses data from 2016 to 2020, and captures decisions made from 2013 onwards. This period coincides with the shift from analog to digital projection in India, which began in 2008-09 but gathered steam in the 2010s. Digital projection was initially adopted by the lare multiplex chains, and only later by independently owned and single screen cinemas, implying that most of the data used in this study (which focuses mostly on non-chain cinemas) represent the first time cinemas adopted digital projection. The first digital projectors were compliant with standards set by the Digital Cinema Initiative (DCI), a joint project of US-based motion picture studios[16] to develop standards for digital cinema, and needed to be imported from the US (since only US-based producers were licenced to produce DCI-compliant projectors). Hollywood movies can only be projected on DCI-compliant projectors. Subsequently, cheaper non-DCI equipment became available, but cinemas using these projectors do not have access to international content.

DCE, including projectors and powerful computers called servers, cost much more than older analog projectors. Commonly used analog projectors cost around USD 30,000 and had a lifespan of 30 years, while early digital projectors cost up to USD 150,000, and had an expected life of about 8 years. This raised the cost for cinemas, whereas the main saving of not having to create and transport multiple physical prints flowed to distributors and studios. The VPF was introduced as a subsidy from distributors to cinemas towards the purchase of digital projection equipment, and was meant to match the savings from not having to create and ship physical prints. VPF arrangements have largely been phased out in most of the developed world, where it is believed exhibitors have recouped the cost of the equipment. However, India digitized later, and the VPF is still an important stream of revenue for cinemas. Moreover, DCE imports are subject to steep tariffs, which further raise the cost of DCE for Indian cinemas, and average ticket prices are a lot lower than in the West, averaging around INR 100 (approximately USD 1.5) from 2016 to 2019.

Unlike in the West, where all cinemas typically buy their DCE, it is common in India for small cinemas to lease their DCE as part of a bundle also including in-cinema advertising services, as explained below.

A final relevant institutional factor is that barring the large chains, most cinemas sold tickets offline and relied on cash transactions. Online booking and digitization took off for non-chain cinemas after 2020, as part of a much broader embracing of online transactions fueled by India's Unified Payments Interface. Consequently, ticket revenues were essentially unobservable to anyone but the cinemas. Distributors' shares would be calculated based on manual reports, and there was widespread concern that cinemas were underreporting sales to evade both tax and paying the distributor. Distributors sometimes conducted costly audits, but these were infrequent. In many cases, distributors relied on DCE providers for accurate box office information, as explained below.

[16] Disney, Fox, MGM, Paramount, Sony Pictures, Universal and Warner Bros

3.3 DCE Providers' Business Model

DCE is primarily provided by two large firms in India – UFO Moviez and Qube Cinema – along with other minor providers. All providers import DCE from abroad. They offer the DCE for sale, and arrange for installation. They also offer a bundle involving a DCE lease and in-cinema advertising platform services, where they retain ownership of the equipment, are responsible for maintaining it, and gain the right to sell in-cinema advertising slots. DCE providers have three main streams of revenue from customers who buy the bundle. First, they charge a fixed monthly rent which by itself would not cover the costs of financing and maintaining the equipment. Second, they charge a commission on advertising revenue they are able to generate. They aggregate and sell slots to advertisers through thier own in-cinema advertising platforms. UFO and Qube run two of the three largest in-cinema advertising platforms in India – the third is run by PVR-INOX. Lastly, DCE providers collect and keep the entirety of the VPF due to cinemas who opt for the bundle.

This business model allows DCE providers to observe two major components of cinemas' revenues. These components do not have any associated operating costs, so contribute wholly towards operating profits. Taken together, these components typically account for more than enouch operating profit over the lifetime of DCE to cover providers' costs and margins. Further, the arrangement incentivizes cinemas to accurately reveal box office revenue since the value of advertising slots is correlated with box office revenue. UFO has installed digital ticketing software at many of the cinemas it serves. This reduces administrative costs for cinemas, and makes accurate sales information available to all stakeholders, including distributors. UFO can also estimate food and beverage collections using industry average food and beverage spends per ticket.

UFO also offers a third option, where sells in-cinema advertising for cinemas who own their DCE. Here, UFO only charges a commission on ad revenue. The of a standalone DCE lease is available at the tiem of writing, but was not offered during the time period the data for this paper cover.

4 Data

I received data on UFO and competitor DCI screens for the period 2016 to 2020. I do not have any data on non-DCI screens, so I exclude them from the analysis. I observe weekly gross box office collections, number of shows and nubmer of tickets sold for UFO-served screens that have their ticketing software installed. UFO also provided estimates for some other UFO and non-UFO screens. In addition, for all UFO-served screens, I observe yearly net ad revenue (revenues net of the costs of selling advertising space), the screen's share of that revenue, the VPF, and average equipment servicing cost. I observe the projector model, projector cost and server cost for all UFO-served screens. I observe the number of seats in all UFO and some competitor screens. I observe the location and type (single screen / multiplex) for all screens. In addition, I observe the average interest rate UFO paid up to 31 December 2022, and have access to UFO's publicly available company accounts. UFO also told me the expected margins for single screen and multiplex cinemas. These data are typical of what antitrust authorities or consultants acting for affected parties might receive during the course of antitrust litigation.

