NBER WORKING PAPER SERIES

EVALUATING VALUE WEIGHTING: CORPORATE EVENTS AND MARKET TIMING

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Working Paper 9049
http://www.nber.org/papers/w9049

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2002

I thank Karl Diether for research assistance. I thank Malcolm Baker, Eugene Fama, Ken French, Robert Shiller, and Jeff Wurgler for supplying data. I thank Eugene Fama, Jay Ritter, and seminar participants at the London School of Economics, New York University Stern School, the University of Chicago, and Yale University for helpful comments. I gratefully acknowledge support from the Alfred P. Sloan Foundation, the Center for Research in Securities Prices at the University of Chicago Graduate School of Business, and the National Science Foundation. The most recent version of this paper is available at: http://gsbwww.uchicago.edu/fac/owen.lamont The views expressed herein are those of the author and not necessarily those of the National Bureau of Economic Research.

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NBER Working Paper No. 9049
July 2002
JEL No. G14, G32

ABSTRACT

Corporate events, such as new issues and new lists, appear in waves. These waves imply that the market portfolio has a time-varying weight in new lists, and one can decompose the market return into a fixed weight return plus a timing return. Most of the reduction in aggregate market returns caused by holding new lists comes from timing, not from average underperformance. When new lists are a high fraction of the market, subsequent returns for both new and old lists are low. A mean variance optimizing investor holding the market would be better off replacing holdings of new lists with old lists, t-bills, or even currency stuffed in a mattress.

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The market, defined as the total value of publicly traded US equities, is an object of intense interest in financial economics for obvious reasons. It represents the total net position of all equity holders. Although one might be interested in many possible portfolios with associated portfolio weights, the market portfolio with its value weights is a central concern. This paper shows how to use these value weights to identify the sources of asset pricing puzzles and understand their economic significance from the perspective of an investor who holds the market. It constructs portfolios consisting of various subsets of the market, and decomposes their contribution to market returns into components due to fixed weights and timing. Fixed weight returns reflect the different portfolio's average returns and their average weights in the market portfolio. Timing returns reflect the effect of varying one's exposure to different portfolios (by changing the market weight given to each portfolio). This paper studies portfolios based on new lists and shows that new lists reduce market returns mostly due to timing, not due to the average underperformance of new lists.

The market is often thought of as the epitome of a passive portfolio. But as emphasized by Grossman (1995), the market is actually an actively managed portfolio due to incomplete equitization of assets. When a nontraded firm decides to go public, the composition of the market changes. This makes the market an active portfolio where the portfolio managers are corporate managers who make decisions about holding assets and issuing securities. The market portfolio automatically buys all new IPOs (initial public offerings) in proportion to their market capitalization. Since IPOs come in waves, this rule means the market is taking bigger positions in IPOs during waves.

The goal of this paper is to understand the contribution of new lists to total returns on the market. To do this, the paper introduces a simple method for decomposing the market into subcategories that have time varying weights. The focus is new lists since that is the case most cleanly matching the existing literature on IPOs.

Consider the following two statements:

1) IPOs have returns that are lower than non-IPOs over the first few years following issuance, but do not have lower risk.

2) An investor who is seeking to maximize his Sharpe ratio would prefer to shun IPOs in the first few years following the IPO, rather than hold the market portfolio which includes IPOs in proportion to their market capitalization.

At first glance, it seems that the two statements say the same thing, and that the answer to statement (2) must be the same as statement (1). In fact, these two statements are different. It is logically possible, for example, that it would be better to shun IPOs even if IPOs on average have *higher* returns than nonissuers. The reason the statements differ is that (1) is static and cannot accommodate the fact that IPOs come in waves. Within the framework of (2), one can include the fact when holding the market, one is engaged in a dynamic strategy with time-varying allocations to IPOs. The returns to dynamic strategies are significantly affected by the covariance between the returns and portfolio weight of IPOs.

