Market Gaming?
An Examination of Aggregate Equity Issue Clustering

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Abstract

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Abstract

Studies of the long-run returns of equity issues find that the poor performance of new issues is common to non-issuers with similar characteristics. This paper examines the view that such evidence suggests that managers game long-run returns of the total market and their respective industry when timing new equity issues. This form of the timing hypothesis is modeled formally to motivate the empirical tests. Using aggregate new equity offering volume from 1970 to 1993, the empirical evidence in this paper supports some forms of successful gaming of market and industry valuation. In particular, the clustering of equity issue volume of small-capitalization firms is found to be strongly correlated with subsequent returns of non-issuing, small-capitalization stocks. Industry results suggest that equity offerings appear to also coincide with peaks in the valuation of their respective industries. The economic gains to such timing behavior are highly significant.

The timing hypothesis of equity issuance behavior proposes that managers respond to informative signals about future firm returns by issuing equity at bullishly biased prices. In effect, the market's failure to adequately update prices allows firms to generate quasi trading profits on their own firm's stock. Consistent with this hypothesis, Loughran and Ritter (1995) observe that long-run returns following U.S. new issues are no better than those of Treasury Bills.[1] Other research suggests that such poor performance is not unique to firms issuing equity. Speiss and Affleck-Graves (1995), Brav and Gompers (1997) and Brav, Geczy, and Gompers (2000) find that the weak performance of new issues is contemporaneously common among similar non-issuing firms.

One explanation proposed by Brav et al. (2000) is that investor mispricing affects a large number of firms simultaneously such that firms respond to informative signals of returns for a class of firms, rather than the idiosyncratic performance of a firm's returns. This form of the timing hypothesis suggests, for example, that firms issue equity in response to a signal of ensuing poor long-run performance of firms within the same industry or of the same size class. This paper empirically tests this specification of the timing hypothesis by examining whether aggregate equity offering transactions cluster around periods of peaks in industry, size sector, or total market valuation.[2]

Thus, unlike traditional event study tests which test abnormal performance of event firms, the focus of this paper is on the abnormal performance of the industry or market benchmarks. Some preliminary evidence exists regarding market gaming behavior. Using the closed-end fund discount as a proxy for market-wide investor expectations bias, Lee, Shleifer, and Thaler (1991) find a significant negative correlation between annual IPO issue volume and the average closed-end fund discount suggesting that offering activity coincides with aggregate

[1] Summarizing twelve similar long-run event studies which use samples of equity offerings in other countries, Ritter (1998) observes that the long-run underperformance of new issues is an international phenomenon.

[2] An alternative explanation for this result is that the Loughran and Ritter result is spurious since the poor performance is independent of the equity offering decision.

investor sentiment movements.[3] Lerner (1994), examines industry timing behavior for a sample of initial public offerings (IPOs) in the biotechnology industry. Within the selected industry, he finds that firms tend to go public following run-ups but prior to run-downs in industry returns, implying that equity offerings cluster around peaks in industry values.

Other explanations of new issue clustering are presented in the literature. Hickman (1953), Moore (1980), and Choe, Masulis, and Nanda (1993) find that equity offering clustering is correlated with business cycles. Bayless and Chaplinsky (1996) find that equity issue volume is negatively correlated with time variation in average equity issue announcement costs. Ritter (1984) observes that periods of high initial public offering (IPO) volume tend to follow periods of high average IPO initial-day returns. Korajczyk, Lucas, and McDonald (1990) suggest that seasoned issue activity is concentrated in periods following strong market performance. This paper links the literature on aggregate equity offering clustering with the long-run performance literature by examining whether the clustering of industry or aggregate issue volume is associated with poor subsequent performance of the entire respective industry or market sector. Tests of industry or relevant market sector gaming is a natural extension of the evidence that managers successfully game long-run firm performance. If equity offerings tend to be timed to precede poor abnormal firm performance, perhaps industry issuance clusters are timed to precede poor abnormal industry performance. A similar hypothesis extension can be made for a particular market sector (e.g., small-capitalization stocks) or the market as a whole. In the paper, the various forms of timing behavior are modeled to motivate the empirical analysis and provide testable theoretical implications.

This paper tests the correlation between issue volume and long-run benchmark performance over a 24-year period (1970-1993) and a broad sample of industries (15 industries). The tests control for alternative explanations of new issue clustering. The empirical results provide some support for the notion of successful market-sector and industry valuation gaming. In particular, both IPO and seasoned equity offering (SEO) volume of small capitalization firms

[3]There is also some evidence that idiosyncratic movements of issuing firm returns are negatively correlated with aggregate issue volume. Loughran and Ritter (1995), for example, find that the long-run abnormal returns for issuing firms is higher for those firms that issue during light-aggregate-equity-issue volume periods than for those firms that issue during heavy-aggregate-equity-issue volume periods. Helwege and Liang (1996) find that

follows strong sector returns and precede poor sector returns, consistent with market-timing behavior. Successful timing behavior is less pronounced among the larger sector. At the industry level, pooled cross-section time-series tests find strong negative correlation between industry-specific issue volume and subsequent long-run abnormal returns of the respective industry. Overall, the previous and subsequent performance of industry and market-sector benchmark portfolios provide the dominant explanatory variables for the aggregate equity issue volume patterns. This evidence contributes to the debate of the uniqueness of long-run new issue performance by testing the abnormal performance of similar non-issuing firms. The results suggest that offerings cluster prior to statistically and economically meaningful poor benchmark performance. For example, the 36-month volume weighted average return for the small-capitalization portfolio is 9.8 percent versus 37.8 percent for the equal-weighted average return the small-capitalization portfolio, representing a substantial difference in mean sector performance.

The structure of the paper is as follows. Section I motivates the market timing hypothesis with a formal model. Section II provides background on the data sample. Section III presents empirical tests of aggregate market gaming as an explanation for aggregate equity issuance clustering. Section IV discusses industry issuance volume tests. Section V provides concluding remarks.

I. The Timing Hypothesis

Stein (1996) develops a two-date model of firm investment and financing policy in the presence of potential bias in expected cash flow forecasts by outside investors. I provide a simple model of equity demand, similar in spirit to Stein's model, to provide testable implications of the market and industry forms of the timing hypothesis.

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the firm underperformance is more severe in 1983 (a high IPO-volume year) than in 1988 (a low IPO-volume year).

Consider a two-date, many firm economy with two sets of agents: managers and outside investors.[4] Investors price firm equity in the economy based on their expectations of time 1 equity cash flows. Suppose that time 1 equity returns for firm i in industry j behave according to the following generating function

$$\tilde{r}_{i,j} = E_{out}\left(\tilde{r}_{i,j}\right) + b_{i,j}^{M}\tilde{r}^{M} + b_{i,j}^{I}\tilde{r}_{j}^{I} + \tilde{r}_{i,j}^{F} \tag{1}$$

where $E_{out}\left(\tilde{r}_{i,j}\right)$ is the time 0 expected return by outside investors, $\tilde{r}^{M}$ is the unexpected market return realization, $\tilde{r}^{S}$ is the unexpected market return realization of small-capitalization firms relative to large-capitalization firms, $\tilde{r}^{G}$ is the unexpected market return realization of growth firms relative to value firms, $\tilde{r}_{j}^{I}$ is the unexpected industry return realization which is orthogonal to market return movements, and $\tilde{r}_{i,j}^{F}$ is the idiosyncratic component or unexpected return to the firm not explained by the market or respective industry return realizations. Equity securities are priced such that the time 0 expected value of $\tilde{r}^{M}$, $\tilde{r}_{j}^{I}$, and $\tilde{r}_{i,j}^{F}$ by outside investors is zero for all i and j. All agents know the Equation 1 return-generating process.

Assume that time 0 managers may be either informed or uninformed relative to the time 1 return-generating factor realizations. The manager's private information regarding future firm cash flows is modeled as a market-wide signal, an industry-specific signal, and a firm-specific signal of the time 1 realizations of $\tilde{r}^{M}$, $\tilde{r}_{j}^{I}$, and $\tilde{r}_{i,j}^{F}$ as

$$\hat{r}_{i,j}^{M} = k_{i,j}^{M}\tilde{r}^{M} + \tilde{e}_{i,j}^{M} \tag{2}$$

$$\hat{r}_{i,j}^{I} = k_{i,j}^{I}\tilde{r}_{j}^{I} + \tilde{e}_{i,j}^{I} \tag{3}$$

[4]Outside investors are defined as investors without managerial control of the firm, particularly with respect to the decision to raise new equity.

$$\hat{r}^F_{i,j} = k^F_{i,j}\tilde{r}^F_{i,j} + \tilde{e}^F_{i,j} \tag{4}$$

where $k^M_{i,j}$, $k^I_{i,j}$, and $k^F_{i,j}$ are signal quality coefficients with discrete values of either 0 or 1, and the time 0 expected value by managers of random variables $\tilde{e}^M_{i,j}$, $\tilde{e}^I_{i,j}$, and $\tilde{e}^F_{i,j}$ is zero. Throughout this paper, the tilde '~' symbol represents a realization of a stochastic variable and the hat '^' symbol represents the agent's signal of the variable realization. If $k=0$ for a particular factor, the manager's signal is uninformative and the signal is orthogonal to the respective time 1 factor or idiosyncratic component realization. If $k=1$, the manager's signal is informative and the signal provides an unbiased conditional estimate of the respective time 1 realization. At time 0, the manager observes only $\hat{r}^M_{i,j}$, $\hat{r}^I_{i,j}$, and $\hat{r}^F_{i,j}$, but not any of the components to the signals in Equations 2 through 4. However, the manager behaves as if the signal is informative.

Since the manager knows the return-generating process, the manager uses the signals to determine the expected abnormal return on the respective firm's equity,

$$\hat{r}_{i,j} = b^M_{i,j}\left(k^M_{i,j}\tilde{r}^M + \tilde{e}^M_{i,j}\right) + b^I_{i,j}\left(k^I_{i,j}\tilde{r}^I_j + \tilde{e}^I_{i,j}\right) + \left(k^F_{i,j}\tilde{r}^F_{i,j} + \tilde{e}^F_{i,j}\right) \tag{5}$$

where $\hat{r}_{i,j}$ is the difference in return expectations by insiders and outside investors, $E_{in}\left(\tilde{r}_{i,j}\right) - E_{out}\left(\tilde{r}_{i,j}\right)$, due to managers' assessment of the outside investor forecast error of firm cash flow.

At time 0, managers also observe the functions $f_{i,j}\left(K_{i,j}\right)$ and $r_{i,j}\left(E_{i,j}\right)$, where $f_{i,j}\left(K_{i,j}\right)$ is the present value of the time 1 gross expected proceeds for firm i in industry j from investment K using the appropriate risk-adjusted opportunity cost of capital and $r_{i,j}\left(E_{i,j}\right)$ is the equity price updating function associated with equity issue of size E for firm i in industry

j. The $r_{i,j}(E_{i,j})$ function is measured in total dollar value so that $r_{i,j}(E_{i,j})/E_{i,j}$ can be viewed as the abnormal return associated with an announcement of management's intention to issue equity of size E. To recognize the transaction costs, I assume that the price updating function includes the price impact of issuance transaction costs, as well as the information effects. Unlike the rational-expectations model of Myers and Majluf (1984), equity price updating by investors in the $r_{i,j}(E_{i,j})$ function is not necessarily restricted to systematically eliminate investor forecast error.[5] Since managers receive a signal of the time 0 investor forecast error and know exactly how the price will respond to a new equity offering of size E, their new equity issue decision considers both real investment profits, as well as the potential to gain quasi trading profits from issuing equity at optimistic prices.

The firm maintains an exogenously imposed capital structure and has no financial slack (i.e., all new investments must be financed by raising outside capital and the amount of investment $K_{i,j}$ and new equity $E_{i,j}$ is constrained to be positive, such that there are no stock repurchases). The fixed capital structure is represented by the equity multiplier $f_{i,j}$ and defined as the ratio of capital to equity.

