IPO Pricing and Share Allocation: The Importance of Being Ignorant

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ABSTRACT

Since an underwriter sets an IPO's offer price without knowing its market value, investors can acquire information about its value and avoid overpriced deals ("lemon-dodge"). To mitigate this well-known risk, the bank enters into a repeat game with a coalition of investors who don't lemon-dodge in exchange for on-average underpriced shares. We: 1) derive and test a quantitative IPO pricing rule (showing that tech IPOs were not excessively underpriced during the boom of the 1990s); and 2) analyzing a unique multibank data set, find strong support for the conjecture that a bank preferentially allocates shares to its coalition.

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I do not approve of anything that tampers with natural ignorance. Ignorance is like a delicate exotic fruit; touch it and the bloom is gone.

Lady Bracknel (Gwendolen's lead manager), *The Importance of Being Earnest*

The marked variation in average IPO initial returns (or underpricing) across time and across issuer types (e.g., tech firms and non-tech firms) has thus far eluded explanation. Some theories seek to explain the fact of underpricing (most notably, the information extraction theory developed by Benveniste and Spindt (1989) and Benveniste and Wilhelm (1990)), but these theories cannot account for the variation in underpricing we observe. Other theories seek to identify factors that might increase or decrease underpricing relative to what it would otherwise have been (e.g., Loughran and Ritter (2002), Ljungqvist and Wilhelm (2003)), but these theories take the fact of underpricing as given. However, there is no theory of which we are aware that both explains why underpricing exists in equilibrium and predicts that average initial returns will vary on the scale that is observed. In this paper we derive and test a parsimonious *quantitative* IPO pricing rule by drawing upon Kenney and Klein's (1983) analysis of block-booking. Using this rule, we find that we can largely explain the time-series and tech firm/non-tech firm variation in average initial returns over the 1986 to 2006 period–including the extremely high average initial returns on tech firms at the height of the IPO boom in the late 1990s.[1]

Our analysis follows the "asymmetric information/(potentially) informed investors" path pioneered by Rock (1986), Benveniste and Spindt (1989), and Benveniste and Wilhelm (1990) in that an IPO's equilibrium expected initial return emerges from a process in which the underwriting bank (the "bank") and investors deal rationally with informational frictions. The informational friction we consider is as follows: An investor can engage in research (at some slight cost) to ascertain whether an IPO share's value is below its offer price when presented with a concrete take-it-or-leave-it offer to buy by the bank. Thus, given the option to buy, an investor must choose between: 1) engaging in such research (a choice we refer to "lemon-dodging") and opting out of a deal that the bank has happened to overprice; and 2) just purchasing at the offer price knowing that there is a chance that he may lose money (a choice we refer to as "buying-the-block"). Since having a deal fail is very costly for both the bank and the issuer (Jagannathan and Sherman (2006)), we assume that the bank's objective is to maximize the offer price subject to the condition that the deal succeed. As there is a chance that the deal will fail if investors choose to lemon-dodge, it follows that the bank sets an IPO's offer price at the maximum level such that an investor finds remaining in his state of natural ignorance and buying-the-block to be the more profitable choice.

To see what this price is, suppose that i) IPOs come in a (possibly infinite) number of types, ii) the probability of the bank underwriting a given type in each period is constant, and iii) the bank sets one offer price for each type. For a given offer price, one can divide an IPO's expected return into downside risk (the expected return setting all positive return realizations to zero) and upside risk (the expected return setting all negative return realizations to zero). Now, in a one-time game, an investor will always find lemon-dodging more profitable than buying-the-block for any offer price above the IPO share's minimum possible value, as lemon-dodging enables him to avoid an offering's downside risk. The bank can increase the offer price above this minimum and still guarantee that the deal will succeed by entering into a repeat game with a coalition of investors and excluding any investor who does lemon-dodge from that coalition (this arrangement is known as "block-booking"). A coalition investor must then trade-off the benefits of lemon-dodging in the current period (avoiding downside risk on the current IPO) against the cost of being deprived access to the bank's future IPOs. So, the bank can raise the offer price on the current IPO to the point at which the benefits of lemon-dodging at that price just equal the expected benefits of remaining in the bank's coalition. Since the expected benefit of remaining in the bank's coalition is constant over time, it follows that the bank sets each IPO's offer price such that its level of downside risk given that price equals this constant benefit. In other words, a banks sets offer prices in a manner that equalizes downside risk across its offerings. Since the expected benefit of remaining in the bank's coalition must be positive to make block-booking work, and since this benefit decreases as offer prices (downside risk) increase, the level of downside risk the bank chooses in equilibrium will imply that it underprices its IPO shares on average.

If a bank does set offer prices to equalize downside risk across its offerings, then a firm's offer price is basically determined by the left tail of its share value distribution while its expected return is heavily influenced by the right tail of its share value distribution. It follows that varying the shape of a firm's share value distribution will lead to a predictable change to its equilibrium expected initial return. To see if this approach can explain the variation in IPO average initial returns that we observe, we sort our sample of U.S. IPOs from 1986 to 2006 into types by dividing them along a Tech/NonTech dimension and a time dimension. We find that the predicted average initial return the block-booking theory yields for these IPO types is generally both accurate and precise. To illustrate, we predict that the average initial return on Tech IPOs from the early stages of the Boom (1995 to 1998) will lie between 20.6% and 23.0%. The sample average initial return on these IPOs is 22.7%. Our theory does reasonably well even in the extreme case of Tech IPOs from the height of the Boom (1999 and 2000), where the average initial return on these IPOs of 74.5% falls just outside our predicted range of 76.6% to 101.0%.

To get the block-booking to work, the bank must engage in a repeat game with the investors in its coalition. This prediction also follows from the information extraction theory mentioned above, and this has been extensively investigated (see, for example, Cornelli and Goldreich (2001) and Jenkinson and Jones (2004)). However, previous studies of allocation have been limited to examining the allocation decisions of a single bank, and hence have not been able to completely disentangle the repeat game effect from investor-specific effects (i.e., does a bank preferentially select a set of investors for its IPOs because the bank and those investors are in a repeat game or because those investors are more suitable than others?). We are able to bring a new data set to bear on this issue. Using U.K. data collected for market monitoring purposes, we are able to track (albeit imperfectly) institutional investor participation for a sample of all 130 domestic U.K. IPOs that raised more than £10 million over the 1997 to 2000 period. To the best of our knowledge, this is the first data set to enable one to directly track participation by specific investors across multiple banks. Controlling for investor-specific effects by using an investor's overall level of activity in the IPO market, we find that the probability that a given bank selects a given investor to participate in one of its IPOs is far higher if that investor has participated in the bank's previous IPOs. This evidence suggests that this repeat interaction arises because banks form coalitions rather than because banks simply prefer some investors to others on the basis of investor-specific characteristics.

In sum, the pricing and allocation evidence discussed above suggests to us that the IPO market looks the way it does because banks block-book their IPOs. To the extent banks do block-book their IPOs, the level of average underpricing during the Boom was not "excessive" relative to the observed level of underpricing on non-tech IPOs in the pre-Boom period.

Previous Literature

The most compelling, and probably the dominant, of the existing theories of underpricing is the information extraction (*IE*) theory developed by Benveniste and Spindt (1989) and Benveniste and Wilhelm (1990) and extended by Hanley (1993) and Sherman and Titman (2002).[2] The *IE* theory builds upon the analysis of Rock (1986), who shows that an uninformed bank must place shares with both informed and uninformed investors in a one-time game. Since informed investors decline to participate when the bank happens to set the IPO's offer price above its market value, uninformed investors face a severe winner's curse. To get the uninformed investors to participate, the bank must therefore underprice, on average, to the extent that the uninformed investors expect to break even on the shares they actually get. The *IE* theory begins with the observation that a bank in this situation can do better than Rock's (1986) analysis allows by entering into a repeat game with a coalition of informed investors whereby the bank extracts the information they possess and incorporates that information into the IPO's offer price. Of course, the bank must make it worthwhile for the informed investors to reveal truthfully, so the bank underprices IPO shares on average and excludes from its coalition investors who behave opportunistically (in this context, that mislead the bank). Informed investors then must choose between revealing truthfully or misleading the bank once, and the bank sets the level of underpricing such that the informed investors find revealing truthfully the more profitable action. The *IE* theory therefore predicts both that banks underprice IPO shares on average and that they allocate shares by entering into a repeat game with a coalition of investors. Consider both of these predictions in more detail.

To begin with pricing, according to the *IE* theory the level of expected underpricing will be driven by the extent to which an individual investor can affect an IPO's offer price. Given competition among investors and the large number of investors who participate in an IPO, it seems implausible to us–and we are aware of no empirical evidence to suggest–that the level of underpricing implied by the *IE* theory will be large or will vary much across IPOs (Ljungqvist and Wilhelm (2003), Ritter and Welch (2002)). Furthermore, Jenkinson and Jones (2006), who survey institutional investors to see what factors they think influence IPO share allocation, find that information provision does not figure as very important. Thus, while the *IE* theory is consistent with the fact of underpricing, it cannot explain the underpricing patterns we observe in the data.

This failure by the *IE* theory–the most developed of the rational agent theories of underpricing–has caused attention to turn toward agency conflict and behavioral theories of underpricing. Ljungqvist and Wilhelm (2003), for example, argue that the incentives of entrepreneurs to bargain hard declined during the Boom due to changes in firm ownership structure and insider selling behavior, causing underpricing to increase. Investigating this explanation empirically, they do find a positive relationship between their measures of entrepreneurial incentives and underpricing. However, in the absence of a sound estimate of what the average level of underpricing during the Boom would have been in the absence of the incentive problems that Ljungqvist and Wilhelm (2003) focus upon, it is unclear how important these incentive effects are in practice. Loughran and Ritter (2002) argue that banks exploit limits in entrepreneur rationality to underprice excessively while still keeping entrepreneurs satisfied, but this theory does not yield very definite empirical predictions and so is difficult to test directly (see Ljungqvist and Wilhelm (2005) for an indirect test).

Turning now to share allocation, we note that the *IE* theory and the block-booking theory use the same mechanism to deter opportunistic behavior by investors in the current period, namely, a repeat game with on-average underpricing. So, while the two theories differ with respect to what banks are trying to get coalition investors to do, both theories yield the prediction that banks form investor coalitions. Our contribution here is to provide further evidence that banks do in fact form coalitions.

