Cycles in the IPO Market*

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November 2005

*Preliminary draft.

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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. The model also makes new predictions regarding long-run IPO returns. Adverse selection is shown to be of procyclical severity in the sense that *dispersion* in unobservable quality across firms should be more pronounced during booms. Taking the premise that that uncertainty will only be resolved (and thus private information revealed) over time, we test this hypothesis by looking at dispersion in long-run IPO returns. Consistent with the model, we find that the cross-sectional variance in long-run abnormal returns increases substantially during "hot" IPO markets; none of the other return moments are as closely tied to the business cycle.

Keywords: initial public offerings, adverse selection, underpricing, "hot" issue markets, cumulative abnormal returns, buy-and-hold abnormal returns, crosscorrelations, "heat measures".

1 Introduction

The existence of IPO underpricing has long fascinated financial economists and serves as one of the field's most important anomalies. A second set of stylized facts has begun to attract attention more recently. 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 in their survey:

> "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 association between volume and underpricing is particularly 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]

This paper argues that the key features of "hot" 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 would be able to sell securities. These higher prices increase the temptation of bad firms to pool. In equilibrium, more bad firms do pool.

[1] Lowery and Schwert (2003) lament "we have little understanding of the factors that drive these fluctuations." Loughran and Ritter (2002) 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.

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.* Canonical models such as Rock (1986) and Benveniste and Spindt (1989) posit that IPO underpricing is driven by information asymmetry. Hence, in our framework, this increased dispersion in quality should also result in higher undepricing. Our argument therefore ties together the time-series properties of hot issue markets described above. An exogenous positive shock to the economy (as evidenced by generally rising stock prices) leads to a greater number of firms going public and an increase in total proceeds raised. Moreover, this wave of IPOs exhibits high underpricing.

Ritter (1984) has oberved that adverse selection models can explain these known 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 he concludes [(Ibbotson, Sindelar and Ritter (1994)] that there was no compelling economic story for such variation, concluding that "rational explanations for the existence of hot issue markets are difficult to come by." In other words, 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 in the literature by developing and testing a simple theoretical framework for understanding how and why the composition of firms varies across the business cycle.

Ritter's changing risk composition hypothesis itself has been investigated empirically. Loughran and Ritter (2004) conclude that, although there is some observable variation in firms across time, this variation is insufficient to account for the magnitude of underpricing swings seen empirically. Lowry and Schwert (2002) take a contrary view, arguing that serial correlation in underpricing is explained by clustering of similar firms going public at the same time. These studies do not address the underlying causes of observed variation in firm characteristics.

Moreover, the results of this study suggest a refinement to these existing empirical studies. These papers ask whether changes in *observable* 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 extremely good 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 the private information changes dramatically.

This observation begs the question: how does one measure the time-varying distribution of private information posited by the paper? It cannot be proxied by observable 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 is that IPO waves will be associated with greater dispersion of quality as measured by long-run returns (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.

To analyze the main implications of our model we perform a few highly targeted empirical tests.[2] The tests in this paper are intended *only* to test the hypothesis that dispersion in quality is positively correlated with the intensity of IPO activity (or briefly the "heat" of the IPO market). First, we show that there is a large variation over calendar time in the variance of the IPO returns. Second, when we divide the quarters into "hot" and "cold" ones based on the amount of "heat" in the quarter, we observe that the variance of returns for IPOs that went public in "hot" quarters is much higher than the variance of IPO returns for "cold" quarters. Furthermore, our nonparametric tests show that the distributions of IPO returns in "hot" and "cold" periods are substantially different. Finally, we show that the return variance, the amount of underpricing, the total proceeds raised, and the number of initial public offerings are all significantly positively correlated,

[2]For a more general overview of the time-series properties of initial public offerings, the reader is referred to Loughran and Ritter (2004), Lowery and Schwert (2002) and Jenkinson and Ljungqvist (2001).

which shows that the variance covaries in time with the intensity level of IPO activity (or briefly "heat") in the markets.

Overall, our empirical results confirm the hypothesis of the existance of time-varying adverse selection problem in the IPO market and show that the severity of this imperfection is heavily dependent on the level of IPO activity.

1.1 Relationship to Other Literature

The intuition behind our model is closely related to that of Narayanan (1988). He shows that in IPO markets, marginal firms are of lower quality than average. He does not, however, consider time-series patterns in either volume or underpricing, or allow for shocks to investment opportunities. Rather, his model is intended to be the static counterpart to Myers and Majluf (1984), showing that the asymmetric information problem can lead to overinvestment as well as underinvestment.

To the extent that time-varying adverse selection costs have been modeled, the results have typically been motivated in debt markets rather than equity markets and often have utilized the "credit rationing" environment developed by Stiglitz and Weiss (1981). Azariadis and Smith (1998), Stiglitz and Weiss (1992), Greenwald, Stiglitz and Weiss (1984) and Yung (2005) contribute to that literature. In all of these papers the theoretical results are ambiguous. Moreover, none of the studies brings evidence to bear on the models or suggests specific testable hypotheses regarding security issuance.

More recently, finance theorists have begun to model the IPO wave phenomenon. Rajan and Servaes (2002) and Ljungqvist, Nanda and Singh (2001) use quasi-rational investors and time-varying sentiment to tie together many of the known features of these waves: underpricing, volume patterns and long-run underperformance. This approach is complementary to ours, which uses fully rational investors and makes testable predictions about the variance rather than the mean of IPO returns. Pastor and Veronesi (2002) and Helmental and Sarig (2003) demonstrate waves in models with time-varying risk premia and private benefits, respectively. Again, these approaches are complementary to ours.

Finally, regarding empirical methodology, our view is that changes in observable characteristics over time is a highly imperfect proxy for changes in adverse selection. This is not a new observation. Cook, Jarrell and Kieschnick (2001) argue that aftermarket evidence is consistent with the "asymmetric information profile of firms coming to market" changing over time, even when the observable characteristics need not change. In particular, they find dramatic differences across time in the proportion of IPOs for which underwriters choose to stabilize the price. Noting that price support is widely characterized as a response to information asymmetries (see for example Benveniste, Busaba and Wilhelm (1996)), Cook et. al then note that intertemporal fluctuations in price support then serve as prima facie evidence of fluctuations in adverse selection. Although the premises are the same − adverse selection entails changes in unobservable parameters − our paper and theirs use different methodologies to measure these (ex-ante) unobservable values.

The paper proceeds as follows. *Section 2* developes the model of adverse selection and *Section 3* presents its equilibria and its testable implications. *Section 4* describes the data, the sample selection, and the variables used in the subsequent analysis. *Section 5* tests various hypotheses derived from the model. *Section 6* discusses the model and its possible applications. *Section 7* concludes.

2 The Model

There exists a continuum of potential borrowers 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. Borrowers have no available internal financing, so the project requires external finance.

At T=1, if the new project is undertaken, the firm's assets will be worth either 0 or X. The probability the project is successful (that is, the firm's assets are worth X rather than 0) is given by π_i, where the subscript i indicates the firm's (privately known) type. The net present value of the project of a firm of type i 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 investors. 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, it is without loss of generality to describe the securities as equity. We assume equity shares are sold via a fixed-price mechanism. That is, the firm announces a price per share (equivalently, the proportion of equity α that will be sold to investors in aggregate for supplying capital K). If there is oversubscription, orders must be randomly rationed because the issuing firm cannot tell which orders came from informed investors.

As is well-known, the fixed-price mechanism coupled with investor heterogeneity implies underpricing. Rock (1986) shows that because informed investors purchase only high quality issues, uninformed investors find that their ex-post portfolios consist disproportionately of lower quality issues. This uneven rationing necessitates a discount so that uninformed investors may break even.[3] However, the main results do not depend in any way on this particular choice of mechanism. For the qualitative results, it is necessary only that underpricing is positively correlated with the dispersion in the quality of firms going public, which is true for any mechanism in which underpricing is driven by information asymmetry.

[3]Maksimovic and Pichler (1999) demonstrate that the wealth constraints assumed in Rock's paper (and by extension ours) are not strictly needed. The results are mathematically identical when one assumes that investors place orders for the IPO at random times and the underwriter cannot tell them apart. For expositional simplicity, we follow Rock's approach rather than Maksimovic and Pichler's.

3 Equilibrium

The outcome of this model is a hybrid between pooling and separating equilibria. 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 the investor's capital contribution K. Firms with quality below π_{MIN} opt out of the market. It is shown that, in equilibrium, informed investors avoid the lemons by purchasing only a strict subset of the IPOs being offered. 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*

$$\alpha = \frac{K}{X}\frac{1+\sqrt{p}}{\pi_{MIN}+\sqrt{p}} \tag{1}$$

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

$$\pi_{INFO} = \frac{K}{\alpha X} \tag{3}$$

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

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 $\overline{\pi_i} = \frac{\pi_{MIN}+1}{2}$. If all IPOs were bundled and sold in a full-information world, the resulting equity stake would need to satisfy $\alpha\overline{\pi_i}X = K$. The full-information equity stake is

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

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 it does illustrate 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 is equivalent to higher stock prices. Hence, the second effect is that stock prices rise during an expansion, providing additional incentive for bad firms to pool (even holding the quality of their projects constant).