There were 5,378 screens active at the end of 2021. Figure 1 shows how these are distributed by State (Indian provinces) and by DCE provider or owner network. Blue represents UFO – dark blue represents screens that are served under the bundle, while light blue represents screens where the cinemas own their DCE but use UFO's advertising platform. Orange represents QUBE – to the best of my knowledge, Qube does not provide unbundled access to its advertising platform. Other DCE providers are represented by shades of grey. Green represents PVR-INOX, which owns all its DCE and has its own advertising platform. While UFO, QUBE and PVR are present across across the country, their relative strengths vary by State. Other DCE providers are unimportant, except in a couple of large States. Importantly, the relative share of screens which choose to buy their own DCE varies across States.

Figure 1: Distribution of Screens by State and Network

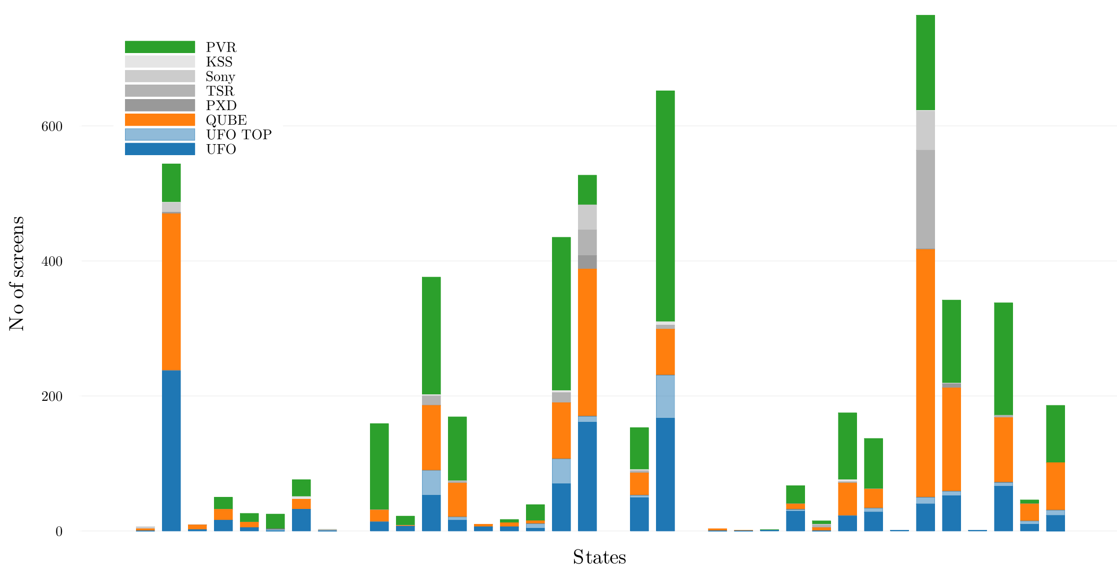
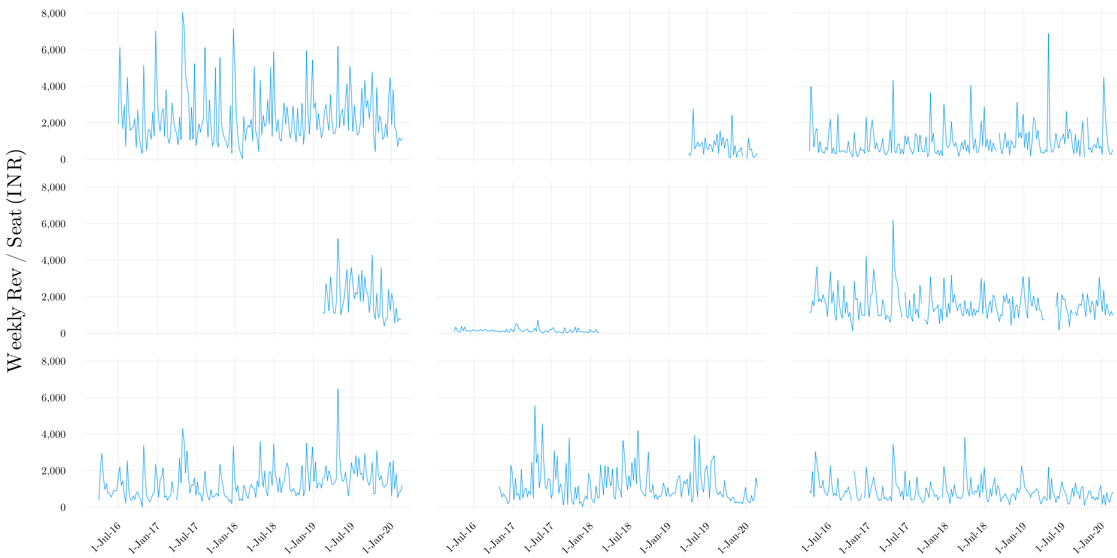


Figure 2 shows weekly gross box office collections per seat for some randomly selected screens served by UFO. First, there is a high degree of volatility. Weeks where extremely popular movies released, and weeks with major festivals or holidays, tend to have extremely high revenue, while others tend to have extremely low revenue. Further analysis revealed a high degree of correlation within States. This makes intuitive sense. Ethno-linguistics were a major factor in delineating Indian States. Languages and festivals vary widely across States, but tend to be more homogenous within States. Popular movies in the regional language of one State are rarely exhibited outside that State. Thus, demand factors tend to be State-specific. Second, there are differences in levels across screens, suggesting screen-specific demand factors are important. Last, the data are incomplete, which means I will need a model to estimate box office collections.