We do not investigate how a bank selects investors for its coalition. Jenkinson and Jones (2006) find that institutional investors believe that being in a broking relationship with the bank is a crucial factor. This idea is supported by Reuter (2006), who finds a strong correlation between broking commissions paid by mutual funds to a given bank and their holdings of that bank's IPOs. One can see why a block-booking bank would put its "best" customers into its coalition, as behaving in this way would encourage an (institutional) investor who was splitting his brokerage business between several banks to concentrate it at the bank offering coalition membership. This "good customers get IPO shares" finding would be inconsistent with the block-booking hypothesis only if the amount that such an investor spent on brokerage *above and beyond what he would have spent anyway* eliminates the profits of coalition membership (as then, according to the theory, an investor would have an incentive to lemon-dodge as the true all-in profits from coalition membership are zero). Since the empirical evidence on this topic suggests that coalition membership is still profitable even when looking at gross commissions (Ljungqvist (2005)), the findings of Jenkinson and Jones (2006) and Reuter (2006) are not inconsistent with the block-booking theory.

In this paper we focus on the implications of the block-booking theory for pricing and share allocation. Barzel, Habib, and Johnsen (2006) use a very similar framework to investigate other aspects of the IPO process, such as syndicate behavior, and find that these features of the IPO market also contribute to ensuring that investors choose to remain ignorant about an IPO share's actual market value when deciding whether or not to participate in an offering.

Organization of the Paper

We derive the pricing and allocation implications of block-booking in Section I. We test the pricing implications of the theory in Section II and the allocation implications in Section III. Conclusions follow in Section IV.

I. The Block-Booking Equilibrium

A. Set-up and Assumptions

We model the IPO process as a game involving entrepreneurs with projects to sell, investors with money to invest, and a bank that intermediates between the two.

Projects: In each period t, $t = 1\ldots\infty$, an entrepreneur presents the bank with a project to bring public. A project's value is determined by a random draw from its share value distribution Ψ_t, with density ψ_t and support $[0, \infty]$. A project's share value distribution (and hence expected value ExV_t) is observable by both the bank and investors, but a project's actual value V_t only becomes observable after its IPO is successful. Each project consists of a single infinitely divisible share.

Each project is also of an observable type, with type determined by a random draw from the set of possible types Ω. The known probability of drawing a given type ω equals σ_ω, and all projects of a given type ω have an identical share value distribution Ψ_ω. All projects are of some type, so when we wish to emphasize IPO t's type we will add a type subscript (e.g., the value of the period t IPO that happens to be of type ω is $V_{t,\omega}$).

The Bank: In each period the bank observes an IPO's type, sets its offer price of P_t, and offers shares to investors. We capture the intuition that banks compete for underwriting mandates by assuming that the offer price the bank sets on an IPO in period t must be the maximum price consistent with guaranteed success.[3] For simplicity, we also assume that the bank sets one offer price for each IPO type.[4] Denote each type's equilibrium price by P^*_ω. The bank selects the investors to whom it offers shares at its discretion. The entrepreneur will compensate the bank for providing this service out of the proceeds of the offering, but we do not model the bank/entrepreneur contract here.

Denote the expected return on IPO t by ExR_t, with

$$ExRt[P_t] = \frac{\$1}{P_t}\int_0^\infty (V_t - P_t)\psi_t \,\mathrm{d}V \,, \tag{1}$$

where the $g[x]$ notation means that g is a function of x. In the analysis below it will be convenient to divide an IPO's expected return into downside risk δ and upside risk U. An offering's downside (upside) risk equals its expected return setting all positive (negative) return realizations to zero, so

$$\delta_t[P_t] \equiv -\left|\int_0^{P_t} \frac{(V_t - P_t)\psi_t \,\mathrm{d}V}{P_t}\right| + \int_{P_t}^\infty \frac{0\,\psi_t \,\mathrm{d}V}{P_t} \tag{2}$$

and

$$U_t[P_t] \equiv \int_0^{P_t} \frac{0\psi_t \mathrm{d}V}{P_t} + \int_{P_t}^{\infty} \frac{(V_t - P_t)\psi_t \mathrm{d}V}{P_t}. \tag{3}$$

Note that $\delta_t\big|_{P_t=0} = 0$, and that $\partial\delta_t/\partial P_t > 0$. It follows from these definitions of δ and U that

$$ExR_t[P_t] = -\,\delta_t[P_t] + U_t[P_t]. \tag{4}$$

Investors: Investors behave competitively, are both risk neutral and identifiable, and maximize expected profits (π). Investors and the bank live forever, implying that the bank and investors can form long-term relationships if they so wish. If selected, an investor invests a fixed amount in an IPO. While this amount can vary across investors, we set it equal to $1 for all investors for convenience. Investors (like the bank) can observe an IPO's share value distribution. We incorporate the idea that investors have the ability to become informed (perhaps by virtue of their trading activities) by assuming that they can detect (at some small cost ϵ) if $V_t < P_t$ when presented with a concrete offer to buy (we treat ϵ as small enough to drop from the analysis below).[5] We also assume that the decision to become informed is observable by the bank. Investors have a discount parameter of γ.

Sequence of Play: Each period consists of the following phases.

Phase 1: An entrepreneur presents his project (of an observable type) to the bank.

Phase 2: The bank sets the project's offer price P_t and offers the shares to investors whom it selects.

Phase 3: The selected investors decide whether or not to pay ϵ and learn if $V_t < P_t$.

Phase 4: Investors decide whether to purchase. If they do purchase, the offering is successful and trading begins.

B. Pricing IPO Shares

Suppose that an entrepreneur acting alone presents an investor with a concrete offer to invest in his IPO t at the offer price P_t. The entrepreneur goes public once, so the entrepreneur and the investors interact on just this one occasion. Given the entrepreneur's offer, the investor must choose between: 1) paying ϵ, learning if $V_t < P_t$, and declining the offer if so (a choice we refer to as *lemon-dodging*), and 2) buying at the offer price, thereby incurring a loss in the event that $V_t < P_t$ (a choice we refer to as *buying-the-block*). The investor's expected profit from lemon-dodging is π_{LD} and from buying-the-block is π_{BB}. It is obvious that

$$\pi_{t,BB} = -\delta_t[P_t] + U_t[P_t] < 0 + U_t[P_t] = \pi_{t,LD} \tag{5}$$

for any $P_t > 0$, as by lemon-dodging the investor avoids nonzero downside risk. It follows that investors always choose to lemon-dodge in this situation. Hence, an entrepreneur acting alone finds it impossible to both set a positive offer price and guarantee an offering's success.

This unhappy situation creates a role for an intermediary (the bank) to act on behalf of entrepreneurs. In order to get an investor to buy-the-block, the bank must offer him an inducement that offsets his gains from lemon-dodging in the current period. The bank does so by block-booking its IPOs, which entails the bank entering into a repeat game with a coalition of investors who agree to buy-the-block in each period. Any investor who violates this membership condition by lemon-dodging is excluded from this coalition.[6] Since in equilibrium the bank underprices IPO shares on average (as we demonstrate below), an investor must then choose between lemon-dodging once and receiving a stream of on-average underpriced IPO shares. The bank sets offer prices such that investors find remaining in the bank's coalition the more profitable choice. Thus, a block-booking bank attracts entrepreneurs with projects to sell by being able to guarantee an offering's success at a positive offer price, and it attracts investors into its coalition by making coalition membership profitable.

Consider now the offer price a block-booking bank sets on IPO *t*. Denoting the present discounted value of the profits an investor expects to obtain by remaining in the bank's coalition by χ_t and recalling $\partial\delta_t/\partial P_t >$ 0, the bank chooses *t*'s offer price $P_{t,BB}$ such that

$$\begin{aligned}\pi_{t,BB} = -\delta_t[P_t] + U_t[P_t] \geq 0 + U_t[P_t] - \chi_t = \pi_{t,LD} \\ \Rightarrow \delta_t[P_t] = \chi_t.\end{aligned} \tag{6}$$

The expected profit an investor obtains by remaining in the bank's coalition is a function of the set of IPO types that the bank brings public (Ω), the probability of each type appearing (σ_ω), the average underpricing on IPOs of each type ($ExV_\omega - P_\omega^*$), the number of shares bought ($\$1/P_\omega^*$), and the discount parameter (γ). It follows that

$$\chi_t = \sum_T \gamma^t \sum_\Omega \sigma_\omega \frac{\$1}{P_\omega^*}\left(ExV_\omega - P_\omega^*\right). \tag{7}$$

Of course, the offer price that the bank selects for an IPO in a given period must be consistent with the offer price the bank selects for IPOs of its type, implying that

$$P_{t,\omega,BB} = P_\omega^* \ \forall \ t,\omega. \tag{8}$$

Consider now the implications of equations (6), (7), and (8) for the pattern of underpricing.

PROPOSITION 1: *A block-booking bank sets offer prices so as to equalize downside risk on its offerings across time and across types.*

Proof: It is obvious from equation (7) that the per-period expected profit an investor obtains by remaining in the bank's coalition is a constant. It follows that $\chi_n = \chi_m \; \forall \; m, n$. Hence, from equation (6),

$$\delta_m \left[P_{m,\varsigma,BB} \right] = \chi = \delta_n \left[P_{n,\kappa,BB} \right] \; \forall \; n, m, \varsigma, \kappa . \tag{9}$$

∴

PROPOSITION 2: *There exists a unique equilibrium level of downside risk.*

Proof: Denote the level of downside risk one observes in the bank's offerings by δ^*. In a block-booking equilibrium it follows from equations (6), (7), and (8) that

$$\delta^* \leq \sum_T \gamma^t \sum_\Omega \sigma_\omega \frac{\$1}{P_\omega^* \left[\delta^* \right]} \left(ExV_\omega - P_\omega^* \left[\delta^* \right] \right). \tag{10}$$

If the bank sets offer prices of all of its IPOs to zero, then $\delta^* = 0$ and $\chi > 0$, implying that the bank could raise offer prices and still guarantee each offering's success. If the bank sets offer prices equal to expected values, then $\delta^* > 0$ and $\chi = 0$, implying that investors find lemon-dodging a more profitable strategy than buying-the-block. The bank must therefore lower downside risk in order to guarantee the success of its offerings. Since $\partial P_\omega / \partial \delta > 0 \; \forall \; \omega$, it follows that $\partial \chi / \partial \delta < 0$. Thus, there exists a unique δ^* (δ_{BB}) such that

$$\delta_{BB} = \sum_T \gamma^t \sum_\Omega \sigma_\omega \frac{\$1}{P_\omega^* \left[\delta_{BB} \right]} \left(ExV_\omega - P_\omega^* \left[\delta_{BB} \right] \right). \tag{11}$$

∴

PROPOSITION 3: *The expected return on a high-risk IPO will exceed that of a low-risk IPO.*

Proof: If a bank block-books, then $ExR_Y = -\delta_{BB} + U_Y[P_{Y,BB}]$ and $ExR_Z = -\delta_{BB} + U_Z[P_{Z,BB}]$. It follows that $ExR_Y = ExR_Z$ if and only if $U_Y[P_{Y,BB}] = U_Z[P_{Z,BB}]$, which in general is not true. If $U_Y[P_{Y,BB}] > U_Z[P_{Z,BB}]$ (intuitively, if *Y*'s share value distribution has a long right tail relative to *Z*'s), then $ExR_Y > ExR_Z$.