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* $\frac{\partial \pi_{MIN}}{\partial V} > 0$. *Thus any shock to the economy that raises the net present value of projects causes induces lower quality firms to pool.*

Corollary 1 provides implications of the model. First, a positive economic shock results in a greater number of firms going public. This fact is not surprising – it is difficult to conceive of a positive economic shock which did increase either the supply or demand for capital.

Second, and less obvious, since the interval $[\pi_{MIN}, 1]$ widens during expansions, the dispersion in firm quality is procyclical. Here the model diverges from the existing literature. In Stiglitz and Weiss (1992), for example, it is *assumed* that 1) the set of firms is constant across economic states and 2) the low quality firm's prospects are more susceptible to poor economic states. Clearly, under those assumptions, quality dispersion is countercyclical. The contrast between this result and ours highlights the importance of the assumption that the the set of firms is constant across states.

One might expect underpricing to go up, since a wider range of firm qualities would result in a greater adverse selection problem for uninformed investors. As the next corollary shows, this intuition is correct.

Corollary 2 *For any shock to X, V, or K that raises the net present value of firm's projects, average percentage underpricing increases.*

3.1 Testable Implications

Given a real positive economic shock, Corollary 1 indicates that more firms go public, i.e. the interval $[\pi_{MIN}, 1]$ widens, while Corollary 2 shows that underpricing increases. These results are consistent with known stylized facts: economic shocks lead to a wave of highly underpriced IPOs.

The widening of the interval $[\pi_{MIN}, 1]$ has a more subtle implication. Not only does the number of firms active in the market rise during expansions, but the differences in quality between these firms should be more pronounced as well. This observation is very closely related to Ritter's changing risk composition hypothesis described in the introduction. As we noted there, however, the existing literature tends to proxy for quality changes by measuring changes in observable parameters thought to be associated with risk. However, Corollary 1 specifically predicts that it is *unobservable* quality rather than observable quality that fluctuates with the business cycle.

A central premise of the empirical component of this paper is that uncertainty will only be resolved − and thus private information revealed − over time. Thus to investigate the hypothesis that dispersion in quality is procyclical, we need to study the dispersion in aftermarket returns within a cohort of firms going public at (approximately) the same time.

The selection of the return horizon involves important tradeoffs. At very short horizons, little privately-known quality will be revealed: the model has only a pooling equilibrium, and because of lockup provisions, insider trading decisions will not yet be incorporated into the immediate aftermarket price. Unfortunately, very long horizons introduce their own problems. First, Barber and Lyon (1997) and Kothari and Werner (1997) show that long-run (1-year to 5-years) abnormal performance measures can be biased, and the latter authors conclude that the inferences from long-run studies "require extreme caution." Second, the relevance of the entrepreneur's ex-ante private information is probably limited at very long horizons. Shocks to firms' returns that occur, for example, five years after the IPO are probably unforeseen by even the most prescient managers.

For these reasons, we focus on the short end of what is traditionally considered long-run return measures. Many of the results we present consider a return horizon of 12 months. We believe this is sufficient to allow for a significant amount of information to enter into the market price: the firm will have released several earnings reports, the "quiet period" will have ended and analysts will be following the stock, and in virtually all cases the lockup period will have expired and insider trading decisions will have been revealed.[4] On the other hand, this horizon is sufficiently short to avoid the most severe biases documented by the long-run return literature.

To the extent that our performance measures are still biased (despite our focus on the short end) we partially mitigate this problem by using alternative measures of excess returns, cumulative-abnormal-returns (CARs) and buy-and-hold returns (BHARs). Although both measures are biased, the biases themselves are different and (in some cases) run in opposing directions.[5] Barber and Lyon (1997) find that cumulative-abnormal-returns (CARs), have a positive bias (on net) and this bias grows as the length of the period covered by the return increases. They also find that buy-and-hold measure (BHAR),

[4]For IPOs for which we have lockup expiration date, % of the them expire within a year. We also considered using the lockup expiration date itself, rather than a fixed time horizon, as the holding period. Ultimately we abandoned this notion since the lockup expiration date is known for only a small subset of the IPOs in our dataset.

[5]We also note that our interest in the variance rather than the mean probably lessens the importance of an upward or downward bias to returns.

can have a slight negative bias. For additional robustness, in addition to using both CAR and BHAR measures, we use as a variety of models of expected return. Finally, we check the results for other holding periods such as 6 months and 9 months.

Our empirical methodolody, then, is to consider a set of firms going public at the same time (or nearly the same time) and to study the variance of long-run returns across firms within this set. A second tradeoff arises when deciding how finely to divide the calendar, i.e. what constitutes going public at "nearly the same time." Grouping firms into yearly cohorts is probably too coarse of a division, as the "heat" of an IPO market can (and frequently does) change midyear. For example, the first half of the year 2000 was extremely hot, but the market cooled considerably by that summer. The year 1983 displayed the opposite pattern. Using months as our cohort division slices our data too finely, however. This is because many months in our sample (particularly in the late 1970s) have an extremely small number of IPOs, making it difficult to estimate within-sample variance. For the purposes of this study, using quarterly cohorts appears to strike an appropriate balance in this trade-off. As a robustness check, we employ alternative calendar divisions for all of our tests.

4 Data and Sample Selection

We use Securities Data Company (SDC)'s database to obtain our initial sample of 10,640 IPOs between 1970 and 2004. This initial sample *excludes* REITs, closed-end funds, and ADRs. The data items we extract from this database are the date of the issue, the dollar value of proceeds raised, the percentage change in the stock price on the issuance day (usually referred to as underpricing), and the CUSIP of the new public firm. To study the long-run returns, we need trading data for each new public firm for twelve months after the issuing date. Therefore, we exclude from the above sample any IPO whose CUSIP does not match with a publicly trading firm recorded in CRSP monthly files (there are 3,239 such firms).

This sample selection procedure leaves us with a sample of 7,401 IPOs with available issuing date and return information. As we will describe below, we replace the missing return observations using two different techniques: replacement with equally-weighted portfolio of IPOs, and replacement with CRSP value-weighted market index. There are some quarters in our sample period when either there is no IPO activity or there are not enough IPOs with available return data to create a replacement portfolio. For example, there is absolutely no IPO activity in 1974/3, 1974/4, and 1975/1 quarters recorded by Security Data Corporation, and there are only one or two IPOs issued in 1974/2, 1975/2, 1975/3, and 1975/4 quarters. Therefore, due to the difficulty of creating equally-weighted portfolio of IPOs in some quarters, we eliminate 68 more IPO firms when we use this replacement technique and so our sample size drops to 7,333 initial public offerings.

Throughout the section we use macroeconomic variables such as Gross Domestic Product (GDP) in current dollars and Consumer Price Index to convert various variables from nominal to real dollars. Annual and Quarterly GDP data is retrieved from the Federal Reserve Bank in St.Louis, and annual CPI data for urban consumers is from the Bureau of Labor Statistics.

Next we briefly describe the calculation of our CAR and BHAR measures. Let R_{it} represent firm i's stock return (including dividends) for the month t, and let R_{mt} be the return on an equally weighted market index (including dividends) for the same month.[6] Then the abnormal return for the same firm in month t can be calculated as $AR_{it} = R_{it} - R_{mt}$. The implicit assumption behind this calculation is that the market indices, like CRSP equally-weighted index, can serve as a proxy for the expected return of each security. We also present the results using alternative measures of expected return, such as Fama-French and the control firm methodology.

The cumulative abnormal return (CAR) of firm i across T periods can be calculated as

$$CAR_{it} = \sum_{t=1}^{T} AR_{it} \tag{5}$$

This return measure is widely used in the IPO literature. It ignores compounding and is subject to various biases (see Kothari and Werner (1997)

[6]The first month included in the return calculation is the first *full* month the firm has been public. For example, if the firm went public in May 9, 1994, then the first month of the return calculation is June, 1994.

and Lyon and Barber(1997)) which have been demonstated to be positive on net. As mentioned previously, a positive bias to returns is probably more important for studies that focus on the mean return of IPO firms than it is for our study, which focuses on cross-sectional variance. However, to be cautious we use an alternative return calculation, buy-and-hold abnormal return (BHAR), which is found to be much less prone to the biases affecting CAR (see Kothari and Werner (1997) and Lyon and Barber(1997)). BHAR for the firm i across T periods can be found through

$$BHAR_{iT} = \prod_{t=1}^{T} (1 + AR_{it}) - 1 \tag{6}$$

The question of how to deal with missing monthly return observations in the CRSP files is an important issue that requires special attention in long-run studies (see Barber, Lyon, and Tsai (1999)). In our sample there are 1,154 IPO firms (or 15.6% of the sampled firms) with missing return information for at least one month of the first 12 months of being publicly traded firm. Occasionally CRSP terminates coverage of the firm before the end of our return horizon, possibly due to delisting from the exchanges. This is the primary reason for existence of missing monthly return observations in our study. Also, for a few of our observations CRSP coverage does not start immediately; instead there is more than one month of delay in the coverage[7]. Naturally these missing observations create a problem for us during the calculation of BHAR.

