A RESEARCH REPORT FROM STOCKHOLM INSTITUTE FOR FINANCIAL RESEARCH

Pseudo Market Timing: Fact or Fiction?

MAGNUS DAHLQUIST
FRANK DE JONG

NO 24 — JUNE 2004

Stockholm Institute
for Financial Research

Stockholm Institute for Financial Research (SIFR) is a private and independent non-profit organization established at the initiative of members of the financial industry and actors from the academic arena. SIFR was launched in January 2001 and is situated in the center of Stockholm. Magnus Dahlquist serves as director of the Institute. The mission of SIFR is to:

- Conduct and stimulate high quality research on issues in financial economics, where there are promising prospects for practical applications,
- Disseminate research results through publications, seminars, conferences, and other meetings, and
- Establish a natural channel of communication about research issues in finance between the academic world and the financial sector.

The activities of SIFR are supported by a foundation based on donations from Swedish financial institutions. Major contributions have been made by: AFA, Alecta, Alfred Berg, AMF Pension, Brummer & Partners, Carnegie, Handelsbanken, Kapitalmarknadsgruppen, Länsförsäkringar, Nordea, Svenska Fondhandlareföreningen, and Östgöta Enskilda Bank.

Sveriges Riksbank funds a position as visiting professor at SIFR.

SIFR also gratefully acknowledges research grants received from Bankforskningsinstitutet, Föreningsbankens Forskningsstiftelse, Jan Wallanders och Tom Hedelius Stiftelse, Riksbankens Jubileumsfond, and Torsten och Ragnar Söderbergs stiftelser.

Stockholm Institute for Financial Research, Saltmätargatan 19A 11, SE-113 59 Stockholm, Sweden
Phone: +46-8-728 51 20, Fax: +46-8-728 51 30, E-mail: info@sifr.org, Web: www.sifr.org

Pseudo Market Timing: Fact or Fiction?

Magnus Dahlquist and Frank de Jong

Stockholm Institute
for Financial Research

Pseudo Market Timing: Fact or Fiction?

Magnus Dahlquist and Frank de Jong*

First version: October 23, 2003

Current version: June 1, 2004

Abstract

The average firm going public or issuing new equity has underperformed the market in the long run. Endogeneity of the number of new issues has been proposed as a potential explanation of this long-run underperformance. Under pseudo market timing of new issues, ex post measures of average abnormal returns may be negative on average despite zero ex ante abnormal returns. We show that, under reasonable stationarity assumptions on the process generating events, traditional measures of average abnormal returns are consistent, and the pseudo market timing effect is a small sample problem. In simulations of an empirical model we demonstrate that the bias is small even in moderate sample sizes. An abnormal return measure capturing a feasible investment strategy is not biased. We argue that it is unlikely that pseudo market timing is the explanation for the long-run underperformance in equity issuances.

Keywords: Abnormal return measures, Endogenous events, Event studies, Initial public offerings, Long-run underperformance.

JEL Classifications: C33, G14, G32.

*We have benefited from the comments and suggestions of Alon Brav, Chris Leach, Jay Ritter, and Paul Söderlind. Magnus Dahlquist is from the Stockholm Institute for Financial Research, and is affiliated with the Centre for Economic Policy Research, London. Frank de Jong is from the University of Amsterdam, and is affiliated with the Centre for Economic Policy Research, London. Send correspondence to: Magnus Dahlquist, Stockholm Institute for Financial Research, Saltmätargatan 19A, SE-113 59 Stockholm, Sweden, Phone: +46 8 7285129, Fax: +46 8 7285130, E-mail: magnus.dahlquist@sifr.org.

I Introduction

Major corporate events are inherently endogenous. For example, a firm may decide when to go public depending on general market conditions. It is well documented that firms tend to go public after high underpricing in initial public offerings (IPOs) and after high market returns. Traditional event study methods, however, treat the timing of events as exogenous. Event studies have shown that the average firm going public has underperformed the market in the long run. In a recent review, Ritter and Welch (2002) report an average 23% underperformance (relative to the market) during the three-year period following a US IPO.[1] The lack of an explanation for the long-run underperformance in IPOs and similar underperformance in seasoned equity offerings (SEOs) has been referred to as the "new issues puzzle."

In a recent paper, Schultz (2003) proposes an explanation for the apparent long-run underperformance of firms that go public. He argues that the underperformance may be a statistical illusion caused by the clustering of IPOs after a period of unusually high abnormal returns on previous IPO firms. This effect is referred to as pseudo market timing. Note that it is not genuine market timing ability that is at work, since abnormal returns of future IPOs are conditionally unpredictable. Instead, when using traditional iid-oriented event study methods the clustering of events after periods with positive abnormal returns causes a statistical bias in estimated average abnormal returns. The pseudo market timing argument, in principal, extends to other endogenous corporate events. For example, SEOs have also shown a long-run underperformance. Hence, the pseudo market timing argument appears to have more wide-spread implications than just for IPOs.

In this paper we provide a thorough evaluation of the endogeneity problem in event studies as it relates to long-run underperformance and undertake both theoretical and simulation analyses. Measuring and testing abnormal returns when the number of events is

[1]The long-run underperformance in IPOs was first documented by Ritter (1991). Reviews on security issuance include Eckbo and Masulis (1995), Ibbotson and Ritter (1995), Jenkinson and Ljungqvist (2001), Loughran, Ritter, and Rydqvist (1994), and Ritter (2003).

endogenous is a non-trivial econometric problem.[2] We approach event studies from a time series perspective, which contrasts to the usual cross-section oriented treatment of event studies. The time series perspective takes into account the dynamic dependence of events on past returns and easily incorporates general forms of pseudo market timing. When reasonable (stationarity) assumptions on the process generating the number of events are imposed, the traditional cumulative abnormal return measures are not problematic in large samples. We also consider an abnormal return measure that captures the returns on a feasible investment strategy in event firms; this measure is in line with the calendar time approach advocated by Fama (1998). We show that this abnormal return measure is unbiased and does not have the problems of the traditional measures—not even in small samples. Hence, pseudo market timing as a potential explanation for long-run underperformance is limited to small samples.

To evaluate the potential small sample bias in the traditional measures, we undertake simulation experiments. As a basis for the simulations, we consider count data regressions where the non-negative integer character of the event data (here IPOs) is explicitly acknowledged. This makes the empirical model well suited for simulations. We find that pseudo market timing is a small sample problem, and that the bias depends on the parameters related to persistence in the number of events, impact of market conditions, and cross-sectional correlations in abnormal returns. An important finding is that dependence of the number of IPOs on past market returns is not sufficient to generate pseudo market timing bias; instead, biases are caused by correlation between past abnormal returns and the number of events. Event abnormal return measures that correct for cross correlations show much less bias than the usual equally weighted measures. But even for the equally

[2]Eckbo, Maksimovic, and Williams (1990) discuss exogenous versus endogenous events. Other problematic issues in measuring long-run abnormal returns relate to the right benchmark model, the use of average abnormal returns or buy-and-hold returns, the use of value-weighted or equally weighted returns, corrections for cross-sectional correlations, time-varying market risk, and non-normally distributed abnormal returns; see, for instance, Barber and Lyon (1997), Brav (2000), Brav and Gompers (1997), Brav, Geczy, and Gompers (2000), Eckbo and Norli (2001), Fama (1998), Gompers and Lerner (2003), Kothari and Warner (1997), Loughran and Ritter (1995), and Mitchell and Stafford (2000).

weighted abnormal return measure, the pseudo market timing effect does not provide sufficient bias to explain the observed long-run underperformance of IPOs in samples of the size typically used in empirical research. We conclude that it is unlikely that the long-run underperformance of IPO firms is explained by pseudo market timing.

Our work relates to two concurrent working papers. Viswanathan and Wei (2004) study the properties of long-run performance measures with endogenous events. They use more restrictive assumptions in their theoretical analysis, but show, as we do, that the cumulative abnormal return measure converges to zero in large samples. In addition, they calculate the finite sample expectation of the cumulative abnormal return for a specific data generating process for the number of IPOs. The calculations show that under a stationary process for the number of IPOs the biases in abnormal return measure are small. Ang, Gu, and Hochberg (2004) conduct simulations and conclude that the IPO underperformance is highly unlikely to be due to small sample problems in abnormal return measures.

We start our analysis in Section II by providing examples similar to Schultz (2003). We then turn to a formal analysis of the event abnormal return measures in Section III. We present an empirical model for the number of events in Section IV, and report the simulation results in Section V. We conclude in Section VI.

II Two Examples

We follow Schultz (2003) and analyze the pseudo market timing hypothesis in a two-period model. Initially we make the same simplifying assumptions as he does; later we relax one crucial assumption.[3] The pseudo market timing effect we consider is couched in a initial public offering (IPO) setting, but extends to general settings with endogenous corporate events. The purpose of this section is to show the exact cause of the pseudo

[3]To focus the discussion on the effects of pseudo market timing, we abstract from problems such as bad benchmark models, value versus equal weighting of events, non-normality and the like. We do pay attention to cross-sectional correlations, because it interacts with pseudo market timing.

market timing effect, and to motivate the use of abnormal return measures that correct for cross-sectional correlation.

