Pseudo Market Timing: Fact or Fiction?

Magnus Dahlquist and Frank de Jong*

First version: October 23, 2003

Current version: September 17, 2004

Abstract

The average firm going public or issuing new equity underperforms the market in the long run. A potential explanation of this long-run underperformance is based on the endogeneity of the number of new issues. That is, due to the clustering of events after periods of high abnormal returns in issues, ex post measures of average abnormal returns may be negative on average despite zero ex ante abnormal returns. This could lead one to incorrectly infer underperformance. 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. We argue that it is unlikely that the endogeneity of the number of new issues explains the long-run underperformance in equity issuances.

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

JEL Classifications: C33, G14, G32.

---

*We have benefited from the comments and suggestions of Alon Brav, Joost Driessen, Campbell Harvey, Chris Leach, Jay Ritter, and Paul Söderlind. A special thanks to Jay Ritter for providing us with data. 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 .

1. Introduction

Major corporate events are inherently endogenous. For example, a firm may decide when to go public depending on general market conditions. It has been 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. 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 known as pseudo market timing. Importantly, this is not reflecting a genuine market timing ability because the 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 abnormal returns when the number of events is 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 in 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. We show that under stationarity assumptions on the process generating the number of events, the traditional cumulative abnormal return measures are not problematic in large samples. Hence, pseudo market timing as a potential explanation

[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).

[2]Eckbo, Maksimovic, and Williams (1990) discuss exogenous versus endogenous events. Other problematic issues in measuring long-run abnormal returns and making inference 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).

for long-run underperformance is limited to small 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.

To evaluate the potential small sample biases 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. The count data regressions suggest that past market returns and past abnormal IPO returns are related to the current number of IPOs. Hence, we confirm previous findings that general market conditions help explain the dynamics for IPO volume. We find, however, no support for past initial underpricing explaining current number of IPOs.

In the simulations we show 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 a dependence of the number of IPOs on past *market* returns is not sufficient to generate a pseudo market timing bias; instead, biases are caused by correlation between past *abnormal* returns and the number of events. Abnormal return measures that correct for cross-correlations show much less bias than the usual equally weighted measures. But even for the equally weighted abnormal return measure, the pseudo market timing effect does not provide sufficient bias to explain the observed long-run underperformance of IPOs in sample sizes 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. Hence, the pseudo market timing phenomenon in itself does not invalidate extant research on long-term underperformance. Note, however, that pseudo market timing is primarily a problem for *measuring* abnormal returns. There may be other problems with some of the existing literature, such the calculation of standard errors or other inference issues, but these are not directly related to the pseudo market timing bias in abnormal return measures

Our work relates to a concurrent working paper by Viswanathan and Wei (2004), who also 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 cumulative abnormal returns for a specific data generating process for the number of IPOs: under a stationary process for the number of IPOs the biases in the abnormal return measures are small.[3]

[3]In another study, Ang, Gu, and Hochberg (2004) conduct simulations and conclude that, under their data generating process with regime switches, the IPO underperformance is highly unlikely to be due to small sample problems in abnormal return measures.

We start our analysis in Section 2 by providing examples similar to Schultz (2003). We then turn to a formal analysis of the event abnormal return measures in Section 3. We present an empirical model for the number of events in Section 4, and report the simulation results in Section 5. We conclude in Section 6.

2. Two Examples

We follow Schultz (2003) and begin to evaluate 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.[4] 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 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, $N_1 = 3$).

[4] 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.

It is important to recognize that the number of IPOs can be a function of past returns, but not 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 1 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 1 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 1 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 equal to the AR_{CW} measure or the AR_{FI} measure, depending on how periods with no events are treated. 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.

3. 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.

3.1. 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 $\sum_{k=1}^{K} r_{i,t+k}$ of 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 $\mathrm{E}(r_{i,t}) = 0$ 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, that is, $\mathrm{E}(CAR_{EW}) = 0$ and $\mathrm{E}(CAR_{CW}) = 0$. 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.[5] We are therefore left with considering large sample properties of these two measures.

To assess the large sample properties, we assess whether these estimators are unbiased under the null that $\mathrm{E}(r_{i,t}|\Omega_{t-1}) = 0$, where Ω_{t-1} denotes information available at time $t-1$. This is exactly the assumption Schultz (2003) makes. The null hypothesis implies that abnormal returns have expectation zero conditional on all previous information, so there is no predictability from either past returns or any other past variables. This assumption captures the key idea of market efficiency and excludes genuine market timing of abnormal returns. The assumption rules out serial correlation in returns, but allows for contemporaneous correlation between the abnormal returns on different event firms (cross-correlation).

