More Competition, Better Buyouts? When Private Equity Sponsors Compete for Deals*

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Abstract

This paper studies, both theoretically and empirically, how competition among private equity (PE) sponsors for leveraged buyout (LBO) targets shapes deal outcomes. Empirically, we document that sponsor competition and deal multiples have increased over time. We further show that greater competition is associated with a shift toward smaller but higher-quality targets, characterized by lower default risk, stronger operating performance, and lower leverage. In a search-and-matching model of the LBO market, we show that greater competition raises acquisition prices, making low-quality deals more costly to pursue and strengthening sponsors' incentives to screen targets. It also pushes sponsors toward less-contested pools of smaller firms, while encouraging greater specialization and more intensive post-buyout engagement. A calibrated version of the model quantifies how the rise in competition over recent decades has significantly reduced PE returns.

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Private equity (PE) has expanded rapidly over recent decades, and leveraged buyouts (LBOs) have become a mainstream acquisition channel for small and middle-market firms. Assets under management by buyout funds exceed $13 trillion (McKinsey, 2024), hundreds of funds raise capital each year, and thousands of sponsors compete for LBO targets (PitchBook). This growth has drawn increasing scrutiny from policymakers[1] and has coincided with a vigorous academic debate over whether LBO returns have declined.[2]

As the industry has grown, sponsors have faced intensifying competition for LBO deal flow. Figure 1 documents this long-run trend: sponsor-level concentration in LBO deal flow—measured by an HHI of sponsors' deal shares within industry-year—has declined sharply since the 1990s, while entry multiples have risen substantially, a pattern historically associated with weaker ex-post performance and fund returns (Brown and Kaplan, 2019). These trends raise several questions. How does competition affect acquisition prices and sponsor profitability, and PE returns? Does it push sponsors toward lower-quality deals and higher leverage? And how do sponsors adjust in response?

This paper studies, both empirically and theoretically, how competition among PE sponsors shapes LBO terms and outcomes. As expected, more competition raises entry multiples and lowers returns; its effects on other margins, however, are less obvious. Conventional intuition holds that fiercer competition for deal flow should push sponsors toward worse targets. We find the opposite: competitive pressure is associated with higher-quality, more profitable targets and less leverage. Our results suggest that rising competition has reshaped buyout activity: it improves selection and shifts private equity away from a passive, leverage-driven model toward greater sponsor specialization and more active engagement.

Motivated by the documented decline in sponsor concentration and the concurrent rise in deal multiples, we develop a search-and-matching model of the LBO market, which delivers

[1] For example, Senator Elizabeth Warren noted: "*The private equity (PE) industry is continuing to grow at a rapid pace... As a result of this growth, PE touches virtually every corner of society.*" Former SEC Chair Gary Gensler called for "*more sunshine and competition to the private funds space*," and former FTC Chair Lina Khan likewise stressed the importance of competition in private capital markets. Despite this policy attention, the consequences of sponsor concentration in leveraged buyouts remain underexplored.

[2] A large empirical literature beginning with Kaplan and Schoar (2005), reviewed in Kaplan and Strömberg (2009), finds that private equity returns generally exceed those of public markets. Brown and Kaplan (2019) show that Public Market Equivalents, while above public comparables, fell through the 2000s. The financial press has also highlighted declining returns (e.g., CNBC).

six predictions that we subsequently test and confirm in the data. In the model, PE sponsors (i.e., PE funds) compete for LBO target firms. An LBO supplies the funds the firm needs to invest and expand. After the buyout, the firm generates cash flows, its capital stock grows, and it chooses its capital structure by trading off the benefits of debt (e.g., a tax shield) against the costs of inefficient liquidation in default.

Target firms are heterogeneous along three dimensions. First, they differ in size, measured by their pre-LBO capital stock or book assets. Sponsors can direct their search by size because measures such as book assets are readily observable and verifiable. Second, firms differ in their operating performance. Sponsors observe a target's profitability upon matching but cannot target it ex ante; intuitively, it is hard information revealed through inspection of financial statements. Third, firms differ in hidden quality ("good" or "bad"), which is soft information correlated with operating performance but otherwise unobservable. Learning about this component requires costly due diligence and screening. Hidden quality determines the firm's default risk. We assume acquiring a good firm has positive NPV, whereas acquiring a bad firm has negative NPV.

After locating a target firm, sponsors observe this firm's operating performance, and conduct costly screening to acquire soft information about hidden quality. In case screening yields a positive signal, the sponsor and firm bargain over the deal terms, with the sponsor facing adverse selection and firms having the outside option to re-enter the market in search of another sponsor. Because this option to continue searching becomes more valuable with competition, acquisition prices rise with competition. This yields the model's **first prediction**: greater sponsor competition increases deal multiples. In the model, these higher deal multiples paid reduce sponsor payoffs and thus PE returns.[3]

Higher acquisition prices also make acquiring bad firms more costly. As such, they strengthen sponsors' incentives to screen out bad targets. More screening raises the average quality of acquired firms and lowers their post-buyout probability of default. This yields the model's **second prediction**: greater sponsor competition leads to higher-quality deals and, in particular, lower post-buyout default probabilities.

[3]Our model should be understood as one of primary buyouts, whose costs rise with entry deal multiples. We do not model secondary buyouts, so the potential positive effect of higher multiples through higher exit or resale values does not arise.

Crucially, we allow screening to also add value to the target, capturing operational or governance engineering, and assume that operating performance is correlated with hidden quality. Together, the value-add channel and the correlation between observed and unobserved firm quality imply that stronger screening translates into higher observed profitability among LBO targets. This yields the model's **third prediction:** greater sponsor competition is associated with stronger operating performance.

Next, when targets are of higher quality, liquidation becomes more costly, raising the expected distress costs of debt. Sponsors therefore optimally choose lower post-buyout leverage for higher-quality targets, delivering the **fourth prediction:** greater sponsor competition is associated with lower target firm leverage. Interpreted more broadly, this relationship is consistent with both (1) sponsors targeting higher-quality firms with stronger financials, and thus lower leverage, and (2) sponsors using less leverage to finance the deal.

Sponsors also choose ex ante whether to search for larger firms or otherwise identical smaller ones. Because of returns to scale, searching for larger firms is more profitable and thus attracts more intense competition. As the number of searching sponsors grows, some sponsors shift toward the less-contested pool of smaller firms. This yields the **fifth prediction:** greater sponsor competition reduces the average size of LBO targets.

Finally, we allow sponsors to become *industry specialists* (Spaenjers and Steiner, 2024) through costly upfront investment in screening technology, yielding the **sixth prediction:** greater competition increases sponsor specialization. Intuitively, as competition compresses profits, sponsors must improve deal selection through specialization in an industry to remain profitable. In a similar vein, we also show that greater competition is associated with more intensive post-buyout engagement and value creation by the sponsor.

We test the model's predictions using novel data on LBO deals and sponsor competition from 2013 to 2023. We combine administrative loan-level data from the Federal Reserve's Y-14 H.1 schedule (henceforth, Y-14 data) with LBO deals from PitchBook to construct a dataset of U.S. buyouts with detailed information on target firms and their bank loans.[4] The Y-14 data provide rich firm- and loan-level information for borrowers at covered banks.

[4]The Y-14 data are collected by the Federal Reserve for annual bank stress tests and cover approximately 70% of U.S. commercial and industrial (C&I) lending (Bidder, Krainer, and Shapiro, 2021). Its post-GFC introduction dictates our 2013 sample start.

Our matching procedure yields approximately 4,500 buyout deals with firm- and loan-level information within a four-quarter window around the LBO date.[5]

We measure sponsor competition at the industry–year level using the lagged log number of (distinct) sponsors conducting LBO deals within a given industry and year. We construct this measure by counting the sponsors participating in LBO deals within a PitchBook industry group and year; a higher number of sponsors thus reflects greater competition for deal flow. This measure maps directly to the theory. Because sponsors often specialize in particular industries (Spaenjers and Steiner, 2024), industries can be viewed as partially segmented markets with differing degrees of competition. Since time-series variation is limited over 2013–2023, our analysis primarily exploits cross-industry differences.[6] Our results are robust to alternative competition measures, such as the number of deals within a given industry–year or the Herfindahl–Hirschman Index of sponsor concentration in LBO deals.

The model is tractable enough to deliver analytical results: all of the model predictions, presented in Section 1.6, are derived analytically. At the same time, the model generates quantitatively relevant output that matches the empirical relationships between deal characteristics and the (lagged) number of sponsors active in a given industry and year, our measure of competition (Figure 3). In both the model and the data, the log number of sponsors varies from about 3.7 to 6.8—from about 40 to slightly fewer than 900 sponsors, or less than three standard deviations.

Over this range, an increase in the number of sponsors, and thus competition, is associated with a rise in EV/EBITDA multiples from about 11 to 19, a decline in average LBO firm size (book assets) from about $110 million to $50 million, and falls in the probability of default from about 5% to 3% and in Debt/EBITDA from 3.4 to 2.8. Importantly, model-implied returns to sponsors fall from about 25% to 5%. The model also matches untargeted aggregate trends: as Figure 4 shows, it captures the rise in EV/EBITDA multiples from 2000 to 2023 (from about 10 to 12, on average) and implies a secular decline in PE returns, with gross returns falling from about 37% to 22%.

[5]The exact number of deals varies across specifications, as some variables are unavailable for some observations.

[6]Figure 1 shows that sponsor concentration declined sharply before 2008 and has remained low since; cross-industry differences, however, remain large and persistent, and identify the effects in our matched sample.

Building on the binscatter plots, we estimate panel regressions of deal-level outcomes on the lagged industry–year log number of sponsors with year fixed effects. The results closely align with the model's predictions. First, a higher number of sponsors is associated with higher deal multiples, measured as deal size (our proxy for enterprise value) scaled by EBITDA: a one-standard-deviation increase in the number of sponsors raises the Deal Size/EBITDA multiple by about 19%.

Second, a higher number of sponsors is positively associated with ROA and the sales-to-assets ratio (measures of operating performance), and negatively associated with bank-reported probabilities of default, which prior work shows to be accurate, forward-looking measures of firm quality (Beyhaghi, Howes, and Weitzner, 2024; Howes and Weitzner, 2025). These results on competition and deal characteristics are both statistically and economically significant: a one-standard-deviation increase raises ROA by more than 1 percentage point (relative to a mean of 7.51%) and lowers the probability of default by about 0.8 percentage points (relative to a mean of 4.4%).

Third, the number of sponsors is negatively associated with target firm size and average loan size (the latter a proxy for firm size); a one-standard-deviation increase reduces average target size by roughly 25%. Fourth, the number of sponsors is negatively related to Debt/EBITDA. Finally, sponsor industry specialization—the share of a sponsor's deals within a given industry—is positively associated with the number of sponsors. Overall, these findings confirm the model's predictions: greater competition among sponsors is associated with higher deal multiples, but also with a shift toward higher-quality and smaller targets. The model also shows that competition significantly compresses PE returns.

A key concern is that the number of sponsors active in a given industry is endogenous: competition may simply be higher in industries intrinsically populated by higher-quality firms, rather than driving better deal selection. To mitigate this concern, we employ a shift-share instrumental-variable strategy that exploits sponsors' presence across multiple industries: shocks to a sponsor's overall activity propagate differentially across industries according to each industry's exposure to that sponsor. As the shifter, we use sponsors' hiring—measured from job-posting data—which captures their capacity to source and execute deals. Staffing decisions reflect fundraising cycles, fund commitments, and organiza-

tional growth and are set over multi-year horizons, making them less likely to respond to short-run conditions in any particular industry.

The instrument is relevant: as sponsors expand hiring, they conduct more deals across industries, raising the number of sponsors active in a given industry. We then show that instrumented competition is associated with higher deal multiples, smaller target firms and loans, and greater sponsor specialization, in line with the reduced-form estimates. For the remaining outcomes—leverage, default risk, and operating performance—the estimates have the same signs but lack statistical significance. We view this analysis as a robustness check that exploits a different source of variation rather than a complete resolution of endogeneity. Our results also hold when competition is measured by the number of deals within an industry–year or by the HHI of sponsor concentration in LBO deals, which inversely measures competition.

Related Literature. This paper contributes to the literature on private equity and leveraged buyouts (Kaplan and Strömberg, 2009). Prior work examines deal characteristics (Axelson, Jenkinson, Strömberg, and Weisbach, 2013), capital structure (Malenko and Malenko, 2015; Haque, Jang, and Mayer, 2025; Shive and Forster, 2025), consumer externalities (Eaton, Howell, and Yannelis, 2019; Gupta, Howell, Yannelis, and Gupta, 2024), labor market effects (Davis, Haltiwanger, Handley, Jarmin, Lerner, and Miranda, 2014; Herkenhoff, Lerner, Phillips, Rebelo, and Sampson, 2025; Isen, Richmond, Smith, and Yannelis, 2025), and post-buyout performance (Guo, Hotchkiss, and Song, 2011; Bernstein and Sheen, 2016; Cohn, Hotchkiss, and Towery, 2022). In contrast, we focus on how competition among PE sponsors affects deal selection. We show that greater competition improves selection through more intensive due diligence and sourcing, and our theory further predicts that heightened competition strengthens post-buyout engagement.

Our paper also relates to the literature on the returns and performance of PE funds and LBOs (Kaplan and Schoar, 2005; Phalippou and Gottschalg, 2009; Sensoy, Wang, and Weisbach, 2014; Braun, Dorau, Jenkinson, and Urban, 2025), with Gourier, Phalippou, and Westerfield (2024) focusing on the commitment and liquidity risks borne by fund investors as drivers of expected returns. Although we do not observe realized returns, we show that rising competition is associated with higher deal multiples and lower leverage. The model

implies that the increase in the number of sponsors over the observed range is associated with a decline in gross PE returns from approximately 25% to 5%.

On the theory side, our work relates to models of leveraged buyouts and private equity (Axelson, Strömberg, and Weisbach, 2009; Malenko and Malenko, 2015; Gryglewicz and Mayer, 2023; Maurin, Robinson, and Strömberg, 2023), as well as to theoretical and structural studies of M&A markets (see, among others, Fishman, 1988; Berkovitch and Khanna, 1991; Gorbenko and Malenko, 2014; David, 2021).[7] Among search-and-matching frameworks, our paper is closest to Sørensen (2007), Inderst and Müller (2004), and Ewens, Gorbenko, and Korteweg (2022) on VC–entrepreneur matching, Khanna and Mathews (2022) on two-sided matching and competition among heterogeneous VCs and startups, and Fishman, Parker, and Straub (2024) on dynamic lending. Our treatment of capital structure builds on models of short-term debt (Abel, 2018; Hu and Varas, 2025; Gryglewicz, Mayer, and Morellec, 2025). Our theoretical contribution is to develop a tractable equilibrium model of the LBO market that integrates OTC search and matching, bilateral bargaining under asymmetric information, and the classical trade-off theory of capital structure. Unlike the structural studies cited above, our model is not designed for structural estimation: it delivers analytical results while still producing quantitatively meaningful output.

Finally, we connect to work on how competition among financial intermediaries affects financing decisions. Yannelis and Zhang (2023) and Beyhaghi, Fracassi, and Weitzner (2025) show that increased competition in loan markets with adverse selection can lead to higher prices, in contrast to classical theories in which lender competition weakens incentives to screen borrowers (Broecker, 1990; Marquez, 2002; Hauswald and Marquez, 2006). We complement this work by studying the LBO market and are, to our knowledge, the first to comprehensively examine competition in this market with both theory and empirics, highlighting how competition in fact strengthens sponsors' incentives to screen targets pre-buyout and to add value post-buyout.

[7] See Gorbenko (2025) for a review of the theory literature on M&A.

1 A Search Model of LBOs and Private Equity

1.1 Motivating Facts and Model

Our study is motivated by concurrent trends in the LBO market, illustrated in Figure 1. Private equity has expanded rapidly, with U.S. buyout assets under management now exceeding $13 trillion (McKinsey, 2024), while competition for deal flow has intensified. These facts motivate a dynamic search-and-matching model in which the number of active sponsors captures competition for LBO deals and shapes deal pricing. The model links competition to deal outcomes such as default risk, leverage, size, and operating performance, and yields model-implied PE returns. It also gives insights into the mechanisms through which increased competition affects deal characteristics.

We calibrate the model to match outcomes from the linear regressions in Figure 2 linking deal characteristics to the (log) number of active sponsors within a given industry and year; see Section 3.2 and Appendix C for details. Using this calibration, we then apply the model to the aggregate trends in Figure 1: we feed the observed industry-level HHI into the calibrated model and compute the model-implied EV/EBITDA multiples and gross returns at each level of HHI.[8] As Figure 4 shows, the model matches the aggregate rise in EV/EBITDA multiples quite well, even though this time series is not targeted. The model further implies that, as competition rises (Panel A), multiples increase while average gross returns decline, with post-2000 gross returns ranging between 20% and 35%.

1.2 Model Overview

We set up a search-and-matching model of the LBO market; a schematic overview is provided in Figure A-1. Time is continuous over an infinite horizon, and the common discount rate is $\rho > 0$; everyone is risk-neutral. A mass of PE sponsors is looking to acquire firms of size K_0 in an LBO. Firms with initial pre-LBO capital stock (size) K_0 seek financing sponsors to cover an investment outlay of IK_0 dollars, for $I \geq 0$. After investment and the LBO, the sponsor collects the firm's cash flows and influences the capital structure by issuing debt.

[8] As explained later, we associate the HHI with $1/N$ in the model, that is, the inverse of the number of active sponsors.

Target firms are heterogeneous along three dimensions: (1) publicly observed pre-LBO size (or assets/capital stock), $K_0 \in \{\gamma, 1\}$; (2) a publicly observable quality component, $x \in \{L, H\}$; and (3) an unobserved quality component, $z \in \{B, G\}$. A firm is thus described by the vector (K_0, x, z).

First, pre-LBO firm size $K_0 \in \{\gamma, 1\}$ is observable: $K_0 = 1$ (as a normalization) captures a large firm, while $K_0 = \gamma$ captures a small firm. Sponsors can direct their search by firm size. Second, the observable quality component, $x = L$ ("low") or $x = H$ ("high"), represents "hard" information, such as those obtained from financial statements. This information becomes known once a sponsor matches with a firm, but it cannot be targeted ex ante. Observable quality determines the firm's operating performance or cash flow rate, $\alpha_x \in \{\alpha_L, \alpha_H\}$. Third, the unobserved quality component, $z = B$ ("bad") or $z = G$ ("good"), reflects "soft" information, which the sponsor can uncover only through costly screening. This dimension determines the firm's credit risk.

The framework has three stages in order: (1) search, (2) the LBO deal, and (3) the post-LBO phase. In the search phase, sponsors and firms match randomly; sponsors can target by size K_0 but not by x or z. In the LBO deal phase, the sponsor observes hard information x, may screen for soft information, and bargains over the acquisition price. If the deal closes, owners cover the outlay IK_0 and exit; the sponsor becomes the new owner. In the post-LBO phase, the sponsor collects the firm's dividends and chooses capital structure in a trade-off theory of debt. While we do not explicitly model the PE sponsor's post-LBO exit or secondary buyouts, the framework could readily accommodate retrading among PE owners. Indeed, the model is consistent with the sponsor being able to sell the firm frictionlessly at fair value.

We solve the model backward (post-LBO, then deal, then search), introducing assumptions stage by stage. The Appendix B provides the formal model treatment and proofs for all results. Parametric conditions for a well-behaved equilibrium are in Appendix B.1; the full equilibrium definition is in Appendix B.2.

1.3 Post-LBO Stage

We solve the post-LBO stage, given the pre-LBO size $K_0 \in \{\gamma, 1\}$, the observable type $x = L, H$, and the belief q_x that the firm is good ($z = G$), which may depend on the observable component x. Details are provided in Appendix B.3. The firm is owned by the PE sponsor, who maximizes the equity value and chooses the firm's debt.

Capital and Cash Flows. Firms of either hidden type $z \in \{B, G\}$ generate cash flows at rate $\alpha_x K_t$, with $\alpha_x > 0$. We interpret K_t as the firm's assets and $\alpha_x K_t$ as its EBITDA. Capital grows at rate $\mu > 0$, but is exposed to risk. At Poisson intensity $\delta > 0$, a firm experiences a one-time permanent cash flow shock, representing a distress event or credit shock. For simplicity, this shock occurs at most once.

The impact of the shock depends on hidden firm quality z. If the firm is bad ($z = B$), cash flows permanently drop to zero and the firm is liquidated, also defaulting on its debt. If the firm is good ($z = G$), a fraction $1 - \psi$ of its capital stock is permanently destroyed, where ψ is uniformly distributed over $[0, 1]$ and realized at the time of the shock. Starting from pre-shock capital K, the firm is left with ψK after the shock.

After the shock, only good firms ($z = G$) continue operating, with capital growing at rate μ. The shock thus fully reveals the hidden type z. To maintain tractability, we set up the post-LBO stage that there is no continuous learning, i.e., agents only learn about the type at the realization of the shock and do not learn at any other time.

Short-Term Debt and Optimization. Following Abel (2018); Gryglewicz et al. (2025), the firm issues short-term debt maturing instantly (over an interval dt). Debt is supplied by risk-neutral creditors with discount rate $r < \rho$, where $\rho - r > 0$ captures the benefit of debt issuance, for instance, originating from a tax shield. Further, $r > \mu$, so that valuations are finite. In our model, creditors and sponsors share the same beliefs about firm type.[9]

Debt with face value D_t is issued at time t and matures at $t+dt$. Absent default, creditors are repaid $D_t\big[1 + (r + \Delta_t)dt\big]$, where Δ_t is the endogenous credit spread. After the LBO, the sponsor becomes the firm's owner and chooses default/liquidation and debt issuance to

[9]This follows from assuming creditors observe the sponsor's screening and due diligence during the LBO stage, or alternatively that repeated interaction with sponsors eliminates asymmetric information, ensuring truthful communication between sponsors and creditors.

maximize equity value. The firm starts debt-free ($D_0 = \theta_0 = 0$) at the buyout: existing debt is paid off and new debt is issued.[10]

In equilibrium, all quantities scale with assets. Specifically, given $K_t = K$, equity value satisfies $E_t = eK$, debt satisfies $D_t = \theta K$ (with θ the debt–asset ratio), and total firm value reads $F_t = E_t + D_t = K(e + \theta)$. We denote the scaled firm value by $f_x(q_x)$, i.e., $f_x(q_x) = e_x(q_x) + \theta_x(q_x)$, where we make explicit the dependence of $f_x(q_x)$ on (x, q).

If the firm survives the shock, it faces no further shocks, and continuation firm value equals Kf_x^*, where $f_x^* = \frac{\alpha_x}{r-\mu}$ is the first-best (risk-free) value—equivalently, the firm fully capitalizes on the benefits of debt. Upon liquidation, creditors recover a fraction of this first-best value: $R_x = \chi f_x^*$ with $\chi \in [0, 1)]$ (liquidation is inefficient).

Default only occurs upon the Poisson shock. A bad firm always defaults. To derive the default probability for a good firm, consider a firm with pre-shock capital K and debt outstanding $K\theta$ experiencing a cash flow that leads to post-shock capital ψK. This means that the firm's total value just after the shock equals $\psi K f_x^*$, while the equity value equals $\psi K f_x^* - K\theta$. Thus, the equity value is negative and the good firm defaults whenever the shock is sufficiently bad and the fraction of capital remaining is sufficiently low, in that $\psi f_x^* < \theta$, yielding the probability of default of $\omega = \frac{\theta}{f_x^*}$ upon arrival of the shock.

Conditional on default, creditors recover in expectation $\frac{R_x}{2f_x^*}$ dollars per unit of debt. The credit spread is fair given the choice of debt θ and the common belief q_x. We solve for credit spread, $\Delta_x(q_x)$, and Debt/Asset ratio, $\theta_x(q_x)$:[11]

$$\Delta_x(q_x) = \delta\left[(1 - q_x) + q_x\omega\left(1 - \frac{\chi}{2}\right)\right], \qquad \theta_x(q_x) = \frac{(\rho - r)f_x^*}{\delta q_x(1 - \chi)}. \tag{1}$$

When choosing leverage $\theta_x(q_x)$, the firm's owners trade-off the benefits of debt issuance $(\rho - r)$ with the cost of debt, here the deadweight losses from inefficient liquidation. An increase in θ_x increases the default probability and deadweight losses from liquidation only

[10] The initial debt issued at time $t = 0$ is paid out as dividends to the firm's owners, as is common in leveraged buyouts (i.e., there is a leveraged payout).

[11] Technically, the choice of debt is subject to the borrowing constraint $\theta_x(q_x) \leq f_x(q_x)$, ensuring the firm's equity value is positive absent a shock, as, for instance, in Abel (2018). If this constraint were to bind, the firm would be fully debt-financed with debt-to-value ratio of 100%. In what follows, we assume parameters are such that this constraint does not bind.

if the firm happens to be good, because only a good firm stands a chance to survive the cash flow shock. This implies that firm owners opt for lower leverage when they perceive the firm of higher quality and q_x is larger. The following Proposition summarizes the findings.

Proposition 1. *The firm value satisfies $Kf_x(q_x)$ where $f_x(q_x)$ solves an HJB equation — presented in (B.5) in the Appendix, with closed form solution in (B.6). The firm's debt/asset ratio is given in (1) and the following holds:*

1. *The Debt/EBITDA leverage ratio $\frac{\theta_x(q_x)}{\alpha_x}$ decreases in target firm quality q_x. When $\alpha_x(q_x) > q_x\alpha_x'(q_x)$, the debt/asset ratio $\theta_x(q_x)$ decreases in q_x too.*

2. *The probability of default $\delta\big[(1-q_x)+q_x\omega\big]$ and interest rate spread $\Delta_x(q_x)$ decreases in target firm quality q_x.*

We assume that, prior to the LBO, the firm has an exogenous autarky (or pre-LBO) firm value, $K_0 f_x^{Pre}$, where K_0 is the initial size and f_x^{Pre} is the scaled firm value. The autarky payoff can be interpreted as deriving from a flow payoff the firm enjoys pre-LBO. Specifically, we assume that pre-LBO, any target firm dies at rate $\kappa > 0$, discounts at rate ρ, and thus has an effective discount rate $\rho+\kappa$. Its flow payoff is $(\rho+\kappa)f_x^{Pre}K_0$, so that f_x^{Pre} corresponds to the scaled firm value. We take both $\kappa > 0$ and f_x^{Pre} as parameters (with $f_L^{Pre} \leq f_H^{Pre}$). As formalized in (B.1), we assume that financing a bad firm yields negative NPV, while financing a firm under equilibrium belief q_x yields positive NPV for $x = L, H$.

1.4 LBO Deal

Given the (scaled) post-LBO and pre-LBO firm values $f_x(q_x), f_x^{Pre}$, we now characterize the LBO deal, including the pricing; details are provided in Appendix B.4. Suppose a sponsor and a firm of known initial size K_0 are matched. If the firm declines the deal, it can re-enter the search market, where it is matched with another sponsor at rate $\Lambda n(K_0)$. Here, $\Lambda > 0$ denotes the matching efficiency, which can be endogenous and is discussed in Section 1.5. And, $n = n(K_0)$ is the mass of sponsors searching for firms of size K_0. Each sponsor can search for at most one firm at a time and can target only one size category. However, once a sponsor acquires a firm, it may immediately restart its search (while simultaneously managing the acquired firm).