We follow Barber, Lyon, and Tsai's (1999) suggestion regarging missing return observations. 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

[7]Some of these are probably "unit" offers: a bundle of stock and a warrant. In these offers, the stock and warrant typical trade together (i.e., as one indivisible bundle) for some fixed period. This period may be a week, it may be two months, etc. The issue is only covered by CRSP when the stock and warrant "detach" and trade separately. Our measure of underpricing is still valid (and accepted procedure) as SDC does give the offer price and the price of the bundle at the end of day T=1. We did not drop these IPOs because unit IPOs are a type of IPOs and thus should be included in the sample.

CRSP or drops out of our moving window of 12 consecutive monthly returns is excluded. That is, our reference portfolio at a particular month includes only those IPO firms that had their issue date within the last 12 months and have non-missing return observations for that month. As we mentioned above, in early 1970s, for some months there are not enough non-missing recent IPO returns per month to create a reference portfolio of IPOs. Thus, when we use this replacement method we eliminate 68 IPOs from our sample and so our sample size falls to 7,333 IPO firms.

An alternative method of dealing with missing return observations used in Barber, Lyon, and Tsai (1999) is by replacement with CRSP value-weighted market index. We report the results when we use this replacement method as well. We opted to include these results to make sure that we have the results for both an equally weighted replacement portfolio and a value weighted one.[8] When this replacement method is used we do not eliminate any firms (i.e. the sample is constituted of 7,401 IPO firms rather than 7,333).

5 Hypothesis Testing

5.1 "Heat" Variables

We construct several measures of the IPO market's "heat." One of these, *TotProc*, is the total dollar amount per quarter raised through IPO activity. We scale these aggregate proceeds by the GDP in current dollars for that period. Another heat measure we use is the number of IPOs observed in each quarter (*NumIPO*). Finally we employ two measures of underpricing. PWU measures the average underpricing of IPOs in each heat-period weighted by the amount of the proceeds raised. We also construct the equally-weighted version of this varaible, $EWUnderp$, as a robustness check.

The model predicts that variance will be contemporaneously correlated with each of these heat measures.

[8] We also note that not replacing the missing returns at all does not qualitatively change our conclusions.

5.2 Variation in Distribution Moments of the Returns and the "Heat" Measures Across Time

Tables 1 and *2* provide descriptive statistics of various "heat" and return variables for the sampled firms. *Table 1* summarizes the 12-month CAR and BHAR returns. The sampling period is divided in 7 sub-periods, each one having a length of 5 years. For each sub-period we find the mean, the variance, the minimum, the maximum, the skewness, and the kurtosis of the 12-month returns of the IPOs that had their issue date during that sub-period. Unless otherwise specified, throughout this section the replacement method for missing return observation is always done using equally-weighted IPO portfolio (in short, *ewretIPO*).

The table clearly shows that there are substantial differences in the distribution statistics of the CAR and BHAR returns across the sub-periods. Though the table employs rather crude divisions, the result seem broadly consistent with the model. In particular, the "hottest" subperiod (1996-2000) has by far the highest within-sample variance, measured both by BHARs and CARs. The variance of BHAR between 1996 and 2000 was *twice* as large as the variance of BHAR for the 1991 - 1995 sub-period and *eight* times larger than the variance of BHAR for 1970-1975 sub-period. Moreover, the results are not driven by this one "hot" subperiod: the "coldest" subperiods (1970-1975, 1976-1980 and 2001-2004) tend to have smaller within-sample variance than do either "hot" periods or normal periods (such as the 1980s).

Table 2 presents our "heat" variables' descriptive statistics. All of these variables – the number of IPOs, the total proceeds raised from initial offerings as a percentage of the GDP in current dollars, and the average proceeds-weighted underpricing – show large fluctuations across the calendar sub-periods. Comparing these results with *Table 1*, it appears that underpricing is positively correlated with both the volume in the IPO market and with return variance, which is broadly consistent with the model.

To summarize, *Tables 1-2* demonstrate that variance, skewness, and kurtosis of initial returns fluctuate rather dramatically across time. Moreover, these fluctuations are consistent with the model, in that subperiods that had more "heat" (measured either by volume or by underpricing) tend to involve higher variance than normal subperiods, which in turn have higher variance than subperiods that were mostly "cold". In the next section, we refine this analysis by defining (quarter-by-quarter) "hot" and "cold" periods, and comparing the properties of returns in these two groups.

5.3 Return Variance Across "Hot" and "Cold" Markets

Next, we perform a simple test. We divide the quarters in our sample into three categories, "hot" quarters, "normal" quarters, and "cold" quarters, using the following classification technique. We rank each quarter according to its "heat" level. If in a particular quarter the "heat" measure is in *the top one-third* (*bottom one-third*) of the ranked sample, then it is considered to be a "hot" ("cold") quarter. The quarter that falls in the middle *one-third* of the ranked sample is classified as a "normal" quarter. Then we group the IPOs in our sample according to the category of their issuance quarter. "Hot-market" ("Cold-market") market IPOs are those that were issued during a "hot" ("cold") quarters. For each IPO we calculate the returns (CAR and BHAR). Within each classification group we find the *variance* of these returns. We repeat this procedure for 12-month and 9-month CARs and BHARs, with replacement of missing returns by *ewretIPO* and *vwretCRSP*, and for the three different "heat" measures.

The results are presented in *Table 3*. As we can see, *the return variance is much higher in "hot" periods than it is for "cold" ones*, regardless of the type of the return, the replacement method, or the "heat" measure used for the classification. For example, the "hot-periods" variance of 12-month CARs using *ewretIPO* for replacement is twice as big as the corresponding "cold-periods" variance, when the "heat" classification is done with *PWU* (60.50% vs. 28.66%). Similar conclusions can be reached when we compare the other pairs of "hot-cold" variances presented in the table.

The last "Number of Observations" rows of *Table 3, Panels A* and *B*, deserve special note. A greater number of observations fall into the "hot" category when using *NumIPO* as our "heat" measure. This result is not surprising; in fact, it follows by definition. The same critique (to a lesser extent) is true of *TotProc* because when more firms go public, it is likely that more capital will be raised. However, the result in the final two columns is nontrivial. When heat is measured by underpricing, a much greater number of firms are seen to go public in hot times, and these hot IPOs exhibit a high variance in long-run returns. This result is consistent with the model's premise that both underpricing and variance in long-run returns follow from dispersion in quality.

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

In our next analysis, we concentrate on testing nonparametrically[9] whether the distribution of "hot" market IPO returns is significantly different from the distribution of "cold" market IPO returns in terms of location(median), in terms of scale or variation (variance), and in terms of the other moments (skewness, kurtosis, etc.).

First, we want to see graphically the differences in the shape and the location of the returns' distributions across "heat" samples. *Figures 1A-F* display the nonparametric kernel density plots for the returns (CAR and BHAR) of the "hot" and "cold" IPO samples, for the three different heat measures used in the classification. Information about the kernel plot, such as type of kernel plot, bandwidth, c-value, and approximate mean integrated square error (AMISE) are shown in the little boxes inside the graph-box. For reference, some sample statistics, sich as minimum, median, maximum, mean, variance, skewness, kurtosis, and number of firms for each "heat" sample are also displayed in a similar box.

A fitted normal distribution is also graphed to help visualize the actual distribution of the returns against a backdrop of normal distribution with the same mean and variance. In one of the boxes we also show the results

[9] We have to rely on nonparametric (or distribution-free) testing, because we do not know the "true" distribution of IPO returns. Without knowing the "true" distribution of returns it is inappropriate to rely on parametric tests.

from the tests for normality of the distributions. The distributions of IPO returns for both "hot" and "cold" samples is highly non-normal. The test results from Anderson-Darling normality test (*Pr > A-Square*), Cramer-von Mises normality test (*Pr > W-Square*), and Kolmogorov-Smirnov normality test (*Pr > D*) unanimously indicate with 1%-confidence level that neither the "cold" market IPO returns nor the "hot" market ones are normally distributed. Deviations from normality are particularly severe for BHARs, which exhibit high skewness and kurtosis. This observation leads us to be wary of potential issues when using inference based on BHARs. In *Section 5.6* we show an alternative test which attempts to partially address this problem.