Consider a two-period model. The market return is normalized to zero in both periods. The idea of pseudo market timing is that more firms go public when past returns have been positive. Returns of private firms (that potentially may go public) and firms that actually go public are assumed to follow a simple binomial process. These firms experience either a positive or negative 10% return with equal probability (in both periods). Since the market return is assumed to be zero in both periods, the binomial process also characterizes the abnormal returns of private firms and firms that go public. Let the abnormal return in period 1 (between date 0 and date 1) be denoted by r_1. Similarly, let r_2 denote the abnormal return in period 2 (between date 1 and date 2). According to the binomial process, the abnormal returns in periods 1 and 2 can take four different paths (or four scenarios, labeled I to IV):

I. $r_1 = +10\%$ and $r_2 = +10\%$;

II. $r_1 = +10\%$ and $r_2 = -10\%$;

III. $r_1 = -10\%$ and $r_2 = +10\%$;

IV. $r_1 = -10\%$ and $r_2 = -10\%$.

The interesting feature of the analysis is that the number of observed IPOs depends on the past performance. When the price in period 1 is higher than the initial price, more IPOs are observed. Conversely, a lower price leads to fewer IPOs. Suppose the number of IPOs in the beginning of the first period, known at date 0, is one (that is, $N_0 = 1$). If a positive (abnormal) return is observed in period 1, the number of IPOs increases to, say, three (that is, $N_1 = 3$). It is important to recognize that the number of IPOs is a function of past returns, but not contemporaneous or future returns. The assumed number of IPOs in period 2 (here three) is not important for the reasoning; it could be any positive number larger than one. Suppose now instead that the return in period 1 is negative, then the number of IPOs decreases to zero (that is, $N_1 = 0$). [Below, we relax Schultz's (2003) assumption that the number of IPOs is zero. It turns out that this is important for the analysis.] Panel A in Table I summarizes the four scenarios with the abnormal returns and the number of IPOs.

The table also reports three measures of average abnormal returns. The first measure is an equally weighted abnormal return measure, denoted AR_{EW}. It simply averages the observed abnormal returns in a scenario. This is the measure that Schultz (2003) focuses on. The second measure, denoted AR_{CW}, is an extension of the equally weighted measure, and corrects for the cross-sectional dependence in the abnormal returns. In the correction for cross-sectional dependence, all event returns in the same period are counted as one observation. The third measure is a feasible investment abnormal return measure, denoted AR_{FI}. It captures the per-period return on a feasible investment strategy that invests in a portfolio of event firms in each period. If there is no event in a period, the investment is in the benchmark (here the market) and the abnormal return for that period is by construction equal to zero. This measure captures the essential idea of Fama's (1998) calendar time abnormal returns by creating a portfolio of all event firms within a single investment period.

Table I shows that the unconditional expectations of the first two measures of average abnormal returns (the AR_{EW} and AR_{CW} measures) are negative (–3.75% and –2.5%), that is, they are both biased downwards. It is also more likely that a negative, rather than a positive measure of abnormal returns is uncovered. These observations are Schultz's (2003) main points. He refers to this as pseudo market timing—despite the ex ante expectation of zero abnormal returns, it is likely that a negative measure of abnormal returns is observed ex post. It is driven by the fact that the number of IPOs is determined by past returns. It is further claimed that this pseudo market timing is not a small sample issue. The AR_{FI} measure is, however, zero. Recall that this measure captures a feasible investment strategy, where the investment is in all IPOs in a period. If there are multiple

IPOs, the investment is divided equally over the event firms. Also, if there are no IPOs in a period, the investment is in the market. This measure yields a zero average abnormal return, which is what should be expected from the zero ex ante abnormal returns.

The setting above is special and restrictive in the sense that after one negative abnormal return, there are no more IPOs. Consider instead a less drastic assumption and let the number of IPOs decline, but remain positive, after a negative abnormal return. For example, start with two IPOs in period 1 (that is, $N_0 = 2$). Then, after a positive abnormal return in period 1, the number of IPOs doubles and after a negative abnormal return it halves (that is, $N_1 = 4$ or $N_1 = 1$ depending on the return in period 1). Panel B in Table I summarizes the four scenarios with the abnormal return measures.

We now observe a different picture. The AR_{EW} measure is still biased downwards, but the AR_{CW} measure is unbiased. Note that the key difference with the previous example is the number of IPOs in scenarios III and IV. In Panel A, scenarios III and IV show no IPOs in period 2, hence the abnormal return in period 2 is not taken into account in these scenarios. In Panel B, there is still one IPO in period 2. This observation exactly offsets the negative abnormal return in period 1 if the abnormal return measure corrects for cross-sectional dependence. The AR_{FI} measure is again unbiased. That the abnormal return in period 2 is not observed in Panel A is not a problem for the AR_{FI} measure as the investment strategy is then to invest in the benchmark, yielding a zero abnormal return. Still, this observation is taken into account in the per-period average.

That cross-sectional dependence for computing average abnormal returns is problematic has been noticed in several studies (including Brav, 2000, and Mitchell and Stafford, 2000). Fama (1998) argues that a better way of gauging abnormal returns is to construct portfolios representing investments in all feasible events in a period and then evaluate the performance of such a strategy in the time series. Note that in the examples above, such a measure is similar to our AR_{CW} and AR_{FI} measures. Depending on how periods with no events are treated it coincides with either AR_{CW} or AR_{FI}. If it is assumed that there is no investment at all in periods with no IPOs, it coincides with AR_{CW}. If it is assumed that the investment is in the benchmark when there are no events, it coincides with AR_{FI}. Finally, note that it is only the AR_{FI} measure that is unbiased in both examples.

III Abnormal Return Measures and Sampling Properties

In this section we derive formal sampling properties of abnormal return measures. We first formalize the way cumulative abnormal return measures are calculated, and then discuss unbiasedness (a small sample property) and consistency (a large sample property) of the measures in relation to endogenous event timing. Finally, we consider a feasible investment abnormal return measure and its sampling properties.

A Cumulative Abnormal Return Measures

Consider a sample period of length $T + K$, where N_t denotes the number of events in period t. We assume the events are realized at the end of the period, so $N_t \in \Omega_t$, for $t = 1, .., T$. The abnormal returns on the event firms, $r_{i,t+k}$, are realized in periods $t + 1$ through $t + K$. We are interested in measuring the average abnormal return on event firms up to K periods after the event period.

Consider the abnormal return measures from the previous section. The equally weighted abnormal return in event period k is calculated as follows:

$$AR_{EW}^{k} = \frac{\sum_{t=1}^{T} \sum_{i=1}^{N_t} r_{i,t+k}}{\sum_{t=1}^{T} N_t}. \tag{1}$$

This expression sums up the abnormal returns over all events in all time periods, and then divides by the total number of events. It is a traditional abnormal return measure. An equally weighted cumulative abnormal return is obtained by aggregating all event periods

$$CAR_{EW} = \sum_{k=1}^{K} AR_{EW}^{k} = \sum_{k=1}^{K} \frac{\sum_{t=1}^{T} \sum_{i=1}^{N_t} r_{i,t+k}}{\sum_{t=1}^{T} N_t} = \frac{\sum_{t=1}^{T} \sum_{i=1}^{N_t} \left(\sum_{k=1}^{K} r_{i,t+k} \right)}{\sum_{t=1}^{T} N_t}. \tag{2}$$

This measure is simply an equally weighted average abnormal return for the cumulative abnormal returns $\sum_{k=1}^{K} r_{i,t+k}$ in firm i.

The measure with correction for cross-sectional dependence first averages the abnormal returns within each period, and then averages the resulting numbers over all time periods. If there is at least one event in each period, we have

$$AR_{CW}^{k} = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{1}{N_t}\sum_{i=1}^{N_t} r_{i,t+k}\right). \tag{3}$$

To allow for periods without events ($N_t = 0$ in some periods), we can generalize it to

$$AR_{CW}^{k} = \frac{\sum_{t=1}^{T} \mathrm{I}\left[N_t > 0\right]\left(\frac{1}{N_t}\sum_{i=1}^{N_t} r_{i,t+k}\right)}{\sum_{t=1}^{T} \mathrm{I}\left[N_t > 0\right]}, \tag{4}$$

where $\mathrm{I}[.]$ is an indicator function (the value is one if $N_t > 0$, and zero otherwise). Like before, this measure can be cumulated to obtain the cross-sectionally weighted cumulative abnormal return measure

$$CAR_{CW} = \sum_{k=1}^{K} AR_{CW}^{k} = \frac{\sum_{t=1}^{T} \mathrm{I}\left[N_t > 0\right]\left(\frac{1}{N_t}\sum_{i=1}^{N_t}\sum_{k=1}^{K} r_{i,t+k}\right)}{\sum_{t=1}^{T} \mathrm{I}\left[N_t > 0\right]}. \tag{5}$$

Again, this is simply a cross-sectionally weighted average abnormal return applied to the individual cumulative abnormal returns.

We now assess the properties of the cumulative abnormal return measures. To fix the idea, start with the case of purely exogenous timing of events. Formally, we assume that $\mathrm{E}\left(r_{i,t}\right) = 0$ and N_t and $r_{i,s}$ are independent for all t and s. This independence implies that $\mathrm{E}\left(\sum_{k=1}^{K} r_{i,t+k} | N_1, \ldots, N_T\right) = \mathrm{E}\left(\sum_{k=1}^{K} r_{i,t+k}\right) = 0$. Under the exogenous market timing assumption one can easily show that both cumulative abnormal return measures are unbiased (i.e., $\mathrm{E}\left(CAR_{EW}\right) = 0$ and $\mathrm{E}\left(CAR_{CW}\right) = 0$). In contrast to the exogenous event situation, the number of events in the pseudo market timing case is endogenous and correlated with past abnormal returns. We therefore cannot set the expectations of $r_{i,t}$ conditional on the full time series of the number of observations $N_1, \ldots, N_T$ to zero. In this case, we generally cannot deliver a proof of unbiasedness.[4] We are therefore left with

[4]The problem is that in both expressions for these estimators, we divide by a function of N_t, which is

considering large sample properties of these two measures.

To assess the large sample properties, we exploit the assumption that abnormal returns have expectation zero conditional on all previous information (i.e., we assess whether these estimators are unbiased under the null that $\mathrm{E}\left(r_{i,t}|\Omega_{t-1}\right) = 0$, where Ω_{t-1} denotes information available at time $t-1$). This is exactly the assumption Schultz (2003) makes. This assumption captures the key idea of market efficiency and excludes genuine market timing of abnormal returns (predictive ability of abnormal returns).

