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Pseudo Market Timing: A Reappraisal

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Abstract

The average firm going public or issuing new equity underperforms the market in the long run. This underperformance could be related to the endogeneity of the number of new issues if new issues cluster after periods of high abnormal returns on new issues. In such a case, ex post measures of new issue abnormal returns may be negative on average, despite the absence of ex ante abnormal returns. We evaluate this endogeneity problem in event studies of long-run performance. We argue that it is unlikely that the endogeneity of the number of new issues explains the long-run underperformance of equity issues.

I. Introduction

Major corporate events are inherently endogenous; for example, a firm may decide, in light of economic conditions, when to go public. It has been documented that firms tend to go public after high underpricing of initial public offerings (IPOs) and after high market returns. However, traditional event study methods treat the timing of events as exogenous. Studies have demonstrated that the average firm going public underperforms the market in the long run. For example, in a review Ritter and Welch (2002) report a 23% average underperformance (relative to the market) over the three-year period following an IPO.[1] The lack of an explanation for the long-run underperformance of IPOs and similar underperformance of seasoned equity offerings (SEOs) has been referred to as the "new issues puzzle."

Schultz (2003) proposes an explanation for the apparent long-run underperformance of firms that go public, arguing that the underperformance may be a statistical illusion caused by the clustering of IPOs after a period of unusually

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

high abnormal returns for previous IPO firms. This effect is known as pseudo market timing. Importantly, this does not reflect a genuine market timing ability, because future abnormal returns of IPOs are conditionally unpredictable. Instead, when using traditional IID-oriented event study methods, the clustering of events after periods of positive abnormal returns causes a statistical bias in measured average abnormal returns. The pseudo market timing argument, in principle, extends to other endogenous corporate events (for example, SEOs have also exhibited long-run underperformance) and would have broader implications than just those pertaining to IPOs.

In this paper we thoroughly evaluate the endogeneity problem in event studies as it relates to long-run underperformance and undertake 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 in contrast to the usual cross-sectional treatment used 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 demonstrate that when the process generating the number of events is stationary, the traditional cumulative abnormal return measure is not problematic in large samples. Hence, pseudo market timing as a potential explanation for long-run underperformance is limited to small samples. We also consider an abnormal return measure that captures the returns from a feasible strategy for investing in event firms; this measure is in line with the calendar-time approach advocated by Fama (1998). We demonstrate that this abnormal return measure is unbiased and does not have the problems of traditional measures—not even in small samples.

Our results refute the conclusions of the simulation analysis in Schultz (2003). His results indicate potentially large biases in event studies, but an inspection of his methods reveals that the process for generating the number of IPOs in his simulations is not stationary. We find in this paper that nonstationarity is typically rejected for the observed IPO series. Moreover, we argue that a nonstationary process for the number of IPOs is not plausible, and generates counterfactual time-series properties. Therefore, we carefully calibrate a model of the IPO-generating process that is stationary and exhibits pseudo market timing.

To evaluate the potential for small sample biases in the traditional measures, we undertake simulation experiments. As a basis for the simulations, we consider count data regressions in which the non-negative integer character of the event data (here IPOs) is explicitly acknowledged, making 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, confirming previous findings that economic conditions indeed help explain the dynamics of IPO volume. However, we find no support for the notion that past initial underpricing explains the current number of IPOs.

In the simulations, we quantify the pseudo market timing bias. We demonstrate that it depends on the parameters related to the persistence in the number of events, the impact of past abnormal returns, and cross-sectional correlations in

[2]Eckbo, Maksimovic, and Williams (1990) consider the effect of endogenous events in cross-sectional regressions of announcement effects on exogenous variables.

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abnormal returns. Importantly, 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 the correlation between past *abnormal* returns and the number of events. In other words, even though past market returns help explain IPO volume, it is the correlation with past abnormal returns that generates pseudo market timing. At most, we find biases of -3% over a three-year period for an equally weighted measure of average abnormal returns. This means that 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. Abnormal return measures that correct for cross correlations display much less bias than the equally weighted measure. We conclude that the long-run underperformance of IPO firms is unlikely attributable to pseudo market timing. Hence, the pseudo market timing phenomenon in itself does not invalidate extant research on long-run underperformance.

Our simulation studies also shed light on inference issues in long-horizon event studies. We demonstrate that the pseudo market timing bias is related to the cross-sectional correlation between abnormal returns. However, this cross-sectional correlation also has important implications for the inference. In our simulations, we report the size of the usual *t*-tests, and document that they reject the null of no overperformance far too often. Our simulations also provide the correct critical values of the *t*-test; using these correct values, there seems to be much less evidence of long-horizon IPO underperformance. Our work here relates to an extensive literature treating problematic issues in measuring long-run abnormal returns and making related inferences. These issues relate to the choice of 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, regime switches, and non-normally distributed abnormal returns.[3]

In a concurrent working paper, Viswanathan and Wei (2006) also consider the effects of pseudo market timing. They find, as we do, the theoretical asymptotic result that the abnormal return measures converge to zero in large samples under the assumption of a stationary data-generating process. As we do here, using simulations Viswanathan and Wei (2006) quantify the small-sample biases arising from pseudo market timing and provide evidence of inference properties (size and power) of the abnormal return measures seen in event studies. They are able to provide analytical expressions for the small-sample bias at the cost of making more restrictive assumptions regarding the data-generating process. However, the empirical evidence we provide is richer. First, we consider monthly and annual IPO data at an aggregated level as well as monthly individual IPO data. This allows us to shed further light on the critical stationarity assumption. Indeed, our tests for unit roots, complemented with tests for stationarity, all point in the direction of a stationary process for the number of events. Second, we consider an empirical model that takes into account the non-negative data character,

[3] See, for example, Ang, Gu, and Hochberg (2007), Barber and Lyon (1997), Brav (2000), Brav and Gompers (1997), Brav, Geczy, and Gompers (2000), Eckbo and Norli (2005), Fama (1998), Gompers and Lerner (2003), Kothari and Warner (1997), Loughran and Ritter (1995), and Mitchell and Stafford (2000).

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which Viswanathan and Wei (2006) do not, and the non-negativity is important for matching the new issues in the data. This model yields interesting evidence in itself, particularly in regard to the relation between IPO volume and general market conditions. Finally, the empirical model gives us a more extensive characterization of the event data, which we use in the simulation part of the paper.

Our work also relates to two other recent studies. Baker, Taliaferro, and Wurgler (2006) examine small-sample biases arising from an aggregate time-series version of pseudo market timing for predictive regressions. They find that the predictive power of variables such as equity shares in new issues, corporate investment plans, and dividend initiations cannot be explained by small-sample biases. Their bias is a pure time-series phenomenon and conceptually different from the bias in event studies that Schultz (2003) emphasizes. Ang, Gu, and Hochberg (2007) perform an event study of IPO underperformance using a feasible investment return outperformance measure, which does not suffer from a pseudo market timing bias. They consider whether the observed underperformance of IPOs may be a result of observing too few star performers ex post than were expected ex ante. This "peso problem" is conceptually different as the difference between ex ante and ex post expectations is not driven by pseudo market timing. They conclude that this bias is unlikely to account for the underperformance observed in data.

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

II. Two Examples

Following Schultz (2003), we begin to evaluate the pseudo market timing hypothesis using a two-period model. The pseudo market timing effect we consider is couched in an IPO setting, but extends to settings of endogenous corporate events in general. The purpose of this section is to i) determine the exact cause of the pseudo market timing effect, and ii) encourage the use of abnormal return measures that correct for cross-sectional correlation.

Consider a two-period model in which 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 for private firms, which potentially may go public, and for 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 for private firms and firms that go public. Let the abnormal returns in period 1 (between date 0 and date 1) be denoted by r_1. Similarly, let r_2 denote the abnormal returns in period 2 (between dates 1 and 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:

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

The interesting feature of the analysis is that the number of observed IPOs depends on 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 at the beginning of the first period is one (that is, $N_0 = 1$). If a positive 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 can be a function of past returns, but not of 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. Supposing now that the return in period 1 is instead negative, then the number of IPOs decreases to zero (that is, $N_1 = 0$). The assumption that the number of IPOs is zero is what Schultz (2003) assumes in his examples. This turns out to be important for the analysis; below we relax the assumption. Panel A in Table 1 summarizes the four scenarios in terms of abnormal returns and number of IPOs.

TABLE 1

Analysis of Average Abnormal Returns in Two-Period Examples

Table 1 presents the abnormal return measures for four scenarios (labeled I to IV) for 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 the sum by the total number of events. AR_{CW} counts all events in the same period as one observation; it sums up the period's average abnormal returns and then divides the sum by the number of periods. AR_{FI} denotes the average per period return from 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).

	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 Nonzero 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%

Table 1 also reports three measures of average abnormal returns. The first measure is an equally weighted abnormal return measure denoted by AR_{EW}. It simply averages the observed abnormal returns from a scenario. This is the measure on which Schultz (2003) focuses. The second measure denoted by AR_{CW} is an extension of the equally weighted measure, and corrects for the cross-sectional dependence in the abnormal returns. In correcting for cross-sectional dependence,

all event returns in the same period are considered one observation. The third measure is of feasible investment abnormal returns, denoted by AR_{FI}. It captures the per period return from 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 in that period by definition equals zero. This measure captures the essence of Fama's (1998) calendar-time abnormal returns by creating a portfolio of all event firms in 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 downward. 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, and he refers to the overall phenomenon 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. The negative measure is driven by the fact that the number of IPOs is determined by past abnormal returns. He further claims that this pseudo market timing is not simply a small-sample issue. The AR_{FI} measure is, however, zero. Recall that this measure captures a feasible investment strategy in which the investment is in all IPOs in a period. If there are multiple IPOs, the investment is divided equally among the event firms. 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 would be expected from the assumption of zero ex ante abnormal returns.

