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

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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 (2004) 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. Explanation of these facts is not obvious, and in the leading theories, cognitive bias and persistent mispricing play a critical role.[2]

While finance should strive to capture more of what psychology has to tell us about behavior, progression of the literature also requires more careful consideration regarding the null hypothesis of a rational framework. In the SEO setting, no existing rational theory predicts how returns should vary throughout the runup, announcement, and post-issuance period. Our work fills this gap, providing a simple model of dynamic corporate decisions that captures not only the basic qualitative facts, but an almost exact quantitative match to the primary empirical moments.

Our approach is similar in spirit to Lucas and McDonald (1990), who develop a theory of pre-SEO price runups and announcement effects. While this earlier work uses a risk neutral setting, we allow for risk aversion and focus explicitly on the dynamics of risk-adjusted required returns. More generally, we build on real options models of corporate investment.[3] A rapidly developing literature including Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), and others[4] explores how optimal exercise and movements in underlying state variables affect expected returns. This previous work focuses on the cross-section of returns and asset pricing anomalies such as size

[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.

[3] This approach begins with Brennan and Schwartz (1985) and McDonald and Siegel (1985, 1986), and has been extended in many directions.

[4] See, for example, Carlson, Fisher, and Giammarino (2004), Cooper (2002), and Zhang (2004).

and book-to-market effects. By contrast, we emphasize time series consequences for corporate event studies.

The main idea of our story is transparent. Consider the canonical example of an expansion option: a manager follows demand growth in her product market. There are adjustment costs to increasing scale, so she waits until the option is sufficiently in the money before expanding plant size. Just prior to issuance, the firm is composed of assets in place and an option to expand. This is like a levered position in the expanded plant, and hence riskier. If growth is financed by equity issuance, then a logical consequence is that post-issuance expected returns are lower than pre-issuance. A real options perspective thus leads naturally to the implication that risk should drop discretely following an SEO. This story generalizes easily to multiple (compound) growth options, and even to expansion opportunities in product markets that are riskier than the assets in place.

The simple description above also accounts for a substantial pre-issuance price runup. Because real options are exercised only when they move sufficiently into the money, an SEO announcement will naturally be preceded by a period of above average abnormal returns. This is a direct consequence of *ex post* selection bias, as discussed by Brown, Goetzmann, and Ross (1995) and others in different settings.

To account for the negative average announcement returns at SEO issuance, we need introduce only one additional element. Lucas and McDonald (1990) use a dynamic version of Myers and Majluf (1984), in which managers seek to maximize value to long-term shareholders by selling equity after it has become overvalued. Although this standard adverse selection intuition is economically sensible, one of our goals in this paper is to provide a theory that can be solved in closed form. We thus introduce a simpler implementation in which managers are assumed to maximize intrinsic value of the firm without consideration for potential conflicts between different classes of investors. This abstracts from many interesting issues that arise in real-world settings, but delivers similar announcement effects to earlier literature. The result is a rich dynamic setting that provides closed form solutions for expected returns during all phases of the SEO episode. We specifically assume that firm type takes one of two values and is known only to managers. One type invests optimally as described above, while the second type faces the possibility of exogenously losing its growth option and hence invests earlier. This results in SEO announcement effects that, as in Lucas and McDonald (1990), may be positive or negative in any specific case, but on average must be negative due to a larger information effect from firms that announce early.

Our work relates to previous literature on partially anticipated events, including

Acharya (1988, 1993), Eckbo, Maksimovic, and Williams (1990), and Prabhala (1997). These authors make the important point that conditioning information about the likelihood of an event (or non-event) can often be useful to the empirical researcher. Our framework shows that the conditional probabilities that are the focus of these studies can naturally be derived from a dynamically consistent model of firm decisions.

More generally, we view our model as the first step in a structural approach to event studies. Typically, the runup, announcement effect, and post-announcement performance are studied independently of one another as purely empirical quantities. By contrast, we are guided by a model and can derive explicit characterizations of how all relate to a single set of model parameters. We can also analytically calculate how different types of empirical procedures, such as size and book-to-market matching, will or will not control for risk in our setting.

Fama (1998) discusses the "bad model" problem in the context of long-run event studies, and authors such as Brav, Geczy, and Gompers (2000) and Eckbo, Masulis, and Norli (2000) argue that certain adjustments to empirical specifications for returns can resolve SEO anomalies. We return to theory to develop and analyze one set of assumptions that provides reasonable empirical implications. Our intention is not to rule out other possibilities. In an area ripe with empirical work but almost completely lacking in truly dynamic theoretical predictions, our approach should instead be viewed as a productive first step in advancing to more realistic models with quantitative implications.

The general idea of linking SEOs to expected returns through investment is consistent with empirical evidence. Anderson and Garcia-Feijoo (2003) and Titman, Wei, and Xie (2004) provide empirical evidence that corporate investment is significantly related to subsequent underperformance. Without a theory to guide interpretation, researchers have been led to conclude that real investment followed by lower returns must be a sign of managerial overoptimism. In contrast, we find the decline in risk to be the natural consequence of the exercise of a real option.

A similar link between investment and equity issuance is critical in the rational IPO theory of Pastor and Veronesi (2004). Our work shares related goals and motivation, but the economic fundamentals driving the results are generally different. One similarity is that the runups in both cases are caused by *ex post* selection bias, which is natural since both are real options models of investment. On the other hand, Pastor and Veronesi focus primarily on aggregate moments such as the relation between IPO frequency and market returns. We instead analyze SEOs from a corporate event studies perspective, which includes announcement effects due to information asymmetries, and long-run performance relative to size and book-to-market matches. Our view is that the two approaches are complementary, and that a single model adopting elements from both could account for a wide range of puzzles from asset pricing and corporate event studies.

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

We develop a model that provides clear economic intuition for return patterns around SEO events. The model is of a firm that sells all of its output at exogenously determined stochastic prices. The firm is run by a value maximizing manager whose only decision is to expand output at the optimal time. All plant expansions are financed by the issue of new equity securities. It is assumed that the manager has superior information about the value of the expansion option.

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 $\mathcal{F}_0$.[5]

2.1. The Firm and Investment Opportunities

The firm produces a commodity that is sold in a monopolistic market, with downward-sloping iso-elastic demand given by:

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

where $0 < \gamma < 1$, X_t is an exogenous state variable, and Q_t gives the quantity choice of the firm. 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 $Q(K_t)$. We make a considerable simplifying assumption by allowing

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

only two capital levels, $\kappa_0 < \kappa_1$. The firm begins with capital level κ_0, and can irreversibly increase its scale by $\kappa_1 - \kappa_0$ at a cost $\lambda > 0$. This cost can be interpreted as adjustment cost, the price of new capital, or a combination of the two. It is natural to then define the associated process $D_t \equiv d\mathbf{1}_{\{K_t=\kappa_1\}}$, which represents the firm decision at time t of whether to invest.[6] This process takes a value of one at the instant the firm invests, and zero elsewhere. The firm also has in each period fixed operating costs $F_t = F(K_t) > 0$ that strictly increase in the capital level. For convenience, denote $f_i = F(\kappa_i)$. There are no variable costs of production. The instantaneous cash flows of the firm are thus $C_t = X_t Q_t^\gamma - F_t - \lambda D_t$.