Second, we observe from the graphs that the distributions of "hot" and "cold" periods differ from each other substantially. This difference is clearly visible in location and dispersion moments. The results from formal nonparametric tests of the null hypothesis of *no distribution differences* across "heat" samples are shown in *Table 4*. We perform the following distribution-free tests: Kolmogorov-Smirnov two-sample test, Kuiper two-sample test, Siegel-Tukey test, and Wilcoxon Mann-Whitney U Test.[10] We chose these four tests among many available alternative nonparametric tests in order to have a representative test for location (Wilcoxon Mann-Whitney U), a representative test for scale (Siegel-Tukey), a test sensitive to tails (Kuiper), and a test for overall fit of the distribution (Kolmogorov-Smirnov).[11]

[10]The Kuiper test is sensitive to both the median and to the tails of a distribution, thus it is appropriate in our case. This test is also appropriate for analyzing cyclical variables, like month of the year effects, but that use of the test is not relevant here. The Wilcoxon Mann-Whitney U test is used to test the null hypothesis that the two distributions have identical distribution functions against the alternative hypothesis that the two distribution functions differ only in with respect to location (median). Siegel-Tukey test is designed to be more sensitive to scale parameters of a distribution. Kolmogorov-Smirnov test uses the single maximum difference between two empirical distribution functions.

[11]The results for the following alternative tests are available from the authors: Ansari-Bradley test, Cramer-von Mises test, Klodz test, Kruskal-Wallis test, Median test, Mood test, Savage test, and van der Waerden test. These tests were developed to test similar type of hypotheses. For example, some of them are designed to test the differences in location (median, mode, etc.) between the two samples, and others are testing differences in dispersion (variance, average deviation, maximum deviation, etc.). Each of these tests

The numbers shown in the table are the probability that the test statistics of each test is greater than its corresponding asympthotic critical value ($Prob(Z > |Z_a|)$).[12] This probability is sometimes referred to as Type I error (probability of *rejecting* the null hypothesis while it *is true*). The panels A, B, and C present the results for 12-, 9-, and 6-month CAR and BHAR returns, respectively. Again the classification into "heat" groups is done using the previously described "heat" measures (PWU, *TotProc*, and *NumIPO*). The table shows only the results with replacement method being *ewretIPO*, but the results for *vwretCRSP* are qualitatively the same.

In summary, the results from *Table 4* and *Figure 1A-F* show that *the variance of returns is higher, and the mean return is lower, during "hot" periods. The variance result is of course the main testable implication of the model.* BHARs and CARs distributions differ strongly from *each other*, but the magnitude of these differences do not seem to depend upon market conditions.

The lower long-run returns observed following "hot" periods is not a prediction of the model (although it is not a rejection of the model either). That drop is consistent with the "irrational exuberance" notion that optimistic investors systematically overpay during hot IPO markets. On average, then, these "hot" periods are followed by disappointing long-run returns. In *Table 4* we test this difference in means non-parametrically (using the Mann-Whitney test) and find that, for most specifications, the difference is statistically significant. However, the significance is not as strong as is the case for the variance differences. We also note that a large part of this difference in means is attributed to a single event: the dot-com crash that followed the hot period of 1999-2000. When this period is taken out of our sample, the mean long-run returns of the "hot" and "cold" periods are much closer. In contrast, the variance result does not systematically change when this outlier is removed: the CAR differences between "hot" and "cold" periods become slightly weaker while the BHAR differences become slightly stronger.

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have their own strengths and weaknesses relative to the others.

[12] Exact critical values calculated with Monte Carlo simulations essentially lead to same conclusions.

5.5 Correlation Coefficients

In our next analysis, we want to see to what extent the return variances are correlated to the "heat" variables. If indeed the pooling of good and bad initial offerings during "hot" period causes increased dispersion in quality, then the correlation between the "heat" variables and the variances of long-run returns of firms in the same cohort should be positive. Again, the cohorts on which we focus are quarterly. Thus we find the "heat" of each quarter, and then measure the variance of 9-month or 12-month returns for the firms going public in that quarter.

Table 5 presents the Pearson correlation coefficients between the three heat variables and the return variances, using 9-month and 12-month CARs and 9-month and 12 month BHARs. The results for two different replacements are shown: replacing with equally-weighted portfolio of IPOs (top panel) and replacing with value-weighted CRSP index (bottom panel).

Our findings clearly show that the "heat" and variance variables are *significantly positively correlated*, suggesting that there is evidence of wider pooling during "hot" markets. For example, when replacement is done with *ewretIPO*, the correlation between the total proceeds raised per quarter and the variance of 9-month CARs within the quarter is 0.52126 and the probability of this coefficient being equal to zero is less than 0.01% (the square brackets under the Pearson correlation coefficients show the $Prob > |r| \, under H_0 : \rho = 0$). The correlation coefficient between 12-month CAR and *NumIPO* is 0.19525 and is significant within 5% confidence level. To summarize, most of the correlation coefficients between the "heat" and variance variables are significant within 5% confidence level (18 out of 24 coefficients in the table) and almost all of them are significant within 10% confidence level (22 out of 24 coefficients). The only exception is the correlation between the number of IPOs and the 12-month BHARs. As we will show in *Section 5.6* this coefficient is significant once one sorts on *realized* BHAR means which (as we explain in that section) may mitigate the effect of the extreme skewness in BHARs.

Thus, the basic analysis of correlations demonstrates that the degree of pooling good and bad IPOs, as measured by the return variance, and the "heat" level in the markets are closely related and show signs of comovement.

5.6 Possible Biases in BHAR and CAR Variance Computation

As mentioned in *Section 5.3* our model is silent on the issue of the levels of long-run returns. Investors here are assumed to be rational and bubbles do not arise. Even in a rational world, however, we want to be cognizant of the effect that crashes can have on our ex-post variance computations. Unfortunately, unlike the case in the expanding literature on *mean* long-run returns, we have little guidance from the literature on what biases exist when using BHARs and CARs to study the *variance* of long-run returns. A literature for second moments, analogous to Barber and Lyon (1997) and Kothari and Warner (1997) for first moments, simply does not exist. Hence our comments here are necessarily speculative.

We believe that Var(BHAR) might be biased downward relative to the true economic effect we wish to study. Our arguments are based on the existence of periodic market crashes and the associated impact on skewness in returns. Consider a crash that, to be concrete, destroys 95% of the value of all firms in the economy. Assuming that this crash doesn't affect relative valuations, we would like it to not affect our results. Following this crash, we should interpret a firm with long-run BHAR of −90% as having much higher quality than a firm with −99% BHAR. But to the variance computation, this would period would appear to be characterized by low dispersion in quality (since 90 and 99 are reasonably close numbers) even though this represents a valuation difference of ten times.

On the other hand, Var(CAR) might be biased upward relative to what we wish to capture. Consider a quarterly cohort of firms for which a prolonged bear market occurs during the latter half of their return horizon. Firms early in the cohort may have many trading days with favorable returns; the few bear market days at the end of their return horizon have little effect on this (arithmetic average) measure. Firms near the end of this cohort will have only traded during a bear market and so will exhibit very low CARs. Notice that the regime shift itself introduces cross-section variance that is unrelated to true quality dispersion.

At minimum, this difference in biases underscores the importance of using both measures. Moreover, since both biases are driven by market slides, it also suggests that it might be useful to control somehow for this "crash factor." We therefore seek a technique that allows one to make inferences regarding the correlation of cross-section variance and contemporaneous IPO "heat" (as measured by contemporanous volume) while holding "heat" *as measured by long-run returns* as constant. Perhaps the simplest way to do so is by sorting quarters into ex-post long-run return categories: high, normal and low, for example. That is, we sort quarters by realized mean and then look at the correlation between "heat" and cross-sectional variance within these similar-mean groups.

[Insert the results]

5.7 Alternative Measures of Abnormal Return

[Insert the results]

6 Discussion

6.1 The Model

This paper argues that the severity of adverse selection can be procyclical; the same cannot be said of most other market imperfections. As an immediate application, this intertemporal variation is shown to produce IPO waves in which underpricing, quality dispersion and volume co-vary.[13]

In addition, the model makes the prediction that variation in long-run returns should be higher following expansions, because information asymmetry should only gradually be resolved in the secondary market. This test is nontrivial. Even for tests involving the mean of long-run returns − a very widely studied statistic − there is considerable debate about the proper methodology and about the power and size of tests. No such literature exists

[13]In the model, spikes in volume and underpricing occur simultaneously. A model in which one series lead the other might be constructed by allowing for a "pipeline" of private firms. If good firms are quicker to market, then volume waves should precede underpricing waves. If bad firms are quicker to market, then underpricing waves should lead. Any such assumptions are ad-hoc, however, and thus omitted from the analysis here.

for studying the variance of long-run returns. Hence, implemenation of this test involves an exploration into econometric methodology which is beyond the scope of this paper.

