Corporate Investment and Asset Price Dynamics: Implications for SEO Event Studies and Long-Run Performance

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Abstract

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Abstract

We present a rational theory of return behavior around seasoned equity offerings, including a pre-issuance price runup, negative announcement effect, and long-run post-issuance underperformance. The main result uses real option principles to relate SEO's to an endogenous decrease in expected returns. Equity issues are associated with firm expansions. When firms invest, they convert growth options to assets in place. Even when the new assets are risky, they will be less risky than the options they replace. Although both size and book-to-market effects are present in our model, standard matching procedures fail to capture the dynamics of risk and expected return. We calibrate the model, and show that it gives a close match to the primary empirical moments.

JEL Classification: G31, G32

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1. Introduction

The atypical stock market performance of public firms that issue seasoned equity raises an important challenge for financial theory. Summarizing an extensive empirical literature,[1] Ritter (2003) reports average stock market returns of 72% in the year prior to a seasoned equity offering (SEO), an announcement effect of -2%, and five-year post-issuance abnormal returns of about -30% relative to seemingly reasonable benchmarks. A comprehensive explanation of these facts is not obvious, and in the leading theories, cognitive bias and persistent mispricing play a critical role.[2]

In this paper, we develop a rational theory of observed returns throughout the SEO episode. We calibrate the model, and show that it captures not only the basic qualitative facts, but also gives a close quantitative match to the primary empirical moments. The key economic idea relates stock offerings to an endogenous decrease in expected returns. The intuition is straightforward: Equity issuance is associated with firm expansion. As firms grow, they convert real options to assets in place. Even when the new assets are risky, they will be less risky than the options they replace. Our explanation does not rely on changes in financial leverage, since we model an all-equity firm. Instead, the investment associated with SEO's causes a more fundamental change in total firm (or asset) risk.

Our real options theory contradicts the commonly held intuition that investment in risky projects should increase asset risk. Ritter (2003) explains the effect of equity offerings, according to the standard view: "It is ... entirely conceivable that lower leverage is more than offset by increased operating risk, if issuing companies embark on aggressive expansion plans with the money raised in an SEO." Consistent with Ritter, our model allows expansion opportunities to have riskier cash flows than existing assets,

[1] For evidence on long-run performance, see for example Loughran and Ritter (1995); Spiess and Affleck-Graves (1995); Brav, Geczy, and Gompers (2000); Eckbo, Masulis, and Norli (2000); Mitchell and Stafford (2000); and Clarke, Dunbar, and Kahle (2001). Announcement effects are analyzed by Asquith and Mullins (1986), Masulis and Korwar (1986), Mikkelsen and Partch (1986), Bayless and Chaplinsky (1996), and others. Stock price run-up prior to the SEO is discussed by Korajczyk, Lucas, and McDonald (1990) and Loughran and Ritter (1995). Eckbo and Masulis (1995) summarize the earlier literature.

[2] Daniel, Hirshleifer, and Subrahmanyam (1998) show that overoptimistic investors may excessively extrapolate from the positive pre-announcement experience of SEO firms, and underreact to the bad news of an SEO announcement, resulting in slow learning and negative long-run abnormal returns. Alternatively, Loughran and Ritter (1995) and Baker and Wurgler (2002) propose that managers time the market to take advantage of windows of opportunity. Investor underreaction to SEO announcements allows managers to sell overvalued equity, again resulting in long-run underperformance.

due to increased operating leverage. Nonetheless, we arrive at the opposite conclusion. In particular, we show that the riskier the expansion opportunity, the larger the *decrease* in risk upon optimally timed option exercise. This may seem counterintuitive at first, but a growth option is a levered claim. Investment (or option exercise) unlevers the position, and when the underlying cash flows are riskier, the reduction in exposure from delevering is larger.

Real options intuition also accounts for a substantial pre-issuance price runup. Because growth opportunities are exercised only when they move sufficiently into the money, above average returns naturally precede SEO announcements. This is a direct consequence of *ex post* selection bias, as discussed by Brown, Goetzmann, and Ross (1995) and others in different settings.

To complete the characterization of SEO episode returns, we incorporate announcement effects using a very simple form of asymmetric information. Managers have superior knowledge regarding the characteristics of their growth option, and optimal SEO timing reveals this to investors. We show that on average, the announcement of a stock offering in our environment is bad news.

The model we propose captures additional empirical features that are relevant beyond the SEO setting. We adapt the technology of Carlson, Fisher, and Giammarino (2004), and thereby obtain both small-stock and value premia. The empirical literature on long-run SEO underperformance often attempts to control for risk by matching on firm characteristics. Using this approach in our environment is reasonable, since both size and book-to-market are explicit determinants of conditional asset beta. We nonetheless show theoretically why the standard matching procedure fails to fully capture risk, and quantify the effects in our calibration.

The model also has implications for the relationship between investment and subsequent returns. Authors including Anderson and Garcia-Feijoo (2003), Lamont (2000), Polk and Sapienza (2004), and Titman, Wei, and Xie (2004) have shown correlation between investment and subsequent stock underperformance. Many of these authors argue that overinvestment due to either managerial or shareholder overoptimism is the most plausible explanation for these findings.[3] By contrast, we propose that a decline in returns following investment is a natural consequence of growth option exercise.[4]

Although not explicitly a model of an initial public offering (IPO), intuition from

[3]See also the survey of behavioral corporate finance by Baker, Ruback, and Wurgler (2004).

[4]Although not the focus of our paper, operating performance is also highest before equity offerings and investment and lowest afterwards in our environment. This prediction is consistent with empirical evidence in Loughran and Ritter (1997), and also does not rely on overinvestment.

our model can be applied in this context as well. Run-up and announcement effects are not observable in firms going public, but our theory does predict the empirically observed post-IPO underperformance relative to standard benchmarks.[5] Moreover, our theory suggests the decline in risk following a stock issuance should be largest for small firms with substantial growth options, which are common characterististics of IPO firms. (See, e.g., Brav, Geczy, and Gompers (2000)).

Our explanation for low returns following equity issuance differs from Pastor and Veronesi (2004). In their model, low required returns cause investment-driven issuance, and low average returns naturally follow.[6] This can be characterized as a discount rate (or denominator) channel, driven by exogenous changes in required returns. By contrast, in our theory discount rates are constant as long as the characteristics of cash flows are unchanged. Instead, variation in asset risk derives from changes in the composition and riskiness of firm cash flows, due to investment and product demand dynamics. Hence, the cash flow (or numerator) channel drives our results, and changes in risk are endogenous.

The framework we develop relates most broadly to the prior literature on real options models of corporate investment.[7] Lucas and McDonald (1990) develop a theory of pre-SEO price runups and announcement effects in a risk neutral setting. We allow for risk aversion and focus on the dynamics of risk-adjusted required returns. Our work also closely relates to recent contributions by Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Kogan (2004), and Zhang (2005). This previous research explores how optimal investment and movements in underlying state variables affect expected returns, focusing on the cross-section of returns and asset pricing anomalies such as size and book-to-market effects.[8] We instead emphasize time series consequences for corporate event studies.

Our work is also relevant to the literature on conditional event studies, which considers corporate decisions that are partially anticipated by the market (Acharya, 1988, 1993; Eckbo, Maksimovic, and Williams, 1990; Prabhala, 1997.) In these studies, conditional expectations are typically formed only for a snapshot in time when the event occurs. By contrast, we explicitly derive the evolution of investor beliefs over the entire

[5] An extensive literature on IPO performance begins with Ritter (1991), and is surveyed by Ritter (2003).

[6] A similar phenomenon occurs in the model of Berk, Green, and Naik (1998) when the risk-free rate is stochastic.

[7] Among the early real options research, our work is closest to Brennan and Schwartz (1985) and McDonald and Siegel (1985, 1986).

[8] Zhang (2004) explores how Q-theory relates to a number of return anomolies.

SEO episode, and our model of investor anticipation is dynamically consistent. We thus extract information not only from the cross-section of event and non-event firms, but also from the time-series of returns around the event.

The plan of the paper is as follows: Section 2 presents the model, analyzing valuation and conditional risk. Section 3 derives closed form results on the runup, announcement effects, matching and long-run performance. Section 4 calibrates the model to empirical data using simulated method of moments, and examines the effects of parameter changes through sensitivity and scenario analysis. Section 5 concludes.

2. A Model of SEO Timing and Expected Return Dynamics

In our setting, a firm sells its output into a market with stochastic demand. A value maximizing manager chooses when to irreversibly expand output. The firm issues new equity to finance expansion, and the manager has superior information about the value of the growth opportunity.