We show that the cumulative average abnormal return measures converge in large samples to zero (that is, we prove consistency in all cases). The proof for the equally weighted average abnormal return measure is straightforward:

$$\mathrm{plim}_{T\to\infty} CAR_{EW} = \frac{\mathrm{plim}_{T\to\infty} T^{-1} \sum_{t=1}^{T} \left(\sum_{i=1}^{N_t} \sum_{k=1}^{K} r_{i,t+k} \right)}{\mathrm{plim}_{T\to\infty} T^{-1} \sum_{t=1}^{T} N_t} = \frac{0}{n} = 0, \tag{6}$$

where n is the long-run average number of events per period. It is assumed that

(*i*) n is strictly positive, and

(*ii*) $\sum_{i=1}^{N_t} \sum_{k=1}^{K} r_{i,t+k}$ is a martingale difference sequence, i.e. $\mathrm{E}\left(\sum_{i=1}^{N_t} \sum_{k=1}^{K} r_{i,t+k} | \Omega_t \right) = 0$, with finite variance, i.e. $\mathrm{E}| \sum_{i=1}^{N_t} \sum_{k=1}^{K} r_{i,t+k}|^2 < Q < \infty$ for some Q.[5]

Condition (*i*) rules out processes that die out over time (i.e., processes where the number of events over time almost surely converges to zero). Condition (*ii*) rules out processes where the number of events grows without bound. Combined, these two conditions guarantee that the event process is stable (stationary) over time. The martingale difference property in condition (*ii*) is implied by the null hypothesis $\mathrm{E}\left(r_{i,t}|\Omega_{t-1}\right) = 0$. Using the law of iterated expectations and the timing convention $N_t \in \Omega_t$, the martingale property $\mathrm{E}\left(\sum_{i=1}^{N_t} \sum_{k=1}^{K} r_{i,t+k} | \Omega_t \right) = 0$ follows immediately.

For the cross-sectionally weighted average abnormal return measure, we find a similar

---

not independent of the abnormal returns in the numerator, and conditioning on past information only is not possible.

[5]See Hamilton (1994) page 191, Proposition 7.7 and the text following that proposition.

result:

$$\text{plim}_{T\to\infty} CAR_{CW} = \frac{\text{plim}_{T\to\infty} T^{-1} \sum_{t=1}^{T} \text{I}\left[N_t > 0\right] \left(\frac{1}{N_t}\sum_{i=1}^{N_t}\sum_{k=1}^{K} r_{i,t+k}\right)}{\text{plim}_{T\to\infty} T^{-1} \sum_{t=1}^{T} \text{I}\left[N_t > 0\right]} = \frac{0}{p} = 0, \quad (7)$$

where p is the long-run average fraction of time periods with at least one event. It is assumed that

(i) p is strictly positive, and

(ii) $\frac{1}{N_t}\sum_{i=1}^{N_t}\sum_{k=1}^{K} r_{i,t+k}$ is a martingale difference sequence and $\text{E}|\frac{1}{N_t}\sum_{i=1}^{N_t}\sum_{k=1}^{K} r_{i,t+k}|^2 < Q < \infty$ for some Q.

Again, condition (i) guarantees that the event process does not die out (i.e., the number of events does not converge to zero). Condition (ii) is again implied by the null and is slightly weaker than the condition for the consistency of the equally weighted average abnormal return measure. Both conditions seem reasonable in a stationary environment.

The consistency results imply that, although possibly biased in small samples, event studies using the equally weighted abnormal return measure or the cross-sectionally weighted abnormal return measure give consistent estimates in large samples. Hence, we find that the possible bias of the equally weighted average abnormal return measure is only a small sample problem. Our conclusion contradicts Schultz's (2003) statements and seems at odds with the results of his multi-period simulations. We conjecture that his simulations violate the stationarity condition we impose above. His simulations increase the number of events after a price increase, and decrease the number of events after a price decrease. As Schultz (2003) states, this is reminiscent of a doubling strategy. The problem with such a process is that the unconditional variance of the number of events N_t grows without bound over time. As a result, his simulations violate condition (ii) which requires the variance of the sum of abnormal returns to be bounded.

B A Feasible Investment Abnormal Return Measure

Fama (1998) suggests an alternative measure of the event effect, captured by the return on a feasible investment strategy in the event firms. For every time period t, define the excess return (over a benchmark) on an investment strategy in all firms that had an event in the window from $t-K$ to $t-1$

$$r_t^{FI} = \mathrm{I}\left[\sum_{k=1}^{K} N_{t-k} > 0\right] \frac{\sum_{k=1}^{K}\sum_{i=1}^{N_{t-k}} r_{i,t}}{\sum_{k=1}^{K} N_{t-k}}, \tag{8}$$

The indicator function $\mathrm{I}\left[.\right]$ implies that if there are no events in the period $(t-K,\ldots,t-1)$, the feasible investment return equals zero, reflecting an investment in the benchmark. The abnormal return measure is obtained by averaging r_t^{FI} over time:

$$AR_{FI} = \frac{1}{T}\sum_{t=1}^{T} r_t^{FI}. \tag{9}$$

This measure reflects the averages per period return on an investment strategy in events in the previous K periods. To compare the excess return with the cumulative abnormal returns, the AR_{FI} measure has to be multiplied by K (the length of the event window).

It is straightforward to show the unbiasedness of the measure capturing a feasible investment strategy. Recall that the abnormal investment return in a period is the cross-sectional average of abnormal return. Unbiasedness follows from the fact that this abnormal investment return is a martingale difference, so that

$$\mathrm{E}\left(r_t^{FI}|\Omega_{t-1}\right) = \mathrm{E}\left(\mathrm{I}\left[\sum_{k=1}^{K} N_{t-k} > 0\right] \frac{\sum_{k=1}^{K}\sum_{i=1}^{N_{t-k}} r_{i,t}}{\sum_{k=1}^{K} N_{t-k}}|\Omega_{t-1}\right) = 0, \tag{10}$$

where the second equality follows from the conditional independence of N_{t-k} and $r_{i,t}$. Applying this result to all the returns we find

$$\mathrm{E}\left(AR_{FI}\right) = \mathrm{E}\left(\frac{1}{T}\sum_{t=1}^{T}\mathrm{E}\left(r_t^{FI}|\Omega_{t-1}\right)\right) = \mathrm{E}\left(\frac{1}{T}\sum_{t=1}^{T} 0\right) = 0, \tag{11}$$

Consistency is also immediate, since

$$\text{plim}_{T\to\infty} AR_{FI} = \text{plim}_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} r_t^{FI} = 0, \tag{12}$$

where we use that r_t^{FI} is a martingale difference sequence with finite variance. For this to hold, we need essentially the same conditions as for the consistency of the cumulative abnormal return measure CAR_{CW}.

IV Data and Empirical Model

In this section we fit an empirical model of the number of IPOs to actual data. We first describe the data used, then discuss and estimate the model, and finally provide simulation evidence.

A Data Description

We study the effects of market conditions on the number of IPOs using U.S. data. The sample period is January 1960 to June 2003, yielding 522 monthly observations. Data on the number of IPOs in a month, denoted N_t, are taken from the web pages of Jay Ritter.[6] We consider two variables that proxy for market conditions: returns on the S&P 500 index and average initial underpricing in IPOs. They are denoted by $R_{m,t}$ and $R_{u,t}$. The S&P 500 returns are from Ibbotson Associates; the data on initial underpricing are taken from the web pages of Jay Ritter. The initial underpricing variable is the equally weighted initial underpricing across all IPOs in a month. An individual initial underpricing is measured as the percentage change in the closing price within a month from the IPO offer price.[7]

Figure I shows the number of IPOs aggregated into a quarter together with monthly

[6]The number of offerings excludes Regulation A offerings, REITs, and close-end funds, but includes ADRs. The web pages of Jay Ritter give a detailed description with references to data sources.

[7]The definition of underpricing varies somewhat in the sample as described in Ibbotson and Jaffe (1975), Ritter (1984), and updates of Ibbotson, Sindelar, and Ritter (1988, 1994) at Jay Ritter's web pages.

observations of the log of cumulative returns (labeled log of market index in the figure) and the initial underpricing. There are four distinct periods of relatively low IPO activity (1963-67, 1973-79, 1988-90, and 2001 to the end of the sample). Consequently, there are also four periods of relatively high IPO activity (up to and including 1962, 1968-72, 1980-87, and 1991-2000). In each of the low activity periods the annual number of IPOs was well below 240 (a monthly average of less 20 IPOs), whereas the annual number of IPOs in high activity periods ranges from 238 to 953. It is evident from the figure that immediately before a period of low IPO activity there are severe falls in equity values. It is also evident that there is clustering in the initial underpricing. Further, it seems as a large underpricing is followed by a period of high IPO activity. However, the most recent period of low IPO activity (after a dramatic fall in prices in aftermath of the internet boom) is preceded by a period of large initial underpricing.

Table II presents summary statistics of the three variables. The total number of IPOs in the sample is 14,860. The average and median number of IPOs in a month is 28.5 and 22. The number of IPOs in a month varies a lot (the standard deviation is 24.7); there are 18 months with no IPOs, and the maximum number of IPOs in a month is 122. Note that the variance is much larger than the mean, which for count data is referred to as overdispersion. The average return on the S&P 500 is about 0.91% per month (10.9% annualized). The standard deviation is about 4.34% per month (15.0% annualized). The average initial underpricing is 18.1%, but it ranges between a minimum of -28.8% and a maximum of 119.1% (also seen in Figure I). The median underpricing is about 13%.

From the returns on S&P 500 and initial underpricing, we compute 12-month moving average series. They are denoted $R_{m,t}^{12}$ and $R_{u,t}^{12}$. We will use the 12-month moving averages in the count data regressions below to capture general market conditions in the previous year.

