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Article (Accepted Version)

Yung, Chris, Colak, Gönül and Wang, Wei (2008) Cycles in the IPO market. *Journal of Financial Economics*, 89 (1). pp. 192-208. ISSN 0304-405X

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Cycles in the IPO Market*

Chris Yung
Department of Finance
University of Colorado at Boulder
Leeds School of Business
Boulder, CO 80309
(303) 492-7437
chris.yung@colorado.edu

Gönül Çolak
Florida State University
College of Business
Tallahassee, FL 32306-1042
(316) 304-7987
gcolak@sbcglobal.net

Wei Wang
Department of Finance
University of Colorado at Boulder
Leeds School of Business
Boulder, CO 80309
(303) 492-4865
wei.wang@colorado.edu

June 2007

*We would like to thank Chris Anderson, Wolfgang Aussenegg, Cem Demiroglu, Geoffrey Friesen, Jean Helwege, Eric Hughson, Chris Leach, Paul Koch, Nathalie Moyaen, Jay Ritter, Ashish Tiwari, Toni Whited, Jaime Zender, and Janis Zvingelis for their helpful suggestions. Comments from seminar participants at 2006 EFMA Madrid, 2006 FMA Salt Lake City, 2006 FMA Stockholm, Florida State University, George Mason University, Koç University, SUNY Buffalo, University of Kansas, University of Nebraska, and Wichita State University are also appreciated.

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Abstract

We develop a model in which time-varying real investment opportunities lead to time-varying adverse selection in the market for initial public offerings. The model is consistent with several stylized facts known about the IPO market: economic expansions are associated with a dramatic increase in the number of firms going public, which is in turn positively correlated with underpricing. Adverse selection is procyclical in the sense that *dispersion* in unobservable quality across firms should be more pronounced during booms. Taking the premise that uncertainty is resolved (and thus private information revealed) over time, we test this hypothesis by looking at long-run abnormal returns and delisting rates. Consistent with the model, we find a) greater cross-sectional return variance and b) higher incidence of delisting for hot-market IPOs.

Keywords: initial public offerings, adverse selection, underpricing, delisting rates, cross-sectional return variance.

JEL Classification: C14, D82, G24, G30, G32, G33, E22, E32

1. Introduction

IPO underpricing is highly autocorrelated, as is the volume of activity in the IPO market. Perhaps more surprisingly the two series — volume and underpricing — are positively correlated. These facts are difficult to reconcile with most existing theoretical models, as Jenkinson and Ljungqvist (2001) point out:

“Conceptually, the magnitude of initial returns will vary when the fundamental parameters identified in theoretical underpricing models change. For instance, if underpricing serves to insure against litigation, greater underpricing will be necessary as the likelihood of future lawsuits increases. However, there is as yet no convincing effort to endogenize how and why these parameters change with macroeconomic and stock market conditions: why, for instance, would litigation risk increase in buoyant markets?”

The positive relation between volume and underpricing is perplexing; it apparently implies that firms prefer to go public precisely when they are least able to obtain full pricing. While empirical papers have begun to investigate the magnitude and robustness of these regularities, our understanding of the economics behind them is certainly lagging.¹

¹Lowry and Schwert (2002) state “we have little understanding of the factors that drive these fluctuations.” Loughran and Ritter (2004) attribute some of the pattern to changing issuer preference across time. They suggest that, during booms, issuers care less about pricing than about analyst following and that the reverse is true during contractions. Jenkinson and Ljungqvist (2001) conclude that no consensus exists on the matter.

We argue that the key features of “hot” IPO markets follow from time variation in adverse selection. The basic idea is straightforward. Consider a positive shock to the economy. Improving investment opportunities raise the price at which a fixed cohort of firms can sell securities. Higher prices increase the temptation of bad firms to pool. In equilibrium, more bad firms do pool.

This increase in the number of firms going public is a wave. In addition, marginal firms entering the market given a positive economic shock are of relatively lower quality. This fact implies a second, more subtle result which is central to this paper: *the IPO market is characterized by procyclical dispersion in quality*. Because more information asymmetry leads to more underpricing² it follows that this shock increases underpricing. Our argument therefore ties together the time-series properties of hot issue markets described above. An exogenous positive shock to the economy leads to a greater number of firms going public. Moreover, this wave of IPOs exhibits high underpricing.

Ritter (1984) observes that adverse selection models can explain these time-series patterns if, for some reason, the composition of firms changes across time. The literature has termed this idea the *changing risk composition hypothesis*. Yet Ibbotson, Sindelar and Ritter (1994) conclude that there is no compelling economic story for such variation. Thus, given the state of the literature, one needs to simply assume that the composition of firms changes for exogenous reasons in order to generate underpricing waves. Our work fills this gap by developing and testing a simple theoretical framework for understanding how and why the composition of firms varies across the IPO cycle.

²See for example Rock (1986), Grinblatt and Hwang (1989) and Benveniste and Spindt (1989).

The changing risk composition has been investigated empirically. Loughran and Ritter (2004) document the trend in firm characteristics such as age, sales, assets, industry, and underwriter prestige in a large sample of IPOs from 1980-2003. They conclude that variation in firm characteristic is insufficient to account for the trend in underpricing during this period. Helwege and Liang (2004) isolate hot and cold markets, as opposed to studying general intertemporal trends, and obtain a related finding. On a variety of dimensions (industry, age, profitability, etc.) firms do not differ in economically significant ways in hot and cold markets. Lowry and Schwert (2002), Fink et. al (2005) and Howe and Zhang (2005) take contrary views, arguing that at least some of the stylized patterns are explained by clustering in the types of firms going public (for example, firm age and underwriter quality). Cook, Jarrell, and Kieschnick (2001) find indirect evidence of these changes, arguing that differing proportions of IPOs are stabilized in hot and cold markets. These studies do not address the underlying causes of observed variation in firm characteristics.

Our study suggests a refinement to this literature. These papers ask whether changes in *observable* firm characteristics are correlated with changes in underpricing over time. The underlying assumption is presumably that observable characteristics are associated with a *fixed* probability distribution of private information. In contrast, in this paper, firms have identical observable characteristics. Yet, in bad times, only a small subset of these firms (those with favorable private information) go public. In good times, more apparently identical firms go public. Thus, observable characteristics need not change over time even when the probability distribution of private information changes

dramatically.

This observation begs the question: how does one measure the time-varying distribution of private information? It cannot be proxied by observable firm characteristics; private information is, by definition, private. We propose that, for a given cohort of firms, the within-sample differences are only revealed over time. Hence, the main prediction of the paper regards the cross-sectional variance of long-run returns³ (this prediction is discussed in more detail after the model is developed). The key methodological point is that the variation in observable characteristics, or lack thereof, noted in previous literature may not indicate anything about issuers' private information. In this spirit, we perform a few highly targeted empirical tests,⁴ focusing *only* on the model's predictions that a) shocks to the value of private firm's projects lead to IPO waves and b) within these waves, dispersion of quality is higher than during cold times.

We classify quarters as "hot" or "cold" in terms of the traditional variables used in the literature (number of IPOs and average underpricing) as well as based on a proxy for shocks to private firms' demand for capital. We find that the cross-sectional variance of abnormal returns across firms issuing during hot quarters is much higher than for cold quarters, confirming the model's central prediction. In addition, compared to cold markets, IPOs underwritten in hot markets are nearly twice as likely to delist within three years, again consistent with the notion that the left tail of the distribution expands

³Lowry, Officer, and Schwert (2006) also consider the variability of returns, but focus on initial returns rather than long-run returns.

⁴The IPO market's empirical regularities are covered more broadly by Loughran and Ritter (2004), Lowry and Schwert (2002), Lowry (2003), and Jenkinson and Ljungqvist (2001).

during hot markets. Finally, we show that these results are not driven by a market-wide effect rather than an IPO effect, i.e., it is not simply the case that all firms become riskier during buoyant markets, heightening return variability and the probability of delisting.