To aid exposition, all random variables are defined on a filtered probability space $(\Omega, \mathcal{F}, \mathbf{F}, \mathbb{P})$, where $\mathbf{F} \equiv \{\mathcal{F}_t\}_{t\geq 0}$ is the information filtration and $\mathcal{F}_t \subseteq \mathcal{F}$ for all t. Time t subscripted random variables are measurable with respect to $\mathcal{F}_t$ and all unsubscripted random variables are measurable with respect to $\mathcal{F}_0$.[9]

2.1. The Firm and Investment Opportunities

A monopolist faces downward-sloping iso-elastic demand,

$$P_t = X_t Q_t^{\gamma-1}, \tag{1}$$

where P_t is price, X_t is an exogenous state variable, Q_t is the instantaneous output rate, and $0 < \gamma < 1$. We specify

$$dX_t = \mu_X X_t dt + \sigma X_t dz_t, \tag{2}$$

where z_t is a standard Brownian motion, and μ_X and σ are, respectively, the mean and volatility of the growth rate of X_t.

The firm produces goods from installed capital K_t under the strictly increasing production function $Q_t \leq Q(K_t)$. To simplify, we assume two capital levels, $\kappa_0 < \kappa_1$. The firm begins with capital level κ_0, and can irreversibly increase its scale to κ_1 at a cost $\lambda \geq \kappa_1 - \kappa_0$, which includes both the direct cost of new capital and adjustment

[9] We largely follow the notational conventions of Duffie (2001). See this reference for further details.

costs. We let $D_t \equiv d\mathbf{1}_{\{K_t=\kappa_1\}}$ represent the firm's investment decision at time t.[10] This process takes a value of one at the instant the firm invests, and zero elsewhere. The firm also has in each period operating costs $F_t = F(K_t) \geq 0$ that strictly increase in the capital level, but are fixed with respect to the output level Q_t. For convenience, denote $f_i = F(\kappa_i)$. There are no other costs of production.

The firm may be one of two types $\theta \in \{b, g\}$, distinguished by the characteristics of its expansion option. Specifically, the firm may randomly lose its growth option, and a stopping time $\tau_Y > 0$, independent of all other variables, gives the instant at which this occurs. Let

$$Y_t \equiv \begin{matrix} 0 & \text{if } t < \tau_Y \\ 1 & \text{if } t \geq \tau_Y \end{matrix}$$

be the associated indicator function. We assume τ_Y has exponential distribution with parameter ρ_θ, and thus the unconditional probability that $Y_t = 0$ is $\exp(-\rho_\theta t)$. If $Y_t = 0$, an immature firm with capital level κ_0 may invest to grow to κ_1, but if $Y_t = 1$ the firm cannot expand. The value of Y_t has no effect on a mature firm already possessing capital κ_1. We assume $\rho_b > \rho_g$, so a type b firm is likely to lose its growth opportunity sooner than type g.

This model of growth option loss can be thought of as a reduced form for preemption risk. A firm facing no rival for a growth opportunity can optimally time investment without consideration for outside factors. On the other hand, a firm whose expansion opportunity is at risk may invest earlier in order to itself preempt challengers. The choices of ρ_b and ρ_g allow considerable heterogeneity in how strongly preemption risk affects firm decisions.

In the remainder of the paper, we assume $\rho_g = 0$ and $\rho_b = \rho$. This simplifies notation and does not materially affect our main results.

2.1.1. The Pricing of Risk

We assume the existence of traded assets that can hedge demand uncertainty. Let B_t denote the price of a riskless bond with dynamics $dB_t = rB_t dt$, and let M_t be a risky asset with dynamics $dM_t/M_t = \mu_M dt + \sigma dz_t$. Note that M has transitions identical to X except for the difference $\delta = \mu_M - \mu_X > 0$ in their drifts. Thus, returns on M are perfectly correlated with percentage changes in the demand state variable. We can now construct a portfolio with possibly time-varying weights in M and B that

[10] For any random event Z, the indicator function $\mathbf{1}_{\{Z\}}$ takes the value 1 when Z occurs and 0 otherwise.

exactly reproduces the dynamics of firm value. This combination is called a replicating or hedging portfolio.

Without loss of generality, we normalize M to have a beta of one, so that the proportion of M held in the replicating portfolio determines the beta of the portfolio. This simplifies notation, aids interpretation, and places no restrictions on our theory.[11]

The traded assets M and B allow us to define a new measure under which the process $\hat{z}_t = z_t + \frac{\mu_M - r}{\sigma} t$ is a standard Brownian motion. For this risk-neutral measure, demand dynamics satisfy $dX_t = (r - \delta) X_t dt + \sigma X_t d\hat{z}_t$.

2.2. Intrinsic Value, Optimal Investment, and Equity Issuance

We assume that shareholders delegate to a manager full responsibility for running the firm. The manager has complete information regarding firm type, but cannot communicate this to shareholders. The objective of the manager is to maximize *intrinsic value*, defined as the price that would be paid for the firm by a competitive market with access to the same information as the manager. We explicitly rule out conflicts of interest between managers and different classes of investors that are important in many areas of the literature. We also do not focus attention on compensation contracts that could give rise to intrinsic value maximization as a managerial goal.[12] By choosing this simple objective function, we generate our main results in closed form, and also show that strategic managerial behavior is not essential to obtaining announcement effects.

The manager chooses among operating policies Q and investment policies D to maximize intrinsic value:

$$V_t \equiv \max_{Q,D} \hat{\mathbb{E}} \left\{ \int_t^\infty e^{-r(s-t)} \left[(P_s Q_s - F_s) \, ds - \lambda D_s \right] | \mathcal{F}_t \right\}.$$

Using standard arguments, one can easily verify that V_t is a function of (X_t, Y_t, K_t, θ). It is therefore useful to define for capital level indices $i \in \{0, 1\}$ and firm types $\theta \in \{b, g\}$ functions $V_{i\theta}(X_t, Y_t)$ that explicitly recognize this dependence.

We now solve for V and determine optimal policies. To choose output conditional on the capital level, observe that operating revenue is $QP(Q) = XQ^\gamma$, increasing in Q.

[11]To interpret our theory most generally, think of our beta as measuring exposure to M, where M simply captures the priced risk in X, and need not be "the market."

[12]It would be straightforward to give the manager a contract that would make this behavior optimal, by imposing penalties for outcomes that appear inconsistent with intrinsic value maximization (e.g., Dybvig and Zender, 1991). We expect that the economics driving our results would still have first order importance if managerial objectives were more generally specified. Separating equilibria, qualitatively similar to the one studied here, commonly arise in these settings.

The firm thus produces at full capacity, denoted by $q_i = Q(\kappa_i)$, $i = 0, 1$.

Mature firms ($K_t = \kappa_1$) of either type $\theta \in \{b, g\}$ are identical, and valuation requires only that we discount operating profits under the risk-neutral measure. This gives $V_{1\theta}(X_t, Y_t) = \hat{\mathbb{E}}\left\{\int_0^\infty e^{-rs}\left(X_{t+s}q_1^\gamma - f_1\right) ds|\mathcal{F}_t\right\}$ or

$$V_{1b}(X_t, Y_t) = V_{1g}(X_t, Y_t) = X_t\frac{q_1^\gamma}{\delta} - \frac{f_1}{r}. \tag{3}$$

Mature firm value is thus the present value of a risky, growing perpetuity (revenues), less the present value of a riskless perpetuity (costs).[13]

Prior to maturity, firms hold one real option to expand, and optimal investment is characterized by the demand level at which expansion occurs. Let x_b and x_g respectively denote the values of X_t at which types b and g invest, and define stopping times $\tau_\theta \equiv \inf\{t : X_t \geq x_\theta\}$. Using backward recursion, we prove in the Appendix:

PROPOSITION 1: *For $\theta \in \{b, g\}$, the optimal investment strategy is*

$$x_\theta = \varepsilon_\theta \frac{\delta \nu_\theta}{q_1^\gamma - q_0^\gamma}$$

where $x_b < x_g$. The firm's intrinsic value prior to investment is

$$V_{0\theta}(X_t, Y_t) = X_t\frac{q_0^\gamma}{\delta} - \frac{f_0}{r} + \left(\frac{X_t}{x_\theta}\right)^{\nu_\theta}\varepsilon_\theta(1 - Y_t), \tag{4}$$

where expressions for ε_θ and $\nu_b > \nu_g > 1$ are in the Appendix.

The first result in this proposition is that type b firms invest earlier than type g. By waiting to invest, a firm foregoes current profits, but retains its timing option. For type b, waiting is less valuable because the growth opportunity may disappear. The manager of firm b thus optimally invests at a lower demand level.