B An Empirical Model of the Number of IPOs

To study the effects of market conditions on the number of IPOs we use count data regressions. We explicitly acknowledge the non-negative integer character of the data (the number of IPOs in a month). This non-negativity is, in general, a concern for the fitted values of the number of IPOs, and, in particular, a concern for simulations of the number of IPOs. The empirical model is a count regression model and has two major components, first a distributional assumption, and second a specification of the mean parameter as a function of explanatory variables. This makes the model well suited for simulations.[8]

The basic Poisson regression model in the time series assumes that the occurrence of event counts (here the number of IPOs in a month N_t) conditional on variables known at time $t-1$, denoted by x_{t-1}, has a Poisson distribution. The density is

$$f\left(N_t|x_{t-1}\right) = \frac{\exp\left[-\mu(x_{t-1})\right]\left[\mu(x_{t-1})^{N_t}\right]}{N_t!}, \qquad N_t = 0, 1, 2, \ldots, \tag{13}$$

where $\mu(x_{t-1}) > 0$ is the intensity or rate parameter that completely determines the density. It is well known that the first two central moments of the Poisson distribution are equal, that is,

$$\mathrm{E}\left(N_t|x_{t-1}\right) = \mathrm{Var}\left(N_t|x_{t-1}\right) = \mu(x_{t-1}). \tag{14}$$

This equality of the mean and variance is referred to as equidispersion. When the variance is a larger (smaller) than the mean, we have overdispersion (underdispersion).

Empirically, overdispersion is common (for example, we have noted that the number of IPOs is unconditionally overdispersed). To allow for overdispersion, we let the number of IPOs in a month be drawn from the mixing of a Poisson distribution and a gamma

[8]Indeed, predicted values in Schultz (2003) are negative in some periods (see his Figure 1). Simulated values of the model suffer from this drawback as well.

distribution. That is,

$$\eta_t \sim \text{Gamma}\left[1/\sigma_\eta^2, 1/\sigma_\eta^2\right], \tag{15}$$

$$N_t|x_{t-1}, \eta_t \sim \text{Poisson}\left[\eta_t \mu_t\left(x_{t-1}\right)\right], \tag{16}$$

where η_t is drawn from a gamma distribution with a unit mean and a variance equal to σ_η^2. The error term η_t is a multiplicative error term that accounts for unobserved heterogeneity in the data over time. It is straightforward to show that conditional mean and variance are now

$$\mathrm{E}\left(N_t|x_{t-1}\right) = \mu\left(x_{t-1}\right), \tag{17}$$

$$\mathrm{Var}\left(N_t|x_{t-1}\right) = \mu\left(x_{t-1}\right) + \sigma_\eta^2\left[\mu\left(x_{t-1}\right)\right]^2. \tag{18}$$

These moments are equal to the mean and variance of the negative binomial II model in Cameron and Trivedi (1986), and extensively discussed in Cameron and Trivedi (1998) and Winkelmann (2003).

The Poisson regression model is derived from the Poisson distribution by parameterizing the relation between the mean parameter and its regressors. Consider the exponential mean parameterization

$$\mathrm{E}\left(N_t|x_{t-1}\right) = \mu(x_{t-1}) = \exp(\beta' x_{t-1}), \qquad t = 1, 2, \ldots, T, \tag{19}$$

where β and x_{t-1} are both vectors with dimension l. The vector of regressors x_{t-1} may include a constant term. As described in detail below, we include functions of lagged number of IPOs, lagged market returns, and lagged initial underpricing in x_{t-1}.

We use the Generalized Method of Moments (GMM) of Hansen (1982) to estimate parameters. We consider the following moment conditions:

$$\mathrm{E}\left(\left[N_t - \exp(\beta' x_{t-1})\right] x_{t-1}\right) = 0. \tag{20}$$

$$\mathrm{E}\left(\left[N_t - \exp(\beta' x_{t-1})\right]^2 - \exp(\beta' x_{t-1}) - \sigma_\eta^2\left[\exp(\beta' x_{t-1})\right]^2\right) = 0. \tag{21}$$

The parameter vector β is identified in the first l moment conditions (20), and σ_η^2 is identified in the last moment condition (21).[9] Together this is an exactly identified system with $l+1$ equations and $l+1$ parameters. In practice the moments are replaced with their sample counterparts.[10] Note that the Poisson regression model is intrinsically heteroskedastic, and GMM provides a consistent covariance matrix robust to autocorrelation and heteroskedasticity.

We consider model specifications where the number of IPOs is a function of past number of IPOs (similar to an autoregressive model) and measures of market conditions. The following is our base line specification:

$$\mathrm{E}\left(N_t | N_{t-1}, R_{m,t-1}\right) = \exp\left[\beta_0 + \beta_1 R_{m,t-1} + \beta_2 \ln(N^*_{t-1})\right], \tag{22}$$

where $R_{m,t-1}$ is the lagged S&P 500 return and $N^*_{t-1} = \max(d, N_{t-1})$. The value $0 < d < 1$ in the max operator prevents potential problems in taking the logarithm when $N_{t-1} = 0$. We let $d = 0.5$, but experimenting with different values reveals that the results are not sensitive to the choice of 0.5. We further use $\ln\left(N^*_{t-1}\right)$ rather than N^*_{t-1} as the model could otherwise explode (see, Cameron and Trivedi, 1998). We also consider specifications with alternatives to the market return as a proxy for market conditions (initial underpricing, and the 12-month moving averages of market returns and initial underpricing), and specifications where more lags of the number of IPOs are included.

The main results from the count data regressions are presented in Table III. Specification (i) shows that the measured coefficient on the lagged S&P 500 returns is about 1.4 and statistically significant at usual significance levels. The interpretation is that a 1% point increase in the current month's return leads to a 1.4% increase in the expected

[9] Alternative ways of identifying σ_η^2 (see, for instance, Gourieroux, Monfort, and Trognon, 1984) yield similar estimates. See also Hall, Griliches, and Hausman (1986) for an application.

[10] Another natural estimator is maximum likelihood (ML). It turns out that the set of sample moment conditions related to (20) equals the score of the log likelihood function for the ML estimator of the basic Poisson model, and GMM and ML yield identical point estimates. It is well known that as long as the conditional mean is correctly specified the estimates are consistent even if the Poisson distribution assumption is not appropriate.

number of IPOs in the next month. Specifications with the lagged initial underpricing (*ii*) or a lagged 12-month moving average of S&P 500 returns (*iii*) show significant coefficients as well. The market condition in the last 12 months is particular important for the number of IPOs. Specification (*iii*) suggests that a year with a one 1% point increase in the average S&P 500 return is followed by a month with an 8.4% expected increase in the number of IPOs. The effect of market conditions on the number of IPOs seems economically significant. The coefficient on a lagged 12-month moving average of initial underpricing in specification (*iv*) is only marginal significant (a p-value of 6%). We also run specifications with multiple measures of market conditions. The results in specification (*v*) suggest that the lagged S&P 500 return as well as the lagged initial underpricing is important; they are both significant at usual significance levels. The results in specifications (*vi*) and (*vii*) indicate that the 12-month moving average of S&P 500 returns is the main driver of the results.

In all specifications the measured coefficients on the lagged number of IPOs indicate a high degree of persistence in the number of IPOs—the coefficients are in the range 0.79 to 0.84. We also estimate models with further lags of the number of IPOs. The results are reported in Table IV. The coefficients on additional lags are often significant, however, the sum of the coefficients on the lags are less than 0.85 in all specifications. Importantly, the inclusion of further lags does not considerably affect the estimates on the measures of market conditions. The R-square measures do not strongly favor a particular specification, though it is important to include at least one lag of the number of IPOs.

Following Lowry (2003) and Pástor and Veronesi (2004), we also consider specifications with a dummy for observations in the first quarter of a year. We do not find any evidence in favor of a quarterly seasonality. However, specifications with monthly dummies for January, February, and March show that (conditionally) there are significantly fewer IPOs in January.

In sum, we show that current market conditions have information about the number of IPOs in the future. This is consistent with the idea of pseudo market timing. Next we use the empirical model to simulate from.

V Simulation Evidence

We have shown that the abnormal return measure that captures a feasible investment strategy is unbiased under pseudo market timing. In order to assess the small sample performance of the other two average abnormal return measures (the equally weighted abnormal return measure and the measure that takes into account cross-sectional dependence), we undertake simulation experiments. The basis of the simulations is the empirical model for the number of IPOs fitted in the previous section.

A Simulation Set-Up

The steps in the experiments are:

1. The data generating process of market returns.

   Monthly market returns are drawn (with replacement) from the actual S&P 500 returns. Based on the sampled monthly market returns, 12-month moving averages are constructed. The sample size varies in different simulations (100, 200, or 500 observations).

2. The data generating process of abnormal returns.

   The following error components model is used for abnormal returns

$$\hat{r}_{i,t} = c_t + \epsilon_{i,t} \tag{23}$$

   where $c_t \sim \mathrm{N}(0, \sigma^2\rho)$ and $\epsilon_{i,t} \sim \mathrm{N}(0, \sigma^2(1-\rho))$. The cumulative abnormal return for any time period and firm is then given by $\sum_{k=1}^{K} \hat{r}_{i,t+k} = \sum_{k=1}^{K} c_t + \sum_{k=1}^{K} \epsilon_{i,t}$. This error component model implies an interesting correlation structure for the cumulative abnormal returns. It is straightforward to show that the variance of the cumulative return is $K\sigma^2$ and the cross-sectional covariance is $K\sigma^2\rho$. The correlation between two cumulative abnormal returns is then ρ, independent of the cumulation horizon K. The parameters σ and ρ are set to match empirical estimates in Brav (2000) and Mitchell and Stafford (2000) of the cross-sectional correlation in abnormal returns and the variance of abnormal returns. Initially we pick $\rho = 2.6\%$ and $\sigma = 17\%$.