1.1. Comparison to Existing Models of Security Issuance Waves

Much of the neoclassical economics literature reaches the opposite conclusion to ours, arguing that adverse selection costs are countercyclical in severity.⁵ This intuition is motivated by considering a positive shock to balance sheet quality (e.g., collateral) in a commercial lending environment that suffers from Stiglitz and Weiss (1981) type credit rationing. Balance sheet strengthening reduces the probability of default and credit rationing becomes less severe. Hence, this market imperfection is countercyclical. Comparing this literature's conclusions with ours highlights the importance of the type of economic shock assumed. We regard growth opportunities as particularly relevant in the IPO market, whereas collateral is the key determinant of the health of the commercial lending market.

The literature's countercyclical adverse selection costs are difficult to reconcile with the stylized facts, namely, high initial returns during hot markets. Consequently the IPO waves literature diverges from the neoclassical framework. For example, Rajan and Servaes (2003), Ljungqvist, Nanda, and Singh (2006), and Bachmann (2005) tie together underpricing, hot issue markets, and long-run underperformance in theoretical

⁵See for example, Hubbard (1998) and Bernanke, Gertler, and Gilchrist (1996). Mishkin (1999) surveys this literature without entertaining the idea the adverse selection costs could be procyclical.

models that rely upon quasi-rational investors or investor sentiment. On the managerial side, Ljungqvist and Wilhelm (2003) argue that CEO ownership can explain some of the underpricing spike seen during the internet bubble.

Like us, Pastor and Veronesi (2005) model IPO waves in an environment with fully rational investors and managers with neoclassical utility functions. They assume time-varying equity premia and (exogenously specified) time-varying average profitability of new investments. More firms go public when the equity premium drops or when the average profitability of new firms increases. Benninga, Helmantel, and Sarig (2005) obtain long-run underperformance in a model with private benefits and time-varying differences between public and private valuations. In their model, going public is not a one-time decision. Rather, private firms always retain the option to go public and vice versa. Neither model obtains predictions regarding underpricing or return variability since there is no information asymmetry. Similarly, there is no interaction between investment and financing as firms are specified to follow first-best investment policy in all economic states.

Another strand of the theoretical literature on IPO clustering focuses on information spillovers. Late IPOs may free-ride on the information production occurring in earlier IPOs, thereby causing a wave (Hoffman-Burchardi (2001)). Informed investors may therefore have a strategic incentive to withhold their information (Alti (2005)). The resulting market breakdowns create a role for investment banks in bundling IPOs and cross-subsidizing early wave offerings (Benveniste, Busaba, and Wilhelm (2002)). These theoretical analyses are complementary to ours, in which insiders and informed investors

have only firm-specific private information. In our model all industry-wide shocks are publicly observed, preventing any information spillover effects.

The paper proceeds as follows. *Section 2* develops the model. *Section 3* describes the data. *Section 4* tests the implications of the model. *Section 5* concludes.

2. The Model

There exists a continuum of private firms in the economy with assets-in-place worth V in current use. A new project is available which redeploys existing assets at a cost K . This project requires external funding.

At $T = 1$, if the new project is undertaken, the firm's assets will be worth X with probability π_i , or else 0. Subscript i indicates the firm's privately known type. Net present value is therefore $X\pi_i - K - V$. We assume that $K + V \in (0, X)$ and that success probabilities π_i are uniformly distributed on $[0, 1]$. Hence, some firms in the economy have positive NPV projects while others have negative NPV projects.

Investors are atomistic. Some proportion p are uninformed. The others know the quality of the issuing firm, which creates an adverse selection problem for the uninformed. Both investor classes are assumed insufficiently wealthy to purchase the entire issue, so that the participation of the uninformed is necessary.

Since the firm's assets return X or 0, we model the securities as equity. We assume shares are sold via a fixed-price mechanism: the firm announces a price per share; if there is oversubscription, orders are rationed randomly.

Rock (1986) shows that a fixed-price mechanism coupled with investor heterogeneity

implies underpricing. Informed investors purchase only high quality issues; uninformed investors disproportionately invest in lower quality issues, leading to a discount to ensure they break even. Our main results do not depend on this particular mechanism; they require only that underpricing is positively correlated with dispersion in IPO quality, which is true for any mechanism in which underpricing is driven by information asymmetry (e.g., Benveniste and Spindt (1989) and Grinblatt and Hwang (1989)).

2.1. Equilibrium

The outcome of this model is a semi-separating equilibrium. All firms with quality lying within the interval $[\pi_{MIN}, 1]$ for some π_{MIN} choose to go public by offering an equity stake α in exchange for investors' capital contribution K . Firms with quality below π_{MIN} opt out of the market. In equilibrium, informed investors avoid the lemons by purchasing only a strict subset of the IPOs on offer. Denote the interval of firm quality on which the informed investors purchase by $[\pi_{INFO}, 1] \subseteq [0, 1]$, where $\pi_{INFO} > \pi_{MIN}$.

We now characterize the unique Bayesian Nash equilibrium (BNE) of this environment. The triple $\{\alpha, \pi_{MIN}, \pi_{INFO}\}$ forms a BNE if and only if no participants, holding fixed the behavior of others, can profitably change their behavior. Specifically, firms with quality $\pi_i \in [0, \pi_{MIN})$ would prefer not to mimic high quality firms by issuing α shares of equity. Firms with $\pi_i \in [\pi_{MIN}, 1]$ do issue equity but cannot lower α without causing uninformed investors to earn negative profits.

Theorem 1 *The triple $\{\alpha, \pi_{MIN}, \pi_{INFO}\}$ that jointly satisfies*

$$\alpha = \frac{K}{X} \frac{1 + \sqrt{p}}{\pi_{MIN} + \sqrt{p}} \quad (1)$$

$$\pi_{MIN} = \frac{V}{X(1 - \alpha)} \quad (2)$$

$$\pi_{INFO} = \frac{K}{\alpha X} \quad (3)$$

is a Bayesian Nash equilibrium. Furthermore, $\pi_{MIN} < \pi_{INFO}$.

Proof: See the Appendix.

Condition (1) illustrates the existence of an adverse selection discount faced by good firms. Since firms go public if and only if $\pi_i \in [\pi_{MIN}, 1]$, the average quality is $\bar{\pi}_i = \frac{\pi_{MIN} + 1}{2}$. If all IPOs were bundled and sold in a full-information world, the resulting equity stake would need to satisfy $\alpha \bar{\pi}_i X = K$. The full-information equity stake is

$$\alpha = \frac{K}{X} \frac{2}{\pi_{MIN} + 1}, \quad (4)$$

which is smaller than that indicated by (1) whenever $p < 1$. Thus, whenever informed investors exist, they cause an adverse selection problem for the uninformed, which forces the price down.

Condition (3) is the statement that informed investors purchase only when the project has a positive NPV. Since $\pi_{INFO} > \pi_{MIN}$, some bad firms issue stock in equilibrium. These firms pool because the mispricing available in the public markets more than compensates for the unprofitability of the project, i.e. mispricing turns otherwise negative NPV projects into privately positive ones.

Two effects visible in Theorem 1 suggest that improving economic conditions draw in lower quality firms. The following argument is heuristic (because it examines the equilibrium conditions in isolation) but illustrates the basic intuition. Consider a positive shock to X . Since a bad firm's project NPV is now less negative, a smaller amount of mispricing is required to turn this project into a privately profitable one. This observation corresponds to noting that in condition (2), as X rises, π_{MIN} falls.

The second effect relates to the market price of IPOs. A positive shock to X makes investors easier to satisfy; that is, for a given capital contribution, investors are willing to take a smaller stake in the firm. This effect is seen in condition (1), as a rise in X causes α to fall. This drop in α feeds back into condition (2), causing an additional drop in π_{MIN} . The intuition behind this drop is compelling. Effectively, lower α implies higher stock prices. Hence, the second effect is that stock prices rise during an expansion, providing additional incentive for bad firms to pool.

These heuristic claims are formalized in Corollary 1.

Corollary 1 $\frac{\partial \pi_{MIN}}{\partial X} < 0$, $\frac{\partial \pi_{MIN}}{\partial K} > 0$, and $\frac{\partial \pi_{MIN}}{\partial V} > 0$; shocks to the economy that raise the NPV of projects induce lower quality firms to pool. Thus,

- (a) **(Waves)** Positive NPV shocks increase private firms' demand for capital, which leads to more firms entering the IPO market.
- (b) **(Dispersion)** Within these waves, dispersion in firm quality is high.

