Financial Slack, Strategy, and Competition in Movie Distribution*

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Abstract

Organizations that enjoy some slack are believed to make good use of it in their strategic decisions. Using panel data on firms in the U.S. film distribution industry between 1985 and 2007, this article examines how financial slack affects the volume of new product introductions, the competitive strategies for those releases, and their economic performance. Unexpectedly successful "sleeper" films are exploited as a source of exogenous financial slack in the econometric analysis. The results suggest that unexpected financial slack leads to more product introductions, less marketing support for the new products, and no increase in performance. These findings are consistent with an attribution process in which managers attempt to replicate extraordinary success even if it is largely random, providing real-world evidence of a mechanism recently developed in theory and laboratory research.

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1 Introduction

Organizations that enjoy some slack are believed to make good use of it in their strategic decisions. Building on this idea, a large and important literature has explored the consequences of organizational slack (e.g., Cyert and March 1963, Bourgeois 1981, Singh 1986, Bromiley 1991, Nohria and Gulati 1996). However, relatively little is known about the direct effects of *financial slack*, or the amount of liquid resources owned by the firm for the discretionary uses of management. What do firms do when they have more financial slack? And how is that behavior consistent with current theories of organization and strategy? This paper addresses these questions by examining the role of financial slack in determining the volume of new product introductions and the competitive strategies for such releases. Focusing on the influence of financial slack on competitive strategy is a meaningful step in the broader assessment of whether slack represents a distinct force. The influence of financial slack is perhaps most easily observable in the decision between how many new products to launch versus how to release them in the marketplace. This is a decision-making process in which managers calibrate their beliefs about suitable strategies with their slack resources at hand. By understanding the role of financial slack in these decision-making processes, the question of whether and why financial slack may influence performance can be more thoroughly examined.

Prior research on the impact of slack resources has been somewhat dismissive of the role that financial slack plays in organizational decisions. This may in part be due to the perception of a weak empirical link between performance and unabsorbed slack — the most liquid category of slack resources, encompassing financial slack (see Daniel et al. (2004) for a meta-analysis). One challenge in studying financial slack is the possibility that managers endogenously adjust the level of slack resources in ways not observable to the researcher but potentially related to past performance. Highly performing firms, for example, may manage their financial slack better; moreover, financial slack itself may be a result of high performance. These endogenous patterns raise the concern that a reduced-form statistical relationship between financial slack and subsequent decisions might be spurious. A second challenge in studying the impact of financial slack is the difficulty in observing the micro mechanisms that connect financial slack with firm behavior and performance. To address both challenges, this paper presents an in-depth analysis of the U.S. film distribution industry between 1985 and 2007, offering a novel exogenous measure of financial slack based on unexpectedly successful projects, and exploiting detailed micro data on firm strategies and outcomes.

Specifically, to identify the impact of financial slack, this paper implements a simple yet powerful empirical strategy based on "sleepers." Sleepers are films that start showing on relatively few screens but suddenly acquire visibility and expand significantly (see Appendix). These unexpectedly successful films yield excess financial resources that become available to managers making decisions about the next set of film releases. For the purpose of this study, the main virtue of these unexpectedly successful projects is that they bring about genuine and substantial variation in financial slack. A second key feature of sleepers is their luck component, which may trigger informational and behavioral reactions that must be carefully considered when assessing the causal link between financial slack and subsequent strategic actions. There are a number of other cultural markets in which the sleeper phenomenon exists, but its impact on firm behavior and performance has not been systematically studied before.

The empirical design seeks to analyze how much and why financial slack matters for organizational decisions. There are three main results. First, the unexpected financial slack brought about by sleepers leads to more film introductions and less marketing support for new films. These findings are consistent with a vast literature on financial slack and investment (e.g., Fazzari, Hubbard, and Petersen 1988), but inconsistent with arguments about expansive competitive aggressiveness typically linked to financial slack (e.g., Rauh 2006, Fresard 2010). Second, the effects of unexpected financial slack are mostly due to the financial dimension of slack rather than to luck or information arguments. This distinction has been particularly hard to disentangle empirically, even if it speaks to a large theoretical literature (e.g., Gilchrist and Himmelberg 1995, Bernardo and Chowdhry 2002). Third, unexpectedly high past performance seems to be erroneously incorporated by managers into their decision processes, leading to a wasteful search for extraordinary success as its sources are largely random. Specifically, when film distributors have more unexpected financial slack, they attempt to enact a new set of sleepers, daring to open films on fewer screens but ultimately failing to achieve sleepers or attain higher performance. These decision-making patterns are consistent with theory and laboratory research on attribution biases (e.g., Curren, Folkes, and Steckel 1992, Ratner and Herbst 2005, Denrell and Fang 2010), a background literature with potentially many ramifications for organizations research but no prior emphasis on financial slack and little real product-market validation.

Taken together, the findings advance the organizations literature on slack resources (e.g., Nohria and Gulati 1996, Argote and Greve 2007) by studying the direct effects of financial slack and uncovering the various mechanisms through which financial slack drives outcomes in the context of product market competition. In this study, the analysis of financial slack is facilitated by a design centered on surprisingly successful projects, thus allowing for a nuanced depiction of managerial attribution processes. However, credible proxies for the opposite case — an unexpected *reduction* of financial slack —

are unavailable in this study, thus hindering an analysis of other theoretically interesting patterns. For example, as proposed by the behavioral theory of the firm, financial slack may have asymmetric effects on behavior. Overall, this paper offers a new perspective to the literature on slack resources and managerial decision-making, and it opens paths for future work.

Methodologically, given the paucity of prior research dealing with the endogeneity of financial slack in organizational decisions, this paper employs a "back-end theory" approach, briefly introducing the theoretical constructs of interest (Section 2), then devoting most attention to the empirical design (Sections 3 to 5), and only addressing theoretical considerations later (Sections 6 and 7). This approach is valid to the extent that current theories of financial slack and success in organizations are well known, but prior measurement has been either infeasible or problematic. Importantly, the very same data on film distribution employed here can be shown to produce radically different results when the endogenous nature of financial slack is overlooked (Section 3). More broadly, in view of the ever-growing theoretical, simulation, and laboratory work in organizations research, an empirical approach that both validates and qualifies organizational constructs in real-world competitive markets may prove useful to expand the frontiers of the field going forward.

2 Financial Slack in Organizations and Strategy: Background

Though definitions vary, the term financial slack is typically used to refer to the amount of liquid resources owned by a company for the discretionary uses of management. Originally, Penrose (1959) proposed that the availability of excess resources is fundamental for growth. Cyert and March (1963) advanced the idea that these excess resources are necessary to keep social coalitions inside the firm in balance. No particular emphasis was placed on whether slack resources should be liquid. Starting with Bourgeois (1981), organizations scholars have distinguished between 'unabsorbed' slack, liquid resources readily available, and 'absorbed' slack, excess resources that are difficult to reassign to new uses (e.g., Singh 1986, Nohria and Gulati 1996, Bromiley 1991). Financial slack, the discretionary amount of liquid monetary resources, is thus a specific class of unabsorbed slack that may enable flexible redirections of a firm's organizational decisions.

In view of the diverse lines of research dealing with the nature and consequences of organizational slack (Argote and Greve 2007), an assessment of prior work on slack resources is beyond the scope of this paper. However, the themes and methods of this literature can be briefly sketched as follows. Theoretically, slack resources have often been conceptualized as a driver of innovation (e.g., Nohria and Gulati 1996, Kim, Kim, and Lee 2008) and entrepreneurial behavior (e.g., Baker and Nelson 2005, Mishina, Pollock, and Porac 2004), building on the idea that slack is an excess resource that may alleviate constraints and yet at the same time hinder organizations through a safety buffer for low performers. This body of work emphasizes the effects of financial slack within the organization, typically without exploring its ramifications on product market competitive behavior.

Empirically, financial slack has been modeled in this literature using mostly firm-level variables based on accounting statements, such as the current ratio, debt over equity, or long-term debt over assets (see Daniel et al. 2004 for a review). This tradition in measuring financial slack, possibly rooted in Bourgeois's (1981) methodological arguments, offers the advantage of being unobtrusive, thus letting researchers conduct observational studies without the explicit cooperation of the firms of interest. Thus, proxies for financial slack in this tradition have been relatively easily accepted into empirical work, placing more emphasis on the contextual and theoretical motivations for studying the impact of financial slack rather than on the micro measurement of financial slack itself.

Building on and extending this prior work, I seek to investigate the effects of financial slack on organizational decisions by adding a theoretical dimension and, primarily, by overhauling the empirical approach to how financial slack could be analyzed. Theoretically, I propose that the literature on organizational slack has the opportunity to bring competitive strategy in product markets into a broader research agenda on what organizations do with their financial slack. Empirically, I raise the concern that much of the (so far weak) influence attributed to financial slack in organizational decisions may amount to inadequate or infeasible measurement, and I introduce a simple methodology that more squarely addresses this problem. I briefly elaborate on these two aspects of my study below.

First, scholars looking exclusively inside the firm to understand the effects of financial slack are likely to miss the theoretical connection between internal practices and external competitive behavior in product markets. In fact, as highlighted by recent work, there might be an important link between the financial position of a firm and its subsequent competitive behavior in the marketplace (Rauh 2006, Fresard 2010). However, this parallel line of inquiry on the competitive impact of financial slack is not easy to reconcile with the ongoing work of organizations scholars because the mechanisms proposed there seem to be primarily motivated by industry-level forces rather than more nuanced micro organizational processes typical of managerial actions. Take, for example, the well-established view in macroeconomics that financial slack has a positive influence on investment (Fazzari, Hubbard, and Petersen 1988); according to this logic, any organizational decision that gains market share could be conceptualized as an investment, such that we would expect a positive relationship between financial slack and competitive decisions that increase market share. In this paper, I attempt to bridge the internal and external views of how organizations use their financial slack by more fully analyzing the micro mechanisms of managerial decision-making processes while at the same time building on extant work on the macro relation between financial slack and real investment.