Managers behave in a risk-neutral manner on behalf of passive, existing shareholders as in Myers and Majluf. Managers choose the level of new equity to maximize combined net profit both from real investing, which generates real investing profits of $f_{i,j}(K_{i,j}) - K_{i,j}$, and from quasi trading on the firm's own equity, which generates quasi trading profits of $-\tilde{r}_{i,j}E_{i,j} - r_{i,j}(E_{i,j})$, where $\tilde{r}_{i,j}$ is the difference between $\tilde{r}_{i,j}$ and $E_{out}(\tilde{r}_{i,j})$. For example,

[5]DeLong, Summers, Shleifer, and Waldman (1990) and Shleifer and Vishny (1997) provide two multi-period-model theoretical rationales for why arbitrageurs might be discouraged from fully eliminating pricing inefficiencies in equilibrium. In the DeLong *et al.* model, by introducing non-idiosyncratic noise traders and requiring that investors liquidate their positions before asset values are fully revealed to noise traders, a noise-trader risk factor is created which allows security prices to deviate from unbiased values in equilibrium. The mispricing persists because arbitrageurs are discouraged from fully exploiting and eliminating security mispricing due to the presence of noise-trader risk. Shleifer and Vishny use an agency model to show that agent arbitrageurs may be unwilling to take risky long-run arbitrage positions for fear that adverse short-term security movements might create withdrawals of arbitrage funds by principals.

if the manager's signals suggest that future abnormal returns will be negative, managers generate trading profits through quasi short selling by issuing equity of amount $E_{i,j}$ at time 0 at cost $r_{i,j}(E_{i,j})$. At time 1, the firm receives a net payoff of $-\tilde{r}_{i,j}E_{i,j} - r_{i,j}(E_{i,j})$ which may or may not be close to the manager's expected payoff of $-\hat{r}_{i,j}E_{i,j} - r_{i,j}(E_{i,j})$ depending on the informativeness of the signal. Combining the features of the model, the manager's objective function for firm i in industry j at time 0 can be written as

$$\max_{E_{i,j}} f_{i,j}(f_{i,j}E_{i,j}) - f_{i,j}E_{i,j} - \hat{r}_{i,j}E_{i,j} - r_{i,j}(E_{i,j}) \tag{6}$$

which gives the first-order condition

$$f_{i,j} f'_{i,j}(f_{i,j}E_{i,j}) - f_{i,j} - \hat{r}_{i,j} - r'_{i,j}(E_{i,j}) = 0 \tag{7}$$

Incorporating Equation 5 for the manager's expected investor forecast error, and making the simplifying assumption that the gross proceeds function and the price updating function are quadratic in $K_{i,j}$ and $E_{i,j}$, so that $f'_{i,j}(f_{i,j}E_{i,j}) = a_{i,j} + b_{i,j} f_{i,j} E_{i,j}$ and $r'_{i,j}(E_{i,j}) = c_{i,j} + d_{i,j}E_{i,j}$,[6] firm i's demand function for new equity can be written as

$$E_{i,j} = g_{0\,i,j} + g^{M}_{i,j}\tilde{r}^{M} + g^{I}_{i,j}\tilde{r}^{I}_{j} + g^{F}_{i,j}\tilde{r}^{F}_{i,j} + \tilde{e}_{i,j} \tag{8}$$

where $g_{0,i,j} = \left[f^{2}_{i,j}b_{i,j} - d_{i,j}\right]^{-1}\left[f_{i,j}(1 - a_{i,j}) + c_{i,j}\right]$,

$g^{M}_{i,j} = \left[f^{2}_{i,j}b_{i,j} - d_{i,j}\right]^{-1} k^{M}_{i,j}b^{M}_{i,j}$,

$g^{I}_{i,j} = \left[f^{2}_{i,j}b_{i,j} - d_{i,j}\right]^{-1} k^{I}_{i,j}b^{I}_{i,j}$,

[6] If we impose the assumption that the gross proceeds function is an increasing function with diminishing marginal returns to investment and the price updating function is an increasing convex function in E, the coefficient b will be negative and d will be positive.

$$g^F_{i,j} = \left[f^2_{i,j} b_{i,j} - d_{i,j}\right]^{-1} k^F_{i,j} \text{, and}$$
$$\tilde{e}_{i,j} = \left[f^2_{i,j} b_{i,j} - d_{i,j}\right]^{-1} \left[b^M_{i,j} \tilde{e}^M_{i,j} + b^I_{i,j} \tilde{e}^I_{i,j} + \tilde{e}^F_{i,j}\right].$$

By the second-order condition of Equation 6, the term $\left[f^2_{i,j} b_{i,j} - d_{i,j}\right]^{-1}$ is negative. The demand equation in Equation 8 is an identified, reduced-form solution for demand, since the market supply function is included in *r(E).* If managers perceive that investor expectations are unbiased, the firm's demand for new equity is the intercept term $g_{0,i,j}$ which is a function of the relative effects of the firm's marginal investment opportunities and the investor's marginal forecast updating based on new equity demand.[7]

The critical implication of the model is that the informativeness of managers' signals determines whether firm equity is correlated with subsequent abnormal movements in returns at the market, industry, and firm level. To show this, I note that the sensitivity of new equity demand to the various forms of forecast errors is adjusted by the relative sensitivity of the firm's investment opportunities and the price updating function as represented by the factor $\left[f^2_{i,j} b_{i,j} - d_{i,j}\right]^{-1}$. If the particular coefficients $b^M_{i,j}$ and $b^I_{i,j}$ are positive, the expected sign on the g coefficients is negative as long as the respective $k^M_{i,j}$ and $k^I_{i,j}$ are positive. Thus, with informative manager's signals ($k=1$), a firm's demand for new equity is a decreasing function of the future returns to investors on the firm's stock. With uninformative manager's signals ($k=0$), a firm's demand for new equity is unrelated to the future returns to investors on the firm's stock.

[7]Bayless and Chaplinsky (1996) suggest that managers time windows of opportunity in the expected price response function. If the coefficients c and d change over time, equity issue volume should increase during periods of relatively low values for c and d. They find that firms which issue during implied windows of opportunity achieve on average a 200 basis point reduction in the price response to seasoned equity issue announcements. As in the Korajczyk, Lucas, and McDonald (1992) model, firms appear to be willing to accelerate or delay their investment opportunities in order to increase the proceeds raised from issuing claims on the firm. This argument is further empirically supported by Dierkens (1991), Korajczyk, Lucas, and McDonald (1991), and Choe, Masulis, and Nanda (1993).

To test the informativeness of managers' signals at the market and industry level, I propose two forms of the timing hypothesis: a market-wide form and an industry-specific form. If the industry or market signals received by managers correctly anticipate industry or market movements, abnormal aggregate capital acquisition should be negatively correlated with the subsequent abnormal performance of the respective industry or the market. To show this result, I aggregate Equation 8 across all n_j firms within any industry j to obtain an industry demand function for new equity,

$$E_j = \sum_{i=1}^{n_j} E_{i,j} = g_{0,j} + g_j^M \tilde{r}^M + g_j^I \tilde{r}_j^I + \left(g^F \tilde{r}^F\right)_j + \tilde{e}_j \tag{9}$$

where $g_{0,j} = \sum_{i=1}^{n_j} \left[f_{i,j}^2 b_{i,j} - d_{i,j}\right]^{-1} \left[f_{i,j}\left(1 - a_{i,j}\right) + c_{i,j}\right]$,

$$g_j^M = \sum_{i=1}^{n_j} \left[f_{i,j}^2 b_{i,j} - d_{i,j}\right]^{-1} k_{i,j}^M b_{i,j}^M ,$$

$$g_j^I = \sum_{i=1}^{n_j} \left[f_{i,j}^2 b_{i,j} - d_{i,j}\right]^{-1} k_{i,j}^I b_{i,j}^I ,$$

$$\left(g^F \tilde{r}^F\right)_j = \sum_{i=1}^{n_j} \left[f_{i,j}^2 b_{i,j} - d_{i,j}\right]^{-1} k_{i,j}^F , \text{ and}$$

$$\tilde{e}_j = \sum_{i=1}^{n_j} \tilde{e}_{i,j} .$$

If managers across industry j receive informative signals for future industry returns ($k_{i,j}^I = 1$) and $b_{i,j}^I$ is greater than zero, the sum g_j^I must be negative. The magnitude of g_j^I depends on the proportion of managers with informative signals and the strength of the industry loading. The relationship between industry issue volume and subsequent industry returns motivates the industry form of the timing hypothesis.

INDUSTRY FORM OF THE TIMING HYPOTHESIS (H$_0$: $g_j^I = 0$; H$_a$: $g_j^I < 0$). *If managers across industry j systematically use informative signals of industry-specific investor forecast bias (represented by* $k_{i,j}^I = 1$*) to successfully gain quasi trading profits by timing equity issues, the weighted sum*

$$g_j^I = \sum_{i=1}^{n_j} \left(k_{i,j}^I \frac{b_{i,j}^I}{f_{i,j}^2 b_{i,j} - d_{i,j}} \right)$$

is negative for positive $b_{i,j}^I$*. If industry managers' estimate of the industry forecast error is generally uninformative (represented by* $k_{i,j}^I = 0$*), the coefficient* g_j^I *is zero.*

Now, aggregating Equation 8 across all firms creates a market-wide demand function for new equity,

$$E^M = \sum_{i,j} E_{i,j} = g_0^M + g^M \tilde{r}^M + g^S \tilde{r}^S + g^G \tilde{r}^G + \left(g^I \tilde{r}^I\right)^M + \left(g^F \tilde{r}^F\right)^M + \tilde{e}^M \tag{10}$$

where $g_0^M = \sum_{i,j} \left[f_{i,j}^2 b_{i,j} - d_{i,j} \right]^{-1} \left[f_{i,j} \left(1 - a_{i,j}\right) + c_{i,j} \right]$,

$g^M = \sum_{i,j} \left[f_{i,j}^2 b_{i,j} - d_{i,j} \right]^{-1} k_{i,j}^M b_{i,j}^M$,

$\left(g^I \tilde{r}^I\right)^M = \sum_{i,j} \left[f_{i,j}^2 b_{i,j} - d_{i,j} \right]^{-1} k_{i,j}^I b_{i,j}^I$,

$\left(g^F \tilde{r}^F\right)^M = \sum_{i,j} \left[f_{i,j}^2 b_{i,j} - d_{i,j} \right]^{-1} k_{i,j}^F$, and

$\tilde{e}^M = \sum_{i,j} \tilde{e}_{i,j}$.

If managers across the market receive informative signals for the market factor, for example, ($k_{i,j}^{M}=1$) and $b_{i,j}^{M}$ is greater than zero, the weighted sum g^{M} must be negative. This result motivates the market form of the timing hypothesis.

MARKET FORM OF THE TIMING HYPOTHESIS (H$_0$: $g^{M}=0$; H$_a$: $g^{M}<0$). *If managers systematically use informative signals of market-wide investor forecast bias (represented by $k_{i,j}^{M}=1$) to successfully gain quasi trading profits by timing equity issues, the weighted sum*

$$g^{M}=\sum_{i,j}\left(k_{i,j}^{M}\frac{b_{i,j}^{M}}{f_{i,j}^{2}b_{i,j}-d_{i,j}}\right)$$

is negative for positive $b_{i,j}^{M}$. If managers' estimate of the market forecast error is generally uninformative (represented by $k_{i,j}^{M}=0$), the coefficient g^{M} is zero.

Sections III and IV empirically evaluate managers' success at timing the market and industry returns with equity offerings. In Section III, I investigate the market timing hypothesis by examining the correlation between abnormal aggregate issue volume and measures of market investor forecast error, to test the sign of the g^{M} coefficient. In Section IV, I investigate the correlation between abnormal industry issue volume and measures of industry-specific investor forecast error, to test the sign of the g_{j}^{I} coefficient of the industry timing hypothesis.

II. Aggregate New Issues Volume

A. Equity Issue Volume Series Construction

Aggregate equity issue volume is computed as the number of primary offerings divided by the total number of firms listed on the Center for Research in Security Prices (CRSP) dataset.[8] The series is computed on a monthly basis for the aggregate market volume measures and on a quarterly basis for the industry volume measures using offering data from the Securities Data Company (SDC) Corporate New Issues dataset from January 1970 to December 1993. A separate series is constructed for both IPO and SEO volume. The SDC sample is composed almost exclusively of firm-commitment offerings, which generally eliminates the smaller, speculative, "penny" stock best-efforts issues as discussed by Ritter (1987). Moreover, the issue data does not include overallotment shares which generally are issued at the prerogative of the underwriter, not to exceed 15 percent of the original primary shares offered. As in Loughran and Ritter (1995), all regulated utility issuers (SIC code 481, 491-494), closed-end funds (SIC code 672-673), real estate investment trusts (SIC code 6798), and American Depository Receipts are excluded from the sample due to the unique nature of their offerings and the equity issue restrictions they face.[9]

B. Issue Volume Clustering

Panel A of Table I provides summary statistics and Figure 1 plots the monthly time series for both IPO and SEO volume over the 24-year sample period. The average sample IPO and SEO volume are nearly identical with 0.32 percent and 0.31 percent, respectively, of CRSP firms issuing each month. The IPO volume is greatest at 1.47 percent of CRSP firms issuing stock in December 1983, while the SEO volume peaks six months earlier with 1.59 percent of CRSP firms. While the contemporaneous cross-correlation coefficient for the two series is 0.683, the SEO volume appears to somewhat lead the IPO volume. Although not reported in

[8] In December 1972 the number of CRSP-listed firms suddenly jumps by 110 percent with the addition of NASDAQ firms to the CRSP tape. To adjust for the omission of NASDAQ firms in the early part of the sample period, the number of CRSP-listed firms used in the denominator is multiplied by 2.1 for all observations before December 1972.

[9] The industry screens reduce the number of issues by 11 percent for regulated utilities, 3 percent for closed-end funds, and 2 percent for REITs.

the table, the cross-correlation of the two series is highest at 0.743 with an IPO-volume lag of four months. The clustering behavior of new issues is evident by the strong serial correlation of the two series. The IPO and SEO series have a first-order autocorrelation coefficient of 0.85 and 0.81, respectively. Five major issue periods: 1/70-1/73, 6/80-12/81, 10/82-1/84, 2/86-10/87, and 3/91-12/93 (comprising 40 percent of the sample months), capture 76 percent and 74 percent of the respective total sample IPO and SEO volume.