Proof: See the Appendix.

The main insights of the model all flow from the result that the interval $[\pi_{MIN}, 1]$ widens with positive shocks. First, more firms become active; the interval is simply larger (Corollary 1a). Second, dispersion in firm quality grows: the differences between the marginal, low-quality firms ($\pi_i = \pi_{MIN}$), average firms ($\pi_i = \frac{\pi_{MIN}+1}{2}$) and the highest quality firms ($\pi_i = 1$) all increase (Corollary 1b).

Recalling that π_i is the probability of success (in the sense that the project's value is X rather than zero), the above result has another immediate implication.

Corollary 2 *For shocks to X , K or V that raise the NPV of projects, the proportion of firms that are (ex-post) worthless is increased.*

Proof: See the Appendix.

Finally, these shocks increase underpricing, since more dispersion in quality leads to a more pronounced adverse selection problem in the primary market:

Corollary 3 *For shocks to X, K or V that raise the NPV of projects, average percentage underpricing increases.*

Proof: See the Appendix.

2.2. Testable Implications

We now briefly outline the empirical research design suggested by the three corollaries. Corollary 1a proposes that a positive shock to project value leads to a wave of firms

going public. We test this by examining the correlation between a proxy for private firms’ capital demand (described in Section 3.3) and the number of firms going public.

Corollary 1b predicts high cross-sectional dispersion in returns during waves. There are important tradeoffs in selecting the appropriate return horizon for testing this hypothesis. The model exhibits a pooling equilibrium, and so immediate aftermarket prices are not fully informative. Institutional features such as underwriter price support and the “quiet period” further frustrate the market’s price discovery role, and so it is our view that short horizons cannot yield accurate proxies of a firm’s true value. Unfortunately, long horizons introduce their own problems (Barber and Lyon (1997) and Kothari and Warner (1997)). Moreover, the relevance of the entrepreneur’s ex-ante private information — the relevant imperfection in our setting — is probably limited at very long horizons.

As a compromise, we present results over 3-month, 6-month, 9-month, and 12-month holding periods.⁶ These periods are sufficiently long to allow for a significant amount of private information to enter into the market price. By 3 months, the firm will have released an earnings report, the “quiet period” will have ended, and analysts may start following the stock. By 6 months, the firms will have released a second earnings report. Perhaps more importantly, in most cases the lockup period will have expired and insider trading decisions will have been revealed.

Our empirical methodology for testing the model’s first prediction, then, is to consider a set of firms going public at the same time (or nearly the same time) and to

⁶Cornelli, Goldreich, and Ljungqvist (2006) make similar choices.

study the cross-sectional variance of long-run returns across firms within this set. What constitutes going public at “nearly the same time?” Grouping firms into yearly cohorts is probably too coarse, as the heat of an IPO market can (and frequently does) change midyear. Using months slices our data too finely, however, as many months have few IPOs. Using quarterly cohorts strikes an appropriate balance in this trade-off. Our results are robust to alternative calendar divisions.

Corollary 2 predicts that more firms going public during waves will become (ex-post) worthless, due to the drop in π_{MIN} , despite the fact that more total value is generated during a wave. The most natural empirical proxy for worthlessness is bankruptcy or delisting. This test necessitates longer horizons than the returns tests mentioned above. IPO firms have recently had a large cash infusion, and few of them are of sufficiently poor quality as to be in financial distress a few months after such a significant fundraising event. We therefore follow IPOs for three to five years.

3. Data and Measurement Issues

3.1. Sample Selection

Our initial source of data is Thompson Financial’s SDC database, from which we obtain 7,409 IPOs from 1973 to 2004.⁷ This sample excludes REITs, closed-end funds, ADRs, unit offers, MLPs, and all issues with an offer price below \$5. The data items we obtain from SDC are the date of the issue, the dollar value of proceeds raised, the

⁷SDC’s pre-1973 coverage is less comprehensive. See Gompers and Lerner (2003).

percentage change in the stock price on the first trading day (usually referred to as underpricing), and the CUSIP of the newly public firm. We supplement the SDC sample with Jay Ritter’s IPO dataset for 1975-1984, applying the same filters. This enlarges our sample by 137 firms. We use Ritter’s data to fill in missing variables in SDC; in case of disagreement, we always use Ritter’s value. Our third data source is the SEC’s Registered Offering Statistics dataset, obtained from the National Archives. This yields 44 new observations not covered by either of the two aforementioned sources.

We obtain trading data from CRSP for each IPO firm for 3-to-12 months after the issuing date. For some IPOs, the CUSIP given in SDC has no match in CRSP. In other cases, we obtain a CUSIP match but the full complement of 12 monthly returns is not available. We eliminate firms for which fewer than six of the first twelve monthly returns are available, because missing returns do not add information about return variability. Our final sample after these two screens consists of 7,056 initial public offerings.

3.2. Measuring IPO Market Heat

The number of IPOs in each quarter serves as our most direct measure of market heat. We obtain aggregate issuance data from Jay Ritter’s website, which tabulates the number of IPOs and the equally-weighted underpricing of these offerings in each month going back to 1960.

We divide issuance quarters into three categories: “hot”, “normal”, or “cold” by comparing the moving average $MA(4)$ ⁸ of IPOs in each quarter (denoted $NumIPO$) with

⁸ $MA(4)$ controls for the strong seasonality effects present in our data: for example, there are ap-

the historic average of the IPO activity in all previous quarters going back to 1960. If this moving average is 50% above (below) the historical average, the quarter is classified as hot (cold). Remaining quarters are classified as normal.⁹

As an alternative measure, Ritter (1984) defines a hot market as one in which average underpricing is high. In this spirit, we perform a similar categorization as above, based on the moving average MA(4) of equally-weighted underpricing (denoted EWU) in each quarter from 1973 to 2005 relative to historical average underpricing.

3.3. Measuring Private Firms' Demand for Capital

The primitive shock in the model consists of changes in profitability of private firms' projects. The finance literature employs a variety of proxies for project profitability (or investment opportunities), one of which is market-to-book ratio. Unfortunately, this variable is also widely used as a measure of investor sentiment. Because much of the literature associates hot markets with overvaluation or investor irrationality, we prefer an alternative measure. Candidates include income statement-based variables, such as ROE or sales growth. However, these variables may capture shocks to the value of assets-in-place rather than to investment opportunities.

Instead, we follow Lowry (2003) and Pastor and Veronesi (2005) who use the quarterly percentage change in *real private non-residential fixed investment* ($InvestGr$),

approximately 40% more IPOs issued in the 4th quarter than in the 1st.

⁹The 50% cutoff yields a reasonable number of quarters in each heat classifications. Our qualitative conclusions are not significantly altered using 20%, 33%, 40%, or 60% cutoffs, or by using the entire time series to rank quarters into hottest and coldest terciles.

tained from the Bureau of Economic Analysis. This has the advantage that it reflects actual investment behavior rather than trying to use income statements to infer the value of investment opportunities.

We refer to the moving average MA(4) of *NumIPO*, *EWU*, and *InvestGr* as “heat measures.” *Section 4* shows that the correlations among these three variables are all significant.

3.4. Measuring Returns

In our baseline tests, we employ a simple market model. Let R_{it} represent firm i ’s stock return (including dividends) for month t . We define the abnormal return as $AR_{it} = R_{it} - R_{mt}$, where R_{mt} is the contemporaneous return on the CRSP equally-weighted market index (including dividends). Later, we present results using alternative measures of expected return.