Other natural applications of this paradigm are to security design. For example, IPO "lockups" − precommitments made by insiders that limit the ability to sell shares − have been viewed as a response to information asymmetry. If this asymmetry varies over time, then the length of the lockup required to mitigate information asymmetry should vary over time. This argument is tempered by the fact that lockups can also be motivated by moral hazard: insiders whose wealth is tied to the firm's long-run prospect have greater incentive to put forth effort. Complicating matters, this effort-incentive problem is thought to be countercyclical in severity (Rampini 2003). Intertemporal variation in lock-up length (controlling for firm characteristics) may thus provide preliminary evidence as to the relative importance of these two imperfections. Similary, it may be fruitful to apply this model to observed intertemporal variation in other stylized facts about IPOs, particularly those thought to be motivated by asymmetric information: price support, unit offerings, underwriter quality, etc.

The theory of time variation in adverse selection developed in this paper may be of independent interest. Adverse selection plays a key role in many areas, from mergers and acquisitions to labor markets and capital structure. These markets suffer from other imperfections, which also vary across the business cycle, complicating the analysis. An important direction for future research is to find ways to distinguish empirically between competing paradigms.

6.2 Hypothesis Testing

In all of the analyses performed in this study we tried to avoid regressions and econometric modeling. Instead we relied on one way analyses between the "heat" measures and the adverse selection proxies we have developed for hypothesis testing purposes. The primary reason for this is related to the objective of this study. The sole purpose behind our empirical testing is to determine *whether or not* the level of IPO activity is related to adverse selection and to the pooling of good and bad IPO firms that may be associated with it. This is the main prediction of our model.

The second reason for avoiding multivariate and/or regression analyses is related to the state the IPO literature is in at this point. We still lack a good understanding of what causes the IPO waves and what are the explanatory factors one has to control for in a possible multivariate regression model. Recent works by Lowry (2003) and Loughran and Ritter (2004) attempt to do just that and they discovers certain factors that can explain the IPO waves. However, in our context to run a multivariate regression one needs to control for *all the other factors* affecting the IPO returns first, and then test for the effect of the "heat" factor on these returns' variance. Clearly, this is a task that is beyond the scope of this study. Further, we don not think that an *incomplete* multivariate regression model with *many missing explanatory variables* would provide new insights to the strength of the relationhsip between the amount of "heat" in the marketplace and the variance of the IPO returns beyond what the detailed and thorough one-way analysis showed us.

Third, there is the obvious issue of endogeneity between rising "heat" level and related IPO return volatility. It is not difficult to imagine a scenario where the rise in the "heat" level induces new bad firms to go public, and thus raises the level of pooling (more bad IPOs are issuing equity). On the other hand, the rise in the number of bad IPOs will naturally increase the total number of IPOs and the amount of proceeds raised. Not only that, the rise in the number of bad firms will increase the severity of adverse selection and thus, will likely increase the amount of underpricing. As we mentioned in the introduction, one of the functions of underpricing is to protect the underwriters and other investors against asymmetric information (see Benveniste and Spindt (1989) and Rock (1986) among others). Therefore, it is possible that the "heat" measures and the degree of adverse selection measures, such as post-return variance, are endogenous. This endogeneity will create major bias problems when one runs multivariate regressions (see Colak and Whited (2005) for an example).

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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

$$\underbrace{\left[\frac{\pi_{INFO}-\pi_{MIN}}{1-\pi_{MIN}}\right]\left(\alpha X\frac{\pi_{MIN}+\pi_{INFO}}{2}-K\right)}_{only\ uninformed\ purchase}$$
$$+\underbrace{\left[\frac{1-\pi_{INFO}}{1-\pi_{MIN}}\right]p\left(\alpha X\frac{\pi_{INFO}+1}{2}-K\right)}_{all\ investors\ purchase}. \tag{7}$$

The parenthetical terms, expected profit in each event, rely on the uniformed 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 (7) equal to zero and substituting in the equilibrium value of π_{INFO} yields (1) after some simplification[14]. The final claim in the Theorem is proved as follows.

$$\pi_{MIN} \;<\; \underbrace{\frac{\pi_{MIN}+\sqrt{p}}{1+\sqrt{p}} = \frac{K}{\alpha X}}_{by\ (1)} \;=\; \pi_{INFO} \tag{8}$$

Q.E.D.

[14]The omitted simplification is tedious; details are available upon request.

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

$$\frac{K}{\pi_{INFO}} = K\frac{1+\sqrt{p}}{\pi_{MIN}+\sqrt{p}} \qquad \text{and} \qquad \pi_{\mathrm{MIN}} = \frac{\mathrm{V}}{\mathrm{X}-\frac{\mathrm{K}}{\pi_{\mathrm{INFO}}}} \tag{9}$$

which together imply

$$\pi_{MIN}\left(X - K\frac{1+\sqrt{p}}{\pi_{MIN}+\sqrt{p}}\right) = V. \tag{10}$$

The comparative statics in the corollary follow from (10) via the implicit function theorem.

Q.E.D.

Proof of Corollary 2: Letting the average quality be denoted by $\overline{\pi_i}$, percentage underpricing is

$$\frac{\alpha X\overline{\pi_i}-K}{\alpha X\overline{\pi_i}} = \underbrace{1-\frac{(\frac{K}{\alpha X})}{\overline{\pi_i}} = 1-\frac{(\frac{\pi_{MIN}+\sqrt{p}}{1+\sqrt{p}})}{(\frac{\pi_{MIN}+1}{2})}}_{by\ (1)} = 1-2\frac{(\pi_{MIN}+\sqrt{p})}{(\pi_{MIN}+1)}(1+\sqrt{p}), \tag{11}$$

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

Q.E.D.

Figure 1A: Nonparametric Kernel Density Plot of CAR for "Cold" and "Hot" Periods ("Heat" Measure is TotProc)

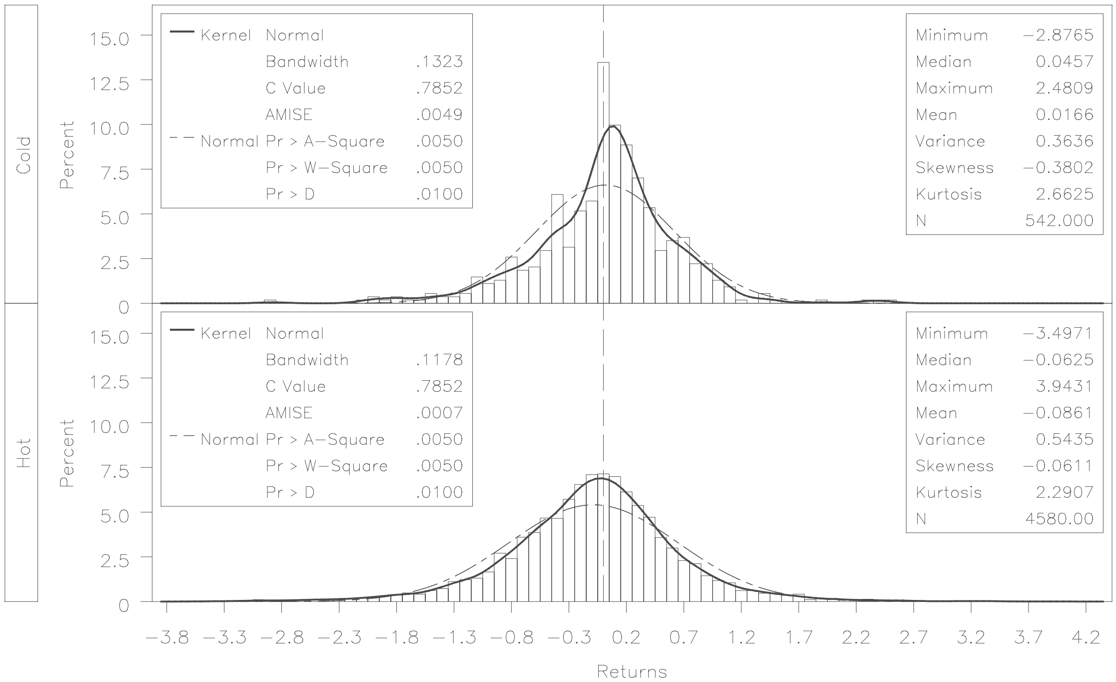

Figure 1B: Nonparametric Kernel Density Plot of BHAR for "Cold" and "Hot" Periods ("Heat" Measure is TotProc)