Second, the methodological premise for this paper is that financial slack is endogenously related to organizational decisions. This poses a challenge to the development of new theory and empirical work. Financial slack is generally the result of good performance — when firms do well, they have more slack. Because financial slack leads to behavior, and through that channel to performance, the endogenous relationship between success and slack makes causal inference a formidable task. Strategic decisions and performance may, for instance, follow unobservable superior quality or unobservable information about quality, even if they instead appear (spuriously) correlated with financial slack. The goal of this in-depth analysis of the film distribution industry is to gain new empirical insight into whether and how financial slack affects organizational decisions in competitive product markets, and how this influence may be consistent with current theories of organization.

3 Empirical Setting

Distribution is the central segment in the value chain of many cultural activities, especially the American film industry. Distribution is not retail; in fact, some creative activities include only a relatively thin distribution segment because production meets retail more directly (e.g., Broadway musicals). By contrast, film production and retail are only linked through the mediating role of a very active distribution industry. The relationships between distribution and production (Sorenson and Waguespack 2006) and distribution and retail (Chisholm and Norman 2006) have been well characterized in prior work, and this paper focuses more directly on distribution itself. To be sure, the most important task of distributors is to bring films — artistic products with uncertain quality — to the screening market. Distributors therefore choose release dates (Einav 2007), support a release with advertising and sales efforts (Joo 2009), and contract screens accordingly (Moretti 2011).

Two key decisions for distributors are *how many* films to distribute and *how* to introduce them in the marketplace (Hayes and Bing 2004, Sorenson and Waguespack 2006). Though packaging artistic products for the market may seem less complex than actually creating art, the product portfolio decisions of distribution companies are difficult and have lasting consequences for profitability. For example, given the limited number of high-grossing weekends (i.e., holidays) in a year, distributors must carefully assess which film projects are not only better than other projects within the company's slate but other films across the market. Given the fierce competitive dynamics at the box office, casting release strategies can be quite challenging.

The inherent risk in introducing new films suggests that financing plays a crucial role. Films are quintessential examples of asymmetric information goods about which very little is known externally before the release date. Hence, theoretically it can be expected that internal financial resources should matter for investment in this setting (Myers and Majluf 1984), in particular in the context of film-specific sunk-cost investments in intangibles and advertising.

The U.S. film distribution industry between 1985 and 2007 offers an appropriate environment to explore the effects of financial slack on managerial decisions such as new product introductions and competitive releasing strategies, policies that ultimately affect economic performance. Besides the inherent interest of distribution in creative industries, there are also a few empirical reasons that make the film setting fruitful. First, proxies for these key managerial decisions are transparent and reflect the conventions of the industry. For example, new feature film releases are risky product introductions, yet economic success in theatrical markets can be ascertained in a matter of weeks or even days. Second, rich data repositories allow for the construction of refined proxies that help explore specific mechanisms. Third, the uncertain nature of films as goods dependent on fads, moods and tastes offers a quasi-experimental setting to study the effects of financial slack with clarity.

Data

The analysis is conducted at the distributor-year firm level, based on primary data available at the project level. The data draw on the population of feature films released in U.S. theaters between 1 January 1985 and 31 December 2007.[1] *Variety*, the leading industry periodical, and AC Nielsen EDI, a market research provider, report weekly box office revenue and weekly screens for all films released since 1985. Studio System and *Variety* provide company information. IMDB, an online database owned by Amazon.com, contains film- and person-level data, as well as some corporate information. Proprietary information on production and advertising budgets through 2007 was acquired from Baseline Intelligence, a *New York Times* company, supplemented with data from TNS Media Intelligence; these providers are reputable well-trusted sources used by industry decision-makers.

Table 1 reports summary statistics on the main variables of the study for the 1,518 observations on

[1] I seek to understand the new product introductions, competitive strategies, and economic performance of film distribution companies in relation to the U.S. theatrical market; by this demarcation of the research setting, other revenue streams related to distribution in other countries or other formats may not be relevant for my investigation, even if they became important for entertainment firms in the last few years of the sample period.

267 distribution companies. All dollar values are expressed in millions of 2009 real dollars. Interestingly, the key dependent variables of the study — the number of new film releases and the median opening week screens — are strongly positively correlated, suggesting that film distributors who release more films also market them more aggressively.

Illustrating the Endogeneity of Financial Slack in Organizational Decisions

Before characterizing the empirical design, it is helpful to grasp the main difficulty in studying the relationship between financial slack and organizational decisions. To do this, I now present an initial set of regressions similar to the main regressions of the paper (to be introduced) later but without taking into account (for now) the endogenous nature of financial slack. As will be shown by this simple exercise, a naive reduced-form specification of financial slack can be misleading.

Table 2 presents panel fixed-effects regressions with financial slack on the right-hand side. (All variables will be described in the next section.) The panel is cast at the distributor-year level, so the inclusion of distribution company fixed effects and year fixed effects controls for the unobserved linear variation along these dimensions. In these initial regressions, financial slack is the sum of film-level box office revenue minus production costs in all cases when this difference is positive; all types of films of each distributor in a given year are indistinguishably considered to capture financial slack.

The results in Table 2 suggest that financial slack has a statistically strong but economically negligible influence on the number of new releases (Model 1), no influence on the opening week strategy of those releases (Model 2), and a substantially positive effect on the box office revenue of the new film slate (Model 3). Taken together, these initial models would support the view that financial slack is very good for future performance even if it only minimally affects the quantity of products released and it does not affect at all the way in which these products compete in the marketplace. This view would be correct if financial slack in Table 2 were exogenous.

However, these results and interpretation cannot be taken at face value because financial slack is endogenous. To be clear, the main endogeneity concerns in using financial slack in a reduced-form specification are the omitted variable problem and the reverse causality problem. In the former problem, if some distribution companies have superior competencies or capabilities largely unobserved in the regressions, then these firms expect to attain higher performance through a channel that is only noisily correlated with financial slack per se, a pattern that is consistent with the weak coefficients for financial slack in Models 1 and 2 and a large positive coefficient in Model 3. In the latter problem, to the extent that financial slack (i.e., the right-hand side variable) is a result of box office revenue (i.e., the left-hand side variable), it is therefore possible that the dependent variable influences the independent variable in non-trivial dynamic ways, thus rendering Model 3 biased and inconsistent. In sum, Table 2 could be very misleading in trying to understand the consequences of financial slack.

Given the absence of prior empirical work untangling the endogenous role of financial slack in product introductions, competitive strategy and performance, it is impossible to determine ex ante how serious the endogeneity problem might be, or put differently, how far Table 2 is off the mark. The next sections provide a first step towards understanding the strategic consequences of financial slack. As a key goal of this endeavor, theories of organizations are addressed after presenting the main results.

4 Empirical Specification

To assess the consequences of financial slack for organizational decisions, my identification strategy is simple but demanding of the data. Empirically, I partition the space of all projects generating financial slack to pay differential attention to a set of past films — sleepers — that became unexpectedly successful, thus providing an exogenous source of variation in financial slack. Conceptually, whereas financial slack may generally be available for a pre-established purpose, unexpected financial slack is unlikely to be tied to an organization's current plans, thus allowing for an appropriate investigation of how financial slack shapes organizational decisions.[2]

Instrumental in this empirical design are sleepers, unexpectedly successful films that provide an intuitive proxy for financial slack in the context of all other films in the industry throughout the sample period. Sleepers are a well known phenomenon in creative industries but this is the first paper to use sleepers systematically. I describe sleepers in more detail in section A.1 of the Appendix.

To examine the impact of financial slack, consider distributor i's decision y in year t:

$$y_{i,t} = \beta * UFS_{i,t-1} + \gamma * OFS_{i,t-1} + \eta * X_{i,t-1} + \delta_i + \tau_t + \epsilon_{i,t} \quad (1)$$

where UFS is unexpected financial slack, defined as financial slack accruing from sleeper films; OFS is ordinary financial slack, defined as financial slack accruing from films that are not sleepers; X is a vector of control variables; δ is a distributor fixed effect; τ is a year fixed effect; and ϵ is the error term. To account for serial correlation and non-independence, errors are clustered at the distributor level.

[2]While one needs exogenous variation in financial slack to draw causal inference about the impact of financial slack on organizational decisions, the theoretical implications of this analysis apply to endogenous changes in financial slack, as well. The difference is that an endogenous increase in financial slack will be more difficult to isolate empirically from other factors, thus complicating the analysis, as shown in Table 2.

In specification (1), the financial slack of a distribution company in a given year is split into unexpected (UFS) and ordinary (OFS) depending on which projects are the source of each component of financial slack: sleepers or non-sleepers.[3] Conceptually, unexpected financial slack is the component of slack that is surprising as opposed to anticipated. Empirically, this strategy is appropriate to the extent that project-level exogenous variation in the expectedness of financial slack can overcome the problems of omitted variables and reverse causality, thus making β the coefficient of interest.[4] Before seeing how sleepers may achieve this, first note that when UFS is modeled after unexpectedly successful events, introducing it in equation (1) eliminates concerns about an omitted variable because randomness in the exogenous variable by definition is not systematically related to $\epsilon_{i,t}$, and no systematically omitted variable can explain such random influence. Second, if the unexpectedly successful events behind UFS are indeed unpredictable, it is unlikely that y leads to UFS, as y is not exogenous but systematically linked to the right-hand side variables in equation (1), making reverse causality unlikely. Identification of β therefore hinges on exogenous variation in the projects that are a source of UFS.