3. The data generating process of number of IPOs

   We consider two alternative processes of the number of IPOs. The first alternative conditions on the time series of 12-month moving averages and uses the empirical model directly to generate a time series of the number of IPOs (denoted $\hat{N}_t$). The initial number of IPOs is drawn from a Poisson distribution with an unconditional intensity parameter equal to $\exp\left(\frac{\hat{\beta}_0+\hat{\beta}_1\hat{\mu}_m}{1-\hat{\beta}_2}\right)$, approximated from equation (22) with $\hat{\mu}_m$ being the average market return and $\hat{\beta}_0$, $\hat{\beta}_1$, and $\hat{\beta}_2$ being estimated parameters. This generates about 30 IPOs for the first month, close to the unconditional average number of IPOs per month in the sample. For subsequent observations we have the following structure: a multiplicative error term is first drawn from a gamma distribution with unit mean and variance $\hat{\sigma}^2_\eta$; then the number of IPOs is drawn from a Poisson distribution with a conditional mean (based on the estimated parameters $\hat{\beta}$, and lagged number of IPOs and 12-month moving average return) times the multiplicative error term. Parameter estimates from specification (*iii*) in Table III are used as default parameters.

   The second alternative data generating process uses the same structure as the first alternative, but allows the lagged common component of the abnormal returns c_t to affect the future number of IPOs. This will impose a pseudo market timing effect in the model, since the number of IPOs is affected by the abnormal IPO returns in the previous period. The equation for the number of IPOs then contains the expression

$$\beta' x_{t-1} = \beta_0 + \beta_1 R_{m,t-1} + \beta_2 \ln(N^*_{t-1}) + \beta_3 c_{t-1}. \tag{24}$$

However, since we did not include the lagged common IPO return component in the empirical model (as it is unobserved), we have to assume a particular value for the coefficient β_3. In the simulations, we pick values so that the effect of market and previous IPO returns are in the same order of magnitude.

4. The average abnormal return measures.

   The abnormal return measures are calculated according to:

$$\begin{aligned}
CAR_{EW} &= \frac{\sum_{t=1}^{T} \sum_{i=1}^{\hat{N}_t} \left(\sum_{k=1}^{K} \hat{r}_{i,t+k} \right)}{\sum_{t=1}^{T} \hat{N}_t}, & (25)\\
CAR_{CW} &= \frac{\sum_{t=1}^{T} \mathrm{I}\left[\hat{N}_t > 0\right] \left(\frac{1}{\hat{N}_t} \sum_{i=1}^{\hat{N}_t} \sum_{k=1}^{K} \hat{r}_{i,t+k} \right)}{\sum_{t=1}^{T} \mathrm{I}\left[\hat{N}_t > 0\right]}, & (26)\\
AR_{FI} &= \frac{1}{T} \sum_{t=1}^{T} \mathrm{I}\left[\sum_{k=1}^{K} \hat{N}_{t-k} > 0 \right] \left(\frac{\sum_{k=1}^{K} \sum_{i=1}^{\hat{N}_{t-k}} \hat{r}_{i,t}}{\sum_{k=1}^{K} \hat{N}_{t-k}} \right). & (27)
\end{aligned}$$

   These calculations correspond to Equations (2), (5), and (9) above. We consider cumulative returns with horizons of 1, 36, and 60 months. To make the monthly feasible investment returns comparable to the K-month cumulative abnormal returns, we multiply AR_{FI} by K in all the tables.

The four steps above are repeated 1,000, 2,500, or 5,000 times (depending on the length of the series simulated). The averages of the generated measures are reported. We also report Monte Carlo standard errors of the averages, constructed from the standard deviation of the generated abnormal return measures.

B Simulation Results

Table V reports the results of our simulations when the generating process of the number of IPOs exactly follows the empirical model above (i.e. $\beta_3 = 0$). The table shows bias estimates of the three abnormal return measures CAR_{EW}, CAR_{CW}, and AR_{FI} expressed in % over the horizons of 1, 36, and 60 months. We consider four parameter set-ups. Panel A shows the results for the default case where parameters is from specification (*iii*) in Table III. Further, the cross-correlation in abnormal returns is set to 2.6% and the standard deviation of the abnormal returns is set to 17% per month. The magnitudes of the reported biases are economically small (less than 0.16% in absolute value in the 60-months period). There is no tendency for an overall negative or positive bias. Indeed, no reported bias is larger than its Monte Carlo standard error (given below the bias and within parenthesis).

To see how sensitive the results are to the chosen parameter values, we presents simulations where we expect to get significant biases. Panel B shows the results where the persistence in the event generating process is higher (the coefficient on the lagged number of IPOs is increased from 0.8 to 0.95); Panel C shows the results where the coefficient on lagged 12-month moving average returns is doubled (from 8.438 to 16.876) in addition to the higher persistence; Panel D shows results where the cross-sectional correlations in abnormal returns is increased (from 2.6% to 15%). All augmented set-ups reveal the same result: there is no bias in the abnormal return measures.

Table VI reports the results of our simulations when we allow the lagged common component of the abnormal returns c_t to affect the future number of IPOs. We do this by choosing $\beta_3 = 5$ as the default value; this choice makes the variance of $\beta_3 c_t$ approximately equal to the variance of $\beta_1 R_{m,t}$. We consider again four parameter set-ups. Panels A (default) and B (high persistence) follow the set-ups in the previous table and show a consistently negative bias for the equally weighted measure due to the pseudo market timing. However, the magnitudes are small. The cross-sectional corrected measure and the measure of the feasible investment strategy show now biases. In Panel C, the impact of the lagged common component is set to 10 and together with high persistence the bias for the equally weighted measure is larger (about 2% over a 60-month horizon). In Panel

D the cross-sectional correlations is set at 15% and the equally weighted measure now show a bias of about 6% over a 60-month horizon. The bias is significantly negative for the equally weighted measure; the largest bias is -6% for the 60-month horizon and 100 observations, which is still quite much less than the underperformance of IPO firms found in most empirical studies. Panels C and D also reveal that the cross-sectional corrected measure and the measure of the feasible investment strategy show almost no biases.

To conclude, in our simulations we find no or only small biases in the average abnormal return measures. It is crucial to have a correlation between IPO returns and the process for the number of IPOs in order to generate a pseudo market timing effect. Based on our results, pseudo market timing does not seem to be a problem in sample sizes typically used in empirical work on IPO underperformance.

C A Comparison with Other Studies

How can we reconcile our results with Schultz's (2003) results? A critical assumption in the simulations is that the event generating process is stationary. We explicitly acknowledge that the number of IPOs in a month is a non-negative integer; we also allow for high persistence in the process, though the process cannot be absorbed at zero and does not explode. The key in Schultz (2003) is that the simulations violate the stationarity assumptions made above. However, then the probability limit of the abnormal return estimator is not well defined. Several studies, including Lowry (2003), Schultz (2004) and Viswanathan and Wei (2004) have tested for a unit-root in the level of the number of IPOs, but these tests seem inconclusive. We do not find it economically plausible that the process is exploding or have an absorbing state at zero. Recall that if we let the process be near-integrated but still stationary (the autoregressive coefficient is set to 0.95), there is still not a bias in typical sample sizes.

Schultz (2004) argues that there is a bias in the traditional equally weighted measure even when the data generating process is stationary. We find this odd. Looking closer at the way he generates abnormal returns, we find that his seemingly uncorrelated abnormal returns (*i*) share a common market component that induces cross-sectional correlations in abnormal returns, and (*ii*) contain a complex dependence structure with market returns and the number of IPOs. To see this, consider the way IPO returns are generated:

$$R_{i,t} = a + \beta_{i,m} R_{m,t} + \nu_{i,t}, \quad R_{m,t} \sim \mathrm{N}(\mu_m, \sigma_m^2), \quad \nu_{i,t} \sim \mathrm{N}(0, \sigma_\nu^2), \tag{28}$$

where $a = -0.43695$ is a constant term, $\beta_i = 1.4634$ is the estimated beta in a market model regression, $\mu_m = 0.94293\%$ is the market mean return, $\sigma_m^2 = 0.002254$ is the market variance, and $\sigma_\nu^2 = 0.002631$ is the residual variance in the market model regression. The abnormal return is then given by

$$r_{i,t} = R_{i,t} - R_{m,t} = a + (\beta_{i,m} - 1) R_{m,t} + \nu_{i,t}. \tag{29}$$

Note that the constant a is chosen such that the abnormal return is forced to have an expected value of zero, that is, $\mathrm{E}(r_{i,t}) = 0$. However, abnormal returns share a market component. It is straightforward to show that the cross-sectional correlation between the abnormal returns is non-zero and given by

$$\mathrm{Corr}(r_{i,t}, r_{j,t}) = \frac{\mathrm{Cov}(r_{i,t}, r_{j,t})}{\mathrm{Var}(r_{i,t})} = \frac{(\beta_{i,m} - 1)^2 \sigma_m^2}{(\beta_{i,m} - 1)^2 \sigma_m^2 + \sigma_\nu^2}. \tag{30}$$

Plugging in the values yields a cross-sectional correlation of 15%, which is much higher than what data suggest; Brav (2000) and Mitchell and Stafford (2000) report cross-correlations close to zero (about 2% to 3%). In addition, the common component of abnormal returns in equation (29) equals $(\beta_{i,m} - 1) R_{m,t}$ and is therefore perfectly correlated with the market returns. These market returns also determine the number of IPOs in future periods. Hence, Schultz's (2004) simulations contain a complex dependence structure between market returns, number of IPOs, and abnormal returns.

VI Conclusion

Returning to the question in the title of paper whether pseudo market timing is a fact or fiction, the answer is that in theory there may be a bias, but that the bias is small and negligible for typical sample sizes. An abnormal return measure that captures a feasible investment strategy exhibits no bias at all. For other, maybe more traditional, measures, it is a small sample problem that disappears in large samples (yielding consistent measures). However, even in moderate sample sizes, the bias is small. Based on this, it seems unlikely that the long-run underperformance of firms going public or issuing equity is explained by pseudo market timing.

References

Ang, Andrew, Li Gu, and Yael V. Hochberg, 2004, Small Sample Inference of Long-Run IPO Underperformance, Working Paper, Columbia University and Cornell University.

Barber, Brad M., and John D. Lyon, 1997, Detecting Long-Run Abnormal Stock Returns: The Empirical Power and Specification of Test Statistics, *Journal of Financial Economics* 43, 341–372.