The valuation equation (4) has three components. The first two give the value of assets in place, similar to the mature firm value (3), and are independent of firm type. The final term is the value of growth options. The quantity ε_θ gives the incremental value of firm expansion when undertaken, and $1 - Y_t$ cancels out the entire term if preemption occurs. Option value increases in X_t/x_θ, which measures the closeness of demand to the exercise boundary, and ν_θ relates to convexity. To understand why $\nu_b > \nu_g$, think of $\left(\frac{X_t}{x_\theta}\right)^{\nu_\theta}$ as a discount factor for ε_θ, and note that firm b option value is discounted more heavily due to the higher probability of preemption.

[13]Substitute $\delta = \mu_M - \mu_X$ to recognize the Gordon growth formula.

Figure 1 depicts the intrinsic value of the firm for each type and for different values of the state variable X_t. We choose as parameter values for this figure a specification that is found in Section 4 to provide a reasonable approximation of various empirical moments. The figure shows that mature firm value is linear in X. The growth option makes pre-SEO intrinsic values convex in X, and the degree of convexity is determined by model parameters.

2.3. Bayesian Learning and the Dynamics of Investor Beliefs

Investors have incomplete information about firm type but learn over time by observing the actions of the firm and other variables in their information set. Specifically, at time $t = 0$, investors begin with prior belief $\Pi_0 \in (0, 1)$ that firm type θ is equal to g. At any instant $t \geq 0$, investors have access to the public firm history $H_t = (X_s, Y_s, K_s, s)_{s \leq t}$, which is a random vector. It is also useful to define the information partition $\mathcal{H}_t$, which is the σ-algebra generated by H_t. We note that $\mathcal{H}_t$ is itself a filtration, and satisfies $\mathcal{H}_t \subseteq \mathcal{F}_t$, corresponding to investors having a coarser information set than managers. Using the firm history, investors generate updated beliefs about type:

$$\Pi_t \equiv \mathbb{P}\left(\theta = g | \mathcal{H}_t\right).$$

We then show in the Appendix

PROPOSITION 2: *At any time t, investor beliefs are*

$$\Pi_t = \begin{cases} 0 & \text{if } (t \geq \tau_b \text{ and } D_{\tau_b} = 1) \text{ or } Y_t = 1 \\ 1 & \text{if } (t \geq \tau_b \text{ and } D_{\tau_b} = 0) \\ \frac{\Pi_0}{\Pi_0 + (1 - \Pi_0)e^{-\rho t}} & \text{otherwise.} \end{cases} \tag{5}$$

The intuition for this result is straightforward. If demand passed the investment threshold at $\tau_b \leq t$ and the firm issued equity, then investors know firm type is b. Investors reach the same conclusion if the firm loses its growth opportunity prior to t. On the other hand, if at $\tau_b \leq t$ the firm did not invest, then investors infer that type is g. Finally, if none of these events occurs, uncertainty remains, and investors revise their beliefs monotonically upward. This is because as time passes without the firm losing its growth option, investors become more confident that type is g. In other words, "no news is good news."

We can also use recursive updating to describe the dynamic path of investor beliefs:

Corollary 3: *Revisions to beliefs follow*

$$d\Pi_t = \rho\Pi_t\left(1-\Pi_t\right)dt - \Pi_t dY_t + \left(1 - D_t - \Pi_t\right)\mathbf{1}_{\{t=\tau_b\}}. \tag{6}$$

The first term is the "no news is good news" effect related to the passage of time. The second shows that if the firm loses its growth options then $\Pi_t = 0$. The third term specifies that when demand reaches the investment threshold x_b, beliefs jump to zero if investment occurs, or to one otherwise.

Equation (6) provides a link to the conditional event studies literature. Previous authors such as Acharya (1988,1993), Eckbo, Maksimovic and Williams (1990), and Prabhala (1997) make the important point that conditioning information about the likelihood of an event (or non-event) can be useful to empirical researchers. In these studies, conditional expectations are typically formed only for a snapshot in time when the event occurs. By contrast, we explicitly derive the evolution of investor beliefs over the entire SEO episode, and our model of investor anticipation is dynamically consistent. We thus extract information not only from the cross-section of event and non-event firms, but also from the time-series of returns around the event.

2.4. Market Value of the Firm and Expected Returns

Market value,

$$S_t \equiv \mathbb{E}\left(V_t|\mathcal{H}_t\right),$$

is the expectation of intrinsic value conditioned on public information. One can verify that market value is a function of the state variables (X_t, Y_t, K_t) and current beliefs Π_t. We recognize this dependence by defining for each capital level index $i = 0, 1$, a market value function $S_i\left(X_t, Y_t, \Pi_t\right)$. We then show

Proposition 4: *Market value*

$$S_i\left(X_t, Y_t, \Pi_t\right) = \Pi_t V_{ig}\left(X_t, Y_t\right) + \left(1-\Pi_t\right) V_{ib}\left(X_t, Y_t\right)$$

is a belief weighted-average of intrinsic values.

If the firm has invested or lost its growth option, then type is known, and market value equals the appropriate intrinsic value. Otherwise, market value is strictly between the two intrinsic values.

We calculate asset betas using replicating portfolios composed of the risky asset M and riskless bond B. Define $V_\theta^G\left(X_t, Y_t\right) = \left(X_t/x_\theta\right)^{\nu_\theta}\varepsilon_\theta\left(1-Y_t\right)$ as the value of growth options, and $V_i^F = f_i/r$ where $i = 0, 1$ as the present value of fixed costs. We first derive the *intrinsic beta*, defined as the covariance of percent change in intrinsic value with percent change in M, divided by the variance of M. We then calculate the *market beta*, which as usual measures the covariance of observed market returns. It is easy to verify that for either measure, beta is given by the percentage of the replicating portfolio invested in M. Following this logic, we prove in the Appendix:

PROPOSITION 5: *Intrinsic betas are*

$$\beta_{i\theta t} = 1 + \frac{V_i^F}{V_\theta} + \frac{V_\theta^G}{V_\theta}(\nu_\theta - 1) \tag{7}$$

for $\theta \in \{g, b\}$ *and* $i = 0, 1$. *Market beta depends on investors' perceptions of firm type:*

$$\beta_i(X_t, Y_t, \Pi_t) = \omega_{it}\beta_{igt} + (1 - \omega_{it})\beta_{ibt}, \tag{8}$$

where the state-dependent weights $0 \leq \omega_{it} \leq 1$ *are*

$$\omega_{it}(X_t, Y_t, \Pi_t) = \frac{\Pi_t V_{ig}(X_t, Y_t)}{\Pi_t V_{ig}(X_t, Y_t) + (1 - \Pi_t) V_{ib}(X_t, Y_t)}. \tag{9}$$

The intrinsic beta contains three terms. The first is the revenue beta, which we previously normalized to one by assuming that the demand state variable X and the pricing instrument M have identical diffusions.[14] The second term accounts for operating leverage, driven by fixed costs associated with plant size. The third term is linear in the fraction of firm value contributed by growth options, and depends on firm type. The market beta is simply a value-weighted average of the intrinsic betas. This follows the logic of Proposition 4, which shows that market value is a belief-weighted average of intrinsic values. Note that market beta stochastically evolves, driven by 1) underlying product market demand, 2) exogenous loss of growth options, 3) optimally timed investment, and 4) rationally updated investor beliefs.

3. Implications for SEO Event Studies and Long-run Performance

We now characterize the SEO episode features implied by the model in Section 2. Our analysis focuses on the price run-up, the announcement effect, and post-issuance changes in risk for SEO firms and their matches.

[14]This normalization is without loss of generality. To account for revenue betas other than one, the intrinsic beta would be adjusted proportionately.

3.1. Selection Bias and Pre-Issuance Price Run-up

Selection bias in financial settings has been extensively studied (e.g., Brown, Goetzmann, and Ross, 1995). In our model, equity issuance enables new investment, and occurs after a sequence of positive shocks in the product market. Selection bias should thus significantly impact pre-SEO returns. Although the mechanism is different, the consequence is similar to Lucas and McDonald (1990), where managers undertake investment only when equity is overpriced, which also typically occurs after a sequence of positive returns. These types of price run-ups are not, however, a necessary implication of a real options model of investment. For example, in the Berk, Green, and Naik (1998) model with constant riskless rates, there is no such effect because investment opportunities arrive in an iid fashion, and must be accepted or declined immediately.