Firm i ’s cumulative abnormal return (CAR) and buy-and-hold abnormal return (BHAR) across T periods are defined as

$$CAR_{it} = \sum_{t=1}^T AR_{it} \quad (5)$$

$$BHAR_{iT} = \prod_{t=1}^T (1 + R_{it}) - \prod_{t=1}^T (1 + R_{mt}). \quad (6)$$

We follow Barber, Lyon, and Tsai’s (1999) suggestion regarding missing return observations in the CRSP files. They argue for replacing missing returns with an equally-weighted reference portfolio of all the other IPOs in the final sample with available return

data for that month. The reference IPO portfolio is rebalanced monthly in the following fashion: any IPO that is delisted from CRSP or drops out of our moving window of 12 consecutive monthly returns is excluded. That is, our reference portfolio in a particular month (denoted *ewretIPO*) includes only those IPO firms that had their issue date within the last 12 months and have non-missing return observations for that month.

4. Results

Figures 1A through 1C plot *NumIPO*, *InvestGr* and *EWU* over time from 1960 to 2004. Our heat measures based on *NumIPO* and *InvestGr* are positively correlated ($\rho = .2918$, significant at the 5% level) consistent with the prediction in Corollary 1a that shocks to investment opportunities lead to more firms going public. Similarly, the heat measures based on *NumIPO* and *EWU* are positively correlated ($\rho = .2176$, significant at the 5% level) and also for *InvestGr* and *EWU* ($\rho = .2787$, significant at the 1% level), consistent with Corollary 3.

The connections between demand for capital and IPO volume, and between underpricing and IPO volume, are of course already widely documented; see for example Jenkinson and Ljungqvist (2001), Lowry and Schwert (2002), Lowry (2003), and Pastor and Veronesi (2005). The rest of this section emphasizes tests of Corollary 1b and Corollary 2.

4.1. Cross-Sectional Variance Across Hot and Cold Markets

We group IPOs according to the heat of their issuance quarter and compute the cross-sectional variance of the CAR and BHAR measures within each heat-group. As *Table 1* shows, Corollary 1b is strongly supported. For example, using 3-month BHARs and the *InvestGr* measure, the cross-sectional variance is .0861 for IPOs issued during cold markets and .1957 for those issued during hot markets. Similar results hold for other entries in the table. In fact, the number for hot markets is higher in all 24 such comparisons (4 horizons, 3 heat measures, 2 measures of abnormal returns), and these differences are significant at the 1% level in 22 of 24 cases. The two exceptions have borderline significance (p-values .0592 and .0461) and both involve BHARs and *EWU*. We return to these cases in Section 4.3 where we show that they are highly significant under alternative measures of abnormal return.¹⁰

4.2. Variation in Distribution Moments of the Returns Across Hot and Cold Periods: Non-parametric Analysis

Next, we consider the entire distribution of IPO returns. Because we do not know the true distribution, we investigate nonparametrically whether IPO returns differ across heat groups in terms of location (mean or median), scale or variation (variance), or

¹⁰In further robustness tests, we eliminate outliers (e.g., an extended cold period from 1973/2 to 1980/3) and redo *Table 1*. While most of our findings are qualitatively unchanged, removing the 1999/1 to 2000/3 period weakens the *EWU* results (especially when using BHARs). Overall, we conclude that our results are not attributable to any one period of extreme activity.

higher moments (skewness and kurtosis).

To save space, *Figures 2A-B* present kernel density plots for only the 3-month returns (CAR and BHAR) of the hot and cold IPO samples. These plots differ from each other substantially, especially in terms of dispersion.

The results from formal nonparametric tests of the null hypothesis of no distribution differences across heat samples are shown in *Table 2*. We perform the following distribution-free tests: the Wilcoxon Mann-Whitney U Test (for location differences), the Siegel-Tukey test (for dispersion or scale differences), the Kuiper two-sample test (sensitive to tails), and the Kolmogorov-Smirnov two-sample test (for overall fit of the distributions).

The dispersion in returns is much higher during hot periods, consistent with Corollary 2. In addition, while the BHAR and CAR distributions differ strongly from each other (as seen in Figure 2), they both display inflated variance during hot markets with similar statistical power (significant at the 1% level in all but one test). Finally, *Table 2* suggests that this second moment effect is much stronger than differences in first moments, as indicated by the typically high Mann-Whitney p-values.

4.3. Alternative Measures of Abnormal Return

In view of criticism of market-adjusted returns (see Mitchell and Stafford (2000)) this section employs two alternative measures of abnormal returns popular in the long-run event study literature: the Fama-French-Carhart four-factor model and returns relative to matched control firms.

4.3.1. Four-Factor Abnormal Returns

For each IPO in our sample, we compute the return using the following regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_iSMB_t + h_iHML_t + u_iUMD_t + \epsilon_{it} \quad (7)$$

where R_{it} is the return of the IPO firm, R_{ft} is the return on three-month Treasury bills, R_{mt} is the return on a value-weighted market index, SMB_t is the difference in the returns of value-weighted portfolios of small stocks and big stocks, HML_t is the difference in the returns of value-weighted portfolios of high book-to-market stocks and low book-to-market stocks, and UMD_t is the difference in returns of value-weighted portfolios of firm with high and low prior momentum.¹¹

Normally, equation (7) is estimated in a pre-event period to obtain parameters of the market factor, size factor, value factor, and momentum factor, which are then used in the event period to compute the abnormal returns. The underlying assumption is that the factor parameters remain constant for the pre-event period and during the event period. For IPO studies, we do not have a pre-event period. However, if we assume the factor parameters remain constant in the event period and in the post-event period that immediately follows, we can estimate the parameters in the post-event period instead. We take the first 60 months (or as many months as possible, if the total number of months available is smaller than 60) after the IPO as the estimation period to obtain the factor loadings and then apply those loadings to the horizon of interest (e.g., 3 months) to compute abnormal returns. To ensure that our factor loadings are driven primarily by the firm's returns rather than the replacement portfolio returns, we eliminate 1,187 firms

¹¹The construction of these factors is discussed in detail in Fama-French (1993) and Carhart (1997).

with fewer than 30 return observations available, leaving a final sample of 5,869 IPO firms.

Table 3, Panel A compares cross-sectional variances across hot and cold markets. These variances tend to be much smaller than their counterparts in *Table 1*, because the added size, value, and momentum factors explain additional fractions of the total variability. Again the data supports Corollary 1b. For example, using the 3-month BHAR and *InvestGr* measures, cross-sectional variances are .1505 and .0724, respectively, for IPOs underwritten during hot markets and during cold markets. Similar results hold for other comparisons in *Table 3*. We conclude that our results in Section 4.1 are invariant to controlling for size, book-to-market, and momentum effects.

4.3.2. Control Firm Approach

Next, we consider the difference between the sample firm’s return and that of a matching control firm. This approach is popular in the long-run event study literature, in part because it yields less biased, if noisier, tests (Barber and Lyon (1997)).

Control firms are chosen using three criteria: industry, market capitalization, and market-to-book ratio. Specifically, we match an IPO firm with all existing firms in the same 2-digit SIC industry.¹² To avoid matching with recently-issued firms, firms issued within three years of the sample firm are excluded from the candidate control firm pool. From this candidate pool, we retain firms with market capitalizations between 0.7-1.3

¹²Though Barber and Lyon (1997) do not use industry matching, the literature subsequent to their work has emphasized industry clustering, pointing to the importance of controlling for changes along this dimension.

times the IPO firm’s market capitalization. Finally, we compare the market-to-book ratios of the candidates with market-to-book ratio of the IPO firm, and pick as the control firm the one with the market-to-book ratio closest to that of the IPO firm, as long as the control firm market-to-book ratio is between 0.2 to 5 times the IPO firm’s market-to-book ratio. Otherwise the IPO firm gets no match.

The use of market-to-book ratio as matching criterion entails the introduction of COMPUSTAT. Mapping between CRSP data and COMPUSTAT data, along with the requirements that no more than six months of returns are missing and the aforementioned size and book-to-market restrictions, leads to a smaller final sample of 5,151 firms.

One methodological change is worth noting. For the *EWU* measure, we change our threshold for categorizing “hot” and “cold” to $\pm 33\%$ from $\pm 50\%$. Otherwise we classify too few quarters as cold. The reduced sample size using the control firm approach then yields too few cold IPOs. To see why, note in *Figure 1C* an extended period between 1984 and 1998 in which average underpricing was neither exceptionally high nor low.