Brav, Alon, 2000, Inference in Long-Horizon Event Studies: A Bayesian Approach with Application to Initial Public Offerings, *Journal of Finance* 55, 1979–2016.

Brav, Alon, Chris Geczy, and Paul Gompers, 2000, Is the Abnormal Return Following Equity Issuances Anomalous, *Journal of Financial Economics* 56, 209–249.

Brav, Alon, and Paul Gompers, 1997, Myth or Reality? The Long-Run Underperformance of Initial Public Offerings: Evidence from Venture and Nonventure Capital-Backed Companies, *Journal of Finance* 52, 1791–1820.

Cameron, A. Colin, and Pravin K. Trivedi, 1986, Econometric Models Based on Count Data: Comparisons and Applications of Some Estimators and Tests, *Journal of Applied Econometrics* 1, 29–53.

Cameron, A. Colin, and Pravin K. Trivedi, 1998, *Regression Analysis of Count Data.* (Cambridge University Press , Cambridge).

Eckbo, B. Espen, Vojislav Maksimovic, and Joseph Williams, 1990, Consistent Estimation of Cross-Sectional Models in Event Studies, *Review of Financial Studies* 3, 343–365.

Eckbo, B. Espen, and Ronald W. Masulis, 1995, Seasoned Equity Offerings: A Survey, in Robert A. Jarrow, Vojislav Maksimovic, and William T. Ziemba, eds.: *Handbooks in Operations Research and Management Science* (North-Holland, Amsterdam).

Eckbo, B. Espen, and Øyvind Norli, 2001, Risk and Long-Run IPO Returns, Working Paper, Dartmouth College and Univeristy of Toronto.

Fama, Eugene F., 1998, Market Efficiency, Long-Term Returns, and Behavioral Finance, *Journal of Financial Economics* 49, 283–306.

Gompers, Paul A., and Josh Lerner, 2003, The Really Long-Run Performance of Initial Public Offerings: The Pre-Nasdaq Evidence, *Journal of Finance* 58, 1355–1392.

Gourieroux, Christian, Alain Monfort, and Alain Trognon, 1984, Pseudo Maximum Likelihood Methods: Applications to Poission Models, *Econometrica* 52, 701–720.

Hall, Bronwyn H., Zvi Griliches, and Jerry A. Hausman, 1986, Patents and R and D: Is There a Lag?, *International Economic Review* 27, 265–283.

Hamilton, James D., 1994, *Time Series Analysis.* (Princeton University Press , Princeton).

Hansen, Lars Peter, 1982, Large Sample Properties of Generalized Method of Moments Estimators, *Econometrica* 50, 1029–1054.

Ibbotson, Roger G., and Jeffrey F. Jaffe, 1975, 'Hot Issue' Markets, *Journal of Finance* 30, 1027–1042.

Ibbotson, Roger G., and Jay R. Ritter, 1995, Initial Public Offering, in Robert A. Jarrow, Vojislav Maksimovic, and William T. Ziemba, eds.: *Handbooks in Operations Research and Management Science* (North-Holland, Amsterdam).

Ibbotson, Roger G., Jody L. Sindelar, and Jay R. Ritter, 1988, Initial Public Offerings, *Journal of Applied Corporate Finance* 1, 37–45.

Ibbotson, Roger G., Jody L. Sindelar, and Jay R. Ritter, 1994, The Market's Problems with the Pricing of Initial Public Offerings, *Journal of Applied Corporate Finance* 7, 66–74.

Jenkinson, Tim J., and Alexander Ljungqvist, 2001, *Going Public: The Theory and Evidence on How Companies Raise Equity Finance, 2nd Edition.* (Oxford University Press , Princeton).

Kothari, S.P., and Jerold B. Warner, 1997, Measuring Long-Horizon Security Performance, *Journal of Financial Economics* 43, 301–339.

Loughran, Tim, and Jay R. Ritter, 1995, The New Issue Puzzle, *Journal of Finance* 50, 23–51.

Loughran, Tim, Jay R. Ritter, and Kristian Rydqvist, 1994, Initial Public Offerings: International Insights, *Pacific-Basin Finance Journal* 2, 165–199.

Lowry, Michelle, 2003, Why Does IPO Volume Fluctuate so Much?, *Journal of Financial Economics* 67, 3–40.

Mitchell, Mark L., and Erik Stafford, 2000, Managerial Decisions and Long-Term Stock Price Performance, *Journal of Business* 73, 287–329.

Pástor, Ľuboš, and Pietro Veronesi, 2004, Rational IPO Waves, *forthcoming in Journal of Finance.*

Ritter, Jay R., 1984, The Hot Issue Market of 1980, *Journal of Business* 57, 215–240.

Ritter, Jay R., 1991, The Long-Run Underperformance of Initial Public Offerings, *Journal of Finance* 46, 3–27.

Ritter, Jay R., 2003, Investment Banking and Securities Issuance, in George M. Constantinides, Milton Harris, and René M. Stulz, eds.: *Handbooks of the Economics of Finance* (North-Holland, Amsterdam).

Ritter, Jay R., and Ivo Welch, 2002, A Review of IPO Activity, Pricing and Allocations, *Journal of Finance* 57, 1795–1828.

Schultz, Paul, 2003, Pseudo Market Timing and the Long-Run Underperformance of IPOs, *Journal of Finance* 58, 483–517.

Schultz, Paul, 2004, Pseudo Market Timing and the Stationarity of the Event-Generating Process, Working Paper, University of Notre Dame.

Viswanathan, S., and Bin Wei, 2004, Endogenous Events and Long Run Returns, Working Paper, Duke University.

Winkelmann, Rainer, 2003, *Econometric Analysis of Count Data, 4th Edition.* (Springer-Verlag , Berlin).

Table I: Analysis of Average Abnormal Returns in Two-Period Examples

	Number of IPOs and Abnormal Returns					Abnormal Return Measures		
Scenario	N_0	r_1	N_1	r_2		AR_{EW}	AR_{CW}	AR_{FI}
Panel A. Example with Zero IPOs after a Negative Return								
I	1	+10%	3	+10%		+10%	+10%	+10%
II	1	+10%	3	–10%		–5%	0%	0%
III	1	–10%	0	+10%		–10%	–10%	–5%
IV	1	–10%	0	–10%		–10%	–10%	–5%
					Average	–3.75%	–2.5%	0%
Panel B. Example with Non-Zero IPOs after a Negative Return								
I	2	+10%	4	+10%		+10%	+10%	+10%
II	2	+10%	4	–10%		–3.33%	0%	0%
III	2	–10%	1	+10%		–3.33%	0%	0%
IV	2	–10%	1	–10%		–10%	–10%	–10%
					Average	–1.67%	0%	0%

This table presents the abnormal return measures in four scenarios (labeled I to IV) of the two-period examples. N_0 and N_1 refer to the number of events in periods 1 and 2 (known at dates 0 and 1). r_1 and r_2 refer to the abnormal returns in periods 1 and 2. AR_{EW} denotes the equally weighted average abnormal return measure. It sums up the abnormal returns over all events in all time periods, and then divides by the total number of events. AR_{CW} corrects for the fact that there is cross-sectional dependence in the abnormal returns. It counts all events in the same period as one observation. AR_{FI} denotes the average per-period return on a feasible investment strategy that invests in a portfolio of event firms in each period (if there is no event in a period, the abnormal return for that period is equal to zero).

Table II: Summary Statistics

Statistic	Number of IPOs N_t	Return on S&P 500 $R_{m,t}$	Initial Underpricing $R_{u,t}$
Mean	28.5	0.91	18.11
Median	22	1.07	13.15
Std.Dev.	24.7	4.34	21.31
Minimum	0	-21.52	-28.80
Maximum	122	16.57	119.10

This table presents summary statistics of monthly observations of the number of IPOs in a month (N_t), S&P 500 returns ($R_{m,t}$), and the average initial underpricing in IPOs in a month ($R_{u,t}$). The sample period is January 1960 to June 2003, yielding 522 observations. The number of months with zero IPOs is 18 (or 3.5% of all observations). The moments of $R_{m,t}$ and $R_{u,t}$ are expressed in % per month.

Table III: Empirical Models of the Number of IPOs in a Month

	(i)	*(ii)*	*(iii)*	*(iv)*	*(v)*	*(vi)*	*(vii)*
Moment Conditions (20)							
Constant	0.554	0.517	0.615	0.542	0.514	0.599	0.573
	(0.069)	(0.071)	(0.073)	(0.071)	(0.074)	(0.073)	(0.077)
$R_{m,t-1}$	1.384				1.256		0.849
	(0.546)				(0.529)		(0.560)
$R_{u,t-1}$		0.228			0.197		0.074
		(0.094)			(0.089)		(0.125)
$R^{12}_{m,t-1}$			8.438			8.335	6.988
			(1.736)			(1.759)	(1.832)
$R^{12}_{u,t-1}$				0.192		0.167	0.109
				(0.103)		(0.101)	(0.157)
$\ln(N^*_{t-1})$	0.845	0.847	0.800	0.842	0.846	0.795	0.804
	(0.019)	(0.019)	(0.023)	(0.020)	(0.019)	(0.023)	(0.024)
Moment Condition (21)							
σ^2_η	0.309	0.309	0.297	0.309	0.307	0.297	0.297
	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Diagnostics							
R-square I	0.793	0.792	0.803	0.794	0.795	0.803	0.895
R-square II	0.867	0.867	0.876	0.868	0.868	0.876	0.876
T	521	521	510	510	521	510	510

This table presents results of count data regressions for the number of IPOs in the U.S. (N_t) for the period January 1960 to June 2003. Lagged S&P 500 returns ($R_{m,t-1}$), lagged initial underpricing ($R_{u,t-1}$), 12-month moving averages of S&P 500 returns ($R^{12}_{m,t-1}$) and initial underpricing ($R^{12}_{u,t-1}$), and functions of lagged number of IPOs ($N^*_{t-1} = \max(0.5, N_{t-1})$) are used as regressors. The initial underpricing variable is set to zero when there are no IPOs in a month. Sample counterparts to moment conditions (20) and (21) in the text are used to identify parameters:

$$\mathrm{E}\left([N_t - \exp(\beta' x_{t-1})]\, x_{t-1}\right) = 0. \tag{20}$$

$$\mathrm{E}\left([N_t - \exp(\beta' x_{t-1})]^2 - \exp(\beta' x_{t-1}) - \sigma^2_\eta\, [\exp(\beta' x_{t-1})]^2\right) = 0, \tag{21}$$

where x_{t-1} contains a one, $R_{m,t-1}$, $R_{u,t-1}$, $R^{12}_{m,t-1}$, $R^{12}_{u,t-1}$, and $\ln(N^*_{t-1})$. Heteroskedastic and autocorrelation consistent standard errors are shown within parentheses below the point estimates. R-square I refers to the pseudo R-square in Cameron and Trivedi (1986) for the basic Poisson model. R-square II refers to the squared correlation coefficient between the number of IPOs and the predicted value. T refers to the number of observations used in the count regression.