To analyze the pre-SEO price runup, we calculate the distribution of the state variable X_t prior to τ_θ, the first arrival of X at the optimal exercise boundary x_θ. We show in the Appendix:

PROPOSITION 6: *The conditional density of the state variable, X_t, $t < \tau_\theta$ is*

$$\mathbb{P}(\ln X_t | s = \tau_\theta - t > 0) = \frac{(\ln x_\theta - \ln X_t)\phi\left(\ln X_t; \ln x_\theta - \mu s, \sigma\sqrt{\frac{s}{2}}\right)}{\mu s \Phi\left(\sqrt{2s}\frac{\mu}{\sigma}\right) + \frac{\sigma^2 s}{2}\phi\left(0; -\mu s, \sigma\sqrt{\frac{s}{2}}\right)} \tag{10}$$

where the support of the distribution is $X_t < x_\theta$, the function $\Phi(\cdot)$ is the standard normal CDF, the function $\phi(\cdot)$ is the normal PDF, and $\mu = \mu_X - \frac{1}{2}\sigma^2$ adjusts the drift for Jensen's inequality.

The conditional distribution of X_t is bounded above by x_θ, due to selection bias from conditioning on the SEO event. In addition, the conditional mean decreases with the amount of time s that one looks backward. The formula allows us to calculate in closed form expected values of an issuing firm at any date prior to issuance. Recognizing that realized returns consist of capital gains and dividends, we can calculate in closed form the capital gains. To fully characterize conditional expected returns, we must numerically integrate path by path over realizations of the state variable X and accumulate dividends. We defer this exercise until Section 4, which conducts simulation based analysis of the model.

3.2. SEO Announcement Effects

Announcement effects associated with SEO's have been widely studied, and the average abnormal return is about -2%.[15] The traditional explanation for this finding is adverse selection, in which issuing firms reveal that their intrinsic value is lower than the market value. These ideas were first developed in a static setting by Myers and Majluf (1984), and extended to a dynamic setting by Lucas and McDonald (1990). In this early literature, the market immediately and fully incorporates the information content of the announcement, and shares are issued at fair value. More recently, Loughran and Ritter (1995) and others have argued that market price does not fully react to the announcement of an SEO, allowing managers to issue overvalued equity and thus leaving a window of opportunity for firms to exploit.

Our announcement effects similarly derive from the release of negative information. We achieve this, however, while assuming that investors fully incorporate the information in firm decisions, and that managers choose investment and equity issuance to maximize intrinsic value.

To calculate announcement effects in our model, define the *decision-censored history* $H_t^* \equiv \left([X_s, Y_s, s]_{s \leq t}, [K_s]_{s<t}\right)$, which includes everything normally available in H_t except the current capital level. With this information set, investors cannot generally infer the investment decision D_t. We then define $\Pi_t^* \equiv \mathbb{E}(\Pi_t | H_t^*)$ and $S_t^* \equiv \mathbb{E}(S_t | H_t^*)$, which are decision-censored beliefs and market prices.

The *announcement effect* is the percentage price change explained by the date t SEO decision:

$$AN_t(D_t) \equiv \frac{S_t - S_t^*}{S_t^*}.$$

We show in the Appendix,

PROPOSITION 7: *Announcement effects are:*

$$AN_t(D_t) = \begin{cases} \dfrac{-\Pi_t^*}{\Pi_t^* + \left(\frac{V_{0g}(x_b)}{V_{0b}(x_b)} - 1\right)^{-1}} < 0 & \text{if } t = \tau_b,\ Y_t = 0, \text{ and } D_t = 1 \\ \dfrac{1 - \Pi_t^*}{\Pi_t^* + \left(\frac{V_{0g}(x_b)}{V_{0b}(x_b)} - 1\right)^{-1}} > 0 & \text{if } t = \tau_b, Y_t = 0, \text{ and } D_t = 0 \\ 0 & \text{otherwise.} \end{cases} \tag{11}$$

[15] For early evidence see Asquith and Mullins (1986), Masulis and Korwar (1986), and Mikkelsen and Partch (1986). Eckbo and Masulis (1995) and Ritter (2004) conveniently summarize more recent work.

This result is intuitive and relates to the belief dynamics (6). Since $x_b < x_g$, the only time that the SEO decision resolves uncertainty about firm type is when demand reaches x_b while the growth option is still alive. The market then learns that type is b if the firm issues equity, or g if it does not. The change in beliefs causes a discrete jump in firm value, which is positive for type g and negative for type b. Announcement effects are proportional to the change in beliefs, and their magnitude increases with the difference in intrinsic values. Similar to Eckbo, Maksimovic, and Williams (1990), not issuing can be as informative as issuing.

At any time other than $t = \tau_b$, announcement effects are zero because SEO decisions are predictable. This is true in particular when type g firms invest at τ_g, because investors learn type with certainty at $\tau_b < \tau_g$. In data generated by our model, an SEO sample would consist of both type b firms that issue with negative announcement effects and type g firms with no announcement effects. The average depends on the composition of the sample, and must be negative.

3.3. Matching and Long-Run SEO Underperformance

The decision of whether to issue equity and increase scale has important consequences for (1) intrinsic risk of the firm's operations, (2) investor beliefs about risk, (3) expectations of long-run stock returns, and (4) stock returns relative to size and book-to-market matches. We can analyze each of these explicitly in our model.

3.3.1. Changes in Risk and Expected Return

The previous literature recognizes that stock issuance decreases financial leverage, mechanically reducing risk as in Hamada (1972).[16] We model an all-equity firm, so none of our effects are driven by this purely financial explanation. In our setting, the investment associated with SEO's causes a more fundamental change in total firm, rather than equity, risk.

Denote the intrinsic beta change at equity issuance by $\Delta\beta_{\theta t} \equiv \beta_{1\theta t} - \beta_{0\theta t}$. We show

[16] Empirical researchers have tested the implications of Hamada (1972) for seasoned equity offerings. Healy and Palepu (1990) find increases in risk subsequent to issuance. Denis and Kadlec (1994) argue that this result is caused by differential liquidity and corresponding beta estimation biases in the pre- and post- SEO periods. After correcting for this effect, they document a post-issuance decrease in risk.

PROPOSITION 8: *When a firm of type θ announces at time $t = \tau_\theta$ new financing for a scale increase, the intrinsic beta of the firm changes discretely by*

$$\Delta\beta_{\theta t} = \frac{-\lambda}{V_{0\theta}(x_\theta, 0)} \left[1 + \frac{f_1/r}{V_{1\theta}(x_\theta, 0)}\right] < 0. \tag{12}$$

We first analyze this formula when there is no operating leverage, i.e., $f_1 = 0$. The reduction in systematic risk then equals SEO proceeds λ as a proportion of firm value. The larger this proportion, the greater the drop in beta. To further illuminate this effect, rewrite the exercise price to firm value ratio as $\lambda/V_{0\theta}(x_\theta, 0) = \left(V_\theta^G/V_\theta\right)(\nu_\theta - 1)$. This is the proportion V_θ^G/V_θ of firm value in growth options multiplied by the beta differential $\nu_\theta - 1$ of growth options relative to assets in place. When new equity is issued, the systematic risk of this portion of firm value falls from ν_θ to 1.

When $f_1 > 0$, so that operating leverage is present in the mature firm, an additional term strengthens this effect. This may seem surprising, since operating leverage causes cash flows to have higher risk. What we are measuring, however, is the change in risk due to exercising a growth option. Even if fixed costs are very high, so that the expanded plant is extremely risky, it is still the case that an option on those assets is riskier than the assets themselves. Thus, substituting assets in place for a growth option reduces firm risk.

3.3.2. Matching and Long-Run Stock Returns

Finance researchers have been guided by empirical regularities and common sense in developing matching methodologies for long-horizon event studies. We now analyze how these matching procedures behave in our environment.

We define an *ideal match* for an SEO firm as a non-issuing firm whose entire history, except the issuing decision, is identical. In our environment, an ideal match often does not exist. In fact, the only case where the ideal matching set is nonempty is when $t = \tau_b$ and $Y_t = 0$. In this case, the ideal match has identical size, book-to-market, and investor perception of type just prior to t, but does not invest. The decision separates types: b invests while g does not. We can then show:

PROPOSITION 9: *When* $t = \tau_b$ and $Y_t = 0$, *an investing firm and its ideal match have a post-announcement difference in market beta quantified by*

$$\Delta\beta_{ideal} = \frac{f_1}{r}\left(\frac{1}{V_{1b}(x_b, 0)} - \frac{a}{V_{0g}(x_b, 0)}\right) - \frac{a\lambda + (1-a)\frac{f_0}{r}}{V_{0g}(x_b, 0)} \tag{13}$$

where $a = \left(\frac{x_b}{x_g}\right)^{\nu_g} < 1$.

Thus, even when the empirical researcher has access to the closest match possible, there is still a post-announcement difference in risk due purely to the issuance decision.