The above setting 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, it becomes $N_1 = 4$ or $N_1 = 1$ depending on the return in period 1). Panel B in Table 1 summarizes the four scenarios in terms of the abnormal return measures.

We now observe a different situation. The AR_{EW} measure is still biased downward, but the AR_{CW} measure is now unbiased. Note that the key difference from the previous example is the number of IPOs in scenarios III and IV. In Panel A of Table 1, scenarios III and IV result in 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 to gauge ab-

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normal 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 above examples, such a measure is equal to the AR_{CW} or the AR_{FI} measures, depending on how periods with no events are treated. If it is assumed that there is no investment at all during periods with no IPOs, this coincides with AR_{CW}. If it is assumed that the investment is in the benchmark when there are no events, this coincides with AR_{FI}. Finally, note that it is only the AR_{FI} measure that is unbiased in both examples.

In summary, these examples demonstrate that the pseudo market timing bias in abnormal return measures is related to the dependence between the number of events and previous abnormal returns. The examples also demonstrate differences between the equally weighted cumulative abnormal return, the cross-sectionally weighted cumulative abnormal return, and the performance measure of a feasible investment. However, these examples are stylized and consider only two periods. In the next section, we analyze the properties of these measures in more detail, applying them to both small and large samples.

III. Abnormal Return Measures and Sampling Properties

In this section, we derive the formal sampling properties of abnormal return measures. We first formalize the way cumulative abnormal return measures are calculated, and then discuss the unbiasedness (a small-sample property) and consistency (a large-sample property) of the measures in relation to endogenous event timing. Finally, we consider a measure of feasible investment abnormal returns 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 that the events are realized at the end of the period so $N_t \in \Omega_t$, where Ω_t denotes the information available at time t for $t = 1, \ldots, T$. 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 for 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:

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

This expression sums up the abnormal returns for all events in all time periods, and then divides the sum 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:

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

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

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

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

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

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

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

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

Again, this is simply the 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 a 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 $\mathrm{E}(\sum_{k=1}^{K} r_{i,t+k} | N_1, \ldots, N_T) = \mathrm{E}(\sum_{k=1}^{K} r_{i,t+k}) = 0$. Under the exogenous market timing assumption, one can easily demonstrate that both cumulative abnormal return measures are unbiased, that is, both $\mathrm{E}(CAR_{EW}) = 0$ 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.[4] We are therefore left to consider large sample properties of these two measures.

[4]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 only on past information is incorrect.

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To assess the large sample properties, we assess whether these estimators are unbiased under the null hypothesis that $\mathrm{E}(r_{i,t}|\Omega_{t-1}) = 0$. This is exactly the assumption Schultz (2003) makes. The null hypothesis implies that abnormal returns have an expectation of zero, conditional on all previous information, so there is no predictability based on 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 for different event firms (cross correlation).

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

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

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., $\mathrm{E}(\sum_{i=1}^{N_t}\sum_{k=1}^{K} r_{i,t+k}|\Omega_t) = 0$, 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 in which the number of events almost surely converges to zero over time). Condition (ii) rules out processes in which the number of events grows without bound. These two conditions are satisfied when the abnormal returns r_{it} are a martingale difference sequence with bounded variance, and the event process N_t is stable over time in the sense that the number of events neither converges to zero nor diverges (i.e., N_t must have finite variance for all t). We refer to such a process as stationary though it need not be covariance stationary. Later in the paper we argue that stationarity is a reasonable assumption regarding the time series of the 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 $\mathrm{E}(\sum_{i=1}^{N_t}\sum_{k=1}^{K} r_{i,t+k}|\Omega_t) = 0$ follows immediately.

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

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

$$= \frac{0}{p} = 0,$$

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

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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) requires that the event process does not die out (i.e., the number of events does not converge to zero). Condition (ii) requires that the cross-sectional average of the abnormal returns in any given period has an expectation of zero and finite variance. Under the null hypothesis of no predictability, this condition will be satisfied in a stationary environment, but also under some forms of nonstationarity as long as the number of IPOs per period does not degenerate to zero. For example, this condition will be satisfied when there is an upward 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. However, condition (ii) may be violated if the number of IPOs contains a random walk component as that implies an unbounded variance of N_t.

The consistency results imply that although possibly biased in small samples event studies using either the equally weighted or the cross-sectionally weighted abnormal return measure produce consistent estimates in large samples. Hence, we find that the possible bias of the equally weighted measure of average abnormal returns is only a small-sample problem. Our conclusion is not consistent with Schultz's (2003) findings and seemingly at odds with the results of his multi-period simulations. We conjecture that his simulations violate the stationarity condition imposed 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) for the equally weighted cumulative abnormal return, which requires the variance of the sum of abnormal returns to be bounded.

B. A Measure of Feasible Investment Abnormal Returns

Fama (1998) discusses the calendar-time returns as an alternative measure of the event effect.[6] The idea is to measure abnormal returns as the return from a feasible strategy for investment in the event firms. For every time period, t, we define the excess return, over a benchmark, from an investment strategy in all firms that had an event in the window from $t-K$ to $t-1$:

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

[6] Jaffe (1974) and Mandelker (1974) were the first to consider such a calendar-time abnormal return approach.

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The indicator function 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 average per period returns from a strategy for investment 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 demonstrate the unbiasedness of the measure that captures 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

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

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 that

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

Consistency is also immediate since

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

where we use the result 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}.

C. Summary

We find that under certain stationarity conditions, the usual cumulative abnormal return and feasible investment performance measures are consistent (i.e., they converge to the true ex ante expected performance in large samples). The feasible investment performance measure indicates no pseudo market timing bias, but in finite samples the cumulative abnormal return measures may exhibit pseudo market timing bias. In the next two sections, we investigate the magnitude of this bias. We first calibrate an empirical model for the number of events, and then specify a realistic model for the abnormal returns. Using these inputs, we measure the pseudo market timing bias in samples of a size typically used in empirical research.

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IV. The Empirical Model

In this section, we fit an empirical model of the number of IPOs to actual data. We first describe the data used, arguing that the data series is in fact stationary, and then discuss the empirical model and the estimation results.

A. Data

The main data set we consider is based on monthly aggregated data. The number of IPOs in a month, denoted by N_t, is taken from Jay Ritter's Web site.[7] We consider returns on the S&P 500 index and the average initial underpricing of IPOs, denoted by $R_{m,t}$ and U_t, as proxies for market conditions. The S&P 500 return data are from Ibbotson Associates, while the initial underpricing data are from Jay Ritter's Web site. The initial underpricing variable captures the equally weighted initial underpricing across all IPOs in a month. An individual initial underpricing is measured as the percentage change between the closing price and the offer price within a month of the IPO.[8] The sample period for these variables is January 1960 to December 2003. Figure 1 presents the number of IPOs aggregated by quarter, together with monthly observations of the log of cumulative market returns (labeled log of market index in the figure) and the initial underpricing. We also consider a portfolio of abnormal IPO returns, as studied in Ritter and Welch (2002) and later updated, for the January 1973 to December 2003 period. The abnormal returns are the returns on an equally weighted portfolio of IPOs from the previous 36 months, adjusted for market risk; the abnormal returns are denoted by $r_{IPO,t}$.

From the returns on the S&P 500, the initial underpricing, and the abnormal IPO returns, we compute six- and 12-month moving average series. We will use these moving averages, denoted by $R^6_{m,t}$, $R^{12}_{m,t}$, U^6_t, U^{12}_t, $r^6_{IPO,t}$, and $r^{12}_{IPO,t}$, in the count data regressions below to capture past economic conditions.

Table 2 presents summary statistics of the variables. The total number of IPOs in the sample is 14,889. The average and median numbers of IPOs in a month are 28.2 and 22, respectively. The number of IPOs in a month varies considerably, the standard deviation being 24.6; there are 20 months with no IPOs, and the maximum number of IPOs in a month is 122. Note that the variance is much greater than the mean, which in the case of count data is referred to as overdispersion. The average return on the S&P 500 is 0.93% per month (11.2% annualized) with a standard deviation of 4.3% per month (15.0% annualized). The average initial underpricing is 18%, but ranges from a minimum of −28.8% to a maximum of 119.1%; the median underpricing is 13%. The average abnormal return is −0.17% per month, that is, the IPO portfolio has underperformed the market by approximatively 2% per year. The standard deviation of the abnormal

[7]The number of offerings excludes Regulation A offerings and offerings of REITs and closed-end funds, but includes ADRs. Jay Ritter's Web site (http://bear.cba.ufl.edu/ritter/) provides detailed descriptions and references to data sources.

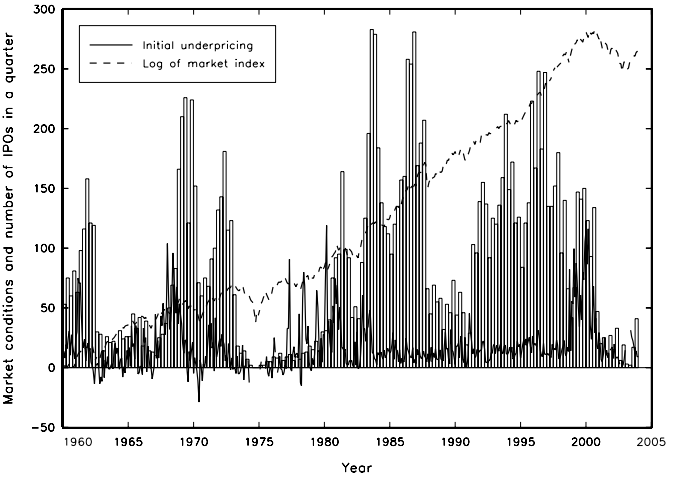
[8]The definition of underpricing varies somewhat in the sample as described in Ibbotson and Jaffe (1975), Ritter (1984), and updates of Ibbotson, Sindelar, and Ritter (1988), (1994) available on Jay Ritter's Web site.