Table IV: Empirical Models of the Number of IPOs in a Month: Robustness

	(viii)	*(ix)*	*(x)*	*(xi)*
Moment Conditions (20)				
Constant	0.615	0.553	0.503	0.459
	(0.073)	(0.068)	(0.068)	(0.073)
$R^{12}_{m,t-1}$	8.438	8.310	8.879	9.926
	(1.736)	(1.730)	(1.816)	(1.961)
$\ln(N^*_{t-1})$	0.800	0.624	0.573	0.531
	(0.023)	(0.041)	(0.046)	(0.051)
$\ln(N^*_{t-2})$		0.197	0.066	0.044
		(0.038)	(0.049)	(0.045)
$\ln(N^*_{t-3})$			0.195	0.100
			(0.036)	(0.043)
$\ln(N^*_{t-4})$				0.124
				(0.052)
$\ln(N^*_{t-5})$				0.019
				(0.044)
$\ln(N^*_{t-6})$				0.027
				(0.036)
Moment Condition (21)				
σ^2_η	0.297	0.293	0.285	0.281
	(0.017)	(0.018)	(0.017)	(0.016)
Diagnostics				
R-square I	0.803	0.811	0.820	0.825
R-square II	0.876	0.879	0.884	0.886
T	510	510	510	510

This table presents results of count data regressions for the number of IPOs in the U.S. (N_t) on lagged S&P 500 12-month moving averages of S&P 500 returns ($R^{12}_{m,t-1}$) and functions of lagged number of IPOs ($N^*_{t-1} = \max(0.5, N_{t-1})$) for the period January 1960 to June 2003. Sample counterparts to moment conditions (20) and (21) in the text are used to identify parameters. See also the note in Table III. Heteroskedastic and autocorrelation consistent standard errors are shown within parentheses below the point estimates. R-square I refers to the pseudo R-square in Cameron and Trivedi (1986) for the basic Poisson model. R-square II refers to the squared correlation coefficient between the number of IPOs and the predicted value. T refers to the number of observations used in the count regression.

Table V: Simulation Results, Biases with No Pseudo Market Timing Effect

	1-Month Horizon			36-Month Horizon			60-Month Horizon		
Measure	100	200	500	100	200	500	100	200	500
Panel A. Default Case									
CAR_{EW}	0.00	–0.00	–0.00	–0.08	–0.04	0.01	0.16	0.01	0.03
	(0.01)	(0.01)	(0.01)	(0.14)	(0.15)	(0.16)	(0.22)	(0.24)	(0.25)
CAR_{CW}	–0.00	–0.00	0.01	–0.12	–0.12	–0.09	0.13	0.08	0.02
	(0.01)	(0.01)	(0.01)	(0.14)	(0.14)	(0.15)	(0.22)	(0.23)	(0.24)
AR_{FI}	–0.01	–0.00	–0.01	–0.04	–0.08	0.03	–0.00	0.10	–0.02
	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.15)	(0.17)	(0.21)	(0.23)
Panel B. High Persistence									
CAR_{EW}	–0.01	–0.01	0.02	0.34	–0.01	0.01	0.45	0.26	–0.04
	(0.01)	(0.01)	(0.01)	(0.16)	(0.19)	(0.21)	(0.24)	(0.28)	(0.32)
CAR_{CW}	–0.00	0.00	0.01	0.31	0.01	–0.01	0.37	0.03	0.07
	(0.01)	(0.01)	(0.01)	(0.15)	(0.16)	(0.16)	(0.23)	(0.24)	(0.24)
AR_{FI}	0.01	0.02	–0.01	0.23	–0.11	–0.07	0.17	–0.25	0.39
	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.15)	(0.18)	(0.21)	(0.23)
Panel C. High Persistence and Large Market Impact									
CAR_{EW}	–0.01	0.01	0.00	0.27	–0.27	0.22	0.27	0.16	0.01
	(0.01)	(0.01)	(0.01)	(0.18)	(0.22)	(0.27)	(0.26)	(0.31)	(0.38)
CAR_{CW}	–0.03	–0.00	0.01	0.02	–0.26	0.01	0.21	0.16	–0.19
	(0.01)	(0.01)	(0.01)	(0.16)	(0.17)	(0.17)	(0.25)	(0.26)	(0.25)
AR_{FI}	–0.01	0.01	0.01	0.11	–0.21	0.04	0.01	0.03	–0.25
	(0.01)	(0.01)	(0.01)	(0.14)	(0.15)	(0.16)	(0.18)	(0.22)	(0.23)
Panel D. High Persistence and Extreme Cross-Correlations									
CAR_{EW}	–0.00	0.01	0.00	–0.28	–0.15	–0.03	–0.55	0.05	0.80
	(0.02)	(0.02)	(0.02)	(0.27)	(0.32)	(0.37)	(0.39)	(0.47)	(0.55)
CAR_{CW}	0.00	0.00	–0.01	–0.20	–0.02	0.03	–0.44	–0.30	0.43
	(0.02)	(0.02)	(0.02)	(0.23)	(0.24)	(0.25)	(0.37)	(0.39)	(0.40)
AR_{FI}	0.01	0.01	–0.01	–0.19	–0.02	0.11	–0.06	–0.29	–0.42
	(0.01)	(0.01)	(0.01)	(0.21)	(0.23)	(0.24)	(0.29)	(0.36)	(0.38)

This table presents the average biases of the equally weighted cumulative abnormal return measure (CAR_{EW}), the cross-sectionally weighted cumulative abnormal return measure (CAR_{CW}), and the average abnormal return in the feasible investment strategy (AR_{FI}) in simulations of an empirical model for the number of IPOs. The biases are expressed in % over the horizon of 1, 36, and 60 months with three different sample sizes (100, 200, and 500 months). The number of replications are 5,000, 2,500, and 1,000 for the three sample sizes. Below each bias estimate the standard error is given within parenthesis. There are four different set-ups. Panel A presents results for the default case. Parameters for the conditional mean is from specification (*iii*) in Table III. The cross-correlation in abnormal returns is set to 2.6%. The standard deviation of the abnormal returns is set to 17% per month. Panel B presents results where the coefficient on the lagged number of IPOs is increased from 0.8 to 0.95 compared to the default case. Panel C presents results where the coefficient on the lagged number of IPOs in increased from 0.8 to 0.95 and the effect of the lagged 12-month moving average of the S&P 500 return is increased from 8.438 to 16.876 compared to the default case. Panel D presents results where the cross-correlations in abnormal returns are set to 15% (rather than 2.6%), remaining the high persistence. The average number of IPOs in a month is comparable in all panels (about 30).

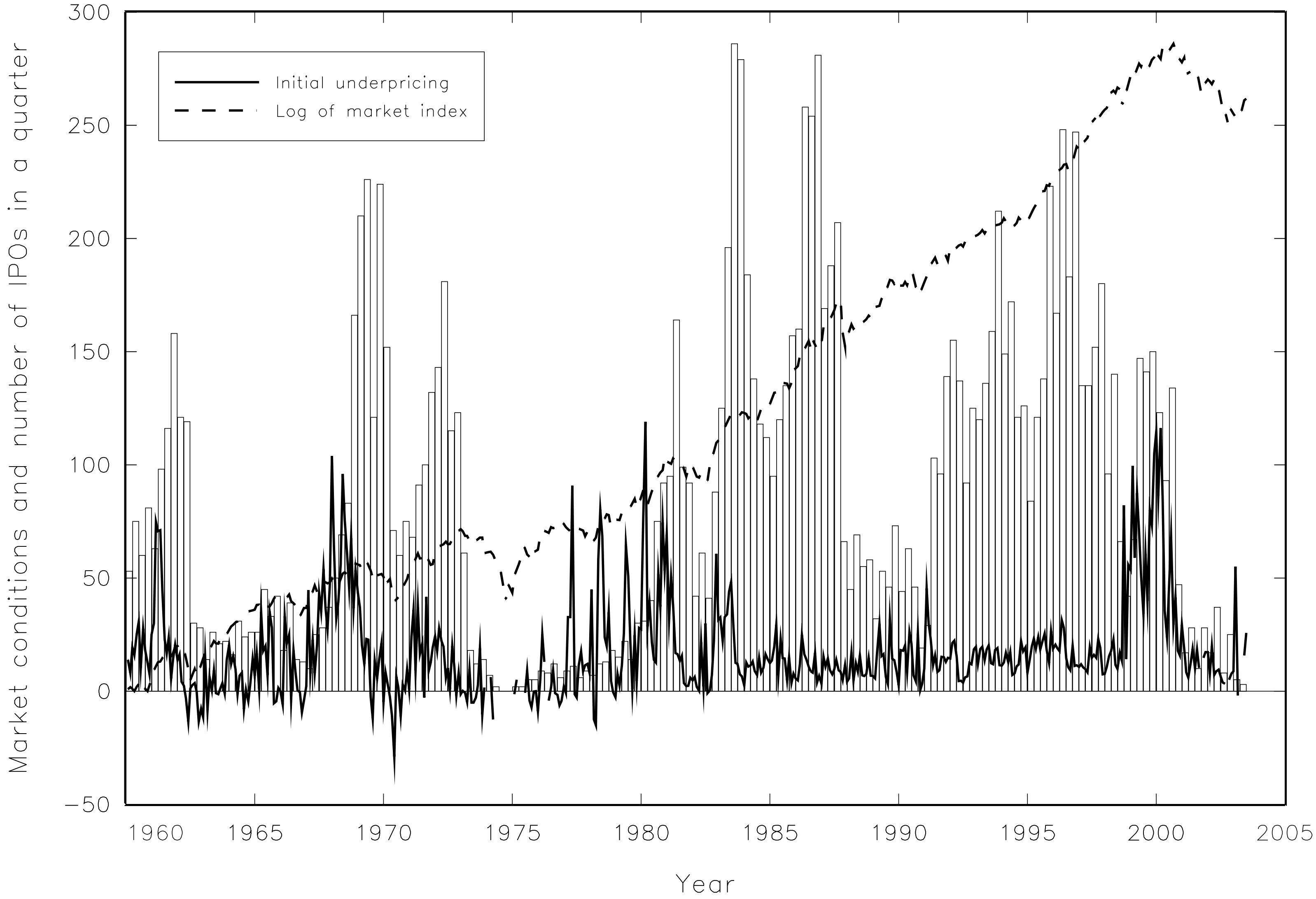
Table VI: Simulation Results, Biases with a Pseudo Market Timing Effect