The firm may be one of two types, distinguished by the characteristics of its expansion option. A type g firm has a growth opportunity that never expires. It can thus wait arbitrarily long to increase scale without endangering its investment option. The type b firm, on the other hand, risks losing its investment opportunity if it is not undertaken. Specifically, a Poisson process independent of all other variables governs the elimination of the growth option. Letting $\tau_Y > 0$ denote the first Poisson arrival, define the indicator function for a type b firm by[7]

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

Denoting the arrival intensity by ρ, we note that the unconditional probability that $Y_t = 0$ at time $t > 0$ is $e^{-\rho t}$. At any date t, if $Y_t = 0$ then firm b can expand in exactly the same manner as type g, but if $Y_t = 1$ type b can not invest. This assumption captures, in reduced form, the fact that some firms encounter greater preemption risk than others. Firm g faces no competitive threats and can wait to invest without concern for losing its growth option. Firm b risks losing its growth option to an unmodeled competitor while it is waiting to invest, but once it has invested, we assume it has itself preempted the competitive challenge, and is henceforth identical to a g firm with capital level κ_1. Because the threat of preemption imposes an additional cost on waiting to invest, we expect firm b to optimally increase scale sooner than firm g.[8]

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

[7] For type g, Y_t is trivially equal to zero for all t.

[8] We note that all of the results in the paper are essentially unchanged if the type g firms have a positive probability of losing their growth option, as long as it is lower than the probability for type b.

2.1.1. The Pricing of Risk

It aids valuation to permit 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 exactly reproduces the dynamics of firm value. This combination is called a replicating or hedging portfolio. It is natural to think of M as having a beta of one, so that the proportion of M held in the replicating portfolio determines the beta of the portfolio.

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 $dX_t = (r - \delta)X_t dt + \sigma X_t d\hat{z}_t$. This greatly simplifies firm valuation.

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 we assume he cannot communicate this information to shareholders. The manager chooses production and investment to optimize the discounted value of cash flows, without consideration for how his actions will influence the inferences of investors. The objective of the manager is thus 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.[9] By choosing this simple objective function, we easily generate our main results in closed form, and also observe that conflicts of interest are not necessary to obtain the return patterns commonly observed around SEO events.[10]

The manager chooses operating and investing policies to maximize the value of the

[9]It would be straightforward in this setting to give the manager a contract that would make this behavior optimal even when the manager accounts for the effect of his actions on investor inferences. This would involve penalizing for actions that are revealed to be suboptimal ex-post (e.g., Dybvig and Zender, 1996).

[10]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.

firm. Specifically, let $D : \Omega \longrightarrow \{0,1\}$ and $Q : \Omega \longrightarrow [0,\infty)$, both adapted to $\mathcal{F}_t$. The intrinsic value of the firm is then defined by

$$V_t \equiv \max_{D,Q} \hat{\mathbb{E}} \left\{ \int_0^\infty e^{-rs} C_{t+s} ds | \mathcal{F}_t \right\},$$

which is the date t present value of cash flows under the optimal policies and the information set of the manager. Using standard arguments, one can easily verify that V_t is a deterministic function of (X_t, Y_t, K_t, θ). It is therefore useful to define for $i \in \{0,1\}$ 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 production and investment policies. To choose optimal output conditional on the capital level, observe that operating revenue is $QP(Q) = XQ^\gamma$, increasing in Q. 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

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

which we note is independent of the state variable Y_t. Mature firm value is thus the present value of a risky, growing perpetuity, less the present value of a riskless perpetuity.[11]

Prior to maturity, firms hold one real option to expand, and the optimal policy is characterized by the demand level at which investment occurs. Let x_b and x_g respectively denote the values of X_t at which type b and g invest. It is also useful to define stopping times $\tau_\theta \equiv \inf \{ t : X_t \geq x_\theta \}$ to indicate when the demand process arrives at the critical levels x_b and x_g. An optimally chosen strategy maximizes a firm's intrinsic value at any point in time. 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

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

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

where expressions for ε_θ and $\nu_b > \nu_g > 1$ are in the Appendix, and ε_θ can be interpreted as the incremental value of firm expansion when undertaken.

The valuation expression contains three components, two of which are independent of firm type. The first is the value of a growing perpetuity generated by assets-in-place and is straightforward. The second term is the present value of future fixed costs associated with the current capital level, and has value identical to a fixed perpetuity.

The final term is the value of growth options. Type b firms invest earlier than type g firms. To understand this result, recognize that waiting to invest implies that the firm foregoes some current profits. These foregone profits are a cost of not investing, and must be offset by a more valuable timing option to motivate waiting. The option to defer investment for type b firms is less valuable since the growth option may disappear at any instant. As a result, the manager of firm b optimally investments at a lower demand level.

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, which is always the case. The growth option makes pre-SEO intrinsic firm 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 given by*

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

The intuition behind this result is simple. If the investment threshold for type b has been met at a previous date $\tau_b \leq t$ and the firm invested at that time, then the market infers with certainty that firm type is b. The same conclusion can easily be drawn if the investment opportunity is lost prior to date t. On the other hand, if at $\tau_b \leq t$ the firm did not invest, then the market infers that the firm type is g. Either of these events gives rise to an announcement effect that we describe in the next section. Finally, if none of these events occurs, then uncertainty remains regarding firm type, and investors revise their beliefs monotonically upward that the firm type is g. This is a "no news is good news" effect, whereby the passage of time without any discrete events leads investors to infer that the firm is less likely to be a type that can lose its growth option.

These observations lead us to think of the dynamic path of investor beliefs, which expresses the same ideas in terms of recursive updating:

COROLLARY 3: *Revisions to beliefs follow*

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

The first term is the "no news is good news" effect related to the passage of time. The second shows that when the firm loses its growth options then $\Pi_t = 0$. From the third term we see that when the investment threshhold x_b is reached, beliefs go immediately either to zero (if investment occurs) or one (if investment does not occur).