Hard (Financial) Information. The firm's (hard) financial information $x \in \{L, H\}$ affects operating performance α_x (i.e., $\alpha_L < \alpha_H$) and is correlated with hidden firm type $z \in \{B, G\}$:

$$\Pr(x = H|z = G) = \phi_G > \Pr(x = H|z = B) = \phi_B, \tag{2}$$

for probabilities $\phi_x \in (0, 1)$. The sponsor observes x when matched with a firm. Let $g \in (0, 1)$ denote the prior probability that the firm is good. Observing x, the sponsor updates to $g_x = \Pr(z = G|x)$, with:

$$g_H = \frac{g\phi_G}{g\phi_G + (1-g)\phi_B}, \quad g_L = \frac{g(1-\phi_G)}{g(1-\phi_G) + (1-g)(1-\phi_B)}. \tag{3}$$

In what follows, we discuss screening related to soft information, taking the hard information (i.e., the observed signal) x and the corresponding belief g_x for $x \in \{L, H\}$ as given.

Screening and Soft Information. In addition to observing x, the sponsor receives a signal $\mathcal{S}_x$ about the firm's hidden quality. The precision of this signal depends on the sponsor's screening effort S_x, chosen after observing $x \in \{L, H\}$. Screening entails a cost $K_0 C(S_x)$, where $C(\cdot) \geq 0$ is increasing and convex, with $C(0) = 0$. The total screening cost scales in the size of the target firm (needed to maintain scale invariance). For simplicity, the level of screening effort is publicly observable and verifiable by the involved firms and creditors.[12]

The signal $\mathcal{S}_x$ is binary: $\mathcal{S}_x = 1$ ("good") or $\mathcal{S}_x = 0$ ("bad"). If the firm is good ($z = G$), the signal is always good, $\mathcal{S}_x = 1$. If the firm is bad ($z = B$), the signal is good with probability $1 - S_x$ and bad with probability S_x. Hence, screening detects a bad firm with probability S_x. Conditional on observing $\mathcal{S}_x = 1$, the sponsor updates its belief to

$$q_x(S_x) = \Pr(z = G \mid \mathcal{S}_x = 1, x) = \frac{g_x}{1 - S_x(1 - g_x)}. \tag{4}$$

If instead the signal reveals the firm as bad ($\mathcal{S}_x = 0$), no LBO takes place, since condition (B.1) implies that investment in a bad firm is never profitable. Then, the sponsor and firm return to the search market. Other sponsors cannot observe the signal or that a firm had a

[12] Otherwise, if screening effort were only privately observable to the sponsor, there would be asymmetric information in the post-LBO stage between creditors and firms/sponsors, complicating our analysis without additional insights.

"cancelled" LBO deal, so the firm may still secure financing from another sponsor.[13]

Operating Performance and Sponsor Value-Add. Screening may not only distinguish good from bad firms but also generate information that improves post-LBO performance through operational or governance engineering (Kaplan and Strömberg, 2009). We capture this channel in reduced form by allowing α_x to depend on screening effort. Because $q_x(S_x)$ increases in S_x, we equivalently write $\alpha_x(q_x)$, with $\alpha_x'(q_x) \geq 0$ and $\alpha_L(q_L) < \alpha_H(q_H)$ for all $q_x \in [0,1]$. Thus, $x = H$ signals better operating performance than $x = L$. Our qualitative results accommodate both $\alpha_x' = 0$ and $\alpha_x' > 0$, while the value-add channel may affect the quantitative results. We suppress the dependence on q_x where no confusion arises.

Bargaining. Following a positive signal $\mathcal{S}_x = 1$, the firm and sponsor bargain over the acquisition price. We model bargaining through the random proposer model.[14] With probability $1-\beta$, the sponsor makes a take-it-or-leave-it (TIOLI) offer to the firm. Otherwise, with probability β, the firm makes a TIOLI offer. Here, β captures firms' bargaining power vis-a-vis sponsors. In bargaining, the sponsor and firms take as given the screening S_x and belief $q_x = q(S_x)$ of the sponsor matched to the firm. They also take as given the mass of other sponsors $n = n(K_0)$ that actively search for firms of size K_0, as well as other sponsors' screening choice $\hat{S}_x$ and (equilibrium) beliefs $\hat{q}_x = q_x(\hat{S}_x)$ following a positive signal. In equilibrium, all sponsors act symmetrically, so $q_x = \hat{q}_x$, and $S_x = \hat{S}_x$.

Because the firm knows its type while the sponsor does not, bargaining must feature pooling among firms that pass screening: the sponsor cannot price-screen types, so any offer acceptable to a good firm is also accepted by a bad firm, and both types offer the same price in equilibrium.[15] When an LBO occurs, the sponsor pays the original owners an acquisition price $p_x K_0$ (which depends on who makes the offer). From this amount, the owners finance the required capital outlay IK_0 and exit with net payoff $K_0(p_x - I)$.[16] The bargaining protocol yields the following result, given K_0, $n = n(K_0)$, and x.

[13] The probability that the same sponsor and firm meet again is negligible given a continuum of firms and sponsors. Alternatively, one could assume that a revealed bad firm exits the market and is replaced by a new entrant. This would yield the same results.

[14] It is well-known that Nash bargaining is not possible in the presence of asymmetric information.

[15] If good and bad firms offered different prices, the sponsor would reject the bad firm's offer, incentivizing the bad firm to mimic the good firm.

[16] Without loss of generality, we define the acquisition price gross of the capital outlay, so that the (scaled) net price is $p_x - I$.

Proposition 2 (LBO Deal and Pricing)**.** *An LBO occurs if and only if the screening signal is good, i.e.,* $\mathcal{S}_x = 1$*. In this case:*

1. *If the firm makes a take-it-or-leave-it (TIOLI) offer, the acquisition price is* $K_0 p_x^{Firm}(q_x)$*, with* $p_x^{Firm}(q_x) = f_x(q_x)$*. If the sponsor makes a TIOLI offer, the acquisition price is* $K_0 p_x^{Sponsor}(\hat{q}_x)$ *and depends on other sponsors' equilibrium beliefs* $\hat{q}_x$*, where*

$$p_x^{Sponsor}(\hat{q}_x) - I = \frac{\beta\Lambda n\big(f_x(\hat{q}_x) - I\big) + (\rho + \kappa) f_x^{Pre}}{\rho + \kappa + \beta\Lambda n}\,.$$

2. *The average acquisition price is* $K_0\overline{p}_x$*, so* $\overline{p}_x$ *is the price-to-assets ratio, with*

$$\overline{p}_x = I + f_x^{Pre} + \eta[f_x(\hat{q}_x) - I - f_x^{Pre}] + \beta[f_x(q_x) - f_x(\hat{q}_x)], \tag{5}$$

where η *as a measure of sponsor competition for targets:*

$$\eta = \eta(K_0) := \beta + \frac{(1-\beta)\beta\Lambda n}{\rho + \kappa + \beta\Lambda n}. \tag{6}$$

Since EBITDA is $\alpha_x(q_x)K_0$, the corresponding EV/EBITDA deal multiple is $m_x = \overline{p}_x/\alpha_x(q_x)$. The parameter η is a monotone function of n, the number of sponsors searching within a given size bucket, and thus provides a measure of competition.

Screening. After a match takes place and observing the firm's (hard) fundamentals $x \in \{L, H\}$, the sponsor chooses its screening effort S_x, taking as given the expected price $p_x^{Sponsor}(\hat{q}_x)$ and its prior beliefs g_x that $z = G$. In particular, the sponsor maximizes expected value of an LBO minus screening cost:

$$\max_{S\in[0,1]} K_0\left[\big(g_x + (1-g_x)(1-S)\big)\big[f_x(q_x) - \overline{p}_x\big] - C(S)\right]. \tag{7}$$

The following Proposition characterizes the equilibrium level of screening:

Proposition 3 (Deal Screening and Due Diligence)**.** *Fix* K_0*. Screening satisfies:*

$$C'(S_x) = (1-g_x)\big[q_x(1-\beta)f_x'(q_x) - (1-\eta)(f_x(q_x) - I - f_x^{Pre})\big]. \tag{8}$$

Screening effort S_x — capturing sponsors' ability to select target firms — and target firm quality q_x increases with rising competition among PE sponsors, i.e., with η and n.

Crucially, sponsors exert higher screening efforts in equilibrium, as the number of sponsors searching and thus competition (within the size bucket) increases. The mechanism is that higher competition leads to higher LBO prices $\overline{p}_x$, as it strengthens good firms' outside option to re-enter the search market. Given the higher LBO price $\overline{p}_x$, it becomes more costly for sponsors to acquire a bad firm, thus making it optimal to screen more.

We conclude with the following Corollary:

Corollary 1 (Average LBO Quality and Price)**.** *Fix K_0, and consider $n = n(K_0)$. As the number of sponsors n and competition increase, then:*[17]

1. *LBO Quality* $\Pr(z = G|LBO)$ *increases.*

2. *Operating performance* $\mathbb{E}[\alpha|LBO]$ *increases, provided* (B.19) *holds (which is satisfied whenever ϕ_B is not too large).*

3. *The price-to-assets ratio $\overline{p}_x$ increases for each x, and its unconditional average increases provided* (B.19) *holds. The EV/EBITDA multiple $m_x = \overline{p}_x/\alpha_x(q_x)$ increases, when $\frac{1}{\overline{p}_x}\frac{d\overline{p}_x}{dn} > \frac{1}{\alpha_x(q_x)}\frac{d\alpha_x(q_x)}{dn}$ (this is always satisfied when α'_x is sufficiently small).*

In particular, as competition among sponsors increases (through higher $n = n(K_0)$ and hence higher η), the average acquisition price and EV/EBITDA multiple rise. All else equal, the returns to PE sponsors therefore decrease with greater competition, as we show below (see Figure 3).

Because sponsors must pay higher acquisition prices, their screening incentives strengthen, leading to higher-quality LBOs, as captured by the unobserved component z. Stronger screening also translates into better operating performance, as captured by average α, through two channels. First, the unobserved and observable components z and x are correlated, and $x = H$ is associated with better operating performance; better selection on z thus tilts the deal pool toward H-firms. Second, screening itself adds value, raising operating cash flow.

[17] Since we fix K_0, all expectations below are also conditional on K_0 and $n(K_0)$ — which we suppress for convenience.

1.5 Search Stage

Having characterized the LBO deal, screening, and pricing, we now characterize the sponsor's search for deals; details are provided in Appendix B.5. In total, there is a mass of $N > 0$ sponsors, where N is fixed. These sponsors either search for small or large firms, with $n(K_0)$ sponsors searching for K_0-firms.

There is a mass $M > 0$ of both small and large potential firms, where fraction g of firms with size K_0 are good ($z = G$), while the remainder is bad ($z = B$). Out of the good (bad) firms in either size bucket, fraction ϕ_G (ϕ_B) has observed quality $x = H$ and fraction $1 - \phi_G$ ($1 - \phi_B$) has $x = L$. Assume, for simplicity, these fundamentals are the same across size buckets; that is, the distribution of (x, z) and all other parameters are independent of K_0. For now, assume that, once a firm is acquired, it is replaced with a firm of identical type and with the same α_x.[18]

Given $n(K_0)$ sponsors searching for $M > 0$ firms, where the total number of matches is $\Lambda n(K_0)M$ within a given size bucket. Thus, each firm meets a sponsor at rate $\Lambda n(K_0)$. And, a sponsor meets a firm at rate $\Lambda M > 0$. That is, for simplicity, we assume a quadratic matching technology, as, e.g., in Duffie, Gârleanu, and Pedersen (2005). However, the model could easily accommodate an alternative matching technology, in which case Λ would become a function of M and $n(K_0)$, and all the preceding formulae remain intact.[19]

The payoff of an individual sponsor in the search stage becomes $K_0 v(n)$ where $v(n)$ is a decreasing function of n, with a more explicit expression presented in the Appendix in (B.21). This value reflects the expected discounted payoff of conducting LBO deals, in addition to potentially some fees earned from operating a PE fund, which we capture in reduced form by assuming that the sponsor earns private flow benefits $K_0 b$ for fixed $b \geq 0$ from operating.

[18] This leaves the number and distribution of firms unchanged over time. Hence, the target pool remains constant in the baseline, and is the same across size buckets. That is, we focus on a "partial equilibrium" setting where the number of sponsors and firms is fixed, as, e.g., in Inderst and Müller (2004). However, Section 4.2 and Appendix D.3 endogenize the composition and pool of target firms, which introduces additional effects on top of what we have characterized.

[19] For instance, a Cobb Douglas matching technology, which produces $\lambda n^{\omega} M^{1-\omega}$ for $\omega \in (0, 1)$, $\lambda > 0$, and $n = n(K_0)$ matches could be accommodated upon setting $\Lambda = n^{\omega-1} M^{-\omega}$ (i.e., Λ is a function of n, M), leading to total number of matches $\Lambda n M = n^{\omega} M^{1-\omega}$ indeed. Under such technologies the sponsor's meeting rate declines in n, adding a congestion channel that reinforces the decline of sponsor value in competition; the characterization of the search stage would adjust accordingly.

Any sponsor chooses the targeted size bucket $K_0 \in \{\gamma, 1\}$ according to:

$$\max_{K_0 \in \{\gamma,1\}} K_0 v(n(K_0)),$$

taking as given the equilibrium values of $n(K_0)$ for $K_0 \in \{\gamma, 1\}$. In equilibrium, $n(K_0) \in [0, N]$ for $K_0 \in \{\gamma, 1\}$ where $n(\gamma) = N - n(1)$. The following Proposition summarizes results.

Proposition 4 (Competition, Sponsor Value, and LBO Size)**.** *The following holds:*

1. *The value function $v(n)$, capturing the returns to conducting LBOs, decreases in n, i.e., $v'(n) < 0$, that is, the model-implied return on LBOs declines with n.*

2. *As the number of sponsors N increases, $n(1)$ and $n(\gamma) = N - n(1)$ increase weakly, and both increase strictly when the allocation is interior (i.e., when $n(1), n(\gamma) \in (0, N)$).*

3. *Suppose $b \geq 0$ is sufficiently small. Then, the average size of LBO targets (that is, $\mathbb{E}[K_0|LBO]$ calculated in (B.25)) equals 1 for $N \in (0, N_L]$, and is strictly smaller than 1 for $N > N_L$, where N_L is an endogenous cutoff. Average LBO target size decreases in N on some interval contained in (N_L, ∞).*

Thus, when N is low, sponsors concentrate on larger firms to exploit economies of scale; as N increases, acquiring large firms becomes more costly, reducing sponsors' returns and making it attractive to search for small firms.

Sponsor Specialization. Empirical evidence in Bernstein and Sheen (2016), Spaenjers and Steiner (2024), and Haque, Mayer, and Wang (2026) highlights that PE sponsors often specialize by industry and outperform generalists, in part through more effective due diligence. To study how competition shapes specialization, we allow sponsors to choose an upfront investment that lowers future screening costs.[20] With quadratic screening costs $C_i S_x^2$, each sponsor privately chooses C_i at $t = 0$ subject to a one-time cost $\overline{C}(C_i)$, where $\overline{C}'(C_i) < 0$ and $\overline{C}''(C_i) > 0$, taking other sponsors' choices as given. Reducing C_i (greater specialization) thus requires a larger upfront investment; conditional on the technology choices, the remainder of the model is unchanged. Appendix D.1 formally introduces this model variant. The

[20] This can be interpreted as industry-specific expertise, or as the opportunity cost of forgoing deals outside the industry.

following Proposition shows that fiercer competition makes specialization more attractive, intuitively, as a way to remain profitable.

Proposition 5 (Competition Fosters Specialization)**.** *Fix K_0, and suppose sponsors' specialization choices have an interior and stable symmetric equilibrium, as detailed in Appendix D.1. Then, greater competition raises specialization: $\frac{dC}{d\eta}, \frac{dC}{dn} < 0$.*

1.6 Model Predictions

This section summarizes the model's predictions, established through our analytical results from the previous Sections or the numerical analysis presented in Section 3.2. Notably, Figure 3 plots model outcomes alongside data and illustrates the model results noted below. We study rising competition among sponsors searching for a target, captured by an increase in N, interpreted as within-industry competition. Empirically, we measure competition by an industry-level logged number of sponsors based on realized acquisitions.

Predictions. *As the LBO market becomes more competitive and the number of active sponsors N increases, the model implies*:

Prediction 1: Deal Pricing and Returns. *Average deal multiples increase. Sponsor and PE returns in turn decrease.*

Prediction 2: Deal Selection, Firm Quality, and Default Risk. *Sponsors conduct more due diligence and engage more with target firms: the average quality of LBO targets increases and default risk declines.*

Prediction 3: Operating Performance. *The average ROA or sales-to-assets ratio of LBO firms, capturing operating performance, increase.*

Prediction 4: Leverage and Credit Outcomes. *Post-LBO debt-to-assets and debt-to-EBITDA ratios decline, as do credit spreads.*

Prediction 5: Target Size. *Sponsors increasingly search for smaller target firms, and the average LBO firm size declines.*

Prediction 6: Sponsor Specialization. *Sponsor industry specialization increases.*

In Sections 2 and 3, we directly test Predictions 5–6, providing support for our model pre-

dictions. Likewise, Figure 3 both illustrates these predictions as well as quantifies them by linking model and data.

2 Data and Empirical Setting

2.1 Data and Sample

Appendix A provides an overview of all variables used in the main analysis. We combine PitchBook data on LBO transactions with regulatory Y-14Q data on bank loans. First, the Y-14Q (henceforth, Y-14) data provide detailed quarterly information on U.S. firms and the commercial and industrial (C&I) loans they obtain with commitments exceeding $1 million, originated and held by the largest U.S. bank holding companies by assets.[21] Loan sizes range from the $1 million reporting threshold to several billion dollars, covering a wide spectrum of privately held firm sizes. Our sample spans 2013 to 2023, with the start date reflecting the introduction of Y-14 reports after the Global Financial Crisis for supervisory stress-testing purposes.[22]

Second, PitchBook extracts information from public filings, press releases, regulatory disclosures, and proprietary surveys, and provides comprehensive deal-level data on PE transactions, including deal timing, transaction value, capital structure, sponsor identity, and target firm identity. We restrict our sample to PitchBook-reported PE buyout deals, omitting other private capital deals, such as venture capital.

We merge these datasets to construct a sample of LBO deals with matched firm- and loan-level information. A deal is retained if it can be matched to at least one Y-14 observation within a four-quarter window around the buyout date, ensuring that we capture timely firm- and loan-level characteristics at the time of the acquisition. The resulting sample consists of about 4,500 buyout deals with matched firm- and bank-loan information within this window.[23] We also link every deal to a unique PitchBook industry group, and this classification defines the industry dimension of our analysis. We rely on PitchBook's own

[21] In the United States, loans with commitments below $1 million are classified as small business loans.

[22] While Y-14 data collection began in 2011, we rely on observations from 2013 onward due to improved data quality.

[23] The exact sample size depends on the variable considered, as some characteristics may be missing.

industry codes.[24] There are about 30-40 industry groups, a granularity similar to NAICS 2. Not all industry groups necessarily feature buyout deals within a given year: in our estimation sample, on average about 29 industry groups contain at least one matched deal per year. To ensure the competition measure is meaningful, we exclude industry–year observations with very little deal activity (those in the bottom percentile of annual PitchBook deal counts)

Each buyout deal may correspond to multiple loan observations within the window, potentially reflecting different loans from different banks. For our baseline analysis, we collapse the data to the LBO deal (firm) level. In robustness checks, we show that our results are similar when collapsing to the firm-year level, allowing for multiple deal-level observations across years. When collapsing to the deal level, we compute equally weighted averages of firm- and loan-level characteristics whenever multiple observations are available. This procedure yields a single observation per deal for each variable of interest. Loan-level characteristics are likewise aggregated to the firm level; for example, we compute the average loan size held by the firm within the four-quarter window around the buyout date.

Finally, we construct deal multiples, subject to some data attrition, since deal size is reported only for a subset of transactions. Common private equity multiples include EV/EBITDA and EV/Sales, while EV/Assets is less frequently used. We approximate enterprise value (EV) using PitchBook-reported deal size and take measures of EBITDA, sales, and assets from Y-14. We consider all three multiples in our empirical analysis.

Table 1 provides summary statistics for the matched sample. The data exhibit substantial heterogeneity across deal sizes, borrower characteristics, and credit risk, consistent with a sample spanning both mid-market and large-cap sponsor transactions. Notably, the median Deal Size/EBITDA multiple is 13.10, the mean ROA is 7.51%, and the average bank-reported probability of default is 4.40%.

[24] That is, we do not map deals to the NAICS classification, for two reasons. First, PitchBook assigns its codes directly to each deal, whereas a crosswalk from PitchBook codes to NAICS is imperfect and would introduce additional measurement error into the definition of industry markets. Second, PitchBook's classification reflects how deal makers and sponsors themselves segment the market, which aligns with our interpretation of industries as (partially) segmented markets for deal flow.

2.2 Main Specification

The model Predictions 1–6 link deal characteristics to the degree of competition among sponsors, as captured by the number of active sponsors in our model, N. Our empirical approach builds on the fact that many PE sponsors specialize and operate within particular industries (see, e.g., Spaenjers and Steiner (2024)), so that industries can be viewed as segmented markets with differing degrees of competition.[25] Thus, one can view the model as capturing PE sponsor competition within a given industry, and N as capturing the number of active sponsors within that industry. Motivated by the model, we therefore proxy the degree of competition by the number of active sponsors in an industry. Recall that we use Pitchbook industry groups as industry classification. We believe that PitchBook's classification reflects how sponsors themselves segment the market, which aligns with our interpretation of industries as (partially) segmented markets for deal flow.

Concretely, consider a given PitchBook industry group i in year t. Let $\mathcal{N}_{i,t}$ denote the number of LBO deals in industry i during year t, and index individual deals by $d \in \{1, \ldots, \mathcal{N}_{i,t}\}$. For each deal d, we observe the set of involved sponsors, denoted $\mathbb{S}_{i,t}(d)$, which may include multiple sponsors. Define $\overline{\mathbb{S}}_{i,t} := \bigcup_{d=1}^{\mathcal{N}_{i,t}} \mathbb{S}_{i,t}(d)$ as the set of all sponsors participating in at least one deal in industry i during year t. The number of active sponsors within a given industry–year is then the number of unique sponsors, $Sponsors_{i,t} := \#\,\overline{\mathbb{S}}_{i,t}$, and our competition measure is its logarithm, $Log\ Sponsors_{i,t} := \log\big(Sponsors_{i,t}\big)$. That is, in each industry–year, we count the number of distinct investor IDs.[26]

To test the model's predictions, we use the deal-level sample described above. Our main empirical specification is

$$y_{f,t} = \beta \cdot Log\ Sponsors_{i,t-1} + \delta_t + \epsilon_{f,t}, \tag{9}$$

where $y_{f,t}$ denotes a firm-level or loan-level outcome in year t, with loan-level outcomes collapsed to the deal level as described above. We include year fixed effects, δ_t, and cluster

[25] Over our sample period from 2013 to 2023, time-series variation is limited, and our analysis therefore primarily exploits cross-industry differences in sponsor competition within a given year.

[26] We exclude acquiring firms listed as investors, as these are typically platform companies in buy-and-build transactions rather than PE sponsors. We count sponsors at the firm level rather than the fund level, so a sponsor's individual funds are not counted separately.

standard errors at the industry level.

The key explanatory variable is the lagged industry–year number of active sponsors (in logs), $Log\ Sponsors_{i,t-1}$. Using a lag helps mitigate, though not eliminate, concerns about endogeneity; in subsequent sections, we further address endogeneity by instrumenting for $Log\ Sponsors_{i,t-1}$. The coefficient of interest is β, which captures how greater competition among sponsors for deal flow is associated with deal characteristics.

2.3 Endogeneity Concerns and Instrument

The industry-level number of sponsors is potentially endogenous, because unobserved industry or firm shocks may affect both sponsor competition and deal outcomes. For example, a positive productivity or demand shock may attract more private equity sponsors to an industry (increasing entry and raising the number of sponsors) while simultaneously improving firm performance. We therefore further implement a sponsor-hiring shift-share IV that uses sponsors' capacity expansion as a measure of their ability to compete for deals.

Throughout, the endogenous regressor is the log number of sponsors, $Log\ Sponsors_{i,t-1}$, measured at the industry–year level and lagged by one year. We estimate two-stage least squares (2SLS) specifications of the form

$$\begin{aligned} Log\ Sponsors_{i,t-1} &= \pi Z^{H}_{i,t-1,d} + \delta_t + v_{i,t-1,d} && \text{(First stage)}, \\ y_{f,t} &= \beta Log\ \widehat{Sponsors}_{i,t-1} + \delta_t + \epsilon_{f,t} && \text{(Second stage)}, \end{aligned}$$

where f denotes a firm or deal, d the associated deal, and i an industry. The first stage is estimated at the deal level, because the leave-out instrument (introduced below) varies across deals within an industry–year. The second stage mirrors our baseline OLS specification, replacing $Log\ Sponsors_{i,t-1}$ with its fitted value from the first stage. Standard errors are clustered at the industry level.

Our instrument uses sponsors' hiring activity—measured using job-posting data from Lightcast—as a shifter of their capacity to source and execute deals. When a sponsor expands its team, it can compete more aggressively for targets across the industries in which it operates. Because industries differ in their mixes of active sponsors, a given sponsor-level

hiring shock generates differential changes in competitive pressure across industries. For each sponsor s and year t, we compute the log of cumulative job postings over the preceding five years,

$$h_{s,t} = \log\left(\sum_{\tau=t-4}^{t} \text{postings}_{s,\tau} + 1\right).$$

This window is intended to capture sustained organizational capacity building rather than transitory fluctuations. We separately compute $w_{s,i,t-1}$, sponsor s's share of attributed deals in industry i over the five-year window ending in $t-1$.[27] The sponsor-hiring instrument for *Log Sponsors*$_{i,t-1}$, for a deal d in industry i, is

$$Z^{H}_{i,t-1,d} = \sum_{s \notin \mathbb{S}_d} w_{s,i,t-1} h_{s,t-1},$$

where $\mathbb{S}_d$ is the set of sponsors participating in deal d, so the sum runs over sponsors active in industry i during the rolling window *excluding the deal's own sponsors*. This leave-out construction ensures the instrument for a given deal is built only from the hiring of *other* sponsors in its industry. The timing ensures that both the exposure shares and the hiring measure are predetermined relative to outcomes in year t.

Notably, the instrument is relevant: a higher value of the instrument is associated with a larger number of active sponsors within a given industry–year, with first-stage F-statistics near or above 100 (Tables 2–6). Intuitively, as sponsors expand hiring, they are more likely to conduct deals and be active within a given industry, thereby exerting competitive pressure.

The exclusion restriction requires that, conditional on year fixed effects, sponsors' hiring affects outcomes in industry i only through its effect on the number of sponsors competing in that industry. The identifying assumption is that sponsors' multi-year hiring trajectories reflect organization-wide factors—such as fundraising cycles, fund commitments, and long-run capacity planning—rather than short-run conditions in any particular target industry. Year fixed effects absorb common macroeconomic shocks.