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:

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

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.[6]

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. Later in the paper we argue that stationarity is a reasonable assumption on the time series of number of events. The martingale difference property in condition (*ii*) is implied by the null hypothesis $\mathrm{E}(r_{i,t}|\Omega_{t-1}) = 0$. 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 result:

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

[5] The problem is that in both expressions for these estimators, we divide by a function of N_t, which is not independent of the abnormal returns in the numerator, and conditioning on past information only is not possible.

[6] See proposition 7.7 on page 191 in Hamilton (1994), and the text following the proposition.

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 $\mathrm{E}|\frac{1}{N_t}\sum_{i=1}^{N_t}\sum_{k=1}^{K} r_{i,t+k}|^2 < Q < \infty$ 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 are satisfied in a stationary environment, but also when there is an upward deterministic trend in the number of IPOs per period, for example due to general economic growth. In such a situation, the probability of an event in each period will converge to one, and the variance of the per-period average abnormal IPO return decreases over time, and is therefore also bounded from above. Hence, both conditions (*i*) and (*ii*) will be satisfied with a trend growth in the number of IPOs.

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. We return to this point at the end of the paper.

3.2. A Feasible Investment Abnormal Return Measure

Fama (1998) suggests calendar time returns as an alternative measure of the event effect. The idea is to measure abnormal returns as 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 $\mathrm{I}[.]$ 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 $r_{i,t}$ for $k > 0$. 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

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

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}.

4. 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 the empirical model, and finally provide the estimation results.

4.1. Data Description

We study the effects of market conditions on the number of IPOs using US data. The number of IPOs in a month, denoted N_t, are taken from the web pages of Jay Ritter.[7] We consider returns on the S&P 500 index and average initial underpricing in IPOs as proxies for market conditions. They are denoted by $R_{m,t}$ and 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.[8] The sample period for these variables is January 1960 to June 2003 (yielding 522 monthly observations). We also consider a portfolio of abnormal IPO returns, studied in Ritter and Welch (2002), for the period January 1973 to September 2001 (345 observations). The abnormal return is the return on an equally weighted portfolio of IPOs from the previous 36 months adjusted for market risk (the raw IPO portfolio has a market beta of 1.4). The abnormal return is denoted by $r_{ipo,t}$.

Figure 1 shows the number of IPOs aggregated in a quarter together with monthly observations of the log of cumulative market 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 than 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 that 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 the aftermath of the internet boom) is preceded by a period of large initial underpricing.

Table 2 presents summary statistics of the 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 1). The median

[7] 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.

[8] 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.

underpricing is about 13%. The average abnormal return is -0.32% per month, that is, the IPO portfolio has underperformed the market with about 4% per year. The standard deviation of the abnormal return is about 5% per month, which means that the abnormal return volatility is somewhat higher than the market return volatility. The high standard deviation can also be seen in the extreme minimum and maximum abnormal returns.

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

4.2. 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). The 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.[9]

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 larger (smaller) than the mean, we have overdispersion (underdispersion).

Empirically, overdispersion is common (for instance, we have noted that the number of IPOs is unconditionally overdispersed). To allow for overdispersion, we let the number of IPOs in a

[9]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.

month be drawn from the mixing of a Poisson distribution and a gamma distribution. We have,

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

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

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

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

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

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

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

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

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

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

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

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).[10] 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.[11] 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

[10] 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.

[11] 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.

IPOs (similar to an autoregressive model) and measures of market conditions. The following is our base line specification:

$$\beta' x_{t-1} = \beta_0 + \beta_1 R_{m,t-1} + \beta_2 \ln(N^*_{t-1}), \tag{22}$$

where $R_{m,t-1}$ is the lagged S&P 500 return and $N^*_{t-1} = \max(d, N_{t-1})$. 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). 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 also consider specifications with alternatives to the market return as a proxy for market conditions (initial underpricing, abnormal IPO returns, and the 12-month moving averages of the variables), and specifications where more lags of the number of IPOs are included.

The main results from the count data regressions are presented in Table 3. We consider several model specifications to find a model that can characterize data well and at the same time capture the idea behind pseudo market timing. 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 number of IPOs in the next month. Specifications with the lagged initial underpricing (*ii*), lagged abnormal returns (*iii*) or a lagged 12-month moving average of S&P 500 returns (*iv*) show significant coefficients as well. The market condition in the last 12 months is particularly important for the number of IPOs. Specification (*iv*) suggests that a year with a one 1% point increase in the average S&P 500 return over the last year is followed by a month with an 8.4% expected increase in the number of IPOs. This 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 (*v*) is only marginal significant (a p-value of 6%), and the coefficient on lagged 12-month moving average of abnormal returns in (*vi*) is not significant at usual significance levels.