The significance of (6) is that it leads us to think of extending the existing notion of event studies. Previous authors such as Acharya (1988,1993), Eckbo, Maksimovich and Williams (1990), and Prabhala (1997) have made the important point that conditioning information about the likelihood of an event (or non-event) can often be useful to the empirical researcher. Our framework shows that the conditional probabilities that are the focus of these studies can naturally be derived from a dynamically consistent economic model of firm decisions. While the belief dynamics in (6) are fairly simple, it is easy to contemplate adding to their realism with additional sources of noise.

2.4. Market Value of the Firm and Expected Returns

Publicly traded firm market value is defined by

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

which is the expectation of intrinsic value conditioned on the public information available to investors. One can easily verify that market value is a function of the state variables, (X_t, Y_t, K_t), and of the current beliefs regarding firm type, Π_t. We recognize this dependency by defining for each capital level κ_i, $i = 0, 1$, a market value function $S_i(X_t, Y_t, \Pi_t)$. We then show

PROPOSITION 4: *Market value*

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

is a belief weighted-average of intrinsic values.

When $K_t = \kappa_1$, the firm has invested in the past. Intrinsic value thus consists only of assets in place, and is therefore independent of firm type. Although investors know firm type with certainty after investment takes place, beliefs have no impact on valuation for a mature firm. When $K_t = \kappa_0$, the firm may have previously lost its growth option, in which case $\Pi_t = 0$ and again the value of the firm is derived entirely from assets in place. Finally, if the firm has not yet invested and also not lost its growth option, investors have non-trivial uncertainty regarding firm type. In this case market value will be strictly between the full-information intrinsic values.

We can also infer expected returns from replicating hedge portfolios composed of the risky asset M and riskless bond B. This gives intuitive expressions for beta. First, define $V_\theta^G(X_t, Y_t) = (1 - Y_t) X_t^{\nu_\theta} \varepsilon_\theta / x_\theta^{\nu_\theta}$ as the value of growth options, and $V_i^F = f_i / r$ where $i = 0, 1$ as the present value of committed fixed costs. We are first interested in deriving 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 also 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 given by:*

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

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 $0 \leq \omega_t \leq 1$ *are given by:*

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

First examining the intrinsic beta, we note that it 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.[12] 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 the intrinsic values. Note that market beta stochastically evolves, driven by 1) underlying product market demand, 2) exogenous changes to growth options, 3) optimally timed investment, and 4) rationally updated investor beliefs.

In a simpler setting, Carlson, Fisher, and Giammarino (2004) show that operating leverage and growth options are sufficient to deliver separate size and book-to-market effects. Our current framework adds to that setting by permitting heterogeneity in the characteristics of firm growth options. We retain the size and book-to-market results of this earlier work, and document significant changes in expected returns following SEO's even after controlling for these characteristics.

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

A substantial literature has shown three empirical regularities around SEO events. First, prior to equity offerings, firm stock price tends to increase on average relative to benchmark firms. Second, the announcement of a seasoned offering tends to result in a short run negative announcement effect. Third, in the five years subsequent to an SEO, financial and operating performance tend to be low relative to seemingly comparable benchmarks. We now show that the model developed in Section 2 gives all of these results in a dynamically consistent rational expectations setting.

[12]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 in prior research (e.g., Brown, Goetzmann, and Ross, 1995). In our model, equity issuance funds new investment, which occurs after a sequence of positive shocks in the product market. We thus expect that in our environment selection bias will have a significant impact on 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 Berk, Green, and Naik (1998) there is no such effect, because investment opportunities arrive in an iid fashion, and must be accepted or declined immediately.

In much of the prior literature on selection bias, a statistical model of return dynamics and the inter-temporal sample selection criterion uniquely determines the magnitude of the bias. Our approach adds economic structure to the selection rule because we model SEO's as an optimally timed endogenous decision of the firm. Our economic model of real option exercise thus has implications for the magnitude and dynamics of the pre-SEO price run-up. We show in the Appendix that these quantities are related to

PROPOSITION 6: *The distribution of the state variable, X, at any date t prior to the first arrival at x_i,$i = g, b$ is given by:*

$$f(\ln X) = \frac{(\ln x_\theta - \ln X)\phi\left(\ln X; \ln x_\theta - \mu s, \sigma\sqrt{\frac{s}{2}}\right)}{\mu s \Phi\left(\sqrt{2s}\frac{\mu}{\sigma}\right) + \frac{\sigma^2 s}{2}\phi\left(0; -\mu s, \sigma\sqrt{\frac{s}{2}}\right)} \tag{10}$$

where the support of the distribution is $X < x_\theta$, the function $\Phi(\cdot)$ is the standard normal CDF, the function $\phi(\cdot)$ is the normal PDF, $\mu = \mu_X - \frac{1}{2}\sigma^2$ adjusts the drift for Jensen's inequality, and $s = \tau_\theta - t$.

We observe that the distribution of the state variable is bounded above by x_θ, reflecting the selection bias in conditioning on the SEO event. The distance between the mean and x_θ is proportional to the amount of time s 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 are composed of a capital gain component and a dividend, we are thus able to calculate in closed form only the capital gain component. We can fully characterize conditional expected returns by numerically integrating path by path over realizations of the state variable X and accumulating dividends. We defer this exercise until Section 4, which conducts simulation based analysis of the model, including prior period returns for SEOs.

3.2. SEO Announcement Effect

Announcement effects associated with SEO's have been widely studied, and the average abnormal return is about -2%.[13] The traditional explanation for this finding is adverse selection, in which firms that issue reveal that their intrinsic value is lower than 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.

The announcement effects in our model are similarly driven by the release of negative information about intrinsic value. We achieve this, however, while assuming that managers time investment and equity issuance to maximize intrinsic value, without consideration for conflicts between different classes of investors. This abstracts from many interesting issues that arise in real-world settings, where managers' objectives are complex, contracts are second-best, and strategic interaction between managers and investors can be difficult to model. We obtain the same qualitative announcement effects as earlier literature, but in a rich dynamic setting that provides implications for expected returns during all phases of the SEO episode.