Figure 2: Weekly Revenue per Seat for Some UFO Screens



5 Model

The main goal of this model is to illustrate the market expansion effect created from completely shifting the borrowing burden from smaller cinemas to larger DCE providers. Moreover, since such situations can arise during antitrust investigations operating on short timelines, a subsidiary goal is for the model to be simple, easy to implement, and computationally light; and to be estimable given the data already provided. Hence, I only study small cinemas' choice of business model – should they enter, and if so whether to buy their DCE or not. I do not model competition between DCE providers once a business model has been chosen. I also do not model downstream interactions between cinemas and consumers, nor upstream interactions between cinemas and distributors. I do not model DCE providers' pricing choices, nor do I model how advertising revenue depends on the extent of the advertisign platform's network. These would add significant complexity, would require additional data, and may not significantly alter the market expansion effect. However, some or all of these factors may be important if the goal is something other than to illustrate the market expansion effect, which I leave for future work.

5.1 Set Up

In the status quo, all DCE providers also run ad platforms, and tie these to a DCE lease. Ad platforms are also available separately. There are thus three options available to small cinemas – **option B**, i.e. lease DCE and use the ad platform from the same provider (like those who consume UFO's and QUBE's bundles); **option A**, i.e. buy their DCE but use a third party ad platform (like UFO's clients who own their DCE); and **option O**, i.e. do not enter (or, for pre-existing cinemas with analog projectors, exit). While large cinema chains like PVR-INOX own their DCE and operate their own ad platforms, this option is not available to small cinemas. Ad platforms benefit from network effects and independent cinemas or small chains would not have access to enough screens to make it worth advertisers' while.

Cinemas' choice of whether to enter, and if so which of these models to choose, is static. For each screen i, total payoffs for each business model are given by profits over the lifespan of the DCE in years (τ) from that model. These are given by

$$\pi_i^B = \sum_{w=1}^{52\tau} \left[\underbrace{R_{iw}^B}_{\text{revenues}} - \underbrace{P_{iw}^B}_{\text{payment to provider}} - \underbrace{OC_{iw}}_{\text{operating cost}} \right], \tag{1}$$

$$\pi_i^A = \sum_{w=1}^{52\tau} \left[R_{iw}^A - P_{iw}^A - OC_{iw} - \underbrace{SC_{iw}}_{\text{DCE servicing cost}} \right] - (1 + \underbrace{r_i}_{i\text{'s borrowing rate}})^\tau \underbrace{PC_i}_{\text{DCE cost}}, \tag{2}$$

$$\pi_i^O = 0, \tag{3}$$

where

$$R_{iw}^s = \underbrace{GBO_{iw}^s}_{\text{gross box office collections}} + \underbrace{FB_{iw}^s}_{\text{food \& beverage}} + \underbrace{AD_{iw}^s}_{\text{net advertising revenues}} + \underbrace{VPF_{iw}^s}_{\text{virtual print fee}}. \tag{4}$$

Cinemas make a static *a priori* decision between these choices for each screen. The values of static variables are known, but those of time varying variables must be predicted. For each option s, cinemas also receive a shock ε_i^s, which is independtly drawn from a Type 1 Extreme Value with the scale parameter σ. Shocks capture unobserved screen specific profit shifters.

The *a priori* payoff from optin s then becomes

$$\mathbb{E}\left[\pi_i^s\right] + \varepsilon_i^s, \tag{5}$$

where the expectation is with respect to the distribution of time varying variables.

Through standard arguments, the probability of choosing option s^* is

$$Pr_i(s^*) = \frac{\exp\left\{\frac{\mathbb{E}\left[\pi_i^{s^*}\right]}{\sigma}\right\}}{\sum_s \exp\left\{\frac{\mathbb{E}\left[\pi_i^{s}\right]}{\sigma}\right\}}. \tag{6}$$

Implicit in this formulation is an abstraction from risk – cinemas do not go bankrupt during the DCE lifespan. However, this is functionally immaterial for cinemas' decisions. DCE is not screen specific, and UFO often moves used DCE from one screen to another if it loses a customer. In the context of increasing penetration in India, if a small cinema with its own DCE were to go bankrupt, it would be able to sell the DCE to another cinema. Given this, the approximate effect of introducing bankruptcy risk into the model would be to reduce the expected pfofits of all options by a fixed proportion, which would leave the ultimate probabilities in equation 6 unchanged.

Another implicit assumption in this formulation is that the loan to finance DCE is repaid in full at the end of the DCE lifespan rather than being amortized. Amortization would introduce a fixed per-period payment, which would suffer from the same inefficiencies as a lease discussed in section 2 – given volatile operating profits, accumulated profits in some periods may not be enough to meet the fixed payment, which might require further short-term borrowing. While it is possible to incorporate a back-heavy payment scheme, I do not have information on what cinema loans to finance DCE purchases look like. Consequently, any such choice would be arbitrary, and would need to be complex to avoid the need for short-term borrowing to meet loan payments. A single payment at the end of the DCE lifespan is the simplest way of avoiding short-term borrowing. Moreover, incorporating short-term borrowing would require simulating revenue paths, [17] which would require additional assumptions and add significantly to computational complexity.

To the extent that loans taken to finance DCE include a payment schedule, the model would underestimate interest rates. Identification in this model (discussed in more detail in section 5.3 below) rests on identifying the total borrowing costs (principal plus interest) under option A that is consistent with the observed choice. Any payment before the end of the loan term would reduce interest costs, and so the same total borrowing cost would be consistent with a higher interest rate. The estimated interest rates in section 6 should therefore be interpreted as 'ex-post repayment equivalent' rates.