Previous research finds that much of the clustering which characterizes the time series of aggregate new equity issue volume is empirically explained using such notions as business cycle effects, market run-up chasing, and “hot market” (periods of systematic high initial-day returns) timing. Despite such explanations for new issue bunching provided by the finance literature, many industry professionals maintain that new issue bunching is largely a result of gaming periods of strong, if not excessive, investor demand for equity.[10]

Further, if, on average, firm management is able to successfully anticipate long-run realizations of industry or market returns as modeled in Section I, equity issues will cluster over time as profit-maximizing managers seek to generate “quasi trading profits” on their own stock.

In addition to examining clustering behavior at the aggregate market level, I also look at clustering across market capitalization sectors and industries.[11] To look at small-capitalization relative to long-capitalization firm equity issue patterns, I construct a separate issue volume series for relatively larger and smaller IPOs and SEOs. Those issuing firms assigned in the year of issue to the CRSP capitalization deciles 1 through 4 are defined as

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[10] A quotation from a 1997 *Wall Street Journal* article provides an illustrative example of such perspective, "*Investors will remember 1996 as a microcosm of almost every possible IPO environment. First there was the spring's reckless buying frenzy. Investors snapped up shares of virtually any small speculative company--especially those with the 'Internet' in their prospectus--without regard to the price they were paying for companies that might not turn a profit in years....IPOs suffered a reversal after investors began having doubts about technology stocks in June,...as a result, IPOs that would have soared only weeks before--such as OzEmail...and Infoseek Corp.--priced below their ranges and faltered in early trading...Before long, underwriters were delaying deals in the hope that the small cap, as well as the IPO environment, would rev up again."* Cited from Deborah Lohse, "1996 Year-end Review of Markets and Finance," *The Wall Street Journal*, January 2, 1997, Section R, p. 4.

[11] Motivation for the construction of this series is provided in Section III.

small-capitalization issuers. Those issuing firms assigned in the year of issue to the CRSP capitalization deciles 7 through 10 are defined as large-capitalization issuers. The CRSP decile break points are based on all active, non-ADR, securities on CRSP. CRSP assigns each security a capitalization decile based on the beginning of the year capitalization (if available), otherwise by the earliest available market capitalization in the respective year. Because of the importance of the NASDAQ market for new issues, the series does not begin until 1972, the first year CRSP includes NASDAQ firms.

Panel A of Table I provides summary statistics and Figures 2 and 3 plot the respective small- and large-capitalization issue volume measures for both IPOs and SEOs for the sample period. The correlation is relatively high across the small- and large-capitalization measures with a correlation coefficient of 0.55 for IPOs and 0.61 for SEOs. The figures show particularly strong small-capitalization volume from 1972 to 1973 for IPOs, and strong volume for large-capitalization IPOs in the early 1990s. Cross-correlations for both IPO and SEO small-capitalization volume and IPO and SEO large-capitalization volume are 0.59 and 0.65 respectively.

To explore industry clustering behavior, I construct industry equity issue volume series based on the Fama and French (1997) industry classifications. Fama and French argue that these classifications are more representative of true current industries than traditional classifications such as 2-digit SIC-codes. In order to obtain industry volume series with sufficient issue data to give reasonably powerful tests, I eliminate all industries with less than 250 total issues over the 24-year sample period, leaving 16 industries of focus. Panel B of Table I lists the 16 selected industries, the associated SIC Codes used for classification, and the respective total number of sample period offerings. The banking industry (BANKS) and business services (BUSSV) generated the most equity offerings with 1113 and 985 offerings, respectively.

Because of the reduced number of issues at the industry levels, industry issue volume is measured quarterly rather than monthly. To explore the differences in industry issue volume patterns relative to aggregate market issue volume, Panel B also reports the correlation coefficients of industry issue volume with aggregate market offering volume. Among the 16 industries, issue volume by the *BUSSV* industry and wholesale (WHLSL) industry is the most highly correlated with the aggregate market, both with correlation coefficients of 0.89. Issue volume by the petroleum and natural gas (*ENRGY*) industry is the least correlated with the aggregate market, with a correlation coefficient of 0.307. The issue volume by the *ENRGY* industry is also the least correlated with the other selected industries. Although not reported, the correlation coefficient between *ENRGY* issue volume and that of other industries is between -0.07 for *BANKS* and 0.41 for electronic equipment (*CHIPS*). Among the individual industries, the transportation (*TRANS*) industry and *BUSSV* industry have the most highly correlated issue volume with a correlation coefficient of 0.80.

III. Tests of Aggregate Market Performance Timing

A. Time-series Tests

I now turn to explicit tests of the correlation between aggregate equity offering volume and market returns motivated by the market form of the timing hypothesis. Estimates of g^M are obtained using a time-series set up. In the tests, I also include variables which capture the impact of business cycles, previous IPO initial-day returns, time-varying expected returns, as well as previous and subsequent market performance. For my initial tests, I adopt the following empirical model,

$$\begin{aligned} EQVOL(t) = \quad & b_0 + b_1 LEAD(t-1) + b_2 INITRET(t-6, t-3) + b_3 BILL(t-1) \\ & + b_4 DEBT(t) + b_5 r_m(t-12, t-1) + b_6 r_m(t+1, t+36) + e(t) \end{aligned} \tag{11}$$

where the dependent variable, $EQVOL$, is the equity issue volume measure defined in Section II. The independent variables are defined in the following paragraphs.

LEAD(t) is the logarithm of one plus the average monthly growth in the Department of Commerce Composite Index of 11 Leading Indicators from Citibase over the previous rolling quarter (months *t*, *t-1* and *t-2*). This variable follows from the Choe, Masulis, and Nanda (1993) proxy for business cycle effects. Choe, Masulis, and Nanda find this variable to be significantly positively correlated with the fraction of aggregate new equity relative to new capital.

INITRET(t-6,t-3) is the monthly average initial-day return realized by IPOs between months *t-6* and *t-3* over the sample period.[12] Ritter (1984) suggests that firms facing monopsony exploitation from underwriters should time their offerings immediately after hot market periods. By issuing at this time, he finds that firms increase the proceeds received per share offered and reduce the amount of money "left on the table" with the underpricing discount. A hot-market timing hypothesis suggests that issue activity is positively correlated with lagged values of *INITRET*. The one-quarter lag specification for *INITRET* is recognizably ad hoc, but selected based on the evidence in Ritter (1984). (Footnote 9 provides further discussion of the specification of *INITRET*.)

BILL(t) is the average 30-day Treasury Bill yield from Citibase for month *t* less its twelve-month moving average. This variable controls for the impact of time variation in the opportunity cost of capital. Increases in the opportunity cost of capital are expected to lead to declines in aggregate issue activity. Including this variable on the right-hand side of Equation 1 also helps distinguish variation in long-run returns due to changes in risk-based expected returns from variation in long-run returns due to changes in expected cash flows. Disentangling explanations of variation in realized returns based on changes in investor forecasts from explanations based on risk factors is, in fact, extremely challenging. In light of this difficulty, one must evaluate the likelihood of risk-factor based arguments as explanations for the results reported in this paper.

DEBT(t) is the annual first-differenced ratio of total long-term debt for all companies listed by Compustat for the year of month *t* divided by total book equity for all companies listed by Compustat for the year of month *t*. So the *DEBT* value for June 1991 equals the aggregate debt-to-equity ratio for the end of year 1991 less the aggregate debt-to-equity ratio for the end of year 1990. As shifts in the aggregate capital structure f substitute equity for debt, the aggregate debt-to-equity ratio falls, and the equity issue volume rises. Adopting this logic, the expected sign on the *DEBT* coefficient is negative.[13]

$r_m(t+k_1, t+k_2)$, is measured as the T-month cumulative excess market return described in Equation 12,

$$r_m(t+k_1, t+k_2) = \sum_{t=t+k_1}^{t+k_2} \left(R_m(t) - R_{TBill}(t) \right) \tag{12}$$

where $R_m(t)$ is the return on the value-weighted (VW) or equal-weighted (EW) CRSP market portfolio for month t and $R_{TBill}(t)$ is the return on the 30-day Treasury Bill for month t. Loughran and Ritter (1995) show that issuing firms perform poorly on average over a five-year horizon. Since the standard CRSP portfolios used to calculate market returns include many issuing firms following periods of heavy issue activity and few issuing firms following periods of light issue activity, the portfolio returns may be biased towards finding negative correlation with market-wide volume when, in fact, issuing firms are only gaming firm-specific, not market-wide performance. Since the potential for finding negative correlation between issue volume and portfolio returns which include issuing firms is known ex-ante, I need to control for the potential test bias. I calculate long-run market returns using portfolios which exclude all firms which have issued equity in the past five years. Due to the lack of availability of issuing firms from the SDC database prior to 1970, the market portfolio excludes firms issuing only after 1970.[14]

Korajczyk, Lucas, and McDonald (1991) show that equity issue volume is positively correlated with market performance during the prior 12 months. The control variable

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[12]See Ritter (1984) for details of the construction of this series. I obtained the series from Jay Ritter's web site.
[13]Since *DEBT* is measured in the same year as the equity issue, the expected sign is somewhat mechanical, since increases in equity issuance (keeping outstanding debt constant) must decrease the contemporaneous debt-to-equity ratio.

$r_m(t-12, t-1)$ is included to identify evidence of past market performance chasing. To measure subsequent long-run returns, I use $r_m(t+1, t+36)$ which gives the 36-month cumulative excess return of the market portfolio. The long-run return horizon is chosen to mirror the horizon length used in other long-run return studies. As with all long-run horizon studies in finance, one of the most difficult empirical challenges is finding suitable benchmarks for the expectations of long-run returns. I presume that the proxy benchmarks used in this study are sufficiently correlated with the true long-run factors so as to generate reasonable inferences. However, this leap of faith advises caution in interpreting the empirical results and emphasizes the need for further research consideration in understanding the nature of long-run expected returns.

Table II provides estimates of Equation 11. The residuals in the regression are modeled as a first-order autoregressive process, and the GLS estimates are obtained using the Yule-Walker or two-step full transform procedure described in Gallant and Goebel (1976).[15] Each regression is run with and without the post-market performance variable. The inclusion of this variable appears to have little effect on the other coefficient estimates.

Consistent with Choe, Masulis, and Nanda, the coefficient on *LEAD* is consistently positively correlated with aggregate equity issue volume but with insignificant t-statistics (at the 95-percent level) that range between 0.61 and 1.12. Consistent with Ritter, the aggregate issuance appears to follow "hot markets." The results show positive correlation between the equity issue volume measures and lagged average initial-day IPO returns, *INITRET*. Although not significant, the t-statistics are relatively stable across the regressions at between 1.50 and 1.76.[16] The coefficient on *BILL* is also consistently negative as predicted. The t-

[14] Sensitivity tests which exclude this part of the sample suggest that the inclusion of issuing firms in the early 1970s has little impact on the overall inferences.

[15]The Yule-Walker or two-step full transform estimation procedure starts by using residuals from the ordinary-least-squares coefficient estimates to estimate the sample autocorrelation coefficients. Using the procedure of Gallant and Goebel, the sample autocorrelation estimates are used to form the variance-covariance estimate which is then used to obtain the standard generalized-least-squares estimates of the equation.

[16] Some work was done to examine the correlation structure of issue volume and various lag lengths of monthly average IPO initial-day returns. The positive correlation, which is frequently statistically significant across lag

statistics are all relatively low between –0.05 and –0.72. The coefficient on *DEBT* is also insignificant at the 95-percent confidence level. Three of the eight coefficients have the predicted negative sign.

Aggregate equity issue volume is strongly correlated with previous market performance. The coefficient on market returns over the past twelve months is consistently and significantly positive with t-statistics between 3.20 for the IPO volume with equal-weighted returns and 5.40 for the SEO volume with value-weighted returns.

Finally, the results suggest that both IPO- and SEO-issue volume is negatively correlated with the subsequent performance of equal-weighted market returns, yet insignificantly correlated with the subsequent performance of value-weighted market returns. A coefficient estimate of less than zero on the subsequent market performance measure suggests that managers successfully game future underperformance in the market, consistent with the market-gaming hypothesis. The t-statistic on the $r_m(t+1, t+36)$ coefficient is 0.01 and –0.24, respectively, for the IPO- and SEO-volume measures when value-weighted market returns are used, whereas the t-statistic is –2.69 and –3.01, respectively, for the IPO and SEO volume measures when equal-weighted market returns are used.

B. Test Specification

The customary t-statistics used in Table II may potentially be highly biased in finite samples (see Kendall (1954), Granger and Newbold (1974), Stambaugh (2000), and Nelson and Kim (1993)). Such biases may stem from both the known serial correlation of the dependent and many of the independent variables (in particular, the overlapping long-run return measures), as well as the potential autocovariance across the time series of regressors and residuals (e.g., the Treasury-Bill yield may be correlated with lagged and future returns producing biased estimates in finite samples).

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lengths of between one and six months, peaks at a lag length of between two and four months for both the IPO and SEO. Neither series is significantly correlated with contemporaneous initial-day returns.

In order to control for finite-sample bias in the test statistics, I follow the approximate randomization procedure of Nelson and Kim. In contrast to Monte Carlo sampling methods which are used to test a hypothesis concerning the population from which a random sample is drawn, randomization is used to test whether one set of variables is related to another set of variables in a hypothesized manner.[17] I use an approximate randomization exercise by shuffling the observations in the data sample to see how the alignment of variables affects the estimated relationship. The exact specification of the procedure is provided in the appendix.