To explicitly describe the link between model parameters and market reaction, it is useful to define the *decision-censored history* $H_t^* \equiv \left([X_s, Y_s, s]_{s \leq t}, [K_s]_{s<t} \right)$, which includes all information normally available in H_t to investors at date t, except the current capital level. We note that this prevents investors from deducing the current investment decision D_t. Consistent with previous notation, $\mathcal{H}_t^*$ is the σ-algebra generated by H_t^*. It is then natural to define the *announcement effect*

$$AN_t\left(D_t\right) \equiv \frac{\mathbb{E}[S_t|\mathcal{H}_t^*, D_t] - \mathbb{E}[S_t|\mathcal{H}_t^*]}{\mathbb{E}[S_t|\mathcal{H}_t^*]}.$$

This quantity is the percentage movement in price that is explained purely by the date t announcement of the investment decision. We note that, similar to Eckbo, Maksimovich,

[13]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.

and Williams (1990), a decision not to invest is potentially just as informative as a decision to invest. We also define

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

which are beliefs conditioned on the information set $\mathcal{H}_t^*$ that omits the date t investment decision. We then show in the Appendix

PROPOSITION 7: *Announcement effects are described by*

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

This result is intuitive and relates to the dynamics of the belief updating process (6). Since $x_b < x_g$, the only time that the investment decision resolves uncertainty about firm type is when the boundary x_b is first reached and the firm has not lost its growth option. In this case, beliefs about firm type jump either to 0 if investment occurs or to 1 if investment does not occur. This revision in beliefs is accompanied by a discrete jump in firm value, which is positive if the firm is revealed to be type g and negative for type b. The magnitudes of price movements are proportional to the size of the change in beliefs. The higher is the prior probability that firm type is g, the more negative the announcement effect will be if the firm invests. Announcement effects also have larger magnitudes when the difference in intrinsic values for g and b type firms is bigger at x_b.

At any time other than $t = \tau_b$, announcement effects are zero because beliefs move predictably. This is true in particular when type g firms invest at τ_g. By the time the g firm reaches τ_g investors have already learned its type and are not surprised by the investment decision. In an empirical study of the SEO's from this model, the sample will consist of both type b firms that have issued with a negative announcement effect and type g firms that have no announcement effect. The average announcement effect will thus be determined by the composition of each type in the sample, and must be negative. We further pursue the empirical implications of announcement effects in Section 4.

Figure 2 illustrates value changes on the announcement date τ_b. The market price S^* is between the two intrinsic values V_g and V_b. If the firm announces an SEO, market value drops immediately to V_b, and if no announcement is made, investors learn that the firm is type g and value increases accordingly. The magnitude of the effect is determined by beliefs Π^* just prior to reaching τ_b and the size of the difference between V_g and V_b.

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 effects explicitly in our model.

3.3.1. Changes in Risk and Expected Return

The previous literature has considered two distinct channels through which SEO proceeds may change equity risk. Clearly, stock issuance decreases financial leverage, mechanically reducing risk as in Hamada (1972).[14] Because we model an all-equity firm, none of our effects are driven by this purely financial explanation. Instead, we analyze a setting where the investment associated with SEO's causes a more fundamental change in total firm, rather than equity, risk. This explanation has not previously been considered in a theoretical setting.[15]

Earlier work has put forth unmodeled intuition to support our notion that investment can discretely change firm risk. For example, Ritter (2004) comments, "It is, however, 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." We depart from this intuition by showing that, if the possibility of an expansion is rationally anticipated, then the effect must be to *decrease* risk. This is because the

[14]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.

[15]Although investment timing is central to the real options literature, this analysis typically uses a risk-neutral pricing kernel where changes in risk are not the focus. See, e.g., Lucas and McDonald (1990). A more recent literature including Berk, Green, and Naik (1998), Gomes, Kogan, and Zhang (2003) and others explicitly allow investment to change firm risk, but their focus has been on the cross-section of returns rather than event studies.

option to increase scale is like a levered position in the larger firm, and exercising the growth option therefore reduces risk.

Following this logic, we denote the intrinsic beta change $\Delta\beta_{\theta t} \equiv \beta_{1\theta t} - \beta_{0\theta t}$, which occurs at equity issuance, and show

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 so that $f_0 = f_1 = 0$. 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 operating leverage is present, an additional term strengthens this effect. This may seem surprising, since our initial intuition might be that more operating leverage should be associated with 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 assets in place are extremely risky for the mature firm, it is still the case that an option on those assets is even 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. Our framework additionally permits careful theoretical analysis of both optimal matching as well as properties of the commonly used empirical procedures.

At any point in time, the history H_t of a firm identifies it to investors. An agent interested in obtaining a set of benchmark firms to match against will naturally partition the firm history into the decision D_t and the decision-censored history H_t^*. The agent might ideally like to know how the same firm would have behaved if all identifying information in H_t^* were held constant, but the decision D_t was different. Alternatively, perhaps due to practical limitations, the agent might only seek to hold constant some function $\Gamma(H_t^*)$ of the history. This suggests we define the *matching set*

$$MA_\Gamma(D_t, H_t^*) \equiv \{H \in \mathcal{H}_t : D(H) \neq D_t, \Gamma(H^*) = \Gamma(H_t^*), H^* = H \backslash D_t\}.$$

If the conditioning function is trivial so that $\Gamma(H^*) = H^*$, the agent holds constant in the matching set all characteristics of the firm except the decision. This is the ideal "counterfactual" of experimental science – what the firm would have been if it had only changed this one decision. In our environment, this set is often empty. 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 match to the investing firm with $D_t = 1$ has identical size, book-to-market, and age, just prior to t but does not invest. The decision separates firm types. Type b invests while type 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*

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

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 decision of whether to issue.

The empirical researcher more typically uses much coarser information to condition its match, for example matching to size only, or to size and book-to-market.[16] In our setting where there are more than two sources of firm heterogeneity that affect expected returns, matching on size and book-to-market alone may give rise to systematic biases, as we now show. We first seek to define the equity value and book value that we would match to under the standard procedures. Denote for $\theta \in \{b, g\}$ the *size match value* $S_t^* \equiv \mathbb{E}\left[S_t | \mathcal{H}_{\tau_\theta}^*\right]$. This represents the equity value that would be observed if, at decision point $t = \tau_\theta$, the market has access to all current information except the firm's announcement of whether it will issue securities. Furthermore, since all firms that have not issued have not invested, book value prior to $t = \tau_\theta$ will be κ_0. The conditioning function is then $\Gamma(H^*) = (S_t(H^*), K_t(H^*))$, and the matching set is characterized by

[16]For example, 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).

Proposition 10: *When* $t = \tau_b$ and $Y_t = 0$, *matching on size and book-to-market gives the set* $MA_\Gamma\left(D_t, H_t^*\right) = \left\{\omega : X_t \leq x_b, \Pi_t = \frac{S_t^* - V_{0b}(X_t,0)}{V_{0g}(X_t,0) - V_{0b}(X_t,0)}\right\} \cup \left\{\omega : V_{0b}\left(X_t, 1\right) = S_t^*\right\}$.

Matching firms thus have by definition the same equity value, but systematically have a lower plant size K_t. One group of matches has residual type uncertainty, lower current demand state variable X_t, and compensates in value because investors attach a higher probability to them being of type g than the sample firm. These matches are thus systematically older. 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.

This proposition is illustrated in Figure 3. Using the same parameters as previously, we see that the set of potential matches who have not lost their growth option is described by firms with higher probabilities Π of being type g and lower values of the demand state variable X.