Table 3, Panel B summarizes the results. Two patterns emerge. First, the cross-sectional variances are uniformly higher than their market-adjusted or four-factor counterparts in *Table 1* and *Table 3, Panel A*. This is because control firm returns are more volatile than index returns, thereby increasing variability of the difference between the IPO firm and its control firm. More importantly in our context, cross-sectional variances are higher in hot markets than in cold markets for all 24 comparisons in the table. Each of these differences is significant at the 5% level. We again conclude that Corollary 1b is supported.

4.4. Are *All* Stocks Riskier During Hot IPO Markets?

Sections 4.1 through 4.3 demonstrate that Corollary 1b is supported in our sample, and that this conclusion is invariant to return cumulation methodologies and the benchmark return considered. However, maybe hot IPO markets are associated with periods of generally heightened uncertainty, and hence all stocks are riskier during these periods. In other words, our previous results may represent a market-wide phenomenon rather than an IPO-specific phenomenon.¹³ Although we are not aware of any prior literature that identifies such a trend¹⁴ we investigate this issue in our data set.

To check whether increased dispersion is a market-wide phenomenon, we return to the same control firms selected in Section 4.3.2, matched on industry, size, and book-to-market. In that section, control firm returns were used as benchmarks to measure the abnormal returns of IPO firm. Now we are interested in the control firms' (market-adjusted) returns themselves. Specifically, we seek to characterize (1) how the cross-sectional variance in control firms' returns behaves across hot and cold IPO markets and (2) whether there is any difference in this pattern and that for IPO firms.

Table 4 tabulates the results. For example, considering 3-month BHARs and the heat measure *InvestGr*, during cold markets the standard deviation across IPO firms and control firms is .2680 and .2140 respectively, a difference of .0540. Thus, IPO firms

¹³We thank Wolfgang Aussenegg for this observation.

¹⁴Brandt, Brav and Graham (2005) show that idiosyncratic volatility has generally risen over time. Theirs is a time-series rather than cross-sectional measure. Moreover, the time-trend they identify does not appear obviously correlated with business cycles, let alone hot IPO markets; see, for example, their Table 3.

exhibit slightly higher cross-sectional dispersion even during cold markets. The existence of this differential is unsurprising. Even if our matching procedure were perfect (i.e., the exposures of IPO firms and of control firms to macroeconomic risk factors were identical) the seasoning process itself makes prices more efficient. Historical price discovery will tend to make seasoned firms less risky than otherwise similar IPO firms in all market conditions.

During hot markets these numbers increase to .4230 and .2700, respectively, a difference of .1530. While both types of firms show higher cross-sectional dispersion during hot markets, the effect is nearly three times as large for IPO firms.

In fact this pattern is typical. In 22 of 24 such comparisons in the table, the difference in variability between IPO firms and control firms is larger in hot markets. Ranging over all 24 comparisons, the average difference between IPO firms and control firms is +0.0450 in cold markets and +0.1230 in hot markets, again nearly three times in magnitude.

5. Delisting Rates Across Hot and Cold Markets

We test Corollary 2 by measuring the incidence of delisting within 3 years (or 5 years) of an IPO. Not all delistings represent failure. Delisting due to liquidation (CRSP codes between 400 and 499) and due to inability to meet listing exchange requirements (codes from 500 to 599, or code= 700) capture the spirit of Corollary 2. But if a firm stopped trading because it switched to another major exchange (NYSE, AMEX, or NASDAQ; delisting codes 501, 502, and 503), we do not include it in our sample of failed IPOs unless it subsequently delists from its new exchange for the aforementioned reasons.

Firms classified as voluntarily going private (code 573) are not considered failed IPOs.

Delistings due to mergers and acquisitions represent a gray area. Managers who enjoy private benefits may be reluctant to cede control unless forced to do so because of financial distress. This suggests that M&A related delistings belong in the failed-IPO sample; Fama and French (2004) also argue that low-quality IPO firms are more likely to merge. On the other hand, Zingales (1995) argues that the IPO may be the first step in a gradual sale of the company. Thus, subsequent acquisition may not indicate failure. Given this ambiguity, we elect to report results using both specifications.

Our results support Corollary 2, as Table 5 illustrates. Under every heat measure, hot-market IPOs are much more likely to subsequently delist.¹⁵ Most dramatically, under the *NumIPO* measure only 7 out of 355 cold-market IPOs (or 1.97%) were pure, non-M&A delistings within the first three years, making this quite a rare event in our sample. Hot-market IPOs were three and a half times as likely (6.93%) to do so. All such comparison in the table are statistically significant.

To control for changes in firm characteristics, we also address the likelihood of delisting in a logistic regression. Specifically, we consider the risk proxies suggested by Demers and Joos (2006), to which we add a continuous measure of the heat of the quarter during which the IPO was issued. The coefficient on heat identifies whether, controlling for relevant firm characteristics, issuing in a hot quarter is associated with a higher probability of delisting.

¹⁵We are unable to follow quarters near the end of our sample for the full three (five) years. Truncating our sample to eliminate these quarters results in minimal changes to Tables 5 and 6 because most of the affected quarters are neither hot nor cold.

Matching with Compustat and requiring nonmissing data items is a restrictive screen, and can lead to serious sample selection bias. We therefore select control variables identified by Demers and Joos that are widely available in COMPUSTAT for the first quarter of firm’s public trading: size (one plus log sales), leverage (total debt divided by total assets), and the log of one plus selling, general and administration expenses. Age, offer price, VC backing, underpricing, and underwriter reputation variables are obtained from SDC data or Jay Ritter’s web site (we extrapolate reputations before 1980 by substituting the 1980-1984 reputation when available). In total, these screens reduce our sample size to 3,198 IPOs, 207 (354) of which were delisted within three (five) years of issuance.

The logit results are as expected. Older and larger firms are less likely to delist, as are firms backed by VCs or reputable underwriters. Controlling for these characteristics, issuing a hot market increases the likelihood of subsequent delisting. The coefficient on “Heat Degrees” is statistically significant at the 5% level in all six models. We judge economic significance by considering the effect of a one-standard deviation shock to “Heat Degrees” while holding all other independent variables fixed at their sample means. Depending on the model, this increases the delisting probability by between .51% (model (2)) and 2.20% (model (6)). By comparison, an analogous shock to leverage yields roughly similar magnitude changes, while shocks to age and size lead to only slightly stronger changes. Given the overall low likelihood of delisting mentioned above, these impacts are substantial.

6. Conclusion

The IPO literature has provided researchers with many puzzling stylized facts. This paper demonstrates that some of them may be linked, by showing theoretically that exogenous shocks to investment opportunities cause time-varying adverse selection in the IPO market.

In the model, positive shocks lead to more firms going public. It is not surprising, of course, that an increase in the productivity of capital leads to greater demand for capital, and in turn, more active IPO markets. Importantly, however, marginal firms are of lower quality than the average pre-shock firm. This implies that the dispersion in quality is higher during waves, and so the asymmetric information problem is heightened. This paradigm is consistent with higher underpricing during waves.

The model generates new testable implications regarding a statistic which has received little attention: the cross-sectional *variance* of long-run abnormal returns. This allows for an independent test of the model. Our tests strongly confirm the existence of the channel suggested by the model; cross-sectional variance in long-run returns is much higher for firms that issue during hot markets.

Another prediction of the model is related to survival rates. IPOs issued during hot quarters are much more likely to delist than those in cold quarters, which is consistent with the expansion of the left tail of the distribution posited by the model.

Our empirical analysis omits several measures of adverse selection widely used in the literature, such as bid-ask spreads and dispersion in analyst forecasts. While our model may have implications regarding these measures, we caution that our analysis is based

upon private information of insiders rather than secondary market traders. Because of IPO lockups, these two groups do not coincide in the first few months after the IPO.

By abstracting from timing delays (e.g. lags in registration) our model is unable to make predictions regarding lead-lag relationships between IPO volume and underpricing that have featured prominently in the empirical literature (Lowry and Schwert 2002). This may represent a fruitful direction for future research. We suspect that a critical element in this analysis is the speed-to-market of bad ideas as opposed to good ideas, because this controls the extent to which bad firms can mimic good firms. In such an environment, the strategic timing decision of firms becomes a nontrivial signalling problem, and the lag between economic shocks and the filing date constitutes important value-relevant information.