5.2 Identifying Assumptions

Since I only aim to model cinemas' choice of business model, I assume that R_{iw}^s and all its components are random variables unaffected by cinemas' choice, i.e. $z_{iw}^s = z_{iw}$ for $z \in \{GBO, FB, AD, VPF, R\}$. Effectively, each screen is endowed with revenue streams.

Further, I need a model to fill in the gaps in the incomplete revenue data. The most complete data I have on any screen characteristic is the number of seats N_i, which I observe for 1,990 screens. Since I observe advertising revenue and VPF yearly for some screens, I assume

$$z_{iy} = \delta^{0z}_{y \times s(L_i) \times T_i} + \delta^{1z}_{y \times s(L_i) \times T_i} N_i + \nu^z_{iy}, \quad z \in \{AD, VPF\}, \tag{7}$$

or a year-state-screen type specific linear relationship with the number of seats. Since in some instances I observe weekly gross box office collections, the number of tickets sold NT_{iw}, and the number of shows NS_{iw}, I assume

$$z_{iw} = \delta^{0z}_{w \times s(L_i) \times T_i} + \delta^{1z}_{w \times s(L_i) \times T_i} N_i + \nu^z_{iw}, \quad z \in \{GBO, NT, NS\}, \tag{8}$$

or a week-state-screen type specific linear relationship with the number of seats. I assume all errors are mean-zero. However, given that there are differences in observed levels between cinemas, I allow for the errors to be correlated within each i. Essentially, this allows each cinema to have consistently higher or consistently lower actual revenues than the average in its time-state-screen type group, but it does not know

[17] See the discussion around the second counterfactual in section 7, which also requires such simulation.

which way this consistent difference will go *a priori*. This is similar to, though less restrictive than, allowing an ex-post screen specific revenue shock. While an ex-ante screen specific shock would be desirable, there is no way to identify this for screens for which I have no revenue data.

However, there might still be screens for which the relationships in equations 7 and 8 are not identidied in some periods because of a lack of data. In such cases, I assume that the revenue component is the average of that component for that screen in all periods where the relationships in equations 7 and 8 are identidied.

I further assume that advertising revenues and VPF are realized in the last week of the month, that yearly advertising revenues are distributed over time in proportion to box office colletions, and that yearly VPF is distributed over time in proportion to the number of shows. I assume food and beverage revenue is a (known) constant multple of the number of tickets sold, with different constants for single screens and multiplexes.

I assume that payments to providers take the form of a revenue share, so that

$$P_{iw}^{B} = \alpha^{B} R_{iw}, \text{ and} \tag{9}$$

$$P_{iw}^{A} = \alpha^{A} R_{iw}. \tag{10}$$

Since I do not model DCE providers' or ad platforms' price setting behaviour, I assume α^B and α^A are constant. While the actual fee structure involves a fixed component, I want to abstract away from questions of optimal fee structure.

I assume that DCE cost and servicing costs are known given attributes, and where these are not observed, these are equal to the average of those screens for which they are observed. All these assumptions taken together imply that once a screen chooses the bundle, there is no difference in payoff across DCE providers. This alows me to ignore the choice between DCE poviders and focus on the choice between three options – the bundle, buing DCE and accessing a third party advertising platform, and not entering.

To model credit frictions, I assume that the interest rate r_i is related to firm size. Specifically, I assume

$$r_k\left(TR_k \mid \beta, \gamma\right) = r_0 + \beta e^{-\gamma TR_k}, \tag{11}$$

where r_0 is the minimum lending rate and TR_k is the total revenue of the parent company. This is a convex declining function that approaches r_0, where the curvature and levels are governed by the two parameters.

Finally, since I only observe at maximum four years of data, while the expected life of DCE is longer, I assume that variables and coefficients over the observed period are representative of their values in unobserved periods.

5.3 Identification

α^A and α^B are calibrated from UFO data. The δ parameters in equations 7 and 8 are identified by standard OLS arguments, and the assumptions in Section 5.2 allow me to construct expected weekly figures for each revenue component. The assumptions also allow me to express payments in terms of revenues. Terms involving revenue shocks drop out while taking expectations because revenue shocks are mean zero. Unobserved operating costs are identified by the expected margin condition for each screen, allowing the construction of expected profits.

Two factors identify the borrowing cost parameters β and γ. First, cinemas of different sizes have different propensities of choosing options A and B; and second, cinemas who bought their DCE in my data chose to enter. Intuitively, I expect that borrowing rates are lower for cinemas with higher total revenue. As the interest rate falls, buying DCE becomes more attractive as interest payments reduce. This would translate into cinemas with higher total revenues being more likely to buy their own DCE, as is consistent with the data (see Table 1 below). Further, interest rates need to be low enough for expected profits to be positive for those who bought DCE.

σ is identified by assuming expected profit shocks are independent and identically distributed.

5.4 Estimation

I estimate the vectors of coefficients $\hat{\delta}^{0z}$ and $\hat{\delta}^{1z}$ for $z \in \{AD, VPF, GBO, NT, NS\}$ that characterize the time-State-theater type specific linear relationships with the number of seats using OLS on equations 7 and 8. I use these combined with the identifying assumptions to form $\hat{R}_{iw} = \widehat{GBO}_{iw} + \widehat{FB}_{iw} + \widehat{AD}_{iw} + \widehat{VPF}_{iw}$.

I eliminate $\sum_w OC_{iw}$ using the margin condition $\frac{\mathbb{E}\left[\pi_i^{s^*}\right]}{\sum_w \hat{R}_{iw}} = m_i$, where $m_i = m^S$ if i is a single screen, $m_i = m^M$ if i is a multiplex screen, and s^* is the option actually chosen.