[27] We attribute each deal equally to its participating investor. When PitchBook explicitly flags an investor as an acquiring firm, we exclude that investor (since the acquiring firm is typically the platform company in buy-and-build transactions, rather than a sponsor) and redistribute attribution equally among the remaining sponsors; acquiring firms receive attribution only if they are the sole investor in the transaction. The same attribution procedure underlies the HHI construction in Section 3.4.

The principal threat is that sponsors may hire in anticipation of industry-specific opportunities; a lagged, cumulative five-year hiring measure mitigates—but does not eliminate—this concern, as industry-specific hiring is unlikely to dominate a sponsor's staffing trajectory over such a horizon. A second threat is that staffing decisions may affect deal outcomes directly through a sponsor's *own* sourcing and due-diligence capacity, rather than through industry competition: the model posits that competing sponsors exert greater screening effort, and past hiring naturally expands their capacity to do so. The leave-out construction addresses this most direct threat: identification comes only from *other* sponsors' hiring, which affects the deal only through industry competition. Overall, this supports the IV as a meaningful robustness check exploiting variation distinct from the OLS estimates.

3 Empirical Results

3.1 Binscatter Plots

Figure 2 presents binned scatter plots of key outcomes against lagged number of sponsors, $Log\ Sponsors_{i,t-1}$. In each panel, observations are sorted by $Log\ Sponsors_{i,t-1}$ and grouped into ten bins of equal size. We then plot the bin-level mean of the outcome against the bin-level mean of $Log\ Sponsors_{i,t-1}$ and overlay the fitted linear relationship. This visualization serves two purposes. First, it provides a transparent, nonparametric check on whether the relationships predicted by the model are visible in the raw data. Second, it allows us to assess whether these patterns reflect systematic variation over the relevant support of $Log\ Sponsors_{i,t-1}$ rather than a small number of extreme concentration observations.

Across panels, the binned relationships align with Predictions 1–6 and with the patterns in Figure 3, both qualitatively and quantitatively. The bins span values of $\log(\text{Sponsors}_{i,t-1})$ from approximately 3.7 to 6.8, a range of about 3.1 log points, or slightly less than three standard deviations. That is, the number of sponsors active in a given industry-year can vary from about 40 to a little less than 900.

Over this plotted range, the fitted Deal Size/EBITDA multiple rises from approximately 11 to 19, while the fitted Deal Size/Assets multiple rises from approximately 2.2 to 3.0 (Pre-

diction 1). At the same time, average LBO target size falls from roughly $110 million to $50 million, and average loan size falls from approximately $9 million to $6 million (Prediction 5).

The probability of default falls from about 5% to 3% (Prediction 2) and Debt/EBITDA from roughly 3.4 to 2.8 (Prediction 4), while Sales/Assets increases from about 155% to 190% and ROA from about 1% to 9% (Prediction 3); sponsor industry specialization likewise increases, from about 34% to 53% (Prediction 6). Although individual bins display some dispersion—particularly at low levels of $Log\ Sponsors_{i,t-1}$—the fitted lines summarize the bin means in the predicted direction, and the associations are visible across the observed support rather than being driven solely by the highest-concentration bin.

3.2 Linking Theory to Empirics

We now connect the model to these empirical outcomes from Figure 2 and assess whether it can quantitatively reproduce similar relationships. To this end, we choose the model parameters to match the empirical patterns. Appendix C explains in detail how the model-implied outcomes are constructed and how the parameters are selected.[28] Appendix Table A-1 provides an overview.

Figure 3 plots the resulting model-implied outcomes. We restrict the model-implied comparative statics $x = log(N) \in [3.64, 6.8]$; the model admits a well-behaved solution over this range. In all Panels, the solid black line depicts model outcomes, the blue dots depict the empirical bins, and the dashed red line the linear regression (also found in Figure 2). We see that the model exhibits a kink: above this point, N is large and competition is sufficiently fierce that sponsors search for both large and small firms, as they are indifferent between the two options. While searching for large targets is generally more profitable because of returns to scale, it then becomes optimal to also target smaller firms, as they command lower multiples. Below the kink, when N is low, competition is weak, and returns to scale make focusing on large firms strictly optimal because their prices are not too high.

Panel A reports the logarithm of the deal multiple (EV/EBITDA); Panel B reports the

[28] Our calibration assigns externally plausible values to parameters with natural empirical counterparts, such as the risk-free rate and the growth rate of capital, while choosing the remaining parameters to match empirical levels.

Sales/Assets ratio, our measure of operating performance; and Panel C reports leverage ratio, that is, Debt/EBITDA. Panel D plots the logarithm of firm size, measured by book assets, while Panel E reports the probability of default. Panel F presents the model-implied gross return. In Panels A–E, the dashed line is the corresponding fitted regression line from Figure 2. Because our data do not contain a comparable measure of returns, Panel F does not include an empirical fitted line.[29] The model-implied relationships have the same direction as their empirical counterparts and generally track the empirical bins well.

Finally, the model produces PE returns in an economically plausible range. These returns are static model-implied returns, rather than conventional IRRs, because the model does not specify an exit horizon or the timing of interim cash flows. The average return ranges from approximately 5% to 25% over the plotted sponsor range. A possible non-monotonicity arises because higher competition induces sponsors to focus on smaller targets, which offer higher returns, boosting average returns across size buckets. The kink again arises at the point, where the sponsor starts also searching for small firms, when N further increases.

Can the Model Explain Aggregate Trends? Using the calibration underlying Figure 3, we apply the model to the aggregate trends in Figure 1—a non-targeted moment. Specifically, we feed the empirical industry-level number of sponsors into the calibrated model and compute the model-implied EV/EBITDA multiples and gross returns at each level of sponsorship. As Figure 4 shows, the model matches the aggregate rise in EV/EBITDA multiples quite well, even though this time series is not targeted and the calibration is based only on the cross-sectional regression results. The model further implies that, as competition rises (Panel A), multiples increase while gross returns decline, with post-2000 gross returns ranging between about 20% and 40%.[30]

[29] As explained in Appendix C, Panels B and D involve level normalizations. The model is scale invariant with respect to firm size. Moreover, it determines net operating cash flow—sales minus operating costs—but does not separately determine gross sales and operating costs, provided that their difference equals net cash flow. These normalizations affect levels but not the underlying comparative statics.

[30] Finally, because EV/EBITDA multiples are right-skewed, the mean exceeds the median, which may explain why the reported median multiple sits somewhat below the model-implied values, which are mean outcomes.

3.3 Estimation Results

Tables 2–6 report OLS estimates of equation (9) together with IV estimates that instrument for lagged sponsors using the sponsor-hiring shift-share instrument (with year fixed effects). First-stage F-statistics are large throughout, near or above 100 and well above conventional weak-instrument thresholds. This suggests that our instrument is relevant.

Deal Multiples. Table 2 presents the regression results when the outcome variable is the logarithm of a deal multiple. Consistent with Prediction 1, intensified competition among sponsors should drive up acquisition prices. Table 2 reports a robust positive relationship between the lagged number of sponsors ($Log\ Sponsors_{t-1}$) and various measures of deal valuation, significant at the 5% level for the Deal Size/EBITDA multiple.

A one-standard-deviation increase in *Log Sponsors* (equal to 1.1 as reported in Table 1) is associated with an approximately 19% increase in the Deal Size/EBITDA multiple and an approximately 10% increase in the Deal Size/Assets multiple. The IV estimates are larger: the corresponding estimates imply increases of approximately 36% and 22%, respectively. These findings indicate that greater competition for deal flow forces sponsors to pay substantially higher acquisition prices. The results confirm Prediction 1 and suggest that as competition for deal flow intensifies, sponsors are forced to pay significantly higher premiums.

Although we do not observe realized returns for the vast majority of deals in our sample, higher acquisition prices mechanically reduce sponsors' expected returns. This finding therefore suggests that intensified competition for deal flow is associated with lower expected returns to PE sponsors, as also implied by Prediction 1.

Firm and Loan Size. Heightened competition also appears to fundamentally alter the types of firms that sponsors target. Prediction 5 states that as the primary market for large-cap LBOs becomes more contested, sponsors expand their search toward previously less-contested pools of smaller firms. Table 3 presents the regression results with firm or loan size as the outcome variable. When the logarithm of firm assets is the outcome variable, the estimated coefficient on $Log\ Sponsors_{t-1}$ is negative and statistically significant, indicating that greater competition among sponsors is associated with smaller LBO targets—confirming

Prediction 5.

A one-standard-deviation increase in *Log Sponsors* is associated with an approximately 26% decline in target firm size and an approximately 13% decline in average loan size.[31] The latter corresponds to roughly $2.3 million relative to the sample mean loan size of $17.9 million. The IV estimates imply declines of approximately 22% in firm size and 12% in loan size. Thus, the IV estimates are slightly smaller than, but economically similar to, the corresponding OLS estimates.

Operating Performance (ROA and Sales/Assets). We then turn to measures of target operating performance (Prediction 3). Despite the move toward smaller targets and higher entry prices, we find no evidence that increased competition leads sponsors to acquire lower-quality assets. Table 5 indicates a "flight to quality" in competitive environments: lower sponsor concentration is associated with significantly higher asset turnover (Sales/Assets) and profitability (ROA). A one-standard-deviation increase in *Log Sponsors* raises Sales/Assets by approximately 12.7 percentage points, equivalent to about 7% of its sample mean of 175.6%.

The same increase raises ROA by approximately 1.22 percentage points, or about 16% of its sample mean of 7.51%. Both OLS coefficients are statistically significant at the 5% level. The IV coefficients retain the predicted positive signs but are smaller and imprecisely estimated, implying increases of approximately 4.2 percentage points in Sales/Assets and 0.79 percentage points in ROA.[32] They are statistically indistinguishable from the OLS coefficients, suggesting that precision is an issue. Overall, these results are consistent with Prediction 3.

Firm Quality (Probability of Default). We further assess target quality using the bank-reported probability of default (PD), averaged across available observations. Prior work shows that bank-reported default probabilities are accurate and informative measures of firm quality, capturing soft information acquired through monitoring (Howes and Weitzner, 2025; Beyhaghi et al., 2024). Table 4 presents the results when probability of default and

[31] Note that the standard deviation of *Log Sponsors* is 1.1, which is shown in Table 1.

[32] These magnitudes are broadly in the range of the LBO operating-performance literature. For example, Guo et al. (2011) find an approximately 11% increase in EBITDA-to-sales relative to matched firms in a selected public-reporting sample.

leverage are taken as outcome variables. Consistent with Prediction 2 and with the operating performance results, the number of sponsors is negatively and significantly associated with target default risk: firms acquired in more competitive markets exhibit substantially lower bank-reported default probabilities.

A one-standard-deviation increase in *Log Sponsors* lowers the probability of default by approximately 0.83 percentage points, or about 19% of the sample mean of 4.40%. The OLS coefficient is statistically significant at the 10% level. The IV estimate has the same negative sign and implies a somewhat smaller decline of approximately 0.54 percentage points, although it is not statistically significant. The evidence therefore suggests that firms acquired in more competitive sponsor markets have lower default risk, and hence increased deal quality.

Deal Leverage. We examine leverage using Debt-to-EBITDA ratios; see Table 4. We find that targets acquired in more competitive buyout markets carry lower leverage. A one-standard-deviation increase in *Log Sponsors* lowers Debt/EBITDA by approximately 0.18, or about 6% of its sample mean of 3.10. The OLS coefficient is statistically significant at the 10% level. The IV estimate has the same negative sign and implies a decline of approximately 0.15. The OLS and IV coefficients are statistically indistinguishable. Overall, the leverage results provide suggestive evidence consistent with Prediction 4 that LBOs conducted in more competitive environments employ lower leverage.

Specialization. Table 6 examines the relationship between sponsor industry specialization and competition (Prediction 6). Our measure of specialization captures how concentrated a sponsor's deal activity is in the focal industry. For each sponsor and year t, we compute the share of the sponsor's LBO deals (from PitchBook) that fall within each industry group over the five-year window $t-4$ through t.[33] A share of 100% indicates that all of the sponsor's deals over the window are in that industry. The outcome variable in Table 6 is then, for each deal, the average of this share across the deal's participating sponsors, evaluated in the deal's industry and in the deal year.

Crucially, the number of sponsors is positively associated with our measure of sponsor

[33]When a lead sponsor can be reliably identified, the deal is attributed entirely to the lead sponsor; otherwise it is split evenly across participating sponsors.

industry specialization under both OLS and the IV. Consistent with Prediction 6, greater competition for deals is associated with heightened sponsor specialization within a given industry. A one-standard-deviation increase in *Log Sponsors* raises specialization by approximately 7.9 percentage points, or about 21% of its sample mean of 37.7%. The IV estimate is very similar, implying an increase of approximately 7.2 percentage points. Both estimates are statistically significant at the 1% level. The intuition is that as competition intensifies and deal multiples rise, sponsors must screen targets more effectively to remain profitable. This, in turn, incentivizes investment in deal selection and screening through increased specialization within particular sectors.

Taken together, the OLS and IV results align closely with Predictions 1–6: greater competition among PE sponsors is associated with higher acquisition prices (deal multiples), smaller targets, higher target quality and operating performance, and lower leverage. Further, competition is associated with increased sponsor specialization. The IV estimates indicate that these patterns are not driven solely by endogeneity in the number of sponsors or reverse causality, and it is reassuring that the magnitudes are similar in both the OLS and IV specifications.

3.4 Alternative Competition Measures

In this Section, we show that our empirical results are robust to employing two additional measures of sponsor competition for deals within a given industry and year: (1) the Herfindahl–Hirschman Index (HHI), capturing concentration of sponsors in deals (an inverse measure of sponsor competition), and (2) the number of deals. Before discussing the results, we explain how to construct the HHI index.

3.4.1 Constructing HHI

We construct $HHI_{i,t}$ using observed LBO transactions from PitchBook, relying on PitchBook's industry group classification. Concretely, consider a given PitchBook industry i in year t. Let $\mathcal{N}_{i,t}$ denote the number of LBO deals in industry i during year t, and index individual deals by $d \in \{1, \ldots, \mathcal{N}_{i,t}\}$.

For each deal d, we observe the set of involved sponsors, denoted $\mathbb{S}_{i,t}(d)$, which may include multiple sponsors. Let $\#\mathbb{S}_{i,t}(d)$ denote the number of sponsors reported for deal d, and let $s \in \mathbb{S}_{i,t}(d)$ index an individual sponsor. Define $\overline{\mathbb{S}}_{i,t} := \bigcup_{d=1}^{\mathcal{N}_{i,t}} \mathbb{S}_{i,t}(d)$ as the set of all sponsors that participate in at least one deal in industry i during year t.

To measure each sponsor's contribution to deal flow, we attribute deals equally to participating sponsors.[34] Given this construction, let $f_d(s)$ denote the fraction of deal d attributed to sponsor s (with $\sum_s f_d(s) = 1$ for each deal). We can then calculate the implied market share $\omega_{i,t}(s)$ of sponsor s in industry i and year t, as well as the HHI, i.e., $HHI_{i,t}$:

$$HHI_{i,t} := \sum_{s \in \overline{\mathbb{S}}_{i,t}} \omega_{i,t}(s)^2 \quad \text{where} \quad \omega_{i,t}(s) := \frac{1}{\mathcal{N}_{i,t}} \sum_{d=1}^{\mathcal{N}_{i,t}} f_d(s).$$

The model analogue for the HHI would be $1/N$, the inverse of the number of active sponsors. Predictions 1–6 can be reformulated in terms of HHI, respectively. We next employ the HHI as an alternative measure of competition, noting that it inversely captures competition.

3.4.2 Results

As a robustness check, we replace the baseline log number of sponsors with the two alternative measures of competition intensity at the industry–year level introduced above: the log number of deals and the (log) sponsor HHI. Both measures are lagged one year, paralleling our baseline specification; the HHI enters in logs to address its pronounced right skew. A higher number of deals indicates a more competitive buyout market, whereas a higher HHI indicates a more concentrated—i.e., less competitive—market, so its coefficients should take the opposite sign of the count-based measures.

Appendix Tables A-2–A-6 report the results. The estimates are broadly consistent with the baseline findings: greater competition is associated with higher deal multiples, smaller

[34] We attribute each deal equally to its participating sponsors. Although PitchBook contains a lead investor field, we find that this field is inconsistent and often flags acquiring financial firms—which are not sponsoring PE funds—as leads. Hence, we are unable to confidently assign deal shares beyond a naive split. Additionally, PitchBook often explicitly flags investors as acquiring firms; these are typically the platform companies in buy-and-build transactions, rather than PE sponsors. In such cases, we exclude these investors from the deal and redistribute attribution equally among the remaining sponsors. Acquiring firms receive attribution only if they are the sole investor in the transaction.

target firms and loan sizes, lower leverage, lower default probabilities, and greater sponsor industry specialization. For operating performance, both alternative measures indicate a positive association between competition and target operating performance. Thus, the empirical predictions are also confirmed under alternative measures of sponsor competition.

4 Model Extensions and Other Results

4.1 Post-LBO Effort

Our baseline model allows sponsors to add value, with this value-add explicitly linked to screening effort. The idea is that the sponsor engages with the firm—for instance, to improve operations or governance—and that the effects of this engagement are larger when the sponsor is more informed about the firm, that is, when it has screened more. This modeling choice implies that higher competition is associated with increased value-add through sponsor engagement.

While this reduced-form approach is convenient, we next model the sponsor's post-buyout engagement explicitly, separately from screening at the time of the buyout. The PE sponsor adds value post-LBO through monitoring or operational and governance engineering. We model this effort as increasing the growth rate of assets and capital in (B.2). That is, we stipulate $\mu \equiv \mu(a_t)$, where $a_t \geq 0$ is the sponsor's costly effort at time $t \geq 0$, with $\mu'(a) > 0$ and $\mu''(a) < 0$. The sponsor incurs a private cost $K_t \zeta a$ from exerting effort, with the cost scaling in the firm's capital stock and the parameter ζ. We assume that $\mu(a)$ is sufficiently concave and ζ is sufficiently large so that $r > \mu(a)$ (needed for finite valuations).

Appendix D.2 presents the solution details and proves the following Proposition:

Proposition 6 (Post-LBO Engagement and Competition)**.** *Fix the size K_0 and $n(K_0)$, the number of sponsors searching for K_0-targets. Post-LBO sponsor engagement (effort) satisfies*

$$a = a(f_x) = (\mu')^{-1}\left(\frac{\zeta}{f_x}\right),$$

where $f_x = f_x(q_x)$ is the value function prior to the shock (resulting in effort a_x), and $f_x^* = f_x^*(q_x)$ is the value function after the shock (resulting in effort a_x^*). Both a_x and a_x^*

increase weakly with target quality and competition η (or $n = n(K_0)$). The pre-shock effect is strict when $f'_x(q_x) > 0$, while the post-shock effect is strict when $\alpha'_x(q_x) > 0$.

The above Proposition demonstrates how a rise in competition among sponsors — captured by higher η or $n(K_0)$ — leads to higher engagement by the PE sponsor post-buyout. In other words, facing fierce competition, the sponsor becomes more active. The mechanism leading to that result is as follows. First, increased competition raises acquisition prices and thus the screening incentives of sponsors. This, in turn, raises the quality of the average LBO target, q_x. A higher quality means lower default risk and makes engagement with the firm more valuable. Indeed, engagement (raising a) boosts the capital stock over the long-run: This is less valuable when the firm is bad and likely to default, while being more profitable when the firm is good. Thus, sponsor post-LBO effort increases in q_x and, through the screening channel determining q_x, also in sponsor competition.

4.2 Long-Run Target Pool Composition

So far, we have considered a fixed target pool, something that is appropriate to analyze short-run effects of sponsor competition. However, competition may endogenously shape target firm quality and pool over the long-run.

Short-Run and Fixed Target Pool. The core mechanism driving our results is that heightened competition among PE sponsors raises acquisition prices. This makes indiscriminate acquisitions more costly, thereby incentivizing sponsors to engage in more rigorous screening and due diligence. As a result, increased competition improves the quality of acquired firms. Notably, this mechanism operates even when the pool of potential targets is held fixed — an assumption that may be appropriate for analyzing short-run dynamics (Inderst and Müller, 2004).

Long-Run and Endogenous Target Pool. In the long run, however, the pool and composition of target firms are likely to adjust in ways that could influence our results, as formalized in Appendix D.3. In this extension, we assume that when firms exit the target pool — due to an LBO or exogenous death at rate $\iota \geq 0$ — they are replaced by a firm of the same size, thus keeping the total number of firms within a given size bucket constant at

one. We assume that any exiting firm is replaced by a good firm ($z = G$) with probability ν and a bad firm with probability $1 - \nu$, where, conditional on firm type, the ROA is realized according to (2). We then characterize the steady-state target pool composition:

Proposition 7 (Endogenous Target Pool)**.** *Fix firm size K_0 and the number of sponsors $n(K_0)$ searching for firms of that size. The fraction of good target firms in the pool for this size bucket satisfies (if $g \in (0,1)$):*

$$g \;=\; \frac{\nu\big(\Lambda n(K_0)(1-\overline{S})+\iota\big)}{\big(\Lambda n(K_0)+\iota\big)(1-\nu)+\nu\big(\Lambda n(K_0)(1-\overline{S})+\iota\big)},$$

where $\overline{S} := 1-\big[\phi_B(1-S_H)+(1-\phi_B)(1-S_L)\big]$. When the death rate $\iota \geq 0$ is small, increased competition locally worsens the target pool, i.e., g declines with $n(K_0)$, along a differentiable, locally stable equilibrium branch satisfying the condition stated in Appendix D.3.

We focus on the steady state. The remainder of the solution remains unchanged, except that g is determined according to Proposition 7. Now there are two effects at work, potentially leading in opposite directions.

First, greater competition and screening enhance the value of being identified as a high-quality target, thereby strengthening firms' incentives to invest in becoming attractive buyout candidates. This amplifies the positive effect of competition on firm quality. Second, intensified screening and competition can lead to cream-skimming, where sponsors disproportionately acquire the best firms. This reduces the average quality of the remaining pool of targets—as shown above. While this deterioration in average quality may further increase screening efforts by sponsors, it could also attenuate or even reverse overall quality gains from increased competition. Which effect dominates crucially depends on the assumptions made on new target firm creation, a fundamental of the economy.

5 Conclusion and Implications

We analyze, both theoretically and empirically, the effects of competition among private equity (PE) sponsors for leveraged buyout (LBO) targets. Using data from Pitchbook combined with the Federal Reserve's Y-14, we construct a novel measure of sponsor competition

for LBO deals across industries and years, along with a dataset of LBO transactions containing detailed information on target firms and their bank loans. Our empirical analysis shows that greater competition is associated with higher deal multiples and a shift toward the acquisition of smaller but higher-quality firms—characterized by lower default risk, stronger financials, and better operating performance. As competition intensifies, sponsors also rely less on debt, resulting in lower leverage and Debt-to-EBITDA ratios.

Our theoretical framework rationalizes these findings. Heightened competition raises acquisition prices, increasing the cost of pursuing low-quality deals and strengthening sponsors' incentives for due diligence and careful deal selection. At the same time, intensified competition pushes sponsors toward previously less-contested pools of smaller firms. Because higher-quality targets make excessive leverage more costly, sponsors optimally choose lower debt levels, further reducing default risk. Overall, the model illustrates how rising PE sponsor competition for LBO targets leads to higher-quality LBOs, increases deal multiples, and compresses PE returns, such as IRRs.

The model is both tractable enough to deliver analytical results, and sufficiently rich to generate quantitatively relevant output that matches the empirical relationship between deal characteristics and the number of sponsors, our measure of competition (Figure 3). In both model and data, an increase in the number of sponsors over the observed range—from about 40 to slightly fewer than 900, or less than three standard deviations—raises EV/EBITDA multiples from about 11 to 19 and lowers average firm size (book assets) from about $110 million to $50 million; over the same range, model-implied gross returns to sponsors fall from about 25% to 5%. The model also matches untargeted aggregate trends: as Figure 4 shows, it captures the rise in EV/EBITDA multiples from 2000 to 2023 (from about 10 to 12, on average) and implies a secular decline in gross PE returns, from about 37% to 22%.

Taken together, our results suggest that rising competition among PE sponsors has reshaped buyout activity along several dimensions. First, it has improved deal selection and altered capital structure choices, with important implications for the nature and outcomes of private equity investments. Our framework suggests that if competition remains high, deal quality will remain at elevated levels but returns may be lower in the foreseeable future. This has important implications for investors, especially given the growth of PE and increased

exposure of retail investors through private credit products. Second, increased sponsor competition has shifted private equity away from a passive, leverage-driven model toward more active sponsor engagement and greater specialization.

Additionally, while we provide a new framework for the theoretical analysis of PE deals, there remain many potential future extensions. Competition at acquisition may affect not only the entry price but also the sponsor's preferred exit strategy, including a possible exit by selling to continuation vehicles. Moreover, there may be macroeconomic implications of the framework depending on whether the screening mechanism is stronger during credit booms, when financing is plentiful and multiples are high, or during downturns, when default risk and lender discipline become more important. Finally, there remains important work to be done regarding the welfare consequences of buyouts. The model currently focuses primarily on sponsor returns, target quality, default, leverage, and operating performance. A welfare extension could incorporate workers, consumers, suppliers, creditors, taxpayers, and incumbent owners in order to clarify whether competition is socially beneficial despite raising acquisition prices and reducing sponsor returns, and whether greater competition leads to too much costly screening or socially excessive acquisition activity.