The empirical strategy exploits the fact that sleepers are highly uncertain, unpredictable sources of financial slack. In a complete panel of all active year-distributor combinations, I define $UFS_{i,t} \equiv \sum_j 1(j = \mathit{Sleeper}) * (R_j - C_j)$ and $OFS_{i,t} \equiv \sum_j 1(j \neq \mathit{Sleeper}) * (R_j - C_j)$ where j is each of the films carried by distributor i in year t, $1(\cdot)$ is an indicator variable, R_j is the box office revenue of the sleeper, C_j is its production cost; only films with $R_j - C_j > 0$ are considered for either UFS or OFS. Clearly, the specification relies on three conditions: (i) sleepers are identifiable ex post but can be shown to be largely unpredictable ex ante; (ii) R_j and C_j are observable; and (iii) $R_j - C_j$ is financial slack. Condition (i) is shown to be satisfied empirically in section A.2 of the Appendix. Condition (ii) is satisfied by including unique data on production budget C_j, totaling 6,857 different films between 1985 and 2007, that is, 81% of any film ever released in that period; for robustness, this series is supplemented with film-level advertising expenses, as described below. Finally, condition (iii) is also satisfied here, as the institutional practice consists of judging a film financially successful if it breaks even at the box office, achieving at least $R_j = C_j$. Therefore, even if specific contracts might change the split of R_j across films within a given distributor, the project-level measure of $R_j - C_j$ constitutes the most reasonable proxy for the financial slack generated by film j given the data at hand.[5]

[3] A different empirical strategy would not care about setting aside projects with unexpected financial slack, but would instead estimate within each and every project an empirical residual that is unexpected with respect to a predicted baseline. Such an alternative strategy, however, would raise concerns typical of generated regressors.

[4] By contrast, even if OFS in equation (1) also captures financial slack, its coefficient γ is not likely to reflect the true effect of financial slack; see Bertrand and Mullainathan (2001) for similar arguments in the context of CEO pay for luck.

[5] See Ravid (1999) for a lengthy discussion of why film profitability can be reasonably captured by box office revenues minus production costs, which is the $R_j - C_j$ measure employed here. Two advantages over Ravid's specification —the use of 6,857 projects rather than 175 projects, and the use of panel fixed effect models rather than a cross-section — suggest

To implement specification (1), sleepers must be defined. In the population of films I define sleepers as those films that meet two criteria: (a) the weekly number of screens rises at least 5 times between week 3 and week 10 of exhibition, and (b) the weekly box office revenue rises at least 4 times between week 3 and week 10 of exhibition. The choice of these parameters responds both to the empirical distribution of weekly film dynamics and to prior research. First, because less than 5% of films show such an uncharacteristic rise of screens, and less than 5% of films show such an unconventional growth in weekly box office, the proposed parameters for number of weeks and growth trajectories in the definition of sleepers are based on a standard cutoff, yielding only 335 (3.9%) of all films released between 1985 and 2007 as sleepers. Second, the parameters are also in line with prior work on weekly sales dynamics (Einav 2007, Sorensen 2007). Importantly, all models of the paper are robust to either more stringent parameters (i.e., more instances of weekly growth) or less stringent parameters (i.e., fewer instances of weekly growth) in defining sleepers. Panel A of Figure 1 depicts the average weekly dynamics of sleepers, comparing them with the rest of films in the industry.

Dependent Variables

Number of new releases. In the film distribution industry, the count of new feature films distributed to theaters is a precise measure of new product introductions, thus capturing the phenomenon of how innovations are commercialized.

Median opening week screens. In the film setting, opening week screens have been shown to be a clean proxy to capture the primary competitive intent of distribution companies (Sorenson and Waguespack 2006, Moretti 2011). At the distributor-year level, the median of opening week screens is calculated over the distributor's new releases, and this metric is more appropriate than mean opening screens because it is less affected by outliers within a firm's portfolio.

Box office revenue and *Box office revenue minus production budget.* To assess the performance implications of unexpected financial slack, I construct the first dependent variable summing over the box office revenue of all films on a distributor's slate. In addition, I exploit the availability of cost data by using the net of box office minus production cost.

Perceived quality. I construct a third performance variable to effectively capture benefits to moviegoers: the average user rating for a film on IMDB. Consumer ratings are a clean proxy for consumer surplus in this industry because prices are uniform.

Independent Variables and Controls

that the proxy appropriately captures the concept of interest here. See below for its robustness.

Unexpected financial slack. Per equation (1) and the explanation thereafter, the key independent variable is $UFS_{i,t}$, defined as $\sum_j (R_j - C_j)$ for all sleeper films of distributor i in year t, where R is the box office revenue of the sleeper, and C is its production cost; only cases in which $(R_j - C_j) > 0$ are considered. While the main specification uses only production budget to construct C_j, for robustness cost is also implemented as C_{1j}, defined as advertising expenses for each film j, or C_{2j}, defined as the sum of production budget and advertising expenses for each film j; for untabulated models in which financial slack is defined as either $R_j - C_{1j}$ or $R_j - C_{2j}$, the results are essentially the same as the ones presented here.

Ordinary Financial Slack. This variable is defined exactly as UFS (also in its alternative definitions) but for the case of non-sleeper films. OFS in some sense captures other sources of positive surprises in film profitability not reflected by sleepers; however, because much of the excess financial slack behind OFS may be expected, no causal interpretation is given to this variable in the empirical analysis.

Control variables. Distributor fixed effects (267 dummies) and year fixed effects (23 dummies) take care of many possible sources of heterogeneity in the final panel data design. Additionally, I introduce a number of control variables, as well. Distributor *age* and the *number of production companies* involved in the films released by the distributor help capture the most basic information and experience effects that may directly affect the dependent variables. *Specialty distributor* is a dummy that controls for the type of distributor.[6] *High number of genres* is a dummy for whether the yearly slate of a distributor carries more than four distinct genres, a cutoff based on the frequency of film genres per firm. *Business promotion*, defined as the number of film festivals in which the distributor's films — sleepers and non-sleepers separately counted — participated in each given year, proxy for business-to-business information transmission. *Size quintile dummies* controlling for size are created every year for the industry based on the number of film releases of each distributor, and each distributor is assigned into one of these quintiles every year. Though intending to bolster robustness, the inclusion of controls in specification (1) may raise the concern that some of these variables could be endogenous; in untabulated models, I drop all control variables, finding essentially the same results as the ones reported throughout.

5 Main Results

Effects of Financial Slack on New Product Introductions

[6] Recall that specification (1) uses distributor fixed effects; therefore, distributor type can only be introduced as a control variable if the distributor changes its type over time; major distributors never change that status in the period studied, and independent distributors only change their type when they become specialty distributors.

Table 3 reports results for equation (1) using the number of new film releases as the dependent variable. All explanatory variables are lagged one year with respect to the number of new releases, to follow the institutional practice that distribution companies plan their film slates in advance.[7] To show that no spurious correlation is driving the effect of unexpected financial slack, I start with a simple cross-sectional specification and later add fixed effects and control variables to reach specification (1). A simple ordinary least squares specification shown in Model 4 yields a large positive effect of 0.066 with a standard error of 0.008. In other words, an increase of one standard deviation in unexpected financial slack is associated with an increase of 34% in the unconditional mean of new product releases, equal to 3.90. Model 5 shows an univariate regression on ordinary financial slack instead, yielding a smaller point estimate of 0.028; this model is important because it shows how the number of releases is influenced by ordinary financial slack when unexpected financial slack is ignored.

Similarly, Model 6 in Table 3 shows that unexpected financial slack leads to more new product introductions considered after accounting for ordinary financial slack in the same cross-sectional regression. An untabulated Wald test rejects the null of equality of coefficients for UFS and OFS at the 1% level, suggesting that one dollar of capital from unexpected financial slack has an effect statistically much larger than one dollar of ordinary financial slack. However, to the extent that sleepers are rare events, some distributors may have never even carried a sleeper. Model 7 restricts the specification to analyze the effect of treatment on the treated, thus leaving in the sample only distributors that ever carried a sleeper in the past or in the future; the cross-sectional point estimate on unexpected financial slack is smaller but still economically and statistically strong, and statistically different from that of ordinary financial slack per a Wald test. It is thus sensible to keep the complete panel of all distributor-year combinations as the main testing frame for all subsequent specifications.

Model 8 introduces distributor fixed effects and year fixed effects, thus moving from a cross-sectional design to a panel specification that conservatively clusters robust standard errors at the level of each distributor. The results show that unexpected financial slack is strongly significant. This specification is particularly appealing because it accounts for any unobserved time-invariant heterogeneity at the level of each distributor; moreover, year fixed effects capture any change in new product releases due to industry-wide events that affect all firms equally. Finally, Model 9 adds age, number of production companies, distributor type, genre variety, business promotion, and size quintiles as control variables, leaving the results largely unchanged. This specification confirms that unexpected

[7] A one-year lag is by no means short, as distributors assess market conditions many times during a given year; see a detailed characterization of distribution dynamics in Einav (2007). The results are robust to varying lags, as well.

financial slack is strongly significant in the context of many alternative factors influencing outcomes.[8]

Effects of Financial Slack on Competitive Release Strategies

The results thus far indicate that unexpected financial slack leads to more product introductions. The next set of tests, available in Table 4, investigates how unexpected financial slack affects the way distribution companies release their new films. The main dependent variable is the median number of opening week screens, a direct proxy for release strategies. For robustness, the median advertising budget of films in a distributor's yearly portfolio is also analyzed. The panel now includes only distributor-years for which there are films being released, thus decreasing the number of observations from 1,518 to 1,104. All models include the full set of control variables as in Model 9 of Table 3.