$\therefore$

Note that we have been assuming in this analysis that coalition investors face downside risk. If in practice banks eliminate downside risk for these investors through their price stabilization efforts in the aftermarket, then the block-booking theory will provide a poor explanation for IPO pricing and share allocation behavior. However, Aggarwal (2000) shows that underwriters repurchase only a small proportion of the shares allocated to institutional (presumed coalition) investors in the course of their stabilization efforts for poorly performing IPOs, and Prabhala and Puri (1999) find no evidence that "price support is a manipulative practice to permit transfers of IPO ownership at artificially high prices." Furthermore, Boehmer, Boehmer, and Fishe (2006) find that institutional investors flip an average of only 30% of their initial allocation in poorly performing IPOs on their first two trading days (and not all of these sales are necessarily executed at an above true market value price). The empirical evidence on price stabilization and flipping therefore suggests that institutional investors do indeed face downside risk.

Given that investors do face downside risk, a bank must engage in a repeat game with a coalition of investors in order to get the block-booking equilibrium to work. In the empirical analysis below we look for evidence of this repeat game, but we do not test any additional implications of our theory on share allocation. In particular, though we know that banks offer a portion of each offering to retail investors, we do not model the factors that determine the optimal institutional (coalition investor)/retail split. To discuss this matter briefly, suppose that the non-block-booking factors that determine the optimal institutional/retail split for a given offering are independent of the expected return on that offering. In this case, how would one expect a block-booking bank to behave? On the margin, the benefits of increasing the allocation to coalition investors is higher for high expected return IPOs as doing so increases the benefits of being in the bank's coalition (all else equal) and enables the bank to increase offer prices generally. Thus, one would expect to see a block-booking bank allocate a relatively higher proportion of high expected return IPOs to coalition investors and a relatively higher proportion of low (but nonnegative) expected return IPOs to retail investors. This is indeed the pattern that one finds for the institutional/retail split (Boehmer, Boehmer, and Fishe (2006)). To push this line of argument further, Boehmer, Boehmer, and Fishe (2006) also find that institutional investors flip a higher proportion of their allocation in higher return offerings. The ultimate (post-flip) proportion of the offering held by the original institutional investors therefore differs hardly at all (on average) across high and low return offerings, suggesting that the observed initial allocation pattern creates benefits for the bank (increasing coalition profits) without distorting the post-offering (issue date + 3 days) share holding structure for the underwritten firms. To be sure, the factors determining the optimal institutional/retail split are still not fully understood. So, while it would be rash to claim that the block-booking theory predicts this pattern, one can say that this pattern is not inconsistent with the theory.

The key distinguishing implication of the block-booking theory is that a block-booking bank sets offer prices so as to equalize downside risk across its offerings. It follows that, if banks do behave in this way, then average initial returns will vary across IPO types in a predictable (both qualitatively and quantitatively) manner. We test the pricing implications of the block-booking theory in Section II. We test the repeat game implication of the block-booking (and information extraction) theory in Section III.

II. Downside Risk and IPO Pricing

Since we cannot observe an individual IPO's downside risk, we are unable to test the equalization of downside risk implication of the block-booking theory on an IPO-by-IPO basis. Instead, we proceed as follows. We sort a sample of IPOs into distinct types, and designate one of these types as the *Benchmark*. If it is true that $\delta_{Benchmark} = \delta_{BB}$ for each individual *Benchmark* IPO, then it will also be true that $\Delta_{Benchmark} = \delta_{BB}$, where $\Delta_{Benchmark}$ is the observable level of downside risk for the *Benchmark* IPO initial return distribution. The same line of reasoning implies that $\Delta_{\phi} = \delta_{BB}$, where Δ_{ϕ} is the observable level of downside risk for the type ϕ initial return distribution. We then test the pricing implication of the block-booking theory by seeing if

$$\Delta_{Benchmark} = \Delta_{\phi} \ \forall \ \phi. \tag{12}$$

A. The IPO Sample and IPO Types

Our sample consists of all common stock U.S. IPOs with an offer date on or between January 1, 1986 and December 4, 2006 that: 1) were listed on the SDC Platinum database; 2) had an SDC Exchange Code equal to the American Stock Exchange, Nasdaq, NYSE, or OTC; 3) were not classified by SDC as either "financial sector" (closed-end funds, REITs, etc.), unit offerings, or rights issues; 4) had an offer price of at least \$5; and 5) had a closing price on the offer date of at least \$1. These criteria yield a sample of 5,002 IPOs. An IPO's Initial Return is measured from its offer price to its closing price on the offer date.[7]

As we wish to explore the extent to which the block-booking theory can explain the time-series and Tech/NonTech variation in average initial returns, we sort our sample IPOs along a Tech/NonTech dimension and along a time dimension. Sorting along the Tech dimension is straightforward–we simply classify an IPO as a Tech IPO if SDC assigns that IPO a High Tech Industry classification and as a NonTech IPO if SDC does not. We present average initial returns (*AvIR*), number of IPOs (*N*), and *N* * *AvIR* for Tech and NonTech IPOs by year in Table I.

TABLE I ABOUT HERE

There are not enough Tech or NonTech IPOs in any one year to get an accurate measurement of their downside risk. We therefore group IPOs into continuous multiyear periods that, insofar as possible, form distinct *N* and *AvIR* regimes. Taking Tech IPOs first and examining the *N* * *AvIR* column of Table I, there is clear evidence of a boom starting around 1995 and continuing through 2000, with the years of 1999 and 2000 being particularly unusual. We therefore define a *Tech/LowBoom* type, consisting of Tech IPOs from the years 1995 to 1998, and a *Tech/HighBoom* type, consisting of Tech IPOs from 1999 and 2000. Given the Boom, we also define a *Tech/PreBoom* type, consisting of Tech IPOs from 1986 to 1994, and a *Tech/PostBoom type*, consisting of Tech IPOs from 2001 to 2006. Turning to the NonTech IPOs, the regime shifts are more muted. For consistency with our Tech IPO types, we define the following types: *NonTech/PreBoom*, *NonTech/Boom*, and *NonTech/PostBoom*. We present summary statistics on these types in Table II.

TABLE II ABOUT HERE

These types are necessarily a bit arbitrary, and we explore alternative ways of dividing the sample in a robustness check below. But the exact definitions do not matter very much. The problem we wish to avoid is the following: If all IPOs were of a single type and priced according to some rule, then the downside risk of, for example, this year's return distribution would equal that of last year's return distribution because IPOs of the same type are being priced using the same rule rather than because the bank is setting offer prices to equalize downside risk. In order to provide a test of the block-booking theory, then, one must sort IPOs into types with very different return distributions. In this case, the idea that banks use a pricing rule that just so happens to equalize downside risk across types is highly implausible. The types we define do have very different return distributions (see Table II). So, if we do find that banks set offer prices to equalize downside risk, we can be confident that this result is unlikely to be the result of chance.

B. Testing for Downside Risk Equalization

We designate *NonTech/PreBoom* IPOs as our benchmark type, and we therefore test for downside risk equalization between *NonTech/PreBoom* IPOs and type ϕ IPOs, where ϕ = {*Tech/PreBoom*, *Tech/LowBoom*, *Tech/HighBoom*, *NonTech/Boom*, *Tech/PostBoom*, *NonTech/PostBoom*}. To carry out this test, denote the vector of type ϕ offer prices by $\boldsymbol{P}_\phi$ and its vector of market values by $\boldsymbol{V}_\phi$ (measured by the closing price on the offer date). Holding $\boldsymbol{V}_\phi$ constant, consider the impact on the downside risk of the type ϕ return distribution (Δ_ϕ) of multiplying $\boldsymbol{P}_\phi$ by a scalar α (the block-booking offer price adjustment factor). It is obvious that $\partial\Delta_\phi/\partial\alpha > 0$ and that $\Delta_\phi|_{\alpha = 0} = 0$. It follows that there exists an α (α_ϕ) such that

$$\Delta_{NonTech/PreBoom} = \Delta_\phi[\boldsymbol{V}_\phi,\ \alpha_\phi\boldsymbol{P}_\phi]. \tag{13}$$

If banks block-book their IPOs, then $\alpha_\phi \approx 1$, as the offer prices a bank sets will be precisely those that bring about the equalization of downside risk across the two types. If instead banks systematically price type ϕ IPOs higher (lower) than the block-booking theory predicts relative to *NonTech/PreBoom* IPOs, then $\alpha_\phi < 1$ ($\alpha_\phi > 1$). Consequently, one may test our equalization of downside risk result by estimating α_ϕ and seeing if it is close to one.

Arriving at a point estimate of α_ϕ is straightforward. Denote sample values of a parameter by a subscript "*Sample*." The point estimate of α_ϕ ($\alpha_{\phi,Sample}$) then equals the α such that

$$\Delta_{NonTech/PreBoom,Sample} = \Delta_{\phi,Sample}[\boldsymbol{V}_{\phi,Sample},\ \alpha_{\phi,Sample}\boldsymbol{P}_{\phi,Sample}]. \tag{14}$$

Estimating the plausible range of α_ϕ is not so straightforward, as we see no way of deriving valid confidence intervals analytically. We instead use a bootstrap consisting of 10,000 trials to do so (denoting each trial τ with a "τ" subscript) as follows:[8]

Step 1: Draw bootstrap samples *NonTech/PreBoom*$_{\tau}$ and ϕ_{τ}.

Step 2: Measure $\Delta_{NonTech/PreBoom,\tau}[\boldsymbol{V}_{NonTech/PreBoom,\tau}, \boldsymbol{P}_{NonTech/PreBoom,\tau}]$.