Empirical p-values for the coefficients on the forecast-error measures can be calculated using the simulated distribution of coefficient estimates on $\hat{r}_m(t+1, t+36)$. Both the parametric and empirical p-values are reported in brackets in Table II. Comparing the p-values suggests that inferences from the parametric t-tests are generally meaningful. Both of the coefficients for the regressions using equal-weighted returns are highly significant using both methods. For the IPO volume, the parametric p-value is 0.004, whereas the empirical p-value is 0.005 (5 of the 1000 simulated regressions had values of less than –0.2619). For the SEO volume, the parametric p-value is 0.001, whereas the empirical p-value is 0.013. Despite the slight bias in the parametric test statistics, the empirical distribution is generally close to a t-distribution. The randomization procedure suggests that there is little cause for concern about test misspecification due to spurious correlations.[18]

In summary the tests in Table II suggest that aggregate new equity issue volume clusters subsequent to both strong value-weighted and equal-weighted market performance, but prior

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[17] See Noreen (1989) for additional discussion on the relative merits of Monte Carlo and randomization techniques.

[18] An additional specification issue surrounds the proper calculation of long-run returns. Barber and Lyon (1998) recommend a buy-and-hold return method, whereas Fama (1998) argues for the traditional cumulative excess return approach as in Equation 2 when calculating long-run abnormal returns of firms. It is important to note that the issue in this study is somewhat different from the typical long-run event study in that I am interested in identifying long-run abnormal performance of the entire market, rather than the long-run abnormal performance of an individual firm. To test the importance of the long-run excess return methodology, I rerun the regressions in Table II using the difference in buy-and-hold returns for the market portfolio and Treasury Bills, rather than cumulative excess returns. The results for the alternative specification are similar to those of the original specification.

to weak performance of only the equal-weighted market portfolio. Such evidence suggests that managers may be successfully timing the aggregate performance of the small-capitalization sector of the market.

C. Large-capitalization Issues versus Small-capitalization Issues

To better explore the notion that managers time valuations of their respective capitalization sector of the market, I re-estimate Equation 11 separating large-capitalization issuer volume from small-capitalization issuer volume for the 1972 to 1993 period. For the dependent variable, I use the small-capitalization and large-capitalization issuer series discussed in Section I. I construct a capitalization-based market sector return series which mirrors the capitalization-based categorization of the issue volume series, by creating portfolio returns based on the same CRSP capitalization-decile portfolio categories. All CRSP-listed firms which are assigned to the four smallest capitalization-decile rankings (Deciles 1-4) are assigned to the small-capitalization portfolio; all CRSP-listed firms which are assigned to the four largest capitalization-decile rankings (Deciles 7-10) are assigned to the large-capitalization portfolio. The firms in each portfolio are reassigned and rebalanced to equal weights at the beginning of each calendar year. All firms which issue equity within five years of the current calendar year are excluded from the portfolios.

Table III provides the results of tests incorporating the capitalization-based issue volume and market performance variables. In general, the tests are consistent with those of Table II. The coefficients on *LEAD* and *INITRET* are generally positive, but not significant at the 95-percent confidence level. The small-capitalization SEO volume series provides the one exception with a slightly negative coefficient for *LEAD* and a significantly positive coefficient for *INITRET*. The coefficients on *BILL* and *DEBT* are again nearly all slightly negative and the coefficients on $r_m(t-12, t-1)$ are all strongly positive.

The coefficients on the subsequent portfolio returns suggest that evidence of successful aggregate market gaming is limited to the small-capitalization sector. The t-statistics for the coefficient on the 36-month subsequent returns are respectively –7.32 and –3.86 for the small-capitalization sector of IPO and SEO volume. For the large capitalization sector the coefficients on $r_m(t+1, t+36)$ are insignificant at –0.88 and –0.75, respectively, for the IPO and SEO volume. To confirm that the correlation observed for the small-capitalization sector is not spurious, I conduct an additional randomization experiment using the methodology used in Table II, while incorporating the respective capitalization-based issue volume and returns series. Table III reports the p-values for both the parametric and empirical distributions. Again the t-distribution appears to adequately approximate the empirically generated distribution and the tests appear to be well specified.

To test the robustness of the results in Table III, I split the series into two time periods: 1972-1979 and 1980-1993. In test results reported in Panel B of Table III, I find the results to be somewhat robust to time-period specification. For the IPO-volume series, issue volume is significantly negatively correlated with subsequent small-capitalization sector performance in both periods, but is also significantly negatively correlated for the large capitalization sector during the 1970s. Also, the clustering of IPO volume following strong prior performance of the sector appears to be limited to the latter part of the sample period. For the SEO-volume series, the t-statistic on the $r_m(t+1, t+36)$ coefficient is highly significant (-7.52) for the early period, but only –1.29 for the latter part of the sample period. As for the IPO volume, I find that large-capitalization issue volume is also significantly negatively correlated with subsequent large-capitalization sector performance during the 1970s.

D. Alternative Test Specifications

Many of the market-level findings in this section mirror findings in other studies at the firm level. Brav and Gompers (1997) find that long-run firm-specific abnormal performance is less when IPOs are value weighted, rather than equal weighted. Fama (1998) and Mitchell and Stafford (2000) also argue that the results of many long-run return studies are dependent on the event-weighting scheme. Consistent with such observations, I find that the evidence of successful gaming at the market level is dependent on the choice of method. In unreported tests, I rerun the tests of Table II substituting a dollar-based issue volume series for the previous number-based issue-volume series. For some of the regressions, the substitution dramatically alters the results. The coefficient on the subsequent total market return measure varies from insignificantly negative for the equal-weighted portfolio to significantly positive for the value-weighted portfolio (implying that the average dollar of new equity precedes total market run ups not run downs). In contrast, the results for small capitalization firms do not substantially change. To explain such puzzling results, Loughran and Ritter (2000) argue that such method-dependent outcomes are to be expected. They suggest that the transaction costs of arbitrage allow greater misvaluations to persist for small-capitalization stocks then for large-capitalization stocks. The result is that value-weighted tests effectively reduce the power since such tests give larger weights to those firms least likely to experience misvaluations. A similar argument explains the results in this paper. If managers have a greater difficulty gaming long-run returns in large-capitalization stocks than small-capitalization stocks, it is not surprising to find less predicted correlation in tests using value-weighted market portfolios than in tests using equal-weighted portfolios.

In a number of other unreported tests, I use various specifications of the empirical model in Tables II and III. In one test I include additional variables to proxy for time variation in the opportunity cost of capital. Although not theoretically founded, these variables have been shown to be correlated with future market returns and have become standard proxies for public information variables.[19] The inclusion of a term premium (the 5-year Treasury Note yield less the 1-year Treasury Bill yield from Citibase), a default premium (the difference between the average yields on Moody's Baa- and Aaa-rated seasoned corporate from Citibase), and an aggregate dividend yield (the dividend-to-price ratio for the value-weighted or equal-weighted CRSP stock portfolio based on a 12-month rolling sum of dividends for the

[19]See Ferson and Harvey (1991) and Pesaran and Timmerman (1995) for evidence on the predictive properties of these variables.

portfolio from CRSP)[20] has little impact on the test inferences. The observation that the inclusion of such variables has little impact on the results suggests that the tests of Table II and III are not merely picking up the timing of time-varying expected returns, but rather the timing of variation in cash-flow forecast error.

In other non-reported tests, I rerun the regressions accommodating potential seasonalities in monthly issue volume. I rerun the regression results adding dummy variables for each calendar month (December is omitted). The results suggest a strong turn-of-the-year effect for new issues. January and February generate significantly less issue activity than the other months. One plausible argument for such an issue volume seasonality could be a decline of issue activity following the end-of-year holidays. The month of June appears to generate the largest amount of issue activity (particularly SEO activity). Adding the seasonal dummies does not materially affect the estimates on the long-run return coefficients.

E. A Comparison of Average Market Returns

The time-series tests do not allow for an assessment of the economic importance of the return timing differences across periods of heavy and light issue volume. To look at the market return realization experienced by the average issuer, I calculate the weighted-average 36-month cumulative excess return for the various market portfolio constructions over the sample period. The market return experienced by the average issuer is then compared to the average market return realization over the sample period.

Panel A of Table IV contains the average cumulative excess returns based on the CRSP value-weighted and equal-weighted portfolios. Again, the portfolios include the returns of all firms not issuing stock within the past 5 years relative to the return on the 30-day Treasury Bill for months $t+1$ to $t+36$. The simple average cumulative excess return for the total value-

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[20] One popular explanation for the predictive power of *DIVYLD* is based on the notion that dividend yield captures temporary departures of equity values from fundamental values. If rather than providing estimates of time-varying opportunity cost of capital, *DIVYLD* predicts investor cash-flow-forecast bias, including *DIVYLD* in Equation 11 biases the estimates of the coefficient on the market forecast error toward zero.

weighted portfolio over the 288-month sample period is 19.17 percent (an annual market premium of 6.4 percent). If the value-weighted portfolio returns are weighted by monthly IPO or SEO volume, the average return is similar at 19.93 percent and 17.85 percent, respectively. The simple average cumulative excess return for the total equal-weighted portfolio is 28.33 percent (an annual market premium of 9.4 percent). If the equal-weighted portfolio returns are weighted by monthly IPO or SEO volume, the average return drops to 18.19 percent and 20.97 percent, respectively. Although the overlapping returns prohibit standard statistical testing of the differences, the differences in point estimates appear to be economically important. The average SEO and IPO appear to be clustered such that they precede cumulative returns of the equal-weighted portfolio which are 7 to 10 percentage points lower than a random distribution.

The results in Panel A illustrate again that successful timing behavior may be limited to the small-capitalization sector of the market. Panels B and C provide further evidence of this distinction. In Panel B, I provide the equal-weighted and volume-weighted long-run cumulative excess returns of the large-capitalization portfolio over the 1972 to 1993 period. The equal-weighted average of 27.35 percent is moderately above the IPO-volume-weighted average of 23.21 percent and the SEO-volume-weighted average of 24.49 percent.

In Panel C, I provide the equal-weighted and volume-weighted long-run cumulative excess returns of the small-capitalization portfolio. The equal-weighted average of 37.80 percent is strikingly larger than the IPO-volume-weighted average of 9.78 percent and the SEO-volume-weighted average of 23.48 percent. The small-capitalization IPOs appear to be distributed such that they precede cumulative returns of the small-capitalization portfolio which are 28 percentage points (9.3 percentage points annually) lower than if evenly distributed over time. The small-capitalization SEOs appear to also successfully time poor performance of the small-capitalization sector with a 36-month cumulative return difference of 14.3 percentage points. Such large differences in average market returns are arguably economically important.

In summary, the various test results of aggregate equity issue suggest that although explanations for new issue clustering such as business-cycle effects or hot-market timing appear to find some empirical support, the dominant explanatory variable appears to be the previous and subsequent returns of the market. In particular, managers or underwriters of small-capitalization new issues appear on average to successfully time peaks in valuations of the small-capitalization sector.

IV. Tests of Industry Timing

In this section I turn to the industry form of the timing hypothesis. To begin, I adapt the empirical model of Equation 1 to allow for an industry-specific mean-IPO-initial-day-return measure and capital-structure measure. I also include the aggregate equity issue volume less the respective industry volume on the right-hand side to distinguish aggregate economy-wide issue activity from issue activity unique to the respective industry. For the long-run return measures, I construct cumulative abnormal returns series for each industry.

$$\begin{aligned} EQVOL(j,t) = \; & b_0 + b_1 LEAD(t-1) + b_2 INITRET(j,t-6,t-3) + b_3 BILL(t-1) \\ & + b_4 \left(EQVOL(t) - EQVOL(j,t) \right) + b_5 DEBT(j,t)) \\ & + b_6 r_I (j,t-4,t-1) + b_7 r_I (j,t+1,t+12) + e(j,t) \end{aligned} \tag{13}$$

The *INITRET* and *DEBT* variables are constructed identically to their counterparts in Section II, except that only those firms within the respective industry are used in their formulation. The coefficient b_7 proxies for the g^I coefficient of the model. To build the industry abnormal return, I form annual industry equal-weighted portfolios based on all the CRSP-listed firms for each of the 16 industries selected in Section II for each calendar year between 1950 and 1996. Since issuing firms have been shown to exhibit poor subsequent performance for up to five years, I exclude all those firms which have issued equity within the past five years so as to avoid biasing the performance of the industry portfolio returns by including the anticipated poor firm-specific performance of issuing firms. One of the industries, healthcare, is excluded from the tests in this section since it has very few non-issuing benchmark firms in the early part of the sample period.

To estimate industry-specific investor abnormal returns $r_I(j,t+k_1,t+k_2)$, I first calculate rolling coefficient estimates for a_t and b_t from Equation 14 using the industry and market portfolio returns for quarters q over the range (*t-80* to t-k_2),

$$\sum_{t=q+k_1}^{q+k_2} \left(R_I(j,t) - R_{TBill}(t) \right) = a_t + b_t \left(\sum_{t=q+k_1}^{q+k_2} \left(R_m(t) - R_{TBill}(t) \right) \right) \qquad (14)$$

where $R_I(j,t)$ is the return on the industry portfolio for quarter t. The estimation period ends in quarter t-k_2 to avoid using any data from the forecast period in estimating the rolling industry loading (for example, if k_2=12 then the loading estimation uses data up to 12 quarters prior to t). Using the estimates of b_t based on returns from quarters *t-80* to t-k_2, I estimate out-of-sample forecast error by applying the loading estimate to the contemporaneous market return realizations as described in Equation 15.

$$r_I(j,t+k_1,t+k_2) = \sum_{t=q+k_1}^{q+k_2} \left(R_I(j,t) - R_{TBill}(t) \right) - b_t \left(\sum_{t=q+k_1}^{q+k_2} \left(R_m(t) - R_{TBill}(t) \right) \right) \qquad (15)$$

This measure of long-run abnormal returns gives the difference between the cumulative excess return for the industry portfolio return premium to investors and the expected return premium conditional on knowing the rolling industry betas and the subsequent realization of the market return. By using rolling coefficient estimates, the measure provides a contemporaneous out-of-sample estimate of the industry-specific abnormal returns.