Empirical researchers use coarser information, and we focus now on pre-issuance size and book-to-market matching.[17] When $t = \tau_b$ and $Y_t = 0$, we find two types of firms that are potential matches. For one group, the demand state variable has not yet reached x_b, so type uncertainty remains. Matches from this group have a lower current demand state variable X_t, and in order to achieve the same pre-issuance market value as the issuing firm, must have a probability of being type g larger than Π_t^*, (the pre-issuance beliefs about the SEO firm). The second group has no residual type uncertainty because it has previously lost its growth option, and compensates in value by having a higher level of the demand state variable X_t. Because we know that market beta is a function of all these variables, we correspondingly expect systematic risk to be different for the matched sample.

Figure 2 further shows the changes in firm risk upon issuance, and the difference in risk between SEO firms and their matches. Here, β^* is the beta of the issuing firm, determined by a weighted average of the intrinsic betas of the two types. When an SEO occurs at time τ_b, risk decreases as a result of real option exercise. Relative to its ideal match, the post-issuance beta of the SEO firm is lower by the amount $\Delta\beta_{ideal}$.

4. Replicating Observed SEO Return Dynamics

In this section, we demonstrate that a reasonable parameterization of our model captures the pre-SEO price run-up, the negative announcement return, and the post-SEO underperformance that have been extensively documented in previous literature. These empirical regularities have motivated behavioral explanations such as the windows of opportunity theory. Our calibration shows that these findings are also consistent with a fully rational, dynamically consistent model of SEO decisions.

The specific moments we seek to match are taken from the recent survey by Ritter (2003). These are: (1) For the SEO sample an average return of 72% in the year prior to issuance; (2) An SEO announcement effect of -2%; (3) Five year post-SEO average annualized returns of 11.3%; and (4) Average five-year annualized returns for size and book-to-market matches of 14.7%.

[17] Loughran and Ritter (1995) match on pre-issuance size, while Eckbo, Masulis, and Norli (2000) match to pre-issuance size and book-to-market. This is consistent with the general methodology advocated by Barber and Lyon (1997).

In replicating these moments, we impose the restriction $f_0 = f_1 = 0$. Carlson, Fisher, and Giammarino (2004) emphasize the role of fixed costs in generating realistic size and book-to-market effects, so eliminating these components might seem to endanger the goal of obtaining a reasonable cross-section for matching. We find, however, that even with these restrictions, the current model has sufficient heterogeneity to capture return dynamics around seasoned offerings.[18] We are thus able to focus greater attention on the other parameters in the model. For a more elaborate analysis that emphasized additional moments such as accounting performance, the parameters f_0 and f_1 could play a more central role.

Without fixed costs, firm values are homogeneous in q_0, and we normalize to $q_0 = 1$. The parameters κ_0 and κ_1 also are not identified by return moments, and we specify their difference as $\lambda = \kappa_1 - \kappa_0$. When fixed costs are zero and with the weak condition that the distribution $\mathbb{P}(X_0/x_b)$ is independent of λ, firm value is proportional to λ, and hence λ does not affect returns.[19] Finally, the demand elasticity γ does not appear central to either our economic intuition or the quantitative matching of the moments above, and we choose $\gamma = 0.5$.

The parameters r, σ, and μ_M can be related to long-run averages from financial data. We set $r = 0.04$ annually, consistent with time series averages of t-bill rates. The parameter σ is set to 0.20, consistent with market portfolio return volatility. Finally, in the absence of fixed costs, setting the drift $\mu_M = \log(1 + 0.113)$ gives a risk premium of about 7%, and matches the post-event returns of SEO firms reported by Ritter.[20]

We use the simulated method of moments to estimate the three remaining parameters: the demand growth rate μ_X, the preemption intensity ρ, and the post-SEO output rate q_1. Since we use post-event returns of SEO firms to calibrate μ_M, three moments

[18] In CFG, operating leverage provides one of two sources of firm heterogeneity, along with the ratio of growth options to assets in place. At least two sources of heterogeneity are necessary to have separate size and book-to-market effects. Our model has an additional source of heterogeneity due to beliefs about firm type. Thus, even without fixed costs, there are two distinct sources of risk that give separate size and book-to-market effects, which is sufficient for the matching we seek to implement.

[19] To see this, denote $\xi_\theta = X_0/x_\theta$ and $\varphi_t = X_t/X_0$ and write $X_t = x_\theta \xi_\theta \varphi_t$. Substitute into equation (4) to see that intrinsic values are proportional to x_θ, which is in turn proportional to λ. Note also the economic meaning of the assumption that $\mathbb{P}(X_0/x_b)$ is independent of λ: For different λ, the initial distribution of $\log X_0$ must shift so that the distribution of stopping times to arrive at the critical investment level x_b remains unchanged. Without a shift, this property approximately holds when $\log X_0$ is drawn from a diffuse distribution (e.g., a uniform with large support or normal with large variance).

[20] This assumption is consistent with an interpretation that M represents the "market portfolio," or with our (weaker) explicit assumption that M captures the priced risk of the state variable X, and has a beta of one.

remain (runup, announcement, and post-event matched firm returns), and the model is exactly identified.

The basic idea of the estimation procedure is as follows: Given any set of the parameters (μ_X, ρ, q_1), we simulate a large cross-section of firms with a period of "burn-in" to randomize the initial draws, and then record returns for $T = 7 * 252$ days. We choose as sample firms those who have an SEO in their second year of observation (to ensure one year of returns prior to issuance and five subsequent). For each sample firm, we find the closest non-SEO size and book match on the SEO date and place these in a control group. We continue this procedure until we arrive at $N = 3,000$ sample and control firms, arranged in event time. Our objective is to minimize the distance between the mean simulated moments and those in the empirical data, after iterating over parameter values. Further details on the simulation, estimation, and matching algorithms are in the Appendix.

Table 1 summarizes our results. Panel A shows empirical values of the four primary return moments. For the run-up, we report the average return in excess of the risk-free rate for SEO firms in the year prior to issuance, which is 68%. The event return of -2% is in excess of the average daily market return. Finally, the post-event returns are five-year buy and hold net returns for issuers (70.9%) and their size and book-to-market matches (98.5%).

A broad range of parameter estimates generate close matches to the data. Rather than rely strictly on an arbitrary weighting function to provide one "best" set of parameter estimates, we instead use the search algorithm described in the appendix to identify an area of the parameter space with good and roughly equivalent results. We then report several from this area that appear economically interesting. This approach allows us to further explore the model through comparative statics and scenario analysis.

Panel B gives results for our primary calibration, which is a vector of round-number parameter values roughly in the middle of the area with closely matching moments. The reported demand growth rate μ_X is 7.5% per year, about halfway between the risk-free rate of 4% and the expected return on equity of 11.3%. The arrival intensity ρ that controls growth option loss is 20% per year. This implies that the average half-life for loss of a growth option is about 3.5 years. The output level for firms that have exercised their growth option is 4.0. This implies that growth option value is large relative to assets in place, consistent with the idea that SEO firms are generally small, growth firms. (See, e.g., Brav, Geczy, and Gompers, 2000). With these parameter values, the one year run-up in excess of the risk-free rate is approximately 49%. This is lower than the 68% reported by Loughran and Ritter (1995), but higher than the 47% two-year cumulative abnormal return reported by Lucas and McDonald (1990) and Koraczyk, Lucas, and McDonald (1990). The one-day event return of -2.19% is close to the value reported by Ritter (2003). Finally, the post-event buy and hold returns of 71.5% for issuers and 98.0% for matches are good approximations of the empirical moments. In parentheses we report simulation errors, which are small and show that $N = 3,000$ independent sample firms and matches are sufficient to estimate the true model moments with good precision. We thus find that the primary calibration accurately replicates the main features of the empirical run-up, announcement effect, and post-event returns for issuers and matches.

In Panel C, we conduct a sensitivity analysis of our results. By differentiating ν_θ with respect to μ_X, one can verify that increases in the growth rate of demand make the growth option less risky. When μ_X is larger, pre-event SEO firms and post-event matches have smaller returns, because the growth options both possess are less risky. We also see that when μ_X increases, the announcement return is more negative. This is because a higher demand growth causes firms to defer investment longer, so the wedge between intrinsic values is larger.[21] Increasing ρ raises the risk of the growth option, but decreases the value of growth options relative to assets-in-place. In the parameter region we are considering, the latter effect dominates, and the beta of pre-SEO firms decreases in ρ. When ρ increases the announcement effect is also more negative, again because the difference between intrinsic values is larger. Finally, raising q_1 increases the magnitude of all effects because growth options are proportionately more important.

In Panel D, we present a scenario analysis, which permits variations in all three parameters away from the primary calibration. The first four scenarios demonstrate that a variety of different parameters can give similar results for the simulated moments. The last two show that the model is also flexible in being able to produce large or small values of run-up, announcement effects, and underperformance.