Step 3: Calculate $\alpha_{\phi,\tau}$ such that $\Delta_{NonTech/PreBoom,\tau} = \Delta_{\phi,\tau}[\boldsymbol{V}_{\phi,\tau}, \alpha_{\phi,\tau}\boldsymbol{P}_{\phi,\tau}]$.

Step 4: Repeat steps 1-3 10,000 times.

Step 5: Sort the set of $\alpha_{\phi,\tau}$'s this process yields into an ordered list $\boldsymbol{\alpha}_{\phi,Boot}$.

Step 6: The λ% confidence interval for α_{ϕ} ($CI_{\phi,\lambda}$) then equals

$$CI_{\phi,\lambda} = \left\{\boldsymbol{\alpha}_{\phi,Boot}\left[\left[10{,}000\left(\frac{1-\lambda}{2}\right)\right]\right], \boldsymbol{\alpha}_{\phi,Boot}\left[\left[10{,}000\left(\frac{1-\lambda}{2}\right)\right]\right]\right\}, \tag{15}$$

where the "G[[q]]" notation denotes the qth element of list G.

We subject this method to extensive Monte Carlo testing below and demonstrate that it yields accurate confidence intervals.

C. Results

We report point estimates and confidence intervals for α_{ϕ} for each IPO type in Table III. Consistent with our prediction that $\alpha_{\phi} = 1$, we find that: i) the point estimate of $\alpha_{\phi} \approx 1$ for all IPO types; ii) the plausible range of α_{ϕ} is very narrow for all IPO types; and iii) the 99% confidence interval of α_{ϕ} includes one in all cases except (barely) that of *Tech/HighBoom* IPOs.

TABLE III ABOUT HERE

To illustrate these results, consider the case of *Tech/LowBoom* IPOs. Recall from Table II that the *Tech/LowBoom* and *NonTech/PreBoom* return distributions are very different, with both the average initial return and the standard deviation of initial returns on *Tech/LowBoom* IPOs being almost three times as high as that on *NonTech/PreBoom* IPOs (average initial return, 22.69% vs. 8.22%; standard deviation of initial returns, 37.11% vs. 15.53%). Yet, despite these considerable differences in mean and standard deviation, the downside risk of the two distributions is virtually identical. The point estimate of $\alpha_{Tech/LowBoom}$ is only 1.011, with a 99% confidence interval ranging from 0.996 to 1.025. That is, offer prices on *Tech/LowBoom* IPOs are almost certainly within a percentage point or two of where they need to be to exactly equalize the downside risk of *Tech/LowBoom* IPOs with that of *NonTech/PreBoom* IPOs. The equalization of downside risk result holds even more closely in the case of *Tech/PreBoom* and *NonTech/Boom* IPOs, with $\alpha_{Tech/PreBoom}$ = 1.003 and $\alpha_{NonTech/Boom}$ = 1.009. The point estimates of α are a bit further from (but still not statistically significantly different than) one in the case of *NonTech/PostBoom* and *Tech/PostBoom* IPOs, with $\alpha_{NonTech/PostBoom}$ = 0.986 and $\alpha_{Tech/PostBoom}$ = 0.964.

The *Tech/HighBoom* results do not fit the theory quite as nicely as the results for the other IPO types, but they depart in a very interesting way. The point estimate of $\alpha_{Tech/HighBoom}$ = 0.93, with the 99% confidence interval ranging from 0.868 to 0.988. So, the true value of $\alpha_{Tech/HighBoom}$ is probably a bit lower than what the block-booking theory predicts. But, even in this highly extreme case (average return of 74.53% vs. 8.22% for *NonTech/PreBoom* IPOs), *Tech/HighBoom* offer prices are probably well within 10% of the level needed to exactly equalize downside risk.

The most surprising aspect of the *Tech/HighBoom* case is that $\alpha_{Tech/HighBoom}$ is less than one rather than greater than one. Recalling that an α_ϕ of less than one means that type ϕ IPO offer prices are systematically *too high* relative to those of *NonTech/PreBoom* IPOs, rather than too low, our analysis suggests that the average initial return on Tech IPOs during the high boom years of 1999 and 2000 should have been higher than it was. In other words, far from leaving money on the table (relative to what one would expect on the basis of issuer characteristics alone), issuers took money from the table. The late 1990s was therefore an excellent time to go public from a Tech issuer's perspective.[9]

The analysis above demonstrates that the data that we have are not inconsistent with the conjecture that $\alpha_\phi \approx 1$. One way to assess the strength of our results is to ask: What would the data have to look like to be inconsistent with this conjecture? The very narrow confidence intervals that we find above (arising from the fact that our theory yields quantitative predictions) suggests that systematically altering $\boldsymbol{P}_\phi$ by only a few percentage points either up or down would shift $\mathrm{CI}_{\phi,99\%}$ to the extent that it would no longer include one, and such is indeed the case (except for *Tech/HighBoom* IPOs, of course). Thus, the block-booking theory is nothing if not falsifiable.

D. Evaluating the Method

We test the downside risk equalization implication of the block-booking theory by estimating the plausible range of α_ϕ and seeing if it is narrow and close to one, where the plausible range of α_ϕ is given by $CI_{\phi,99\%}$. The validity of our results therefore hinges on the accuracy of the confidence intervals that our bootstrap estimation procedure yields. In this section we explore the accuracy of our bootstrap estimation procedure using a Monte Carlo analysis.

We begin by assuming that $NonTech/PreBoom_{Sample}$ and ϕ_{Sample} are the population of *NonTech/PreBoom* and type ϕ IPOs. Based upon these populations, we calculate $\alpha_{\phi,True}$. We then draw 1,000 bootstrap samples from these populations and analyze each of these samples as we did our actual sample above. This process yields a set of 1,000 confidence intervals for α_ϕ (at each level of coverage), which we denote by $CI_{\phi,\lambda,\tau}$, τ = 1...1,000. A confidence interval is accurate if $A_{\phi,\lambda}$ = Prob ($\alpha_{\phi,True} \in CI_{\phi,\lambda}$) = λ. To estimate $A_{\phi,\lambda}$, we first form an indicator function $I_{\phi,\lambda,\tau}$, with $I_{\phi,\lambda,\tau} = 1$ if $\alpha_{\phi,True} \in CI_{\phi,\lambda}$ and $I_{\phi,\lambda,\tau} = 0$ otherwise. Our point estimate of $A_{\phi,\lambda}$ equals

$$A_{\phi,\lambda} = \frac{\sum_{T} I_{\phi,\lambda,\tau}}{1{,}000}. \tag{16}$$

We report the results of our Monte Carlo analysis in Table IV. We find that the point estimate of $A_{\phi,\lambda}$ is close to and not statistically significantly different from λ (with one exception) for all IPO types and for λ = 0.95 and 0.99. These results suggest that the confidence intervals we estimate above are accurate.

TABLE IV ABOUT HERE

In carrying out our downside risk equalization test, we sort our sample of IPOs into types. Since this necessarily somewhat arbitrary sorting introduces the possibility of "partition bias," we experiment with alternative sorting schemes for the IPOs in our sample. In particular, we examined the following IPO types: *AllTech* (all Tech IPOs in the sample), *Tech/HighBoomA* (Tech IPOs from 1998, 1999, and 2000), *Tech/LowBoomA* (Tech IPOs from 1995, 1996, and 1997), *Tech/AllBoom* (Tech IPOs from 1995 to 2000), *Tech/HighReturn* (Tech IPOs from years in which the average initial return on Tech IPOs exceeded 20%), *Tech/LowReturn* (Tech IPOs from years in which the average initial return on Tech IPOs did not exceed 20%), and *NonTech/Post1994*. In the case of the Tech IPO types, we also test for the equalization of downside risk with a benchmark consisting of all NonTech IPOs in addition to the *NonTech/PreBoom* benchmark we use above. For each IPO type/Benchmark combination we obtain results that conform to those presented above. We therefore conclude that our equalization of downside risk result is not an artifact of the way we classify our sample IPOs.

E. The Time-Series and Tech/NonTech Variation in Average Initial Returns

We now explore the extent to which the block-booking theory can illuminate the causes of the heretofore puzzling time-series and Tech/NonTech variation in average IPO initial returns. One may calculate the average initial return one would expect to observe on type ϕ IPOs given that banks do block-book by: 1) multiplying type ϕ IPO offer prices by α_ϕ; and 2) calculating an average initial return with these adjusted offer prices holding share market values constant. Denote the average initial return predicted by the block-booking theory by $AvIR_{\phi,BB}[\boldsymbol{V}_\phi, \alpha_\phi \boldsymbol{P}_\phi]$, and the sample average initial return on type ϕ IPOs by $AvIR_{\phi,Sample}[\boldsymbol{V}_\phi, \boldsymbol{P}_\phi]$. The difference between the block-booking implied average initial returns and actual average initial returns is $RGap_\phi$, with

$$RGap_\phi = AvIR_{\phi,BB}[\boldsymbol{V}_\phi, \alpha_\phi \boldsymbol{P}_\phi] - AvIR_{\phi,Sample}[\boldsymbol{V}_\phi, \boldsymbol{P}_\phi]. \tag{17}$$

Since we observe α_ϕ imperfectly, we plot *RGap* using the plausible range of α_ϕ that we derived above (see Table III). We present these *RGap* measures in Table V.

TABLE V ABOUT HERE

Table V reveals that, in the case of *Tech/PreBoom*, *NonTech/Boom*, *Tech/LowBoom*, *NonTech/PostBoom*, and *Tech/PostBoom* IPOs, the block-booking point estimate of average initial returns is within a few percentage points of the sample average initial return. Furthermore, the plausible range of the block-booking predicted average initial return for these IPOs is very narrow. In these cases, then, the average initial return predicted by the block-booking theory accurately and precisely tracks the actual average initial return on IPOs across time and across Tech and NonTech IPOs. As one might expect from the downside risk analysis above, the average initial return the block-booking theory predicts for *Tech/HighBoom* IPOs is a bit further from the sample average initial return (*RGap* point estimate, 13.2%; *RGap* range, 2.1% to 26.5%). But, given that the average initial returns on these IPOs is 75%, our predicted return is still in the right ballpark. The block-booking pricing rule can therefore largely explain both the time-series and Tech/NonTech variation in average IPO initial returns over the 1986 to 2006 period. This result suggests that this variation in average initial returns primarily arises from differences in the share value distributions of the IPOs hitting the market rather than from any change of behavior by either the underwriting banks or the entrepreneurs.