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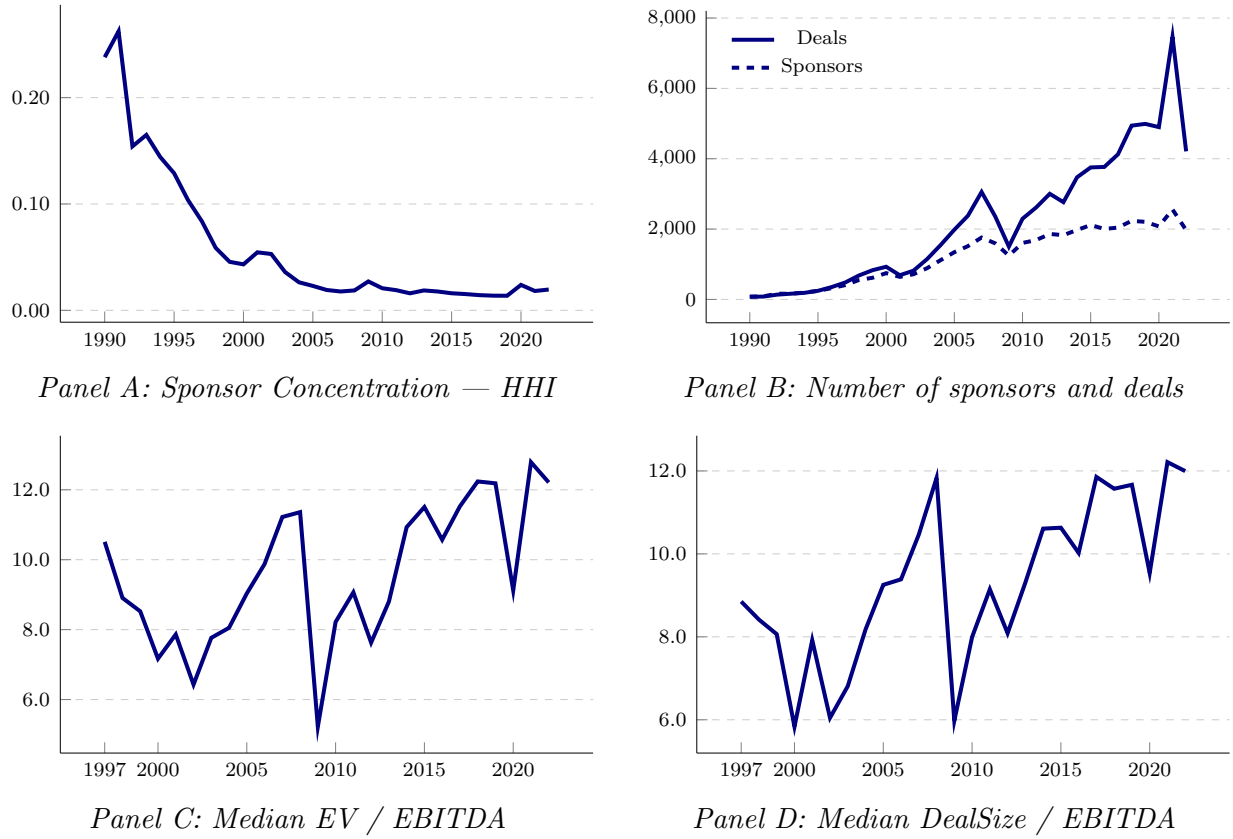
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Panel A: Sponsor Concentration — HHI

Panel B: Number of sponsors and deals

Panel C: Median EV / EBITDA

Panel D: Median DealSize / EBITDA

Figure 1: **Sponsor Concentration, Market Activity, and Deal Multiples over Time**. Panel A plots the sponsor-level Herfindahl–Hirschman Index (HHI) of LBO deal flow within industry–year; Panel B the annual number of LBO deals and of active sponsors; and Panels C and D the annual median EV/EBITDA and DealSize/EBITDA multiples, respectively. All series are constructed from PitchBook LBO transactions. Variable definitions are provided in Appendix A.

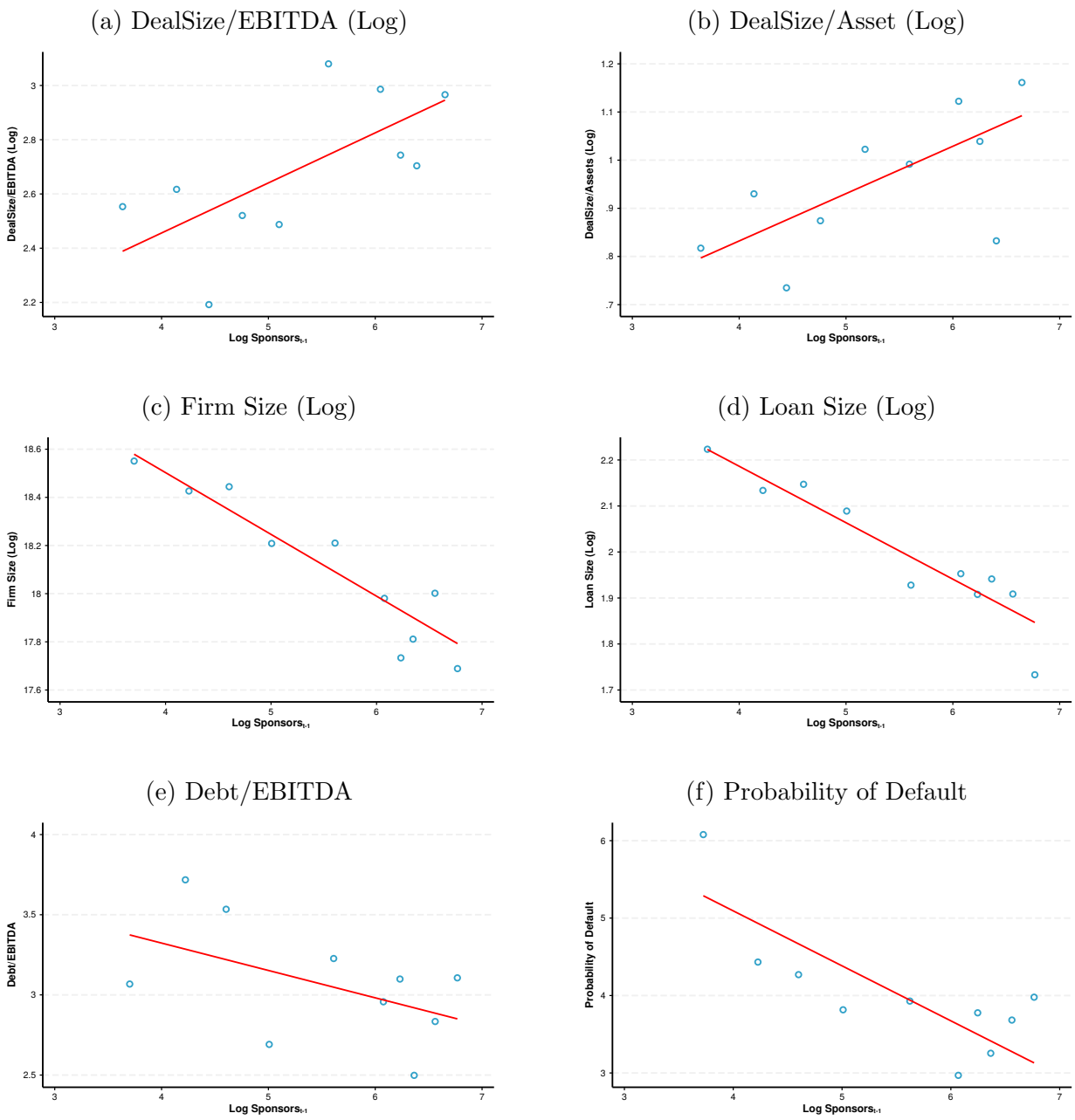


Figure 2: **Number of Sponsors and Outcomes**. Binned scatter plots of deal- and firm-level outcomes against the lagged number of active sponsors, $\log(\text{Sponsors})_{i,t-1}$, measured at the PitchBook industry-group × year level; a higher value reflects greater competition among sponsors for deal flow. In each panel, deals are sorted by $\log(\text{Sponsors})_{i,t-1}$ and grouped into ten equally sized bins; each point is the bin mean of the outcome and the solid line is the fitted linear relationship. Because deal activity is concentrated in high-competition industry-years, the bins reflect the deal-weighted distribution of the competition measure, whose location lies above the industry-year-level percentiles reported in Table 1. Panels (a)–(f) report the (log) deal multiples—deal size scaled by EBITDA and by assets—together with (log) target firm size, (log) average loan size, the Debt/EBITDA ratio, and the bank-reported probability of default (PD). Remaining outcomes are shown in the continued figure. Variable definitions are provided in Appendix A.

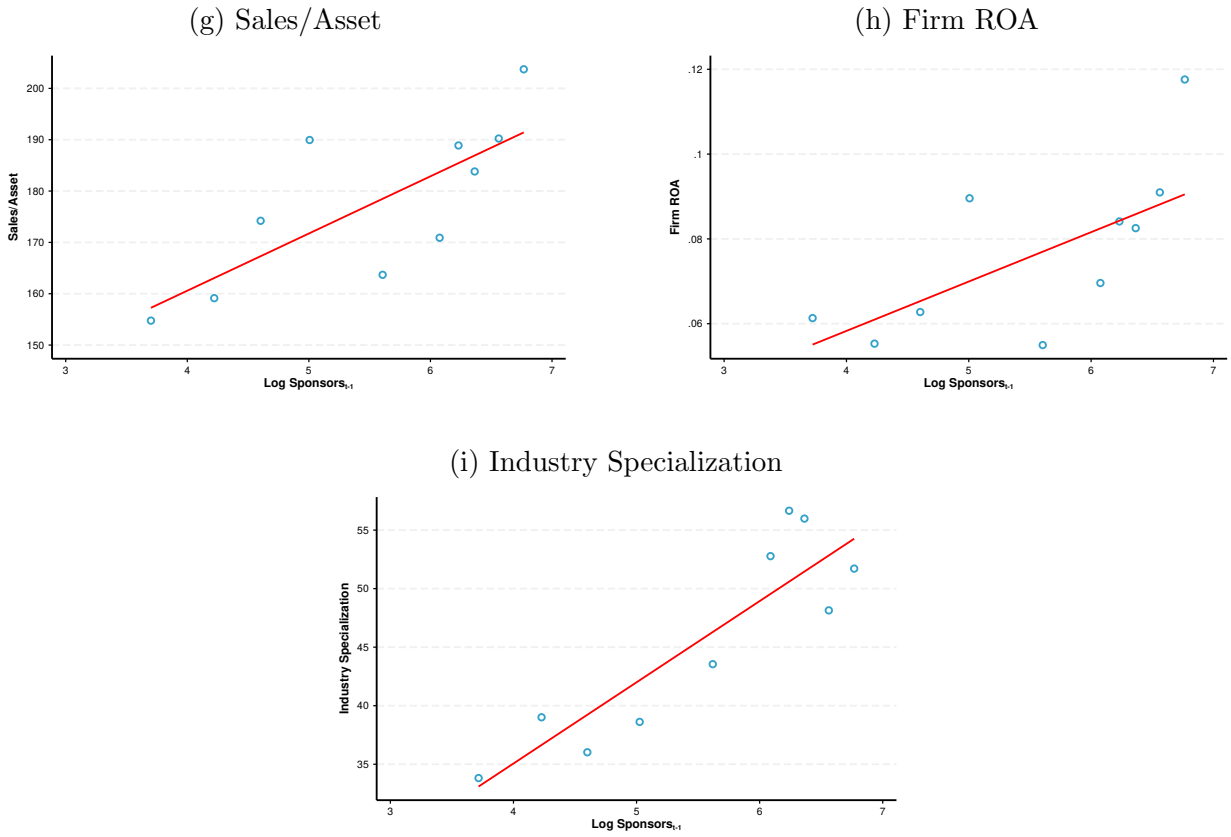


Figure 2: **Number of Sponsors and Outcomes (continued)**. Continuation of the previous figure. Panels (g)–(i) report the Sales/Asset ratio, firm return on assets (ROA), and sponsor industry specialization—the share of a sponsor's deals within a given industry. Bins and fitted lines are constructed as described above. Variable definitions are provided in Appendix A.

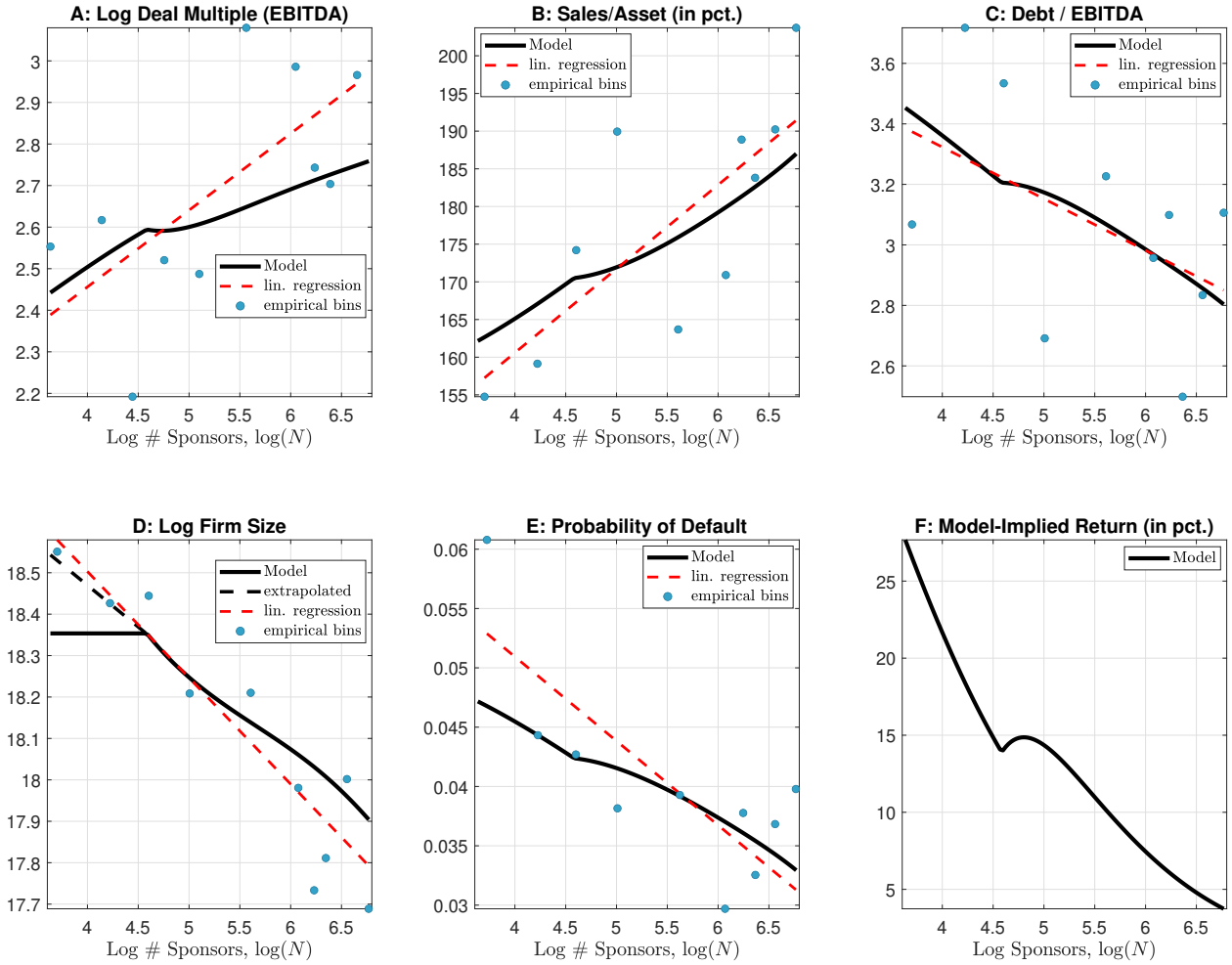


Figure 3: **Numerical illustration and Model Fit**. The solid black line depicts model-implied average quantities. We restrict the model-implied comparative statics for $x = log(N) \in [3.64, 6.77]$; the model admits a well-behaved solution over this range. The kink arises due to firm size being binary. Whenever applicable, blue dots depict the empirical bins and the dashed red line depicts the linear regression line from Figure 2. The parameter choice and calculation of model-implied quantities is discussed in Appendix C, with an overview provided in Appendix Table A-1

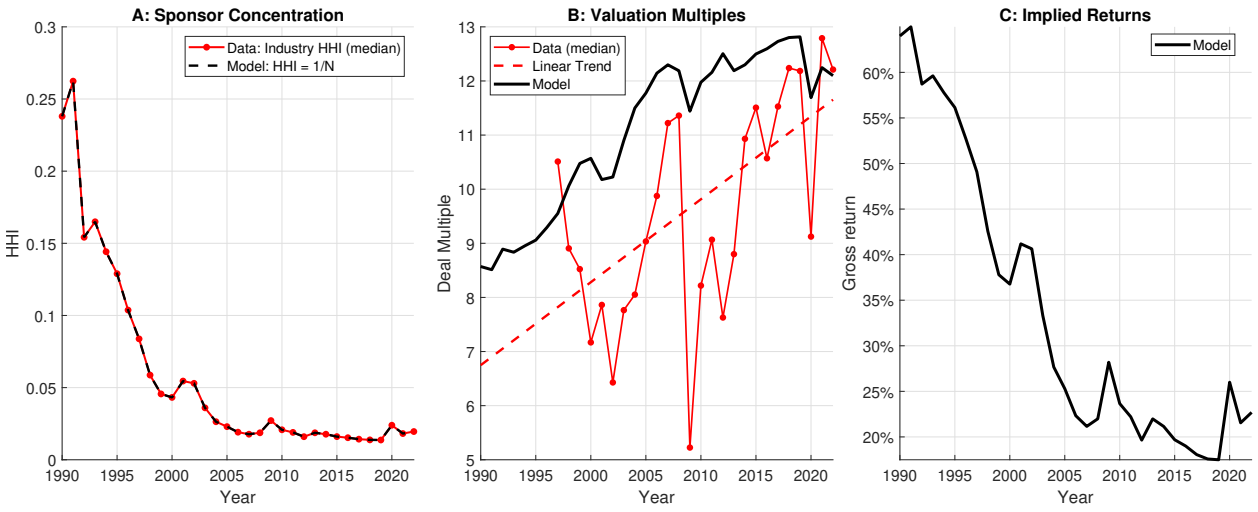


Figure 4: **Model-implied Quantities and Aggregate Trends.** This figure illustrates the model-implied EV/EBITDA multiples and returns for the levels of sponsor concentration (median on Pitchbook industry level) observed from 1990 onward. Panel B also plots the median EV/EBITDA multiples, when available. The parameter choice and calculation of model-implied quantities is discussed in Appendix C, with an overview provided in Appendix Table A-1

Table 1: Summary Statistics for Full Sample

Variable	N	p10	p25	Mean	p50	SD	p75	p90
Panel A: Loan Characteristics								
PD	9,200	0.31	0.64	4.40	1.38	12.07	3.23	7.72
Secured	11,186	0.11	1.00	0.86	1.00	0.32	1.00	1.00
Loan Size	11,186	1.50	2.75	17.93	7.89	50.36	20.65	42.67
Log Loan Size	11,186	0.91	1.29	2.19	2.08	1.03	2.94	3.58
Maturity	11,149	13.50	37.78	59.28	59.00	43.33	66.71	91.44
Log Maturity	11,149	2.64	3.61	3.85	4.09	0.69	4.16	4.47
Panel B: Deal Size Characteristics								
Deal Size ($M)	851	30.00	122.00	1,519.45	500.00	3,144.04	1,400.00	4,000.00
Val Mult (Assets)	850	0.25	0.66	2.51	1.15	7.54	1.99	4.01
Val Mult (Sales)	848	0.17	0.52	3.52	1.35	18.69	3.01	6.09
Val Mult (EBITDA)	770	2.75	7.37	47.53	13.10	268.01	22.99	49.49
Log Val (Assets)	850	0.22	0.51	0.88	0.77	0.65	1.09	1.61
Log Val (Sales)	848	0.16	0.42	1.00	0.85	0.76	1.39	1.96
Log Val (EBITDA)	770	1.32	2.12	2.69	2.65	1.14	3.18	3.92
Panel C: Firm Characteristics								
EBITDA ($M)	4,598	0.36	2.10	68.61	7.25	420.86	23.52	80.77
Debt/Asset (%)	4,547	2.03	13.80	31.83	30.07	22.32	46.55	61.84
Debt/EBITDA	4,278	0.00	0.48	3.10	2.09	5.76	4.67	8.38
EBITDA/Asset (%)	4,237	2.70	7.30	15.41	12.54	13.46	20.11	32.89
Sales/Asset (%)	4,604	40.26	77.23	175.64	147.95	128.55	238.15	344.85
ROA (%)	4,511	−5.93	−0.08	7.51	4.72	14.01	12.72	25.04
ICR	4,308	83.96	267.95	3,841.15	737.77	10,499.51	2,403.30	8,637.50
Firm Size ($M)	4,607	8.27	18.98	985.13	63.61	8,291.48	257.75	1,112.60
Log Firm Size	4,607	15.91	16.72	18.14	17.92	1.88	19.29	20.69
Panel D: Competition and Specialization (Industry × Year)								
HHI ($t-1$)	319	0.01	0.01	0.04	0.02	0.05	0.04	0.12
Log Deals ($t-1$)	319	2.20	3.53	4.09	4.04	1.24	4.67	5.93
Log Sponsors ($t-1$)	319	2.48	3.85	4.25	4.28	1.10	4.84	5.64
Specialization	319	11.15	24.02	37.65	36.72	19.47	51.12	59.59

Notes: The table reports summary statistics for the matched sample. Panels A–C are at the deal (loan) level; Panel D is at the PitchBook industry-group × year level. PD is the bank-reported probability of default (in percent). Loan Size and Firm Size are in millions of dollars unless otherwise noted. Valuation multiples are Deal Size divided by the corresponding Y-14 measure of EBITDA, assets, or sales. Variable definitions are provided in Appendix A.

Table 2: Deal Multiples

	DealSize/EBITDA (Log)			DealSize/Assets (Log)		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	IV	OLS	OLS	IV
Log Sponsors$_{t-1}$	0.185**	0.158**	0.281**	0.098**	0.090**	0.184***
	(0.078)	(0.073)	(0.117)	(0.042)	(0.039)	(0.057)
Observations	716	716	716	771	771	771
Adjusted R^2	0.023	0.039	−0.009	0.019	0.048	−0.016
First Stage F			118.7			118.0
Year FE	NO	YES	YES	NO	YES	YES

Notes: The table reports deal-level OLS and IV regressions of deal multiples on sponsor competition, measured by the lagged number of active sponsors in the industry (in logs). Columns labeled IV instrument the number of sponsors using a leave-out sponsor-hiring shift-share instrument that excludes each deal's own sponsors. Standard errors, clustered at the industry level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Firm Size and Loan Size

	Firm Size (Log)			Loan Size (Log)		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	IV	OLS	OLS	IV
Log Sponsors$_{t-1}$	−0.257***	−0.272***	−0.224***	−0.123***	−0.125***	−0.114***
	(0.056)	(0.057)	(0.062)	(0.022)	(0.022)	(0.032)
Observations	4,297	4,297	4,292	4,328	4,328	4,323
Adjusted R^2	0.019	0.023	0.018	0.020	0.019	0.017
First Stage F			100.5			101.3
Year FE	NO	YES	YES	NO	YES	YES

Notes: The table reports deal-level OLS and IV regressions of firm size and loan size on sponsor competition, measured by the lagged number of active sponsors in the industry (in logs). Columns labeled IV instrument the number of sponsors using a leave-out sponsor-hiring shift-share instrument that excludes each deal's own sponsors. Standard errors, clustered at the industry level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Leverage and Probability of Default

	Debt/EBITDA			Probability of Default		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	IV	OLS	OLS	IV
Log Sponsors$_{t-1}$	−0.171*	−0.167*	−0.138	−0.710*	−0.758*	−0.495
	(0.084)	(0.086)	(0.133)	(0.398)	(0.412)	(0.326)
Observations	4,087	4,087	4,082	3,745	3,745	3,740
Adjusted R^2	0.001	0.000	−0.002	0.005	0.009	0.002
First Stage F			100.4			100.8
Year FE	NO	YES	YES	NO	YES	YES

Notes: The table reports deal-level OLS and IV regressions of Debt/EBITDA and Probability of Default on sponsor competition, measured by the lagged number of active sponsors in the industry (in logs). Columns labeled IV instrument the number of sponsors using a leave-out sponsor-hiring shift-share instrument that excludes each deal's own sponsors. Standard errors, clustered at the industry level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Firm Performance

	Sales/Asset			Firm ROA		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	IV	OLS	OLS	IV
Log Sponsors$_{t-1}$	11.142**	11.525**	3.822	1.164**	1.109**	0.717
	(4.910)	(4.818)	(9.200)	(0.430)	(0.412)	(1.061)
Observations	4,294	4,294	4,289	4,207	4,207	4,202
Adjusted R^2	0.007	0.009	0.002	0.007	0.007	0.003
First Stage F			101.7			96.2
Year FE	NO	YES	YES	NO	YES	YES

Notes: The table reports deal-level OLS and IV regressions of Sales/Asset and Firm ROA on sponsor competition, measured by the lagged number of active sponsors in the industry (in logs). Columns labeled IV instrument the number of sponsors using a leave-out sponsor-hiring shift-share instrument that excludes each deal's own sponsors. Standard errors, clustered at the industry level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Specialization

	Specialization		
	(1)	(2)	(3)
	OLS	OLS	IV
Log Sponsors$_{t-1}$	6.938***	7.161***	6.582***
	(1.383)	(1.440)	(1.358)
Observations	4,249	4,249	4,249
Adjusted R^2	0.050	0.055	0.049
First Stage F			101.8
Year FE	NO	YES	YES

Notes: The table reports deal-level OLS and IV regressions of Specialization on sponsor competition, measured by the lagged number of active sponsors in the industry (in logs). Columns labeled IV instrument the number of sponsors using a leave-out sponsor-hiring shift-share instrument that excludes each deal's own sponsors. Standard errors, clustered at the industry level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

A Variable Definitions

We provide definitions of our main variables below. Firm- and loan-level variables are constructed from the Y-14Q data collected by the Federal Reserve; the item numbers of the data fields refer to Schedule H.1 of the Y-14Q data. Deal-level variables—transaction value, sponsor identities, and industry classification—are from PitchBook. Unless otherwise noted, firm- and loan-level variables are averaged (equally weighted) over the four-quarter window around the buyout date and collapsed to a single observation per deal.

- **Sponsor Concentration (HHI):** Herfindahl–Hirschman index of LBO deal flow across private equity sponsors within a PitchBook industry group and year, constructed from observed LBO transactions with deals attributed equally across participating sponsors (see Section 2). Higher values indicate less competition. Entered lagged by one year, $HHI_{i,t-1}$, in all specifications.
- **Log Number of Deals:** natural logarithm of the number of LBO deals within a given industry group and year (lagged). Alternative competition measure used in Section 3.4.
- **Log Number of Sponsors:** natural logarithm of the number of distinct active sponsors within a given industry group and year (lagged). Alternative competition measure used in Section 3.4.
- **DealSize/EBITDA:** log(Deal Size/EBITDA), where Deal Size is the PitchBook-reported transaction value—a proxy for enterprise value—and EBITDA is from Y-14. Our primary deal multiple.
- **DealSize/Assets:** log(Deal Size/Total Assets), with total assets from Y-14.
- **DealSize/Sales:** log(Deal Size/Net Sales), with net sales from Y-14.
- **Firm Size:** natural logarithm of the book value of total assets.
- **Loan Size:** natural logarithm of the average committed exposure across the bank loans held by the firm within the four-quarter window.
- **Debt/EBITDA:** long-term debt (maturing in more than one year) over EBITDA. Our measure of firm leverage.

- **Sales/Asset:** net sales over total assets, i.e., asset turnover; our measure of operating performance.
- **Firm ROA:** return on assets, computed as net income over total assets (expressed in percent).
- **Probability of Default (PD):** bank-reported obligor probability of default (expressed in percent).
- **Industry Specialization:** for each deal, the average across its participating sponsors of the share of each sponsor's own (attributed) LBO deals that fall within the deal's industry group. Shares are computed over a five-year rolling window ($t-4$ through t, where t is the deal year). A value of 100% indicates the sponsor invests exclusively in that industry.
- **Leave-out Hiring Shift-Share Instrument ($Z^H_{i,t-1}$):** industry–year instrument for $HHI_{i,t-1}$, constructed as the exposure-weighted sum of *other* sponsors' hiring, excluding each deal's own sponsors (see Section 2).

B Model Solution and Proofs

The Appendix provides solution details and proofs for the main text. We start with parameter conditions.