Though all agents in our model are rational, the paradigm in this paper is not inconsistent with models that allow for changes in investor sentiment. One can envision an environment in which time-varying investment opportunities lead to both a) heightened adverse selection problems and b) time-varying sentiment, leading to long-run underperformance in some states. Future work may illustrate subtle interconnections between these effects; that is, models involving both features may behave differently than models involving only one or the other.

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7. Appendix

Proof of Theorem 1: The derivations of (2) and (3) are obvious: informed investors will purchase if and only if $\alpha\pi_i X \geq K$ and firms will pool if and only if $\pi_i X(1 - \alpha) \geq V$.

Condition (1) is derived by finding the minimal α such that uninformed investors earn nonnegative profit. We assume for now, but check later, that $\pi_{MIN} < \pi_{INFO}$. Under this assumption, when firm quality is in the interval $[\pi_{MIN}, \pi_{INFO}]$ only the uninformed purchase, whereas when firm quality is in the interval $[\pi_{INFO}, 1]$ all investors purchase. Thus expected profit to the uninformed is

$$\underbrace{\left[\frac{\pi_{INFO} - \pi_{MIN}}{1 - \pi_{MIN}} \right] \left(\alpha X \frac{\pi_{MIN} + \pi_{INFO}}{2} - K \right)}_{\text{only uninformed purchase}} + \underbrace{\left[\frac{1 - \pi_{INFO}}{1 - \pi_{MIN}} \right] p \left(\alpha X \frac{\pi_{INFO} + 1}{2} - K \right)}_{\text{all investors purchase}}. \quad (8)$$

The parenthetical terms, expected profit in each event, rely on the uniform distribution's property that expected quality is the average of the endpoints. The bracketed terms are probabilities of each event, and the factor p reflects rationing when informed investors compete. Setting (8) equal to zero and substituting in the equilibrium value of π_{INFO} yields (1) after some simplification¹⁶. The final claim in the Theorem is proved as follows.

$$\pi_{MIN} < \underbrace{\frac{\pi_{MIN} + \sqrt{p}}{1 + \sqrt{p}} = \frac{K}{\alpha X}}_{\text{by (1)}} = \pi_{INFO} \quad (9)$$

Q.E.D.

Proof of Corollary 1: Substituting (3) into (2) and (1) yields

$$\frac{K}{\pi_{INFO}} = K \frac{1 + \sqrt{p}}{\pi_{MIN} + \sqrt{p}} \quad \text{and} \quad \pi_{MIN} = \frac{V}{X - \frac{K}{\pi_{INFO}}} \quad (10)$$

which together imply

¹⁶The omitted simplification is tedious; details are available upon request.

$$\pi_{MIN} \left(X - K \frac{1 + \sqrt{p}}{\pi_{MIN} + \sqrt{p}} \right) = V. \quad (11)$$

The comparative statics in the corollary follow from (11) via the implicit function theorem.

Q.E.D.

Proof of Corollary 2: The probability that the project's value is X rather than zero for firm i is given by π_i . Thus, the probability of failure for average issuing firms is given by

$$1 - \frac{\pi_{MIN} + 1}{2} \quad (12)$$

The result now follows immediately from Corollary 1.

Q.E.D.

Proof of Corollary 3: Letting the average quality be denoted by $\bar{\pi}_i$, percentage underpricing is

$$\frac{\alpha X \bar{\pi}_i - K}{\alpha X \bar{\pi}_i} = 1 - \underbrace{\frac{(\frac{K}{\alpha X})}{\bar{\pi}_i}}_{by (1)} = 1 - \frac{(\frac{\pi_{MIN} + \sqrt{p}}{1 + \sqrt{p}})}{(\frac{\pi_{MIN} + 1}{2})} = 1 - 2 \frac{(\pi_{MIN} + \sqrt{p})}{(\pi_{MIN} + 1)(1 + \sqrt{p})}, \quad (13)$$

which is decreasing in π_{MIN} . The conclusion follows by applying Corollary 1.

Q.E.D.

Figure 1: The Heat Measures Over Time

Figures 1A-1C plot our heat measures over time for each quarter during the period of 1960 to 2004. *InvestGr* is the annualized growth rate in real private nonresidential fixed investment (in %), *NumIPO* is the number of IPOs per quarter, and *EWU* is the equally-weighted underpricing per quarter (in %)

Figure 1A: Investment Growth (*InvestGr*)

Figure 1B: Number of IPOs (*NumIPO*)

Figure 1C: Underpricing (*EWU*)

Figure 2: The Nonparametric Kernel Density Plots

Figures 2A-F display the nonparametric kernel density plots for the 3-month returns (CAR and BHAR) of the hot and cold IPO samples, and for the three different heat measures described in the text. Type of kernel plot, bandwidth, c-value, and approximate mean integrated square error (AMISE) are shown in a little box on the graph. Some sample statistics, such as minimum, median, maximum, mean, variance, skewness, kurtosis, and number of firms for each heat sample are also displayed in another box. Dotted graph shows the fitted normal distribution with the same mean and variance as the actual distribution. In one of the boxes the results from three tests for normality of the distributions (the Anderson-Darling ($Pr > A-Square$), the Cramer-von Mises ($Pr > W-Square$), and the Kolmogorov-Smirnov ($Pr > D$)) are also displayed.

Figure 2A: Nonparametric Kernel Density Plot of CAR for Cold and Hot Periods (Heat Measure is InvestGr)

Figure 2B: Nonparametric Kernel Density Plot of BHAR for Cold and Hot Periods (Heat Measure is InvestGr)

Figure 2C: Nonparametric Kernel Density Plot of CAR for Cold and Hot Periods (Heat Measure is NumIPO)

Figure 2D: Nonparametric Kernel Density Plot of BHAR for Cold and Hot Periods (Heat Measure is NumIPO)

Figure 2E: Nonparametric Kernel Density Plot of CAR for Cold and Hot Periods (Heat Measure is EWU)

Figure 2F: Nonparametric Kernel Density Plot of BHAR for Cold and Hot Periods (Heat Measure is EWU)

Table 1: Relationship Between Return Variance and IPO Cycles

The table presents the number of IPO firms and the variance of their long-run returns across hot and cold markets. The results for 3-month, 6-month, 9-month, and 12-month returns (CAR and BHAR) and for replacement with *ewretIPO* are shown. Three different heat proxies are used to classify the firms into hot and cold samples: *InvestGr* - growth rate in real private nonresidential fixed investment, *NumIPO* - number of new issues per quarter, and *EWU* - equally-weighted underpricing per quarter (in %). The quarters are divided into hot and cold by comparing the four-quarters moving average, MA(4), of the heat measure to the historic average of the same measure going back to 1960. If it is 50% above (below) the historic average, the quarter is classified as hot (cold). The remaining quarters are considered normal. The return variance within each heat-group is computed for all IPOs with issuing dates during the hot (cold) years. Probability statistics ($Prob > F$) from F-test for *equal* sample variances under the assumption of *normality* is also provided.