I calibrate α^A and α^B as the observed fees recovered by UFO as a proportion of predicted revenue for the subset of theatres that chose each option.

Since I observe TR_{UFO} from company accounts, I eliminate β using equation 11, which implies $\beta = (r_{UFO} - r_0)e^{\gamma TR_{UFO}}$. For TR_i, I use the total predicted revenue of all the screens in my sample owned by the same entity. I identify owners of each screen manually. I calibrate r_0 to be 5.5% in real terms, which is roughly in line with the 20th percentile of rates offered by banks in India on term loans during the period covered by the data.[18]

Out of the 1,990 screens for which I have information on the number of seats, I can only construct expected total revenue for 1,935, which form my final estimation sample. I then estimate γ and σ using maximum likelihood.

[18] The Reserve Bank of India only releases the first, 20th, 80th and 100th percentiles. I use the median of the 20th percentile across banks to account for rates which may be artifically low because of stochastic reasons unrelated to fundamentals. The 20th percentile is generally similar across Indian public sector banks, Indian private sector banks, and foreign banks. The 1st percentile is close to the 20th percentile for Indian public sector and Indian private sector banks, but is significantly lower for foreign banks. The data are available in Table 1 at `https://www.rbi.org.in/rbi-sourcefiles/lendingrate/LendingRates.aspx`.

Throughout, to eliminate the effects of inflation, which can be significant in India, I deflate all values to 2012 prices using State-specific consumer price indices published by the Government of India.[19]

6 Estimation Results

Table 1 shows the mean number of seats, mean TR_i and the number of screens which chose options B and A within my estimation sample of 1,962 screens. Single screens on average have more seats than multiplex screens. However, as expected single screens have a lower TR_i than multiplexes, since multiplexes typically have many screens in one cinema, and are much more likely to be chains. Crucually, in both types, those which chose B have a lower mean TR_i than those which chose A, with the difference being extremely large for multiplexes.

Table 1: Mean TR_i and Number of Screens Choosing Options B and A

Theater Type	Option	Mean No. Seats	Mean TR_i (INR mn, 2012 prices)	No. Screens
Single Screen	B	571.22	57.69	639
	A	605.73	60.87	55
Multiplex	B	294.86	621.50	1,006
	A	266.83	1,171.79	235

Figure 3 plots the estimated real borrowing rate function $r_0 + \hat{\beta}e^{-\hat{\gamma}TR_i}$. The 95% confidence band is bootstrapped. The model correctly predicts the cinema's choice (defined as the highest estimated probability being for the same option as actually chosen) for 81.24% of screens, though in aggregate it overpredicts choosing B (1,786 predicted vs. 1,645 actual) and underpredicts choosing A (146 predicted vs. 290 actual). It incorrectly predicts 3 screens as choosing not to enter.

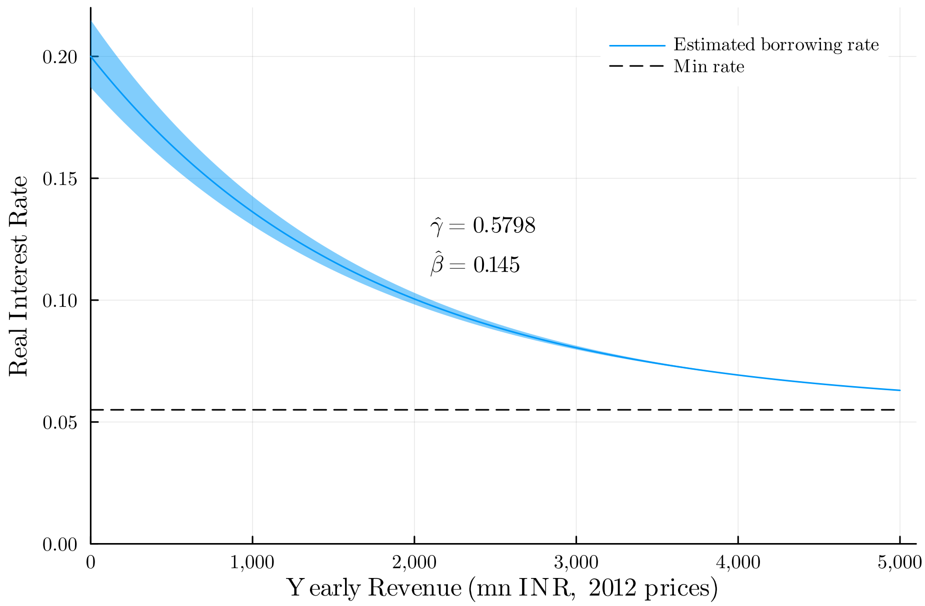
The estimates imply non-trivial credit frictions, with larger firms facing lower borrowing costs than small firms. The average real borrowing rate is 17.90% for cinemas predicted to choose B and 13.73% for those predicted to choose A. For comparison, UFO's real borrowing rate was 6.60%. These value are in the same range as estimates from industry participants. They also fall within the range that Indian banks gave loans at during the period of the data, suggesting that even the smallest cinemas were large enough to access formal sector credit.

7 Counterfactuals

I now evaluate the market expansion effect of bundling by considering the viability of cinemas under two counterfactuals – one where all screens are forced to buy their DCE if they must enter, and another where

[19] The Ministry of Statistics and Programme Implementation publishes State-specific consumer price indices at `https://cpi.mospi.gov.in/`. A general index is available, as well as separate indices for constituent product groups. Each index is also available separately for rural and urban areas. I use the general index for urban areas, since most cinemas are in urban areas. The index for the small border State of Arunachal Pradesh is not available for the relevant time period. For these, I use the rates for Assam – a large State and the Indian State sharing a border with Arunachal Pradesh.