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FIGURE 1

Market Conditions and Number of IPOs

Figure 1 presents the number of IPOs in a quarter (bars) as well as monthly observations concerning 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.



return is 5% per month, which means that the abnormal return volatility is somewhat higher than the market return volatility; this high volatility can also be seen in the extreme minimum and maximum abnormal returns.

TABLE 2

Summary Statistics

Table 2 presents summary statistics for monthly observations of the number of IPOs in a month (N_t), S&P 500 returns ($R_{m,t}$), average initial underpricing of 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 December 2003, yielding 528 observations. The sample period for $r_{IPO,t}$ is January 1973 to December 2003, yielding 372 observations. The number of months with zero IPOs is 20 (or 3.8% of all observations). The $R_{m,t}$ and $r_{IPO,t}$ statistics are expressed in % per month.

Statistic	Number of IPOs N_t	Return on S&P 500 $R_{m,t}$	Underpricing U_t	Abnormal IPO Return $r_{IPO,t}$
Mean	28.20	0.93	18.03	−0.17
Median	22	1.09	13.30	−0.50
Std. Dev.	24.63	4.33	21.19	5.24
Minimum	0	−21.52	−28.80	−17.37
Maximum	122	16.57	119.10	34.07

For the period from January 1975 and onward, we have more detailed information on individual IPOs. We collect monthly return data for each stock from the Center for Research in Security Prices, and perform an event study of these IPO returns. Based on market model residuals and Fama and French's (1996) three-factor model residuals, we calculate the equally weighted cumulative abnormal return, the cross-sectionally weighted cumulative abnormal return, and the feasible investment abnormal return on a 36-month horizon. Table 3 summarizes the results. The market beta of IPO returns is 1.4, which is in line with the findings of other studies, e.g., Ritter and Welch (2002) and Schultz (2004). The size and

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value factors in the Fama-French model are significant and the coefficients are of the expected sign. The α of the regression, which represents the outperformance of the feasible investment strategy, is also not significant.[9] The abnormal return measures are always negative, but only the equally weighted cumulative abnormal return for the market model residuals is (borderline) significant at the 5% level; all the other measures are not significant at the usual significance levels.[10] We also note that the cumulative abnormal returns of the three-factor model residuals are closer to zero than the cumulative abnormal returns based on the market model.

TABLE 3

Event Study Results

Table 3 presents the results of an event study of monthly IPO data. The sample period is January 1975 to December 2003, yielding 348 monthly observations with a total of 8,383 event firms. Monthly IPO portfolio returns are calculated as the average return on all the firms that had an IPO in the preceding 36 months. The first columns of the table report coefficients of regressions of the IPO portfolio returns on the market excess return ($R_M - R_f$) and the returns on the Fama and French (1996) size and value factors, denoted by *SMB* and *HML*. The factor returns are obtained from Ken French's Web site at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. Standard errors are reported in parentheses. The column ρ is the cross-sectional correlation between regression residuals. The columns labeled CAR_{EW}, CAR_{CW}, and AR_{FI} are the 36-month equally weighted and cross-sectionally weighted cumulative abnormal returns and the abnormal return measure of the feasible investment strategy, respectively. For the performance measures, the numbers in curly brackets are *t*-statistics, not corrected for potential serial or cross correlation in the abnormal returns. Simulated distributions of the *t*-statistics are used to obtain correct *p*-values, which are reported in square brackets.

Model	α	$R_M - R_f$	*SMB*	*HML*	ρ	CAR_{EW}	CAR_{CW}	AR_{FI}
Market-Adjusted	−0.22	1.40			0.057	−15.99	−7.78	−7.94
	(0.26)	(0.06)				{−11.79}	{−3.34}	{−0.84}
						[0.05]	[0.22]	[0.20]
FF Three Factor	−0.20	1.13	1.04	−0.33	0.012	−0.54	−0.22	−7.22
	(0.18)	(0.04)	(0.06)	(0.06)		{−0.41}	{−0.12}	{−1.17}
						[0.45]	[0.47]	[0.11]

In the case of the individual IPOs, we also collect information regarding the industry of the firms going public. These data are later used to investigate whether there are industry-specific patterns and to calibrate simulation parameters.

We complement the monthly aggregated data with longer time series of the number of IPOs and of abnormal IPO returns obtained from Gompers and Lerner (2003). These are annual data covering the period 1935 to 1976, and we combine them with monthly data to obtain annual series from 1935 to 2004 of the number of IPOs and of market returns, and of abnormal returns from 1935 to 2003.[11] The annual data indicate fewer IPOs earlier in the sample, but in total we have 15,519 IPOs; the average number of IPOs per year is 225 and the median is 84. The

[9] Ang, Gu, and Hochberg (2007) report significant IPO underperformance of an alternative trading strategy, which considers a portfolio of firms going public within a 12- or 36-month formation period and holds these firms for a period longer than one month.

[10] To obtain the correct *p*-values for the tests, we simulated our DGP from Section V using 348 monthly observations and considering a 36-month event horizon. We use the simulated distribution of the *t*-statistics of the cumulative abnormal return measures to obtain correct *p*-values for the inference. These simulations also indicate that the pseudo market timing bias is small; the largest value (in absolute terms) is 0.24% for the equally weighted cumulative abnormal return, which is extremely small compared to the measured cumulative abnormal return of −16% and does not affect the inference.

[11] The Ritter (1991) and Gompers and Lerner (2003) data are collected from similar databases and using similar sample criteria though there are some differences. We compare the two data sets for the overlapping periods and conclude that they display similar patterns. For example, the correlation between the annual number of IPOs from 1960 to 1972 is 0.97, and the correlation between abnormal returns from 1971 to 1976 is 0.96. In the combined annual series of the number of IPOs, we use the Gompers-Lerner data up to 1972 and the Ritter data from 1973 onward.

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annual data also indicate great dispersion in the number of IPOs, the minimum and maximum numbers of IPOs in a year being one and 953, respectively. Finally, note that Gompers and Lerner (2003) do not find any long-run abnormal IPO performance on average. This is not critical for our analysis, as we mainly want to measure the response of the abnormal performance in a year for firms' decisions to go public the next year. This larger sample allows us to check the robustness of our results, in particular, regarding the dynamics of the number of IPOs and of the baseline model used in the simulations.

B. Stationarity of the Number of IPOs

Much of the debate on the effect of pseudo market timing in event studies concerns the stationarity of the number of events. Several studies, including Lowry (2003), Schultz (2004), and Viswanathan and Wei (2006), test for a unit root in the number of IPOs. These tests are inconclusive. We perform unit root tests ourselves. We perform the tests both on N_t and on $\ln(N_t^*)$, where $N_t^* = \max(N_t, d)$. The value $0 < d < 1$ in the max operator prevents potential problems in taking the logarithm when $N_t = 0$. We let $d = 0.5$, but experimenting with different values reveals that the results are not sensitive to the choice of d.

Augmented Dickey-Fuller (ADF) test statistics of the monthly series, N_t, are -3.66 (constant term only) and -3.75 (constant term and trend) with five lags of the change in N_t. These values are below the 1% critical value in the case without trend and below the 5% critical value in the case with trend. The preferred model fitted using the SIC criterion is a model with two lags and no trend; for this model, the ADF test statistic is -3.99, which is below the 1% critical value. For the transformed variable, $\ln(N_t^*)$, the preferred model has three lags and no trend. The ADF test statistic is -2.82, which is just above the 5% critical value (-2.85), but below the 10% critical value (-2.59) of the test. Hence, we reject the unit root hypothesis at reasonable significance levels for the monthly IPO data. An alternative test of stationarity, the KPSS test developed by Kwiatkowski, Phillips, Schmidt, and Shin (1992), takes trend stationarity as the null hypothesis and tests against the alternative of a unit root. The KPSS test does not reject stationarity for either N_t or $\ln(N_t^*)$ at the usual levels of significance.[12] The measured autocorrelation coefficients are 0.91 for N_t and 0.94 for $\ln(N_t^*)$.

We also perform unit root tests on the annual series, which span a longer time period than the monthly data (70 years versus 45 years). For N_t, the ADF test statistic (with trend) is -4.06, which is significant at the 5% level, and almost significant at the 1% level. We also reject nonstationarity at the 5% level for $\ln(N_t^*)$; the ADF test statistic is -3.82 in that case. The KPSS tests do not reject stationarity at the 5% level for either N_t or $\ln(N_t^*)$: the test statistics are 0.061 for N_t and 0.133 for $\ln(N_t^*)$, respectively, with a 5% critical value of 0.146. From these results, we conclude that the annual series are stationary around a

[12] The KPSS test requires the choice of a lag length for the calculation of Newey-West standard errors; this lag length is determined by the autocorrelation of the residuals of a regression of the time series on an intercept and a trend. In our application, the autocorrelation is significant up to 36 lags or more, and we calculate the tests with 36 lags. This gives test statistics of 0.077 for N_t and 0.094 for $\ln(N_t^*)$, neither of which is significant at the 10% level.

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deterministic trend and contain no random walk component. The measured autocorrelation coefficients for the annual series are 0.42 for N_t and 0.72 for $\ln(N_t^*)$, which means that the mean reversion in the annual series is stronger than in the monthly series—exactly what is expected for a stationary series.

To gain further insight into the aggregated number of IPOs, we use the data regarding individual IPOs that we have from 1975 onward. We use industry codes to aggregate these data by industry, and then evaluate whether any industry patterns are evident in the dynamics of the numbers of IPOs. The industries (number of IPOs) are: Basic industry (700), Capital goods (1,023), Construction (139), Consumer durables (1,213), Finance/real estate (1,261), Food/tobacco (167), Leisure (458), Petroleum (187), Services (2,167), Textiles/trade (540), Transportation (207), Utilities (501), Public (7), and Non-Classifiable (15). The industries with the most IPOs all display cycles in IPO volume. The industry with a seemingly upward trend is Services. We further divide Services into Software (466), Other computer services (684), Other business services (312), Health services (289), Engineering/research/management (284), and Other services (132). We find that the trend in Services is mainly driven by Software and Other computer services, which are strongly related to the so-called technology bubble of the late 1990s. This period of many new entries came to a dramatic end with the sudden stock price drop in March 2000; these patterns can be seen in Figure 2. That the number of new entries in an industry can increase without bound seems unreasonable and finds no support in the data. We view the strong cyclicality of industry IPO activity as casual evidence of the implausibility of a nonstationary process for the number of IPOs.