Model 10 shows that unexpected financial slack has a negative and significant influence on opening week screens: an increase of one standard deviation in sleeper financial slack leads to an average decrease of 12% of median opening week screens. This result is striking considering that the number of product releases is positively correlated with the median number of opening week screens, as shown in Table 1. In other words, when explaining median opening week screens, a negative coefficient on unexpected financial slack reflects a purposeful decision not to book more screens. Moreover, this negative coefficient cannot be attributed to a mechanically lower allocation to marketing efforts triggered by the fact that distributors are releasing more products, as on average this marketing allocation grows with the number of films introduced.[9]

The results of Model 10 suggest that unexpected financial slack positively effects the volume of product introductions yet negatively effects marketing support for these new products. Although these results are internally consistent as financial slack should not be unbounded, their opposite effects raise the question of whether the measurement is adequate. Three arguments support the specification employed. First, these different decisions —how many feature films to release and what strategy to employ in their release— are made at different moments (Hayes and Bing 2004). Institutionally, the separation of decisions over time indicates that managerial considerations for each case may be specific, if not entirely independent. Second, the regressions analyze the marginal influence of sleeper financial

[8] While the nice consistency properties of a linear panel fixed effects specification make it suitable for my design, I check the robustness of Model 9 to alternative estimation techniques. First, the dependent variable is an integer, so negative binomial models could be argued as appropriate; the untabulated regression equivalent to Model 9 yields essentially the same results. Second, new product introductions are non-negative, thus suggesting that a truncated variable model would also be appropriate; an untabulated Tobit specification following Model 9 leaves the results unchanged.

[9] I supplement the direct evidence provided by the simple correlation coefficient between new product introductions and the median number of opening week screens of Table 1 with more detailed tests; in untabulated kernel regressions of median opening week screens on new product introductions, or median advertising budget on new product introductions, I observe a clear non-negative pattern in the relation between these variables.

slack on the number of films to release and the average number of opening screens for those films. Therefore, the relationship between these dependent variables is not a point of contention. Third, I implement a seemingly unrelated regression (SUR) model to analyze jointly the causal impact of unexpected financial slack on the number of films released and on the median opening week screens. The untabulated SUR estimation of Model 9 and Model 10 jointly yields results that are essentially unchanged from the ones reported here.

Because sleeper films — the source of unexpected financial slack — can be viewed as following a limited-release strategy that may be persistent over time, it is important to further probe the explanation that it is unexpected financial slack that leads to fewer opening screens. Specifically, if distributors persistently release films on fewer screens over time, this dynamic tendency may explain away the proposed differential effect of financial slack on strategy. Because the results in section A.2 of the Appendix fail to find distributor specific, persistently lucky patterns in the data, and recent empirical work actually interprets "sustainable luck" as not luck at all (Bebchuk, Grinstein, and Peyer 2010), the recurrence of a competitive strategy of limited screen openings does not call into question the exogeneity of sleepers. Moreover, Panel B of Figure 1 shows that sleepers are unpredictable even with respect to their closest limited-release 'neighbors,' as described in the Appendix. To deal more explicitly with the alternative hypothesis that a distributor's past release strategy may nullify the effect unexpected financial slack in shaping future strategies, I now introduce a new set of tests.

Model 11 in Table 4 uses the lagged dependent variable as an independent variable alongside unexpected financial slack. While unexpected financial slack changes its magnitude downward by more than 25%, its negative direction and statistical power remain strong. Even if we are not interested here in testing for the persistence of firm policies (e.g., the coefficients on the lagged dependent variable), the results of Table 4 suggest that unexpected financial slack drives competitive strategy above and beyond the inertial strategic choices of the firm. Further arguments regarding the mechanisms for the effect of unexpected financial slack are provided in the next section.

The finding that unexpected financial slack negatively influences the number of opening screens raises the question of whether this dependent variable may be too noisy to capture a purposeful desire of a distributor to reduce its marketing support. Even if the use of screens as a proxy for advertising support is well grounded in prior work (Sorenson and Waguespack 2006, Moretti 2011), I replicate the main findings using the median advertising budget per film as the dependent variable. Model 12 of Table 4 indicates that unexpected financial slack has a strong negative influence on the advertising dollars spent in the next slate of films. Moreover, when including the dependent variable lagged as an independent variable in Model 13, the influence of unexpected financial slack is significant at the 10.3% level of confidence and still negative. It is therefore clear that having more unexpected financial slack leads distributors to release their future products on fewer screens, a result that is at odds with a macro view of advertising as an investment that should positively follow financial slack (Fee, Hadlock, and Pierce 2009). Moreover, by negatively influencing advertising, financial slack does not seem to trigger agency-prone empire building, which would predict a positive relation.[10]

Effect of Financial Slack on Performance

Results described in the previous subsections detail the impact of unexpected financial slack on new product introductions and competitive strategy. Table 5 reports estimates of how unexpected financial slack affects performance at the distributor-year level. Leveraging the richness of the data, I go beyond prior work on assessing box office performance (Model 14) by also introducing dependent variables more directly tied to profitability (i.e., box office revenue minus production budget in Model 15) and to consumer welfare (i.e., perceived quality of the film per consumer ratings in Model 17). In addition, to the extent that unexpected financial slack per se is a successful outcome, it is reasonable to study it also as a dependent variable to assess its dynamics (Model 16). The message of all models in Table 5 is that unexpected financial slack does not lead to higher performance. In fact, the coefficient on unexpected financial slack in the first two columns is negative and significant. Moreover, in untabulated regressions using further lags of unexpected financial slack, the coefficients are also non-positive, suggesting that the results are not due to the relative time window for measurement.

Comparing the Main Results with Endogenous Reduced-Form Analysis

Because all three main findings reported above are in stark contrast with those obtained when ignoring the endogenous nature of financial slack (Table 2), it is useful to consider why these differences may occur. Clearly, the different results across designs are not due to any asymmetry in the definition of financial slack — all regressions define financial slack only as positive values. However, the design in Table 2 pools all projects whereas the main design gives focalized attention to sleeper films vs. other successful films. Thus, the endogeneity of financial slack is most likely operating through the expectedness of many films, as managers may already factor in performance when deciding their future set of projects. By identifying a subset of films with unexpected success, I effectively circumvent these expected and endogenous links in the empirical analysis.

[10] A different interpretation of the negative impact of unexpected financial slack on opening screens and advertising would suggest that distributors lack discipline when they have more slack; however, recall that incentives are high powered in this setting, as rewards and reputation are typically based on film revenues. See Section 7 for a discussion of agency.

6 Theoretical Mechanisms for the Effects of Financial Slack

I now build on the main results to explore the potential mechanisms linking financial slack to organizational decisions and interpret additional findings in the context of different theories of organization.

Financial Slack or Qualitative Success?

First, I assess whether financial slack is simply a proxy for organizational success regardless of its monetary quantity. In other words, the amount of financial slack may not be all that important when compared with the qualitative nature of success surrounding it. Success has been conceptually and empirically viewed as a binary event in related work (e.g., Powell 2003, Lefgren, Platt, and Price 2011, Denrell, Fang, and Zhao 2011), whereas financial slack is a continuous construct (measurable in dollars). To empirically assess what may be driving the results found so far, I transform the financial slack measures to binary variables and replicate the main models of the paper.

Model 18 and Model 21 of Table 6 indicate that financial slack is not tantamount to a qualitative proxy for success. Specifically, the coefficient on whether the distribution company had a positive amount of unexpected financial slack is not significant when explaining either the number of new releases or the number of opening week screens. This result is important because, had the results shown a significant effect for the binary variable, the distinct influence of financial slack would have been somewhat undercut. For example, a key property of both success and financial slack is that they provide a signal about positive underlying qualities to external investors or competitors (Bernardo and Chowdhry 2002); however, these external investors would find it hard to interpret a coarse success signal, whereas they could quantify financial slack more clearly.

Building on this argument, the differential effect of financial slack (a continuous variable) vs. qualitative success (a binary variable) can be probed by introducing both measures in the same regression. Model 19 and Model 22 of Table 6 implement these tests. The results show that unexpected financial slack has strong statistical significance in explaining new product introductions and competitive strategies, whereas the binary variable for sleeper success yields no significant estimate. In a sense, the binary variable "cleans" unexpected financial slack from its qualitative effects, letting it reveal its quantitative influence, quite distinct from simply past success. In sum, these results give empirical substance to the conjecture that random success may accumulate over time (e.g., Denrell 2004) present here in the form of financial slack, thus offering a connection between work on surprises in organizations and work on organizational slack (e.g., Nohria and Gulati 1996).

Finance vs. Information in Financial Slack

The finding that unexpected financial slack has a positive influence on the number of new releases is consistent with a vast literature documenting a positive link between financial slack and investment (e.g., Fazzari, Hubbard, and Petersen 1988). However, a thorny issue in this relationship is that financial slack has different components — financial liquidity and information about investment opportunities — that are typically hard to separate when explaining investment (Bernardo and Chowdhry 2002). Although the extended models just described showed that financial slack affects the number of product introductions beyond the mere signaling value of past success, it is important to further analyze the information component inherent in financial slack.