A numerical example of the logical distinction is as follows. Suppose the risk free rate is zero. At the beginning of year 1, suppose IPOs are one percent of the entire market, while at the beginning of year 2, IPOs are ten percent of the market. Suppose the year 1 return for IPOs is 20 percent and for non-IPOs is 10 percent, while the year 2 return for IPOs is -10 percent and for non-IPOs is -5 percent. The important feature of this example is that IPOs do relatively poorly following “hot” markets where IPOs have larger weight. In this example, average calendar time returns are 5 percent for IPOs and 2.5 for non-IPOs, so IPOs have average outperformance.

IPOs have a large positive α, and IPOs and non-IPOs have identical Sharpe ratios of 0.33. Thus statement (1) is false. But the average calendar time market return is 2.3 percent with a Sharpe ratio of 0.29, and since both of these numbers are less than non-IPO values, statement (2) is true: one would be better off shunning IPOs entirely despite their average outperformance, and replacing one's IPOs with non-IPO stock. A further statement about this example, which previews some results of this paper, is that it would be even better for one's Sharpe ratio to substitute cash holdings (rather than non-IPOs) for IPOs holdings, since when IPOs have greater weight non-IPOs have low returns.

Statement (1) is the traditional concern of an extensive literature on IPOs starting with Ritter (1991). How to test hypotheses such as statement (1) is a hotly debated topic.[1] Some advocate using calendar time portfolios rather than event time (weighting each month equally rather than weighting each observation equally) and value weighting rather than equal weighting (within each month, weighting each stock's return by its market capitalization). These two procedures generally decrease the observed magnitude of mispricing. Loughran and Ritter (1995, 2000) argue that calendar time returns obscure mispricing because they average over hot markets (with high mispricing) and cold markets (with low mispricing).

Statement (1) is an interesting economic hypothesis to examine, but from the perspective of an investor it is not the only relevant question to ask. This paper tests statement (2). I use calendar time value weighted portfolios, but take value weighting a step further to examine how it affects the ultimate value weighted portfolio, the market. In doing so, I am able to identify the timing component of investing in new lists, and address in a natural way the "windows of opportunity" hypothesis put forth in Ritter (1991) and Loughran and Ritter (1995, 2000).

The results show that is possible to beat the market, in terms of constructing a portfolio with a higher Sharpe ratio, by deviating from market weights. This deviation involves both average weights that are different from market weights, and time-varying weights that are different from market weights. Thus the benefit of shunning new lists comes both from avoiding the average underperformance of new lists and avoiding the timing strategy pursued by the aggregate market. Most of this benefit comes from the timing component. One can earn higher profits at lower risk by being contrarian: when the market is investing a lot in new lists, underweight new lists relative to the market. The strategy of completely shunning new lists is mispriced by the 3-factor model of Fama and French (1993).

What do these results say about market efficiency? Testing for underperformance of issuing firms is a joint test of market efficiency plus a specific asset pricing model. The proponents of value weighting and the Fama French (1993) three-factor model have interpreted previous failures to reject the null hypothesis as consistent with market efficiency. Thus by this standard, the evidence presented here is evidence against market efficiency, at least along with the joint hypothesis that the Fama French (1993) three-factor model is correct. Since the whole basis of the analysis is market weights, one cannot dismiss this evidence as reflecting only a small and economically unimportant part of the market.

However, it is not obvious that the profitability of contrarian strategies in this setting really says much about the rationality of market participants. For example, virtually any story involving rational firms should have firms issuing equity and stock prices rising when future expected returns fall. Thus, by itself, the existence of market timing does not distinguish between rational and irrational stories. What is certainly rejected is any story involving constant expected returns on all stocks or the same expected returns on new and old lists.

The main contributions of this paper are first to present a general framework for understanding the economic significance of market timing for any arbitrary portfolio, and second to estimate the importance of market timing for the specific case of new lists over the period of 1926-2001. This paper is organized as follows. Section I presents the quantitative framework for identifying market timing. Section II examines the evidence for new lists, and shows the relative importance of timing and fixed weight components. Section III discusses the benefits of shunning new lists from the perspective of a mean variance investor, and shows the dynamic interpretation of seemingly static optimization techniques. Section IV looks at the more general case of net corporate issuance. Section V looks briefly at decomposing the market based on value, growth, and size. Section VI presents conclusions.