Figure 3: Estimated Real Borrowing Rate



DCE providers must unbundle the DCE lease from access to the ad platform. Since the model only considers cinemas' choice of business model, the counterfactuals cannot allow for equilibrium effects. The simulations should be understood as first order effects only.

7.1 Counterfactual 1: All Screens must Buy DCE

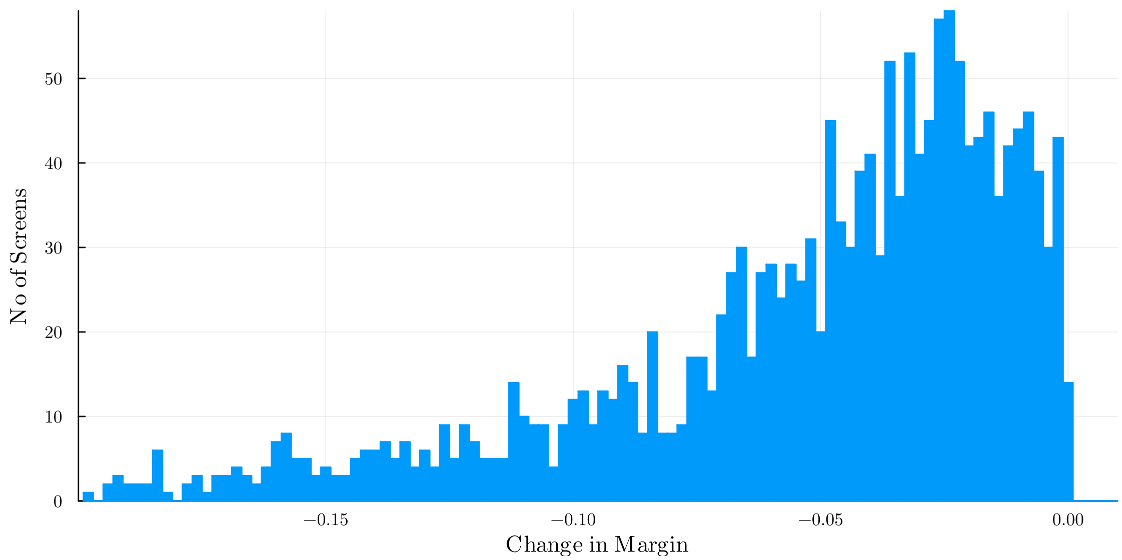
This counterfactual attempts to evaluate the market expansion that occurs when both credit and information frictions are overcome. It does so by asking how many screens which currently choose option B would become unviable if they were forced to choose option A. To implement this, I remove option B and calculate the probabilities for each screen of choosing A and O.

Figure 4 shows, for the subset of screens which the model predicts as choosing B, the change in margin if they were forced to choose A. Since each screen's preffered option is taken away, all margins fall. The average reduction in margin is 6.02 percentage points, and the median reduction is 4.12 percentage points. Of the 1,786 screens, 1,278 (71.56%) would choose not to enter, while the rest would choose A. Therefore, the procompetitive mechanism described in section 2 is large in absolute magnitude.

7.2 Counterfactual 2: Unbundling

This counterfactual attempts to evaluate the possible effects of an antitrust authority imposing unbundling on DCE providers. DCE providers cannot now condition on revenues in designing thier lease charge, and must charge a monthly rent. The informational friction is not solved, which may lead to a borrowing burden for cinemas.

Figure 4: Change in Margins under Counterfactual 1



I assume that the rent becomes due in the last week of the month. Conservatively, I assume that DCE providers set the monthly rent to break even on the cost of financing the DCE, which I use UFO's rate of interest to calculate. I assume that if at the end of each month a screen's accumulated profits are not enough to pay the rent, the cinema must take a short term (one month) loan to cover the shortfall. Conservatively, I assume they can access short term credit at the same annualized rate as long term credit. I also assume conservatively that OC_{iw} is proportional to $\frac{R_{iw}}{\sum_w R_{iw}}$, i.e., operating costs rise and fall in sync with revenues.

The expected borrowing burden for cinemas depends not only on the expected values of revenues in each week, but on volatility as well. This necessitates simulating revenue paths. To see this, note that profits in week w are given by by the recursive equation

$$\begin{aligned}\pi_{iw}^{CF2} &= (1-\alpha^A)R_{iw} - OC_{iw} \\ &\quad - \mathbf{1}\left\{\text{month}(w+1) > \text{month}(w)\right\}\left[Rent_{iw} + r_i^M \max\left\{0, -\left(\sum_{l=1}^{w-1}\pi_{il}^{CF2} - Rent_{iw}\right)\right\}\right],\end{aligned} \tag{12}$$

where r_i^M is the monthly interest rate and $\pi_{i1}^{CF2} = (1-\alpha^A)R_{i1} - OC_{i1}$. The revenue errors do not enter profits linearly, so do not disappear when expectations are taken.

To simulate profit paths, I need a model for revenue errors. I assume revenue errors follow a first order Markov process for each screen. I first retrieve the errors from the OLS regressions of equation 7 and 8. Using these, I construct a state space consisting of 20 states, each responding to 5% of observed values. I attribute the mean of errors in each state as the value in that state. Given the relative sparsity of my data, and that there are five revenue components, each with twenty states, I cannot estimate a joint distribution for initial values. I therefore assume that initial values for each revenue component are independent. The estimated transition matrices are given in Figure 5. There is a reasonable degree of persistence in the errors.