Figure 4 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, β falls as investors learn the firm is of type b and the real option is exercised. Relative to its ideal match, the post-issuance beta of the SEO firm is lower by the amount $\Delta\beta_M$.

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 development of behavioral explanations such as the windows of opportunity theory. Our calibration shows that these findings can also be interpreted in the context of a fully rational, dynamically consistent model of SEO decisions.

The specific moments we seek to match are taken from the recent survey by Ritter (2004). 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) Size and book-to-market matched five year average annualized returns of 14.7%.

In replicating these moments, we analyze the restricted version of our model where $f_0 = f_1 = 0$. Carlson, Fisher, and Giammarino (2004) emphasize the role of fixed costs in generating realistic size and book-to-market effects, so at first 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.[17] 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.

With the above restrictions on fixed costs, firm values are homogeneous in q_0. We therefore arbitrarily choose the normalization $q_0 = 1$. The demand elasticity γ also 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. The riskless interest rate is set to $r = 0.04$ 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, the post-event returns of SEO firms reported by Ritter are exactly matched by setting the drift $\mu_M = \log(1 + 0.113)$.

The parameters κ_0 and κ_1 are not identified by return moments, and their particular values do not affect matching since book value is binary. We specify $\lambda = \kappa_1 - \kappa_0$, and this difference has the potential to affect returns. 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 linearly homogeneous in λ, and hence in this case returns are not affected.[18]

A simulated method of moments approach is adopted to estimate the values of the three remaining model parameters: the growth rate of demand μ_X, the intensity of the growth opportunity loss process ρ, and the post-SEO output rate q_1. The basic idea is that for any potential set of these three parameters, we simulate a large cross-section of

[17]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. The model in the current paper 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.

[18]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).

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 the SEO 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 function minimizes the distance between the mean simulated moments (runup, announcement, and post-event returns for sample and matches) and those observed in the empirical data. This procedure is iterated for different values of the model parameters. Further details on the simulation, estimation, and matching algorithms are in the Appendix.

Table 1 reports parameter estimates and the corresponding simulated moments. In Panel A, we report empirical values of the four moments to be matched. 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, roughly halfway between the risk-free rate of 4% and the expected return on equity of 11.3%. The arrival intensity ρ that controls loss of growth options 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% run-up 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 almost exactly as reported by Ritter (2004). Finally, the post-event buy and hold returns of 71.5% for issuers and 98.0% for matches are also extremely close to the empirical moments. In parentheses below we report simulation errors for the moments, which are quite 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 is able to accurately replicate 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. Differentiate ν_θ with respect to μ_X to see that increases in the growth rate of demand make the growth option less risky. We thus observe that when μ_X is larger, both the pre-event run-up and the post-event return for matches are smaller. This is because neither pre-event SEO firms nor post-event matches have exercised their options to expand. We also see that when μ_X increases, the announcement return is more negative. This is because a higher demand growth causes firms to optimally want to defer investment longer. 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 type g firms is small. But when μ_X is large, the wedge in optimal policies (and values) is larger, and hence learning that the firm is type b causes a more negative announcement effect. Increasing ρ has similar effects, but with different magnitudes. The run-up and post-event returns for matches both decrease, but the logic is different: an increase in ρ increases the risk of the growth option, but at the same time, the value of growth options relative to assets-in-place decreases. In this region, the latter effect dominates, and the beta of pre-SEO firms decreases in ρ. The announcement effect is more negative when ρ increases, which is again explained because differences in intrinsic value between type b and g firms are larger. Finally, we consider increases in q_1, which 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 quite flexible in being able to produce large or small values of run-up, announcement effects, and underperformance.

We summarize the effects of our model in Figure 5 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. During different periods, different control portfolios are utilized, which is consistent with the literature. For example, 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 the run-up (in fact run-ups are commonly reported in raw terms), we measure relative to the risk-free rate.[19] An important message conveyed by Figure 5 is that the facts motivating the windows of opportunity theory can be captured in a purely rational real options setting, 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 rational expectations framework with dynamically consistent corporate decisions and investor behavior. This provides an almost exact quantitative match to the primary empirical moments.

The economics underlying our theory are surprisingly simple. Consider a manager facing stochastically evolving product demand, who must choose when to expand capacity in the presence of adjustment costs. Prior to increasing scale, firm value consists of assets in place and a growth option. This is like a levered position in the expanded plant, and hence riskier. If equity issuance finances firm growth, then a decrease in expected returns is the logical consequence of issuance. To explain announcement effects, we add 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 an SEO in our environment is bad news. Finally, a pre-issuance price runup occurs due to *ex post* selection bias. Issuance occurs only after the growth option moves substantially into the money, implying recent positive shocks to returns. We obtain all of these results with one set of parameters in a unified rational framework.

Our work is also relevant to the literature on conditional event studies. Previous methodological contributions have considered corporate decisions such as SEOs that are partially anticipated by the market. Conditional expectations are formed, however, only for a snapshot in time when the event occurs, and there is no consideration for how these may relate to previous beliefs. In contrast, we explicitly derive the evolution of

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

investor beliefs over the entire SEO episode, and hence our model of investor anticipation is dynamically consistent. We anticipate that this approach can be extended to 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.

Finally, we analyze the standard practice of using size and book-to-market matches to control for risk. In our setting, these characteristics provide a partial but incomplete characterization of expected returns. Our conclusion is that using one empirically motivated model of returns to control for risk in every corporate event study can potentially be misleading. Theory can provide better guidance about how expected returns should relate to firm characteristics in specific circumstances.

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.

Appendix

Proof of Proposition 1

The first term in equation (4) represents the discounted present value of cashflows 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 the fixed cost component.

The final term is the value of the firm's growth option and is derived as follows. Given the independence of Poisson increments, the conditional expectation of Y_t is given by $\hat{\mathbb{E}}_t(Y_{t+s}) = e^{-\rho s}$. Firms invest so as 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 the value of the growth option if immediately exercised, conditional on $Y_t = 0$. The objective is:

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

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

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

The possibility of the investment opportunity disappearing is, thus, mathematically equivalent to the effect of 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 $\varepsilon = \frac{f_1 - f_0 + \lambda r}{(\nu - 1)r}$ where $\nu = \sqrt{(\frac{1}{2} - \frac{r-\delta}{\sigma^2})^2 + \frac{2(r+\rho)}{\sigma^2}} + \frac{1}{2} - \frac{r-\delta}{\sigma^2} > 1$. The value of the growth option is given by $V^G(X_t) = \varepsilon\left(\frac{X_t}{x}\right)^\nu$.