In addition to this evidence, we argue that given the distribution of the data, it is not plausible for the process generating the number of IPOs to be nonstationary. To support this point, we reestimate from the data our preferred count data model in the next subsection, but with a unit coefficient imposed on the lagged number of IPOs. We then simulate time series of 500 monthly observations, starting with 30 events in the first month (close to the sample average). 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 the actual data and for the time series of the number of events generated from our preferred stationary specification. These distributions are plotted in Figure 3, Graphs A–C. The data (Graph A) and the stationary process (Graph B) display basically a similar, mildly hump-shaped pattern. The pattern for the unit coefficient case (Graph C) is much more skewed. The median of the generated distribution is smaller than the sample median; in contrast, the mean of the generated distribution is larger than the sample mean. On one hand, the left tail of the distribution has too many observations comprising zero or only a few events. On the other hand, the right tail of the distribution has too many observations with extremely high numbers of events per month (occasionally reaching 10,000 at which level we truncate the process).[13] Note that in the estimation, the conditional mean and the variance are

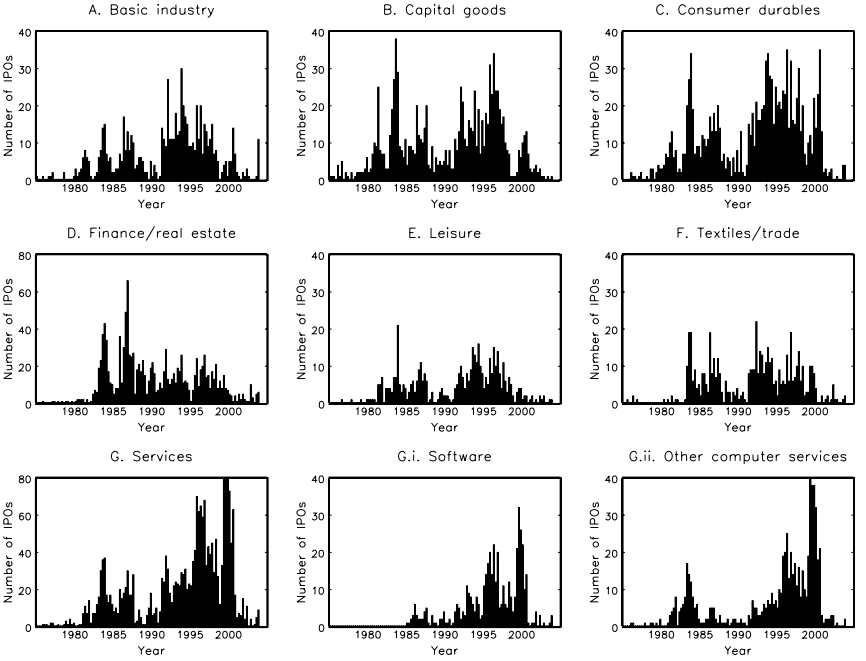
[13]This extreme skewness can also be noted from the coefficient of variation (standard deviation divided by mean) of the number of observations per month. In the actual data, the coefficient of variation is 0.87, while in the simulations of the stationary model it is 0.84. In contrast, for the unit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

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FIGURE 2

Number of IPOs in Industries

Graphs A–G in Figure 2 present the number of IPOs in a quarter for seven industries based on two-digit SIC codes: Basic industry, Capital goods, Consumer durables, Finance/real estate, Leisure, Textiles/trade, and Services. Graphs G.i and G.ii present the number of IPOs for two sub-groups of Services: Software and Other computer services. The scale in Graphs D and G runs from 0 to 80 IPOs per quarter, whereas the scale in all other graphs runs from 0 to 40 IPOs per quarter. There are two quarters in Graph G with more than 80 IPOs (84 and 90 IPOs in Quarters III and IV, respectively, in 1999). The sample period is 1975 to 2003.



matched to capture the time-series dynamics of the number of events, whereas the graphs display the unconditional 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 result, we find that a unit root process for the number of IPOs is implausible.

C. An Empirical Model of the Number of IPOs

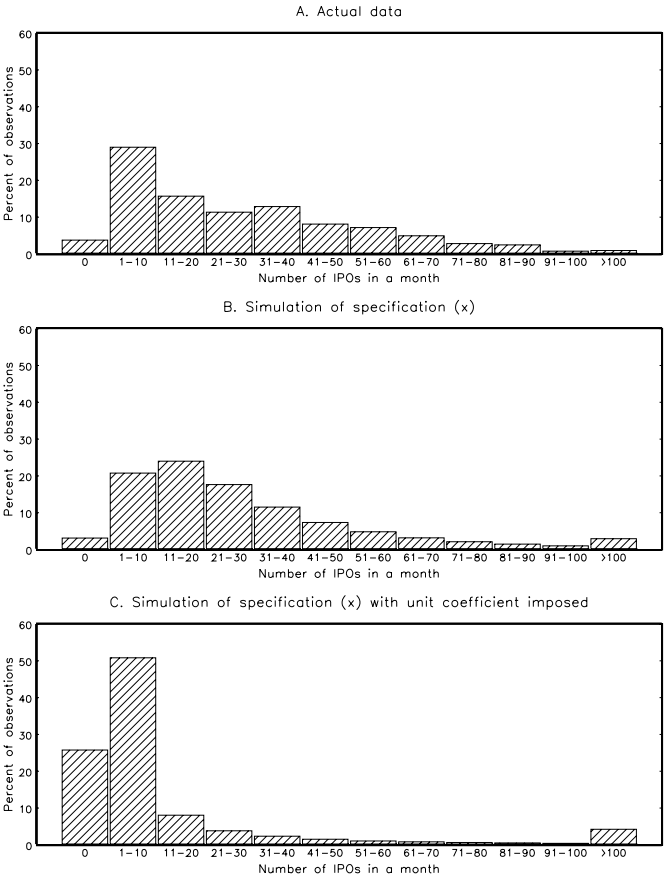
In this subsection, we describe the empirical model, which is first fitted to the monthly and then to the annual data. This model will form the basis of our small-sample simulation study of the pseudo market timing bias in Section V. We first take a closer look at the data. In the model, we are interested in the effects of economic conditions on the number of IPOs. Figure 1 shows that there are four distinct periods of relatively low IPO activity: 1963–1967, 1973–1979, 1988–1990, and 2001 to the end of the sample. Consequently, there are also four periods of relatively high IPO activity: up to and including 1962, 1968–1972, 1980–1987, and 1991–2000. In each of the low activity periods, the annual number of IPOs is well below 240 (a monthly average of less than 20 IPOs), whereas the annual

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FIGURE 3

Number of IPOs in Industries

Graphs A–C in Figure 3 present 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, and 91–100, and observations above 100. Graph A presents the distribution of actual data. Graph B presents the distribution of a simulation of specification (x) in Table 4. Graph C presents the distribution of a simulation of specification (x) when a unit coefficient on the lagged number of IPOs is imposed in the estimation. The distributions in Graphs B and C are generated by simulating 200 time series of 500 observations in which the initial value is set to 30 and then considering the percentage of the observations in each bin.



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 though substantial underpricing is followed by a period of high IPO activity. However, the most recent period of low IPO activity (after the dramatic fall in prices in the aftermath of the technology bubble) is preceded by a period of substantial initial underpricing.

To estimate the effects of market conditions on the number of IPOs, we use count data regressions in which the non-negative integer character of the data (the number of IPOs per month) is explicitly acknowledged. The non-negativity is, in general, of concern for the fitted values of the number of IPOs, and, in particular,

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of concern for simulations of the number of IPOs.[14] 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 the explanatory variables. This makes the model well suited for simulations.

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

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

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

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

This equality of the mean and variance is referred to as equidispersion. When the variance is larger (smaller) than the mean, there is overdispersion (underdispersion). Empirically, overdispersion is common (for example, we have noted above 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 distribution; thus we have

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

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

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 demonstrate that the conditional mean and variance are now

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

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

These moments are equal to the mean and variance of the negative binomial II model of Cameron and Trivedi (1986), and are 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,

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

where β and x_{t-1} are both vectors of dimension l. As described in detail below, we include a constant term, lagged six- and 12-month moving averages of market

[14] Indeed, predicted values in Schultz (2003) are negative in some periods (see his Figure 1); simulated values in his model suffer from this drawback as well.

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returns, lagged initial underpricing, lagged abnormal returns, and a function of the lagged number of IPOs in x_{t-1}. To capture this autoregressive component in the number of IPOs, we use $\ln(N^*_{t-1})$, where $N^*_{t-1} = \max(N_{t-1}, 0.5)$ as a regressor. The reason for using $\ln(N^*_{t-1})$ rather than N^*_{t-1} is that the model could otherwise explode (see Cameron and Trivedi (1998)).

We use the generalized method of moments (GMM) of Hansen (1982) to estimate parameters, using the moment conditions:

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

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

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).[15] 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.[16] Note that the Poisson regression model is intrinsically heteroskedastic, and that GMM can provide a consistent covariance matrix robust to autocorrelation and heteroskedasticity.

The first results of the count data regressions are presented in Table 4. We consider several model specifications to find a model that can characterize data well while capturing the underlying idea of pseudo market timing. Specifications (i) to (vi) each include one of the measures of past economic conditions. The lagged six-month moving averages of market returns, initial underpricing, and abnormal returns are all statistically significant; the lagged 12-month moving average of market returns is also statistically significant. The economic effect of market conditions on the number of IPOs seems significant. For example, the measured coefficient on the lagged 12-month moving average of market returns in specification (iv) is 8.507. This means that after a year with a one percentage point increase in the average S&P 500 return, the number of IPOs in the following month is expected to increase by 8.507%. Given the moving average feature of the variable, this effect only dies out after a 12-month period.