B.1 Parameter Conditions

We assume the following conditions are satisfied:

1. We assume that (B.8) holds. This ensures that conditional on a positive signal in the screening stage and, in equilibrium, under an LBO, we have that $\theta_x < f_x(q_x)$. A necessary condition that we assume is $\frac{\rho - r}{\delta g_x(1-\chi)} < 1$, which, as we show, implies $\theta_x(q_x) < f_x^*$ and the conditional default probability $\omega = \frac{\theta_x(q_x)}{f_x^*} < 1$ is well-defined.

2. We assume:[35]
$$\frac{\alpha_x}{r + \delta - \mu} - I - f_x^{Pre} < 0 < f_x(q_x) - I - f_x^{Pre}. \tag{B.1}$$
The first inequality states that the value of the firm with $q_x = 0$, that is, $f_x(0) = \frac{\alpha_x}{r+\delta-\mu}$ is below $I + f_x^{Pre}$, which means financing a bad firm has negative NPV. The second inequality means that under equilibrium beliefs q_x after a positive signal, financing the firm has positive NPV.[36] Note $f_L^{Pre} \leq f_H^{Pre}$.

3. We assume that (B.15) holds, so that firm value is nondecreasing in beliefs, i.e., $f_x'(q_x) \geq 0$. We further assume that the optimal screening choice is interior and satisfies the first-order condition (B.9) and the second-order condition (B.13). These conditions ensure that the screening choice is an interior strict local optimum.

4. For every relevant equilibrium belief pair (q_L, q_H), we assume that $\alpha_H(q_H) \geq \alpha_L(q_L)$ and $f_H(q_H) \geq f_L(q_L)$. This assumption is not necessary for our findings, but supports the notion that $x = H$ is associated with good hard information, and thus higher operating cash flow and firm value than $x = L$.

Note that some of these conditions depend on endogenous model quantities, e.g., beliefs q_x. Throughout the theory, we assume that parameters are such that the conditions are satisfied; our numerical analysis explicitly verifies that.

[35] The condition relies on endogenous equilibrium beliefs, and ensures that the market does not break down. By assuming (B.1) holds for both values of $x = L, H$, we avoid distracting case distinctions while preserving the core intuition.

[36] In the edge case, $q_x = 0$ the firm is fully-debt financed as default occurs always upon Poisson shock. Then, the (scaled) value of the firm is simply the perpetuity value of cash flows at rate α_x, discounted at effective discount rate $r + \delta$ and growth rate μ. Alternatively, for a derivation using later results, insert $q_x = 0$ into the firm value HJB equation (B.5). This immediately implies $\theta = f_x(q_x)$, and $f_x(0) = \frac{\alpha_x}{r+\delta-\mu}$.

B.2 Full Equilibrium Definition

An equilibrium consists of

$$\left\{f_x(q_x), q_x, \theta_x(q_x), S_x, p_x^{Firm}, p_x^{Sponsor}\right\}_{x\in\{L,H\}} \quad \text{and} \quad \big(n(1), n(\gamma)\big),$$

such that:

1. Given q_x, K_0, and α_x, the firm's owners choose debt issuance and default to maximize equity value in (B.3). Creditors price debt competitively given q_x, $\theta_x(q_x)$, and α_x. All quantities scale with capital, K_t.

2. An LBO occurs if and only if the screening signal is positive, $\mathcal{S}_x = 1$. Condition (B.1) ensures that the LBO has positive expected NPV after a positive signal and negative NPV when the firm is revealed to be bad. Conditional on $\mathcal{S}_x = 1$, bargaining follows the random-proposer protocol: the firm (sponsor) makes an offer with probability β $(1-\beta)$, and parties accept when weakly indifferent. The equilibrium is pooling: sponsors offer a single price $p_x^{Sponsor}$, and good and bad firms offer the same price p_x^{Firm}. We show that no separating equilibrium exists and establish uniqueness of the pooling equilibrium under passive off-equilibrium beliefs; worst-case beliefs support the same on-path allocation.

3. After observing x, the sponsor chooses $S_x \in [0,1]$ to maximize (7). Following a positive signal, beliefs satisfy
$$q_x = \frac{g_x}{1 - S_x(1-g_x)}.$$

4. Given search value $K_0 v(n(K_0))$, sponsors choose a size bucket according to (B.22). Equilibrium masses satisfy $n(1) + n(\gamma) = N$ and
$$n(1) = \begin{cases} N, & \text{if } v(N) \geq \gamma v(0), \\ \text{the unique } n \in (0,N) \text{ satisfying } v(n) = \gamma v(N-n), & \text{if } v(N) < \gamma v(0). \end{cases}$$

5. On-path beliefs are updated according to Bayes' rule. Following an off-equilibrium price offer that could benefit both firm types conditional on acceptance, the Intuitive Criterion does not restrict the sponsor's posterior: neither type can be excluded as the possible deviator. We select passive off-path beliefs, under which the sponsor retains its prior bargaining belief q_x and treats the offer as uninformative cheap talk.

The equilibrium definition is expanded when endogenizing the pool of target firms. See Proposition 7 and Appendix D.3.

B.3 Solution Post-LBO Stage: Proof of Proposition 1

The post-LBO stage is set up in continuous time over an infinite horizon, where $t \geq 0$ denotes the time that has elapsed since the LBO. Time $t = 0$ refers to the time of the LBO, with K_0 denoting the capital stock or firm size at LBO deal. For simplicity, we omit time subscripts, unless needed.

Fix the observable type $x \in \{L, H\}$ and the belief q_x that the acquired firm has hidden type $z = G$. We solve the post-LBO stage taking these quantities as given. Operating cash flow α_x may depend on screening S_x. Since $q_x = \frac{g_x}{1-S_x(1-g_x)}$ increases with S_x, we can equivalently write $\alpha_x = \alpha_x(q_x)$. We suppress this dependence when no confusion arises.

Formally, before the shock time T^{Shock}, capital evolves as

$$\frac{dK_t}{K_{t^-}} = \mu\, dt - dN_t\big[\mathbb{I}\{z = B\} + (1-\psi)\mathbb{I}\{z = G\}\big], \tag{B.2}$$

where $\mu > 0$ is the constant growth rate, N_t is a Poisson process with intensity δ, and $K_{t^-} = \lim_{s\uparrow t} K_s$ is the pre-shock capital stock. We assume $\mu < r$ to ensure finite valuations. After T^{Shock}, only good firms ($z = G$) continue operating, with capital growing at rate μ, i.e., $\frac{dK_t}{K_t} = \mu dt$. The shock therefore fully reveals the hidden type z. To maintain tractability, agents do not learn the firm's type before the shock.

Objective Function. Debt with face value D_t is issued at time t and matures at $t + dt$. Absent default, creditors are repaid $D_t\big[1 + (r + \Delta_t)dt\big]$, where Δ_t is the endogenous credit spread. Thus, the net cash flow from debt issuance over $[t, t + dt]$ equals $D_{t+dt} - D_t\big[1 + (r + \Delta_t)dt\big]$ and is distributed as dividends; here, $dD_t = D_{t+dt} - D_t$. If the firm defaults, creditors seize the firm and liquidate it for recovery value $R_x K_t$, where $R_x \geq 0$ depends on x.

The firm's owners choose debt issuance and the default time to maximize equity value:

$$E_0 = \max_{(D_t)_{t\geq 0},\tau} \mathbb{E}\left[\int_0^\tau e^{-\rho t}\Big(\alpha_x K_t dt + (dD_t - (r + \Delta_t)D_t dt)\Big)\Big| q_x; K_0; \alpha_x\right]. \tag{B.3}$$

The firm starts with zero debt, $D_0 = 0$, at the LBO date ($t = 0$). Absent a shock, equity value must remain nonnegative; otherwise, shareholders exercise limited liability and default immediately. As in Abel (2018), this generates the borrowing constraint $F_t \geq D_t$.

Scaling. We focus on an equilibrium in which quantities scale with capital. Before the shock, firm value and debt are $F_t = K_t f_x(q_x)$ and $D_t = K_{t^-}\theta_x(q_x)$, respectively, so equity value is $K_t f_x(q_x) - K_{t^-}\theta_x(q_x)$. Absent a shock, $K_t = K_{t^-}$, and the borrowing constraint becomes $\theta_x(q_x) \leq f_x(q_x)$. If a shock occurs and the firm is good, then $K_t = \psi K_{t^-}$ and its post-

shock value is $\psi K_{t^-} f_x^*$. Equity value is therefore $K_{t^-}(\psi f_x^* - \theta_x(q_x))$, which is negative—and triggers default—when ψ is sufficiently low, as shown below.

Post-Shock (First-Best) Value. After a good firm survives the shock, it faces no further credit risk and can be fully debt-financed, thereby capitalizing on creditors' lower discount rate. This simplifying benchmark yields post-shock firm value Kf_x^*, where

$$f_x^* = \frac{\alpha_x}{r - \mu}.$$

Thus, firm value is that of a growing perpetuity with payout rate α_x and growth rate $\mu < r$. This is Gordon's growth formula.

Because α_x may depend on q_x, so may f_x^*; we write $f_x^* = f_x^*(q_x)$ when useful. The shock fully reveals the firm's type because only a good firm can survive.

Default Probability. Conditional on a shock, a bad firm (which occurs with probability $1-q_x$) defaults with certainty. A good firm (which occurs with probability q_x) defaults when $\psi f_x^* < \theta$, so its conditional default probability is $\omega = \theta / f_x^*$. We suppress the dependence of ω and θ on x. The maintained assumptions $\theta \leq f_x(q_x) < f_x^*(q_x)$ ensure that $\omega \in [0, 1]$.

Credit Spread. By assumption, when the firm is bad, the firm defaults/liquidates and creditors recover zero upon the shock, since the full capital stock is destroyed.

If the firm is good, the firm defaults with probability ω — which is the default probability conditional on the firm being good and a shock occurring. In case of default, the average remaining (post-default) capital stock equals

$$K\mathbb{E}\left[\psi \middle| \psi < \frac{\theta}{f_x^*}\right] = \frac{K\theta}{2f_x^*},$$

given that ψ is uniformly distributed on $[0, 1]$. The expected recovery value is therefore

$$K \cdot \frac{R_x \theta}{2f_x^*} = K \cdot \frac{\chi\theta}{2},$$

since $R_x = \chi f_x^*$. Thus, per unit/dollar of debt, creditors recover in expectation $\frac{\chi}{2}$ in case of default, since total debt equals $K\theta$. The fair credit spread is therefore

$$\Delta = \delta \left[(1 - q_x) + q_x \omega \left(1 - \frac{\chi}{2}\right)\right]. \tag{B.4}$$

The fair interest rate on debt is then

$$\hat{r} := r + \Delta = r + \delta \left[(1 - q_x) + q_x \omega \left(1 - \frac{\chi}{2} \right) \right].$$

Again, for $\hat{r}$ and Δ, we suppress the dependence on x.

Value Function. Suppose a credit shock hits. Conditional on a shock, the owners' value is zero when the firm is bad, i.e., with probability $1 - q_x$. With probability q_x, the firm is good. Then, the owners' value is zero in case of default when $\psi < \frac{\theta}{f_x^*}$. When the firm does not default, the expected capital stock is $K\tilde{\psi}$

$$\tilde{\psi} := \mathbb{E}\left[\psi \middle| \psi \geq \frac{\theta}{f_x^*} \right] = \frac{1}{2}\left(1 + \frac{\theta}{f_x^*} \right) = \frac{f_x^* + \theta}{2 f_x^*} = \frac{1 + \omega}{2}.$$

Thus, the expected continuation value for equity holders is

$$\begin{aligned} \Pi_x(q_x) &:= K\mathbb{E}[(\psi f_x^* - \theta)\mathbb{I}\{\psi f_x^* \geq \theta\} | dN_t = 1; q_x] = q_x(1-\omega)K\left\{ f_x^* \left(\frac{f_x^* + \theta}{2 f_x^*} \right) - \theta \right\} \\ &= q_x(1-\omega)K\left(\frac{f_x^*}{2}(1+\omega) - \theta \right) = q_x K \left(\frac{f_x^*}{2}(1 - \omega^2) - \theta(1-\omega) \right). \end{aligned}$$

The scaled payoff satisfies upon issuing $K\theta$ dollars of debt, which are paid out as dividends and debt matures at $t = dt$:

$$\begin{aligned} K f_x(q_x) = K\theta + \alpha_x K dt + e^{-\rho dt}(1 - \delta dt)\big\{ [K + K\mu dt] f_x(q_x) - K\theta(1 + \hat{r} dt) \big\} \\ + e^{-\rho dt}\delta q_x (1-\omega) dt \Big\{ K[\tilde{\psi} + \mu dt] f_x^* - K\theta(1 + \hat{r} dt) \Big\}, \end{aligned}$$

where $\hat{r} = r + \Delta$.

Taking the limit $dt \to 0$, ignoring terms of order $(dt)^2$, and doing some algebra, we can derive that the firm's scaled value function solves

$$(\rho + \delta - \mu) f_x(q_x) = \max_{\theta \in [0, f_x(q_x)]} \Big[\alpha_x + (\rho + \delta - \hat{r})\theta + \delta \frac{\Pi}{K} \Big].$$

Note that the shock arrival rate δ effectively augments the owners' discount rate, i.e., the "effective" discount rate becomes $\rho + \delta$. We can rearrange to obtain the firm's scaled value function:

$$(\rho + \delta - \mu) f_x(q_x) = \max_{\theta \in [0, f_x(q_x)]} \Big\{ \alpha_x + (\rho - r)\theta + \frac{\delta q_x f_x^*}{2} \big[1 - \omega^2(1 - \chi) \big] \Big\}. \tag{B.5}$$

Optimal Debt Level. The FOC with respect to θ reads:

$$(\rho - r) - \delta q_x f_x^* \omega (1-\chi) \frac{1}{f_x^*} = (\rho - r) - \frac{\delta q_x (1-\chi)\theta}{f_x^*} = 0.$$

Thus,

$$\theta = \theta_x(q_x) = \min\left\{ f_x(q_x), \frac{(\rho - r) f_x^*}{\delta q_x (1-\chi)} \right\}.$$

Consider that $\theta < f_x(q_x)$ and insert $\omega = \frac{\theta}{f_x^*}$ into (B.5) to obtain:

$$f_x(q_x) = \frac{1}{\rho + \delta - \mu} \left[\alpha_x \; + \; \frac{(\rho - r)^2 \, f_x^*}{2 \, \delta \, q_x \, (1-\chi)} \; + \; \frac{\delta \, q_x \, f_x^*}{2} \right]. \tag{B.6}$$

When $f_x(q_x) = \theta$, then (B.5) implies:

$$f_x(q_x) = \frac{f_x^*}{\delta q_x (1-\chi)} \left[-(r + \delta - \mu) + \sqrt{(r + \delta - \mu)^2 + \frac{2\delta q_x (1-\chi)}{f_x^*} \left(\alpha_x + \frac{\delta q_x f_x^*}{2} \right)} \right]. \tag{B.7}$$

Note that when $f_x(q_x) = \theta$ (yet $q_x > 0$) and the closed-form expression (B.7) applies. Recall for that equation that both α_x and f_x^* may be functions of q_x.

Finally, note that when $q_x = 0$, we have $\theta_x(0) = f_x(0)$, Then, (B.5) immediately implies $f_x(0) = \frac{\alpha_x}{r + \delta - \mu}$.

Sufficient Parameter Condition for $f_x(q_x) > \theta_x(q_x)$. In equilibrium, q_x is given by (4), and hence $q_x \in [g_x, 1]$. Because $\alpha_x'(q) \geq 0$, define

$$\underline{\alpha}_x := \alpha_x(g_x), \qquad \underline{f}_x^* := f_x^*(g_x) = \frac{\alpha_x(g_x)}{r - \mu}, \qquad \overline{m}_x := \sup_{q \in [g_x, 1]} \frac{f_x^*(q)}{q}.$$

Using (B.6), $\alpha_x(q_x) \geq \underline{\alpha}_x$, $f_x^*(q_x) \geq \underline{f}_x^*$, $q_x \geq g_x$, and $1/q_x \geq 1$, we obtain

$$f_x(q_x) \geq \frac{1}{\rho + \delta - \mu} \left[\underline{\alpha}_x \; + \; \frac{(\rho - r)^2 \, \underline{f}_x^*}{2 \, \delta \, (1-\chi)} \; + \; \frac{\delta \, g_x \, \underline{f}_x^*}{2} \right].$$

Moreover,

$$\theta_x(q_x) = \frac{\rho - r}{\delta(1-\chi)} \frac{f_x^*(q_x)}{q_x} \leq \frac{\rho - r}{\delta(1-\chi)} \overline{m}_x.$$

Therefore, a sufficient parameter condition for $f_x(q_x) > \theta_x(q_x)$ for all $q_x \in [g_x, 1]$ is

$$\frac{1}{\rho+\delta-\mu}\left[\underline{\alpha}_x \;+\; \frac{(\rho-r)^2\,\underline{f}^*_x}{2\,\delta\,(1-\chi)} \;+\; \frac{\delta\, g_x\, \underline{f}^*_x}{2}\right] > \frac{\rho-r}{\delta(1-\chi)}\overline{m}_x \tag{B.8}$$

for $x = L, H$. If $q\alpha'_x(q) < \alpha_x(q)$ on $[g_x, 1]$, then $f^*_x(q)/q$ is decreasing and $\overline{m}_x = \underline{f}^*_x/g_x$, yielding the direct analogue of the baseline condition.

Comparative Statics. Assume now debt is interior, i.e., $\theta = \theta_x(q_x) < f_x(q_x)$. If $q_x\alpha'_x(q_x) < \alpha_x(q_x)$, then $\theta_x(q_x)$ declines with q_x. Irrespective of this additional condition, conditional default probability and credit spreads satisfy

$$\omega = \frac{(\rho-r)}{\delta q_x(1-\chi)} \quad \text{and} \quad \Delta = \delta\left[(1-q_x) + \frac{(\rho-r)}{\delta(1-\chi)}\left(1-\frac{\chi}{2}\right)\right].$$

We note that the conditional default probability ω declines with q_x too. The overall default probability over an instant $[t, t+dt)$ equals

$$\delta dt \cdot [(1-q_x) + q_x\omega] = \delta dt \cdot (1-q_x) + dt \cdot \frac{\rho-r}{1-\chi}$$

declines with q_x too.

Next, consider the firm's Debt/EBITDA ratio

$$\frac{Debt}{EBITDA} := \frac{L}{K\alpha_x} = \frac{\theta_x}{\alpha_x} = \frac{\rho-r}{\delta q_x(1-\chi)(r-\mu)},$$

which also decreases in q_x.

Finally, consider the expected recovery value upon default. If the firm is bad (with probability $1-q_x$), the expected recovery value upon default is zero. If the firm is good (with probability q_x), the expected recovery value upon default (per unit of debt) equals

$$\frac{RK}{K\theta}\mathbb{E}\left[\psi\middle|\psi < \frac{\theta}{f^*_x}\right] = \frac{R}{2f^*_x} = \frac{\chi}{2},$$

since $R = \chi f^*_x$. Overall, the expected recovery value upon default per unit of debt equals

$$\mathbb{E}[\text{Exp. Recovery}|\text{Default}; dN_t = 1] = \frac{\chi q_x\omega}{2\big[(1-q_x)+q_x\omega\big]}$$

and therefore increases in average firm quality.

B.4 LBO Stage

We consider the LBO deal, noting the post-LBO continuation payoff $f_x(q_x)$ where we write $f_x(q_x)$ for $x = L$ and for $x = H$. Further, take the firm size K_0 as given and note that all quantities scale with K_0. Let $(\rho + \kappa) f_x^{Pre}$ be the pre-LBO cash flows of the firm (scaled by K_0); recall that prior to the LBO, firms die at rate $\kappa > 0$. Both κ and f_x^{Pre} are exogenous parameters.

B.4.1 Proof of Proposition 2

Suppose firm and sponsor match, where the firm can be good ($z = G$) or bad ($z = B$). Then, the sponsor observes x, chooses screening effort S_x, and observes the signal $\mathcal{S}_x$ — which equals one for good firms and equals one for bad firms with probability $1 - S_x$,

We note that firms and sponsors proceed to bargaining over the acquisition price, only if the firm passes screening in that the signal equals $\mathcal{S}_x = 1$; a signal $\mathcal{S}_x = 0$ would reveal a bad firm and investing in a bad firm has negative net present value (NPV). Thus, observing the firm is bad with probability one, the sponsor foregoes the investment.

Signals and Beliefs. After observing $x \in \{L, H\}$, the sponsor updates its belief that the firm is good to g_x, as outlined in the main text. In what follows, all quantities will be dependent on the realization of x.

Next, conditional on x, let the equilibrium belief be $\hat{q}_x$ and consider a sponsor-firm match. Take screening of the involved firm, S_x, as given and consider the signal is good, i.e., $\mathcal{S}_x = 1$. The belief of the sponsor is

$$q_x = q_x(S_x) = \frac{g_x}{g_x + (1 - g_x)(1 - S_x)} = \frac{g_x}{1 - S_x(1 - g_x)}.$$

Note that in equilibrium $\hat{q}_x = q_x$, but for bargaining equilibrium beliefs, $\hat{q}_x$, and screening, $\hat{S}_x$, will be taken as given. Also, note that $q_x'(S_x) = \frac{(1-g_x)q_x}{1-S_x(1-g_x)} > 0$. However, since the sponsor's choice of S_x is observed, the firm also knows the sponsor's beliefs q_x.

Random Proposer Bargain Protocol. Take the sponsor's belief q_x (and equilibrium beliefs $\hat{q}_x$) as given and consider the signal has been good, i.e., $\mathcal{S}_x$. The firm's type is private knowledge, so we have asymmetric information.

We consider the random proposer bargaining protocol. With probability β, the firm — which can be good or bad — makes a take-it-or-leave-it (TIOLI) offer $p_{x,z}^{Firm}$, which in principle can depend on the firm's type z (when both types offer different prices). With probability $1 - \beta$, the sponsor makes an offer, $p_{x,z}^{Sponsor}$, which can be a menu of prices for

each type z. Under the passive off-path beliefs specified below, we show that the unique pure-strategy bargaining equilibrium is pooling, i.e., both types of firm offer the same price, i.e., $p_{x,z}^{Firm} = p_x^{Firm}$, and the sponsor offers a single price, i.e., $p_{x,z}^{Sponsor} = p_x^{Sponsor}$. Throughout, parties accept an offer, as long as this puts them weakly better off, relative to rejecting it.

First, consider the sponsor offers, and suppose to the contrary $p_{x,z}^{Sponsor}$ is not constant across z. Then, any firm would always accept the higher price, so the sponsor cannot price screen. Therefore, the sponsor, without loss of generality, offers a single price $p_{x,z}^{Sponsor} = p_x^{Sponsor}$.

Second, consider firms make the offer, and suppose that $p_{x,B}^{Firm} \neq p_{x,G}^{Firm}$, i.e., good and bad firms make different offers. However, in equilibrium, the sponsor could then separate good from bad firms, and would only accept the offer of the good firm, rejecting the bad firm's offer. Recall that financing the bad firm has negative NPV. Consequently, the bad firm would never undergo an LBO, and therefore would strictly benefit from mimicking the good firm, destabilizing the proposed equilibrium. Thus, the unique equilibrium must feature $p_{x,z}^{Firm} = p_x^{Firm}$, i.e., both types offer the same price, with the firm realizing profits of $p_x^{Firm} - I$ (which will be strictly positive in equilibrium).

We next specify off-path beliefs and check potential deviations. Consider an upward deviation from the pooling offer. Conditional on acceptance, both firm types receive the same higher payoff and would strictly prefer the deviation. Consequently, the deviation is not equilibrium-dominated for either type, and the Intuitive Criterion cannot exclude either type as the possible deviator. The criterion therefore leaves the sponsor's posterior following this offer unrestricted; in particular, it does not itself require either optimistic or pessimistic beliefs. We select passive beliefs: after any off-equilibrium price offer, the sponsor retains its bargaining belief q_x and treats the price as uninformative cheap talk.[37] Under this belief, the sponsor rejects every offer above $f_x(q_x)$, while a downward deviation lowers the firm's payoff. Hence, together with weak acceptance at indifference, $p_x^{Firm} = f_x(q_x)$ is the unique pooling offer, and the pooling strategies described above constitute the unique pure-strategy bargaining equilibrium under the passive-beliefs selection.

Acquisition Price. Consider the firm is good, i.e., $z = G$. The signal has been good, and the sponsor attaches belief q_x that the firm is good. We solve for the acquisition prices, which will be such that, whenever a sponsor and firm meet (and screening is passed), the acquisition takes place. Thus, in equilibrium, whenever a sponsor and firm meet, any offer is

[37] Worst-case beliefs yield the same on-path equilibrium allocation. Under the negative known-bad NPV condition in (B.1), the sponsor rejects an upward deviation under either worst-case or passive beliefs, while a downward deviation is unprofitable for the firm regardless of the sponsor's response. The two belief selections may differ only in their off-path implications.

accepted and the LBO takes place, with prices being such that this is individually optimal for firms and sponsors. Moreover, the bad firm will mimic the good firm, i.e., it makes the same offer and accepts any offer the sponsor makes.

We distinguish two cases, depending on who makes the offer in the alternate proposer bargaining model:

1. **Firm makes offer.** With probability β, the firm makes a TIOLI offer. The firm is aware of the sponsor's beliefs and thus the sponsor's valuation of the firm, $K_0 f_x(q_x)$ where $f_x(q_x)$ is the scaled firm value (for the sponsor with belief q_x). Thus, the firm offers the sponsor the opportunity to acquire it at price $K_0 p_x^{Firm}(q_x)$, with scaled price p_x^{Firm}. Of the amount paid by the sponsor, I dollars are invested (per unit of capital), leaving the firm's original owners with (scaled) payoff $f_x(q_x) - I$.

   The sponsor accepts as long as it breaks even, and $p_x^{Firm}(q_x) \leq f_x(q_x)$. We note that the sponsor can continue to search for the next target irrespective of whether an acquisition takes place. Thus, when the sponsor accepts the offer, there is no opportunity cost, i.e., there is no foregone opportunity.

   In optimum, the firm extracts maximum surplus and the sponsor merely breaks even. That is, the firm offers $p_x^{Firm} = p_x^{Firm}(q_x) = f_x(q_x)$. Thus, the K_0-scaled price that depends on q_x (but not $\hat{q}_x$) — we may suppress this dependence for convenience.

2. **Sponsor makes offer.** With probability $1 - \beta$, the sponsor makes a TIOLI offer, denoted $p_x^{Sponsor} = p_x^{Sponsor}(\hat{q}_x)$. We conjecture and verify that the scaled price $p_x^{Sponsor} = p_x^{Sponsor}(\hat{q}_x)$ is a function of $\hat{q}_x$ (but not q_x) — for convenience, we may express this dependence. Acceptance of the offer results in scaled payoff for the firm of $p_x^{Sponsor}(\hat{q}_x) - I$. Consider a deviation, whereby the (good) firm rejects the offer and searches for a new sponsor, conducting the acquisition with the next offer (either offering a price or accepting the next sponsor's offer).