We depict the return implications of our model in Figure 3, using parameters from the primary calibration. Panel A shows buy and hold abnormal returns over the entire SEO episode from year -1 to $+5$ in event time. Consistent with empirical practice, we report returns relative to a different control portfolio during each period. For post event returns we form zero cost portfolios on the event date, long \$1 in SEO firms and short \$1 in their matches. The abnormal return on the event date is measured relative to the market, as is standard practice. Because there is no standard benchmark during

[21] Alternatively, consider firms with very negative growth. Here, even type g firms will invest very soon after the project NPV is positive, and the wedge between the policies of type b and g firms is small.

the run-up (in fact run-ups are commonly reported in raw terms), we measure relative to the risk-free rate.[22] Figure 3 highlights that the facts motivating the windows of opportunity explanation are consistent with a purely rational real options theory, even to the extent of matching quantitative as well as qualitative characteristics.

5. Conclusion

We develop a model of seasoned equity offerings that leads naturally to a pre-issuance price runup, negative average announcement effect, and post-issuance underperformance of SEO firms relative to size and book-to-market matches. Previous literature has largely concluded that these features must be indicative of cognitive biases or persistent mispricing. We instead use a real options framework with rational expectations and dynamically consistent corporate decisions. This provides a close match to the primary empirical moments.

Our work is part of a growing literature that recognizes the importance of optimal dynamic behavior in explaining apparently anomalous financial phenomena. Other important contributions explain IPO waves (Pastor and Veronesi, 2004), optimal capital structure (Hennessy and Whited, 2004), cashflow constraints and investment (Gomes, Yaron, and Zhang, 2004) and the diversification discount (Gomes and Livdan, 2004). Our model is similarly specific to one particular corporate decision, but we focus attention on issues relevant to traditional and long-run event studies in many environments. We hope to motivate future empirical research to consider more carefully the null hypothesis of how returns should behave around corporate decisions. It is apparent to us that for many well studied corporate activities, the traditional view of a constant mean return may be difficult to justify. We thus view our work in the SEO setting as the first step towards a structural approach to event studies, which is one natural way to address the concerns that arise in dynamic environments.

[22]Benchmarking to the market, which would seem natural because it captures the risk premium, introduces an additional issue because market returns are correlated with firm returns. There is thus also a selection bias for market returns in the pre-event period.

Appendix

Proof of Proposition 1

The first term in equation (4) is the present value of the future stream of revenues from assets-in-place. The expression follows from the permanent nature of demand state variable shocks and from the optimal production policy (i.e. production at full capacity). The second term represents the present value of fixed costs.

The final term is the value of the firm's growth option and is derived as follows: Because τ_Y has exponential distribution, Y_t has the property $\hat{\mathbb{E}}_t(Y_{t+s}|Y_t = 0) = e^{-\rho s}$. Firms invest to maximize the value of the growth option. Let $\text{NPV}(X_t) = \left(\frac{q_1^\gamma - q_0^\gamma}{\delta}\right) X_t - \frac{f_1 - f_0 + \lambda r}{r}$ denote growth option value if immediately exercised, conditional on $Y_t = 0$. The objective is:

$$\max_s \hat{\mathbb{E}}[(1 - Y_{t+s})e^{-rs}\text{NPV}(X_{t+s})|\mathcal{F}_t] \tag{14}$$

The independence of Y_t and X_t allows us to first condition on Y_t, leading to the objective:

$$\max_s \hat{\mathbb{E}}_t[e^{-(r+\rho)s}\text{NPV}(X_{t+s})|\mathcal{F}_t] \tag{15}$$

The possibility of preemption is thus mathematically equivalent to a higher riskless interest rate.

Carlson, Fisher, and Giammarino (2004) show that the objective is maximized by a policy where investment is undertaken when the state variable X_t first achieves a critical level x. It is shown there that x has the form described in the proposition, with $\varepsilon = \frac{f_1 - f_0 + \lambda r}{(\nu - 1)r}$ and $\nu = \sqrt{(\frac{1}{2} - \frac{r-\delta}{\sigma^2})^2 + \frac{2(r+\rho)}{\sigma^2}} + \frac{1}{2} - \frac{r-\delta}{\sigma^2} > 1$. The value of the growth option is $V^G(X_t, Y_t) = \left(\frac{X_t}{x}\right)^\nu \varepsilon\,(1 - Y_t)$.

Type b and g firms differ with respect to the value ρ. We consider the special case where $\rho_g = 0$ and $\rho_b = \rho$. Direct inspection verifies that $\nu_b > \nu_g$ and $\varepsilon_b < \varepsilon_g$. To see that $x_b < x_g$, differentiate x with respect to ρ, and note that $\frac{-1}{(\nu-1)^2} < 0$ implies that $\frac{dx}{d\rho} < 0$.

Proof of Proposition 2

The probability that a firm is of type g is determined by Bayes' rule:

$$\Pi_t = \frac{\mathbb{P}(\theta = g, Y_t = 0|\mathcal{H}_t)}{\mathbb{P}(g, Y_t = 0|\mathcal{H}_t) + \mathbb{P}(b, Y_t = 0|\mathcal{H}_t)}.$$

Simple calculations give the result in the proposition.

Proof of Proposition 4

This follows immediately from the definition of S_i as the expectation of $V_{i\theta}$, conditioned on the investor information set $\mathcal{H}_t$.

Proof of Proposition 5

For the derivation of the intrinsic betas in equation (7) see Carlson, Fisher, and Giammarino (2004). Equation (8) follows from the fact that firm beta is the value weighted average of the underlying intrinsic betas.

Proof of Proposition 6

We wish to determine $\mathbb{P}(\ln X_t | s = \tau_\theta - t > 0)$. In the remainder of this Appendix, we suppress the subscript θ and define τ as the first hitting time of X_t at the level x.

If the distribution of $\ln X_0$ is normal and has high variance (i.e. diffuse), then Haussmann and Pardoux (1986) show that for fixed T the time reversed process $\{\ln X_{T-s} : s \geq 0, X_T = x\}$ is a Brownian motion with drift $-\mu$. This implies that $\ln X_{T-s}$ is normally distributed with mean $\ln x - \mu s$ and variance $\sigma^2 s$.

We apply Bayes' rule to additionally condition on the fact that τ is a stopping time:

$$\mathbb{P}(X_t = z | X_\tau = x, t = \tau - s, s > 0) = \frac{\mathbb{P}(\tau = t + s | X_t = z)\mathbb{P}(X_t = z | X_{t+s} = x)}{\int_{-\infty}^{x} \mathbb{P}(\tau = t + s | X_t = z)\mathbb{P}(X_t = z | X_{t+s} = x) dz}. \tag{16}$$

The following expression is given by Karlin and Taylor (1975, Theorem 5.3):

$$\mathbb{P}(\tau = t + s | X_t = z) = \frac{\ln x - \ln z}{\sigma\sqrt{2\pi s^3}} \exp\left[-\frac{\ln x - \ln z - \mu s}{2\sigma^2 s}\right].$$

Combine this expression with the normal pdf to see that the numerator of (16) is:

$$\frac{1}{\sigma\sqrt{4\pi s^3}}(\ln x - \ln z)\phi\left(\ln z; \ln x - \mu s, \sigma\sqrt{\frac{s}{2}}\right) \tag{17}$$

where $\phi(.)$ denotes the normal pdf. The definite integral of this expression is the denominator of equation (16), and equals

$$\frac{1}{\sigma\sqrt{4\pi s^3}}\left[\mu s \Phi\left(\sqrt{2s}\frac{\mu}{\sigma}\right) + \frac{\sigma^2 s}{2}\phi\left(0; -\mu s, \sigma\sqrt{\frac{s}{2}}\right)\right]. \tag{18}$$

Equation (10) is the ratio of (17) to (18).

Proof of Proposition 7

This follows from the definition of the announcement effect as a function of conditional expectations.

5.1. Proof of Proposition 8

We know that $\beta_{1\theta\tau_\theta} = 1 + (f_1/r)/V_{1\theta}(x_\theta, 0)$ and one can easily show that $\beta_{0\theta\tau_\theta} = 1 + [\lambda + (f_0/r)]/V_{0\theta}(x_\theta, 0)$. Value matching requires that $V_{0\theta}(x_\theta, 0) = V_{1\theta}(x_\theta, 0) + \lambda$. Simple algebra leads to the result.

5.2. Proof of Proposition 9

This follows from defining $\Delta\beta_{ideal} \equiv \beta_{1b\tau_b} - \beta_{0g\tau_b}$.

5.3. Calibration by Simulated Method of Moments

Denote the set of true model parameters by

$$\theta_0 = [\mu_X, \rho, q_1].$$

This section describes our estimation procedure.