III. Share Allocation and Investor Coalitions

To get block-booking to work, a bank must engage in a repeat game with a coalition of investors. We know from both the anecdotal evidence and the single-bank studies of share allocation by Cornelli and Goldreich (2001) and Jenkinson and Jones (2004) that banks are far more likely to select some investors than others when allocating IPO shares. Yet, this fact is not in itself sufficient to establish that banks form investor coalitions, as banks may favor a set of investors for two reasons. First, it could be the case that some investors are more suitable than others on the basis of their own characteristics (e.g., they operate under an investment strategy that enables them to commit to not flipping shares). In this case, one would expect banks to disproportionately draw the same (more suitable) investors from the pool of all possible investors each period even if they chose investors independently for each IPO.[10] Second, the allocation pattern we observe could arise because banks and their favored investors are engaged in a repeat game. In this case, a bank will be far more likely to select an investor in its coalition than one would predict on the basis of that investor's own characteristics. So, in order to demonstrate that banks select investors in a manner consistent with what a block-booking equilibrium requires, one must disentangle the *Own Characteristics* effect from the *Coalition* effect and show that it is the *Coalition* effect that drives the favored investor phenomenon.

We propose to disentangle these two effects in the following manner. We have been able to acquire regulatory data from the U.K. that provides (imperfect) investor-level participation data for all large U.K. IPOs over the 1997 to 2000 period.[11] We sort the IPOs into a Control Group and a Test Group. We measure the *Own Characteristics* effect by an investor's overall level of activity in Control Group IPOs, and we measure *Coalition Membership* in a given bank's coalition by determining if an investor participated in *that* bank's control group IPOs. Using these data, we then estimate the probability that a bank selects an investor for IPOs in its Test Group as a function of that investor's *Own Characteristics* and *Coalition Membership*. The block-booking theory predicts that the relationship between *Coalition Membership* and participation will be highly significant both economically and statistically.

A. Description of the Data

Our IPO sample for this portion of the analysis consists of all new equity offerings on the London Stock Exchange (i.e., that appear on the Official List) or the London Stock Exchange's Alternative Investment Market (AIM) over the period January 1, 1997 to August 3, 2000 that raised at least £10 million, excluding unit offerings and investment trusts. These criteria leave us with a sample of 130 IPOs (see Table VI for summary statistics on the IPO sample), which we order chronologically. We assign each IPO to its bookrunner(s). We put (roughly) the first two-thirds of each bank's IPOs into the Control Group and the remaining IPOs into the Test Group. Banks that underwrote less than three IPOs have all of their IPOs allocated to the Control Group (where they affect the *Own Characteristics* measure). One may find the Control Group/Test Group split by bank in Table VII.

TABLE VI ABOUT HERE

TABLE VII ABOUT HERE

Turning now to the investor data, the U.K.'s financial regulator the Financial Services Authoity ("FSA") collected secondary market trading data for each of the IPOs in our sample for their first 40 trading days for market monitoring purposes. Each firm executing a trade was required to report the trade, their counterparty, and the Ultimate Transactor–either the executing firm itself in the case of Principal trades or the firm on whose behalf the trade was executed for Agency trades. Though firms were required to report only secondary market trades, it was often the case that they reported primary market trades as well. Ultimate Transactors are reported on an "Authorized Firm" level, enabling us to track the transactions of individual authorized firms across multiple banks. With the exception of hedge funds, most of the entities that one would think of as "institutional investors" must be authorized by the FSA to carry out investment business activities.[12] It will generally be the case that an "Authorized Firm" will correspond to an economic entity. However, investment banks themselves usually consist of a large number of separate "Authorized Firms." In the case of banks, then, we consult with banking supervisors and aggregate the "Authorized Firms" that constitute an economically defined bank into a single entity for our analysis. We do not count the book or syndicate members as participants in any IPO that they themselves underwrite.[13] Our investor sample therefore consists of authorized firms that took a position in a share allocation sample IPO within its first 40 trading days; 10,303 such firms did so.

We count a sample investor (*SI*) as participating in an IPO if either: 1) that investor bought shares in the IPO at the offer price on the offer date (the direct observation channel); or 2) that investor had a negative net position in the IPO's stock at the close of its 40th trading day. We include the negative net position channel because we reasoned that an investor selling shares from "no where"–recall that our data consist of all secondary market transactions–most likely acquired those shares in an unreported primary market transaction. In total, we identify 4,322 IPO participants. Of this total, 3,804 enter via the original purchase channel and the remaining 518 enter via the negative net position channel (see Table VIII). The investors who participate in at least one IPO participate a total of 7,697 times in the 130 sample IPOs (i.e., each investor who participates in at least one IPO participates in an average of 1.8 IPOs). While only 2% of *SI*'s participate in five or more IPOs, these investors account for 30% of total participation (see Table IX). When allocating IPO shares, banks definitely favor a small charmed circle of all investors.[14]

TABLE VIII ABOUT HERE

TABLE IX ABOUT HERE

B. Testing for Coalitions

The probability that a bank *B* selects an investor *I* to participate in IPO *t* will be a function of that investor's own level of suitability ($OwnCharacteristics_I$), whether or not *I* is in *B*'s coalition ($CoalitionMembership_{I,B}$), the characteristics of the IPO itself ($Deal_t$), and the strength of *B*'s coalition ($CoalitionStrength_B$). We therefore test for the existence (and importance) of investor coalitions by estimating the Probit equation

$$Y_{I,t,B} = F[OwnCharacteristics_I, CoalitionMembership_{I,B}, Deal_t, CoalitionStrength_B]. \tag{18}$$

The dependent variable $Y_{I,t,B}$ is equal to one if investor *I* participates in Test Group IPO *t* underwritten by bank *B*, and zero otherwise.

We capture the impact of $OwnCharacteristics_I$ on an investor's selection probability with the variable $GenPart_I$, where $GenPart_I$ equals the overall proportion of control group IPOs in which investor *I* took a position.[15]

We measure $CoalitionMembership_{I,B}$ with the variables $BookOne_{I,B}$, $BookMany_{I,B}$, and $GenPart_I$ * $BookMany_{I,B}$. $BookOne_{I,B}$ equals one if investor *I* participated in *only* one of *B*'s control group IPOs, and zero otherwise. $BookMany_{I,B}$ equals one if investor *I* participated in *at least* two of *B*'s control group IPOs, and zero otherwise.

Given the noise in our data, we expect *BookMany* to be a stronger indicator of coalition membership than *BookOne*. We include a *GenPart/BookMany* interaction term to take into account the possibility that the boost a given investor's selection probability receives when that investor becomes a member of a bank's coalition may be smaller if that investor's selection probability is already elevated due to that investor's own characteristics.[16]

All else equal, one would expect a bank to choose more investors for bigger IPOs. To capture this $Deal_t$ impact upon investor selection probabilities, we include the natural log of total proceeds ($LnSize_t$) in the Probit.

To explore the extent to which coalition strength varies across banks, we include individual bank coalition strength dummy variables in the regression. A dummy BCS_B equals one if bank *B* is the bookrunner for IPO *t* and if investor *I* participated in *at least* one of B's control group IPOs (i.e., if BookOne or BookMany equals one), and zero otherwise. Each major bank has its own variable, and we assign a single dummy *SecondTier* to all minor banks. For reasons of confidentiality, we label the major bank variables BCS_1 to BCS_9.

One may find summary statistics for these variables in Table X (except IPO size, which we report with the IPO summary statistics in Table VI). For the Probit our investor sample will consist of *SI*'s that took a position in at least one Control Group IPO. Our control group of IPOs yields a list of 7,491 sample investors, and our test group consists of 35 IPOs. We therefore have 262,185 observations of possible participation (35 IPOs * 7,491 investors).

TABLE X ABOUT HERE

C. Results

We report our Probit estimation in Table XI.[17] To begin with the key result for block-booking, the regression indicates that both *BookOne* and *BookMany* are highly significant, with *BookMany* having a considerably stronger effect than *BookOne*. So, an investor's participation in a bank's previous IPOs does significantly increase that investor's probability of participating in that bank's future IPOs after controlling for that investor's general level of suitability.

TABLE XI ABOUT HERE

An investor's selection probability is also significantly influenced by his general level of activity in the IPO market (*GenPart*), providing further evidence to support the hypothesis that banks find some investors to be more suitable recipients of IPO shares than others. The *BookMany/GenPart* interaction term is negative, indicating that coalition membership provides a bigger boost to the selection probability of an investor that the bank would be unlikely to choose on the basis of that investor's specific attributes alone. Our analysis also indicates that the importance of coalition membership varies considerably across the banks in our sample as some of the *BCS* dummies are economically and statistically significant. We expect that banks with strong coalitions will have a competitive advantage in the underwriting market, and we intend to explore this relationship in future work.

To illustrate the economic significance of these results, we present point estimates of an investor's selection probability in Table XII as a function of the investor's general level of involvement in the IPO market, bank coalition strength, and the investor/bank relationship. Consider, for example, the selection probability of a highly suitable investor (*GenPart* = 0.2) for a large IPO (*LnSize* = 5.16). If the investor is a member of the bank's coalition (*BookMany* = 1) and if the bank's coalition is strong, the bank selects that investor with probability 0.45. If the bank's coalition is weak, the investor's selection probability falls to 0.09. If that investor is not a member of the bank's coalition, the bank selects that investor with a probability of 0.02.

TABLE XII ABOUT HERE

We note here that, if anything, our analysis may understate the importance of coalition membership. First, we observe investor participation imperfectly, which weakens our ability to detect coalitions. Second, we assign each IPO to a single bank (its book), whereas IPOs are usually underwritten by multibank syndicates. Our coalition membership variables will then be noisy indicators of actual coalition membership (an investor may appear in a book's coalition because it received shares from a syndicate member rather than the book itself). Third, *GenPart* may measure (in part) membership in multiple coalitions (banks may form coalitions from the same set of suitable investors), implying that *GenPart* will pick up some of the effect of coalition membership. In light of these potential biases, we are confident that our coalition membership results arise because banks form coalitions rather than as an artifact of the data.

In sum, the empirical evidence indicates that banks form coalitions of investors to whom they preferentially allocate shares in their IPOs. It follows that the allocation evidence is also consistent with the hypothesis that banks block-book their IPOs.

IV. Conclusion

"Betrayal on Wall Street" (in the words of a Fortune headline) is perhaps the consensus explanation for the extremely high average initial returns on IPOs during the boom of the late 1990s (though academics typically express this idea using the more refined term "agency conflict," as in Ritter and Welch (2002)). According to this view, "rather than raise the most money for the side they're supposed to be representing...[investment banks] ply mutual funds and hedge funds with artificially cheap shares...and then get repaid with high commission stock trades."[18] IPO firm management fell prey to the machinations of the bankers through a combination of naivety (nonrational decision making) and sloth (incentives insufficiently strong to induce them to perform the job shareholders hired them to do). Indeed, one can seemingly chart the decline of ethical standards in the IPO market by calculating the “money left on the table” as a result of underpricing (see Ritter and Welch (2002) for the numbers).