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:

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

Denoting the prior probability of type g firms by Π_0 and noting that the arrival intensity of the Poisson process Y_t is ρ, we have

$$\Pi_t = \frac{\Pi_0}{\Pi_0 + (1 - \Pi_0)e^{-\rho t}}.$$

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

Let τ denote the time at which the state variable X_t first reaches the level x. We wish to determine the distribution of the state variable at any time s prior to that event, i.e. $\Pr(X_{\tau-s}|X_\tau = x)$.

If the distribution of X_0 is normal and has high variance (i.e. diffuse), then Haussmann and Pardoux (1986) show that the time reversed process $\{X_{T-s} : s \geq 0, X_T = x\}$ is a Brownian motion with drift $-\mu$. This implies that when conditioning only on $X_\tau = x$, importantly not on the fact that τ is a stopping time, $\ln X_{\tau-s}$ is normally distributed with mean $\ln x - \mu s$ and variance $\sigma^2 s$.

Apply Bayes rule to determine the distribution conditional on the fact that X_t first reaches x at τ:

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

The following expression can be found in Karlin and Taylor (1975, Theorem 5.3):

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

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, as indicated in the denominator of equation (16), can be shown to equal:

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

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 $\beta_{0\theta\tau_\theta} = 1 + [\lambda + (f_1/r)]/V_{0\theta}(x_\theta, 0)$. 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. 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 sample firms and their matches. 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, 2004) 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 normalized weights of one on the post-event match and sample firm 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 (2004). 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. This shows that a variety of calibrations are roughly consistent with the empirical evidence.

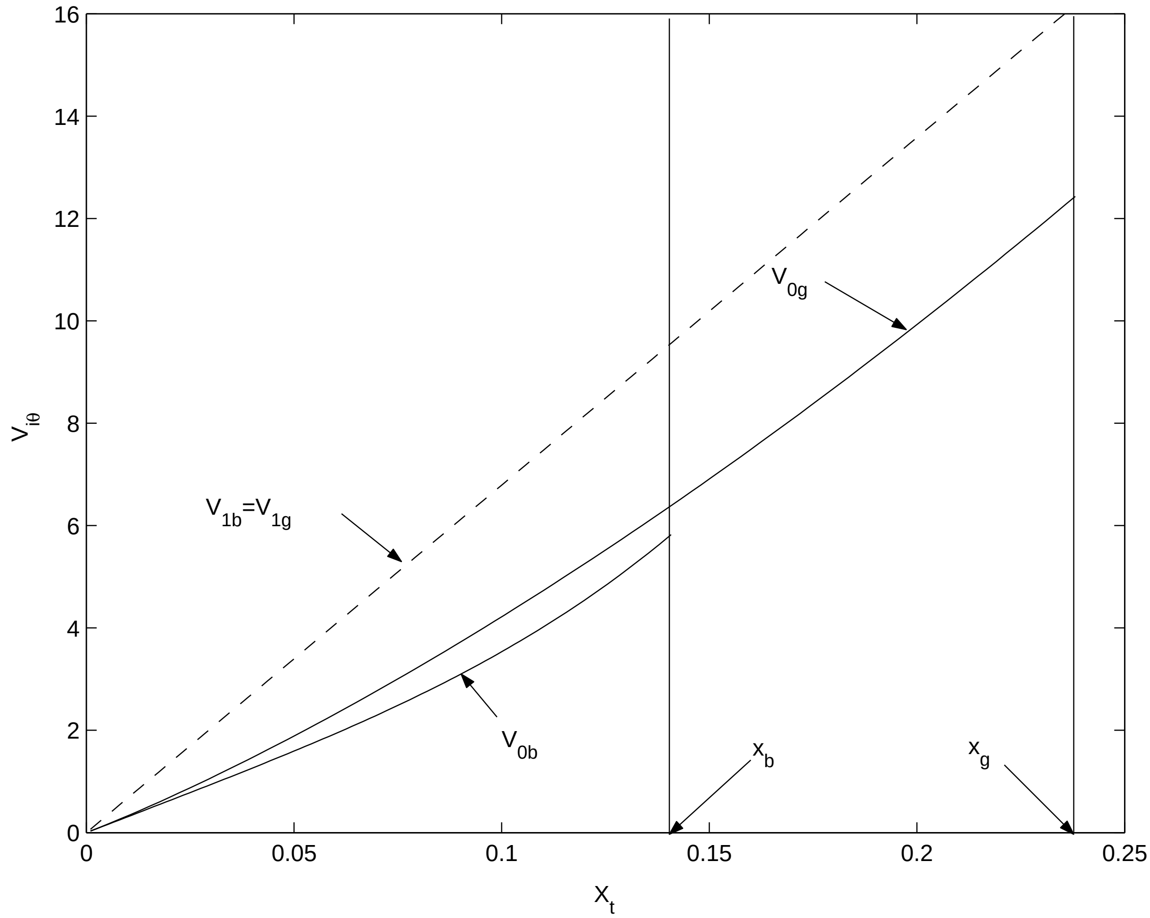

Figure 1: Intrinsic Values. This figure depicts the relationships between the state variable X_t and intrinsic values $V_{i\theta}$, $i = 0, 1$, $\theta \in \{b, g\}$.