To do this, I build on Ackerberg's (2001) idea that the effects of information should be different depending on whether the recipient of information is experienced or inexperienced with respect to the information vehicle in question. Specifically, I analyze whether the distribution company that receives unexpected financial slack had already experienced the benefits of sleepers in the past. If the "information leads to more investment" story is correct, then the effect of financial slack for inexperienced distribution companies should be much stronger than for experienced distribution companies. However, Model 20 in Table 6 indicates that this is not the case: the coefficient on unexpected financial slack interacted with a dummy for experienced distributors is positive and significant, and it is not statistically different from the coefficient on unexpected financial slack interacted with the inexperienced dummy (per an untabulated Wald test). It is thus the financial component of financial slack that drives outcomes. The intriguing fact that informed and uninformed decision-makers react equally to unexpected financial slack is consistent with Camerer, Loewenstein, and Weber's (1989) laboratory evidence. This suggests the existence of some bias, which I further explore below.

Alternatively, I also test for the information story by comparing the within-distributor value of unexpected financial slack employed thus far with the more aggregate across-distributors effect of unexpected financial slack, which sums over the unexpected financial slack of all distributors other than the focal firm. Importantly, information transmitted through product markets is not proprietary: any market participant can use it. However, the financial component of unexpected financial slack should matter differentially for those firms receiving it: they receive both information and financial slack, in contrast to the cross-section of market participants, who only receive information. In an untabulated regression, I find that the effect of the firm-specific unexpected financial slack is statistically different from that of the industry-level unexpected financial slack (the Wald test of differences yielding a 3% level of significance); moreover, the firm-specific unexpected financial slack positively affects new product introductions, whereas industry-level unexpected financial slack negatively impacts new product introductions.

Overall, the results suggest that information about investment opportunities is unlikely to be driving the volume of product introductions. Whether decision-makers appropriately incorporate unexpected financial slack in their competitive strategy decisions is the question I now address.

Learning about Strategy Appropriateness: Bayesian Updating vs. Attribution Bias

The most intriguing result so far is that unexpected financial slack leads to fewer opening week screens for new film releases. This result is puzzling in view of prior research finding a positive link between financial slack and investments (Fee, Hadlock, and Pierce 2009) and a positive relationship between financial slack and expansive competitive aggressiveness (Rauh 2006). The pattern, however, may be illuminated by considering the nature of projects that result in unexpected financial slack. In a Bayesian world, decision-makers factor in all information and draw accurate inferences based on past performance (Denrell, Fang, and Zhao 2011), updating their equilibrium strategies only after unexpected events (Lefgren, Platt, and Price 2011). But decision-makers may introduce distortions in their updating processes (Harrison and March 1984, Denrell and Fang 2010). Precisely because the empirical setting analyzed here exploits random variation to study financial slack, it is possible to extend the models and investigate whether managers are somehow failing to consider such financial success as random, tending to attribute it to their own prior strategy, and seeking to replicate it in the future.

One way to explore this attribution mechanism is to analyze what kind of new releases are affected by financial slack. In an untabulated model replicating Model 9, I modify the dependent variable to include only those new releases in the same film genre as that of past sleeper hits. The coefficient on unexpected financial slack is positive and significant, suggesting that the increased product introductions happen precisely within the same product niche that recently proved financially successful. Therefore, successful outcomes may bias managerial judgment about the suitability of past decisions and erroneously attribute patterns to events that are largely random (i.e., Table A.I in the Appendix).

An alternative way to assess whether and how managers update equilibrium strategies after unexpected events is to focus on the interaction of unexpected financial slack and past strategies (Lefgren, Platt, and Price 2011). To do this, I interact lagged opening week screens with either unexpected financial slack or ordinary financial slack in Model 23 of Table 6. In a Bayesian world, unexpected financial slack helps managers assess the appropriateness of a strategy; however, if there is an attribution bias that mistakes high performance for superior skill, then unexpected financial slack will guide firms to follow the random source, even if it is not replicable. By contrast, ordinary financial slack may not lead firms to follow an unusual source of success because ordinary financial slack has not been brought about by a random event. If managers' judgment is biased towards reenacting the sources of random success, a key empirical implication is that the interaction coefficients of past strategy with unexpected and ordinary financial slack should be statistically different. The results of Model 23 are revealing. First, the interaction of unexpected financial slack with lagged median opening week screens is statistically much smaller than the interaction of ordinary financial slack with lagged median opening week screens (rejecting the equality of coefficients at the 7.9% level in a Wald test); moreover, the direct effect of unexpected financial slack remains negative and significant. Because ordinary financial slack interacted with number of prior screens has a positive effect on the number of future opening screens, but unexpected financial slack does not, it is clear that very different dynamics are in play. There is something special about unexpected financial slack that makes managers choose a risky, unconventional path: it seems to trigger the attribution of success to skill in competitive strategies, even if the source of financial success is random.

Finally, if unexpected financial slack uncovers biases in decision-making, it is likely that performance following these suboptimal policies will deteriorate, showing reversion to the mean. Thus, the negative influence of unexpected financial slack on performance as revealed by Models 14 and 15 in Table 5 can be interpreted as consistent with a suboptimal attribution mechanism (Denrell and Fang 2010). By contrast, the findings of Table 5 that past random success does not increase performance in the future are inconsistent with arguments supporting the benefits of randomness (Denrell 2004).

Taken together, the evidence suggests that managers display an attribution bias in their belief-updating processes when they have more unexpected financial slack. Thus, this paper provides real-world empirical validation to theoretical arguments proposed by Denrell and Fang (2010) and a large body of experimental evidence (Cox and Summers 1987, Baron and Hershey 1988, Curren, Folkes, and Steckel 1992, Ratner and Herbst 2005). This background literature has provided nuanced explanations of how attribution biases operate; the high uncertainty and substantial project heterogeneity of film distribution studied here match reasonably well to the boundary conditions of these theories, thus connecting the observed results to micro mechanisms of decision making.

Exploring the Asymmetric Nature of Financial Slack

By design, the analysis has been centered on positive changes in financial slack, as sleepers are positive surprises. On the one hand, this is an advantage of the data, as the observation of unexpected financial slack is facilitated by surprisingly successful projects and ultimately helps to depict a managerial attribution mechanism. On the other hand, it would be both interesting and useful to analyze the opposite event — an unexpected *reduction* of financial slack. Such an analysis would be motivated by the behavioral theory of the firm predicting that the effects of slack resources may be asymmetric —that is, firms with positive changes in slack would behave differently as compared to firms with negative changes in slack. Unfortunately, the data at hand do not offer credible proxies for unexpectedly unsuccessful projects; specifically, losses in the film industry may not be cleanly measurable (Fee 2002), and the relation between negative expectations and less advertising may enact a self-fulfilling pattern that may not reveal exogenous reductions in financial slack (Elberse and Anand 2007).

Against this background, for completeness I conduct supplementary analyses using films with positive and negative performance. Specifically, I go beyond the main specification of unexpected financial slack of sleepers and specify two covariates that split ordinary financial slack into positive ordinary financial slack and negative ordinary financial slack. The results of these untabulated models indicate that (i) the coefficients on unexpected financial slack remain as before; and (ii) the coefficients on positive ordinary financial slack and negative ordinary financial slack are statistically different and show opposite signs, as confirmed by Wald tests. I interpret these results as compelling evidence of the robustness of the main thrust of this study. I also find these results as suggestive, but not conclusive, evidence that positive and negative changes in financial slack may have asymmetric impact on outcomes, as highlighted by the behavioral theory of the firm for the more general case of slack resources. Because my empirical design can only deal with endogeneity through differences in expectedness, I cannot give a causal interpretation to these additional findings nor offer a conjecture on their specific mechanisms, though they suggest a promising path for future work.

7 Discussion and Conclusion

In this study of the film distribution industry in the United States during the period 1985–2007, I found evidence that companies with more unexpected financial slack (1) release more new feature films, (2) open their new releases on fewer screens, contrary to the convention of the industry, and (3) do not attain higher firm performance or consumer satisfaction. I connect the statistical findings on effects of financial slack with theories of organizational slack, strategy dynamics, and organizational learning. I now briefly discuss how the empirical and theoretical implications of this study may expand the literature more broadly.

One dimension that has received only limited attention here but that could readily inform ongoing research is the role of surprises in organizational learning (e.g., Harrison and March 1984, Lampel and Shapira 2001, Winter 2004). While the approach pursued in this study mostly uses surprises for their exogenous variation in the form of unexpected financial slack, it can also be valuable for further theorizing in two ways. First, surprises have been difficult to robustly model in prior work that typically draws on isolated shocks in the form of case studies. Instead, this study shows that by analyzing a large number of projects in the population of firms over decades of competitive dynamics, surprises can now be more clearly understood as heterogeneous, recurrent, and consequential for action. Second, positive surprises bring about financial slack — a concrete, fungible resource that may have lasting effects in an organization even if the lucky event does not ever occur again. To the extent that organizations scholars have somehow neglected financial slack to focus on other important effects triggered by surprising events, this study opens an avenue for future research that connects surprises and slack.

While some features of the film industry can be more generally applicable, I am also mindful of boundary conditions. Because the study is centered on distribution strategies typically associated with high-powered incentives, it does not address the usual concern of the literature on cash windfalls: agency behavior (e.g., Blanchard, Lopez-de-Silanes, and Shleifer 1994, Duggan 2000). While it is an advantage of the design to focus on distribution decisions clearly linked to seeking profits in a competitive market, it would also be interesting to investigate whether other segments of the film sector may be more prone to wasteful uses of financial slack such as conspicuous consumption. All in all, several hints at generalizability have been provided throughout, even if the orientation of a within-industry study is not to generalize point estimates but to advance a causal relationship with sufficient grounds for internal validity and a nuanced depiction of more general mechanisms.