We also run specifications with multiple measures of market conditions. Specification (*vii*) suggest that the lagged S&P 500 return as well as the lagged abnormal return are important; they are both significant at usual significance levels. Specification (*viii*) suggest that the lagged 12-month moving average of the market return is key. Taken together with the results in specification (*ix*), this indicates that the 12-month moving average of S&P 500 returns and the lagged abnormal IPO returns are the main driver of the results. As we want to simulate with and without lagged abnormal returns, we let specifications (*iv*) and (*x*) be the bases for our simulations. Specification (*iv*) contains a constant term, the lagged 12-month moving average of the market return, and the log of the lagged number of IPOs as regressors. Specification (*x*) contains the lagged abnormal IPO return as an additional regressor.

To check the robustness to the chosen lag length of the abnormal returns and the number of IPOs, we consider some further model specifications. The results are reported in Table 4. Specifications (*xi*) and (*xii*) show that the measured coefficients on lags two and three are lower relative the coefficient on lag one, and they are not statistically significant at usual levels. All specifications indicate that a high degree of persistence in the number of IPOs—the coefficients on the lagged number of IPOs are in the range 0.79 to 0.85. The coefficients on additional lags in specifications (*xiii*) and (*xiv*) are often statistically significant. However, the sum of all coefficients on the lags are always less than 0.85. 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.

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. This is hardly surprising: given the notoriously low power of unit root tests, it is difficult to reject the null hypothesis of a unit root with a relatively short time series of data. We argue that it is not plausible for the process generating the number of IPOs to be non-stationary. To support this point, we re-estimate our preferred count data model, specification (x), but with a unit coefficient on the lagged number of IPOs imposed. We then simulate time series of 500 monthly observations, starting with 30 events in the first month (close to the sample average). Details of the simulation procedure are given in Section 5. We simulate 200 such time series and construct a percent frequency distribution of the number of events per month. For comparison, we also construct distributions for actual data and the time series of the number of events generated from the stationary specification (x). These distributions are plotted in Figures 2a-c. The data (Figure 2a) and the stationary process (Figure 2b) show basically a similar, mildly hump shaped, pattern. The pattern for the unit coefficient case (Figure 2c) is much more skewed than the actual data. The median of the generated distribution is much smaller than the sample median; in contrast, the mean of the generated distribution is much larger than the sample mean. On one hand, the left tail of the distribution has too many observations with zero or only a few events. On the other hand, the right tail of the distribution has too many observations with extremely high number of events per month (occasionally it is over 10,000).[12] Note that in the estimation moments for the conditional mean and the variance are matched to capture the time series dynamics of the number of events, whereas the figures show the unconditional

[12]This extreme skewness can also be noted from the coefficient of variation (standard deviation divided by mean) of the number of observations per month. In the actual data, the coefficient of variation is 0.87. In the simulations of the stationary model, it is 0.84. In contrast, for the unit coefficient model the coefficient of variation is around 2, which is far too high.

distributions. Hence, this exercise can be seen as a visual diagnostic of the specifications. All in all, the distribution for the series simulated from the model with a unit coefficient on the lagged number of IPOs is far from the empirical distribution. Based on this, we find a unit root process for the number of IPOs not to be plausible.

In sum, we show that past market conditions have information about the current IPO volume. In particular, past market returns and past abnormal IPO returns significantly affect (statistically and economically) current number of IPOs. This is consistent with the idea of pseudo market timing. Next we use the empirical model to simulate from.

5. Simulation Evidence

In Section 3 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. In these simulations, there is a pseudo market timing effect, but no genuine market timing, so expected returns are conditional mean zero. The basis of the simulations is the empirical model for the number of IPOs, specification (x), fitted in the previous section.

5.1. 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.

   Cross-correlation between abnormal returns on events in the same month is important in practice, and may be one determinant of the magnitude of the pseudo market timing bias in small samples. The following error components model is used to simulate abnormal returns which exhibit cross-correlation[13]

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

[13] Recall that the null hypothesis allows for such cross-correlation, but not for serial correlation as this would imply predictability of abnormal returns.

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 $\sum_{k=1}^{K} \hat{r}_{i,t+k} = \sum_{k=1}^{K} c_{t+k} + \sum_{k=1}^{K} \epsilon_{i,t+k}$. 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.