We also run specifications with multiple measures of economic conditions in Table 4. Specification (vii) suggests that both the lagged market return and the abnormal returns are important. Specification (viii) suggests that the lagged 12-month moving average of the market returns is key. Taken together with the results for specification (ix), this indicates that the 12-month moving average of S&P 500 returns and the lagged six-month moving average of lagged abnormal IPO returns in specification (x) are the main drivers of the results.

Following Lowry (2003) and Pástor and Veronesi (2005), we also consider specifications with a dummy variable for observations in the first quarter of a year, but find no evidence of quarterly seasonality. However, specifications with

[15] Alternative ways to identify σ_η^2 (see, for example, Gourieroux, Monfort, and Trognon (1984)) yield similar estimates. See also Hall, Griliches, and Hausman (1986) for an application.

[16] 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 inappropriate.

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TABLE 4

Empirical Models of the Number of IPOs

Table 4 presents the results of count data regressions for the number of IPOs (denoted by N_t). Lagged six- and 12-month moving averages of S&P 500 returns ($R^6_{m,t-1}$ and $R^{12}_{m,t-1}$), initial underpricing (U^6_{t-1} and U^{12}_{t-1}), abnormal IPO returns ($r^6_{IPO,t-1}$ and $r^{12}_{IPO,t-1}$), and functions of the 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 demeaned. Sample counterparts of moment conditions (20) and (21) in the text are used to identify parameters:

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

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

where x_{t-1} contains a one, as well as one or several of the following variables: $R^6_{m,t-1}$, U^6_{t-1}, $r^6_{IPO,t-1}$, $R^{12}_{m,t-1}$, U^{12}_{t-1}, $r^{12}_{IPO,t-1}$, and $\ln(N^*_{t-1})$. Heteroskedasticity and autocorrelation consistent standard errors (Newey and West (1987) with four lags) are given in parentheses below the point estimates. R^2 I refers to the pseudo R^2 in Cameron and Trivedi (1986) for the basic Poisson model. R^2 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.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Moment Conditions (20)										
1	0.569	0.535	0.580	0.617	0.549	0.624	0.601	0.722	0.690	0.686
	(0.068)	(0.070)	(0.091)	(0.071)	(0.070)	(0.093)	(0.088)	(0.092)	(0.094)	(0.091)
$R^6_{m,t-1}$	4.616						5.013		0.265	
	(1.036)						(1.046)		(1.667)	
U^6_{t-1}		0.248					0.024		0.084	
		(0.092)					(0.098)		(0.315)	
$r^6_{IPO,t-1}$			2.168				1.667		3.171	1.698
			(0.923)				(1.026)		(1.364)	(0.838)
$R^{12}_{m,t-1}$				8.507				10.663	9.618	10.519
				(1.747)				(1.783)	(2.231)	(1.762)
U^{12}_{t-1}					0.195			−0.002	−0.080	
					(0.103)			(0.130)	(0.375)	
$r^{12}_{IPO,t-1}$						−0.300		−0.226	−3.363	
						(1.228)		(1.370)	(1.873)	
$\ln(N^*_{t-1})$	0.828	0.840	0.848	0.799	0.840	0.834	0.819	0.761	0.773	0.773
	(0.019)	(0.019)	(0.024)	(0.023)	(0.020)	(0.025)	(0.024)	(0.028)	(0.028)	(0.028)
Moment Condition (21)										
σ^2_η	0.305	0.310	0.304	0.297	0.309	0.308	0.298	0.292	0.289	0.290
	(0.016)	(0.017)	(0.020)	(0.017)	(0.017)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Diagnostics										
R^2 I	0.798	0.794	0.803	0.804	0.796	0.799	0.809	0.811	0.814	0.815
R^2 II	0.760	0.754	0.765	0.769	0.756	0.757	0.772	0.775	0.779	0.781
T	522	522	366	516	516	360	366	360	360	366

monthly dummies for January, February, and March indicate that (conditionally) there are significantly fewer IPOs in January.

Specifications (i) to (x) in Table 4 all indicate that there is relatively high persistence in the number of IPOs; the coefficients on the lagged number of IPOs are approximately 0.8. To check how robust the results are to the chosen lag length in the number of IPOs, we consider some further model specifications. These results are reported in Table 5. Specifications (xi) to (xv) in Table 5 indicate that the measured coefficients on lag one are lower when more lags of the number of IPOs are included. However, the coefficients on lags one to six are all positive, and lags up to lag four are often statistically significant at the usual significance levels. The sum of all coefficients on the lags in specifications (xi) to (xv) are higher than the single lag in specification (x); they are, however, always less than 0.85. The

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R^2 measures do not strongly favor a particular specification though it is important to include at least one lag of the number of IPOs. The inclusion of further lags changes some of the effects of market conditions; in particular, the measured coefficient on the six-month moving average of abnormal returns increases from approximately 1.7 to 4.8. This turns out to be important as the effect of lagged abnormal returns is crucial for generating any pseudo market timing bias at all. For this reason, we use specification (xv) as the default data-generating process in our simulations.[17]

TABLE 5

Empirical Models of the Number of IPOs: Different Lag Lengths

Table 5 presents the results of count data regressions for the number of IPOs (denoted by N_t) on lagged 12-month moving averages of S&P 500 returns ($R^{12}_{m,t}$), lagged six-month moving average of abnormal IPO returns ($r^{6}_{IPO,t}$), and functions of lagged number of IPOs ($N^*_t = \max(0.5, N_t)$). Sample counterparts of moment conditions (20) and (21) in the text are used to identify parameters. See also the note in Table 4. Heteroskedasticity and autocorrelation consistent standard errors (Newey and West (1987) with four lags) are given in parentheses below the point estimates. R^2 I refers to the pseudo R^2 in Cameron and Trivedi (1986) for the basic Poisson model. R^2 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.

	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
Moment Conditions (20)						
1	0.686	0.606	0.547	0.506	0.490	0.481
	(0.091)	(0.085)	(0.085)	(0.088)	(0.093)	(0.095)
$r^{6}_{IPO,t-1}$	1.698	2.732	3.443	4.128	4.558	4.804
	(0.838)	(0.877)	(0.913)	(0.940)	(1.054)	(1.147)
$R^{12}_{m,t-1}$	10.519	9.940	10.549	11.458	11.987	12.251
	(1.762)	(1.670)	(1.645)	(1.683)	(1.691)	(1.746)
$\ln(N^*_{t-1})$	0.773	0.572	0.505	0.453	0.435	0.433
	(0.028)	(0.042)	(0.048)	(0.051)	(0.055)	(0.055)
$\ln(N^*_{t-2})$		0.230	0.088	0.066	0.059	0.052
		(0.042)	(0.052)	(0.045)	(0.044)	(0.046)
$\ln(N^*_{t-3})$			0.226	0.120	0.113	0.109
			(0.039)	(0.046)	(0.046)	(0.045)
$\ln(N^*_{t-4})$				0.190	0.151	0.146
				(0.054)	(0.055)	(0.056)
$\ln(N^*_{t-5})$					0.074	0.055
					(0.046)	(0.051)
$\ln(N^*_{t-6})$						0.040
						(0.043)
Moment Condition (21)						
σ^2_η	0.290	0.284	0.271	0.262	0.260	0.260
	(0.020)	(0.020)	(0.019)	(0.018)	(0.019)	(0.019)
Diagnostics						
R^2 I	0.815	0.826	0.837	0.845	0.846	0.846
R^2 II	0.781	0.788	0.802	0.812	0.813	0.813
T	366	366	366	366	366	366

As a robustness check, we also estimate a count data regression model for the annual data. These estimation results are presented in Table 6. The main results are that lagged market and abnormal returns affect the number of IPOs both economically and statistically. For example, a one percentage point increase in the abnormal performance of IPOs and the market in the previous year tend

[17]The inclusion of further lags does not overturn our finding that the 12-month moving average of S&P 500 returns and the lagged six-month moving average of lagged abnormal IPO returns capture market conditions.

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to increase the number of IPOs by 1% and 2%, respectively. Given standard deviations of 36% and 18%, these effects seem economically important. Finally, note that including lags of the number of IPOs marginally improves the fit of the empirical model.

TABLE 6

Empirical Models of the Number of IPOs: Annual Data

Table 6 presents the results of count data regressions on annual data. The regressions are on the number of IPOs (denoted by N_t) on the previous year's IPO return ($r_{IPO,t-1}$), previous year's S&P 500 returns ($R_{m,t-1}$), and lagged log number of IPOs ($\ln(N_{t-1})$, $\ln(N_{t-2})$, and $\ln(N_{t-3})$). Sample counterparts of moment conditions (20) and (21) in the text are used to identify parameters. See also the note in Table 4. Heteroskedasticity and autocorrelation consistent standard errors (Newey and West (1987) with four lags) are given in parentheses below the point estimates. R^2 I refers to the pseudo R^2 in Cameron and Trivedi (1986) for the basic Poisson model. R^2 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.