   If, the firm rejects the offer, it can search for the next sponsor, meeting another sponsor at intensity $\Lambda n(K_0)$ and collecting flow payoffs at a rate of $(\rho+\kappa) f_x^{Pre}$. The firm anticipates that any sponsor it encounters will exert screening effort $\hat{S}_x$ and accordingly have beliefs $\hat{q}_x$. Since the firm is good, it will pass screening with certainty (i.e., $\mathcal{S}_x = 1$ with certainty). Upon meeting the next sponsor (with beliefs $\hat{q}_x$), with probability β, the firm can make the next offer, offering K_0-scaled price $p_x^{Firm}(\hat{q}_x) = f_x(\hat{q}_x)$. Otherwise, with probability $1-\beta$, the sponsor offers scaled price $p_x^{Sponsor}(\hat{q}_x)$, resulting in (scaled) net payoff for the firm of $p_x^{Sponsor}(\hat{q}_x) - I$.

   For the firm to be willing to accept the first sponsor's offer, the price $p_x^{Sponsor}$ is such

that the firm (i.e., its original owners) is indifferent between accepting and continuing searching. This allows the sponsor to extract maximum surplus. As a result, we have

$$p_x^{Sponsor}(\hat{q}_x) - I = \frac{\Lambda n}{\rho + \kappa + \Lambda n}\left(\beta(f_x(\hat{q}_x) - I) + (1-\beta)(p_x^{Sponsor} - I)\right) + \frac{(\rho+\kappa)f_x^{Pre}}{\rho + \kappa + \Lambda n}.$$

Thus, we can solve this equation for

$$p_x^{Sponsor}(\hat{q}_x) - I = \frac{\beta\,\Lambda\,n\left(f_x(\hat{q}_x) - I\right) \;+\; (\rho+\kappa)\,f_x^{Pre}}{\rho + \kappa + \beta\,\Lambda\,n}\,.$$

Next, we can solve for the expected price satisfies $\overline{P}_x = K_0\overline{p}_x$, with $\overline{p}_x = \beta p_x^{Firm}(q_x) + (1-\beta)p_x^{Sponsor}(\hat{q}_x)$. Note that $\overline{p}_x$ depends on both q_x and $\hat{q}_x$, but we suppress the dependence going forward.

In particular, we solve for

$$\begin{aligned}
\overline{p}_x &= \beta f_x(q_x) + (1-\beta)\left(\frac{\beta\,\Lambda\,n\left(f_x(\hat{q}_x) - I\right) \;+\; (\rho+\kappa)\,f_x^{Pre}}{\rho + \kappa + \beta\,\Lambda\,n} + I\right) \\
&= I + \eta[f_x(\hat{q}_x) - I] + (1-\eta)f_x^{Pre} + \beta[f_x(q_x) - f_x(\hat{q}_x)] \\
&= I + f_x^{Pre} + \eta[f_x(\hat{q}_x) - I - f_x^{Pre}] + \beta[f_x(q_x) - f_x(\hat{q}_x)],
\end{aligned}$$

where we define

$$\eta := \eta(n) = \left[\beta + \frac{(1-\beta)\beta\Lambda n}{\rho + \kappa + \beta\Lambda n}\right].$$

Note that $1 - \eta = (1-\beta)\,\frac{\rho+\kappa}{\rho+\kappa+\beta\,\Lambda\,n}$. We interpret η is a measure of competition among sponsors and observe that it is a monotonic transformation of n, in that

$$\eta'(n) = \frac{(1-\beta)\beta\Lambda(\rho+\kappa)}{(\rho+\kappa+\beta\Lambda n)^2} > 0,$$

as $\beta \in (0,1)$.

Finally, note that in equilibrium, we will have $q_x = \hat{q}_x$, so that

$$\overline{p}_x = I + f_x^{Pre} + \eta[f_x(q_x) - I - f_x^{Pre}] = (1-\eta)(I + f_x^{Pre}) + \eta f_x(q_x),$$

and

$$f_x(q_x) - \overline{p}_x = (1-\eta)[f_x(q_x) - I - f_x^{Pre}].$$

We will show later that $\overline{p}_x$ increases in n, while $f_x(q_x) - \overline{p}_x$ decreases in n.

B.4.2 Proof of Proposition 3

Screening Choice and First-Order Condition. Screening is chosen before bargaining according to:

$$\max_{S_x \in [0,1]} K_0 \left[\big(g_x + (1-g_x)(1-S_x)\big) \big[f_x(q_x) - \overline{p}_x\big] - C(S_x) \right]$$

where $g_x + (1-g_x)(1-S_x) = 1 - S_x(1-g_x)$. The sponsor takes as given $p_x^{Sponsor}(\hat{q}_x)$ and equilibrium beliefs $\hat{q}_x$.

Using

$$\overline{p}_x = I + f_x^{Pre} + \eta[f_x(\hat{q}_x) - I - f_x^{Pre}] + \beta[f_x(q_x) - f_x(\hat{q}_x)]$$

from the previous steps, we calculate (for $q_x, \hat{q}_x$):

$$f_x(q_x) - \overline{p}_x = (1-\beta) f_x(q_x) - (I + f_x^{Pre})(1-\eta) - (\eta - \beta) f_x(\hat{q}_x).$$

The first-order condition (FOC) with respect to S_x then becomes:

$$0 = -C'(S_x) - (1-g_x)\big[f_x(q_x) - \overline{p}_x\big] + \big(g_x + (1-g_x)(1-S_x)\big) f_x'(q_x) q_x'(S_x)(1-\beta), \quad \text{(B.9)}$$

where we note that $\frac{\partial \overline{p}_x}{\partial q_x} = \beta f_x'(q_x)$ and

$$\frac{\partial [f_x(q_x) - \overline{p}_x]}{\partial S_x} = \frac{\partial [f_x(q_x) - \overline{p}_x]}{\partial q_x} q_x'(S_x) = f_x'(q_x) q_x'(S_x)(1-\beta).$$

Next, we impose the equilibrium condition $q_x = \hat{q}_x$, leading to

$$f_x(q_x) - \overline{p}_x = (1-\eta)[f_x(q_x) - I - f_x^{Pre}].$$

Using these relationships as well as $q_x'(S_x) = \frac{(1-g_x)q_x}{1 - S_x(1-g_x)}$ and $g_x + (1-g_x)(1-S_x) = \frac{g_x}{q_x}$, we can rewrite the first-order condition as:

$$0 = -C'(S_x) - (1-g_x)(1-\eta)\big[f_x(q_x) - I - f_x^{Pre}\big] + \frac{g_x(1-g_x)}{1 - S_x(1-g_x)} f_x'(q_x)(1-\beta).$$

We can further re-arrange to obtain:

$$C'(S_x) = (1-g_x)\big[q_x(1-\beta) f_x'(q_x) - (1-\eta)(f_x(q_x) - I - f_x^{Pre})\big], \quad \text{(B.10)}$$

as desired. Define the marginal objective, after imposing equilibrium beliefs, by

$$\mathcal{D}_x(S;\eta) := (1-g_x)\Big[q_x(S)(1-\beta)f_x'(q_x(S)) - (1-\eta)\big(f_x(q_x(S)) - I - f_x^{Pre}\big)\Big] - C'(S).$$

In addition to strict concavity, an interior solution requires

$$\mathcal{D}_x(0;\eta) > 0 \qquad \text{and} \qquad \mathcal{D}_x(1;\eta) < 0 \tag{B.11}$$

for $x = L, H$ and the relevant values of η. We maintain these conditions, i.e., we focus on configurations where optimal screening is interior.

Second-Order Condition. We use (B.9) to calculate the second derivative with respect to S_x:

$$\begin{aligned} SOC := &- C''(S_x) - (1-g_x)f_x'(q_x)q_x'(S_x)(1-\beta) - (1-g_x)f_x'(q_x)q_x'(S_x)(1-\beta) \\ &+ \big(g_x + (1-g_x)(1-S_x)\big)\frac{d}{dS_x}\big[f_x'(q_x)q_x'(S_x)(1-\beta)\big] \end{aligned}$$

The second order condition holds whenever this expression SOC is negative. Recall that $q_x = q_x(S_x) = \frac{g_x}{g_x+(1-g_x)(1-S_x)} = \frac{g_x}{1-S_x(1-g_x)}$. Thus,

$$q_x'(S_x) = \frac{(1-g_x)q_x}{1-S_x(1-g_x)} = \frac{(1-g_x)q_x^2}{g_x} \quad \text{and} \quad q_x''(S_x) = 2q_x'(S_x)\frac{q_x(1-g_x)}{g_x}.$$

Next, we calculate

$$\begin{aligned} &\big(g_x + (1-g_x)(1-S_x)\big)\frac{d}{dS_x}\big[f_x'(q_x)q_x'(S_x)(1-\beta)\big] \\ &= \frac{g_x}{q_x}(1-\beta)\left[f_x''(q_x)\left(q_x'(S_x)\right)^2 + f_x'(q_x)q_x''(S_x)\right] \\ &= \frac{g_x}{q_x}(1-\beta)\Big[f_x''(q_x)\left(q_x'(S_x)\right)^2\Big] + 2(1-\beta)(1-g_x)q_x'(S_x)f_x'(q_x). \end{aligned}$$

Using these relationships, the second order condition holds — that is, $SOC < 0$ — whenever

$$C''(S_x) > \frac{g_x}{q_x}(1-\beta)f_x''(q_x)[q_x'(S_x)]^2. \tag{B.12}$$

Next, we derive a sufficient condition for the second order condition. One can show that

$$C''(S_x) > (1-g_x)\big[(\eta-\beta)\,f_x'(q_x) \;+\; (1-\beta)\,q_x\,f_x''(q_x)\big]\;q_x'(S_x) \tag{B.13}$$

implies (B.12). Indeed, $\eta \geq \beta$ and $(\eta - \beta)\, f_x'(q_x) \geq 0$. In addition,

$$\frac{g_x}{q_x}[q_x'(S_x)]^2 = q_x'(S_x)\frac{g_x(1-g_x)}{1-S_x(1-g_x)} = q_x'(S_x)q_x(1-g_x),$$

which yields the claim.

From (B.5), assuming interior leverage, define

$$d := \rho + \delta - \mu, \qquad u := \frac{(\rho - r)^2}{2\delta(1-\chi)(r-\mu)}, \qquad \nu := \frac{\delta}{2(r-\mu)}.$$

Using $f_x^*(q) = \alpha_x(q)/(r-\mu)$, the value function and its total derivatives are

$$\begin{aligned} f_x(q) &= \frac{\alpha_x(q)}{d}\left(1 + \frac{u}{q} + \nu q\right), \\ f_x'(q) &= \frac{1}{d}\left[\alpha_x'(q)\left(1 + \frac{u}{q} + \nu q\right) + \alpha_x(q)\left(\nu - \frac{u}{q^2}\right)\right], \\ f_x''(q) &= \frac{1}{d}\left[\alpha_x''(q)\left(1 + \frac{u}{q} + \nu q\right) + 2\alpha_x'(q)\left(\nu - \frac{u}{q^2}\right) + \frac{2u\alpha_x(q)}{q^3}\right]. \end{aligned} \tag{B.14}$$

Although $\alpha_x'(q) \geq 0$, this restriction alone does not guarantee that $f_x'(q) \geq 0$ because the term $v - u/q^2$ may be negative. We therefore maintain

$$\alpha_x'(q)\left(1 + \frac{u}{q} + \nu q\right) + \alpha_x(q)\left(\nu - \frac{u}{q^2}\right) > 0 \tag{B.15}$$

for all $q \in [g_x, 1]$ and $x \in \{L, H\}$. No sign restriction on $f_x''(q)$ is required.

Using $q_x'(S_x) = (1-g_x)q_x^2/g_x$, a parameter-only sufficient condition for (B.13) is

$$\inf_{S\in[0,1]} \frac{C''(S)}{(1-g_x)^2} > \sup_{\substack{q\in[g_x,1]\\ \eta\in[\beta,1]}} \frac{q^2}{g_x}\left[(\eta-\beta)f_x'(q) + (1-\beta)qf_x''(q)\right] \tag{B.16}$$

for $x = L, H$, where the derivatives are given in (B.14). From now on, we assume that (B.15) and (B.13) are satisfied, with the latter condition being implied by (B.16).

Comparative Statics. We can rewrite (B.10) as:

$$\frac{C'(S_x)}{1-g_x} - q_x(1-\beta)f_x'(q_x) + (1-\eta)(f_x(q_x) - I - f_x^{Pre}) = 0. \tag{B.17}$$

Using the implicit function theorem, we can totally differentiate with respect to η to obtain:

$$\frac{dS_x}{d\eta}\left(\frac{C''(S_x)}{1-g_x} - (1-\beta)q_x'(S_x)[f_x'(q_x) + q_x f_x''(q_x)] + (1-\eta)f_x'(q_x)q_x'(S_x)\right)$$
$$= (f_x(q_x) - I - f_x^{Pre})$$

Thus,

$$\frac{dS_x}{d\eta} = \frac{f_x(q_x) - I - f_x^{Pre}}{\dfrac{C''(S_x)}{1-g_x} - \left[(\eta-\beta)\, f_x'(q_x) \;+\; (1-\beta)\, q_x\, f_x''(q_x)\right]\, q_x'(S_x)}. \tag{B.18}$$

Since the denominator of (B.18) is positive by (B.13) and the numerator is positive too, i.e., $f_x(q_x) - I - f_x^{Pre} > 0$ (by our assumption than an LBO creates value in equilibrium for those firms passing screening), we have $\frac{dS_x}{d\eta} > 0$. Note that

$$S_x'(n) = \frac{dS_x}{dn} = \frac{dS_x}{d\eta}\frac{d\eta}{dn} = \frac{dS_x}{d\eta}\eta'(n) > 0.$$

Because $q_x = \frac{g_x}{1-S_x(1-g_x)}$, this implies that $\frac{dq_x}{d\eta} > 0$ and $\frac{dq_x}{dn} > 0$.

B.4.3 Proof of Corollary 1

Fix K_0, and consider $n = n(K_0)$. Thus, all conditional expectations below are also conditional on K_0, but we suppress this dependence for convenience. Equilibrium screening equals S_x for $x = L, H$, where S_x increases in n.

Average LBO Quality. Average LBO quality is given by $\overline{q} := \Pr(z = G|\text{LBO})$ where

$$\Pr(z = G|\text{LBO}) = \frac{g}{g + (1-g)\left[\phi_B(1-S_H) + (1-\phi_B)(1-S_L)\right]}.$$

Since S_H and S_L increase in n and η, it follows that $\overline{q} = \overline{q}(n)$ increases in n (and η), in that $\overline{q}'(n) > 0$. Likewise, $\Pr(z = B|LBO) = 1 - \Pr(z = G|LBO)$ declines in n.

Operating Performance. Let $\alpha_L = \alpha_L(q_L)$ and $\alpha_H = \alpha_H(q_H)$. The average scaled operating cash flow of an LBO target is

$$\mathbb{E}[\alpha|\text{LBO}] = \Pr(z = G|LBO)\mathbb{E}[\alpha|z = G, LBO] + \Pr(z = B|LBO)\mathbb{E}[\alpha|z = B, LBO]$$
$$= \overline{q}(\phi_G\alpha_H + (1-\phi_G)\alpha_L) + [1-\overline{q}]\left(\frac{\phi_B(1-S_H)\alpha_H + (1-\phi_B)(1-S_L)\alpha_L}{\phi_B(1-S_H) + (1-\phi_B)(1-S_L)}\right).$$

Alternatively, we can calculate

$$\mathbb{E}[\alpha|LBO] = \alpha_L + (\alpha_H - \alpha_L)\Pr(x = H|LBO),$$

where

$$\Pr(x = H|LBO) = \frac{g\phi_G + (1-g)\phi_B(1-S_H)}{g + (1-g)\big[\phi_B(1-S_H) + (1-\phi_B)(1-S_L)\big]}.$$

Differentiating with respect to n gives

$$\begin{aligned}\frac{d}{dn}\mathbb{E}[\alpha|\text{LBO}] = (\alpha_H - \alpha_L)\frac{d}{dn}\Pr(x = H \mid \text{LBO}) \\ + \frac{d\alpha_L}{dn}\big(1 - \Pr(x = H \mid LBO)\big) + \frac{d\alpha_H}{dn}\Pr(x = H \mid LBO).\end{aligned}$$

Because

$$\frac{d\alpha_x}{dn} = \alpha_x'(q_x)q_x'(S_x)\frac{dS_x}{dn} \geq 0,$$

the last two terms are nonnegative. Therefore, provided that $\alpha_H \geq \alpha_L$, a sufficient condition for $\frac{d}{dn}\mathbb{E}[\alpha \mid LBO] \geq 0$ is

$$\frac{d}{dn}\Pr(x = H \mid LBO) \geq 0.$$

Calculate

$$\begin{aligned}\frac{d}{dn}\Pr(x = H \mid \text{LBO}) \propto -\Big(g + (1-g)\big[\phi_B(1-S_H) + (1-\phi_B)(1-S_L)\big]\Big)\phi_B S_H'(n) \\ + \Big(g\phi_G + (1-g)\phi_B(1-S_H)\Big)\Big(\phi_B S_H'(n) + (1-\phi_B)S_L'(n)\Big).\end{aligned}$$

Hence, the sign of $\frac{d}{dn}\Pr(x = H \mid \text{LBO})$ is determined by the sign of

$$(1-\phi_B)\,S_L'(n)\Big[g\phi_G + (1-g)\phi_B(1-S_H)\Big] - \phi_B S_H'(n)\Big[g(1-\phi_G) + (1-g)(1-\phi_B)(1-S_L)\Big].$$

Provided that $\alpha_H > \alpha_L$, a sufficient condition for average operating cash flow to increase in n is therefore given by (as long as $S_H'(n) > 0$):

$$\frac{S_L'(n)}{S_H'(n)} > \frac{\phi_B\big[g(1-\phi_G) + (1-g)(1-\phi_B)(1-S_L)\big]}{(1-\phi_B)\big[g\phi_G + (1-g)\phi_B(1-S_H)\big]}. \tag{B.19}$$

We now argue this condition is met provided that ϕ_B is small, which then implies that average operating performance increases in n. As $\phi_B \to 0$, we have $g_H = \Pr(G \mid x = H) =$

$\frac{g\phi_G}{g\phi_G+(1-g)\phi_B} \to 1$. Thus, in the limit $\phi_B \to 0$, the screening FOC for $x = H$, i.e.,

$$C'(S_H) = (1 - g_H)\Big[q_H(1-\beta)f'_H(q_H) - (1-\eta)\big(f_H(q_H) - I - f_H^{Pre}\big)\Big],$$

implies $S_H \to 0$ (and, under regularity conditions, $S'_H(n) \to 0$). In contrast, g_L converges to an interior value in $(0, 1)$, so screening remains valuable for $x = L$ and, under the maintained interior/SOC assumptions, $S'_L(n) > 0$ (even in the limit $\phi_B \to 0$). Moreover, the right-hand side of (B.19) tends to 0 as $\phi_B \to 0$. Therefore, for ϕ_B sufficiently small, (B.19) holds.

Average Price-to-Assets and Deal Multiple. Since the acquisition price is $K_0\overline{p}_x$ and assets are K_0, $\overline{p}_x$ is the equilibrium price-to-assets ratio:

$$\overline{p}_x = I + f_x^{Pre} + \eta[f_x(q_x) - I - f_x^{Pre}].$$

Calculate

$$\frac{d\overline{p}_x}{dn} = \eta'(n)[f_x(q_x) - I - f_x^{Pre}] + \eta f'_x(q_x)\frac{dq_x}{dn} > 0, \tag{B.20}$$

where we used (1) that η is a monotonic transformation of n (so $\eta'(n) > 0$), (2) that $[f_x(q_x) - I - f_x^{Pre}] > 0$ (i.e., LBO creates value), and (3) that $\frac{dq_x}{dn} > 0$ from what we have shown before.

The unconditional average price-to-assets ratio can be written as

$$\overline{p} := \sum_{x=L,H} \Pr(x|LBO)\overline{p}_x,$$

where $\overline{p}_H - \overline{p}_L = (1-\eta)(f_H^{Pre} - f_L^{Pre}) + \eta[f_H(q_H) - f_L(q_L)] \geq 0$ by the maintained assumptions, and $\Pr(x = L|LBO) = 1 - \Pr(x = H|LBO)$, where $\Pr(x = H|LBO)$ was calculated before. We also now that $\overline{p}_x$ increases in n for both $x = L, H$.

Now, note that

$$\frac{d\overline{p}}{dn} = \sum_{x=L,H} \Pr(x|LBO)\frac{d\overline{p}_x}{dn} + \frac{d\Pr(x = H|LBO)}{dn}\big[\overline{p}_H - \overline{p}_L\big].$$

The first term is strictly positive, due to $\frac{d\overline{p}_x}{dn} > 0$. The second term is positive whenever $\frac{d\Pr(x=H|LBO)}{dn} > 0$, which is satisfied whenever (B.19) holds. Note that naturally, we have $\overline{p}_H \geq \overline{p}_L$.

Thus, provided (B.19) holds (which is true whenever ϕ_B is sufficiently small), the average price-to-assets ratio increases in n (and η).

The corresponding EV/EBITDA deal multiple is

$$m_x := \frac{\overline{p}_x}{\alpha_x(q_x)}, \qquad \overline{m} := \sum_{x=L,H} \Pr(x \mid LBO) m_x.$$

Its sign need not follow from the price result alone when α_x also rises with screening. In particular, m_x increases whenever

$$\frac{1}{\overline{p}_x}\frac{d\overline{p}_x}{dn} > \frac{1}{\alpha_x(q_x)}\frac{d\alpha_x(q_x)}{dn}.$$

This condition is satisfied when α_x' is sufficiently small and close to zero.

B.5 Solution Search Stage

B.5.1 Sponsor Payoff (given K_0)

Take as given K_0 — the size bucket in which the sponsor searches — and the degree of competition there, i.e., $n = n(K_0)$. We assume that the sponsor also derives some private benefits bK_0 from operating; these benefits scale with the size bucket targeted. The interpretation is these private benefits capture fees that the sponsor earns from operating a PE fund. These fees increase with the size of target firms K_0, as looking for larger firms requires, all else equal, more resources and therefore a larger fund, thus mandating higher fees (which, in practice, increase with the fund's AUM). Here, $b \geq 0$ is a parameter (which is not central to the mechanism, qualitatively).

Payoffs and Value Function. Take the optimal screening S_x as given, which is conditional on $x = L, H$. After observing x, under equilibrium effort $S_x = \hat{S}_x$, the sponsor's expected payoff is:

$$\overline{f}_x := \big(1 - (1 - g_x)S_x\big)\big[f_x(q_x) - \overline{p}_x\big] - C(S_x),$$

where $\overline{p}_x$ is the average acquisition price relative to assets and $f_x(q_x)$ the firm value after the LBO (all in scaled terms). Note that with probability g_x, the firm is good and screening leads to $\mathcal{S}_x = 1$ and LBO with certainty. When the firm is bad, with probability $1 - g_x$, it is screened out with probability S_x (i.e., they undergo LBO with probability $1 - S_x$). Overall, the probability an LBO occurs after observing x is then $g_x + (1-g_x)(1-S_x) = 1-(1-g_x)S_x$. Also, recall that (in equilibrium):

$$f_x(q_x) - \overline{p}_x = (1 - \eta)[f_x(q_x) - I - f_x^{Pre}].$$

Before observing x, the expected payoff for the sponsor (conditional on being matched) equals $\overline{f}K_0$ with scaled payoff:

$$\overline{f} = \sum_{x=L,H} \Pr(x) \left[\big(1 - (1-g_x)S_x\big) \big[f_x(q_x) - \overline{p}_x\big] - C(S_x) \right]$$

where $\Pr(x = H) = g\phi_G + (1-g)\phi_B$ and $\Pr(x = L) = 1 - \Pr(x = H)$.

The scaled value function equals

$$v(n) = \frac{\Lambda M}{\rho} \left\{ \sum_{x=L,H} \Pr(x) \left[\big(1 - (1-g_x)S_x\big) \big[f_x(q_x) - \overline{p}_x\big] - C(S_x) \right] \right\} + \frac{b}{\rho}, \tag{B.21}$$

where we note the sponsor has a discount rate of ρ and encounters constant deal flow at rate ΛM. Because the sponsor can immediately re-enter the search market (i.e., an LBO does not incur the foregone cost of searching for the next target), the constant in front of curly brackets is therefore $\frac{\Lambda M}{\rho}$, rather than $\frac{\Lambda M}{\rho + \Lambda M}$.

In addition, note that we assume that fundamentals are the same across size buckets. That is, for given K_0, all the other parameters do not depend on K_0; in other words, the characteristics (K_0, x, z) are independent of each other. If the fundamentals were different across size buckets, the value function would be written as $K_0 v_{K_0}(n)$, where the value function still scales perfectly with K_0, but exhibits some dependence on the size bucket via the model parameters, e.g., the fraction of good firms within each size bucket. The model solution would remain analogous.

Comparative Statics. We show that

$$\frac{d\overline{f}_x}{dn} = -(1-g_x)S_x'(n) \left[f_x(q_x) - \overline{p}_x \right] + \big(1 - (1-g_x)S_x\big) \left(f_x'(q_x)\frac{dq_x}{dn} - \frac{d\overline{p}_x}{dn} \right) - C'(S_x)S_x'(n).$$

Next, in order to simplify, we use the equilibrium identity $f_x(q_x) - \overline{p}_x = (1-\eta)[f_x(q_x) - I - f_x^{Pre}]$ and the first order condition (B.10), that is:

$$C'(S_x) = (1-g_x)\Big[q_x(1-\beta)f_x'(q_x) - (1-\eta)(f_x(q_x) - I - f_x^{Pre})\Big],$$

allowing us to eliminate $C'(S_x)$. This yields after some algebra:

$$\frac{d\overline{f}_x}{dn} = \big(1 - (1-g_x)S_x\big) \left(f_x'(q_x)\frac{dq_x}{dn} - \frac{d\overline{p}_x}{dn} \right) - (1-g_x)q_x(1-\beta)f_x'(q_x)S_x'(n).$$

Now, note that $\frac{dq_x}{dn} = q_x'(S_x)S_x'(n)$, as well as $1-(1-g_x)S_x = \frac{g_x}{q_x}$ and $q_x'(S_x) = \frac{(1-g_x)q_x^2}{g_x}$, allowing us to simplify to:

$$\frac{d\overline{f}_x}{dn} = -\big(1-(1-g_x)S_x\big)\frac{d\overline{p}_x}{dn} + \beta(1-g_x)q_x f_x'(q_x)S_x'(n).$$

Using (B.20) — that is, $\frac{d\overline{p}_x}{dn} = \eta'(n)\big[f_x(q_x) - I - f_x^{Pre}\big] + \eta f_x'(q_x)\frac{dq_x}{dn}$ — together with $q_x(S_x) = \frac{g_x}{1-(1-g_x)S_x}$, $1-(1-g_x)S_x = \frac{g_x}{q_x}$, $\frac{dq_x}{dn} = q_x'(S_x)S_x'(n)$, and $q_x'(S_x) = \frac{(1-g_x)q_x^2}{g_x}$, we can further simplify to obtain:

$$\begin{aligned}\frac{d\overline{f}_x}{dn} &= -\frac{g_x}{q_x}\left[\eta'(n)\big(f_x(q_x) - I - f_x^{Pre}\big) + \eta f_x'(q_x)q_x'(S_x)S_x'(n)\right] + \beta(1-g_x)q_x f_x'(q_x)S_x'(n)\\ &= -\frac{g_x}{q_x}\eta'(n)\big(f_x(q_x) - I - f_x^{Pre}\big) + (1-g_x)q_x f_x'(q_x)S_x'(n)\,(\beta-\eta).\end{aligned}$$

Since $\eta'(n) > 0$, $f_x(q_x) - I - f_x^{Pre} > 0$, the first term is strictly negative. Also $f_x'(q_x) > 0$, $S_x'(n) \geq 0$, and $\eta \geq \beta$ imply that the second term is weakly negative. Therefore, $\frac{d\overline{f}_x}{dn} < 0$.