The paper is not free of limitations. First, as detailed in the previous section, financial surprises are modeled in terms of positive changes, as credible proxies for the opposite (negative) events are not available. Second, the data only speak to one broad class of surprises, those coming from the usual business endeavors of the firm. Perhaps because these extraordinary events are deemed replicable by managers in their future projects, the empirical design uncovers an attribution bias that may be less pronounced in other settings; by contrast, the data have nothing to say about surprises from totally unrelated realms that may also generate financial slack. Although this feature of the data sheds light on the mechanism of interest here, I do not believe it alters the validity of my results. Surprises from the usual business activities of firms can be observed in many settings, and may instead act against finding any strong effects to unexpected financial slack, as managers are more familiar with this kind of source than with unrelated sources. A third limitation is that the data do not allow for a more nuanced separation between the production and distribution of new products releases (Sorenson and Waguespack 2006), interactions in which financial slack may play an important role.

A general-purpose resource somewhat neglected in organizations research, financial slack has been examined here through the lens of unexpected financial slack. So far the literature has mostly avoided building upon idiosyncratic shocks to slack resources in order to focus on the more stable factors guiding organizational decisions and performance. While this focus has provided several mechanisms that drive new product introduction, competitive strategy, and market outcomes, it has been unable to account for some of the most pronounced patterns linking resources and decision-making processes. Without empirically delineating what financial slack means, its consequences for managerial decisions cannot be fully understood. Yet, as this study highlights, it is worthwhile to seek new ways, as slack still holds some surprises for organizational scholars.

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Figure 1: Weekly Dynamics of Sleepers and Other Films

This figure employs data on all films released in U.S. theaters between 1985 and 2007. Panel A displays the average weekly trajectory of sleepers (solid lines) and all other films (dotted lines) for their first 15 weeks of exhibition in theaters. Panel B displays a restricted set of other films (dotted lines) matched with sleepers using Abadie and Imbens's (2006) nearest neighbor algorithm.

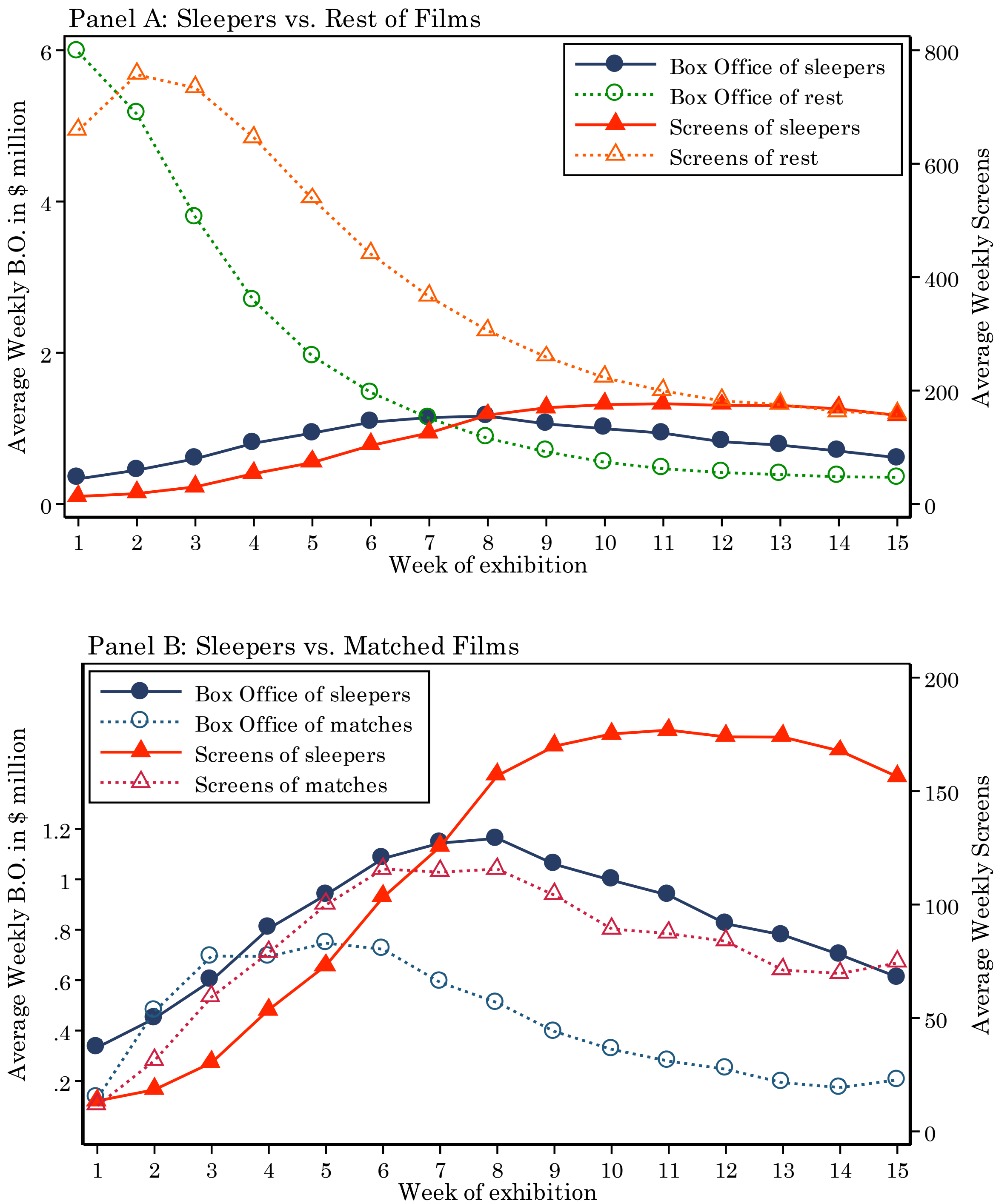

Table 1: Summary Statistics and Correlation Matrix

Observations are at the distributor-year level. The sample is all theatrical distribution companies operating in the U.S. in the period 1985–2007. The number of observations is n=1,518 (or alternatively n=1,104 for distributor-years with at least one film released by the distributor). All dollar values are expressed in millions of real dollars of 2009. Unexpected financial slack is the sum of the surplus of the distributor's sleeper hits box office revenue above their production budget for sleepers in which this value is positive. Ordinary financial slack is the sum of the surplus of all non-sleeper movies' box office revenue above their production budget for all non-sleeper films in which this value is positive. Distributor age is measured in years and is truncated in year 1982 for older distributors. Number of production companies is the count of distinct production companies involved in all films of a distributor in each given year. Specialty distributor is a dummy for whether a distribution company is a specialty distribution arm affiliated with a major distributor. High number of genres is a dummy for whether the yearly slate of a distributor carries more than four distinct genres, a cutoff based on a simple observation of the distribution of film genres. Business promotion is the sum of film festivals in which the distributor's sleepers participated in a given year; an analogous variable for non-sleeper films is also employed. Number of new releases is the count of feature films released by the distributor, excluding any reissued film. Median opening week screens is the number of opening screens of the median film on a distributor's slate in a given year. Perceived quality is the weighted average consumer rating given to a distributor's films.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Unexpected Financial Slack													
2	Ordinary Financial Slack	0.08												
3	Age	0.04	0.35											
4	N. production companies	0.19	0.36	0.43										
5	Specialty distributor	0.14	0.02	0.14	0.41									
6	High number of genres	0.14	0.63	0.35	0.56	0.12								
7	Business promotion, sleepers	0.26	-0.03	0.07	0.38	0.37	0.05							
8	Business promotion, non-sleepers	0.16	0.28	0.28	0.58	0.38	0.37	0.33						
9	Number of new releases	0.20	0.65	0.37	0.71	0.21	0.68	0.18	0.43					
10	Median opening week screens	0.01	0.75	0.49	0.38	0.00	0.60	-0.06	0.28	0.58				
11	Box office revenue	0.07	0.83	0.44	0.45	0.02	0.66	-0.01	0.29	0.73	0.86			
12	Box office minus production budget	0.03	0.68	0.21	0.19	-0.02	0.46	-0.04	0.14	0.47	0.58	0.80		
13	Perceived quality	0.05	0.10	0.14	0.25	0.20	0.10	0.14	0.16	0.19	0.04	0.12	0.13	
	Mean	2.43	52.26	6.11	11.78	0.05	0.15	0.47	1.82	3.90	190.37	103.84	26.87	6.33
	Standard deviation	20.00	149.96	5.10	16.85	n.a.	n.a.	2.54	5.12	5.64	551.77	292.03	121.09	1.15
	Minimum	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-276.98	1.20
	Maximum	434.72	1200.88	23.00	126.00	1.00	1.00	39.00	54.00	35.00	3213.00	1815.28	1179.37	9.80

Table 2: Illustrating the Endogeneity of Financial Slack in Organizational Decisions

This table reports Panel Fixed Effects regresions measuring the relationship between financial slack, organizational decisions and outcomes. In this table, financial slack is the sum of film-level box office revenue minus production costs in all cases when this difference is positive; all types of films of each distributor in a given year are indistinguishably considered to capture financial slack. The unit of observation is a distributor-year, and the sample and variables are as described in Table 1. All explanatory variables are lagged one year with respect to the dependent variables. As explained in the text, the interpretation of these regressions is problematic because financial slack is endogenous.