For any candidate parameter vector θ, we use the following algorithm to generate simulated data:

1. Compute optimal investment policies and the firm value functions for this set of parameters using the results in Section 3.

2. Simulate N_p independent firms following the state variable dynamics in Section 2 at the daily level. We assume that initial beliefs about firm type are drawn exogenously from a uniform distribution on $[0.5, 0.8]$. Firm type is then drawn from a binomial distribution with probability of type g consistent with the initial beliefs. The initial demand level X_0 is drawn from a uniform distribution with support extending from three annualized standard deviations below x_b to x_b. This focuses the simulation on firms most likely to hit the investment region in a reasonable window of time. Select firms that conduct SEOs in the second full year of observation. Record their returns in event time, beginning one trading year prior to issuance and ending five years after issuance. Repeat until N_s sample firms are recorded. All sample firm returns are recorded in an event time return matrix R_s

of size $N_s \times T$ matrix, where $T = 6 * 252 + 1$ is the number of trading days in our observation period.

3. All firms that have not previously conducted an SEO are potential matches. For each sample firm, we match to a firm with identical book (since book is binary) and the closest match on size (market capitalization) on the date of sample firm issuance. Consistent with common empirical practice, a match is dropped if it conducts an SEO and replaced with the next closest match by the original criteria. This generates a matrix R_m of matched firm returns in event time. This matrix again has size $N_s \times T$.

4. Define a function $h(R_{mi}, R_{si})$ of statistics computed for any sample firm i and its match. In this study we focus on one-year pre-event returns in excess of the risk-free rate, one day announcement window returns of the sample firms in excess of the expected market return, and five-year buy and hold returns for SEO matches. (Recall that the post-event returns for SEO firms are used to calibrate μ_M.) Define the function $H(\theta) = \frac{1}{N_s} \sum h(R_{mi}, R_{si}) - \widehat{h}$, where $\widehat{h}$ denotes the empirical estimates (from Ritter, 2003) of the moments we are calibrating to.

5. For any positive definite weighting matrix W, we can define an objective function $G[H(\theta), W] = H'WH$. Minimizing G with respect to θ provides an estimator $\widehat{\theta}_{SMM}(W)$ for the model. Following Cochrane (1996), we allow W to be chosen by economic rather than statistical considerations. Specifically, we choose W to be diagonal with weight one on post-event match returns, weight 0.5 on the run-up, which is less often reported in the literature, and weight 10 on the announcement day return, because it is measured much more precisely than the other moments.

The algorithm above focuses attention on one particular set of estimates that optimize the objective function. Instead, we use a global search on a simplex and save iterations in the neighborhood of the minimized value of the objective function. These are reported in Table 1 to give a fuller picture of the comparative statics in our model and robustness of our results.

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TABLE 1. – SMM Calibration Results

Parameters			Moments			
					Post-Event	
μ_X	ρ	q_1	Run-up	Event	Issuers	Matches
			A: Empirical Moments			
			0.68	-0.02	0.709	0.985
			B: Primary Calibration			
0.075	0.2	4.0	0.4905	-0.0219	0.7151	0.9798
			(0.0052)	(0.0005)	(0.015)	(0.0229)
			C: Sensitivity Analysis			
0.0717	0.2	4.0	0.509	-0.0115	0.7116	1.0319
			(0.0052)	(0.0005)	(0.0152)	(0.0244)
0.0783	0.2	4.0	0.4596	-0.0343	0.7059	0.8947
			(0.005)	(0.0005)	(0.0148)	(0.0209)
0.075	0.1556	4.0	0.494	-0.013	0.7122	0.9962
			(0.0051)	(0.0005)	(0.0151)	(0.0241)
0.075	0.2667	4.0	0.4843	-0.0327	0.7088	0.9195
			(0.0052)	(0.0006)	(0.0147)	(0.0214)
0.075	0.2	3.11	0.468	-0.0144	0.7151	0.9269
			(0.0049)	(0.0004)	(0.015)	(0.021)
0.075	0.2	4.89	0.5086	-0.0278	0.7151	0.952
			(0.0054)	(0.0006)	(0.015)	(0.023)
			D: Scenario Analysis			
0.0739	0.1778	4.89	0.5191	-0.019	0.7084	1.0042
			(0.0054)	(0.0005)	(0.0151)	(0.0244)
0.0717	0.2889	3.33	0.4958	-0.0177	0.7146	0.9491
			(0.0052)	(0.0005)	(0.0149)	(0.0216)
0.0783	0.1333	4.67	0.4829	-0.0219	0.7153	0.9552
			(0.0052)	(0.0005)	(0.015)	(0.0219)
0.0717	0.2889	3.33	0.4958	-0.0177	0.7146	0.9491
			(0.0052)	(0.0005)	(0.0149)	(0.0216)
0.095	0.2	4.0	0.3631	-0.1149	0.7258	0.7464
			(0.0036)	(0.0003)	(0.0152)	(0.017)
0.0717	0.1333	4.0	0.5113	0.0003	0.711	1.1093
			(0.0051)	(0.0004)	(0.0152)	(0.0257)

Notes: This table gives calibration results for our model of return for sample firms and matches throughout the SEO episode. Panel A gives the empirical moments for runup, announcement effect, and long-run returns for sample firms and matches reported in Ritter (2003). Panel B gives parameters and simulated moments from our primary calibration. All simulated means are close to the empirical moments in Panel A. In parentheses below, we report the standard error of the simulation mean relative to the true model expected value, demonstrating that simulation error is small with the sample of 3000 sample firms and matches. Panel C varies each of the three parameters above and below the primary calibration values to demonstrate comparative statics. Panel D conducts scenario analysis, where all three parameters are varied simultaneously.

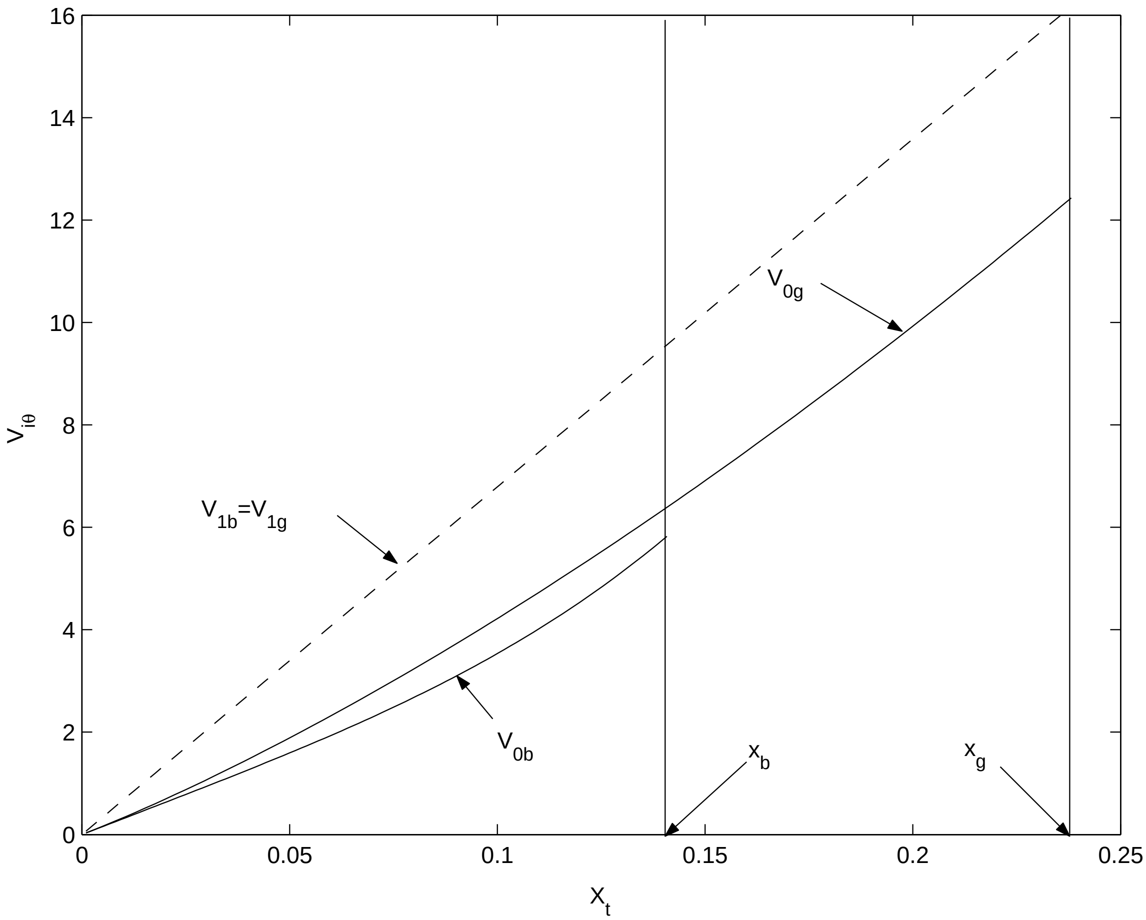

Figure 1: Intrinsic Values. This figure depicts the relationships between the state variable X_t and intrinsic values $V_{i\theta},\ i = 0, 1,\ \theta \in \{b, g\}$.