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 of the market returns 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 $\hat{\sigma}_\eta^2$; then the number of IPOs is drawn from a Poisson distribution with a conditional mean (based on the estimated parameters, and lagged number of IPOs and 12-month moving average return) times the multiplicative error term. Parameter estimates from specification (*iv*) in Table 3 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

$$\beta' x_{t-1} = \beta_0 + \beta_1 R_{m,t-1}^{12} + \beta_2 \ln(N_{t-1}^*) + \beta_3 c_{t-1}. \tag{24}$$

   In the empirical model for the number of IPOs, we used the lagged return on a portfolio of IPO firms as regressor. As these portfolios typically contain several hundreds of IPO firms, this portfolio return is virtually equal to the common component if abnormal returns have a one factor structure, as we assume. Hence, in the simulations we use the empirical estimates of specification (*x*) in Table 3, with $\hat{\beta}_3 = 1.411$ as the impact of lagged common component of abnormal returns on the number of IPOs.

   Finally, we have to choose values for the cross-correlation in abnormal returns, ρ, and the standard deviation of the abnormal returns, σ. 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 $\rho = 0.026$ and $\sigma = 17\%$. This choice implies a standard deviation of the common component of $\sigma\sqrt{\rho} = 2.74\%$, which is lower than the standard deviation of the IPO portfolio abnormal return in the data (approximately 5%). We therefore also conduct simulations with a higher value for the correlation, $\rho = 0.0865$, that matches the variance of the common component with the observed IPO portfolio abnormal return variance from Table 2.

4. The average abnormal return measures.

   The abnormal return measures are calculated according to:

$$CAR_{EW} = \frac{\sum_{t=1}^{T} \sum_{i=1}^{\hat{N}_t} \left(\sum_{k=1}^{K} \hat{r}_{i,t+k} \right)}{\sum_{t=1}^{T} \hat{N}_t}, \tag{25}$$

$$CAR_{CW} = \frac{\sum_{t=1}^{T} \mathrm{I}\left[\hat{N}_t > 0\right] \left(\frac{1}{\hat{N}_t} \sum_{i=1}^{\hat{N}_t} \sum_{k=1}^{K} \hat{r}_{i,t+k} \right)}{\sum_{t=1}^{T} \mathrm{I}\left[\hat{N}_t > 0\right]}, \tag{26}$$

$$AR_{FI} = \frac{1}{T} \sum_{t=1}^{T} \mathrm{I}\left[\sum_{k=1}^{K} \hat{N}_{t-k} > 0 \right] \left(\frac{\sum_{k=1}^{K} \sum_{i=1}^{\hat{N}_{t-k}} \hat{r}_{i,t}}{\sum_{k=1}^{K} \hat{N}_{t-k}} \right). \tag{27}$$

   These calculations correspond to Equations (2), (5), and (8)-(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 standard errors of the averages, constructed from the standard deviation of the generated abnormal return measures.

5.2. Simulation Results: Without Lagged Abnormal Returns

Table 5 reports the results of our simulations when the generating process of the number of IPOs excludes the effect of lagged abnormal returns (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 are from specification (*iv*) in Table 3. 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 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 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 results where the cross-sectional correlations in abnormal returns is increased (from 0.026 to 0.0865), retaining the high persistence parameter (0.95). Panel D shows the results where the coefficient on the lagged 12-month moving average returns is doubled (from 8.438 to 16.876) in addition to the higher persistence and the higher correlation. All augmented set-ups reveal the same result: there is no bias in the abnormal return measures. Hence, we conclude that with lagged market returns affecting the number of IPOs alone, there is no pseudo market timing effect. It is crucial to have a correlation between IPO abnormal returns and the process for the number of IPOs in order to generate a pseudo market timing effect.

5.3. Simulation Results: With Lagged Abnormal Returns

Table 6 reports the results of our simulations when we allow the lagged abnormal returns to affect the future number of IPOs. We consider again four parameter set-ups. Panels A (default) and B (high persistence) follow the set-ups in the previous table and occasionally show a negative bias for the equally weighted measure due to the pseudo market timing. However, the magnitudes are small: the biases are all below 1% in absolute terms. The cross-sectionally corrected measure and the measure of the feasible investment strategy show now biases. In Panel C the cross-sectional correlation is set at the high value of 0.0865. The equally weighted measure on the 60-month horizon now shows a modest bias for the $T = 100$ case, but it is still less that 2% in absolute value. All the other biases are negligible. In Panel D, we keep the high correlation and the high persistence, and double the impact of the lagged common component compared to the default parameter values. Again, the bias is significant only for the equally weighted measure; the largest absolute bias is around 2.5% for the 60-month horizon and 100 observations. For the cross-sectionally weighted abnormal return, there is only one significant bias, for the most extreme setting (100 observations and a 60 month horizon), but this bias is also less than 2%. For the other cases and for the feasible investment abnormal return measures, there are no significant biases.