	(I)	(II)	(III)	(IV)	(V)
Moment Conditions (20)					
1	1.392	1.278	1.161	0.945	0.886
	(0.353)	(0.366)	(0.361)	(0.311)	(0.329)
$r_{IPO,t-1}$	1.704		0.712	0.915	0.963
	(0.398)		(0.208)	(0.177)	(0.189)
$R_{m,t-1}$		0.868	1.575	1.724	1.875
		(0.202)	(0.386)	(0.472)	(0.607)
$\ln(N_{t-1})$	0.723	0.791	0.770	0.612	0.599
	(0.057)	(0.057)	(0.059)	(0.154)	(0.154)
$\ln(N_{t-2})$				0.198	0.295
				(0.161)	(0.247)
$\ln(N_{t-3})$					−0.079
					(0.095)
Moment Condition (21)					
σ_η^2	0.476	0.502	0.455	0.441	0.439
	(0.057)	(0.063)	(0.057)	(0.052)	(0.051)
Diagnostics					
R^2 I	0.762	0.739	0.782	0.793	0.791
R^2 II	0.647	0.615	0.671	0.692	0.691
T	68	68	68	67	66

In sum, we demonstrate that past market conditions convey information regarding the current IPO volume. In particular, past market returns and past abnormal IPO returns significantly affect, both statistically and economically, the current number of IPOs. This is consistent with the idea of pseudo market timing. Next, we use the empirical model to conduct simulation experiments.

V. Simulation Evidence

In Section III, we demonstrated that the abnormal return measure that captures a feasible investment strategy is unbiased under pseudo market timing. 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 of the number of IPOs, i.e., specification (xv), discussed in the previous section.

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A. Simulation Setup

The steps in the experiments are:

1. *The data-generating process for market returns.* For each month, a block of 12 subsequent monthly market returns is 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 for abnormal returns.* Cross correlations between abnormal returns for events in the same month are important in practice, and may be one determinant of the magnitude of the pseudo market timing bias in small samples. In this regard, one should recall that the null hypothesis allows for cross correlation, but not for serial correlation as this would imply predictability of abnormal returns. The following error component model is used to simulate abnormal returns with cross correlation:

$$\hat{r}_{i,t} = c_t + \epsilon_{i,t}, \tag{22}$$

where $c_t \sim \mathrm{N}(0, \sigma^2\rho)$ and $\epsilon_{i,t} \sim \mathrm{N}(0, \sigma^2(1-\rho))$ are independent random variables. Note that ρ captures the correlation across abnormal returns, stemming from the common component c_t, and σ^2 is the variance of the abnormal returns. The cumulative abnormal return for any time period and firm is then given by

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

In subsection B, we calibrate the parameters ρ and σ.

3. *The data-generating process for number of IPOs.* The initial number of IPOs is drawn from a Poisson distribution with an unconditional intensity approximated from the mean equation in the Poisson models. This generates approximately 25 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,

$$\beta' x_{t-1} = \beta_0 + \beta_1 c_{t-1}^6 + \beta_2 R_{m,t-1}^{12} + \sum_{\ell=1}^{L} \beta_{3\ell} \ln(N_{t-\ell}^*), \tag{23}$$

where c_t^6 is a six-month moving average of the common component of the abnormal returns, c_t.[18] The data-generating process allows the lagged market returns to affect the future number of IPOs. It will also impose a pseudo market timing effect as the number of IPOs is affected by the abnormal IPO returns in the previous period. The parameters for the actual simulations are picked from the

[18] In the empirical model of the number of IPOs, we used the lagged abnormal returns on a portfolio of IPO firms as regressor. As these portfolios typically contain several hundreds of IPO firms, this portfolio abnormal return is virtually equal to the common component c_t if abnormal returns have a one-factor structure, as we assume.

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estimated parameters from specification (xv) in Table 5 with six autoregressive lags ($L = 6$).[19]

4. *The average abnormal return measures.* The abnormal return measures are calculated according to:

$$CAR_{EW} = \frac{\sum_{t=1}^{T} \sum_{i=1}^{\hat{N}_t} \left(\sum_{k=1}^{K} \hat{r}_{i,t+k} \right)}{\sum_{t=1}^{T} \hat{N}_t}, \tag{24}$$

$$CAR_{CW} = \frac{\sum_{t=1}^{T} \mathrm{I}\left[\hat{N}_t > 0\right] \left(\frac{1}{\hat{N}_t} \sum_{i=1}^{\hat{N}_t} \sum_{k=1}^{K} \hat{r}_{i,t+k} \right)}{\sum_{t=1}^{T} \mathrm{I}\left[\hat{N}_t > 0\right]}, \tag{25}$$

$$AR_{FI} = \frac{1}{T} \sum_{t=1}^{T} \mathrm{I}\left[\sum_{k=1}^{K} \hat{N}_{t-k} > 0 \right] \left(\frac{\sum_{k=1}^{K} \sum_{i=1}^{\hat{N}_{t-k}} \hat{r}_{i,t}}{\sum_{k=1}^{K} \hat{N}_{t-k}} \right). \tag{26}$$

These calculations correspond to equations (2), (5), (8), 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 10,000 times. The averages of the generated measures are reported; we also report the standard errors of the averages as constructed from the standard deviations of the generated abnormal return measures.

B. Cross-Sectional Correlation

The error component model (22) implies an interesting correlation structure for the cumulative abnormal returns. It is straightforward to demonstrate that the variance of the cumulative returns is $K\sigma^2$ and that the cross-sectional covariance is $K\sigma^2\rho$. The correlation between two cumulative abnormal returns is then ρ, which is independent of the accumulation horizon, K. As we demonstrate later, the cross correlation is a major determinant of the pseudo market timing bias and also of the inference properties in event studies (size and power of the t-tests).

Several different values of the cross correlations can be found in the literature. The empirical estimate used in the analysis of Mitchell and Stafford (2000) is 0.026. Brav (2000) performs a Bayesian analysis and reports the posterior mean of the correlation, ρ, to be 0.027 and the standard deviation, σ, to be 0.157. Our estimates presented in Table 3 show that ρ is 0.057 for market model residuals and 0.012 for the Fama and French (1996) three-factor model residuals. These values bracket the estimates of Brav (2000) and Mitchell and Stafford (2000). In the simulations, we therefore consider two cases with $\rho = 0.01$ and $\rho = 0.05$, respectively. The value used for the standard deviation of the abnormal returns is 0.17. Note that for a ρ of 0.05 and 25 IPOs in a given month, this choice of σ implies a standard deviation of the average abnormal returns of approximately

[19] We also run simulation experiments using model (23) with a deterministic trend added. The trend is chosen such that the expected number of IPOs increases by 0.45% per annum, which is the trend fitted by Lowry (2003). The results of these experiments were qualitatively the same as those of the experiments without the trend.

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5% ($\sigma\sqrt{\rho + (1-\rho)/N} = 5.04\%$), which is very close to the standard deviation of the IPO portfolio abnormal returns of 5.24% in the data (see Table 2).

C. Pseudo Market Timing Bias

Table 7 presents the results of our simulations. Panel A reports the results for low cross correlation, $\rho = 0.01$, and Panel B for high cross correlation, $\rho = 0.05$. The table shows a negative bias for the equally weighted measure due to the pseudo market timing effect. However, the magnitudes are small, the biases almost all being below 1% in absolute terms. Only in the high cross correlation case, the equally weighted measure on the 60-month horizon with 100 observations displays a modest bias, but it is still less than 2% in absolute value. All the other biases are negligible. The cross-sectionally corrected measure and the measure of the feasible investment strategy display no biases.

To see how sensitive the results are to the chosen parameter values, we also present simulations in which we expect more significant biases. In Panels C and D of Table 7, we repeat the analysis but for a more persistent process. We increase the persistence of the process (the coefficient on the lagged number of IPOs) to 0.95.[20] Recall that this is the value obtained from an autoregressive model without explanatory variables, which we estimated for the unit root tests, and is the largest value we found in all the model specifications we estimated. Again, the bias is significant only for the equally weighted measure, the largest absolute bias being approximately 3% for the 36-month horizon and 100 observations. For the cross-sectionally weighted abnormal returns, there is only one significant bias for the most extreme setting (the 60-month horizon), but this bias is less than 1%. For the other cases and for the measures of feasible investment abnormal returns, 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 that we can generate using realistic parameter values are much smaller than the underperformance of IPO firms found in empirical studies; for example, compare the 2% bias for the equally weighted measure in Panel D of Table 7 at the 36-month horizon with the 16% bias measured in the data and reported in Table 3. The simulations also reveal that the cross-sectionally corrected measure and the measure of the feasible investment strategy display no significant biases. Based on our results, pseudo market timing does not seem to be a problem for the sample sizes typically used in empirical research on IPO underperformance.

How can we reconcile these results with Schultz's (2003) results? The key issue is that his simulations violate the stationarity assumptions made above. In the case of nonstationary 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 nonstationary model of the number of IPOs is implausible. A critical assumption in our simulations is therefore that the event-

[20] We do not perform event study simulations for the case in which the coefficient of the lagged number of IPOs equals unity. The results presented in Section IV.B indicate that this coefficient value leads to distributions of the number of IPOs that are far from the empirical distribution, so such simulations are not realistic.

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TABLE 7

Simulation Results, Pseudo Market Timing Biases

Table 7 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 from the feasible investment strategy (AR_{FI}) in simulations of an empirical model for the number of IPOs. Parameters for the conditional mean are from specification (xv) in Table 5. The biases are expressed in % over horizons of 1, 36, and 60 months with three different sample sizes (100, 200, and 500 months). The number of replications is 10,000. Below each bias estimate, the Monte Carlo standard error is given in parentheses. There are four different setups. Panel A presents results for the default case: the cross correlation in abnormal returns is set to 0.01 and the standard deviation of the abnormal returns is set to 17% per month. Panel B presents results where the cross correlation in abnormal returns is set to 0.05 (rather than 0.01). Panel C presents results where the effect of the lagged abnormal IPO return is increased to 0.95 and the cross correlation in abnormal returns is set to 0.01. Finally, Panel D presents results where the coefficient on the lagged number of IPOs is 0.95 and where the cross correlation in abnormal returns is set to 0.05 (rather than 0.01). The average number of IPOs in a month (approximately 25) is comparable in all panels.