Dependent Variable:	**Number of New Releases**	**Median Opening Week Screens**	**Box Office Revenue**
	Model 1	Model 2	Model 3
Financial Slack	0.006^{***}	0.111	0.135^{*}
	(0.002)	(0.214)	(0.082)
Age	-0.066	39.385^{***}	6.575
	(0.064)	(9.380)	(4.429)
N. production companies	0.049^{**}	8.224^{***}	2.291^{***}
	(0.023)	(2.432)	(0.819)
Specialty distributor	-1.317	234.049	114.971^{*}
	(1.770)	(316.271)	(60.227)
High number of genres	1.031^{*}	-62.951	13.286
	(0.610)	(55.091)	(30.490)
Business promotion	0.012	-5.440^{***}	-0.946^{**}
	(0.011)	(1.112)	(0.381)
Size quintile dummies$_{it}$	Yes	Yes	Yes
Fixed effects:			
Distributor	Yes	Yes	Yes
Year	Yes	Yes	Yes
R^2	0.85	0.88	0.89
Sample size	1518	1104	1104
Number of clusters	267	267	267

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors clustered by distributor are in parentheses.

Table 3: Financial Slack and New Product Introductions

This table reports regression models of how unexpected financial slack affects the volume of new product introductions. The unit of observation is a distributor-year, and the sample and variables are as described in Table 1. In addition, size quintile dummies are created for every year based on the number of film releases of each distribution company, and each distribution company is assigned into one of these quintiles every year, to control for size; these quintiles (lagged) are included in Model 9. All explanatory variables are lagged one year with respect to the dependent variable. Ever Sleeper is a sample including all years of distributors that ever carried a sleeper film (in the past or in the future); Model 7 restricts the estimation to only this sample.

	Dependent Variable: **Number of New Releases**					
Sample observations:	All	All	All	Ever Sleeper	All	All
	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Unexpected Financial Slack	0.066^{***}		0.047^{***}	0.036^{***}	0.016^{**}	0.014^{**}
	(0.008)		(0.006)	(0.007)	(0.008)	(0.006)
Ordinary Financial Slack		0.028^{***}	0.027^{***}	0.024^{***}	0.008^{***}	0.006^{***}
		(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Age						−0.058
						(0.065)
N. production companies						0.062^{***}
						(0.016)
Specialty distributor						−1.035
						(1.769)
High number of genres						0.965
						(0.604)
Business promotion, sleepers						−0.047
						(0.032)
Business promotion, non-sleepers						−0.024
						(0.028)
Size quintile dummies$_{it}$	No	No	No	No	No	Yes
Fixed effects:						
Distributor	No	No	No	No	Yes	Yes
Year	No	No	No	No	Yes	Yes
R^2	0.04	0.23	0.26	0.25	0.82	0.85
Sample size	1518	1518	1518	648	1518	1518
Number of clusters					267	267

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are shown in parentheses, clustered by distributor in models 8 and 9.

Table 4: Financial Slack and Competitive Strategy

This table reports Panel Fixed Effects models of how unexpected financial slack drives competitive release strategies. The unit of observation is a distributor-year. The dependent variables are measured within the slate of films released by each distribution company each year. Median opening week screens is in thousands of screens; and median advertising budget is in millions of 2009 dollars; this latter variable is not available for all observations, so the sample size is smaller in Model 12 and Model 13. The sample and explanatory variables are as described in Table 1. In addition, size quintile dummies are created for every year based on the number of film releases of each distribution company, and each distribution company is assigned into one of these quintiles every year, to control for size; these quintiles (lagged) are included in all models. All explanatory variables are lagged one year with respect to the dependent variable.

Dependent Variable:	**Median Opening Week Screens**		**Median Advertising Budget in millions of dollars**	
	Model 10	Model 11	Model 12	Model 13
Unexpected Financial Slack	-1.154^{***}	-0.859^{***}	-0.008^{**}	-0.004
	(0.348)	(0.224)	(0.003)	(0.003)
Ordinary Financial Slack	0.196	0.022	0.001	-0.002
	(0.252)	(0.148)	(0.003)	(0.002)
Lagged dependent variable		0.507^{***}		0.559^{***}
		(0.145)		(0.062)
Age	36.785^{***}	19.522^{***}	0.456^{***}	0.308^{***}
	(9.288)	(6.653)	(0.109)	(0.084)
N. production companies	4.253^{*}	2.771^{**}	0.049^{*}	0.022
	(2.346)	(1.396)	(0.027)	(0.014)
Specialty distributor	185.430	105.043	0.595	-0.170
	(365.232)	(187.507)	(2.974)	(1.121)
High number of genres	-44.909	-83.591^{*}	0.103	-0.409
	(47.384)	(50.560)	(0.560)	(0.555)
Bus. promotion, sleepers	-3.506	3.304	-0.081	-0.030
	(4.698)	(4.546)	(0.055)	(0.054)
Bus. promotion, non-sleepers	1.925	1.277	0.011	-0.018
	(4.287)	(2.257)	(0.050)	(0.034)
Size quintile dummies$_{it}$	Yes	Yes	Yes	Yes
Fixed effects:				
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
R^2	0.87	0.90	0.81	0.87
Sample size	1104	1104	854	701
Number of clusters	267	267	193	144

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors clustered by distributor are in parentheses.

Table 5: Financial Slack and Performance

This table reports Panel Fixed Effects models of how unexpected financial slack affects economic value, using as alternative dependent variables box office revenue, gross profits (box office revenue minus production budget), unexpected financial slack, and perceived quality. The unit of observation is a distributor-year, and the sample and variables are as described in Table 1. All explanatory variables are lagged one year with respect to the dependent variables.

Dependent Variable:	**Box Office Revenue**	**Box Office minus Production Budget**	**Unexpected Financial Slack**	**Perceived Quality**
	Model 14	Model 15	Model 16	Model 17
Unexpected Financial Slack	-0.430^{*}	-0.285^{**}	-0.038	-0.001
	(0.222)	(0.144)	(0.040)	(0.001)
Ordinary Financial Slack	0.173^{**}	0.102	-0.001	0.000
	(0.081)	(0.076)	(0.015)	(0.000)
Age	6.080	-5.397^{*}	-0.473^{*}	-0.002
	(4.422)	(2.986)	(0.252)	(0.014)
N. production companies	1.606^{**}	-0.525	0.033	-0.002
	(0.706)	(0.669)	(0.213)	(0.002)
Specialty distributor	106.847^{*}	102.972^{***}	14.980^{*}	0.128
	(64.350)	(31.413)	(8.838)	(0.278)
High number of genres	18.589	-7.992	-2.865	0.158^{*}
	(30.565)	(17.131)	(5.386)	(0.095)
Bus. promotion, sleepers	1.811	2.165	0.049	-0.002
	(1.462)	(1.348)	(0.206)	(0.006)
Bus. promotion, non-sleepers	-0.203	-0.235	0.110	-0.008^{**}
	(1.228)	(0.818)	(0.232)	(0.004)
Size quintile dummies$_{it}$	Yes	Yes	Yes	Yes
Fixed effects:				
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
R^2	0.89	0.62	0.15	0.64
Sample size	1104	1104	1104	1101
Number of clusters	267	267	267	265

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors clustered by distributor are in parentheses.

Table 6: Mechanisms for the Effects of Financial Slack on Organizational Decisions

This table reports Panel Fixed Effects models of mechanisms that may account for the effect of unexpected financial slack (UFS in shorthand) on new product introductions and competitive strategy. The unit of observation is a distributor-year, and the sample and dependent variables are as described in previous tables. All explanatory variables are lagged one year with respect to the dependent variables. 1(Unexpected Financial Slack>0) and 1(Ordinary Financial Slack >0) are indicator variables. Experienced is a dummy variable for whether the distributor with a sleeper had already had a sleeper in the past; Inexperienced is a dummy for whether the distributor with a sleeper had not had a sleeper in the past.

Dependent Variable:	Number of New Releases			Median Opening Week Screens		
	Model 18	Model 19	Model 20	Model 21	Model 22	Model 23
Unexpected Financial Slack		0.014^{**}			-0.843^{***}	-0.787^{**}
		(0.007)			(0.248)	(0.340)
Ordinary Financial Slack		0.006^{***}			0.022	-0.819^{**}
		(0.002)			(0.148)	(0.413)
1(Unexpected Financial Slack>0)	0.509	0.019		-38.527	-4.189	
	(0.645)	(0.711)		(36.032)	(33.927)	
1(Ordinary Financial Slack>0)	1.377^{***}	1.276^{***}		-11.373	-8.068	
	(0.373)	(0.369)		(31.594)	(31.789)	
UFS × Experienced			0.015^{**}			
			(0.008)			
UFS × Inexperienced			0.009^{**}			
			(0.004)			
OFS × Experienced			0.006^{***}			
			(0.002)			
OFS × Inexperienced			0.001			
			(0.006)			
Lagged median op.week screens × UFS						0.000
						(0.000)
Lagged median op.week screens × OFS						0.001^{**}
						(0.000)
Lagged median op.week screens				0.509^{***}	0.507^{***}	0.347^{*}
				(0.146)	(0.147)	(0.186)
All control variables as in previous tables	Yes	Yes	Yes	Yes	Yes	Yes
Distributor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effectss	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.84	0.85	0.85	0.90	0.90	0.91
Sample size	1518	1518	1518	1104	1104	1104
Number of clusters	267	267	267	267	267	267

$^{***}p<0.01, ^{**}p<0.05, ^{*}p<0.1$. Robust standard errors clustered by distributor are shown in parentheses.

Appendix

This Appendix provides background information on the existence and properties of sleeper hits.