Panel A of Table V reports the regression results using the Yule-Walker estimation method for Equation 13 for IPO volume for each of the 15 industries. The results in the individual regressions show little consistency in coefficient estimates of many of the right-hand-side variables across the industries. The coefficient on the aggregate issue volume is the one variable which is consistently positive and significantly different from zero at the 95-percent confidence level across all industries. It is worth remarking that industry studies which fail to account for aggregate issue volume, such as Lerner (1994), are omitting an important explanatory variable in their tests.

The coefficient on the previous industry abnormal returns measure is positive for 10 of the 15 industries. Five of the coefficients are significantly positive and two are significantly negative at the 95-percent confidence level.

Successful industry timing behavior predicts that the sign on the subsequent abnormal industry performance variable is negative. The regression results find that all but two of the industries, insurance and wholesale, have a negative coefficient on subsequent abnormal performance. Seven of the 15 industries generate coefficients which are significantly negative (*BUSSV*, *CHIPS*, *COMPS*, *ENRGY*, *FIN*, *FUN*, and *RTAIL*).

The test results for SEO volume in Panel B are generally similar to those of Panel A. All but two of the industries (*FIN* and *TRANS*) have positive coefficient estimates for the previous industry returns measure (five of which are significant at the 95-percent level). All but two of the coefficient estimates for the subsequent industry returns measure are negative (five of which are significant). The issue volume for the wholesale industry generates a curious significantly positive coefficient on subsequent returns with a t-statistic of 2.05.

The standard errors in these industry regressions are much larger than those observed in the regressions of Section II. As the reduced consistency with the results provided in Table V may be due to the reduced power created by estimating nine parameters with only 96 quarters of industry data, pooling the industries in a cross-section time-series test may provide an important increase in testing power. Table VI reports associated regression results using a first-order autoregressive error structure with contemporaneous correlations across industries (see Parks (1976)). The tests allow for industry-specific constant terms which are not reported in the table for the sake of brevity. In the pooled regressions, all of the variables which are not unique to the industry are used repeatedly across the 15 industries. Consequently, inference from the t-statistics for these variables is inappropriate due to the bias in standard errors created and the estimates for these variables have thus also been omitted from Table VI.

Regressions 1 and 2 provide the pooled industry tests for industry IPO and SEO volume, respectively. Both industry IPO and SEO volume is positively correlated with initial-day IPO returns as in Section II with respective t-statistics of 2.11 and 0.36. Both IPO and SEO volume are negatively correlated with the industry capital structure measure, as expected, with t-statistics of –2.11 and –2.44, respectively.

The coefficient on the previous industry abnormal returns is strongly positive. The coefficient on the industry IPO volume has a t-statistic of 4.04 and the t-statistic on the seasoned volume is 6.42. Based on the pooled industry tests, industry new issue volume appears to chase strong abnormal performance of the respective industry. Industry performance appears to reverse following heavy volume periods. The coefficients on the subsequent industry performance is highly negatively correlated with issue volume. The t-statistics for the IPO and SEO volume are –4.32 and -5.25, respectively. Consistent with the predictions of industry timing, the pooled estimates of g^I are highly negative.[21]

To examine whether the results in Table VI are period specific, I split the sample into two periods as in Section III. The results appear robust to the two sample periods. All of the coefficients for the previous industry returns variable are significantly positive and all but one of the coefficients for the subsequent industry returns variable are significantly negative (the subsequent performance coefficient for the 1970-1979 SEO volume is not quite significant at the 95-percent level with a t-statistic of –1.69). Both sets of coefficients appear to be particularly large in the latter sub-sample period, 1980-1993.

The empirical evidence in Tables V and VI provides evidence that gaming industry equity valuation is an important motivation of industry issue volume. Industry issue volume appears

[21] In unreported tests, I rerun the industry tests using a 3-digit SIC classification scheme rather than the Fama-French industry classification. Using the 15 industries with the most offering activity, the inferences are similar to those reported in Tables V and VI.

to concentrate following periods of strong abnormal performance of the industry and preceding periods of industry-specific underperformance.

V. Summary and Conclusions

This paper makes a number of important contributions to better understanding both the market for new equity capital and timing behavior for major corporate events. The test results suggest that although explanations for new issue clustering such as business-cycle effects or hot-market timing appear to find some empirical support, the dominant explanatory variable appears to be previous and subsequent returns of the market and industry. In particular, managers of small-capitalization issuing firms (potentially at the encouragement of underwriters) appear on average to successfully time peaks in valuations of the small-capitalization sector. The number of small-capitalization IPOs and SEOs is strongly correlated with long-run returns of non-issuing small-capitalization firms. The return differences captured by such market gaming activity is economically large. Managers also appear to successfully time long-run abnormal returns of their respective industry in issuing new equity.

These findings suggest that the information contained in the equity issue decision may be much larger than previously implied. To modify the words of Loughran and Ritter, this evidence is consistent with a market in which companies announce stock issues when the firm, the industry, and the market sector is grossly overvalued, the market does not revalue appropriately, and the firm, the industry, and the market sector are substantially overvalued when the issue occurs.[22]

If successful market gaming is observed by firms for new issues it should also be apparent in other corporate transactions. Hand and Skantz (1999) observe similar market gaming success for carve-outs transactions. The evidence that managers successfully time long-run market movements is consistent with findings by Seyhun (1992). He finds that aggregate insider

[22] See Loughran and Ritter (1995) , p. 47.

trading activity is negatively correlated with subsequent long-run market returns, and in particular of small-capitalization stocks. His paper suggests that managers also successfully game long-run market returns when trading on their own account. Nelson (1999) and Baker and Wurgler (2000) find that aggregate new equity transactions provide some predictive power of future expected returns.

A hypothesis supported by Lee (1997), Speiss and Affleck-Graves (2000), and Loughran and Ritter (1997) suggests that long-run underperformance of new issuers is due to the Jensen (1986) free-cash-flow problem, where the performance of firms in the market or industry declines as managers in aggregate overinvest in what they believe to be value-creating projects. The free-cash-flow explanation modifies the market gaming explanation only in that it does not require managers to have private information of the future realizations of return factors, but rather requires that managers have systematically biased estimates of the gross proceeds from investment. Seyhun's evidence suggests that managers are not overinvesting in aggregate, but conscientiously timing observed investor forecast errors. Moreover, the free-cash-flow hypothesis does not explain why rational investors do not update their expectations of future factor realizations based on managers' history of biased estimates of the investment schedule.

An alternative story based on time-varying changes in investor price elasticity is also consistent with the prediction of poor returns subsequent increases in issue volume. For example, if investor capital is relatively inelastic in the short-run and elastic in the long-run, one might anticipate poor returns to follow increases in total equity as prices fall due to the short-run inelastic demand for new capital. The results in this study appear inconsistent with this view since 1) the underperformance is occurring with stocks which are not issuing new equity and 2) it is doubtful that such relatively small levels of aggregate issue volume (average monthly dollar-based new equity volume is just 0.09 percent of total market capitalization) would lead to such sustained and extended market and industry underperformance. In addition, the time-series pattern of cumulative abnormal returns appears inconsistent with the downward-sloping demand curve explanation. If the poor performance is due to a downward-sloping demand for equity, one would expect to observe on average a sudden drop in performance at the time the additional equity is placed on the market, followed by a slow improvement in returns as the market absorbs the extra capital. Cumulative returns for issuing firms on average do not follow such a pattern. Speiss and Affleck-Graves (1995) shows that cumulative abnormal returns for seasoned equity issuers are in fact positive for the first few months following the equity offering and then slowly deteriorate.

This study provides a first step in examining the industry and aggregate clustering behavior of major corporate events. The findings stimulate further exploration of market gaming as an explanation for such time-series characteristics. More fundamentally, this research underscores the need for additional work on the source of non-idiosyncratic investor forecast error which appears to be observable ex-ante in a growing body of literature.

Appendix

A randomization procedure is used to estimate an empirical coefficient distribution. I begin by estimating a vector-autoregressive (VAR) process using ordinary least squares,

$$X(t) = AX(t-1) + u(t) \quad \text{(A1)}$$

where $X(t)$ is a vector defined as,

$$X(t) = \big(EQVOL(t), LEAD(t-1), INITRET(t-6,-3), BILL(t-1), DEBT(t), r_m(t),\ldots, r_m(t-12)\big) \quad \text{(A2)}$$

The VAR system captures both the autocorrelation and lead/lag correlation structure of the underlying process under the null hypothesis of no successful new issue gaming. However, the large number of coefficient estimates required from the limited data is likely to generate noisy estimates for the simulation. With 18 elements in the $X(t)$ vector, the VAR requires estimates of 324 coefficients. However, the sample period gives only 288 monthly observations. To decrease the number of coefficient estimates, I restrict the coefficient estimates on monthly excess returns in months *t-2* to *t-12* to be equal. This restriction reduces the number of coefficient estimates to 64 yet is likely to not dramatically alter the relationship structure of the other important variables. Since I do not want to maintain the correlation between issue volume in month *t-1* and monthly returns in month *t*, I change this coefficient (element 1,6 of the A matrix) to zero subsequent to the original VAR estimation.

To begin the randomization procedure, I randomly select a month to obtain initial values for $X(0)$. I then shuffle the $u(t)$ series from the original estimation of Equation 3 (before changing element 1,6 of the A matrix to zero) and recursively build a pseudo $\hat{X}(t)$ series,

$$\hat{X}(t) = A\hat{X}(t-1) + u(t)$$

(A3)

This is done by first multiplying the coefficient estimates to the initial values and adding the vector of values for the first month in the shuffled $u(t)$ series. I then build the full pseudo $\widehat{X}(t)$ series recursively by applying the coefficient estimates to the previous pseudo values and adding the vector of values for the next month in the shuffled $u(t)$ series. The full pseudo $\widehat{X}(t)$ series retains all of the autocorrelation and lead/lag relationships of the control variables of the original data.

Using the definition of Equation 2, the series of pseudo returns generated by Equation 5 is used to create pseudo long-run return measures $\widehat{r}_m(t-12,t-1)$ and $\widehat{r}_m(t+1,t+36)$. With the generated variables, any relation between the pseudo $EQ\widehat{V}OL(t)$ and $\widehat{r}_m(t+1,t+36)$ is purely spurious.

Using the randomized data, I then estimate the empirical model.

$$\begin{aligned} EQ\widehat{V}OL(t) = \quad & b_0' + b_1' L\widehat{E}AD(t-1) + b_2' INI\widehat{T}RET(t-6,t-3) + b_3' B\widehat{I}LL(t-1) \\ & + b_4' D\widehat{E}BT(t) + b_5' \widehat{r}_m(t-12,t-1) + b_6' \widehat{r}_m(t+1,t+36) + v(t) \end{aligned}$$

(A4)

I repeat the estimation procedure described in Equation 5 and 6 for 1000 iterations to produce an empirical distribution of coefficient b_6', which can be used in the tests of b_6 with the non-randomized data.

The mean value for the coefficient estimates for IPO volume is –0.0188 and 0.0198 using the value-weighted and equal-weighted market returns, respectively. The mean value for the coefficient estimates for SEO volume is –0.0257 and 0.0278 using the value-weighted and equal-weighted market returns, respectively. The mean values of the empirical coefficient estimate suggest a slight, albeit significant negative bias for value-weighted portfolio and positive bias for equal-weighted portfolio for the parametric test statistics.

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Table I
Summary statistics of aggregate new equity issue volume measures

The sample is composed of monthly or quarterly data from January 1970 to December 1993. In Panel A, issue volume is defined as number of issuing firms reported by SDC (excluding some industries) as a fraction of all non-ADR firms followed by CRSP. Issuing firms with CRSP capitalization portfolio ranking in the year of issue of 1 through 4 are assigned to the small-capitalization sample; firms with CRSP capitalization portfolio ranking in the year of issue of 7 through 10 are assigned to the large-capitalization sample. The lack of CRSP capitalization data for NASDAQ firms prior to 1972, limits the capitalization-based sample period to 1972 to 1993.

In Panel B, quarterly industry volume is measured as the percentage of primary equity issues for industry *j* reported by SDC in quarter *t* relative to the total number of all non-ADR equities listed on CRSP at the end of quarter *t* divided by 1000. Issuing firms are classified into the 48 Fama and French (1997) industry groupings. Only industries with greater than 250 issues over the sample period are selected.