While the story of greed and corruption destroying a sound institution such as the IPO market in the pre-Boom years is a satisfying one, we find it implausible to suppose that investment bankers have become greedier and/or that entrepreneurs have become more irrational or slothful. The block-booking theory posits instead that the IPO market looks the way it does because it has evolved to solve the very difficult problem of how to place shares of uncertain value with investors who may be knowledgeable enough to lemon-dodge (that is, with investors who might know just enough to know when the bank gets a share’s offer price wrong, giving them the opportunity to decline to participate in offerings the bank happens to overprice). To successfully market IPOs in these circumstances, a bank forms a coalition of investors and offers them the following deal: The investors will always accept the shares the bank offers, the bank will in turn underprice shares on average (though not in each case) so as to make coalition membership valuable, and the bank will exclude any investor that lemon-dodges from the coalition. An investor then faces the choice of remaining in the bank’s coalition and getting on-average underpriced shares in the future or lemon-dodging once. The bank underprices each offering to the extent necessary to make remaining in the coalition the more profitable choice.

The block-booking theory yields the very strong quantitative prediction that banks set offer prices so as to equalize downside risk across the IPOs they underwrite. Testing this implication with data on U.S. IPOs over the 1986 to 2006 period, we find that banks do set offer prices in a manner that equalizes downside risk. The block-booking theory is the only theory of the IPO process of which we are aware that yields this prediction.

The block-booking theory also implies that a bank will allocate IPO shares by engaging in a repeat game with a coalition of investors (in common with the information extraction theory pioneered by Benveniste and Spindt (1989) and Benveniste and Wilhelm (1990)). Using a unique data set that allows us to identify (imperfectly and with noise) original investors in all large U.K. IPOs over the 1997 to 2000 period, we find that banks do indeed form coalitions. To illustrate, a bank with a strong coalition underwriting a large offering is about 20 times more likely to allocate shares to a coalition investor (an investor with whom the bank has dealt before) than to a noncoalition investor, controlling for that investor's general level of activity in the IPO market. The pricing and allocation evidence together suggest to us that the IPO market looks the way it does because banks block-book their IPOs.

If a bank block-books, then an IPO's expected return will be determined by the equilibrium level of downside risk and its share value distribution. That is, if a bank sets an IPO's offer price to equalize downside risk, an IPO's offer price is determined by the left tail of its return distribution. Holding the left tail (and so downside risk) of the share value distribution constant, stretching out the right tail will increase an offering's expected value and thus (given a constant offer price) its expected return. An IPO with a share value distribution with a long right tail will then have a high expected return in equilibrium…and the share value distribution of tech IPOs during the Boom had a very long right tail. Indeed, average initial returns on tech IPOs during the Boom were about where one would expect them to be on the basis of their own characteristics and the equalization of downside risk that follows from block-booking. If one wishes to assign blame for this rise, then, one can but conclude: The fault lies not in the stars (Mary Meeker…), but in the firms themselves.

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Table I
Pricing Analysis: IPO Sample Description and Summary Statistics

Our sample consists of all common stock U.S. IPOs with an offer date on or between January 1, 1986 and December 4, 2006 that: 1) were listed on the SDC Platinum database; 2) had an SDC Exchange Code equal to the American Stock Exchange, Nasdaq, NYSE, or OTC; 3) were not classified by SDC as either "financial sector" (closed-end funds, REITs, etc.), unit offerings, or rights issues; 4) had an offer price of at least $5; and 5) had a closing price on the offer date of at least $1. These criteria yield a sample of 5,002 IPOs. We classify an IPO as a "Tech IPO" if SDC assigns that IPO a High Tech Industry classification and as a "NonTech IPO" if SDC does not. An IPO's Average Initial Return is measured from its offer price to its closing price on the offer date.

	Tech IPOs			*NonTech IPOs*		
Year	*Number (N)*	*Average Initial Return (%)*	*N * AvIR*	*Number (N)*	*Average Initial Return (%)*	*N * AvIR*
1986	102	6.66	6.79	218	5.61	12.23
1987	82	6.53	5.35	168	4.77	8.01
1988	33	6.88	2.27	53	6.54	3.47
1989	36	11.87	4.28	62	6.37	3.95
1990	40	10.54	4.21	58	10.42	6.04
1991	116	22.00	25.52	119	9.79	11.65
1992	143	12.14	17.37	187	8.44	15.77
1993	155	15.23	23.60	276	12.22	33.73
1994	131	11.25	14.74	205	7.69	15.77
1995	209	26.81	56.03	158	13.60	21.50
1996	308	17.87	55.03	239	15.03	35.92
1997	179	16.28	29.14	184	11.98	22.04
1998	123	37.13	45.67	100	13.70	13.70
1999	340	86.55	294.26	74	22.07	20.13
2000	285	60.19	171.54	44	33.23	14.62
2001	40	18.18	7.27	25	26.61	6.65
2002	30	6.38	1.91	33	20.51	6.77
2003	29	12.17	3.52	22	13.18	2.90
2004	84	13.78	11.58	65	10.84	7.04
2005	59	8.92	5.26	76	10.09	7.67
2006	46	7.98	3.67	66	10.64	7.02

Table II
IPO Types

We sort IPOs along a *Tech*/*NonTech* dimension and a time dimension (*PreBoom*, *Boom*, and *PostBoom*). We classify an IPO as a *Tech* IPO if SDC assigns that IPO a High Tech Industry classification and as a *NonTech* IPO if SDC does not. We define *Boom* as the years 1995 to 2000, *PreBoom* as the years 1986 to 1994, and *PostBoom* as the years 2001 to 2006. The extremely high number of Tech IPOs during 1999 and 2000, and the extremely high average initial returns on these IPOs, caused us to split the Boom period into a *LowBoom* (1995 to 1998) and *HighBoom* (1999 and 2000) period for Tech IPOs.

IPO Type	*Definition*	*Number*	*Average Initial Return (%)*	*Standard Deviation of Initial Returns*
NonTech/PreBoom	NonTech, 1986 - 1994	1346	8.22	15.53
Tech/PreBoom	Tech, 1986 - 1994	838	12.43	30.15
NonTech/Boom	NonTech, 1995 - 2000	799	15.53	26.61
Tech/LowBoom	Tech, 1995 - 1998	819	22.69	37.11
Tech/HighBoom	Tech, 1999 - 2000	625	74.53	95.22
NonTech/PostBoom	NonTech, 2001 - 2006	287	13.26	35.31
Tech/PostBoom	Tech, 2001 - 2006	288	11.54	17.48

Table III
The Equalization of Downside Risk

The block-booking theory predicts that a bank sets offer prices to equalize downside risk across its offerings, where downside risk equals an IPO's expected return setting all positive return realizations to zero. We test this conjecture by pooling together our sample IPOs into the types defined in Table II and seeing if the downside risk of the type ϕ return distribution Δ_ϕ, $\phi = \{$*Tech/PreBoom*, *Tech/LowBoom*, *Tech/HighBoom*, *Tech/PostBoom*, *NonTech/Boom*, *NonTech/PostBoom*$\}$, equals that of a benchmark type, which we take to be *NonTech/PreBoom* IPOs. To carry out this test, note that there exists a block-booking offer price adjustment factor α_ϕ such that $\Delta_{NonTech/PreBoom}[\boldsymbol{V}_{NonTech/PreBoom}, \boldsymbol{P}_{NonTech/PreBoom}] = \Delta_\phi[\boldsymbol{V}_\phi, \alpha_\phi \boldsymbol{P}_\phi]$, where $\boldsymbol{P}_\phi$ ($\boldsymbol{V}_\phi$) denotes the offer price (share value) vector of type ϕ IPOs and the $g[x]$ notation means that g is a function of x. If banks do set offer prices to equalize downside risk, then $\alpha_\phi \approx 1$. If $\alpha_\phi > 1$ ($\alpha_\phi < 1$) then type ϕ IPOs are systematically underpriced (overpriced) relative to the benchmark *NonTech/PreBoom* IPOs. The point estimate of α_ϕ ($\alpha_{\phi,Sample}$) equals the α such that $\Delta_{NonTech/PreBoom,Sample} = \Delta_{\phi,Sample}[\boldsymbol{V}_{\phi,Sample}, \alpha_{\phi,Sample}\boldsymbol{P}_{\phi,Sample}]$. We estimate the plausible range of α_ϕ using a bootstrap consisting of 10,000 trials. In each trial τ we draw a bootstrap sample from the type ϕ sample and from the *NonTech/PreBoom* sample and solve for $\alpha_{\phi,\tau}$, which is the α such that $\Delta_{NonTech/PreBoom,\tau} = \Delta_{\phi,Sample}[\boldsymbol{V}_{\phi,\tau}, \alpha_{\phi,\tau}\boldsymbol{P}_{\phi,\tau}]$. We sort the set of $\alpha_{\phi,\tau}$'s this process yields into an ordered list $\boldsymbol{\alpha}_{\phi,Boot}$. The λ% confidence interval for α_ϕ ($CI_{\phi,\lambda}$) then equals

$$CI_{\phi,\lambda} = \left\{ \boldsymbol{\alpha}_{\phi,Boot}\left[\left[10{,}000\left(\frac{1-\lambda}{2}\right)\right]\right], \boldsymbol{\alpha}_{\phi,Boot}\left[\left[10{,}000\left(\frac{1-\lambda}{2}\right)\right]\right] \right\},$$

where the "$G[[q]]$" notation denotes the qth element of list G. We present our results below for each IPO type. The box in the middle of each line marks $CI_{\phi,50\%}$, the inner set of vertical lines marks $CI_{\phi,95\%}$, and the outer set (with their numerical values) marks $CI_{\phi,99\%}$. The vertical line in the box marks $\alpha_{\phi,Sample}$ (with its numerical value underneath).