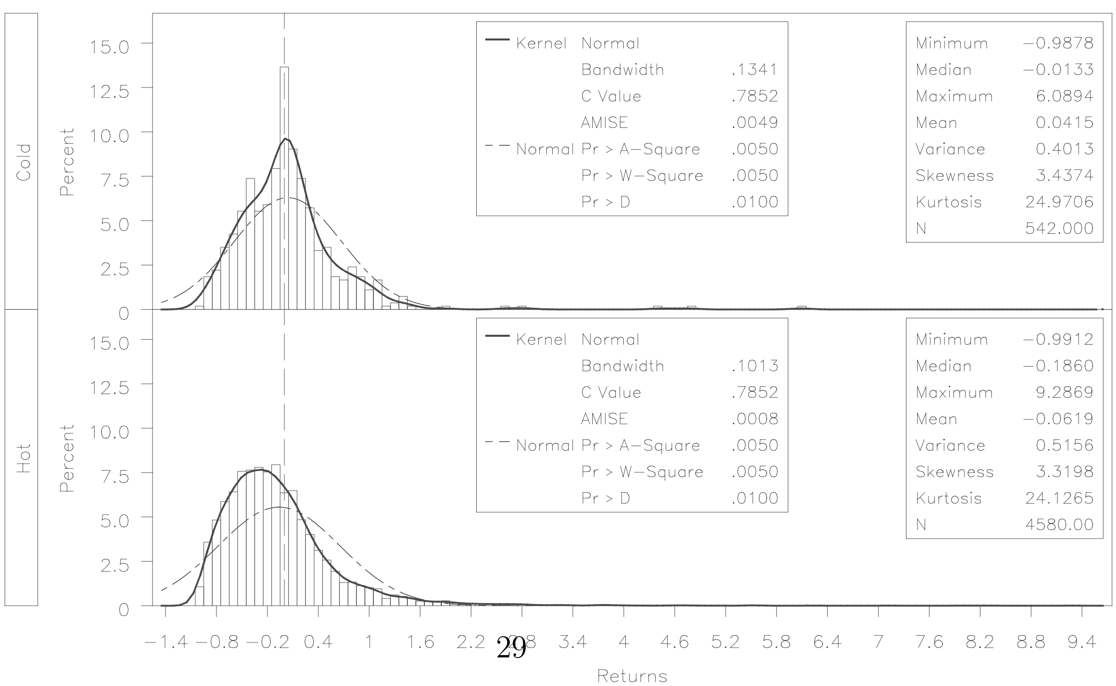

Figure 1C: Nonparametric Kernel Density Plot of CAR for "Cold" and "Hot" Periods ("Heat" Measure is NumIPO)

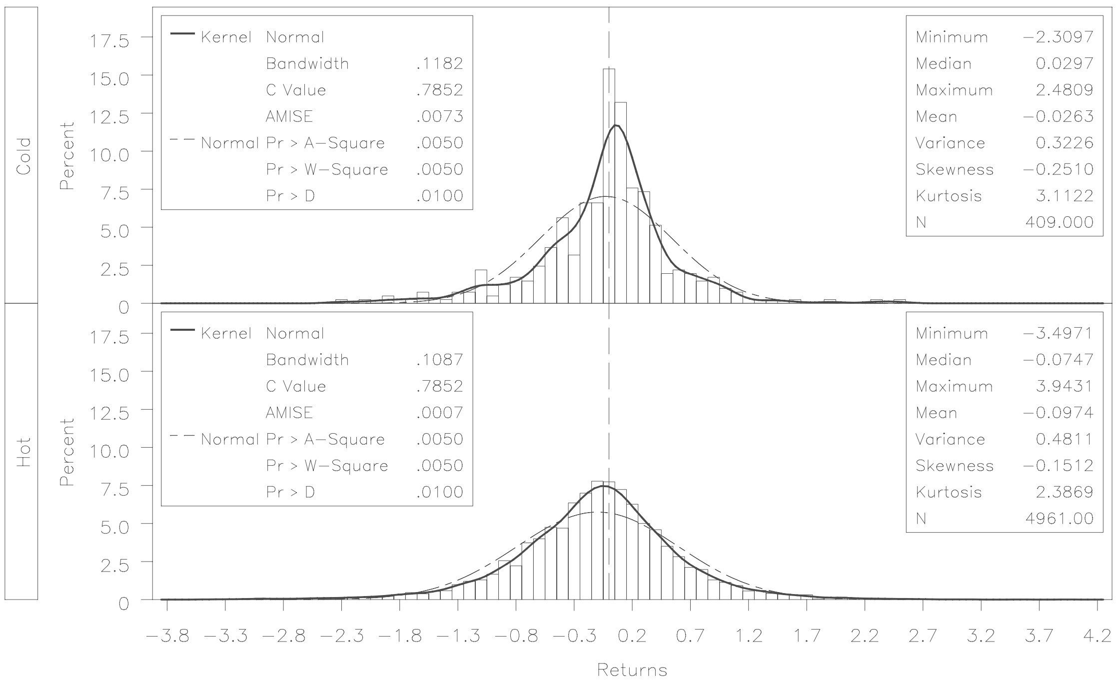

Figure 1D: Nonparametric Kernel Density Plot of BHAR for "Cold" and "Hot" Periods ("Heat" Measure is NumIPO)

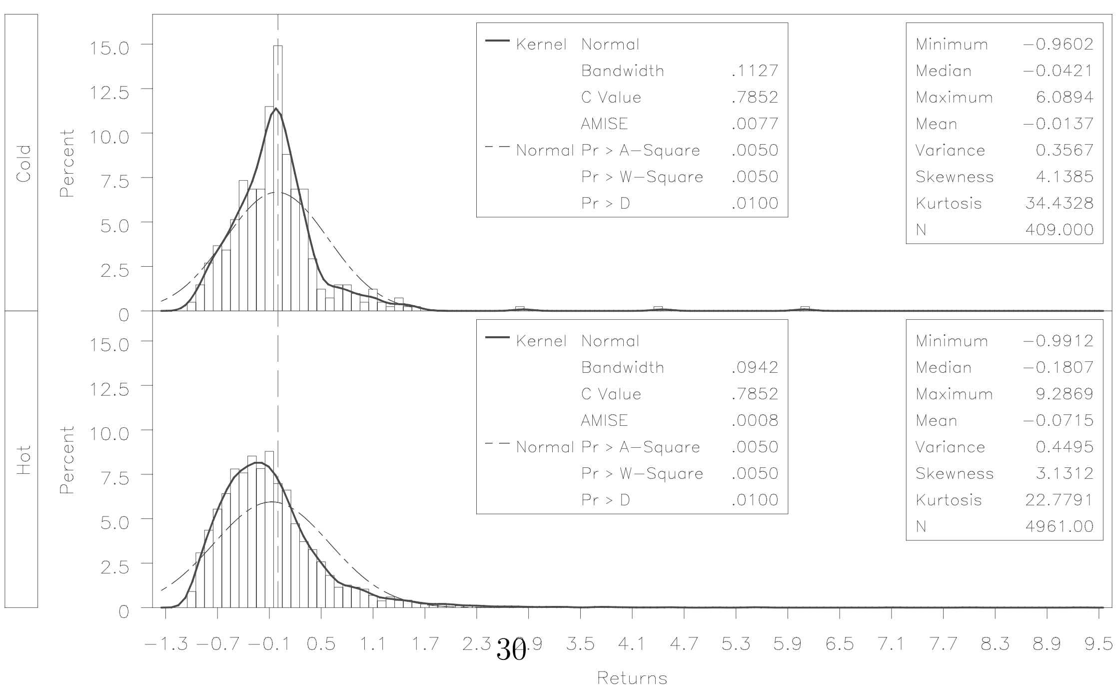

Figure 1E: Nonparametric Kernel Density Plot of CAR for "Cold" and "Hot" Periods ("Heat" Measure is PWU)