CAR and BHAR Variances Across Hot and Cold Markets										
Return	Heat Measure is <i>InvestGr</i>			Heat Measure is <i>NumIPO</i>			Heat Measure is <i>EWU</i>			
	Cold Quarters (N=1,974)	Hot Quarters (N=3,298)	F-test	Cold Quarters (N=355)	Hot Quarters (N=4,808)	F-test	Cold Quarters (N=176)	Hot Quarters (N=1,313)	F-test	
3-month CAR	0.0755	0.1487	0.0001	0.0529	0.0869	0.0012	0.0600	0.2943	0.0001	
3-month BHAR	0.0861	0.1957	0.0001	0.0487	0.0887	0.0001	0.0652	0.4154	0.0001	
6-month CAR	0.1572	0.2738	0.0003	0.1054	0.1737	0.0004	0.1679	0.4825	0.0001	
6-month BHAR	0.2217	0.3684	0.0001	0.1053	0.1916	0.0001	0.3421	0.6166	0.0001	
9-month CAR	0.2197	0.4129	0.0001	0.1526	0.2780	0.0001	0.2285	0.6806	0.0001	
9-month BHAR	0.3094	0.5310	0.0001	0.1681	0.2987	0.0001	0.6316	0.7906	0.0592	
12-month CAR	0.2945	0.5459	0.0001	0.2237	0.3741	0.0001	0.2963	0.9079	0.0001	
12-month BHAR	0.4103	0.7399	0.0001	0.2527	0.4132	0.0001	0.6401	0.8483	0.0461	

Table 2: Nonparametric Tests of Identical Return Distributions Across Hot and Cold IPO Markets

The nonparametric tests results from a Kolmogorov-Smirnov two-sample test, a Kuiper two-sample test, a Wilcoxon Mann-Whitney U test, and a Siegel-Tukey test are presented in this table. The null hypothesis (H_0) for all four tests is that the distribution of the returns is identical for hot and cold samples. Hot and cold sub-samples are classified as in *Table 1*. The Panels A through D show the results for 3-month, 6-month, 9-month, and 12-month returns (CAR and BHAR), respectively. The numbers presented are the p-values with asymptotical test statistics, $Prob\ of Z > |Z_a|$ under H_0 .

Panel A: 3-month Returns						
Test Name	Heat Measure is <i>InvestGr</i>		Heat Measure is <i>NumIPO</i>		Heat Measure is <i>EWU</i>	
	3-mo	3-mo	3-mo	3-mo	3-mo	3-mo
	CAR	BHAR	CAR	BHAR	CAR	BHAR
Kolmogorov-Smirnov	0.0122	0.0025	0.0212	0.0277	0.0032	0.0003
Kuiper	0.0001	0.0001	0.0059	0.0086	0.0001	0.0001
Mann-Whitney	0.6885	0.7866	0.1787	0.1529	0.2214	0.0184
Siegel-Tukey	0.0001	0.0001	0.0001	0.0002	0.0001	0.0001
Panel B: 6-month Returns						
Test Name	Heat Measure is <i>InvestGr</i>		Heat Measure is <i>NumIPO</i>		Heat Measure is <i>EWU</i>	
	6-mo	6-mo	6-mo	6-mo	6-mo	6-mo
	CAR	BHAR	CAR	BHAR	CAR	BHAR
Kolmogorov-Smirnov	0.0006	0.0023	0.0299	0.2132	0.0001	0.0001
Kuiper	0.0001	0.0001	0.0011	0.0311	0.0001	0.0001
Mann-Whitney	0.0282	0.6562	0.2773	0.3537	0.0308	0.0001
Siegel-Tukey	0.0001	0.0001	0.0005	0.0048	0.0001	0.0001
Panel C: 9-month Returns						
Test Name	Heat Measure is <i>InvestGr</i>		Heat Measure is <i>NumIPO</i>		Heat Measure is <i>EWU</i>	
	9-mo	9-mo	9-mo	9-mo	9-mo	9-mo
	CAR	BHAR	CAR	BHAR	CAR	BHAR
Kolmogorov-Smirnov	0.0001	0.0001	0.0445	0.1521	0.0003	0.0001
Kuiper	0.0001	0.0001	0.0003	0.0039	0.0001	0.0001
Mann-Whitney	0.0030	0.6227	0.5529	0.8472	0.0098	0.0001
Siegel-Tukey	0.0001	0.0001	0.0001	0.0003	0.0001	0.0012
Panel D: 12-month Returns						
Test Name	Heat Measure is <i>InvestGr</i>		Heat Measure is <i>NumIPO</i>		Heat Measure is <i>EWU</i>	
	12-mo	12-mo	12-mo	12-mo	12-mo	12-mo
	CAR	BHAR	CAR	BHAR	CAR	BHAR
Kolmogorov-Smirnov	0.0001	0.0001	0.0074	0.0589	0.0001	0.0001
Kuiper	0.0001	0.0001	0.0001	0.0009	0.0001	0.0001
Mann-Whitney	0.0120	0.5703	0.8604	0.6531	0.0001	0.0001
Siegel-Tukey	0.0001	0.0001 ³⁹	0.0001	0.0003	0.0001	0.0101

Table 3: Alternative Measures of Abnormal Returns: Four-Factor Model and Control Firm Approach

The table presents the variances of IPO firms' long-run returns across hot and cold markets. Abnormal returns are computed either with the Fama-French-Carhart four-factor model (Panel A), or relative to control firms matched by industry, size, and market-to-book ratio (Panel B). The results for 3-month, 6-month, 9-month, and 12-month returns (CAR and BHAR) are shown. Missing return observations of IPO firms are replaced with *ewretIPO*, while missing return observations of control firms with *vwretCRSP*. Three different heat proxies are used to classify the firms into hot and cold samples: *InvestGr* - growth rate in real private nonresidential fixed investment, *NumIPO* - number of new issues per quarter, and *EWU* - equally-weighted underpricing in a quarter (in %). The quarters are divided into hot and cold by comparing the four-quarter moving average, $MA(4)$, of the heat measure to the historic average of the same measure going back to 1960. If it is 50% (or 33% for *EWU*) above (below) the historic average, the quarter is classified as hot (cold). The remaining quarters are considered normal. The return variance within each heat-group is computed for all IPOs with issuing dates during the hot (cold) quarters. The probability statistics ($Prob > F$) from F-test for *equal* sample variances under the assumption of *normality* is also provided in both panels.

Panel A: Abnormal Returns Calculated with Four-Factor Model										
Return	Heat Measure is <i>InvestGr</i>			Heat Measure is <i>NumIPO</i>			Heat Measure is <i>EWU</i>			
	Cold Quarters (N=1,790)	Hot Quarters (N=2,701)	F-test	Cold Quarters (N=288)	Hot Quarters (N=4,122)	F-test	Cold Quarters (N=631)	Hot Quarters (N=1,422)	F-test	
3-month CAR	0.0619	0.1229	0.0001	0.0492	0.0813	0.0001	0.0502	0.1635	0.0001	
3-month BHAR	0.0724	0.1505	0.0001	0.0455	0.0847	0.0001	0.0494	0.2153	0.0001	
6-month CAR	0.1278	0.2168	0.0002	0.1056	0.1594	0.0001	0.1201	0.2573	0.0001	
6-month BHAR	0.1864	0.2892	0.0001	0.1132	0.1845	0.0001	0.1528	0.3193	0.0001	
9-month CAR	0.1889	0.3166	0.0001	0.1477	0.2394	0.0001	0.1747	0.3749	0.0001	
9-month BHAR	0.2671	0.4589	0.0001	0.1764	0.2861	0.0001	0.2146	0.4935	0.0001	
12-month CAR	0.3288	0.5714	0.0001	0.2772	0.4123	0.0002	0.3064	0.7944	0.0001	
12-month BHAR	0.3242	0.6937	0.0001	0.2519	0.4106	0.0001	0.2887	0.7064	0.0001	
Panel B: Abnormal Returns Calculated Relative to Control Firms										
Return	Heat Measure is <i>InvestGr</i>			Heat Measure is <i>NumIPO</i>			Heat Measure is <i>EWU</i>			
	Cold Quarters (N=1,242)	Hot Quarters (N=2,565)	F-test	Cold Quarters (N=208)	Hot Quarters (N=3,489)	F-test	Cold Quarters (N=392)	Hot Quarters (N=1,153)	F-test	
3-month CAR	0.1205	0.2024	0.0001	0.1002	0.1353	0.0057	0.0964	0.3771	0.0001	
3-month BHAR	0.1224	0.2417	0.0001	0.0855	0.1331	0.0001	0.0870	0.5277	0.0001	
6-month CAR	0.2395	0.4200	0.0001	0.2183	0.2933	0.0065	0.2200	0.6734	0.0001	
6-month BHAR	0.2627	0.5266	0.0001	0.1670	0.3179	0.0001	0.2151	0.8422	0.0001	
9-month CAR	0.3885	0.6715	0.0001	0.3884	0.4918	0.0287	0.4006	1.0106	0.0001	
9-month BHAR	0.4264	0.7994	0.0001	0.3247	0.5310	0.0001	0.4516	1.0229	0.0001	
12-month CAR	0.5306	0.8739	0.0001	0.5025	0.6410	0.0242	0.5603	1.3154	0.0001	
12-month BHAR	0.5612	1.2564	0.0001	0.4786	0.7524	0.0001	0.6921	1.4801	0.0001	

Table 4: IPO vs. Control Firm Return Variations in Hot and Cold Markets

The standard deviations of IPO firms' market-adjusted returns and those of control firms' market-adjusted returns, and the differences between them are displayed for cold and hot markets, respectively. The results for 3-month, 6-month, 9-month, and 12-month returns (CAR and BHAR) are shown. The heat measures are *InvestGr*, *NumIPO*, and *EWU*, and are calculated as described in the text. The quarters in our sample period are classified into cold and hot using these heat measures and according to the procedure described in the text. Missing return observations of IPO firms are replaced with *ewretIPO*, while missing return observations of control firms with *wvretCRSP*. The probabilities ($Pr > F$) from F-test indicate the significance of differences in return variation between IPO firms and their control firms within each heat group.