It follows for $\overline{f} = \sum_{x=L,H}\Pr(x)\overline{f}_x$ that

$$\frac{d\overline{f}}{dn} = \sum_{x=L,H}\Pr(x)\frac{d\overline{f}_x}{dn} < 0,$$

since

$$\Pr(x=H) = g\phi_G + (1-g)\phi_B \quad \text{and} \quad \Pr(x=L) = g(1-\phi_G) + (1-g)(1-\phi_B)$$

do not depend on n.

As a result, $v(n) = \frac{\Lambda M\overline{f}}{\rho}$ decreases in n, i.e., $v'(n) < 0$, which concludes the proof.

B.5.2 Proof of Proposition 4: Choice of K_0

Let N be the total number of sponsors; each sponsor focuses on one size bucket to search for targets and selects $K_0 \in \{\gamma, 1\}$ according to:

$$\max_{K_0\in\{\gamma,1\}} K_0 v(n(K_0)), \tag{B.22}$$

taking as given the equilibrium values of $n(K_0)$ for $K_0 \in \{\gamma, 1\}$. (In principle, it could be that $\max_{K_0\in\{\gamma,1\}} K_0 v(n(K_0)) < 0$, in which case sponsors would not search. We focus on parameters such that searching is sufficiently profitable, i.e., $v(n(K_0)) > 0$ for at least one K_0.)

In equilibrium, $n(K_0) \in [0, N]$ for $K_0 \in \{\gamma, 1\}$ where $n(\gamma) = N - n(1)$. Whenever there is a positive mass of sponsors searching for both large and small firms (that is, $n(\gamma), n(1) \in (0, N)$) both options must yield equal payoff. Thus, sponsors are indifferent between searching for small and large firms.

Accordingly, the indifference condition holds:

$$v(n(1)) = \gamma v(N - n(1)). \tag{B.23}$$

This condition pins down $n(1)$ and $n(\gamma)$ given N. If there is no solution to (B.23), the equilibrium features sponsors only searching for large firms (i.e., $n(1) = N$), which, all else equal, is more advantageous. Specifically, whenever $v(N) \geq \gamma v(0)$, we have $n(1) = N$, while, otherwise when $v(N) < \gamma v(0)$, $n(1)$ is determined according to (B.23).

In equilibrium, the number of sponsors searching in each size bucket is $n(K_0)$, with $N = n(\gamma) + n(1)$, which sponsors take as given, when making their individual choice of K_0.

The identity $N = n(\gamma) + n(1)$ implies

$$\frac{dn(\gamma)}{dN} = 1 - \frac{dn(1)}{dN}.$$

The value function of searching in size bucket K_0 equals $K_0 v(n)$, as the value function scales with firm size K_0 and the fundamentals are otherwise the same across the two size buckets. Searching in size bucket K_0 gives a scaled value function $v(n(K_0))$, where $v'(n) < 0$ (shown before) and $v(0) > 0$; $v(n)$ is continuously differentiable.

Consider a sponsor's choice of $K_0 \in \{\gamma, 1\}$, taking as given the equilibrium value of $n(K_0)$. Given this optimization in (B.22), equilibrium values of $n(1), n(\gamma)$ therefore satisfy $n(1) + n(\gamma) = N$, and

$$n(1) = \begin{cases} N & \text{if} \quad v(N) \geq \gamma v(0) \\ n(1) \in (0, N) & \text{if} \quad v(N) < \gamma v(0). \end{cases}$$

Put differently, when (B.23) — $v(n(1)) = \gamma v(n(\gamma))$ — does not hold, we have $v(N) > \gamma v(0)$. In this case, $n(1) = N$ mechanically increases in N.

Next, suppose that (B.23) holds, i.e.,

$$v(n(1)) = \gamma v(N - n(1)).$$

Totally differentiating with respect to N yields

$$v'(n(1))\frac{dn(1)}{dN} = \gamma v'(N - n(1))\left(1 - \frac{dn(1)}{dN}\right).$$

We can solve for

$$\frac{dn(1)}{dN} = \frac{\gamma v'(N - n(1))}{v'(n(1)) + \gamma v'(N - n(1))},$$

which implies (1) $\frac{dn(1)}{dN} \in (0, 1)$, and (2) $\frac{dn(\gamma)}{dN} = \frac{d(N-n(1))}{dN} \in (0, 1)$. Thus, as N increases, it holds that, within a given size bucket, the number of searching sponsors increases.

Average LBO Size. We conduct some comparative statics, and examine the average LBO target size. In size bucket $K_0 \in \{\gamma, 1\}$, the number of sponsor-firm matches per unit of time equals $\Lambda n(K_0)M$, with $n(K_0)$ being the endogenous number (mass) of searching sponsors. Within a given size bucket, the number of LBOs conducted per unit of time equals:

$$\mathcal{N}(K_0) := \Lambda n(K_0)M \cdot \Big[\sum_{x=L,H} \Pr(x)\big(1 - (1 - g_x)S_x(n(K_0))\big)\Big]. \tag{B.24}$$

where we make explicit the dependence of $S_x = S_x(n(K_0))$ on target firm size via $n(K_0)$.

The average LBO size is then defined as:

$$\mathbb{E}[K_0 \mid LBO] := \frac{\mathcal{N}(\gamma)\gamma + \mathcal{N}(1)}{\mathcal{N}(\gamma) + \mathcal{N}(1)} = \gamma + \frac{\mathcal{N}(1)(1-\gamma)}{\mathcal{N}(\gamma) + \mathcal{N}(1)} = \gamma + \frac{(1-\gamma)}{\mathcal{N}(\gamma)/\mathcal{N}(1) + 1}. \tag{B.25}$$

We used that $\mathcal{N}(1) > 0$. Thus, to examine how average LBO size changes with N, it suffices to examine how $\frac{\mathcal{N}(\gamma)}{\mathcal{N}(1)}$ changes with N. That is, when $\frac{\mathcal{N}(\gamma)}{\mathcal{N}(1)}$ increases (decreases) in N, then average LBO size decreases (increases) in N.

Comparative Statics in N (Average LBO Size). Since b enters (B.21) only through the additive constant $\frac{b}{\rho}$, we have $v(n; b) = v(n; 0) + \frac{b}{\rho}$ for all n. We prove the claim for $b = 0$; all inequalities below involving v are strict, so the argument extends to $b > 0$ sufficiently small. Due to $v(0) > \gamma v(0) > 0$, there exists an interval $(0, N_L)$ such that $v(N) > \gamma v(0)$ for all $N \in (0, N_L)$. On this interval, $n(\gamma) = 0$ and $n(1) = N$. Thus, $\mathcal{N}(\gamma) = 0 < \mathcal{N}(1)$. Therefore, average LBO target size is constant 1 for $N \in (0, N_L)$, i.e., $\mathbb{E}[K_0|LBO] = 1$.

Next, we define the N_L from above such that it is the largest level of N inducing $n(1) = N$, that is:

$$N_L := \sup\big\{N \geq 0 : v(N) \geq \gamma v(0)\big\}.$$

Observe from (6) that $\lim_{n\to\infty} \eta(n) = 1$, so that, by (5), the deal surplus vanishes, i.e.,

$\lim_{n\to\infty}\left[f_x(q_x)-\overline{p}_x\right]=0$. Screening remains positive in the limit, as the first-order condition (B.10) converges to $C'(S_x^\infty)=(1-g_x)\,q_x^\infty(1-\beta)f_x'(q_x^\infty)$ with solution $S_x^\infty\geq 0$. Hence, by (B.21) with $b=0$,

$$\lim_{n\to\infty} v(n) = -\frac{\Lambda M}{\rho}\sum_{x=L,H}\Pr(x)\,C(S_x^\infty)\leq 0.$$

Thus, there exists $\hat{N}$ such that $v(N)<\gamma v(0)$ for all $N>\hat{N}$, and therefore $n(1)<N$ for all $N>\hat{N}$. This implies $N_L<+\infty$. By definition, $n(1)=N$ and $\mathbb{E}[K_0|LBO]=1$ when $N=N_L$, while $n(1)<N$, $\frac{\mathcal{N}(\gamma)}{\mathcal{N}(1)}>0$, and $\mathbb{E}[K_0|LBO]<1$ for $N>N_L$.

At $N=N_L$ the allocation switches from the corner $n(\gamma)=0$ to an interior allocation. We assume that, on a right neighborhood of N_L, the equilibrium maps $N\mapsto\big(n(1),n(\gamma)\big)$ and $N\mapsto\mathcal{N}(K_0)$ are continuously differentiable from the right, so that

$$R(N):=\frac{\mathcal{N}(\gamma)}{\mathcal{N}(1)}$$

admits a continuous right derivative on $[N_L,N_L+\varepsilon)$ for some $\varepsilon>0$. Since $R(N_L)=0$ and $R(N)>0$ for $N\in(N_L,N_L+\varepsilon)$, the mean value theorem yields some $\xi\in(N_L,N_L+\varepsilon)$ with $R'(\xi)>0$. By continuity of R', there exists an interval $(N_a,N_b)\subset(N_L,\infty)$ on which $R'>0$. Thus $\frac{\mathcal{N}(\gamma)}{\mathcal{N}(1)}$ increases and average LBO target size decreases in N on that interval.

C Numerical Solution and Analysis

We summarize the key equations for the numerical solution, as well as the model-implied quantities. This solution is used in Section 3.2 to produce Figure 3 and Figure 4. We also summarize the parameter choice for the numerical solution, concisely summarized in Table A-1.

Numerical solution. Fix size bucket K_0. Note that $n=n(K_0)$ sponsors search in this size bucket. For each type $x\in\{L,H\}$, beliefs after a positive screening signal are

$$q_x(S_x)=\frac{g_x}{1-S_x(1-g_x)}.$$

The post-LBO value is

$$f_x(q_x)=\frac{1}{\rho+\delta-\mu}\left[\alpha_x(q_x)+\frac{(\rho-r)^2 f_x^*}{2\delta q_x(1-\chi)}+\frac{\delta q_x f_x^*}{2}\right],\qquad f_x^*=\frac{\alpha_x(q_x)}{r-\mu}.$$

Screening effort solves the first-order condition:

$$C'(S_x) = (1 - g_x)\left[q_x(1-\beta)f_x'(q_x) - (1-\eta)\left(f_x(q_x) - I - f_x^{Pre}\right)\right].$$

Competition is quantified by:

$$\eta(n) = \beta + \frac{(1-\beta)\beta\Lambda n}{\rho + \kappa + \beta\Lambda n},$$

where $n = n(K_0)$ is the number of sponsors searching in size bucket K_0. The deal price is:[38]

$$\overline{p}_x = I + f_x^{Pre} + \eta(n)\left[f_x(q_x) - I - f_x^{Pre}\right].$$

The sponsor value from searching in a bucket with sponsor mass n is

$$v(n) = \frac{\Lambda M}{\rho}\sum_{x=L,H}\Pr(x)\left[\left(1-(1-g_x)S_x\right)\left(f_x(q_x) - \overline{p}_x\right) - C(S_x)\right] + \frac{b}{\rho}.$$

For the numerical solution, we restrict $S_x \in [0, \overline{S}]$, with $\overline{S} = 0.95$. We verify numerically that (B.8), (B.1), and (B.15) hold at the parameters below over the full range of N that we consider. We also verify that, for both types and size buckets, the computed screening choices lie strictly within the numerical feasible interval, $S_x \in (0, \overline{S})$, satisfy the first-order condition (B.10), and satisfy the second-order condition (B.13), which implies (B.12). Thus, the computed screening choices are strict global optima, and the equilibrium is uniquely determined, throughout the reported parameter range.

Endogenous allocation across size buckets. For $K_0 \in \{\gamma, 1\}$, the allocation satisfies

$$n(1) + n(\gamma) = N, \qquad v(n(1)) = \gamma v(n(\gamma)).$$

If no interior solution exists, all sponsors search in the large-size bucket:

$$n(1) = N, \qquad n(\gamma) = 0.$$

[38] Strictly speaking, $\overline{p}_x$ is an average deal price that arises in the random-proposer bargaining model; this expression resembles an outcome under Nash bargaining. In calculating quantities, we treat the deal price as deterministic and ignore that it is stochastic (which matters when taking logarithms, for instance), and we work with the average deal multiple "as if" it were deterministic.

Reported outcomes. Within each size bucket, the probability that an LBO target has $x = H$ is

$$\Pr(x = H \mid LBO) = \frac{g\phi_G + (1-g)\phi_B(1-S_H)}{g + (1-g)\left[\phi_B(1-S_H) + (1-\phi_B)(1-S_L)\right]}.$$

Average post-LBO cash flow relative to assets is

$$\mathbb{E}[\alpha(q) \mid LBO] = \alpha_L(q_L) + \left[\alpha_H(q_H) - \alpha_L(q_L)\right] \Pr(x = H \mid LBO).$$

We associate these cash flows with the firm's EBITDA.

Next, we note that the cash flows can be interpreted as sales (revenues) minus operating costs. We stipulate that both sales and costs are proportional to $K\alpha_x(q_x)$, given x, so that their asset-scaled versions satisfy $Sales_x/Assets = \Phi_1\alpha_x(q_x)$ and $Cost_x/Assets = \Phi_2\alpha_x(q_x)$, which requires $\Phi_1 - \Phi_2 = 1$ to preserve $\alpha_x(q_x)$ as net cash flow relative to assets. Otherwise, Φ_1 and Φ_2 can be chosen arbitrarily; their choice is described below. We have

$$\frac{Sales}{Assets} = \Phi_1 \mathbb{E}[\alpha(q) \mid LBO].$$

Average acquisition price relative to assets is

$$\mathbb{E}[\overline{p} \mid LBO] = \Pr(x = H \mid LBO)\overline{p}_H + \big(1 - \Pr(x = H \mid LBO)\big)\overline{p}_L.$$

The corresponding average EV/EBITDA deal multiple is

$$\mathbb{E}[m \mid LBO] := \Pr(x = H \mid LBO)\frac{\overline{p}_H}{\alpha_H(q_H)} + \big(1 - \Pr(x = H \mid LBO)\big)\frac{\overline{p}_L}{\alpha_L(q_L)}.$$

Debt/EBITDA is

$$\frac{Debt_x}{EBITDA_x} = \frac{\rho - r}{\delta q_x(1-\chi)(r-\mu)}.$$

The default probability over $dt = 1$ is

$$PD_x = \delta(1 - q_x) + \frac{\rho - r}{1 - \chi}.$$

Average post-LBO value is

$$\mathbb{E}[f(q) \mid LBO] = \Pr(x = H \mid LBO) f_H(q_H) + \big(1 - \Pr(x = H \mid LBO)\big) f_L(q_L).$$

We also report the following model-implied gross return:

$$\text{Return}_x^{model} = \left(\frac{f_x(q_x)}{\overline{p}_x}\right) - 1.$$

This is a static return analogue within the model, not a real-life realized or annualized IRR: the model does not specify an exit horizon, interim cash flows, or the timing needed to calculate a conventional IRR. Averages across x use the same $\Pr(x = H \mid LBO)$ weights.

Finally, the number of LBOs in size bucket K_0 is

$$\mathcal{N}(K_0) = \Lambda n(K_0) M \sum_{x=L,H} \Pr(x) \left[1 - (1 - g_x) S_x(n(K_0))\right],$$

and average LBO size is

$$\mathbb{E}[K_0 \mid LBO] = \frac{\mathcal{N}(\gamma)\gamma + \mathcal{N}(1)}{\mathcal{N}(\gamma) + \mathcal{N}(1)}.$$

Note that the model is scale invariant. Thus, $K_0 \in \{1, \gamma\}$ is a mere normalization and, more generally, we can write

$$\text{Avg. Firm Size} = \Phi_K \mathbb{E}[K_0 \mid LBO]$$

for any arbitrary scaling parameter, $\Phi_K > 0$.

Outcomes in Logarithms. Consistent with our empirical analysis, whose dependent variables are the logarithms of firm size and deal multiples, we take logarithms at the deal level before calculating model-implied averages. This ensures that the model statistic corresponds to an average log outcome rather than the logarithm of an average outcome.

For each size bucket $K_0 \in \{\gamma, 1\}$, define the type-specific deal multiple as

$$m_{x,K_0} = \frac{\overline{p}_{x,K_0}}{\alpha_x(q_{x,K_0})}, \qquad x \in \{L, H\}.$$

The model-implied average log deal multiple within the bucket is then

$$\mathbb{E}[\log m \mid LBO, K_0] = \Pr(x = H \mid LBO, K_0) \log m_{H,K_0} + (1 - \Pr(x = H \mid LBO, K_0)) \log m_{L,K_0}.$$

We next aggregate across size buckets. Let $\mathcal{N}(K_0)$ denote the model-implied number of LBOs in bucket K_0, and define its share of total LBO activity by

$$w_{K_0} = \frac{\mathcal{N}(K_0)}{\mathcal{N}(1) + \mathcal{N}(\gamma)}.$$

The overall model-implied average log deal multiple is therefore

$$\mathbb{E}[\log m \mid LBO] = w_1 \mathbb{E}[\log m \mid LBO, K_0 = 1] + w_\gamma \mathbb{E}[\log m \mid LBO, K_0 = \gamma].$$

Equivalently,

$$\mathbb{E}[\log m \mid LBO] = \sum_{K_0 \in \{1,\gamma\}} w_{K_0} \sum_{x \in \{L,H\}} \Pr(x \mid LBO, K_0) \log m_{x,K_0}.$$

Firm size is constant within each size bucket but differs across buckets. After applying the scale normalization Φ_K, firm size equals Φ_K in the large-firm bucket and $\Phi_K \gamma$ in the small-firm bucket. Accordingly, average log firm size is

$$\mathbb{E}[\log K \mid LBO] = w_1 \log(\Phi_K) + w_\gamma \log(\Phi_K \gamma).$$

Using $w_1 + w_\gamma = 1$, this can also be written as

$$\mathbb{E}[\log K \mid LBO] = \log \Phi_K + w_\gamma \log \gamma.$$

Parameter Choice. We discuss the parameter choice and calibration, which are summarized in Table A-1. For the numerical analysis, post-LBO operating cash flow is

$$\alpha_x(q_x) = \overline{\alpha}_x + \Omega q_x^\xi.$$

The baseline operating cash-flow parameters are

$$\overline{\alpha}_L = 0.015, \qquad \overline{\alpha}_H = 0.030, \qquad \Omega = 0.10, \qquad \xi = 0.90.$$

Screening raises the posterior probability that the target is good and, through this reduced-form value-add channel, increases post-LBO profitability. We set the prior probability of a good firm to $g = 0.50$. Conditional on the target being good, the probability of drawing the high-profitability type is $\phi_G = 0.50$; conditional on the target being bad, it is $\phi_B = 0.40$. The baseline cash flows and type probabilities primarily determine the level and composition of post-LBO profitability, while Ω and ξ discipline its response to screening and hence the slope of Sales/Assets with respect to competition.

The capital-growth rate is $\mu = 0.02$, in line with long-run asset and GDP growth. The risk-free rate is $r = 0.05$, consistent with the risk-free rate over our sample period. The sponsor's discount rate is $\rho = 0.0564$, the arrival rate of the credit shock is $\delta = 0.103$,

and the recovery parameter is normalized to $\chi = 0$. The spread $\rho - r$, together with δ and χ, primarily disciplines leverage and default risk, while μ affects the capitalization of operating cash flows. These parameters generate leverage and default probabilities in empirically plausible ranges and reproduce their observed responses to sponsor competition with reasonable accuracy.

The required scaled investment is $I = 0.15$, and the pre-LBO scaled firm values are $f_L^{Pre} = f_H^{Pre} = 0.15$. These parameters ensure that condition (B.1) holds. Thus, investment is unattractive without the improvement associated with screening and sponsor value addition but generates positive surplus at the equilibrium posterior q_x. The investment requirement and pre-LBO value therefore discipline the amount of surplus created by sponsor intervention.

The matching intensity is $\Lambda = 0.022$, the pre-match death rate is $\kappa = 0.25$, and the firm's bargaining weight is $\beta = 0.40$. We normalize the mass of potential target firms to $M = \frac{1}{\Lambda} = 45.4545$, so that $\Lambda M = 1$. Consequently, the expected time until a sponsor meets a potential target is normalized to one year. The normalization $M = 1/\Lambda$ fixes the time scale of target meetings, while Λ, κ, and β govern search, sponsor allocation, and the division of deal surplus.

For simplicity, we consider quadratic screening costs:

$$C(S) = c_S S^2, \qquad c_S = 0.435.$$

The screening-cost parameter controls how strongly screening responds to sponsor competition and therefore jointly affects the slopes of profitability, multiples, leverage, and default risk.

Sponsors also receive a (scaled) benefit flow $b = 0.1818$. The benefit flow does not enter within-bucket deal terms directly, but it affects sponsor value and the endogenous allocation of sponsors across firm-size buckets. Under the current calibration, sponsor values remain strictly positive throughout the plotted range.

We set $\gamma = 0.35$, in that $K_0 \in \{1, 0.35\}$. The parameter γ, together with the endogenous allocation of sponsors across the two size buckets, primarily disciplines the model-implied response of average firm size to competition.

Empirical Grid and Scale Normalizations. We normalize the mapping between model sponsor mass, so that N is identified directly with the empirical sponsor count, and the horizontal axis in Figure 3 is $x = \log N$. In Figure 4, we plot against an empirical measure of HHI, which we associate in the model with $HHI = 1/N$.

We now discuss Figure 3, based on which parameters are chosen. The empirical bins

imply the range $x \in [3.6355, 6.7687]$, or, equivalently, $N \in [37.9190, 870.1403]$.

Because the model is invariant to the units in which firm size is measured, it determines the response of firm size to competition but not its absolute level. Similarly, the model determines net operating cash flow but does not separately determine gross sales and operating costs. We therefore introduce the scale coefficients Φ_K, Φ_1, and Φ_2 to translate model-implied quantities into their empirical units. These coefficients affect plotted levels but not the equilibrium or the underlying comparative statics.

We interpret net operating cash flow (scaled by assets), that is, $\alpha_x(q_x)$, as sales minus operating costs:

$$\frac{Sales_x}{Assets_x} = \Phi_1 \alpha_x(q_x), \qquad \frac{Cost_x}{Assets_x} = \Phi_2 \alpha_x(q_x),$$

where we assume both sales and cost are proportional to $\alpha_x(q_x)$. To preserve $\alpha_x(q_x)$ as net operating cash flow relative to assets, we require $\Phi_1 - \Phi_2 = 1$. We can freely choose Φ_1 and Φ_1 (subject to $\Phi_1 - \Phi_2 = 1$) to translate net operating cash flow into gross sales and operating costs without affecting equilibrium choices.

For Sales/Assets, let $\overline{\alpha}(x)$ denote the LBO-count-weighted model value of $\mathbb{E}[\alpha(q) \mid LBO]$ at log sponsor count x. The empirical fitted line, expressed in percentage points, is

$$\widehat{Sales/Assets}^{\,pct}(x) = 116.0373 + 11.1381x.$$

We anchor the model at the most competitive endpoint, $x_0 = \log N_{\max} = 6.7687$. At this endpoint, the empirical fitted value is $\widehat{Sales/Assets}^{\,pct}(x_0) = 191.4270\%$. We normalize the model-implied Sales/Assets ratio to 187% at x_0 for empirical fit. Under this calibration, $\overline{\alpha}(x_0) = 0.0984604$. Consequently, $\Phi_1 = \frac{1.87}{\overline{\alpha}(x_0)} = 18.9924$. Thus, $\Phi_2 = \Phi_1 - 1 = 17.9924$. We can choose Φ_1, Φ_2 (subject to $\Phi_1 - \Phi_2 = 1$) to translate net operating cash flow into gross sales and operating costs without affecting equilibrium choices.

For firm size, we normalize $K_0 \in \{\gamma, 1\}$, but the model is entirely scale invariant and we could equally consider firm sizes $K_0 \in \{\Phi_K, \Phi_K\gamma\} = \Phi_K \cdot \{1, \gamma\}$, where the parameter Φ_K is a free scale parameter that does not affect any equilibrium outcomes. We now choose Φ_K to match the model to the empirical patterns. For firm size, the empirical fitted line is

$$\widehat{\log K}(x) = 19.5293 - 0.256611x.$$

Because the empirical dependent variable is log firm size, the corresponding unscaled model quantity is the LBO-count-weighted average of log size:

$$m_K(x) = w_1(x)\log(1) + w_\gamma(x)\log(\gamma),$$

where $w_1(x)$ and $w_\gamma(x)$ are the model-implied shares of LBOs in the large- and small-firm buckets. With scaling, that is, consider $K_0 \in \Phi_K \cdot \{1, \gamma\}$, the average firm size becomes $M_K(x) = \log \Phi_K + m_K(x)$. To align $M_K(x)$ with the empirical bins, we choose $\log \Phi_K = 18.3535$.

Overall, the model does not directly pin down Sales/Asset or firm size up to scaling, and we can freely choose the above introduced scale parameters Φ_1, Φ_2, Φ_K to better match the model to the data, without affecting equilibrium outcomes (up to scaling).

D Model Extensions

D.1 Investment in Screening Technology (Proposition 5)

Take as given K_0, and $n = n(K_0)$.

Stipulate that sponsor i's screening cost is $C_i S_{ix}^2$, where the sponsor privately chooses $C_i \in \mathcal{C} \subset (0, \infty)$ at $t = 0$. Sponsors play a symmetric Nash equilibrium in this technology choice: a unilateral choice of C_i takes the technology choices of all other sponsors, and hence their screening belief $\hat{q}_x$, as given. Sponsor i pays the one-time cost $\overline{C}(C_i)$, where $\overline{C}$ is twice continuously differentiable, $\overline{C}'(C_i) < 0$, and $\overline{C}''(C_i) > 0$. Thus, a lower C_i represents greater specialization and requires a larger upfront investment.

We impose the following conditions throughout this subsection. In a neighborhood of the specialization equilibrium, each unilateral screening problem (holding $\hat{q}_x$ fixed) and the symmetric continuation screening equilibrium have unique, interior, continuously differentiable solutions. We assume the second-order condition (B.13) holds and screening is interior for every relevant (C, η); moreover,

$$f_x(q_x) - I - f_x^{Pre} > 0, \qquad f_x'(q_x) \geq 0, \qquad \eta \in [\beta, 1].$$

The specialization choice is interior. We also impose the symmetric-equilibrium stability condition stated below in (D.31). This condition is stronger than, and therefore implies, the individual sponsor's second-order condition for its specialization choice.