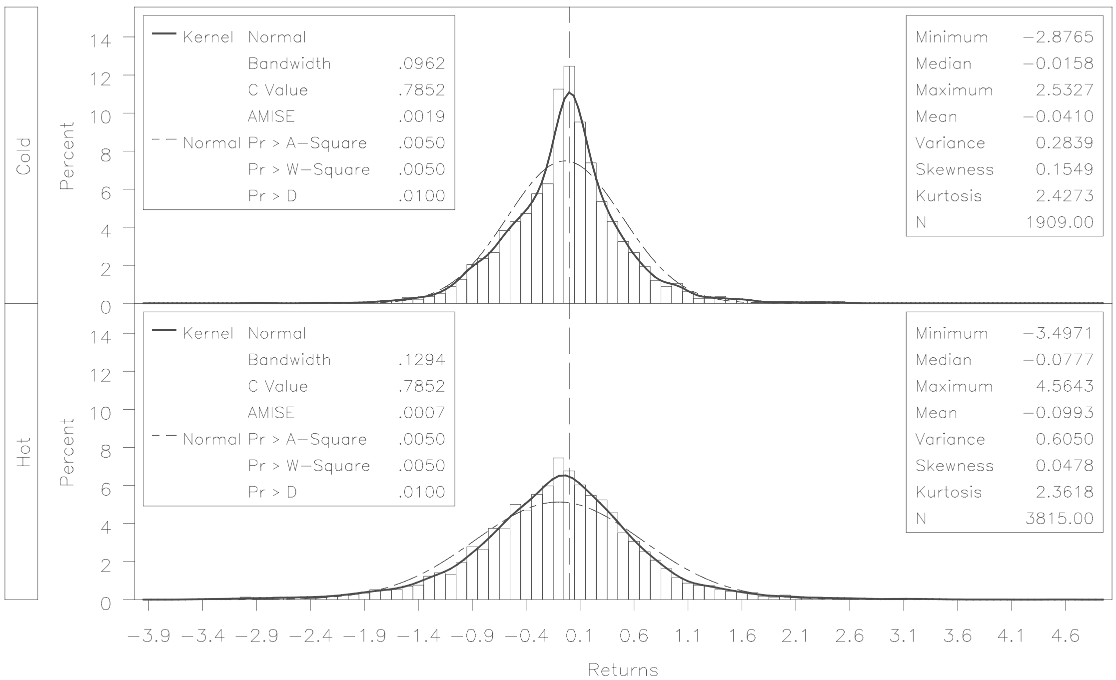

Figure 1F: Nonparametric Kernel Density Plot of BHAR for "Cold" and "Hot" Periods ("Heat" Measure is PWU)

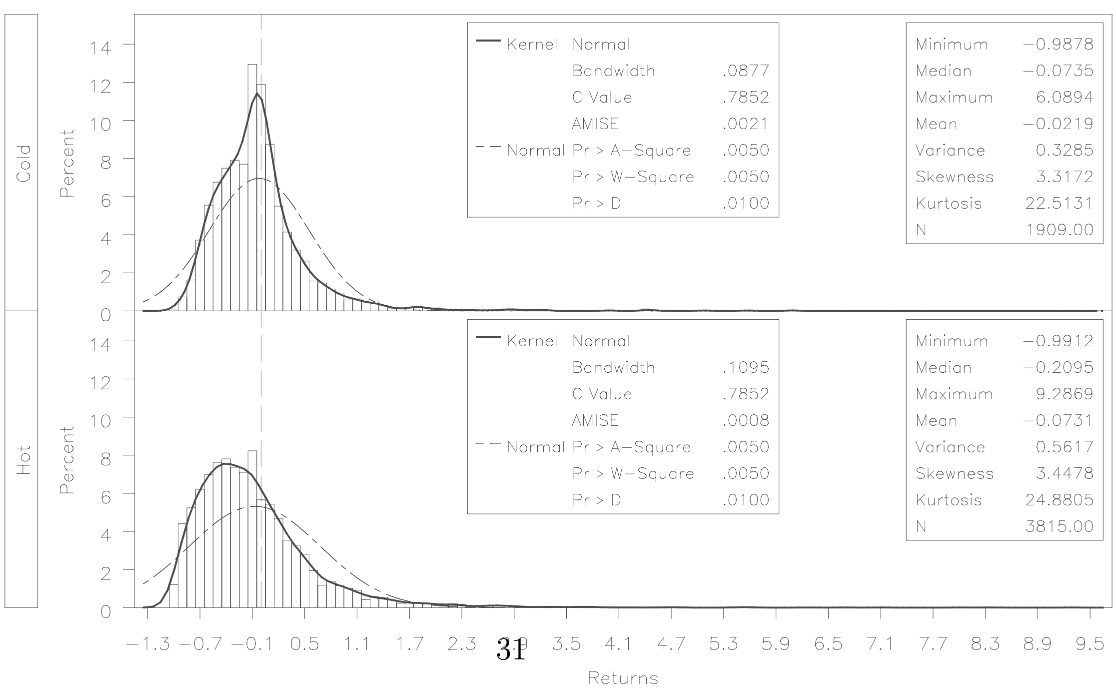

Table 1: Descriptive Statistics of the Returns Over Calendar Time

This panel presents various distribution statistics for our CAR and BHAR returns. To save space only the results for 12-month returns, with replacement using *ewretIPO* are shown, but the results for the alternative return calculations are very similar. The sample period, 1970-2004, is divided into 5-year subperiods according to the calendar time. The return statistics for each subperiod is computed for *all* IPOs with issuing dates during that particular time span i.e. it is not found by averaging the quarterly measure of that statistics.

Calendar Period	Number of Obs.	CAR Mean	BHAR Mean	CAR Variance	BHAR Variance
1970-1975	539	-0.0493	-0.0899	0.0808	0.0853
1976-1980	196	0.0369	0.0303	0.2597	0.3265
1981-1985	1161	-0.0099	-0.0015	0.2774	0.4382
1986-1990	1137	0.0039	0.0035	0.2978	0.4129
1991-1995	1939	-0.0160	-0.0218	0.2961	0.3539
1996-2000	2124	-0.1056	-0.1090	0.7164	0.7140
2001-2004	240	-0.0462	-0.0719	0.2923	0.2540
1970-2004	7333	-0.0399	-0.0452	0.3991	0.4590

Calendar Period	Number of Obs.	CAR Min	BHAR Min	CAR Max	BHAR Max
1970-1975	539	-1.2448	-0.7812	1.2562	1.9591
1976-1980	196	-1.6374	-0.9101	1.5377	4.4478
1981-1985	1161	-2.2675	-0.9878	2.5775	6.0894
1986-1990	1137	-2.2124	-0.9380	2.3745	5.0867
1991-1995	1939	-1.9043	-0.9781	4.8602	5.5643
1996-2000	2124	-3.3894	-0.9912	4.0347	9.2869
2001-2004	240	-2.0454	-0.9602	2.2706	2.5534
1970-2004	7333	-3.3894	-0.9912	4.8602	9.2869

Calendar Period	Number of Obs.	CAR Skewness	BHAR Skewness	CAR Kurtosis	BHAR Kurtosis
1970-1975	539	-0.0407	1.6888	3.1321	9.9788
1976-1980	196	0.0507	3.1387	0.8209	20.0249
1981-1985	1161	0.2308	3.0327	1.6012	17.7920
1986-1990	1137	0.3966	2.3965	1.7798	10.8422
1991-1995	1939	0.3208	2.0056	4.0630	8.7888
1996-2000	2124	0.2091	3.7690	2.1081	25.9735
2001-2004	240	-0.0795	1.2932	2.3816	3.8896
1970-2004	7333	0.1632	3.2683	3.6741	23.7337

Table 2: Descriptive Statistics of the "Heat" Variables Over Calendar Time

This panel presents various distribution statistics for our "heat" variables. These "heat" measures are *TotProc* - total proceeds raised per quarter as a percentage of the GDP in current dollars, *NumIPO* - number of new issues per quarter, and *PWU* - proceeds-weighted underpricing per quarter (in %). The sample period, 1970-2004, is divided into 5-year subperiods according to the calendar time.

Calendar Period	TotProc **Mean**	PWU **Mean**	NumIPO **Mean**	TotProc **Min**	PWU **Min**	NumIPO **Min**	TotProc **Max**	PWU **Max**	NumIPO **Max**
1970-1975	11.3070	–	46.1579	0.4846	–	1	43.9070	–	160
1976-1980	3.2228	–	15.8500	0.0654	–	4	12.4252	–	63
1981-1985	22.4517	–	91.1000	3.1582	–	20	68.4508	–	244
1986-1990	29.9595	15.4086	90.4000	1.4785	0.6472	19	92.6078	58.8715	226
1991-1995	66.3151	12.9152	133.0500	22.1301	4.9094	29	117.1242	23.8552	229
1996-2000	102.3164	31.3053	135.2000	43.0264	12.6946	45	224.5350	95.4541	255
2001-2004	49.0200	7.9976	22.0000	1.5812	-3.3925	3	132.3460	26.5115	49
1970-2004	40.3693	17.8966	79.7939	0.0654	-3.3925	1	224.5350	95.4541	255

Calendar Period	TotProc **Var**	PWU **Var**	NumIPO **Var**	TotProc **Skew**	PWU **Skew**	NumIPO **Skew**	TotProc **Kurt**	PWU **Kurt**	NumIPO **Kurt**
1970-1975	154.6596	–	2354.7000	1.2683	–	0.9892	1.1353	–	0.0437
1976-1980	7.5976	–	221.1868	2.0534	–	2.3659	6.0053	–	5.4563
1981-1985	389.7068	–	3407.9900	1.5607	–	1.2971	1.4544	–	1.6394
1986-1990	500.0925	245.4821	4003.0900	1.4610	2.1765	0.9783	2.0089	4.3226	-0.5199
1991-1995	555.5453	22.5872	2044.2600	0.5629	0.5239	0.2110	0.3512	0.3095	1.4057
1996-2000	2205.6900	519.3015	3338.6900	0.9170	1.6193	0.4630	0.9371	2.1589	0.2522
2001-2004	1287.9700	62.0081	183.8182	0.9851	1.0408	0.4378	1.5602	1.9154	-0.1149
1970-2004	1767.7600	296.2532	4292.1300	1.4923	2.4026	0.7393	2.6378	6.6493	-0.2935

Table 3: Comparing Return Variances Across "Hot" and "Cold" IPO Markets

The table presents the number of IPO firms and the variance of their long-run returns across "Hot" and "Cold" markets. The results for both 9-month and 12-month returns (CAR and BHAR) are shown. The table is divided in two pannels: Panel A includes the results for replacement with *ewretIPO* and Panel B for replacement with *vwretCRSP*. Three different "Heat" proxies are used to classify the firms into "Hot" and "Cold" samples: *TotProc* - total proceeds raised per quarter as a percentage of the GDP in current dollars, *NumIPO* - number of new issues per quarter, and *PWU* - proceeds-weighted underpricing per quarter (in %). The quarters in our sample period are ranked using the "heat" level at that quarter. The top one-third (bottom one-third) of the ranked quarters are considered "Hot" ("Cold") quarters. The return variance for 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.