Return	Firms	<i>InvestGr</i>		<i>NumIPO</i>		<i>EWU</i>	
		Cold	Hot	Cold	Hot	Cold	Hot
3-month CAR	IPOs	0.2670	0.3840	0.2320	0.2980	0.2350	0.5300
	Controls	0.2270	0.2790	0.2390	0.2450	0.2260	0.3940
	Difference	0.0400	0.1050	-0.0070	0.0540	0.0090	0.1360
	$Pr > F$	0.0001	0.0001	0.7019	0.0001	0.4766	0.0001
3-month BHAR	IPOs	0.2680	0.4230	0.2210	0.2940	0.2320	0.5970
	Controls	0.2140	0.2700	0.2090	0.2320	0.2140	0.4560
	Difference	0.0540	0.1530	0.0120	0.0620	0.0170	0.1410
	$Pr > F$	0.0001	0.0001	0.4688	0.0001	0.1313	0.0001
6-month CAR	IPOs	0.3890	0.5360	0.3360	0.4320	0.3460	0.6820
	Controls	0.3080	0.4310	0.3590	0.3590	0.3370	0.5490
	Difference	0.0810	0.1040	-0.0230	0.0740	0.0080	0.1330
	$Pr > F$	0.0001	0.0001	0.3733	0.0001	0.6439	0.0001
6-month BHAR	IPOs	0.4080	0.5750	0.3230	0.4300	0.3430	0.7050
	Controls	0.2760	0.4520	0.2850	0.3420	0.3130	0.6500
	Difference	0.1310	0.1240	0.0380	0.0880	0.0290	0.0550
	$Pr > F$	0.0001	0.0001	0.0950	0.0001	0.0860	0.0061
9-month CAR	IPOs	0.4630	0.6660	0.4150	0.5460	0.4240	0.8350
	Controls	0.4030	0.5360	0.4460	0.4640	0.4490	0.6580
	Difference	0.0600	0.1300	-0.0310	0.0820	-0.025	0.1770
	$Pr > F$	0.0001	0.0001	0.3335	0.0001	0.2643	0.0001
9-month BHAR	IPOs	0.4800	0.6650	0.4070	0.5160	0.4260	0.7680
	Controls	0.3300	0.5180	0.3530	0.4190	0.4200	0.6660
	Difference	0.1500	0.1460	0.0540	0.0970	0.0060	0.1010
	$Pr > F$	0.0001	0.0001	0.0580	0.0001	0.7883	0.0004
12-month CAR	IPOs	0.5370	0.7480	0.5050	0.6190	0.5010	0.9440
	Controls	0.4740	0.5960	0.4500	0.5160	0.5190	0.7230
	Difference	0.0630	0.1530	0.0550	0.1030	-0.0180	0.2210
	$Pr > F$	0.0001	0.0001	0.1231	0.0001	0.4878	0.0001
12-month BHAR	IPOs	0.5310	0.7960 ₄₁	0.4710	0.5870	0.5360	0.9350
	Controls	0.3800	0.5990	0.3830	0.4810	0.4530	0.7340
	Difference	0.1510	0.1970	0.0880	0.1050	0.0840	0.2010
	$Pr > F$	0.0001	0.0001	0.0061	0.0001	0.0011	0.0001
Number of Firms		1,242	2,565	208	3,489	392	1,153

Table 6: The Determinants of IPO Delisting

The results from a logistic regression predicting delisting rates are presented. The dependent variable equals one, if the IPO firm delisted from its exchange within 3 years (or alternatively 5 years) after its IPO date either due to liquidation/bankruptcy or failure to meet exchange requirements (delisting codes between 400 and 599, or code=700); otherwise it is zero. The explanatory variables are *HeatDegrees* (a continuous variable measured as MA(4) of the corresponding heat indicator divided by its historic average), *Age* (which is defined as logarithm of one plus age of the firm at the time of its IPO), *Size* (defined as logarithm of one plus Sales), *OfferPrice* (the price the issue was offered to public), *Reputation* (Underwriter's reputation ranking), *VC* (dummy variable indicating whether or not the issue is backed by venture capital), *Leverage* (Total Debt divided by Total Assets), *Underpricing* (first day return), *LogSGA* (logarithm of one plus Selling, General, and Administrative Expenses). The heat measures are *InvestGr*, *NumIPO*, and *EWU*, and are described in the text. The coefficients are ML estimates from the logistic regression, and the numbers in parentheses below them are the *p*-values from Wald Chi-square test, which are calculated using Huber/White robust standard errors.

Variables	<i>Within 3 Years of Issuedate</i>			<i>Within 5 Years of Issuedate</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
	InvestGr	NumIPO	EWU	InvestGr	NumIPO	EWU
Intercept	-0.6100 (0.0230)	-0.2517 (0.4450)	-0.7834 (0.0020)	-0.1355 (0.5640)	0.0279 (0.9180)	-0.1386 (0.5480)
HeatDegrees	0.1017 (0.0299)	0.0904 (0.0389)	0.3622 (0.0001)	0.1328 (0.0220)	0.0876 (0.0410)	0.2237 (0.0010)
Age	-0.4260 (0.0001)	-0.4398 (0.0001)	-0.4204 (0.0001)	-0.2922 (0.0001)	-0.3023 (0.0001)	-0.2935 (0.0001)
Size	-0.3394 (0.0001)	-0.3367 (0.0001)	-0.1910 (0.0570)	-0.2415 (0.0030)	-0.2454 (0.0020)	-0.1648 (0.0520)
OfferPrice	-0.0724 (0.0040)	-0.0729 (0.0040)	-0.0841 (0.0010)	-0.0660 (0.0010)	-0.0669 (0.0010)	-0.0738 (0.0001)
Reputation	-0.1174 (0.0040)	-0.1219 (0.0030)	-0.1345 (0.0010)	-0.1363 (0.0001)	-0.1428 (0.0001)	-0.1473 (0.0001)
VC	-0.3959 (0.0280)	-0.4099 (0.0240)	-0.4291 (0.0190)	-0.2414 (0.0780)	-0.2441 (0.0760)	-0.2588 (0.0610)
Leverage	0.3191 (0.0070)	0.3134 (0.0010)	0.3443 (0.0080)	0.4417 (0.0230)	0.4317 (0.0300)	0.4612 (0.0310)
Underpricing	-0.0196 (0.9070)	-0.0310 (0.8460)	-0.1895 (0.2730)	-0.0149 (0.9160)	-0.0031 (0.9830)	-0.1236 (0.4240)
LogSGA	0.6539 (0.0001)	0.6515 (0.0001)	0.4428 (0.0010)	0.3656 (0.0010)	0.3978 (0.0010)	0.2663 (0.0230)
Numb. of Failed IPOs	207	207	207	354	354	354
Obs w/ nonmissing data	3,198	3,198	3,198	3,198	3,198	3,198
Nagelkerke R^2	0.0955	0.0948	0.1102	0.1031	0.1014	0.1080