I calculate expected profits by simulating 100 revenue paths for each screen, calculating profits for each simulation, and then taking the average.

Figure 5: Transition Matrices

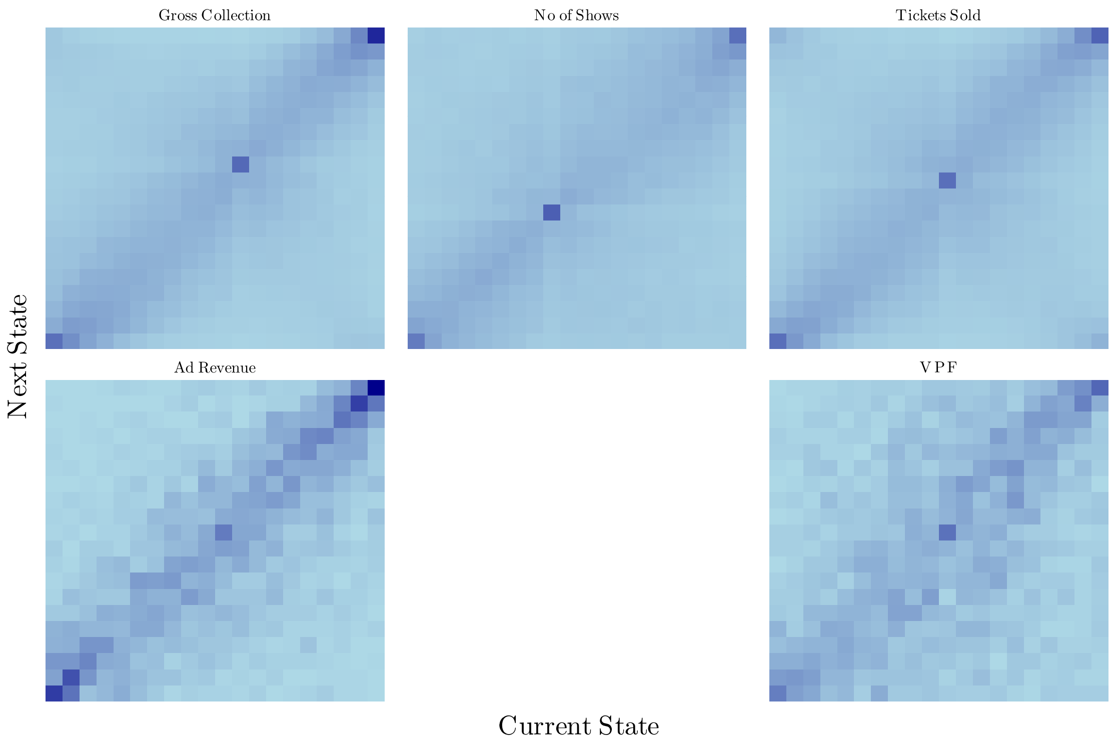
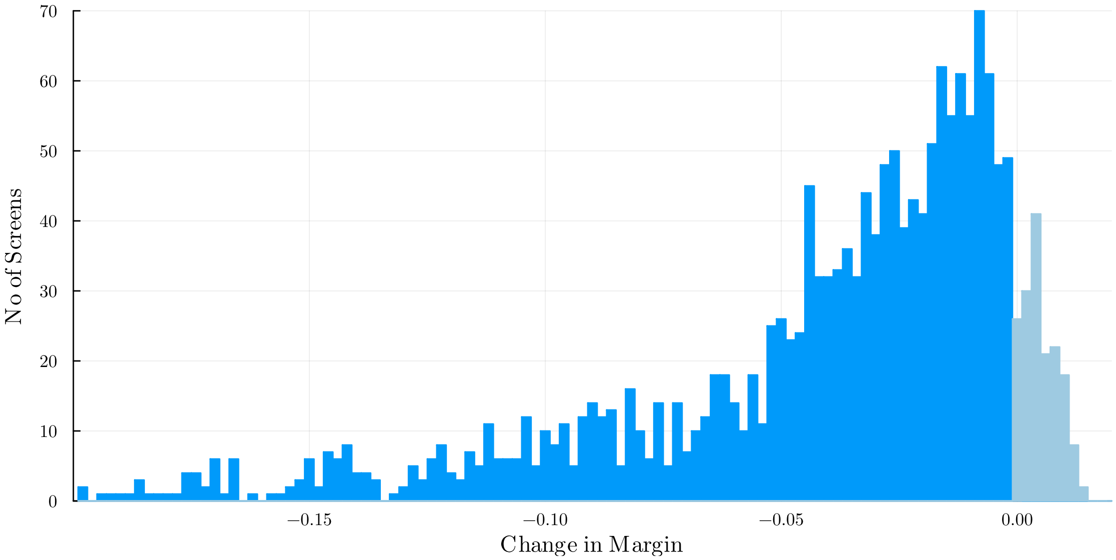


Figure 6 shows, for the 1,786 screens that the model predicts as choosing B, the distribution of the changes in margin from the lease option relative to option B. 168 screens (9.41%), depicted in light blue, experience modestly increased margins. This signals that not having an unbundled option may lead to welfare loss for some screens, though the extent is likely lower given the conservative assumptions made above. However, average change in margin is -5.48 percentage points, and the median change in margin is -2.83 percentage points. 998 screens (55.88%) would choose not to enter, 148 (8.29%) would opt for option B, and 640 (35.83%) would opt for the standalone lease.