A.1 A Primer on Sleeper Hits

Sleepers are defined in the dictionary as "a movie, book or play that achieves sudden unexpected success after initially attracting little attention, typically one that proves popular without much promotion or expenditure" (Oxford) or as "someone or something unpromising or unnoticed that suddenly attains prominence or value" (Merriam-Webster). Intuitively, these definitions associate sleepers with unexpected success. More technically, sleepers can be conceptualized as special cases of diffusion processes in information markets with subjective assessments of product quality: books (Sorensen 2007), radio airplay (Rossman, Chiu, and Mol 2008) and music records (Hendricks and Sorensen 2009). In this kind of diffusion process, sleepers attain visibility and success only after a slow start, a feature that makes them especially salient ex post. While my focus is on the film industry, the inherent dynamics of sleepers and their link to unexpected financial slack can thus be assessed more broadly.

It is commonly accepted that the success of sleeper films such as *Good Will Hunting* (1997) and *There's Something About Mary* (1998) is largely missed by prediction models based on pre-release characteristics. This is due to the unconventional behavior of distributors in releasing sleepers. The standard micro-dynamics in the theatrical market begin by screening in many theaters followed by a decay in weekly box office revenues and screens (Einav 2007). Aware of this pattern, film distributors act upon their expectations about the film when negotiating opening week screens with theater owners (Moretti 2011). Hoping to achieve word-of-mouth effects, which follow a different dynamic from those of advertising (Joo 2009), film promoters to a large extent mortgage the success of the film on their skill and luck in handling the release. Against this standard logic that requires both heavy marketing and many opening week screens to generate positive momentum, sleepers follow a different path, opening small and hoping to grow over time rather than decay.

Sleepers have humble beginnings. Films that do not get picked up when originally pitched; screenings that face resistance by theater owners; complex themes that get sidelined by the mainstream media — all are examples of unconventional films that lack support. Though much of the limited-release strategy is intentional, as some films fit a well-orchestrated corporate strategy in their quasi-grassroots marketing campaigns (Perren 2004), very few of the limited-release films (totaling 3,913 films, when defining limited-platform releases as those opening in fewer than 300 screens) become sleepers. An intentional limited-release strategy is therefore too risky for those films with unobserved ex-ante knowledge that they can do well. The large role of luck makes these films particularly attractive for studying the consequences of unexpected financial slack.

A.2 Empirical Tests of Sleeper Predictability

This section provides empirical support to the stylized fact that sleepers' success is to a great extent unpredictable. Consider each of the 6,857 films, described in Section 4, the day before they open in theaters, a moment when the information set is anterior to any market dynamics. Table A.I presents different regression models of what observable characteristics make a film more likely to become a sleeper. Recall that sleepers are defined among the pool of all films using a mechanical ex post algorithm based on film trajectories in the weeks after release. The first model shows that opening week screens is strongly and negatively associated with the probability of the film becoming a sleeper. Per the marginal effects also reported in Table A.I, the influence of opening week screens is economically meaningful: a decrease of one standard deviation in opening week screens increases the probability of the film becoming a sleeper by 1%; compared with the 3.9% unconditional probability of becoming a sleeper, this is a whopping 26% increase in probability. The second model adds several explanatory variables, including production cost, a dummy for U.S.-based production, a dummy for R rating or more restrictive ratings, and an English language dummy. The introduction of these controls does not alter the statistical or economic significance of opening week screens, nor does it materially improve the overall log-likelihood of the first model. The third model includes a dummy for whether the distribution company is a major,[11] suggesting that majors have a lower probability of releasing a sleeper. This finding does not invalidate including majors in the study of financial slack, as untabulated summary statistics indicate that major distributors are much more successful than non-major distributors in terms of the revenue of the sleeper hits they release, with a mean value of unexpected financial slack that is larger than that of non-major distributors.

The last two models of Table A.I change the specification to a linear probability model with fixed effects and introduces hundreds of additional explanatory variables in the form of dummies: film genre, week of the year, month of the year, calendar year, and distribution company. Importantly, the overall significance of this saturated model is poor ($R^2 = 0.16$). The fifth model includes advertising expenses

[11]Because the identity of major firms has been time-invariant in the industry since the first half of the twentieth century, this variable can only be used in this kind of cross-sectional model that does not include distributor fixed effects; subsequent models in Table A.I introduce distributor fixed effects, thus subsuming any effect from the 'major' category.

in real dollars as an explanatory variable, thus putting the opening screens variable to a more stringent test, as past research has used opening screens to proxy for unavailable data on advertising expenses (Sorenson and Waguespack 2006, Moretti 2011), which is a unique variable in this study.[12] The results remain largely the same, and the overall R^2 does not increase substantially. In sum, sleepers are only poorly predicted using many dimensions of ex ante heterogeneity, and a small number of opening week screens is a robust trait of films that might become sleepers.

Despite these considerations, a question may remain about the exogeneity of sleeper success: Isn't the strategy of "opening small" just one more kind of purposely-sought release strategy? In other words, the results of Table A.I might be interpreted as a ceiling effect by which limited-screen releases are most likely to become sleepers, so that distribution companies somehow expect these films to become successful sleepers. However, two quantitative institutional arguments and a new empirical test help assuage this concern. On the institutional front, peer effects among consumer audiences may depend on strong opening week sales, and adaptive contracting among theater owners may rely on relative performance in previous weeks (Moretti 2011). Therefore, both demand-side effects that enhance sales and supply-side arrangements that spur retailers' investment rely on a conventional strategy of opening on more screens. Sleepers, however, go against these dynamics by opening small, possibly forfeiting a stronger box office record. This risky strategy of going against conventional practice is uncharacteristic of distributors expecting success.

A second argument that may also help to see sleeper success as uncertain and unpredictable is to match sleepers with "quasi-sleepers" and see if they differ. To do this, I test directly for whether the performance of sleepers is indistinguishable from that of other limited-screen releases that are not sleepers but their "nearest neighbors" instead. For this test, I use Abadie and Imbens's (2006) nearest-neighbor matching algorithm to find the closest film to each sleeper in the sample; the criteria for matching are opening week screens, film genre, and date of release. Panel B of Figure 1 shows the results in graphical form: the average weekly trajectory of sleepers and their nearest neighbors. Not surprisingly, sleepers have a stronger box office performance and a longer staying power in theaters, even though they are otherwise indistinguishable from their nearest neighbors ex ante. This empirical pattern is reasonable confirmation that sleeper success is one of a kind, in the broad sense of "randomizing sleeper treatment," thus suggesting that the empirical basis for all subsequent tests is justified.

[12]Because the advertising expenses variable may include decisions made after the film was released, its inclusion as an explanatory variable to predict sleepers could be problematic; moreover, prior work has viewed opening week screens as a proxy for advertising expenses, suggesting that the variables should not be included in the same regression. The fact that opening week screens keeps its direction and significance when forced to enter the same regression as advertising expenses is thus noteworthy.

Table A.I: What makes a Sleeper?

This table reports Probit and Linear Probability Fixed Effects models of what film characteristics may help predict a sleeper. The unit of observation is a feature film, and the sample is all those feature films released between 1985 and 2007 for which production budget information is available. The dependent variable is a dummy for whether the film is a sleeper. Sleepers are defined mechanically as those films complying jointly with two criteria: (1) the weekly number of screens rises at least 5 times between week 3 and week 10 of exhibition, and (2) the weekly box office revenue rises at least 4 times between week 3 and week 10 of exhibition. Opening week screens is expressed in thousands of screens. Advertising budget and production budget are in millions of 2009 dollars. USA production is a dummy for whether any of the production companies for the film is U.S.-based. Rated R is a dummy for films with R or more restrictive MPAA rating. English language is a dummy referring to the original language of the film. Major distributor is a dummy for whether the distribution company is a major (i.e., 20th Century Fox, Columbia, Dinsey, MGM, Paramount, Sony, TriStar, Universal, or Warner Bros.) The specification is Probit for the first three models, and Linear Probability Fixed Effects for the fourth and fifth models. Marginal effects for opening week screens are shown at the bottom of all Probit models. The LPM-FE models includes indicator variables for each distinct genre (14 dummies), week of the year in which the film is released (52 dummies), month (12 dummies), year (23 dummies) and distribution company (267 dummies).

	Dependent Variable: **Sleeper (1/0)**				
Specification:	Probit	Probit	Probit	LPM-FE	LPM-FE
Opening week screens	-2.005^{***}	-1.833^{***}	-1.828^{***}	-0.013^{***}	-0.026^{***}
	(0.310)	(0.305)	(0.304)	(0.004)	(0.005)
Advertising budget					0.002^{***}
					(0.000)
Production budget		0.001	0.005	0.000	−0.000
		(0.003)	(0.003)	(0.000)	(0.000)
USA production dummy		-0.271^{***}	-0.247^{***}	-0.036^{***}	-0.036^{***}
		(0.071)	(0.071)	(0.008)	(0.009)
Rated R dummy		0.138^{**}	0.139^{**}	−0.001	0.001
		(0.060)	(0.061)	(0.006)	(0.006)
English language dummy		−0.049	−0.036	−0.015	-0.020^{*}
		(0.089)	(0.089)	(0.011)	(0.012)
Major distributor dummy			-0.297^{***}		
			(0.105)		
Fixed effects for film genre, week, month, year, and distributor	No	No	No	Yes	Yes
Marginal effect of opening week screens	-0.0094^{*}	-0.0110^{**}	-0.0118^{**}		
R^2				0.16	0.17
Log-likelihood	-1065.36	-1052.25	-1047.99		
Sample size	6857	6857	6857	6857	6118

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$. Standard errors are shown in parentheses.