	1-Month Horizon			36-Month Horizon			60-Month Horizon		
Measure	100	200	500	100	200	500	100	200	500
Panel A. Default Case									
CAR_{EW}	–0.02	–0.01	–0.01	–0.49	–0.33	–0.15	–0.58	–0.06	0.07
	(0.01)	(0.01)	(0.01)	(0.14)	(0.15)	(0.15)	(0.22)	(0.23)	(0.24)
CAR_{CW}	0.00	–0.01	–0.01	–0.04	0.01	0.09	0.04	0.38	0.19
	(0.01)	(0.01)	(0.01)	(0.14)	(0.14)	(0.14)	(0.22)	(0.23)	(0.24)
AR_{FI}	–0.00	0.00	–0.00	0.09	–0.04	0.02	0.09	0.31	0.33
	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.14)	(0.17)	(0.21)	(0.22)
Panel B. High Persistence									
CAR_{EW}	–0.04	–0.05	–0.03	–1.04	–0.60	–0.41	–1.45	–1.25	–0.75
	(0.01)	(0.01)	(0.01)	(0.16)	(0.19)	(0.22)	(0.24)	(0.28)	(0.34)
CAR_{CW}	0.02	–0.02	–0.03	–0.12	–0.13	–0.12	–0.33	–0.24	–0.26
	(0.01)	(0.01)	(0.01)	(0.15)	(0.16)	(0.16)	(0.23)	(0.24)	(0.25)
AR_{FI}	–0.00	–0.01	0.00	–0.18	0.09	0.11	–0.03	–0.18	–0.29
	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.15)	(0.17)	(0.21)	(0.24)
Panel C. High Persistence and Large Pseudo Market Impact									
CAR_{EW}	–0.10	–0.08	–0.06	–1.77	–1.61	–0.84	–2.29	–2.12	–1.17
	(0.01)	(0.01)	(0.01)	(0.16)	(0.19)	(0.23)	(0.24)	(0.28)	(0.35)
CAR_{CW}	0.00	–0.02	–0.03	–0.21	–0.24	0.08	–0.18	–0.35	–0.05
	(0.01)	(0.01)	(0.01)	(0.15)	(0.16)	(0.16)	(0.23)	(0.25)	(0.25)
AR_{FI}	0.00	–0.00	0.00	0.14	–0.07	0.16	0.09	–0.15	–0.14
	(0.01)	(0.01)	(0.01)	(0.13)	(0.15)	(0.15)	(0.18)	(0.21)	(0.24)
Panel D. High Persistence and Extreme Cross-Correlations									
CAR_{EW}	–0.29	–0.21	–0.15	–5.59	–4.60	–4.02	–6.02	–6.72	–4.74
	(0.02)	(0.02)	(0.02)	(0.37)	(0.45)	(0.56)	(0.55)	(0.67)	(0.80)
CAR_{CW}	–0.00	0.03	0.01	–0.82	–0.54	–0.64	0.16	–0.70	–1.53
	(0.02)	(0.02)	(0.02)	(0.33)	(0.34)	(0.33)	(0.51)	(0.54)	(0.55)
AR_{FI}	0.02	0.02	0.00	–0.18	–0.08	–0.45	0.89	0.16	–1.09
	(0.01)	(0.01)	(0.01)	(0.30)	(0.32)	(0.32)	(0.41)	(0.49)	(0.53)

This table presents the average biases of the equally weighted cumulative abnormal return measure (CAR_{EW}), the cross-sectionally weighted cumulative abnormal return measure (CAR_{CW}), and the average abnormal return in the feasible investment strategy (AR_{FI}) in simulations of an empirical model for the number of IPOs but with the additional feature that lagged common components of abnormal returns affect the future number of IPOs. The biases are expressed in % over the horizon of 1, 36, and 60 months with three different sample sizes (100, 200, and 500 months). The number of replications are 5,000, 2,500, and 1,000 for the three sample sizes. Below each bias estimate the standard error is given within parenthesis. There are four different set-ups. Panel A presents results for the default case. Parameters for the conditional mean is from specification (*iii*) in Table III, but the lagged common component c_t enters with a coefficient of 5. The cross-correlation in abnormal returns is set to 2.6%. The standard deviation of the abnormal returns is set to 17% per month. Panel B presents results where the coefficient on the lagged number of IPOs is increased from 0.8 to 0.95 compared to the default case. Panel C presents results where the coefficient on the lagged number of IPOs in increased from 0.8 to 0.95 and the effect of the lagged common component of abnormal returns is increased from 5 to 10 compared to the default case. Panel D presents results where the cross-correlations in abnormal returns are set to 15% (rather than 2.6%), remaining the high persistence. The average number of IPOs in a month is comparable in all panels (about 30).

Figure I: Market Conditions and Number of IPOs

This figure shows the number of IPOs in a quarter (bars) with monthly observations on the average initial underpricing (solid line) and the log of the cumulative return index (dashed line). The sample period is January 1960 to June 2003.



SIFR Research Report Series

All reports can be downloaded from our website www.sifr.org, under the heading Research. Reports no. 1-15 are also available in print. In order to obtain copies of printed reports, please send your request to info@sifr.org with detailed ordering information.

1. **Foreigners' Trading and Price Effects Across Firms**
   Magnus Dahlquist and Göran Robertsson, December 2001
2. **Hedging Housing Risk**
   Peter Englund, Min Hwang, and John M. Quigley, December 2001
3. **Winner's Curse in Discriminatory Price Auctions: Evidence from the Norwegian Treasury Bill Auctions**
   Geir Høidal Bjønnes, December 2001
4. **U.S. Exchange Rates and Currency Flows**
   Dagfinn Rime, December 2001
5. **Reputation and Interdealer Trading. A Microstructure Analysis of the Treasury Bond Market**
   Massimo Massa and Andrei Simonov, December 2001
6. **Term Structures in the Office Rental Market in Stockholm**
   Åke Gunnelin and Bo Söderberg, April 2002
7. **What Factors Determine International Real Estate Security Returns?**
   Foort Hamelink and Martin Hoesli, September 2002
8. **Expropriation Risk and Return in Global Equity Markets**
   Ravi Bansal and Magnus Dahlquist, November 2002
9. **The Euro Is Good After All: Corporate Evidence**
   Arturo Bris, Yrjö Koskinen, and Mattias Nilsson, November 2002
10. **Which Investors Fear Expropriation? Evidence from Investors' Stock Picking**
    Mariassunta Giannetti and Andrei Simonov, November 2002
11. **Corporate Governance and the Home Bias**
    Magnus Dahlquist, Lee Pinkowitz, René M. Stulz, and Rohan Williamson, November 2002
12. **Implicit Forward Rents as Predictors of Future Rents**
    Peter Englund, Åke Gunnelin, Martin Hoesli, and Bo Söderberg, November 2002
13. **Accounting Anomalies and Information Uncertainty**
    Jennifer Francis, Ryan LaFond, Per Olsson, and Katherine Schipper, June 2003
14. **Characteristics, Contracts and Actions: Evidence From Venture Capitalist Analyses**
    Steven N. Kaplan and Per Strömberg, June 2003

15. **Valuing Corporate Liabilities**
Jan Ericsson and Joel Reneby, June 2003

16. **Rental Expectations and the Term Structure of Lease Rates**
Eric Clapham and Åke Gunnelin, October 2003

17. **Dealer Behavior and Trading Systems in Foreign Exchange Markets**
Geir Høidal Bjønnes and Dagfinn Rime, December 2003

18. **C-CAPM and the Cross-Section of Sharpe Ratios**
Paul Söderlind, December 2003

19. **Is there Evidence of Pessimism and Doubt in Subjective Distributions? A Comment on Abel**
Paolo Giordani and Paul Söderlind, December 2003

20. **One for the Gain, Three for the Loss**
Anders E. S. Anderson, May 2004

21. **Hedging, Familiarity and Portfolio Choice**
Massimo Massa and Andrei Simonov, May 2004

22. **The Market Pricing of Accruals Quality**
Jennifer Francis, Ryan LaFond, Per Olsson, and Katherine Schipper, May 2004

23. **Privatization and Stock Market Liquidity**
Bernardo Bortolotti, Frank de Jong, Giovanna Nicodano, and Ibolya Schindele, June 2004

24. **Pseudo Market Timing: Fact or Fiction?**
Magnus Dahlquist and Frank de Jong, June 2004

25. **All Guts, No Glory: Trading and Diversification among Online Investors**
Anders E. S. Anderson, June 2004

Stockholm Institute
for Financial Research