To conclude, in our simulations we find no, or only small, biases in the average abnormal return measures. Even the most extreme biases we can generate, using realistic parameter values, are much smaller than the underperformance of IPO firms found in most empirical studies. The simulations also reveal that the cross-sectionally corrected measure and the measure of the feasible investment strategy show no significant biases. 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.

5.4. A Comparison with Other Studies

How can we reconcile these results with Schultz's (2003) results? The key issue is that his simulations violate the stationarity assumptions made above. For non-stationary processes, the probability limit of the abnormal return estimator is not always well defined and there may be a bias, even asymptotically. We have argued before that a unit coefficient on the lagged number of IPOs in our model is implausible. A critical assumption in our simulations therefore is that the event generating process is stationary. We also explicitly acknowledge that the number of IPOs in a month is a non-negative integer. Even if we allow for high persistence in the process, the process cannot be absorbed at zero and does not explode. Recall that if we let the process be near-integrated but still stationary (the autoregressive coefficient is set to 0.95), there is still no bias in typical sample sizes.

Our results seem to contradict the results of Schultz (2004), who argues that there is a bias in the traditional equally weighted measure even when the data generating process is stationary and only the lagged market return affects the number of IPOs. Looking closer at the way he generates abnormal returns, we find that his abnormal returns contain a complex dependence structure with market returns and the number of IPOs. To see this, consider the way IPO returns are generated in Schultz (2004):

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

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

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

where the constant a is chosen such that the abnormal return is forced to have an unconditional mean equal to zero. However, these abnormal returns still are correlated with the market return, because of the (counterfactual) assumption of a unit beta. Hence, the simulated abnormal returns are not genuine abnormal returns as the wrong benchmark is considered. The correlation with the market induces a pseudo market timing effect in the data generating process. It also induces a spurious cross-sectional correlation between the individual abnormal returns. It is straightforward to show that the cross-sectional correlation between the abnormal returns is non-zero and given by

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

Plugging in the values yields a cross-sectional correlation of 15%, which is much higher than what the data suggest.

6. 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, pseudo market timing 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. Importantly, the pseudo market timing bias in itself does not invalidate extant research on long-run underperformance. Of course, there may be other problems with some of the existing papers, such as inference problems, but these are different from pseudo market timing, which is essentially a measurement issue.

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 1: 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 2: Summary Statistics

Statistic	Number of IPOs N_t	Return on S&P 500 $R_{m,t}$	Underpricing U_t	Abnormal IPO Return $r_{ipo,t}$
Mean	28.5	0.91	18.11	–0.32
Median	22	1.07	13.15	–0.58
Std.Dev.	24.7	4.34	21.31	5.03
Minimum	0	–21.52	–28.80	–16.92
Maximum	122	16.57	119.10	34.58

This table presents summary statistics of monthly observations of the number of IPOs in a month (N_t), S&P 500 returns ($R_{m,t}$), average initial underpricing in IPOs in a month (U_t), and abnormal IPO returns ($r_{ipo,t}$). The sample period for N_t, $R_{m,t}$, and U_t is January 1960 to June 2003, yielding 522 observations. The sample period for $r_{ipo,t}$ is January 1973 to September 2001, yielding 345 observations. The number of months with zero IPOs is 18 (or 3.5% of all observations). The statistics of $R_{m,t}$ and $r_{ipo,t}$ are expressed in % per month.

Table 3: Empirical Models of the Number of IPOs in a Month

	(i)	*(ii)*	*(iii)*	*(iv)*	*(v)*	*(vi)*	*(vii)*	*(viii)*	*(ix)*	*(x)*
Moment Conditions (20)										
1	0.554	0.517	0.554	0.615	0.542	0.650	0.526	0.728	0.646	0.635
	(0.069)	(0.074)	(0.099)	(0.073)	(0.071)	(0.101)	(0.101)	(0.101)	(0.103)	(0.097)
$R_{m,t-1}$	1.384						1.779		1.032	
	(0.546)						(0.607)		(0.639)	
U_{t-1}		0.228					0.014		–0.040	
		(0.094)					(0.115)		(0.166)	
$r_{ipo,t-1}$			1.579				1.892		1.699	1.411
			(0.396)				(0.398)		(0.404)	(0.385)
$R^{12}_{m,t-1}$				8.438				9.953	8.157	9.770
				(1.736)				(1.785)	(1.879)	(1.738)
U^{12}_{t-1}					0.193			–0.028	0.030	
					(0.103)			(0.133)	(0.213)	
$r^{12}_{ipo,t-1}$						0.065		0.061	–1.288	
						(1.311)		(1.499)	(1.500)	
$\ln(N^*_{t-1})$	0.845	0.847	0.854	0.800	0.842	0.828	0.855	0.765	0.791	0.790
	(0.019)	(0.019)	(0.027)	(0.023)	(0.020)	(0.027)	(0.026)	(0.029)	(0.030)	(0.028)
Moment Condition (21)										
σ^2_η	0.309	0.309	0.306	0.297	0.309	0.302	0.298	0.291	0.286	0.287
	(0.016)	(0.017)	(0.020)	(0.017)	(0.017)	(0.021)	(0.020)	(0.020)	(0.020)	(0.021)
Diagnostics										
R-square I	0.793	0.792	0.800	0.803	0.794	0.791	0.806	0.802	0.810	0.810
R-square II	0.867	0.867	0.869	0.876	0.868	0.861	0.872	0.872	0.876	0.878
T	521	521	345	510	510	334	345	334	334	345