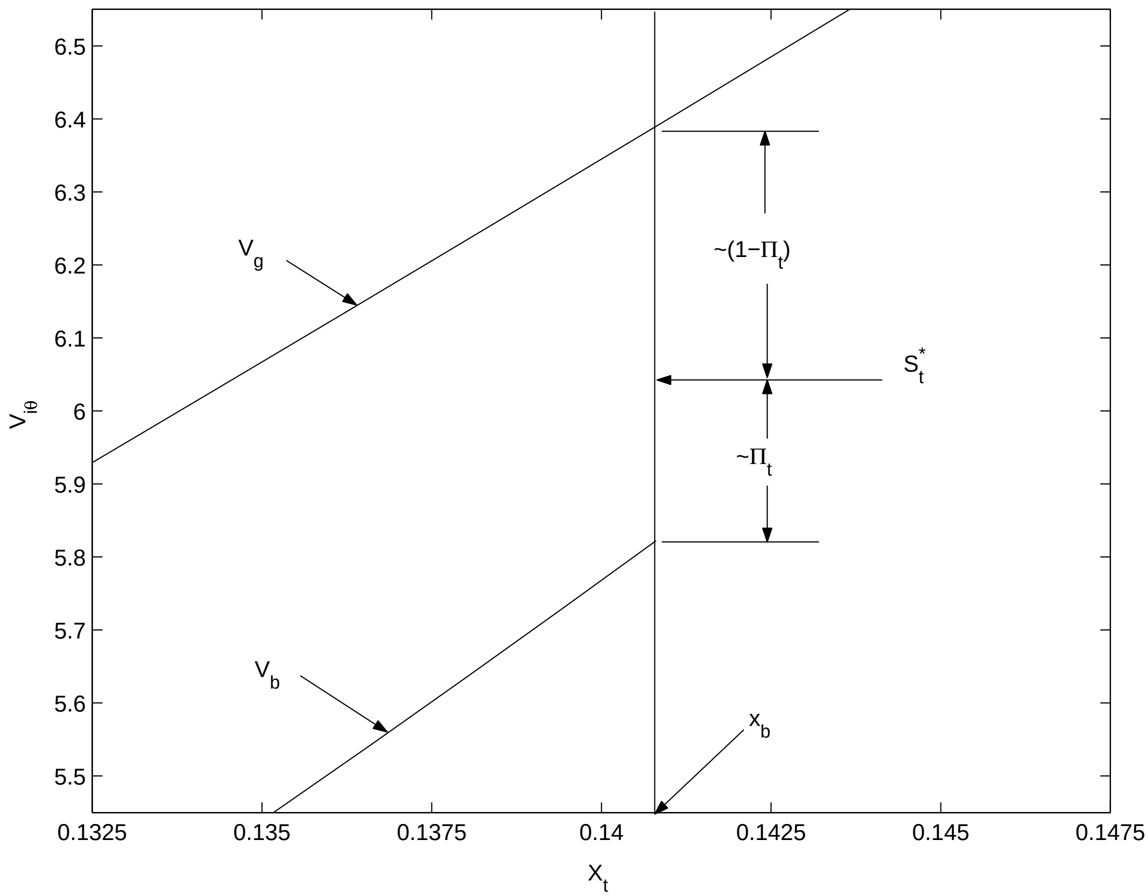

Figure 2: SEO Announcement Effects. This figure shows the relation between the state variable X_t and intrinsic values around x_b. Just prior to issuance, firm value is S_t^*, a belief-weighted average of the intrinsic values V_g and V_b. Announcement of an SEO leads to a reduction in value, whereas no announcement leads to an increase.

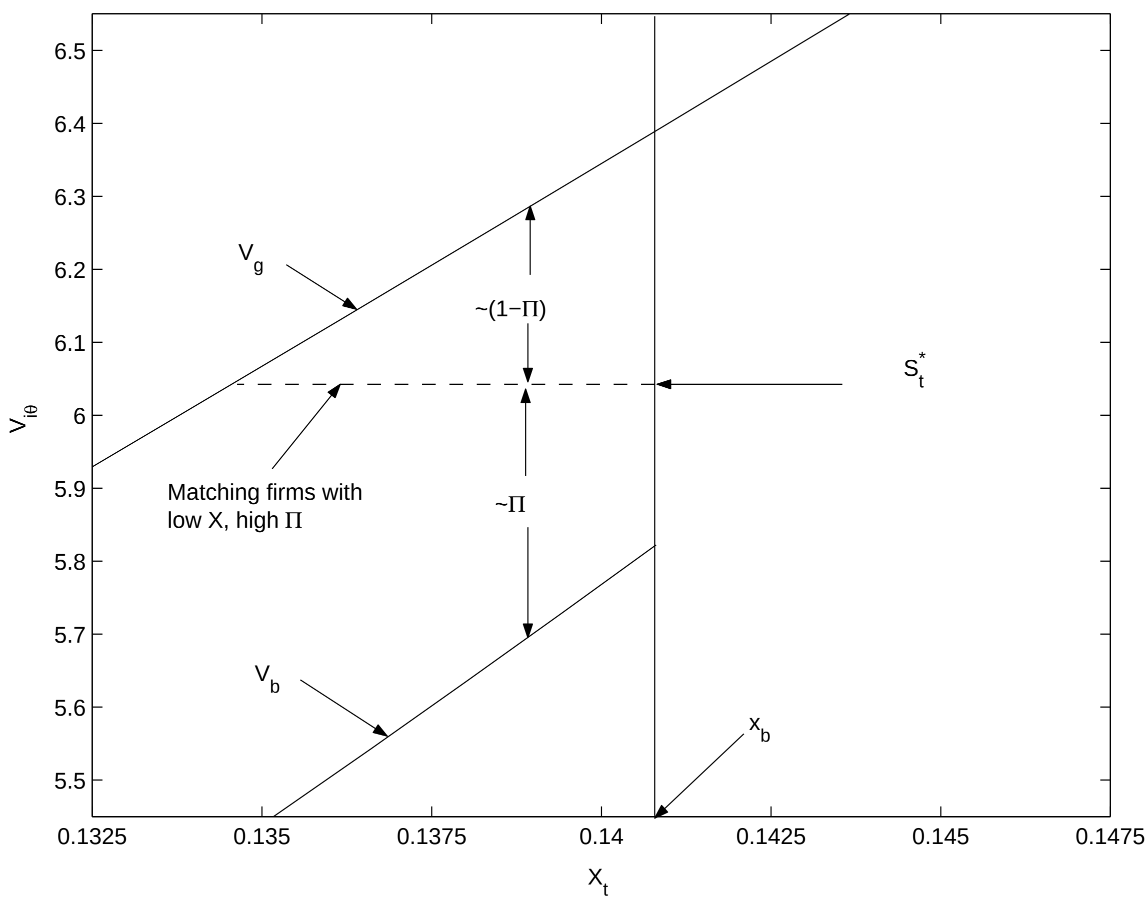

Figure 3: The Set of Potential Matches. This figure shows the relationship between the state variable X_t and intrinsic values V_g and V_b in the neighborhood of x_b. Non-issuing matching firms are located along the dashed line. These have identical market value S^*, and achieve this by having systematically lower demand state variables X_t combined with higher beliefs Π of being type g.