	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}	−0.01	−0.01	0.00	−0.06	−0.18	−0.06	−0.13	−0.28	−0.10
	(0.00)	(0.00)	(0.00)	(0.06)	(0.05)	(0.03)	(0.10)	(0.07)	(0.05)
CAR_{CW}	−0.01	0.00	0.00	−0.11	−0.06	0.00	0.14	−0.01	−0.07
	(0.00)	(0.00)	(0.00)	(0.06)	(0.05)	(0.03)	(0.10)	(0.07)	(0.05)
AR_{FI}	0.00	0.00	0.00	−0.07	−0.12	0.04	0.12	−0.05	0.07
	(0.00)	(0.00)	(0.00)	(0.07)	(0.05)	(0.03)	(0.11)	(0.07)	(0.05)
Panel B. High Cross Correlations									
CAR_{EW}	−0.03	0.00	0.00	−0.77	−0.63	−0.18	−0.90	−0.58	−0.47
	(0.01)	(0.00)	(0.00)	(0.13)	(0.10)	(0.06)	(0.21)	(0.16)	(0.10)
CAR_{CW}	0.00	−0.01	0.00	0.09	−0.12	0.05	0.18	0.23	−0.05
	(0.01)	(0.00)	(0.00)	(0.13)	(0.10)	(0.06)	(0.21)	(0.15)	(0.10)
AR_{FI}	0.00	0.00	0.00	0.12	−0.07	0.05	0.14	0.24	−0.04
	(0.01)	(0.00)	(0.00)	(0.14)	(0.10)	(0.06)	(0.23)	(0.16)	(0.10)
Panel C. High Persistence									
CAR_{EW}	−0.03	−0.02	0.00	−0.52	−0.36	−0.22	−0.61	−0.47	−0.28
	(0.01)	(0.00)	(0.00)	(0.07)	(0.06)	(0.04)	(0.10)	(0.08)	(0.06)
CAR_{CW}	−0.02	−0.01	0.00	0.03	−0.26	−0.03	−0.10	0.02	0.02
	(0.01)	(0.01)	(0.00)	(0.07)	(0.05)	(0.03)	(0.11)	(0.08)	(0.05)
AR_{FI}	0.01	0.00	0.00	−0.11	0.06	0.01	−0.16	0.03	−0.02
	(0.01)	(0.01)	(0.00)	(0.07)	(0.05)	(0.03)	(0.11)	(0.08)	(0.05)
Panel D. High Cross Correlations and High Persistence									
CAR_{EW}	−0.10	−0.07	−0.04	−2.00	−1.65	−0.76	−2.65	−2.44	−1.54
	(0.01)	(0.01)	(0.00)	(0.15)	(0.12)	(0.09)	(0.22)	(0.18)	(0.13)
CAR_{CW}	−0.02	−0.01	−0.01	−0.32	−0.16	0.05	−0.07	−0.28	−0.25
	(0.01)	(0.01)	(0.00)	(0.14)	(0.10)	(0.07)	(0.21)	(0.16)	(0.10)
AR_{FI}	−0.01	0.00	0.00	−0.01	−0.02	0.14	−0.04	−0.18	−0.15
	(0.01)	(0.01)	(0.00)	(0.14)	(0.10)	(0.06)	(0.23)	(0.17)	(0.10)

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, it cannot be absorbed at zero and does not explode. Recall that if we let the process be close to integrated but still stationary, there is still no bias in typical sample sizes.

Our results also seem to contradict those 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 returns affect the number of IPOs. Looking more closely at the way Schultz 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):

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$$R_{i,t} = a + \beta_{i,m} R_{m,t} + \nu_{i,t}, \quad R_{m,t} \sim \mathrm{N}(\mu_m, \sigma_m^2), \quad \nu_{i,t} \sim \mathrm{N}(0, \sigma_\nu^2), \tag{27}$$

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 constant a is chosen such that the IPO returns have the same unconditional mean as does the market. According to his Table III, Schultz (2004) defines abnormal returns as

$$r_{i,t} = R_{i,t} - R_{m,t}. \tag{28}$$

It is straightforward to show that given the DGP defined in equation (27), the mean of the abnormal returns is zero. However, the cross-sectional correlation between the abnormal returns defined in equation (28) is nonzero and given by

$$\mathrm{Corr}\,(r_{i,t}, r_{j,t}) = \frac{\mathrm{Cov}\,(r_{i,t}, r_{j,t})}{\mathrm{Var}\,(r_{i,t})} = \frac{(\beta_{i,m} - 1)^2 \sigma_m^2}{(\beta_{i,m} - 1)^2 \sigma_m^2 + \sigma_\nu^2}. \tag{29}$$

Plugging in the parameter values used by Schultz (2004) yields a cross-sectional correlation of 15%, which is much higher than the data suggest. This high correlation exacerbates the pseudo market timing bias.[21]

D. Inference

To address the impact of pseudo market timing for statistical inference in event studies, we undertake simulations under the null hypothesis of no abnormal returns and under an alternative hypothesis of negative abnormal returns. Mitchell and Stafford (2000) show that the t-statistics of the cumulative abnormal return measures in long-horizon event studies are seriously biased because of serial correlation in the cumulative abnormal return. Interestingly, this serial correlation is related to the cross-sectional correlation between contemporaneous events as demonstrated in the Appendix. In the preceding simulation analysis, we demonstrated that the bias in measured abnormal returns is sensitive to the cross-sectional correlation between the abnormal returns of different firms; we now demonstrate that inference is also sensitive to cross-sectional correlation.

The simulations for the inference are in two parts. First, we simulate under the null hypothesis that expected abnormal returns are zero (i.e., $\mathrm{E}(r_{i,t}|\Omega_{t-1}) = 0$). These are exactly the same simulations as before. In each simulation, we calculate the (unadjusted) t-statistics of the cumulative abnormal returns. From these simulations, we calculate the rejection frequency using the 5% critical value for the one-sided test of the normal distribution (that is, -1.65). We also calculate the actual 5% quantile of the simulated t-statistics. In the second part of the inference analysis, we simulate abnormal returns under the alternative hypothesis

[21] With a cross-sectional correlation of 15%, the pseudo market timing bias under our DGP roughly doubles from that of the case with a cross-sectional correlation of 5% (the case with high cross correlations in Panel B of Table 7).

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that there is genuine underperformance. We assume an expected abnormal return of −0.2% per month. This translates into an expected underperformance of 7.2% over 36 months and 12% over 60 months. Again, we calculate the unadjusted *t*-statistics for the test that abnormal returns are zero. The null hypothesis is rejected if the *t*-statistic exceeds the correct critical value, which was calculated in the simulations under the null hypothesis. The power of the test is then simply the relative frequency of rejection under this alternative.

Table 8 shows that under the null the rejection frequency of the equally weighted measure, CAR_{EW}, is always higher than 5%, and that the 5% quantile of the *t*-statistic is lower than the theoretical value of −1.65. This is also the case for $K = 1$ because CAR_{EW} completely ignores cross-sectional correlation. As expected, the cross-sectionally weighted measure, CAR_{CW}, demonstrates no excess rejection for the one-month horizon. However, for longer horizons both measures display high rejection frequencies of between 25% and 34%. The actual 5% quantile of the *t*-statistic is much smaller than −1.65. The magnitude of the bias in the *t*-statistic is roughly what the theoretical analysis in the Appendix predicts, i.e., approximately a factor of three. In sharp contrast to the two cumulative abnormal return measures, the rejection frequencies and *t*-statistics of the measure of feasible investment abnormal returns, AR_{FI}, are well behaved for all horizons.

TABLE 8

Simulation Results under the Null

Table 8 presents the 5% quantile of the *t*-statistic and the rejection frequency of the null hypothesis of no IPO underperformance for tests based on the equally weighted cumulative abnormal return measure (CAR_{EW}), the cross-sectionally weighted cumulative abnormal return measure (CAR_{CW}), and the average abnormal return from the feasible investment strategy (AR_{FI}) in simulations of an empirical model of the number of IPOs. Parameters for the conditional mean are from specification (xv) in Table 5. The tests are based on the usual *t*-statistic of performance measures over horizons of 1, 36, and 60 months with three different sample sizes (100, 200, and 500 months). The number of replications is 10,000. Below each bias estimate, the Monte Carlo standard error is given in parentheses. There are two different setups. Panel A presents results for the default case: the cross correlation in abnormal returns is set to 0.01 and the standard deviation of the abnormal returns is set to 17% per month. Panel B presents results where the cross correlation in abnormal returns is set to 0.05 (rather than 0.01).

	1-Month Horizon			36-Month Horizon			60-Month Horizon		
Measure	100	200	500	100	200	500	100	200	500
Panel A. Default Case									
5% Quantile of t-Statistic									
CAR_{EW}	−1.90	−1.89	−1.88	−4.92	−5.17	−5.30	−5.84	−6.44	−6.54
CAR_{CW}	−1.69	−1.66	−1.65	−4.09	−4.13	−4.09	−5.07	−5.17	−5.15
AR_{FI}	−1.64	−1.64	−1.67	−1.70	−1.66	−1.69	−1.62	−1.68	−1.65
Size of t-Test									
CAR_{EW}	0.08	0.08	0.08	0.30	0.32	0.31	0.33	0.35	0.35
CAR_{CW}	0.06	0.06	0.05	0.25	0.26	0.26	0.30	0.31	0.30
AR_{FI}	0.05	0.06	0.06	0.06	0.06	0.06	0.05	0.06	0.05
Panel B. High Cross Correlations									
5% Quantile of t-Statistic									
CAR_{EW}	−2.65	−2.65	−2.61	−10.61	−11.07	−11.14	−12.97	−13.50	−14.26
CAR_{CW}	−1.67	−1.67	−1.65	−7.29	−7.09	−6.85	−9.27	−8.94	−8.98
AR_{FI}	−1.62	−1.65	−1.66	−1.67	−1.66	−1.63	−1.66	−1.67	−1.65
Size of t-Test									
CAR_{EW}	0.16	0.16	0.17	0.42	0.43	0.41	0.43	0.43	0.45
CAR_{CW}	0.05	0.06	0.06	0.35	0.36	0.35	0.38	0.38	0.38
AR_{FI}	0.05	0.05	0.05	0.06	0.05	0.05	0.05	0.06	0.06