This table presents results of count data regressions for the number of IPOs in the US (denoted N_t). Lagged S&P 500 returns ($R_{m,t-1}$), lagged initial underpricing (U_{t-1}), lagged abnormal IPO returns ($r_{ipo,t-1}$), 12-month moving averages of S&P 500 returns ($R^{12}_{m,t-1}$), initial underpricing (U^{12}_{t-1}), and abnormal IPO returns ($r^{12}_{ipo,t-1}$), 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. The abnormal return variable is de-meaned. Sample counterparts to moment conditions (20) and (21) in the text are used to identify parameters:

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

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

where x_{t-1} contains a one, and one or several variables of $R_{m,t-1}$, U_{t-1}, $r_{ipo,t-1}$, $R^{12}_{m,t-1}$, U^{12}_{t-1}, $r^{12}_{ipo,t-1}$, and $\ln(N^*_{t-1})$. Heteroskedasticity 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 4: Empirical Models of the Number of IPOs in a Month: Robustness

	(x)	*(xi)*	*(xii)*	*(xiii)*	*(xiv)*
Moment Conditions (20)					
1	0.635 (0.097)	0.633 (0.073)	0.639 (0.097)	0.536 (0.087)	0.484 (0.088)
$r_{ipo,t-1}$	1.411 (0.385)	1.353 (0.385)	1.290 (0.383)	1.661 (0.406)	1.565 (0.384)
$r_{ipo,t-2}$		0.514 (0.438)	0.579 (0.455)		
$r_{ipo,t-3}$			–0.615 (0.515)		
$R^{12}_{m,t-1}$	9.770 (1.738)	9.599 (1.736)	9.617 (1.730)	9.468 (1.668)	10.334 (1.816)
$\ln(N^*_{t-1})$	0.790 (0.028)	0.800 (0.023)	0.790 (0.029)	0.588 (0.045)	0.535 (0.053)
$\ln(N^*_{t-2})$				0.234 (0.044)	0.108 (0.053)
$\ln(N^*_{t-3})$					0.190 (0.043)
Moment Condition (21)					
σ^2_η	0.287 (0.021)	0.286 (0.020)	0.284 (0.021)	0.282 (0.021)	0.274 (0.021)
Diagnostics					
R-square I	0.810	0.812	0.813	0.823	0.830
R-square II	0.878	0.880	0.881	0.882	0.887
T	345	344	343	345	345

This table presents results of count data regressions for the number of IPOs in the US (denoted N_t) on lagged 12-month moving averages of S&P 500 returns ($R^{12}_{m,t}$), lagged abnormal IPO returns ($r_{ipo,t}$), and functions of lagged number of IPOs ($N^*_t = \max(0.5, N_t)$). Sample counterparts to moment conditions (20) and (21) in the text are used to identify parameters. See also the note in Table 3. Heteroskedasticity 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 5: Simulation Results, Biases without Lagged Abnormal Returns

	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 High Cross-Correlations									
CAR_{EW}	0.00	0.03	0.02	–0.16	–0.05	0.22	0.08	–0.41	0.45
	(0.01)	(0.01)	(0.01)	(0.29)	(0.35)	(0.39)	(0.41)	(0.50)	(0.57)
CAR_{CW}	0.02	0.01	0.02	–0.04	0.01	–0.08	0.17	–0.52	0.69
	(0.01)	(0.01)	(0.01)	(0.25)	(0.27)	(0.25)	(0.39)	(0.42)	(0.43)
AR_{FI}	–0.01	0.02	0.00	–0.10	–0.04	–0.02	0.27	–0.32	0.42
	(0.01)	(0.02)	(0.01)	(0.23)	(0.25)	(0.24)	(0.31)	(0.38)	(0.41)
Panel D. High Persistence, High Cross-Correlations and Large Market Impact									
CAR_{EW}	0.01	–0.02	–0.02	–0.02	–1.11	–0.76	0.12	–0.12	–0.41
	(0.01)	(0.02)	(0.02)	(0.31)	(0.38)	(0.43)	(0.44)	(0.53)	(0.65)
CAR_{CW}	–0.00	0.00	–0.01	0.03	–0.67	0.03	–0.31	0.02	–0.42
	(0.01)	(0.01)	(0.01)	(0.25)	(0.26)	(0.25)	(0.39)	(0.42)	(0.43)
AR_{FI}	0.00	–0.02	–0.01	–0.01	–0.47	–0.17	–0.21	–0.29	–0.46
	(0.01)	(0.01)	(0.01)	(0.22)	(0.22)	(0.25)	(0.31)	(0.38)	(0.41)