This implies that trade credit arrangements by themselves would still lead to an inefficient outcome, and that the bundling's profit uncovering function is key to unlock efficiency gains.

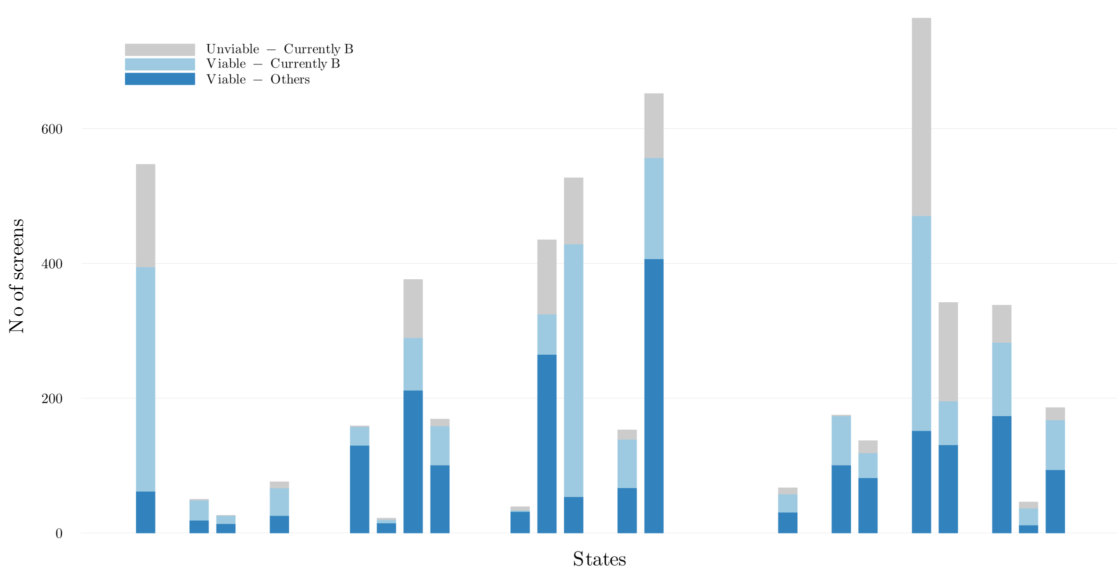
Should 55.88% of all screens currently buying the bundle become unviable, India would lose 33.06% of its screens. Since chain multiplexes tend to be concentrated in metropolitan centres, and since there are important differences between states, the effects are spatially heterogeneous. Figure 7 shows, for states with more than 25 screens, how many screens would be rendered unviable assuming that the unviability propensity is the same for all screens in the state as for screens in my estimation sample in that state. Dark blue represents screens which currently own their DCE, and would therefore remain viable. Light blue represents screens which currently buy the bundle, but would remain viable under the counterfactual. Grey

Figure 6: Change in Margins under Counterfactual 2



represents screens which would currently buy the bundle but would be rendered unviable. More screens are lost in states with a high proportion of screens currently buying the bundle. There is substantial variation the percentge of screens currently buying bundles rendered unviable. Some states accoringly experience minor losses, while some lose almost half their screens.

Figure 7: Change in Margins under Counterfactual 2



8 Conclusion

This paper documents a novel procompetitive mechanism through which bundling can lead to significant market expansion. In a metering type situation where small businesses need both an expensive capital good and consumables to produce, but also face credit constraints and have volatile revenue streams, a bundle containing a lease of the capital good and the consumable expands the market through both cost reduction and price discrimination. The lease shifts the burden of borrowing to cover the cost of the capital good from small downstream firms who face high borrowing costs to the large upstream firm which faces low borrowing costs. The bundling allows the upstream firm to observe downstream revenues and implement a revenue share, which eliminates the need for the downstream firm to access any credit.

This paper also uses data from the Indian movie exhibition industry in conjunction with a structural model to estimate the extent of the market expansion effect. The structural model examines small cinemas' choice between (i) a bundle containing a digital cinema equipment lease and in-cinema advertising distribution services, (ii) buying digital cinema equiment and separately accessing in-cinema advertising distribution services, and (iii) not entering / exiting. It constructs total expected profits for each of these options as a function of borrowing costs, and finds the borrowing costs that best rationalize observed choices. I find that small cinemas which my model predicts as choosing the bundle face average real borrowing rates of 17.90% compared to 6.60% paid by digital cinema equipment providers.

The paper then simulates two counterfactuals. In the first, where all cinemas are forced to buy their own equipment, 71.56% of screens which the model predicts as opting for the bundle in the estimation subsample would be rendered unviable. In the second, where unbundling is imposed and providers are forced to offer a standalone lease with a fixed montly payment, the need to take on short term loans to pay rents during periods of low revenue continues to render 55.88% of screens which my model predicts as opting for the bundle in the estimation subsample unviable.

Apart from illustrating how bundling can be used to achieve large efficiency gains in the presence of credit constraints, the emprical exercise shows the dangers of ignoring this efficiency when evaluating the competitive effects of bundling. Moreover, it illustrates how novel business models can arise to counteract market imperfections.

One could build on the analysis in this paper in several ways. Incorporating a model of the advertising market would allow including larger chains like PVR-INOX into the model, and investigating any anticompetitive effects from traditional leveraging. An interesting question to consider would be, given that the leveraged market is a platform, would it naturally tend to monopoly if bundling were disallowed, and does bundling therefore enforce a more desirable outcome. Further incorporating models of upstream competition between DCE providers and dowmstream cinema demand would allow for a full equilibrium effects analysis.

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