Panel A: Replacement with *ewretIPO*.

	"Heat" Measure is *TotProc*			"Heat" Measure is *NumIPO*			"Heat" Measure is *PWU*		
Return	"Cold" Quarters	"Hot" Quarters	F-test	"Cold" Quarters	"Hot" Quarters	F-test	"Cold" Quarters	"Hot" Quarters	F-test
12-month CAR	0.3636	0.5435	0.0001	0.3226	0.4811	0.0001	0.2839	0.6050	0.0001
12-month BHAR	0.4013	0.5156	0.0001	0.3567	0.4495	0.0023	0.3285	0.5617	0.0001
Numb. of Obs.	542	4580		409	4961		1909	3815	
9-month CAR	0.2589	0.4020	0.0001	0.2324	0.3636	0.0001	0.1981	0.4876	0.0001
9-month BHAR	0.3232	0.3761	0.0198	0.2457	0.3643	0.0001	0.2246	0.4786	0.0001
Numb. of Obs.	562	4475		405	4793		1764	3239	

Panel B: Replacement with *vwretCRSP*.

	"Heat" Measure is *TotProc*			"Heat" Measure is *NumIPO*			"Heat" Measure is *PWU*		
Return	"Cold" Quarters	"Hot" Quarters	F-test	"Cold" Quarters	"Hot" Quarters	F-test	"Cold" Quarters	"Hot" Quarters	F-test
12-month CAR	0.3041	0.5444	0.0001	0.3165	0.4793	0.0001	0.3061	0.6072	0.0001
12-month BHAR	0.3299	0.5239	0.0001	0.3484	0.4558	0.0003	0.3635	0.5735	0.0001
Numb. of Obs.	560	4580		432	5005		1629	3798	
9-month CAR	0.2186	0.4002	0.0001	0.2184	0.3568	0.0001	0.1720	0.4516	0.0001
9-month BHAR	0.2874	0.3797	0.0001	0.2277	0.3622	0.0001	0.2091	0.4454	0.0001
Numb. of Obs.	560	4580		432	5005		1331	3815	

Table 4: Nonparametric Tests of Identical Return Distributions Across "Hot" and "Cold" IPO Markets

The nonparametric tests results from Kolmogorov-Smirnov two-sample test, Kuiper two-sample test, Wilcoxon Mann-Whitney U test, and Siegel-Tukey test are presented in this table. The null hypothesis (H_0) for all three tests is that the distribution of the returns is identical for "hot" and "cold" samples. The classification into "hot" and "cold" samples is done the same way as in *Table 3* using three different "heat" measures. The Panels A-C show the results for 12-month, 9-month, and 6-month returns (CAR and BHAR), respectively. The table includes only the results for replacement with *ewretIPO*, because the results for replacement with *vwretCRSP* are essentially the same. The numbers presented are the probability that the test statistics of each test is grater than its corresponding critical value (*Prob* of $Z > |Z_a|$ under H_0), which is sometimes referred to as Type I error (probability of *rejecting* the hypothesis while it is *true*).

Panel A: 12-month Returns

	"Heat" Measure is *TotProc*		"Heat" Measure is *NumIPO*		"Heat" Measure is *PWU*	
Test Name	12-mo CAR	12-mo BHAR	12-mo CAR	12-mo BHAR	12-mo CAR	12-mo BHAR
Kolmogorov-Smirnov	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Kuiper	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Mann-Whitney	0.0001	0.0001	0.0038	0.0001	0.0024	0.0001
Siegel-Tukey	0.0001	0.0056	0.0001	0.0001	0.0001	0.0001

Panel B: 9-month Returns

	"Heat" Measure is *TotProc*		"Heat" Measure is *NumIPO*		"Heat" Measure is *PWU*	
Test Name	9-mo CAR	9-mo BHAR	9-mo CAR	9-mo BHAR	9-mo CAR	9-mo BHAR
Kolmogorov-Smirnov	0.0095	0.0001	0.0194	0.0003	0.0001	0.0001
Kuiper	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Mann-Whitney	0.2497	0.0006	0.3392	0.0140	0.0749	0.0001
Siegel-Tukey	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

Panel C: 6-month Returns

	"Heat" Measure is *TotProc*		"Heat" Measure is *NumIPO*		"Heat" Measure is *PWU*	
Test Name	6-mo CAR	6-mo BHAR	6-mo CAR	6-mo BHAR	6-mo CAR	6-mo BHAR
Kolmogorov-Smirnov	0.0004	0.0001	0.0941	0.0098	0.0001	0.0001
Kuiper	0.0001	0.0001	0.0006	0.0001	0.0660	0.0169
Mann-Whitney	0.0564	0.0001	0.2897	0.0270	0.1779	0.0001
Siegel-Tukey	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

Table 5: Correlation Coefficients Between Variance Variables and "Heat" Measures

The table displays the Pearson correlation coefficients between the return variances and the "heat" measures. The results for 12-month, 9-month, and 6-month return variances (*VarCAR* and *VarBHAR*) are shown. The variance variables are in quarterly observations, meaning that the return variance is calculated *within* each quarter and then correlated with the "Heat" variables, which are also in quarterly observations. The "Heat" measures are *TotProc* - total proceeds raised per quarter as a percentage of the GDP in current dollars, *NumIPO* - number of new issues per quarter, and *PWU* - proceeds-weighted underpricing per quarter (in %). The table is divided in two pannels: Panel A includes the results for replacement with *ewretIPO* and Panel B for replacement with *vwretCRSP*. The value in square brackets under the coefficient estimate represents $Prob > |r|$ under $H_0 : \rho = 0$, and the value in curly brackets represent the number of nonmissing quarters included in the estimation of each coefficient.

Panel B: Replacement with *ewretIPO*.

"Heat" Variable	VarCAR 12-month	VarBHAR 12-month	VarCAR 9-month	VarBHAR 9-month	VarCAR 6-month	VarBHAR 6-month
TotProc	0.51411	0.22756	0.52126	0.18743	0.48333	0.17545
	[0.0001]{128}	[0.0098]{128}	[0.0001]{125}	[0.0363]{125}	[0.0001]{125}	[0.0503]{125}
NumIPO	0.19525	0.09312	0.23305	0.14930	0.18958	0.09018
	[0.0272]{128}	[0.2958]{128}	[0.0089]{125}	[0.0966]{125}	[0.0342]{125}	[0.3172]{125}
PWU	0.61394	0.21632	0.6927	0.26138	0.59014	0.27346
	[0.0001]{72}	[0.0680]{72}	[0.0001]{72}	[0.0266]{72}	[0.0001]{72}	[0.0201]{72}

Panel B: Replacement with *vwretCRSP*.

"Heat" Variable	VarCAR 12-month	VarBHAR 12-month	VarCAR 9-month	VarBHAR 9-month	VarCAR 6-month	VarBHAR 6-month
TotProc	0.52114	0.23713	0.53658	0.20967	0.49719	0.19381
	[0.0001]{130}	[0.0066]{130}	[0.0001]{130}	[0.0167]{130}	[0.0001]{130}	[0.0271]{130}
NumIPO	0.18696	0.09394	0.24037	0.15920	0.19440	0.09651
	[0.0332]{130}	[0.2877]{130}	[0.0059]{130}	[0.0704]{130}	[0.0267]{130}	[0.2747]{130}
PWU	0.61887	0.23171	0.68993	0.27339	0.58853	0.27635
	[0.0001]{72}	[0.0502]{72}	[0.0001]{72}	[0.0201]{72}	[0.0001]{72}	[0.0188]{72}