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 are from specification (*iv*) in Table 3. The cross-correlation in abnormal returns is set to 0.026. 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 cross-correlations in abnormal returns are set to 0.0865 (rather than 0.026), retaining the high persistence. Panel D presents results where the effect of the lagged 12-month moving average of the S&P 500 return is increased from 8.438 to 16.876, retaining the high persistence and high cross-correlations. The average number of IPOs in a month is comparable in all panels (about 30).

Table 6: Simulation Results, Biases with Lagged Abnormal Returns

	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	–0.00	–0.00	–0.28	0.03	0.07	0.07	–0.03	0.42
	(0.01)	(0.01)	(0.01)	(0.14)	(0.15)	(0.15)	(0.22)	(0.24)	(0.25)
CAR_{CW}	–0.00	–0.00	–0.00	–0.13	0.18	0.22	0.29	0.13	0.59
	(0.01)	(0.01)	(0.01)	(0.14)	(0.14)	(0.14)	(0.21)	(0.23)	(0.24)
AR_{FI}	–0.01	0.01	–0.00	–0.14	0.16	0.13	0.09	0.03	0.21
	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.14)	(0.17)	(0.21)	(0.22)
Panel B. High Persistence									
CAR_{EW}	–0.01	–0.04	–0.00	–0.31	–0.54	–0.34	–0.13	–0.81	–0.05
	(0.01)	(0.01)	(0.01)	(0.16)	(0.19)	(0.22)	(0.23)	(0.28)	(0.34)
CAR_{CW}	0.03	–0.02	–0.03	0.10	–0.27	0.03	0.14	–0.26	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	0.03	–0.07	–0.10	0.25	–0.10	–0.21
	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.14)	(0.17)	(0.21)	(0.23)
Panel C. High Persistence and High Cross-Correlations									
CAR_{EW}	–0.05	0.01	–0.02	–1.43	–1.32	–0.79	–1.19	–1.66	0.02
	(0.01)	(0.01)	(0.02)	(0.29)	(0.35)	(0.41)	(0.43)	(0.50)	(0.61)
CAR_{CW}	–0.01	0.01	0.02	–0.49	–0.41	–0.09	–0.20	–0.68	0.83
	(0.01)	(0.01)	(0.01)	(0.25)	(0.26)	(0.26)	(0.39)	(0.41)	(0.42)
AR_{FI}	0.00	–0.01	0.01	–0.29	–0.30	–0.15	–0.15	–0.29	0.80
	(0.01)	(0.01)	(0.01)	(0.23)	(0.24)	(0.25)	(0.31)	(0.38)	(0.40)
Panel D. High Persistence, High Cross-Correlations and Large Pseudo Market Impact									
CAR_{EW}	–0.08	–0.06	–0.06	–2.08	–1.95	–1.02	–2.43	–2.54	–0.61
	(0.01)	(0.01)	(0.02)	(0.29)	(0.35)	(0.42)	(0.42)	(0.50)	(0.61)
CAR_{CW}	–0.01	0.01	–0.00	–0.58	–0.10	–0.27	0.11	–0.43	0.32
	(0.01)	(0.01)	(0.02)	(0.25)	(0.26)	(0.27)	(0.39)	(0.41)	(0.43)
AR_{FI}	0.01	0.01	0.01	–0.28	–0.00	–0.19	0.25	–0.12	0.54
	(0.01)	(0.01)	(0.01)	(0.23)	(0.26)	(0.27)	(0.31)	(0.37)	(0.41)

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 are from specification (x) in Table 3. The cross-correlation in abnormal returns is set to 0.026. 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 to 0.95. Panel C presents results where the cross-correlations in abnormal returns are set to 0.0865 (rather than 0.026), retaining the high persistence. Panel D presents results where the effect of the lagged abnormal IPO return is doubled compared to the default case, retaining the high persistence and high cross-correlations. The average number of IPOs in a month is comparable in all panels (about 30).