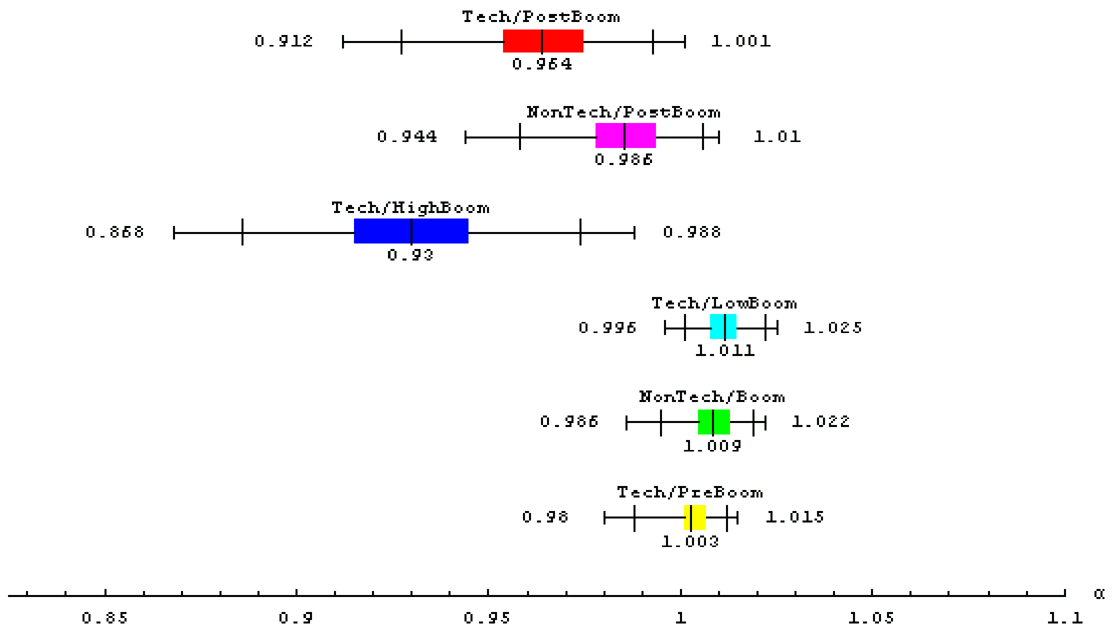

Table IV
The Accuracy of the Bootstrapped Confidence Intervals of the Block-Booking Offer Price Adjustment Factor

To gauge the accuracy of the bootstrapped α_ϕ confidence intervals that we calculate in Table III, we subject our bootstrap process to a Monte Carlo analysis as follows (notation as in Table III). We begin by assuming that our sample of *NonTech/NonBoom* and type ϕ IPOs represents the relevant population. Based upon these populations, we calculate $\alpha_{\phi,True}$. We then draw 1,000 bootstrap samples from these populations and analyze each of these samples as we did our original sample. This process yields a set of 1,000 confidence intervals for α_ϕ (at each level of coverage), which we denote by $CI_{\phi,\lambda,\tau}$, $\tau = 1...1{,}000$. A confidence interval is accurate if $A_{\phi,\lambda}$ = Prob $(\alpha_{\phi,True} \in CI_{\phi,\lambda}) = \lambda$. To estimate $A_{\phi,\lambda}$, we first form an indicator function $I_{\phi,\lambda,\tau}$, with $I_{\phi,\lambda,\tau} = 1$ if $\alpha_{\phi,True} \in CI_{\phi,\lambda}$ and 0 otherwise. Our estimate of $A_{\phi,\lambda}$ equals $\Sigma\, I_{\phi,\lambda,\tau}/1{,}000$. Below we report these estimates and test to see if $A_{\phi,\lambda}$ is statistically significantly different from λ at the 1% level.

	$A_{\phi,95\%}$		$A_{\phi,99\%}$	
IPO Type	*Point Estimate*	*Reject* $A_{\phi,95\%} = 0.95$	*Point Estimate*	*Reject* $A_{\phi,99\%} = 0.99$
Tech/PreBoom	0.96	No	0.99	No
NonTech/Boom	0.94	No	0.99	No
Tech/LowBoom	0.97	Yes	0.99	No
Tech/HighBoom	0.95	No	0.99	No
NonTech/PostBoom	0.93	No	0.98	No
Tech/PostBoom	0.95	No	0.98	No

Table V
The Gap Between Predicted and Actual Average Initial Returns By IPO Type

The block-booking theory predicts that the average initial return on type ϕ IPOs will be that implied by multiplying their offer prices by the block-booking offer price adjustment factor α_ϕ holding their market values (closing price on their offer date) constant. Denote this average initial return by $AvIR_{\phi,BB}$ and the sample average initial return on type ϕ IPOs by $AvIR_{\phi,Sample}$. In this table we plot $RGap_\phi = AvIR_{\phi,BB} - AvIR_{\phi,Sample}$ for the plausible range of α_ϕ, as calculated in Table III. The box on each line marks the values of $RGap_\phi$ implied by the middle 50% of the α_ϕ range in Table III, the inner set of vertical lines mark the values of $RGap_\phi$ implied by the middle 95% of that range, and the outer set of vertical lines (with their numerical values) indicates the $RGap_\phi$ values implied by the middle 99% of that range. The vertical line in the box marks our point estimate of $RGap_\phi$, with its numerical value underneath.

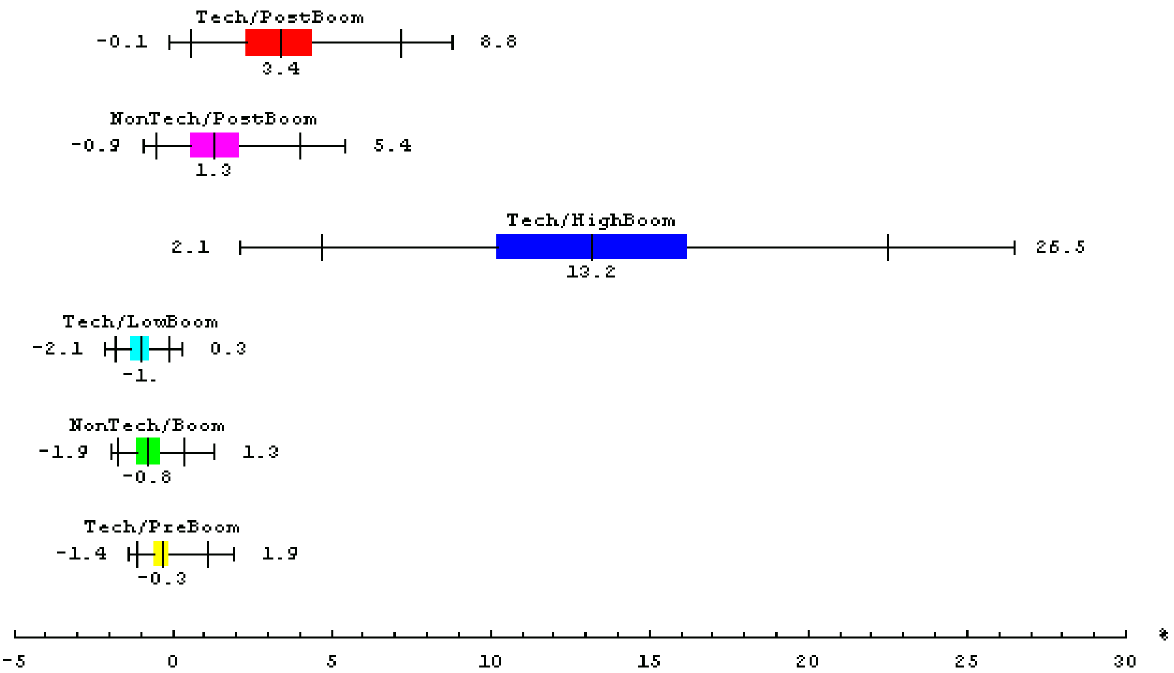

Table VI
Share Allocation Analysis: IPO Sample and Summary Statistics

We investigate IPO share allocation with a sample consisting of the 130 new equity offerings on the London Stock Exchange (i.e., that appear on the Official List) or the Alternative Investment Market (AIM) over the period January 1, 1997 to August 3, 2000 that raised at least £10 million (excluding unit offerings and investment trusts).

Variable	*Mean*	*Standard Deviation*	*Median*
Initial Return (%)	23.25	57.70	9.30
Size (£ Million)	110.95	151.19	77.74
Ln[Size]	4.16	1	4.35

Table VII
The Number of IPOs by Bookrunner

We assign each IPO to (each of) its bookrunner(s). Sorting IPOs by offer date, we assign (roughly) the first two-thirds of each bank's IPOs to the control group and the remaining one-third to the test group. In the event that banks *A* and *B* merge to form *C*, we assign all *A* and *B* IPOs to *C* when determining participation in *C*'s previous IPOs. We treat each second tier bank individually, but pool them together for reporting purposes. Banks that underwrote fewer than three IPOs have all of their IPOs put into the control group. The sample consists of 130 IPOs, 95 control group IPOs, and 35 test group IPOs. The sum of control group and test group IPOs in the table exceeds 130 due to multiple bookrunners.

Bank	*Control Group IPOs*	*Test Group IPOs*
Cazenove	12	5
CSFB	4	2
Deutche Morgan Grenfell	3	1
Dresdner Kleinwort Benson	6	3
Goldman Sachs	5	3
Merrill Lynch	4	3
Morgan Stanley	3	2
UBS Warburg	10	5
WestLB Panmure	5	3
Second Tier	54	10
Total	106	37

Table VIII
IPO Investors

Our investor sample consists of firms authorized by the U.K. financial services regulatory authority (the FSA) to carry out investment business activities (loosely speaking: institutional investors) that took a position in a share allocation sample IPO within its first 40 trading days; 10,303 such firms did so. Generally, an authorized firm corresponds to an economic entity. However, investment banks usually consist of many authorized firms. In consultation with banking supervisors, we therefore aggregate the authorized firms constituting an economically defined investment bank into a single entity. We count a sample investor as participating in an IPO if either: 1) that investor bought shares in the IPO at the offer price on the offer date (the direct observation channel); or 2) that investor had a negative net position in the IPO's stock at the close of its 40th trading day. We do not count an underwriting bank or a member of its syndicate as an investor in its own IPOs.

Panel A. Sample and Participating Investors

Investors	*All IPOs*	*Control Group IPOs*	*Test Group IPOs*	*In Control and Test Group*
Investor Sample	10,303	7,491	4,038	1,226
Participating Investors: Direct Observation	3,804	2,047	2,130	373
Participating Investors: Negative Net Position	1,565	1,133	694	262
Total Participating Investors	4,322	2,529	2,287	494

Panel B. Observed Participation Per IPO

	Mean	*Standard Deviation*	*Median*
Participating Investors Per IPO	58.02	131.74	12

Table IX
The Distribution of IPO Participation

In this table we report the distribution of IPO participation for sample investors (as defined in Table VIII). The 10,303 sample investors participated a total of 7,697 times in sample IPOs.