Panel A. Market-wide aggregate volume

	IPO Total sample	SEO Total sample	IPO Small cap.	IPO Large cap.	SEO Small cap.	SEO Large cap.
Months	288	288	264	264	264	264
Mean (%)	0.319	0.309	0.124	0.096	0.061	0.160
Standard deviation (%)	0.300	0.253	0.131	0.111	0.063	0.145
Minimum (%)	0.000	0.000	0.000	0.000	0.000	0.000
Maximum (%)	1.471	1.593	0.755	0.546	0.344	0.848
1^{st}-order autocorrelation coefficient	0.854	0.806	0.786	0.764	0.674	0.748
Cross-sectional correlation coefficients						
IPO Total sample	1.000	0.683	0.890	0.840	0.733	0.566
SEO Total sample		1.000	0.514	0.729	0.815	0.929
IPO Small cap.			1.000	0.553	0.593	0.360
IPO Large cap.				1.000	0.705	0.650
SEO Small cap.					1.000	0.608
SEO Large cap.						1.000

Table I (Continued)
Summary statistics of aggregate new equity issue volume measures

Panel B. Industry definitions

Industry	Abbreviation	Number of offerings	CORR	SIC codes
Banking	BANKS	1113	0.602	6000-6099, 6100-6199
Business services	BUSSV	985	0.893	2750-2759, 3993, 7300-7372, 7374-7394, 7397, 7399, 7510-7519, 8700-8748, 8900-8999
Electronic equipment	CHIPS	639	0.766	3622, 3661-3679, 3810, 3812
Computers	COMPS	780	0.727	3570-3579, 3680-3689, 3695, 7373
Pharmaceutical products	DRUGS	474	0.567	2830-2836
Petroleum & natural gas	ENRGY	421	0.307	1310-1389, 2900-2911, 2990-2999
Trading	FIN	339	0.709	6200-6299, 6700-6799
Entertainment	FUN	262	0.670	7800-7841, 7900-7999
Healthcare	HLTH	358	0.616	8000-8099
Insurance	INSUR	405	0.701	6300-6399, 6400-6411
Machinery	MACH	389	0.707	3510-3536, 3540-3569, 3580-3599
Restaurants, hotel, motel	MEALS	337	0.714	5800-5813, 5890, 7000-7019, 7040-7049, 7213
Medical equipment	MEDEQ	390	0.710	3693, 3840-3851
Retail	RTAIL	861	0.887	5200-5736, 5900-5999
Transportation	TRANS	330	0.811	4000-4299, 4400-4799
Wholesale	WHLSL	560	0.892	5000-5199

Table II
Time-series regression results for aggregate equity issue volume

The sample is composed of monthly data from January 1970 to December 1993. *EQVOL(t)* is the percentage of aggregate U.S. primary common initial public offerings (IPO) and seasoned equity offerings (SEO) in month *t* reported by SDC to the total number of non-ADR equities listed on CRSP in month *t*. *LEAD(t)* is the average monthly growth in the Department of Commerce Composite Index of 11 Leading Indicators from Citibase for months *t, t-1* and *t-2*. *INITRET(t-6,t-3)* is the average initial-day return for all IPOs for months *t-6* to *t-3*. *BILL(t)* is the average 30-day Treasury Bill yield from Citibase for month *t* less its twelve-month moving average. *DEBT(t)* is the first-differenced ratio with a 12-month lag of total long-term debt for all companies listed by Compustat for the year of month *t* divided total common equity for all companies listed by Compustat for the year of month *t*. $r_m(t\text{-}12,t\text{-}1)$ is the cumulative excess return for months *t-12* to *t-1* based on a CRSP value-weighted (VW) or equal-weighted (EW) stock portfolio which excludes all firms issuing stock within the past 5 years and the return on the 30-day Treasury Bill. $r_m(t+1,t+36)$ is the cumulative excess return for months *t+1* to *t+36*. Reported coefficients are estimated using the Yule-Walker method to model the autoregressive residuals. T-statistics are in parentheses. The p-value that the true coefficient is less than the estimated coefficient is listed in brackets [parametric p-value, empirical p-value].

$$EQVOL(t) = b_0 + b_1 LEAD(t-1) + b_2 INITRET(t-6, t-3) + b_3 BILL(t-1) + b_4 DEBT(t) + b_5 r_m(t-12, t-1) + b_6 r_m(t+1, t+36) + e(t)$$

		N	Constant	LEAD	INIT RET	BILL	DEBT	r_m(t-12,t-1)	r_m(t+1,t+36)	R-sqr
(1)	IPO VW	288	0.2533 (5.08)	6.176 (1.10)	0.2843 (1.71)	-0.2170 (-0.20)	0.4723 (0.48)	0.4715 (3.36)		0.066
(2)	IPO VW	288	0.2507 (4.65)	6.293 (1.12)	0.2906 (1.75)	-0.2535 (-0.23)	0.4888 (0.50)	0.4812 (3.41)	0.0016 (0.01) [0.505, 0.541]	0.070
(3)	IPO EW	288	0.2515 (4.64)	5.256 (0.93)	0.2530 (1.50)	-0.1375 (-0.12)	0.6096 (0.60)	0.3928 (3.39)		0.062
(4)	IPO EW	288	0.3265 (5.66)	4.459 (0.80)	0.2665 (1.61)	-0.0498 (-0.05)	0.4984 (0.51)	0.3649 (3.20)	-0.2619 (-2.69) [0.004, 0.005]	0.092
(5)	SEO VW	288	0.2409 (6.93)	4.322 (0.85)	0.2459 (1.76)	-0.5926 (-0.60)	-0.0769 (-0.10)	0.6487 (5.40)		0.147
(6)	SEO VW	288	0.2451 (6.23)	4.309 (0.85)	0.2472 (1.76)	-0.5974 (-0.61)	-0.0524 (-0.07)	0.6441 (5.28)	-0.0236 (-0.24) [0.407, 0.486]	0.147
(7)	SEO EW	288	0.2363 (6.56)	4.240 (0.82)	0.2186 (1.52)	-0.4824 (-0.48)	0.1829 (0.23)	0.4899 (4.94)		0.127
(8)	SEO EW	288	0.3047 (7.36)	3.097 (0.61)	0.2348 (1.69)	-0.6988 (-0.72)	-0.2020 (-0.26)	0.4542 (4.71)	-0.2167 (-3.01) [0.001, 0.013]	0.169

Table III
Time-series regression results for aggregate equity issue volume
(Small capitalization issuers versus large capitalization issuers)

The sample is composed of monthly data from January 1972 to December 1993. *EQVOL(t)* is the percentage of aggregate U.S. primary common initial public offerings (IPO) and seasoned equity offerings (SEO) in month *t* reported by SDC to the total number of non-ADR equities listed on CRSP in month *t*. *LEAD(t)* is the average monthly growth in the Department of Commerce Composite Index of 11 Leading Indicators from Citibase for months *t, t-1* and *t-2*. $INITRET_{t-6,t-3}$ is the average initial-day return for all IPOs for months *t-6* to *t-3*. $BILL_t$ is the average 30-day Treasury Bill yield from Citibase for month *t* less its twelve-month moving average. $DEBT_t$ is the first-differenced ratio with a 12-month lag of total long-term debt for all companies listed by Compustat for the year of month *t* divided total common equity for all companies listed by Compustat for the year of month *t*. $r_m(t-12,t-1)$ is the cumulative excess return for months *t-12* to *t-1* based on a small-capitalization (Small) or large-capitalization (Large) stock portfolio which excludes all firms issuing stock within the past 5 years and the return on the 30-day Treasury Bill. $r_m(t+1,t+36)$ is the cumulative excess return for months *t+1* to *t+36*. Reported coefficients are estimated using the Yule-Walker method to model the autoregressive residuals. T-statistics are in parentheses. The p-value that the true coefficient is less than the estimated coefficient is listed in brackets [parametric p-value, empirical p-value].

$$EQVOL(t) = b_0 + b_1 LEAD(t-1) + b_2 INITRET(t-6,t-3) + b_3 BILL(t-1) + b_4 DEBT(t) + b_5 r_m(t-12,t-1) + b_6 r_m(t+1,t+36) + e(t)$$

Panel A: Full sample

		N	Constant	LEAD	INIT RET	BILL	DEBT	r_m(t-12,t-1)	r_m(t+1,t+36)	R-sqr
(1)	IPO Small	264	0.1727 (8.28)	1.818 (0.67)	0.0967 (1.35)	-0.3725 (-0.73)	0.0402 (0.10)	0.0859 (1.99)	-0.1914 (-7.32) [0.000, 0.000]	0.232
(2)	IPO Large	264	0.0836 (3.65)	3.799 (1.44)	0.0704 (0.97)	-0.2879 (-0.58)	0.0298 (0.07)	0.1557 (2.64)	-0.0423 (-0.88) [0.379, 0.158]	0.067
(3)	SEO Small	264	0.0617 (5.88)	-0.3107 (-0.21)	0.0939 (2.52)	-0.0530 (-0.19)	-0.1932 (-0.97)	0.0767 (3.47)	-0.0496 (-3.86) [0.000, 0.001]	0.186
(4)	SEO Large	264	0.1393 (5.06)	5.411 (1.61)	0.0847 (0.94)	-0.8122 (-1.28)	-0.3019 (-0.61)	0.2928 (3.97)	-0.0433 (-0.75) [0.457, 0.216]	0.128

Table III (Continued)
Time-series regression results for aggregate equity issue volume
(Small capitalization issues versus large capitalization issues)

Panel B: Sub-samples 1972-79 and 1980-93

		N	Constant	LEAD	INIT RET	BILL	DEBT	r_m(t-12,t-1)	r_m(t+1,t+36)	R-sqr
(1)	IPO Small 1972-79	96	0.1772 (10.17)	4.902 (1.59)	0.0849 (1.08)	-2.709 (-3.29)	0.9073 (1.50)	0.0021 (0.04)	-0.2343 (-9.30)	0.647
(2)	IPO Small 1980-93	168	0.1925 (6.48)	-0.1752 (-0.05)	0.0944 (0.97)	0.2130 (0.37)	-0.3266 (-0.67)	0.1200 (2.14)	-0.1763 (-4.29)	0.188
(3)	IPO Large 1972-79	96	0.0366 (7.84)	-0.5056 (0.46)	0.0171 (0.76)	-0.3259 (-1.28)	0.0153 (0.08)	0.0307 (1.29)	-0.0632 (-5.61)	0.384
(4)	IPO Large 1980-93	168	0.1511 (4.22)	5.704 (1.64)	-0.0482 (-0.50)	-0.4441 (-0.75)	-0.8928 (-2.02)	0.2964 (3.77)	-0.0730 (-0.90)	0.209
(5)	SEO Small 1972-79	96	0.0452 (8.77)	-0.8379 (-0.91)	0.0965 (4.09)	-0.6054 (-2.46)	0.1680 (0.94)	0.0266 (1.76)	-0.0562 (-7.52)	0.624
(6)	SEO Small 1980-93	168	0.0801 (5.56)	1.164 (0.61)	0.0262 (0.55)	0.1035 (0.33)	-0.4578 (-1.89)	0.1234 (4.60)	-0.0239 (-1.29)	0.289
7)	SEO Large 1972-79	96	0.1048 (7.20)	2.207 (0.67)	0.1018 (1.47)	-1.5914 (-2.04)	-0.4321 (-0.70)	0.0733 (1.03)	-0.1290 (-3.71)	0.292
(8)	SEO Large 1980-93	168	0.1708 (3.80)	9.986 (2.32)	0.0056 (0.05)	-0.8392 (-1.15)	-1.114 (-2.00)	0.4256 (4.35)	0.0241 (0.24)	0.249

Table IV
Weighted-average 36-month portfolio cumulative excess returns

The portfolio cumulative excess returns is based on a CRSP value-weighted, equal-weighted, small-capitalization, or large-capitalization stock portfolio which excludes all firms issuing stock within the past 5 years and the return on the 30-day Treasury Bill for months *t+1* to *t+36* over the sample period from January 1970 or January 1972 to December 1993. Each month's respective cumulative excess return is either equally weighted or weighted by the contemporaneous equity issue volume measure. The equity issue volume measures are based on the percentage of aggregate U.S. primary common IPOs and SEOs in the month reported by SDC to the total number of non-ADR equities contemporaneously listed on CRSP. Cumulative excess returns are reported in percentage terms.