Table 9 shows simulations under the alternative hypothesis of genuine underperformance. The bias in the abnormal return measures is similar to the bias under the null hypothesis (reported in Table 7). More interesting, however, is the power of the tests. Loughran and Ritter (2000) argue that the calendar-time portfolio approach implemented in our feasible investment strategy is inefficient because it puts the same weight on a month with few events as on a month with many events. If there were no cross-sectional correlation, this would mean suboptimal weighting of events. In that case, the equally weighted abnormal return measure, CAR_{EW}, would be optimal. In the presence of cross-sectional correlation, however, neither approach is theoretically superior because all methods use suboptimal weighting schemes: CAR_{EW} makes no correction for cross correlation, whereas CAR_{CW} and AR_{FI} apply crude corrections. The simulation results presented in Table 9 indicate that the power (calculated using the correct critical values obtained from the simulations under the null hypothesis) increases slightly with the accumulation horizon, but is fairly low in all cases. Comparing

TABLE 9

Simulation Results under the Alternative

Table 9 presents the average underperformance under the alternative hypothesis that $E(r_{i,t}|\Omega_{t-1}) = -0.2\%$, as measured by the equally weighted cumulative abnormal return measure (CAR_{EW}), the cross-sectionally weighted cumulative abnormal return measure (CAR_{CW}), and the average abnormal return from the feasible investment strategy (AR_{FI}), in simulations of an empirical model of the number of IPOs. Parameters for the conditional mean are from specification (xv) in Table 5. The tests are based on the usual *t*-statistic of performance measures over horizons of 1, 36, and 60 months with three different sample sizes (100, 200, and 500 months). The number of replications is 10,000. Below each estimate, the Monte Carlo standard error is given in parentheses. The table also presents the power of the size-adjusted *t*-test. This power is defined as the rejection frequency of the null hypothesis of no underperformance, using the simulated 5% quantiles of the *t*-statistic from Table 8 as the critical values. There are two different setups. Panel A presents results for the default case: the cross correlation in abnormal returns is set to 0.01 and the standard deviation of the abnormal returns is set to 17% per month. Panel B presents results where the cross correlation in abnormal returns is set to 0.05 (rather than 0.01).

	1-Month Horizon			36-Month Horizon			60-Month Horizon		
Measure	100	200	500	100	200	500	100	200	500
Panel A. Default Case									
Average Cumulative Abnormal Return									
CAR_{EW}	−0.21	−0.20	−0.20	−7.40	−7.36	−7.20	−12.15	−12.04	−12.00
	(0.00)	(0.00)	(0.00)	(0.06)	(0.05)	(0.03)	(0.10)	(0.07)	(0.05)
CAR_{CW}	−0.20	−0.19	−0.20	−7.24	−7.26	−7.14	−11.93	−11.88	−11.91
	(0.00)	(0.00)	(0.00)	(0.06)	(0.05)	(0.03)	(0.10)	(0.07)	(0.05)
AR_{FI}	−0.18	−0.19	−0.19	−7.23	−7.24	−7.14	−11.94	−11.84	−11.96
	(0.00)	(0.00)	(0.00)	(0.06)	(0.05)	(0.03)	(0.11)	(0.07)	(0.05)
Size-Corrected Power of t-Test									
CAR_{EW}	0.12	0.18	0.31	0.32	0.48	0.79	0.36	0.49	0.81
CAR_{CW}	0.11	0.16	0.27	0.32	0.48	0.79	0.33	0.50	0.82
AR_{FI}	0.13	0.17	0.27	0.31	0.49	0.81	0.33	0.49	0.82
Panel B. High Cross Correlations									
Average Cumulative Abnormal Return									
CAR_{EW}	−0.23	−0.21	−0.21	−7.93	−7.90	−7.42	−13.35	−13.03	−12.62
	(0.01)	(0.00)	(0.00)	(0.13)	(0.10)	(0.06)	(0.21)	(0.16)	(0.10)
CAR_{CW}	−0.20	−0.20	−0.20	−7.04	−7.33	−7.15	−12.20	−12.16	−12.19
	(0.01)	(0.00)	(0.00)	(0.13)	(0.09)	(0.06)	(0.21)	(0.15)	(0.10)
AR_{FI}	−0.18	−0.19	−0.19	−7.03	−7.32	−7.17	−12.15	−12.14	−12.16
	(0.01)	(0.00)	(0.00)	(0.14)	(0.10)	(0.06)	(0.23)	(0.16)	(0.10)
Size-Corrected Power of t-Test									
CAR_{EW}	0.09	0.12	0.21	0.14	0.19	0.33	0.15	0.21	0.33
CAR_{CW}	0.09	0.12	0.19	0.14	0.18	0.33	0.15	0.21	0.32
AR_{FI}	0.10	0.13	0.21	0.15	0.19	0.33	0.14	0.20	0.34

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the power of the various performance measures, there is no clear ranking of the various methods: the size-corrected power of the three performance measures is similar in all experiments.

To summarize, we find that inference using cumulative abnormal return measures is very sensitive to cross-sectional correlation in event returns. Even with a small positive correlation, the standard t-tests based on the cumulative abnormal return measures reject the null hypothesis of no abnormal returns too often. Note, however, that these inference issues are not directly driven by the pseudo market phenomenon.

VI. Conclusion

In this paper, we examine the effects of pseudo market timing in event studies. We prove that under stationarity, pseudo market timing is only a problem in small samples. Using a carefully calibrated DGP for the number of events, we demonstrate that the pseudo market timing bias is small and negligible for the sample sizes typically used in empirical research. An abnormal return measure that captures a feasible investment strategy exhibits no bias at all. For other perhaps more traditional measures, pseudo market timing is a small-sample problem that disappears in large samples (yielding consistent measures); however, even in samples of moderate sizes, the bias is small. Based on this finding, it seems unlikely that the long-run underperformance of firms going public or issuing equity is attributable to pseudo market timing. Thus, the pseudo market timing bias in itself does not invalidate extant research on long-run underperformance.

Appendix. Serial Correlation in Long-Horizon Cumulative Abnormal Returns

In this appendix, we demonstrate that the t-statistics of cumulative abnormal return measures in long-horizon event studies are seriously biased because of serial correlation in the measures. We adapt the analysis of Mitchell and Stafford (2000) to our data-generating process and demonstrate that this serial correlation is related to the cross-sectional correlation between contemporaneous events.

For simplicity and to gain some intuition, we present the analysis of the serial correlation under the assumption that the number of IPOs in each month is N. Consider the average cumulative abnormal return over a K-month horizon for all firms with IPOs in the same month from equation (22),

$$CAR_{t+K} = \frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K}\left(c_{t+k}+\epsilon_{i,t+k}\right), \tag{30}$$

where $c_t \sim \mathrm{N}(0,\sigma^2\rho)$ and $\epsilon_{i,t} \sim \mathrm{N}(0,\sigma^2(1-\rho))$ are independent random variables. As only the common component c_t is correlated across firms, the variance of the cumulative abnormal return is

$$\mathrm{Var}\left(CAR_{t+K}\right) = \frac{K}{N}\left(\rho\sigma^2+\frac{1}{N}(1-\rho)\sigma^2\right), \tag{31}$$

and the serial covariance is

$$\mathrm{Cov}\left(CAR_{t+K}, CAR_{t+K-k}\right) = \frac{K-|k|}{N}\rho\sigma^2, \quad |k|<K. \tag{32}$$

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The serial correlation therefore is

$$\text{Corr}\,(CAR_{t+K}, CAR_{t+K-k}) \quad = \quad \frac{K-|k|}{K}\frac{\rho}{\rho+(1-\rho)/N}, \qquad |k| < K. \tag{33}$$

Consider some important properties of this serial correlation. With no cross-sectional correlation in abnormal returns (i.e., $\rho = 0$), the serial correlations of the cumulative abnormal return are also zero. However, for any $\rho > 0$, the serial correlation is positive and converges to $(K - |k|)/K$ for large N.

The variance of the sum of the cumulative abnormal return with K overlapping periods is

$$\text{Var}\left(\frac{1}{T}\sum_{t=1}^{T} CAR_{t+K}\right) \quad = \quad \frac{1}{T}\text{Var}\,(CAR_{t+K})\left[1 + 2\sum_{k=1}^{K-1}\text{Corr}(CAR_{t+K}, CAR_{t+K-k})\right]. \tag{34}$$

Substituting the expression for the correlation (33), we find the variance ratio

$$\begin{aligned}\frac{\text{Var}\left(\frac{1}{T}\sum_{t=1}^{T} CAR_{t+K}\right)}{\frac{1}{T}\text{Var}\,(CAR_{t+K})} &= 1 + 2\sum_{k=1}^{K-1}\frac{K-|k|}{K}\frac{\rho}{\rho+(1-\rho)/N} \\ &= 1 + (K-1)\frac{\rho}{\rho+(1-\rho)/N}.\end{aligned} \tag{35}$$

The usual t-statistic will be biased upward by the square root of this ratio and therefore overstates the precision of the cumulative abnormal return. For any $\rho > 0$, the variance ratio (35) converges to K for large N. For finite N, the ratio is smaller than K but substantially larger than one: with $N = 25$ and $K = 36$, the variance ratio equals 8.01 for $\rho = 0.01$ and 20.81 for $\rho = 0.05$. The t-statistic is therefore overstated by a factor of 3 for $\rho = 0.01$ and a factor of 4.5 for $\rho = 0.05$. These are large numbers, and they may seriously affect the size and power of the t-tests commonly used in event studies.

In the actual simulations, we allow the number of IPOs to vary over time. As it is difficult to calculate exact adjustments to the t-statistics when the number of IPOs per month is time varying, we use the standard t-test in our simulations, but adjust the critical values. These critical values are simulated under the null hypothesis of no abnormal performance.

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