Conditional on x, sponsor i's per-meeting payoff, before the upfront technology cost, is

$$\pi_{ix} = \left[1 - (1 - g_x)S_{ix}\right] \left[(1 - \beta) f_x(q_x(S_{ix})) - (1 - \eta)(I + f_x^{Pre}) - (\eta - \beta) f_x(\hat{q}_x)\right] - C_i S_{ix}^2. \quad \text{(D.26)}$$

This is (7) after substituting the bargaining price, but before imposing symmetry. Sponsor i chooses S_{ix} taking $\hat{q}_x$ as given. After differentiating its objective, impose symmetry $C_i = C$,

$S_{ix} = S_x$, and $\hat{q}_x = q_x(S_x)$. The screening first-order condition becomes

$$2CS_x = (1 - g_x)\left[q_x(1-\beta)f_x'(q_x) - (1-\eta)\big(f_x(q_x) - I - f_x^{Pre}\big)\right], \tag{D.27}$$

which is (B.10) for quadratic screening costs.

For later use, define the unilateral and symmetric screening curvatures, respectively, by

$$\begin{aligned} H_{u,x} &:= 2C - (1-g_x)(1-\beta)q_x f_x''(q_x)q_x'(S_x), \\ H_{s,x} &:= 2C - (1-g_x)\left[(\eta-\beta)f_x'(q_x) + (1-\beta)q_x f_x''(q_x)\right] q_x'(S_x). \end{aligned}$$

The screening condition (B.13) gives $H_{s,x} > 0$. Moreover,

$$H_{s,x} = H_{u,x} - (1-g_x)(\eta-\beta)f_x'(q_x)q_x'(S_x) \leq H_{u,x}, \tag{D.28}$$

so the unilateral screening second-order condition $H_{u,x} > 0$ also holds. Implicit differentiation of (D.27) along the symmetric screening equilibrium gives

$$\left.\frac{\partial S_x}{\partial C}\right|_{\eta} = -\frac{2S_x}{H_{s,x}} < 0, \qquad \left.\frac{\partial S_x}{\partial \eta}\right|_{C} = \frac{(1-g_x)\big[f_x(q_x) - I - f_x^{Pre}\big]}{H_{s,x}} > 0. \tag{D.29}$$

The last inequality also uses the positive-NPV condition $f_x(q_x) > I + f_x^{Pre}$. We now turn to the private screening technology choice. Let $S_{ix}^*(C_i, \hat{q}_x, \eta)$ solve sponsor i's screening problem in (D.26), and define its continuation value, before the upfront specialization cost, by

$$V_i(C_i; \hat{\boldsymbol{q}}, \eta) := \frac{\Lambda M}{\rho} \sum_{x=L,H} \Pr(x)\pi_{ix}\big(S_{ix}^*(C_i, \hat{q}_x, \eta)\big) + \frac{b}{\rho}, \qquad \hat{\boldsymbol{q}} := (\hat{q}_L, \hat{q}_H),$$

where $\frac{\Lambda b}{\rho}$ is merely a positive constant. Sponsor i's time-0 payoff is therefore $V_i(C_i; \hat{\boldsymbol{q}}, \eta) - \overline{C}(C_i)$. Because a unilateral change in C_i holds $\hat{\boldsymbol{q}}$ fixed, the envelope theorem applied to (D.26) gives

$$\frac{\partial V_i}{\partial C_i} = -\frac{\Lambda M}{\rho} \sum_{x=L,H} \Pr(x) S_{ix}^2.$$

Consequently, an interior symmetric Nash equilibrium in specialization satisfies

$$\overline{C}'(C) = -\frac{\Lambda M}{\rho} \sum_{x=L,H} \Pr(x) S_x(C, \eta)^2. \tag{D.30}$$

This envelope calculation is unilateral: it does not assert that the derivative of equilibrium value with respect to a common change in all sponsors' C is equal to the expression on the

right-hand side.

For completeness, holding rival beliefs fixed and differentiating the unilateral screening first-order condition gives

$$0 = -H_{u,x}\frac{\partial S_{ix}}{\partial C_i} - 2S_x, \qquad \text{so} \qquad \frac{\partial S_{ix}}{\partial C_i} = -\frac{2S_x}{H_{u,x}}.$$

Hence, the individual specialization second-order condition is

$$\overline{C}''(C) > \frac{4\Lambda M}{\rho}\sum_{x=L,H}\Pr(x)\frac{S_x^2}{H_{u,x}}.$$

The condition needed for the symmetric-equilibrium comparative static is

$$\Gamma(C,\eta) := \overline{C}''(C) - \frac{4\Lambda M}{\rho}\sum_{x=L,H}\Pr(x)\frac{S_x^2}{H_{s,x}} > 0. \tag{D.31}$$

By (D.28), (D.31) implies the individual second-order condition above. It additionally controls the response of rivals' beliefs when all sponsors' equilibrium technology choices move together.

Finally, totally differentiate the symmetric Nash condition (D.30) with respect to η. Using (D.29) and rearranging gives

$$\begin{aligned}\Gamma(C,\eta)\frac{dC}{d\eta} &= -\frac{2\Lambda M}{\rho}\sum_{x=L,H}\Pr(x)S_x\left.\frac{\partial S_x}{\partial \eta}\right|_C \\ &= -\frac{2\Lambda M}{\rho}\sum_{x=L,H}\Pr(x)\frac{S_x(1-g_x)\left[f_x(q_x) - I - f_x^{Pre}\right]}{H_{s,x}} < 0.\end{aligned}$$

Condition (D.31) therefore implies $dC/d\eta < 0$. Since n affects this specialization problem only through $\eta(n)$ and $\eta'(n) > 0$ by (6), it also follows that

$$\frac{dC}{dn} = \frac{dC}{d\eta}\eta'(n) < 0.$$

Thus, along the locally stable symmetric Nash equilibrium, greater competition induces sponsors to choose a lower screening-cost parameter and hence to invest more in specialization.

D.2 Post-LBO Effort (Proposition 6)

This Appendix presents the solution details to Section 4.1. Throughout this Appendix, we assume that first-order conditions are sufficient and that both the pre-shock and post-shock effort choices are interior. In particular, $\mu'(0)f_x(q_x) > \zeta$ and $\mu'(0)f_x^*(q_x) > \zeta$, and the corresponding first-order conditions admit solutions in the region where valuations are finite. We also maintain the baseline admissibility conditions and assume that the screening second-order condition in (B.13) holds, and screening is interior.

D.2.1 Post-LBO Solution

Given $\mu = \mu(a)$, the solution to the post-LBO model is similar to the baseline described in Proposition 1 and formally derived in Appendix B.3. The only difference is that payoffs include the effort cost ζa. Let $f_x(q_x)$ denote the sponsor's valuation of the firm, net of its private cost of effort ζa. We assume throughout that $f_x(q_x)$ is increasing in q_x, and that leverage is interior, in that $\theta_x(q_x) < f_x(q_x)$. Conditions for these can be derived analogously to the baseline. Further, as in the baseline, let $R_x = \chi f_x^*$, with f_x^* characterized next.

Post-Shock. Post-shock, the firm value (conditional on survival) equals

$$f_x^* = \frac{\alpha_x - \zeta a_x^*}{r - \mu_x^*}$$

for $\mu_x^* = \mu(a_x^*)$. The sponsor chooses effort according to:

$$r f_x^* = \max_{a \geq 0} \left[\alpha_x - \zeta a + \mu(a) f_x^*\right],$$

so that the first-order condition yields:

$$\mu'(a) f_x^* = \zeta \quad \Longleftrightarrow \quad a = a_x^* = (\mu')^{-1}\left(\frac{\zeta}{f_x^*}\right).$$

Although we suppress the dependence on q_x, the envelope theorem applied to the post-shock problem gives

$$f_x^{*\prime}(q_x) = \frac{\alpha_x'(q_x)}{r - \mu(a_x^*)} \geq 0.$$

Pre-Shock. Prior to the shock, we can — similarly to (B.5) — derive the HJB equation:

$$(\rho + \delta) f_x(q_x) = \max_{\theta \in [0, f_x(q_x)], a \geq 0} \left\{\mu(a) f_x(q_x) - \zeta a + \alpha_x + (\rho - r)\theta + \frac{\delta q_x f_x^*}{2}\left[1 - \omega^2(1 - \chi)\right]\right\}.$$

The FOC with respect to a becomes:

$$\mu'(a)f_x(q_x) = \zeta \quad \Longleftrightarrow \quad a = a_x = (\mu')^{-1}\left(\frac{\zeta}{f_x(q_x)}\right).$$

The FOC with respect to θ reads:

$$(\rho - r) - \delta q_x f_x^* \omega(1-\chi)\frac{1}{f_x^*} = (\rho - r) - \frac{\delta q_x(1-\chi)\theta}{f_x^*} = 0.$$

Thus,

$$\theta = \theta_x(q_x) = \min\left\{f_x(q_x), \frac{(\rho - r)f_x^*}{\delta q_x(1-\chi)}\right\}.$$

Consider that $\theta_x(q_x) < f_x(q_x)$ and insert $\omega = \frac{\theta}{f_x^*}$ into the HJB equation, in order to obtain under $a = a_x$ and $\mu = \mu(a_x)$:

$$f_x(q_x) = \frac{1}{\rho + \delta - \mu_x}\left[\alpha_x - \zeta a_x \; + \; \frac{(\rho - r)^2 f_x^*}{2\,\delta\, q_x\,(1-\chi)} \; + \; \frac{\delta\, q_x\, f_x^*}{2}\right]. \tag{D.32}$$

Clearly, $\frac{\partial f_x(q_x)}{\partial \zeta} < 0$, $\frac{\partial f_x^*}{\partial \zeta} < 0$, and $\frac{\partial a_x}{\partial \zeta}, \frac{\partial \mu_x}{\partial \zeta} < 0$.

D.2.2 Pre-LBO Screening

The introduction of post-LBO effort affects LBO deal quantities only via $f_x(q_x)$. Thus, the algebra of the pre-LBO screening problem remains unchanged. As stated above, we assume that the baseline screening second-order and boundary conditions hold for the effort-adjusted value function. Examine pre-LBO screening S_x.

After a match takes place and observing x, the sponsor chooses its screening effort S_x, taking as given the expected price of the LBO deal $\overline{p}_x$ and its prior beliefs g_x that $z = G$. In particular, the sponsor maximizes:

$$\max_{S\in[0,1]} K_0\left[\big(g_x + (1-g_x)(1-S)\big)\big[f_x(q_x) - \overline{p}_x\big] - C(S)\right].$$

Screening is determined by the FOC (B.10), which can be rewritten as:

$$\frac{C'(S_x)}{1-g_x} - q_x(1-\beta)f_x'(q_x) + (1-\eta)(f_x(q_x) - I - f_x^{Pre}) = 0. \tag{D.33}$$

Using the implicit function theorem, we can totally differentiate with respect to η to obtain:

$$\frac{dS_x}{d\eta}\left(\frac{C''(S_x)}{1-g_x} - (1-\beta)q_x'(S_x)[f_x'(q_x) + q_x f_x''(q_x)] + (1-\eta)f_x'(q_x)q_x'(S_x)\right) = f_x(q_x) - I - f_x^{Pre}.$$

The term in large round brackets is assumed to be strictly positive by the maintained screening second-order condition (B.13). The second line is positive too by assumption that an LBO creates value. Thus, $\frac{dS_x}{d\eta} > 0$ and, as in the baseline, screening increases with competition, captured by η or n. Hence, $\frac{dq_x}{d\eta} > 0$.

Post-shock effort therefore satisfies

$$\frac{da_x^*}{d\eta} = -\frac{1}{\mu''(a_x^*)}\frac{\zeta f_x^{*\prime}(q_x)}{[f_x^*(q_x)]^2}\frac{dq_x}{d\eta} \geq 0,$$

with a strict inequality whenever $\alpha_x'(q_x) > 0$. Next, for $a_x = (\mu')^{-1}\left(\frac{\zeta}{f_x(q_x)}\right)$, we can calculate:

$$\frac{da_x}{d\eta} = -\left(\frac{1}{\mu''(a_x)}\right)\frac{\zeta f_x'(q_x)}{f_x(q_x)^2}\frac{dq_x}{d\eta}.$$

Next, due to $\mu''(\cdot) < 0$, $f_x'(q_x) > 0$, and $\frac{dq_x}{d\eta} > 0$, we have $\frac{da_x}{d\eta} > 0$, in that post-LBO (but pre-shock) effort strictly increases in η (and n).

D.3 Endogenous Target Firm Pool (Proposition 7)

Finally, note that we make simplifying assumptions and assume the distribution of target firms is fixed and constant, allowing us to focus on the LBO deal, screening, and the choice of leverage as such. Since firms are heterogeneous alongside three dimensions, it is not straightforward to endogenize the distribution of target firms without losing tractability.

A potential way to endogenize target firm quality, would be to assume that given K_0, the number of good firms g is endogenous, similar to, e.g., Fishman et al. (2024). Specifically, if a good firm with size K_0 is acquired, then it is replaced by a good firm (with the same size) with probability ν and by a bad firm with probability $1-\nu$, where ν is a parameter. Given the hidden firm type $z = B, G$ of the replaced firm, x is drawn according to $\Pr(x = H|z = G) = \phi_G$ and $\Pr(x = H|z = B) = \phi_B$. This implies that conditional on size K_0 and z, the distribution of x is constant. Likewise, the total mass of firms of a given size is normalized to one, i.e., the size distribution is constant too.

We now characterize the outflow of good and bad firms due to LBOs. Consider a good firm. If the sponsor meets a good, it acquires this firm with probability one. Thus, the deal

flow of good firms equals $\Lambda n(K_0)Mg$. Next, consider a bad firm. This firm has $x = H$ with probability ϕ_B — resulting in screening S_H and thus probability of LBO of $1 - S_H$ — and has $x = L$ with probability $1 - \phi_B$ — resulting in screening S_L and thus probability of LBO of $1 - S_L$. Thus, the deal flow of bad firms is

$$\Lambda n(K_0)(1-g)\big[\phi_B(1-S_H) + (1-\phi_B)(1-S_L)\big],$$

where we define

$$\overline{S} := 1 - \big[\phi_B(1-S_H) + (1-\phi_B)(1-S_L)\big].$$

Note that $\overline{S}$ can be viewed as a measure of average screening for bad firms. In addition, we assume that firms (of either type) die randomly at rate ι.

Note that in our baseline analysis, given K_0 and x, screening effort S_x increases with n. Therefore, $\overline{S}$ increases with n as well.

Steady State Fraction of Good Firms. We now derive the law of motion that governs the change in the number of good firms (given a size bucket) and solve for the number of good firms in a steady-state. The law of motion reads

$$\frac{d}{dt}g = \dot{g} = -g\big[\Lambda n(K_0) + \iota\big](1-\nu) + (1-g)\big[\Lambda n(K_0)(1-\overline{S}) + \iota\big]\nu.$$

We can solve $\dot{g} = 0$ for:

$$g \;=\; \frac{\nu\big(\Lambda n(K_0)(1-\overline{S}) + \iota\big)}{\big(\Lambda n(K_0) + \iota\big)(1-\nu) + \nu\big(\Lambda n(K_0)(1-\overline{S}) + \iota\big)}. \tag{D.34}$$

provided that g is interior and satisfies $g \in (0,1)$.

Observe that g exhibits the same comparative statics as

$$\hat{g} := \frac{\nu\big(\Lambda n(K_0)(1-\overline{S}) + \iota\big)}{\big(\Lambda n(K_0) + \iota\big)(1-\nu)}.$$

All else equal, more screening S_x worsens the pool of target firm, i.e., reduces g. But then, given a worse pool of target firms, sponsors may screen more.

The equilibrium is defined as in Appendix B.2, except that (D.34) is added as additional equilibriun condition. The equilibrium requires now to solve the fixed point equation (D.34) for g, where we note that S_x and $\overline{S}$ depend on g. This dependency might lead to multiple equilibria, as, for instance, in Fishman et al. (2024). Since equilibrium multiplicity is not the focus of our study, we for now omit further analysis of this issue. Instead, we characterize

the comparative statics of g when interior with $g \in (0,1)$.

Special Case. In case the death rate ι is small (i.e., in the limit $\iota \to 0$), we have

$$g = \frac{\nu(1-\overline{S})}{1-\nu\overline{S}}, \quad \text{and} \quad \hat{g} = \frac{\nu}{1-\nu}(1-\overline{S}).$$

To make the fixed-point argument explicit, write $g = G(\overline{S})$ and $\overline{S} = s(g,n)$, where $G'(\overline{S}) < 0$ and $s_n(g,n) > 0$. Along a differentiable equilibrium branch,

$$\frac{dg}{dn} = \frac{G'(\overline{S})s_n(g,n)}{1 - G'(\overline{S})s_g(g,n)} < 0$$

provided the local stability condition $1 - G'(\overline{S})s_g(g,n) > 0$ holds. By continuity, the same sign obtains for sufficiently small $\iota > 0$. This is a heuristic local argument: without the stability condition or an equilibrium-selection rule, multiplicity can make the global comparative static ambiguous. Subject to this qualification, more competition worsens target-pool quality.

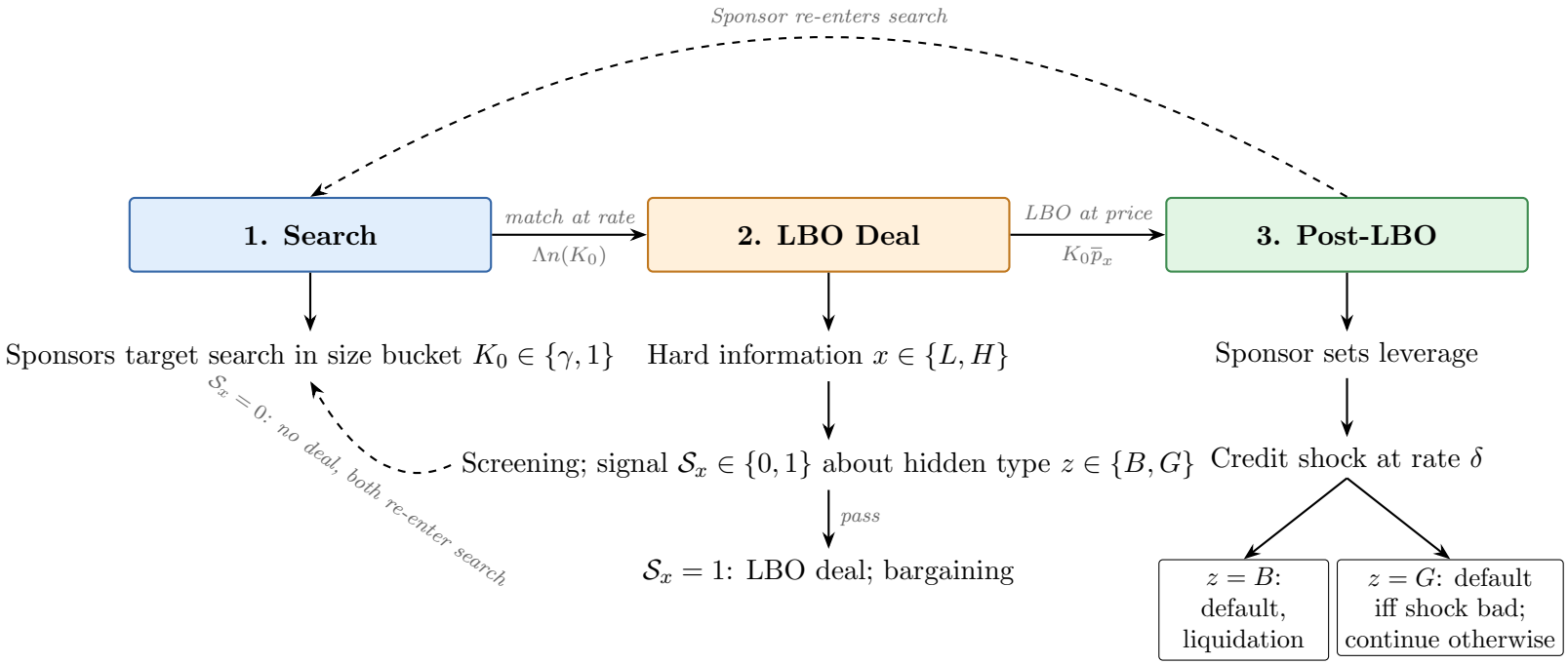


Figure A-1: Schematic Model Overview

Table A-1: Model Parameters

Parameter	Description	Value
Panel A: Firm Profitability and Quality		
$\alpha_x(q_x)$	Operating cash flow (scaled)	$\overline{\alpha}_x + \Omega q_x^{\xi}$
$\overline{\alpha}_L$	Baseline operating cash flow, low type ($x = L$)	0.015
$\overline{\alpha}_H$	Baseline operating cash flow, high type ($x = H$)	0.030
Ω	Sponsor value-add scale	0.10
ξ	Sponsor value-add curvature	0.90
g	Prior share of good firms	0.50
ϕ_G	Prob. of high type, good firms: $\Pr(x = H \mid z = G)$	0.50
ϕ_B	Prob. of high type, bad firms: $\Pr(x = H \mid z = B)$	0.40
Panel B: Cash Flows, Discounting, and Credit Risk		
μ	Capital growth rate	0.02
r	Risk-free rate	0.05
ρ	Sponsors' discount rate	0.0564
δ	Credit shock intensity	0.103
χ	Recovery value in default	0
Panel C: Search, Bargaining, and Screening		
β	Firms' bargaining weight	0.40
Λ	Matching intensity	0.022
M	Mass of potential target firms	45.4545
κ	Pre-match death rate	0.25
$C(S_x)$	Screening cost (scaled)	$c_S S_x^2$
c_S	Screening cost parameter	0.435
b	Sponsor benefit flow (scaled)	0.1818
Panel D: Deal Terms, Firm Size, and Sponsor Count		
I	Required investment	0.15
f_L^{Pre}, f_H^{Pre}	Pre-LBO firm values	0.15
γ	Small-firm size relative to a large firm	0.35
ϕ_N	Sponsor-count normalization	1
N	Number of sponsors in Figure 3	$[37.9, 870.1]$
$\log N$	Competition measure in Figure 3	$[3.635, 6.769]$

Notes: The table reports the parameter values used in the numerical analysis of Figures 3 and 4, further described in Appendix C. The sponsor-count normalization is $\phi_N = 1$, so model sponsor mass is expressed directly in units of the observed number of sponsors. In Figure 3, the numerical range $N \in [37.9, 870.1]$, or equivalently $\log N \in [3.635, 6.769]$, spans the smallest and largest empirical log-sponsor bins used in Figure 2. Figure 4 instead evaluates the model at the annual sponsor-concentration observations, using $N = 1/HHI$. Scale normalizations (Φ_K, Φ_1, Φ_2) affect displayed levels of firm size and Sales/Assets but not the underlying equilibrium or comparative statics and are described in Appendix C.

Table A-2: Alternative Competition Measures: Deal Multiples

	DealSize/EBITDA (Log)		DealSize/Assets (Log)	
	(1)	(2)	(3)	(4)
	Log Deals	Log HHI	Log Deals	Log HHI
Competition Measure$_{t-1}$	0.141**	−0.108*	0.078**	−0.074*
	(0.064)	(0.064)	(0.033)	(0.038)
Observations	716	716	771	771
Adjusted R^2	0.041	0.028	0.050	0.039
Year FE	Y	Y	Y	Y

Notes: The table reports deal-level OLS regressions of deal multiples on alternative measures of industry competition: the lagged log number of deals and the log of the lagged sponsor-level Herfindahl–Hirschman Index (HHI) of deal flow. Higher HHI indicates greater concentration, i.e., *lower* competition, so its coefficients are expected to have the opposite sign of the count-based measure; the log transformation addresses the pronounced nonlinearity of HHI in levels. All specifications include year fixed effects. Standard errors, clustered at the industry level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A-3: Alternative Competition Measures: Firm Size and Loan Size

	Firm Size (Log)		Loan Size (Log)	
	(1)	(2)	(3)	(4)
	Log Deals	Log HHI	Log Deals	Log HHI
Competition Measure$_{t-1}$	-0.230^{***}	0.320^{***}	-0.109^{***}	0.129^{***}
	(0.047)	(0.070)	(0.018)	(0.029)
Observations	4,297	4,297	4,328	4,328
Adjusted R^2	0.023	0.022	0.021	0.014
Year FE	Y	Y	Y	Y

Notes: The table reports deal-level OLS regressions of (log) target firm size and (log) average loan size on alternative measures of industry competition: the lagged log number of deals and the log of the lagged sponsor HHI. Higher HHI indicates lower competition, so its coefficients are expected to have the opposite sign of the count-based measure; the log transformation addresses the pronounced nonlinearity of HHI in levels. All specifications include year fixed effects. Standard errors, clustered at the industry level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A-4: Alternative Competition Measures: Leverage and Probability of Default

	Debt/EBITDA		Probability of Default	
	(1)	(2)	(3)	(4)
	Log Deals	Log HHI	Log Deals	Log HHI
Competition Measure$_{t-1}$	−0.117	0.196**	−0.625*	0.845*
	(0.077)	(0.092)	(0.327)	(0.473)
Observations	4,087	4,087	3,745	3,745
Adjusted R^2	0.002	0.000	0.009	0.009
Year FE	Y	Y	Y	Y

Notes: The table reports deal-level OLS regressions of Debt/EBITDA and the bank-reported probability of default on alternative measures of industry competition: the lagged log number of deals and the log of the lagged sponsor HHI. Higher HHI indicates lower competition, so its coefficients are expected to have the opposite sign of the count-based measure; the log transformation addresses the pronounced nonlinearity of HHI in levels. All specifications include year fixed effects. Standard errors, clustered at the industry level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A-5: Alternative Competition Measures: Profitability

	Sales/Asset		Firm ROA	
	(1)	(2)	(3)	(4)
	Log Deals	Log HHI	Log Deals	Log HHI
Competition Measure$_{t-1}$	9.309**	−15.970***	0.938**	−1.552***
	(4.190)	(5.121)	(0.349)	(0.427)
Observations	4,294	4,294	4,207	4,207
Adjusted R^2	0.009	0.012	0.008	0.010
Year FE	Y	Y	Y	Y

Notes: The table reports deal-level OLS regressions of Sales/Asset and Firm ROA (both in percent) on alternative measures of industry competition: the lagged log number of deals and the log of the lagged sponsor HHI. Higher HHI indicates lower competition, so its coefficients are expected to have the opposite sign of the count-based measure; the log transformation addresses the pronounced nonlinearity of HHI in levels. All specifications include year fixed effects. Standard errors, clustered at the industry level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A-6: Alternative Competition Measures: Specialization

	Specialization	
	(1)	(2)
	Log Deals	Log HHI
Competition Measure$_{t-1}$	6.050***	−7.837***
	(1.189)	(1.738)
Observations	4,249	4,249
Adjusted R^2	0.059	0.047
Year FE	Y	Y

Notes: The table reports deal-level OLS regressions of sponsor industry specialization on alternative measures of industry competition: the lagged log number of deals and the log of the lagged sponsor HHI. Higher HHI indicates lower competition, so its coefficients are expected to have the opposite sign of the count-based measure; the log transformation addresses the pronounced nonlinearity of HHI in levels. All specifications include year fixed effects. Standard errors, clustered at the industry level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.