Panel A: Value-weighted and equal-weighted market portfolios

		Average 36-month cumulative excess returns (%)		
Market return measure	Observations	Equal-weighted	Weighted by IPO volume	Weighted by SEO volume
Value-weighted portfolio	288	19.17	19.93	17.85
Equal-weighted portfolio	288	28.33	18.19	20.97

Panel B: Large-capitalization portfolio

		Average 36-month cumulative excess returns (%)		
Market return measure	Observations	Equal-weighted	Weighted by large-cap. IPO volume	Weighted by large-cap. SEO volume
Large-capitalization portfolio	264	27.35	23.21	24.49

Panel C: Small-capitalization portfolio

		Average 36-month cumulative excess returns (%)		
Market return measure	Observations	Equal-weighted	Weighted by small-cap. IPO volume	Weighted by small-cap. SEO volume
Small-capitalization portfolio	264	37.80	9.78	23.48

Table V

Time-series regression results for equity issuance volume for selected industries

The sample is composed of quarterly data from January 1970 to December 1993. *EVOL(j,t)* is the percentage of primary equity issues for industry *j* reported by SDC in quarter *t* relative to all non-ADR equities listed on CRSP at the end of quarter *t* multiplied by 10. *EVOL(t)* is the percentage of aggregate U.S. primary common equity issues in month *t* reported by SDC to the total non-ADR equities listed on CRSP in month *t*. *LEAD(t)* is the average monthly growth in the Department of Commerce Composite Index of 11 Leading Indicators from Citibase for the months in quarter *t*. *BILL(t)* is the average 30-day Treasury Bill yield from Citibase for quarter *t* less its four-quarter moving average. *DEBT(j,t)* is the first-differenced ratio with a lag of 4 quarters of total long-term debt for all companies listed by Compustat for the year of quarter *t* within the respective industry grouping divided by total common equity for all companies listed by Compustat for the year of quarter *t* within the respective industry grouping. $R_I(j,t)$ is the equal-weighted return on a portfolio constructed with all firms within the respective industry for each calendar year having not issued equity within the past five years. $R_m(t)$ is based on the CRSP equal-weighted stock portfolio. $R_{TBill}(t)$ is the yield on the 30-day Treasury Bill for quarter *t*. The coefficient $b_{j,t}$ is estimated over the past eighty quarters. Reported coefficients are estimated using the Yule-Walker method to model the autoregressive residuals. T-statistics are in parentheses. See Table I for a description of the 15 industries.

$$EQVOL(j,t) = b_0 + b_1 LEAD(t-1) + b_2 INITRET(j,t-2,t-1) + b_3 BILL(t-1) + b_4\left(EQVOL(t) - EQVOL(j,t)\right) + b_5 DEBT(j,t) + b_6 r_I(j,t-4,t-1) + b_7 r_I(j,t+1,t+12) + e(j,t)$$

$$\text{where } r_I(j,t+k_1,t+k_2) = \sum_{t=q+k_1}^{q+k_2}\left(R_I(j,t) - R_{TBill}(t)\right) - b_{j,t}\left(\sum_{t=q+k_1}^{q+k_2}\left(R_m(t) - R_{TBill}(t)\right)\right)$$

Panel A: IPOs

Industry	T (Qrtrs)	Const	LEAD	INIT RET(j)	BILL	EQVOL-EQVOLj	DEBT(j)	r_I(j,t-4,t-1)	r_I(j,t+1,t+12)	R^2
BANKS	96	0.1281	-33.84	0.1069	-3.072	74.43	-0.5761	0.3230	-0.6430	0.214
		(0.45)	(-0.96)	(0.37)	(-0.47)	(4.61)	(-0.46)	(0.34)	(-0.83)	
BUSSV	96	-0.2218	-2.143	1.055	8.889	105.79	1.357	0.1250	-0.5964	0.797
		(-1.82)	(-0.13)	(2.36)	(2.60)	(17.13)	(2.40)	(0.32)	(-2.03)	
CHIPS	96	0.0831	-9.276	0.0848	1.236	44.103	-0.6049	0.5863	-0.2827	0.597
		(1.29)	(-0.72)	(0.34)	(0.47)	(9.80)	(-0.95)	(2.15)	(-2.03)	
COMPS	96	0.0482	38.860	0.4186	1.075	54.885	-2.977	0.2328	-0.4647	0.612
		(0.46)	(2.25)	(1.24)	(0.32)	(9.39)	(-1.50)	(0.68)	(-2.35)	
DRUGS	96	0.0938	7.385	-0.1977	-2.182	31.155	-1.276	0.9490	-0.0103	0.432
		(1.16)	(0.47)	(-1.45)	(-0.69)	(5.40)	(-0.70)	(2.88)	(-0.04)	
ENRGY	96	0.1701	27.239	0.0234	-2.306	11.828	0.8481	0.6875	-0.3789	0.241
		(1.56)	(1.74)	(1.10)	(-0.78)	(1.84)	(0.51)	(3.04)	(-2.68)	
FIN	96	-0.1217	14.764	0.2819	-2.441	34.085	0.2798	-0.6794	-0.8669	0.578
		(-1.83)	(1.45)	(2.13)	(-1.18)	(9.36)	(1.19)	(-2.38)	(-3.23)	
FUN	96	-0.0086	-10.82	0.2282	-0.7863	22.034	0.2921	-0.1191	-0.3396	0.440
		(-0.15)	(-1.10)	(1.75)	(-0.42)	(6.53)	(0.87)	(-0.53)	(-2.16)	
INSUR	96	0.0896	1.0443	0.0459	-2.999	28.683	-0.7434	0.5878	0.2877	0.547
		(1.73)	(0.11)	(0.34)	(-1.67)	(8.73)	(-1.25)	(2.37)	(1.45)	
MACH	96	0.1493	-5.461	-0.1165	-1.180	17.022	-0.7581	-0.0919	-0.0087	0.371
		(4.02)	(-0.61)	(-0.97)	(-0.60)	(6.57)	(-1.31)	(-0.35)	(-0.06)	

Table V (Continued)
Time-series regression results for equity issuance volume for selected industries

$$EQVOL(j,t) = b_0 + b_1 LEAD(t-1) + b_2 INITRET(j,t-2,t-1) + b_3 BILL(t-1) + b_4\big(EQVOL(t) - EQVOL(j,t)\big)$$
$$+ b_5 DEBT(j,t) + b_6 r_I(j,t-4,t-1) + b_7 r_I(j,t+1,t+12) + e(j,t)$$

$$\text{where } r_I(j,t+k_1,t+k_2) = \sum_{t=q+k_1}^{q+k_2}\Big(R_I(j,t) - R_{TBill}(t)\Big) - b_{j,t}\left(\sum_{t=q+k_1}^{q+k_2}\big(R_m(t) - R_{TBill}(t)\big)\right)$$

Panel A (Continued): IPOs

Industry	T (Qrtrs)	Const	LEAD	INIT RET(j)	BILL	EQVOL-EQVOLj	DEBT(j)	r_I(j,t-4,t-1)	r_I(j,t+1,t+12)	R^2
MEALS	96	0.0067	1.987	0.0893	1.376	26.682	-0.3840	0.2115	-0.1204	0.483
		(0.10)	(0.17)	(0.45)	(0.63)	(6.33)	(-1.96)	(1.04)	(-0.75)	
MEDEQ	96	0.1190	12.078	0.0431	-0.0529	26.764	-0.3118	0.4298	-0.0447	0.431
		(1.71)	(1.03)	(0.26)	(-0.02)	(6.41)	(-0.82)	(1.98)	(-0.27)	
RTAIL	96	-0.0908	12.713	-0.1158	-1.084	67.266	-0.1214	0.1136	-0.7812	0.693
		(-0.93)	(0.78)	(-0.60)	(-0.34)	(11.65)	(-0.22)	(0.27)	(-3.09)	
TRANS	96	0.0385	-2.516	0.0841	1.609	19.009	0.0069	-0.0205	-0.1001	0.427
		(0.90)	(-0.32)	(1.08)	(1.01)	(6.95)	(0.03)	(-0.10)	(-0.59)	
WHLSL	96	0.0016	14.991	-0.0143	0.4829	47.018	-0.1549	-1.141	0.0213	0.607
		(0.02)	(1.11)	(-0.06)	(0.18)	(10.15)	(-0.33)	(-2.73)	(0.09)	

Table V (Continued)
Time-series regression results for equity issuance volume for selected industries

$$EQVOL(j,t) = b_0 + b_1 LEAD(t-1) + b_2 INITRET(j,t-2,t-1) + b_3 BILL(t-1) + b_4\left(EQVOL(t) - EQVOL(j,t)\right) + b_5 DEBT(j,t) + b_6 r_I(j,t-4,t-1) + b_7 r_I(j,t+1,t+12) + e(j,t)$$

$$\text{where } r_I(j,t+k_1,t+k_2) = \sum_{t=q+k_1}^{q+k_2}\left(R_I(j,t) - R_{TBill}(t)\right) - b_{j,t}\left(\sum_{t=q+k_1}^{q+k_2}\left(R_m(t) - R_{TBill}(t)\right)\right)$$

Panel B: SEOs

Industry	T (Qrtrs)	Const	LEAD	INIT RET(j)	BILL	EQVOL-EQVOLj	DEBT(j)	r_I(j,t-4,t-1)	r_I(j,t+1,t+12)	R^2
BANKS	96	0.2478	-40.863	0.1288	-1.524	57.136	-0.4239	2.430	-0.0717	0.191
		(0.92)	(-1.12)	(0.47)	(-0.23)	(3.43)	(-0.36)	(2.79)	(-0.11)	
BUSSV	96	-0.2520	13.605	0.4785	-2.107	61.642	0.2145	0.4663	-0.0209	0.532
		(-1.73)	(0.77)	(1.07)	(-0.65)	(8.34)	(0.39)	(1.22)	(-0.07)	
CHIPS	96	-0.1882	25.882	0.7859	-0.2274	47.351	-0.5433	0.8484	-0.7130	0.442
		(-1.41)	(1.39)	(2.16)	(-0.07)	(5.81)	(-0.57)	(2.17)	(-3.10)	
COMPS	96	-0.0208	45.434	0.4541	-1.9414	33.750	-1.320	0.2731	-0.4449	0.430
		(-0.18)	(2.48)	(1.38)	(-0.56)	(4.92)	(-0.69)	(0.81)	(-2.30)	
DRUGS	96	0.1250	5.257	-0.0507	-2.107	17.523	1.077	1.046	-0.2515	0.201
		(0.92)	(0.29)	(-0.29)	(-0.63)	(2.09)	(0.47)	(2.60)	(-0.75)	
ENRGY	96	0.0833	-26.793	0.0111	0.1683	28.957	0.5641	1.0516	-0.2708	0.446
		(0.88)	(-1.75)	(0.53)	(0.06)	(4.59)	(0.41)	(5.99)	(-2.93)	
FIN	96	-0.2543	-1.501	0.1180	-2.328	23.381	-0.2917	-0.2249	-1.2480	0.488
		(-3.94)	(-0.16)	(1.02)	(-1.24)	(6.03)	(-1.39)	(-0.95)	(-5.45)	
FUN	96	-0.0283	3.139	0.0502	0.4023	13.736	0.1623	0.3121	-0.2133	0.267
		(-0.55)	(0.40)	(0.55)	(0.27)	(4.61)	(0.67)	(1.79)	(-1.79)	
INSUR	96	-0.0326	-7.814	-0.1735	-3.324	30.216	0.7295	0.9014	-0.0311	0.227
		(-0.29)	(-0.54)	(-0.77)	(-1.25)	(4.14)	(0.68)	(2.18)	(-0.09)	
MACH	96	0.0740	11.366	-0.1047	3.314	22.794	0.3264	0.1079	-0.1805	0.347
		(1.18)	(1.00)	(-0.69)	(1.48)	(5.41)	(0.45)	(0.34)	(-1.00)	
MEALS	96	0.0220	26.136	0.2864	-0.9392	17.836	-0.3960	0.2002	-0.2673	0.410
		(0.30)	(2.32)	(1.73)	(-0.47)	(3.80)	(-1.90)	(0.99)	(-1.68)	
MEDEQ	96	-0.0254	16.770	0.1442	-2.073	19.817	-0.1639	0.3013	-0.0319	0.404
		(-0.36)	(1.56)	(1.03)	(-0.96)	(4.68)	(-0.53)	(1.71)	(-0.26)	
RTAIL	96	-0.2353	6.700	0.1133	-6.0424	66.165	-0.3757	0.6620	-0.6653	0.713
		(-2.25)	(0.41)	(0.67)	(-1.90)	(10.28)	(-0.74)	(1.70)	(-3.04)	
TRANS	96	-0.0848	-10.214	-0.2231	1.131	35.327	-0.7821	-0.1611	0.2253	0.483
		(-1.17)	(-0.90)	(-1.94)	(0.52)	(7.55)	(-2.08)	(-0.58)	(0.94)	
WHLSL	96	-0.0136	10.268	0.0931	-0.0760	38.744	-0.4844	0.0639	0.3620	0.606
		(-0.18)	(0.93)	(0.46)	(-0.04)	(9.04)	(-1.28)	(0.20)	(2.05)	

Table VI
Pooled time-series regression results for equity issue volume for selected industries

The sample is composed of quarterly data from January 1970 to December 1993. *EVOL(j,t)* is the percentage of primary equity issues for industry *j* reported by SDC in quarter *t* relative to all non-ADR equities listed on CRSP at the end of quarter *t* multiplied by 10. *EVOL(t)* is the percentage of aggregate U.S. primary common equity issues in month *t* reported by SDC to the total non-ADR equities listed on CRSP in month *t*. *LEAD(t)* is the average monthly growth in the Department of Commerce Composite Index of 11 Leading Indicators from Citibase for the months in quarter *t*. *BILL(t)* is the average 30-day Treasury Bill yield from Citibase for quarter *t* less its four-quarter moving average. *DEBT(j,t)* is the first-differenced ratio with a lag of 4 quarters of total long-term debt for all companies listed by Compustat for the year of quarter *t* within the respective industry grouping divided by total common equity for all companies listed by Compustat for the year of quarter *t* within the respective industry grouping. $R_I(j,t)$ is the equal-weighted return on a portfolio constructed with all firms within the respective industry for each calendar year having not issued equity within the past five years. R_m(t) is based on the CRSP equal-weighted stock portfolio. R_{TBill}(t) is the yield on the 30-day Treasury Bill for quarter *t*. The coefficient $b_{j,t}$ is estimated over the past 80 quarters. The variable *D(j)* is dummy variable for fourteen industries. Not all of the coefficient estimates are reported. Reported coefficients are estimated using the Parks method to model the autoregressive residuals. T-statistics are in parentheses. See Table I for a description of the 15 industries.