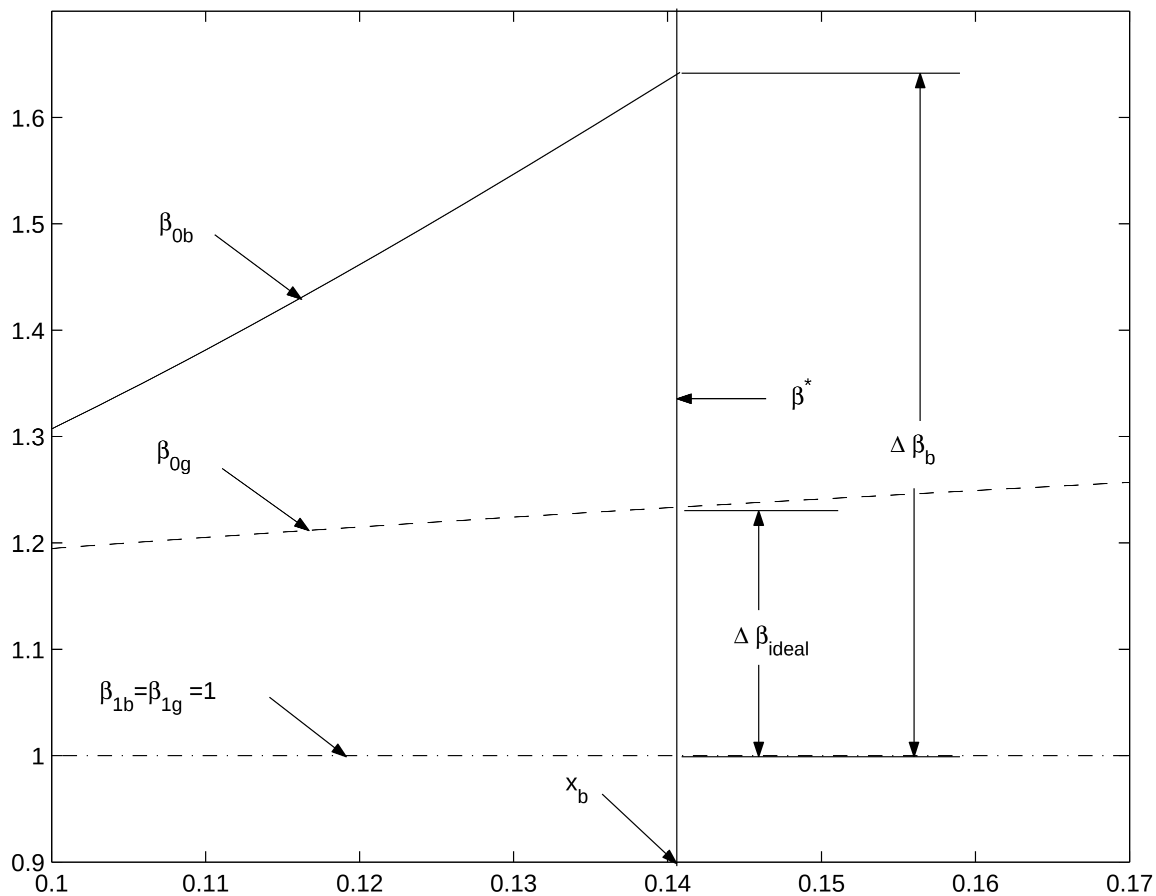

Figure 2: Systematic Risk of SEO Firms and Their Matches. This figure shows the relationship between the state variable X_t and the intrinsic betas. Intrinsic betas for type b firms drop by the amount $\Delta\beta_b$ when an SEO is announced. Relative to the ideal match, beta of SEO firms is lower by the amount $\Delta\beta_{ideal}$. The value β^* represents the riskiness of a firm just prior to the SEO decision. This value must be between the intrinsic betas.

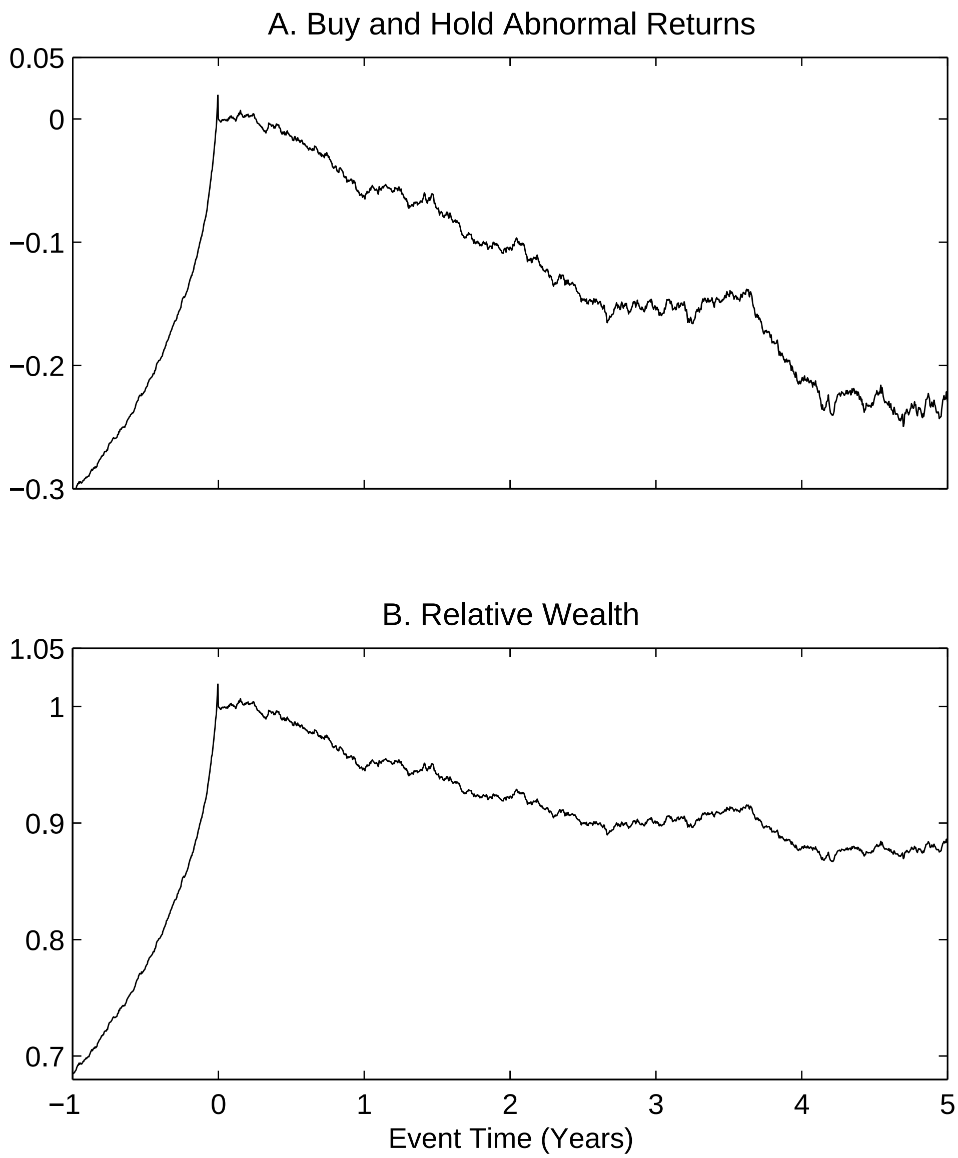

Figure 3: Simulated BHAR's and Relative Wealth. This figure shows that our real options model captures important features of the SEO episode as documented in the empirical literature: pre-SEO price runup, an event window negative announcement effect, and post-event underperformance relative to size and book-to-market matches. Panel A shows buy-and-hold abnormal returns, where different benchmarks are used in each subperiod reflecting common practice. In the post-announcement period, we calculate sample firm returns relative to size and book-to-market matches. The announcement day return is relative to the expected market return. The pre-announcement return is relative to the risk-free rate, consistent with our calibration. Panel B shows relative wealth, defined as the ratio of wealth from the buy-and-hold strategy in the sample firms relative to the benchmarks.