Sample investors who participate in…	*Proportion of total sample investors*	*Proportion of total investor appearances*
0 IPOs	58%	0%
1 IPO	33%	35%
2 – 4 IPOs	7%	35%
5+ IPOs	2%	30%

Table X
Investor Selection Probabilities: Variable Summary Statistics

We track the participation of each of the 7,491 sample investors that took a position in a control group IPO in each of the 35 test group IPOs, leaving us with a data set consisting of 262,185 observations of possible participation (35 IPOs * 7,491 investors). $Y_{I,t,B}$ equals one if investor *I* participated in test group IPO *t* underwritten by bank *B*, and zero otherwise. *BookOne* equals one if investor *I* participated in only one control group IPO brought public by the bank (*B*) underwriting test group IPO *t*, and zero otherwise. *BookMany* equals one if investor *I* participated in at least two control group IPOs brought public by the bank underwriting test group IPO *t*, and zero otherwise. *GenPart* equals the proportion of all control group IPOs in which investor *I* took a position. BCS_B equals one if bank *B* is the bookrunner for test group IPO *t* and if investor *I* participated in at least one of its control group IPOs, and zero otherwise. For reasons of confidentiality, we cannot identify the bank to which each individual *Bank Coalition Strength* Dummy applies. We therefore sort *BCS* variables by the magnitude of their coefficient estimates in Table XI. We report the standard deviation of *GenPart* alone, as the other variables are all zero-one dummies.

Variable	*Mean*	*Variable*	*Mean*
$Y_{I,t,B}$	0.0056	BCS_4	0.0022
BookOne	0.0441	BCS_5	0.0039
BookMany	0.008	BCS_6	0.0004
GenPart	0.022	BCS_7	0.0029
	(StDev: 0.051)		
BCS_1	0.0019	BCS_8	0.0023
BCS_2	0.007	BCS_9	0.0189
BCS_3	0.0018	$BCS_{SecondTier}$	0.0067

Table XI
Investor Selection Probability Regression

In this table we estimate the probability that a bank selects a control group investor to participate in a test group IPO using a probit specification. The dependent variable is $Y_{I,t,B}$, which equals one if control group investor *I* participated in test group IPO *t* underwritten by bank *B*, and zero otherwise. The independent variables are defined in Table X. Our data set consists of 262,185 observations. A "*" denotes statistical significance at the 1% level. To avoid overidentification, we omit BCS_9 from the regression.

	Coefficient	*Standard Error*	*t-Stat*
Constant	– 4.08*	0.06	68.93
BookOne	0.29*	0.05	5.31
BookMany	1.06*	0.08	13.3
GenPart	3.64*	0.09	38.72
BookMany * GenPart	– 1.70*	0.19	– 8.93
Ln[Size]	0.26	0.01	22.17
BCS_1	1.20*	0.08	14.26
BCS_2	0.55*	0.06	8.85
BCS_3	0.51*	0.1	5.23
BCS_4	0.45*	0.09	5.11
BCS_5	0.33*	0.07	4.39
BCS_6	0.22	0.19	1.16
BCS_7	– 0.04	0.12	0.31
BCS_8	– 0.06	0.09	0.61
$BCS_{SecondTier}$	– 0.01	0.12	0.82
McFadden R^2	0.28		

Table XII
Investor Selection Probabilities: Point Estimates

In this table we report our point estimate of the probability that a bank selects an investor for one of its large IPOs (Ln[Size] = 5.16) as a function of the investor's general level of activity in the IPO market, bank coalition strength, and the relationship between the investor and the bank. We calculate these probabilities using the regression reported in Table XI. We consider two levels of investor activity: *Highly Active* (*GenPart* = 0.2) and *Inactive* (*GenPart* = 0.01). We consider two bank types: *Strong Coalition* (BCS_1) and *Weak Coalition* ($BCS_{SecondTier}$). We consider two levels of the Investor/Bank relationship: *Coalition* (*BookMany* = 1) and *Non-Coalition* (*BookMany* = 0 and *BookOne* = 0).

Panel A. A Highly Active Investor's Selection Probability

In Bank's Coalition?	*Coalition Type*	*Selection Probability*
Yes	Strong	0.45
Yes	Weak	0.09
No	–	0.02

Panel B. An Inactive Investor's Selection Probability

In Bank's Coalition?	*Coalition Type*	*Selection Probability*
Yes	Strong	0.33
Yes	Weak	0.05
No	–	0.001

Notes

[1] This success suggests that our pricing rule may also help to gauge the empirical relevance of the other initial return affecting factors identified in the underpricing literature by providing a sound counterfactual against which to measure their impact.

[2] See Ritter and Welch (2002) and Ljungqvist (2005) for excellent surveys of the vast literature on underpricing for a discussion of the alternative theories.

[3] We assume that the bank must set an IPO's offer price in a manner that guarantees the offering's success for convenience, but our results require only that having a deal fail imposes a cost. This assumption is consistent with the analysis of Jagannathan and Sherman (2006), who: i) show that IPO auctions have a higher probability of failure than book-building (of which block-booking is an example); and ii) argue that this risk accounts for why underwriters do not use auctions to allocate IPO shares.

[4] Intuitively, the assumption that the bank must maximize each IPO's offer price rules out implausible pricing strategies in which the bank arbitrarily increases offer prices on some set of IPOs and gets investors to participate by bundling them together with other IPOs with arbitrarily decreased offer prices. Hence, we believe that allowing more complicated pricing strategies would not alter our results but would force the analysis below to become far more opaque. We also assume that the bank cannot set a project's offer price at a level higher than its expected value. For simplicity, we assume that this constraint does not bind in the analysis below.

[5] The investors we discuss here are institutional investors, and we assume that the bank must sell at least a given proportion of each IPO to these investors. The remainder can be sold to retail investors (who lack the ability to obtain private information on share value, and so can't lemon-dodge) at the offer price if in equilibrium the expected return on an IPO share is nonnegative. We do not explicitly model the retail allocation aspect of this process.

[6] For simplicity, we assume that the bank can detect lemon-dodging with probability one. As lemon-dodging becomes harder to detect, the average discount the bank must offer to get block-booking to work will increase. And, of course, if banks cannot detect lemon-dodging at all, then they will not block-book. In these circumstances, one would not expect the pricing implications of the block-booking theory to hold in the data.

[7] We omit 167 firms that did not have closing prices reported on SDC, and we omit 5 firms with a closing price of less than $1 (suggesting a decimal place error). We are able to track down offer prices for about 60% of these IPOs through other sources; including them with these corrected offer prices does not affect our results. We do not include these IPOs in the analysis below so as to make it easier to replicate our sample.

[8] For a description of the Bootstrap, see Efron and Tibshrani (1993), Chernick (1999), or Horowitz (2001). To construct bootstrap sample τ of ϕ_{Sample}, which consists of N_{Sample} observations, one makes N_{Sample} draws at random with recall from $\phi_{Sample.}$ This process yields a new sample of type ϕ IPOs, ϕ_{τ}, which in turn yields a new offer price vector $\boldsymbol{P}_{\phi,\tau}$ and a new market value vector $\boldsymbol{V}_{\phi,\tau}$. The idea behind the bootstrap is that one's sample provides a good estimate of the population. So, drawing a large number of bootstrap samples from

one's original sample and calculating the value of the parameter under investigation for each bootstrap sample should provide a good estimate of that parameter's plausible range.

[9] It is possible that this systematic increase in Tech IPO offer prices (of approximately 7%) during the height of the IPO boom was due to increased competition between underwriters for IPO business.

[10] It is unlikely that an individual investor would suffer from a "capacity constraint" and be unable to accept an offer to purchase on-average underpriced shares, so investors with only slightly more desirable characteristics could be selected far more often than the typical investor.

[11] Ideally, of course, we would have investigated pricing and share allocation using a common set of IPOs, but lack of U.S. allocation data prevents us from doing so. We think that the U.K. case can shed light on the question of bank coalitions as banks in the U.K. also can allocate IPO shares at their discretion (implying that they can form coalitions) and because most of the IPOs in the sample were underwritten by banks that are also active in the U.S. IPO market. Thus, if these banks block-book in the U.S., one would also expect them to block-book in the U.K.

[12] There are about 55,000 Authorized Firms in the U.K. See http://www.fsa.gov.uk/pages/Doing/Do/index.shtml for a discussion of which firms must be authorized.

[13] Transactions that do not involve Authorized Firms (e.g., those with retail customers) are reported by executing firms using their own codes. Hence, there is no way to track a given retail investor's activity across multiple banks. We therefore focus our analysis upon Authorized Firms (institutional investors). Strictly speaking, firms authorized in non-U.K. jurisdictions (e.g., the Bank of New York) are at least sometimes tagged with their Bank Identifier Code (or BIC) number, which enables us to track the activities of these institutions across multiple banks as well. We include the small number of firms identified by BIC codes in our analysis.

[14] The median number of investors that we find per IPO is 12, and so we obviously do not find all of them using these data. While the imperfections in our data do not prevent us from establishing the general point that banks form coalitions, these imperfections do prevent us from using these data to explore detailed questions about exactly how a bank runs its coalition.

[15] We use this broad activity-based measure of *GenPart* rather than a narrow participation-based measure because we know that we track participation imperfectly. We are worried that these imperfections might lead to a downward bias in a participation-based *GenPart* measure, which might lead us to underestimate the importance of investor-specific factors in selection probabilities. However, we note that we also experiment with a narrow measure of *GenPart* based only upon (our measure of) direct IPO participation, and that this narrow measure does not materially affect the coefficients on the coalition membership variables that are the focus of our analysis.

[16] Note that several of the banks in our sample merged over the course of our sample period. To deal with ownership changes, we assume that if banks *A* and *B* merge to form *C*, then *C* inherits the coalitions of both *A* and *B*. So, for a bank *C* IPO in our test group, we include both bank *A* and bank *B* IPOs in *C*'s control group. In addition, we treat the case of multiple bookrunners as a temporary merger: If a given test group deal is underwritten by banks *A* and *B*, we construct our coalition membership variables on the basis of both *A* and *B* control group IPOs.

[17] We estimate our probit using the package *Shazam*.

[18] "Betrayal on Wall Street," Fortune, May 14, 2001. It is interesting to note that, in retrospect, issuers had little to complain about.