$$EQVOL(j,t) = b_0 + b_1 LEAD(t-1) + b_2 INITRET(j,t-2,t-1) + b_3 BILL(t-1) + b_4\left(EQVOL(t) - EQVOL(j,t)\right) + b_5 DEBT(j,t) + b_6 r_I(j,t-4,t-1) + b_7 r_I(j,t+1,t+12) + b_{8-21} D(j) + e(j,t)$$

$$\text{where } r_I(j,t+k_1,t+k_2) = \sum_{t=q+k_1}^{q+k_2}\left(R_I(j,t) - R_{TBill}(t)\right) - b_{j,t}\left(\sum_{t=q+k_1}^{q+k_2}\left(R_m(t) - R_{TBill}(t)\right)\right)$$

	Volume measure/ Sample	T (Qrtrs)	Const	INIT RET(j)	EQVOL-EQVOLj	DEBT(j)	r_I(j,t-4,t-1)	r_I(j,t+1,t+12)
(1)	IPO 1970-1993	1440	0.1587 (3.51)	0.0341 (2.11)	35.684 (47.32)	-0.1976 (-2.11)	0.2166 (4.04)	-0.1975 (-4.32)
(2)	SEO 1970-1993	1440	0.0077 (0.19)	0.0063 (0.36)	29.861 (20.23)	-0.2417 (-2.44)	0.4302 (6.42)	-0.2481 (-5.25)
(3)	IPO 1970-1979	600	0.2708 (2.36)	0.0192 (2.23)	32.721 (40.54)	-0.0420 (-0.30)	0.1313 (2.94)	-0.0922 (-2.46)
(4)	IPO 1980-1993	840	0.0926 (2.15)	0.1665 (2.57)	35.008 (34.23)	-0.2268 (-2.34)	0.2924 (3.95)	-0.3259 (-5.51)
(5)	SEO 1970-1979	600	-0.0214 (-0.49)	-0.0030 (-0.25)	26.538 (23.09)	-0.0861 (-0.60)	0.2231 (3.60)	-0.0749 (-1.69)
(6)	SEO 1980-1993	840	-0.0478 (-0.90)	-0.0085 (-0.12)	32.249 (17.63)	-0.2647 (-2.66)	0.5687 (7.02)	-0.2610 (-4.65)

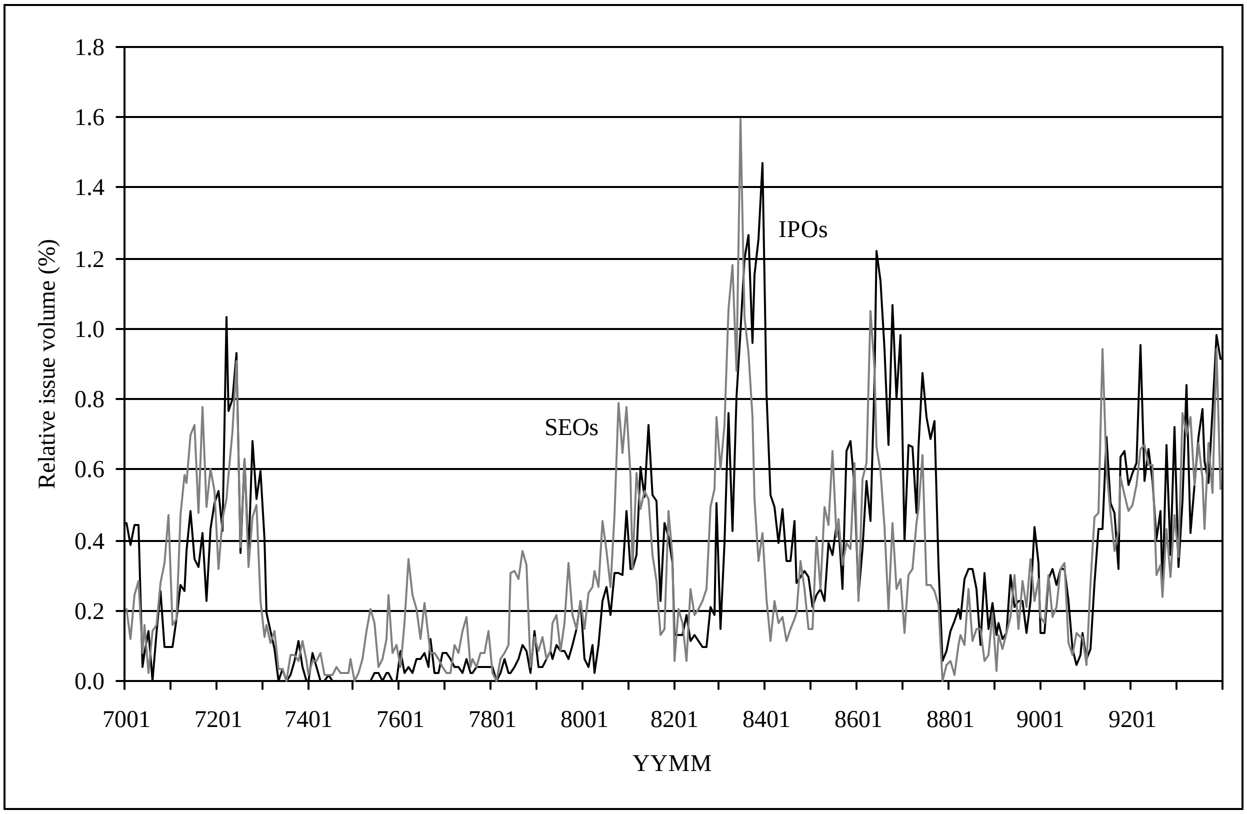

Figure 1. Aggregate monthly IPO and SEO issue volume. Issue volume is defined as number of issuing firms reported by SDC (excluding some industries) as a fraction of all non-ADR firms followed by CRSP.

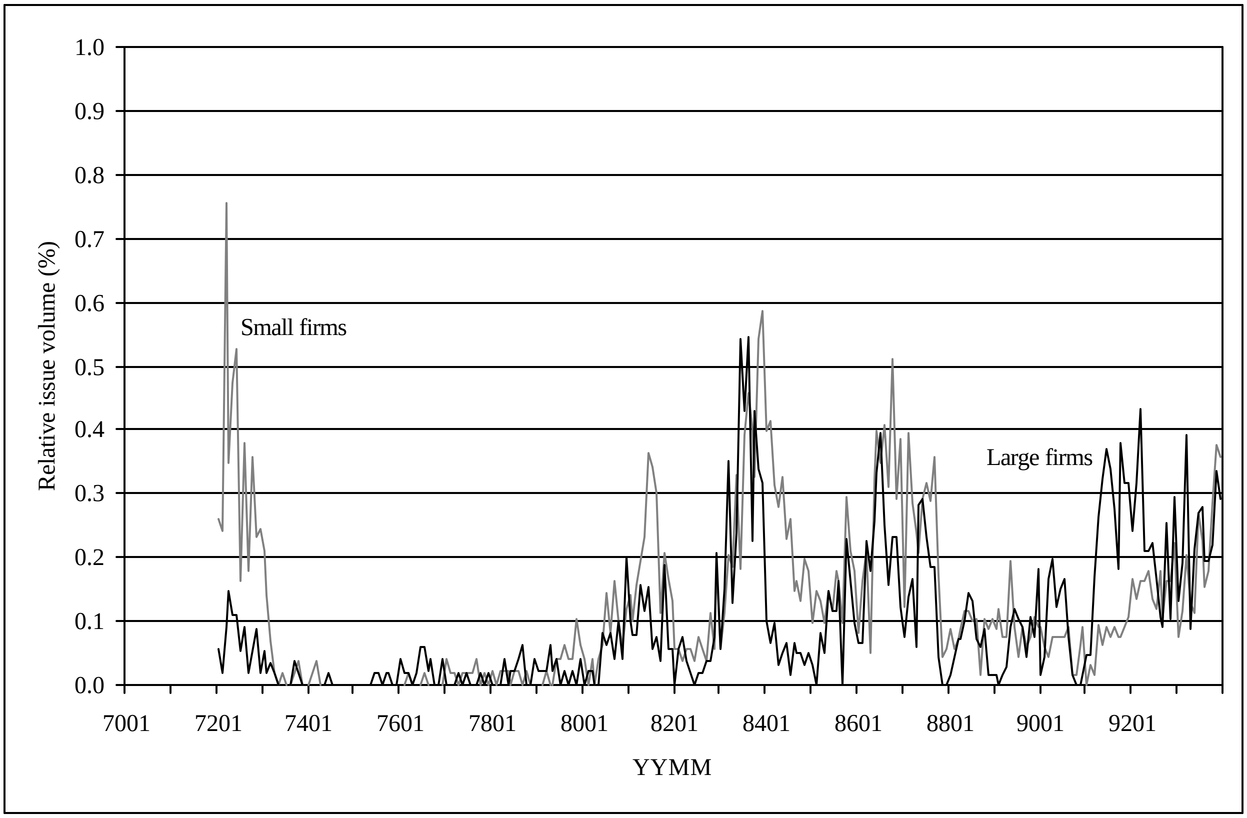

Figure 2. IPO volume by size of firm. Issue volume is defined as number of issuing firms reported by SDC (excluding some industries) as a fraction of all non-ADR firms followed by CRSP. Issuing firms with CRSP capitalization portfolio ranking in the year of issue of 1 through 4 are assigned to the small-firm sample; firms with CRSP capitalization portfolio ranking in the year of issue of 7 through 10 are assigned to the large-firm sample.

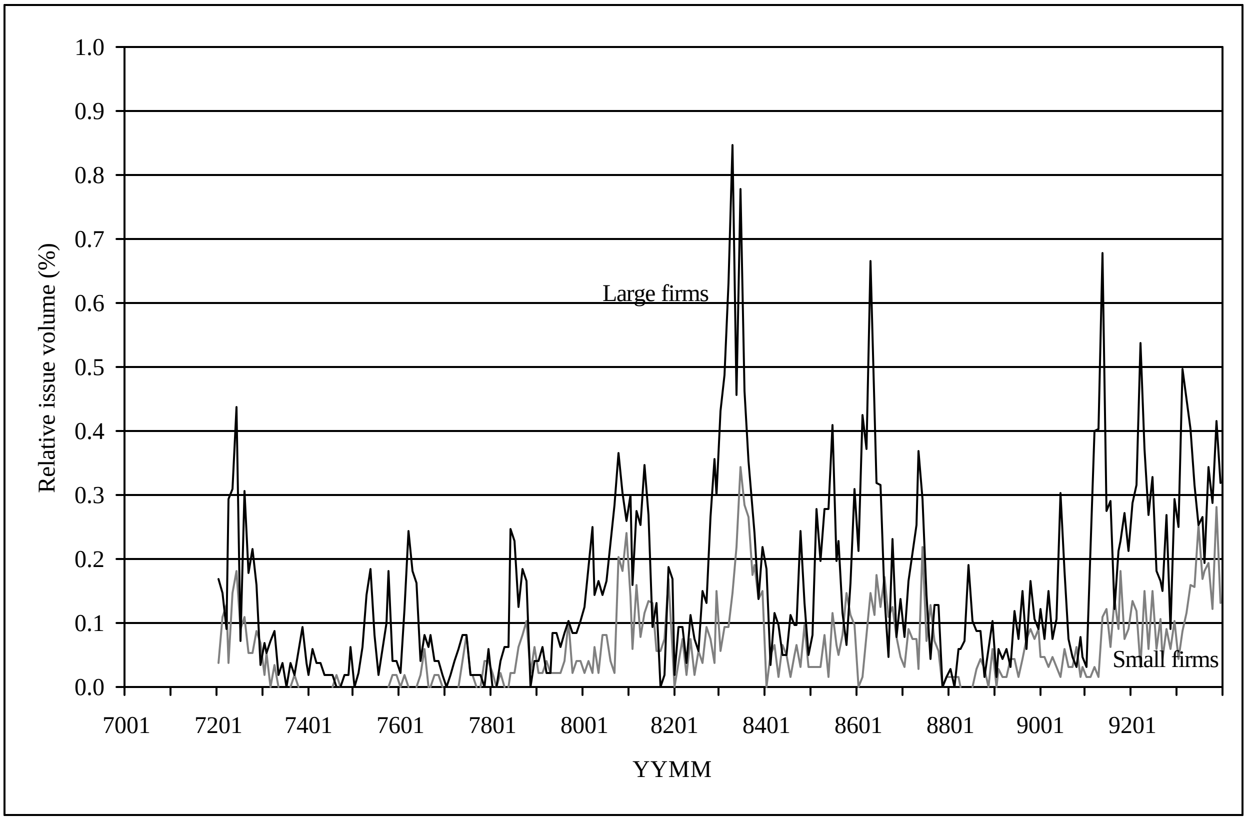

Figure 3. SEO volume by size of firm. Issue volume is defined as number of issuing firms reported by SDC (excluding some industries) as a fraction of all non-ADR firms followed by CRSP. Issuing firms with CRSP capitalization portfolio ranking in the year of issue of 1 through 4 are assigned to the small-firm sample; firms with CRSP capitalization portfolio ranking in the year of issue of 7 through 10 are assigned to the large-firm sample.