Figure 1: 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.

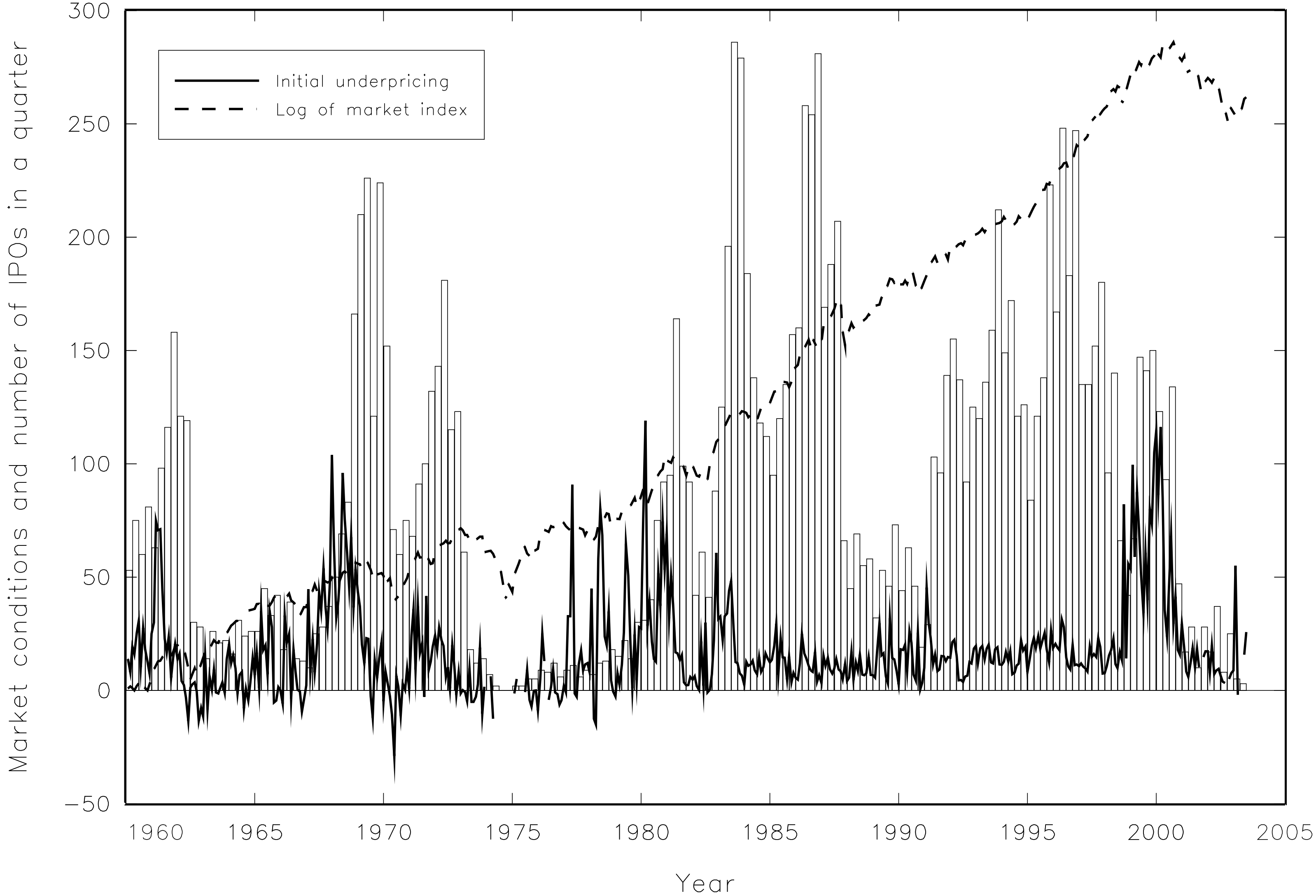

Figure 2: Percent Frequency Distributions of the Number of IPOs in a Month

The figures show frequency distributions of the number of IPOs in a month. The percentage of monthly observations is shown for bins defined by observations that equal zero, observations in the intervals 1-10, 11-20, 21-30, 31-40, 41-50, 51-60, 61-70, 71-80, 81-90, 91-100, and observations above 100. Figure a shows the distribution of actual data. Figure b shows the distribution from a simulation of specification (x) in Table 3. Figure c shows the distribution from a simulation of specification (x) when a unit coefficient on the lagged number of IPOs is imposed in the estimation. The distributions in Figures b and c are generated by simulating 200 time series of 500 observations where the initial value is set to 30, and then considering the percentage of the observations in each bin.