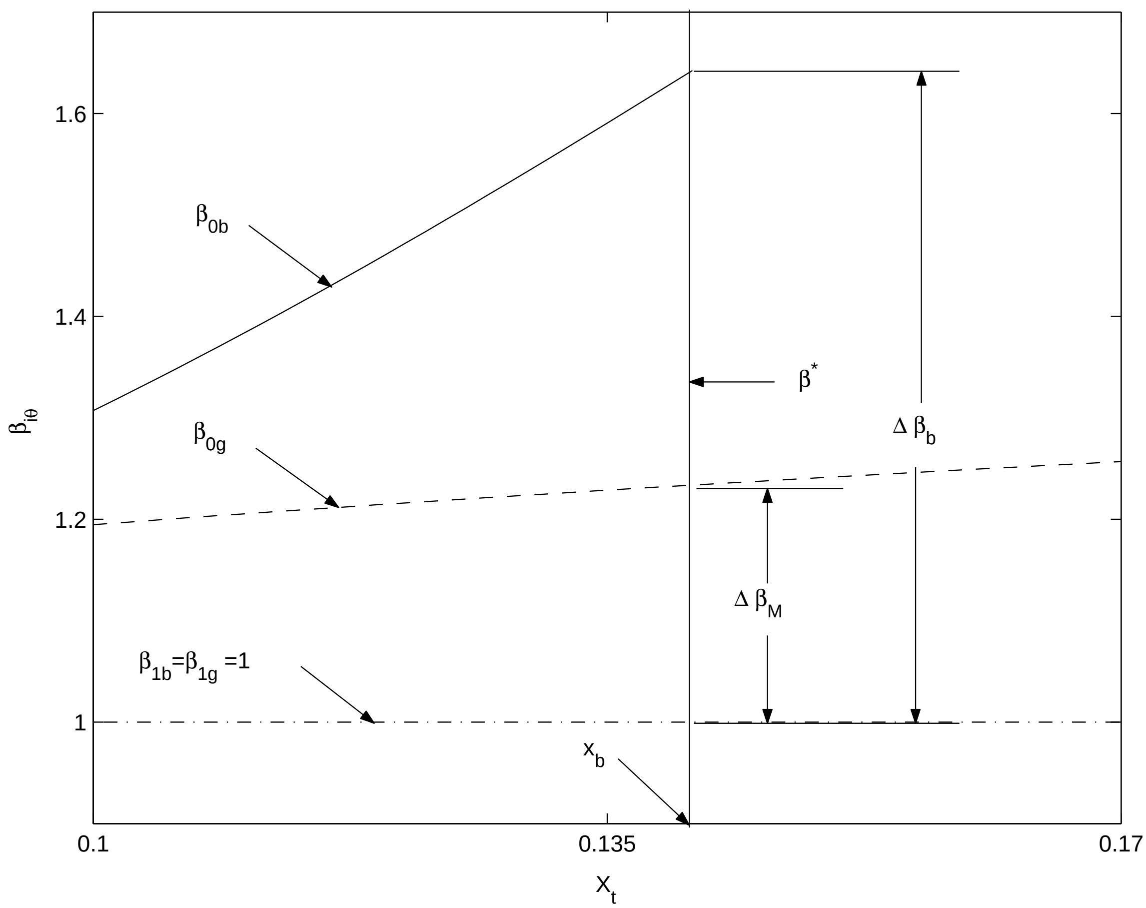

Figure 4: Systematic Risk of SEO Firms and Their Matches. This figure shows the relationship between the state variable X_t and the intrinsic betas. Intrinsic betas for type b firms drop by the amount $\Delta\beta_b$ when an SEO is announced. Relative to the ideal match, beta of SEO firms is lower by the amount $\Delta\beta_M$.

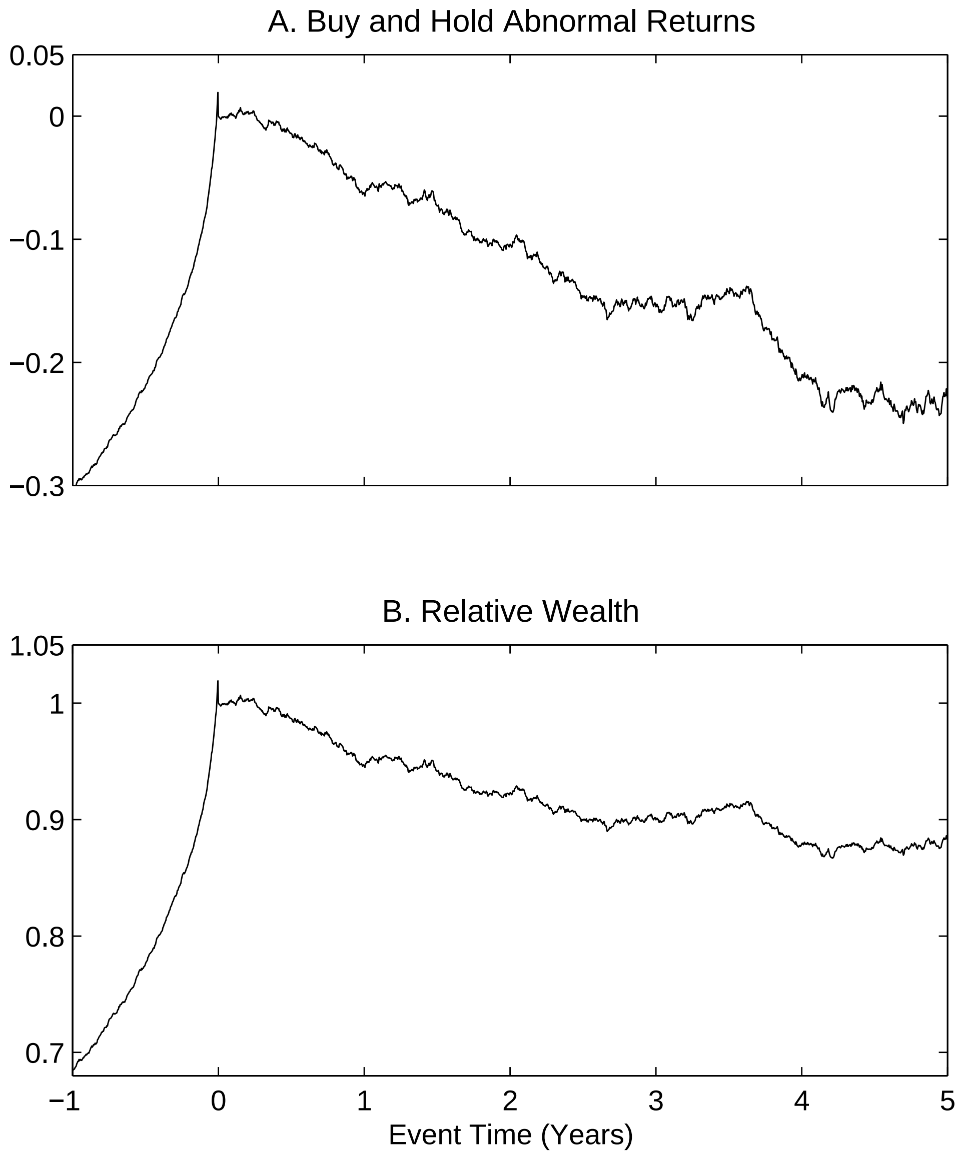

Figure 5: Simulated BHAR's and Relative Wealth. This figure shows that our real options model captures important features of the SEO episode as documented in the empirical literature: pre-SEO price runup, an event window negative announcement effect, and post-event underperformance relative to size and 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.