I. A framework for evaluating time-varying weights

This section describes a simple framework for identifying the contribution of asset class timing for total market returns in the case of K assets. The body of the paper focuses on the case of two assets only, so the math is even easier.

Consider K different value weighted portfolios with returns R_t^k between the end of period t-1 and t. Suppose one combines these portfolios into a single portfolio using value weights w^k for each asset, where the w's sum to one. Value weights are based on market equity (ME) in the previous period,

$$\text{(1)} \qquad \mathrm{w}_t^k \equiv \frac{\mathrm{ME}_{t-1}^k}{\sum_{j=1}^{K} \mathrm{ME}_{t-1}^j}$$

Call the market portfolio using value weights M. The returns on the market are:

$$\text{(2)} \qquad R_t^M = \sum_{j=1}^{K} w_t^j R_t^j$$

One can always rewrite the return on M as

$$(3) \qquad R_t^M = \sum_{j=1}^{K} w_t^j R_t^j = \sum_{j=1}^{K} \overline{w}^j R_t^j + \sum_{j=1}^{K} \left(w_t^j - \overline{w}^j \right) R_t^j = FIXWEIGHT_t + TIMING_t$$

using the sample average of the time-series of weights. The first term, *FIXWEIGHT*, is the return one would get using fixed weights to combine the K different portfolios,

$$(4) \qquad FIXWEIGHT_t = \sum_{j=1}^{K} \overline{w}^j R_t^j$$

The second term, TIMING, is a differential return one would get from a strategy that deviates from the fixed weights in order to hold varying weights.

$$(5) \qquad TIMING_t = \sum_{j=1}^{K} \left(w_t^j - \overline{w}^j \right) R_t^j$$

This decomposition is similar to standard performance attribution for portfolio managers, for example in Daniel, Grinblatt, Titman, and Wermers (1997), except that it uses market weights instead of the weights of an individual portfolio manager.

Using these definitions and taking averages, one can write the mean return on a portfolio with time-varying weights as a function of the mean returns on its constituent components and on the way the weights covary with returns:

$$(6) \qquad \overline{R^M} = \overline{FIXWEIGHT} + \overline{TIMING} = \sum_{j=1}^{K} \overline{w}^j \overline{R}^j + \sum_{j=1}^{K} \mathrm{cov}\left(w^j, R^j \right)$$

A. The effect of excluding some portfolios

One can use this framework to examine a specific economic hypothesis: what is the benefit of including a particular set of assets in the market portfolio? Call this set "candidate" portfolios. One can answer this question by calculating the returns that one would earn by holding the market excluding this set of assets. Suppose one is interested in excluding portfolios

1 through K-1 from the market, and just holding portfolio K. For example, if one is interested in the effect of excluding new lists, one could calculate the returns that one could earn on a portfolio of old lists (portfolio K), and compare that with the actual market portfolio including new lists (portfolio M). What would be the benefit of including the candidate assets in the market portfolio using value weights? The answer is simple: just take the difference between the market portfolio and the market excluding the assets in question: $R_t^M - R_t^K$. Once one has calculated market returns and portfolio K returns, one can look at their properties, for example mean, variance, Sharpe ratio, α, etc.

This difference, $R_t^M - R_t^K$, is directly related to the framework of timing and fixed weights. Since the portfolio weights have to add to one:

$$R_t^M - R_t^K = \sum_{j=1}^{K-1} w_t^j \left(R_t^j - R_t^K\right) = \sum_{j=1}^{K-1} \overline{w}^j \left(R_t^j - R_t^K\right) + \sum_{j=1}^{K-1} \left(w_t^j - \overline{w}^j\right)\left(R_t^j - R_t^K\right) \tag{7}$$

The average difference is

$$\begin{aligned} \overline{R}^M - \overline{R}^K &= \sum_{j=1}^{K-1} \overline{w}^j \left(\overline{R}^j - \overline{R}^K\right) + \sum_{j=1}^{K-1} \operatorname{cov}(w^j, R^j - R^K) \\ &= \sum_{j=1}^{K-1} \overline{FIXED^j} + \sum_{j=1}^{K-1} \overline{TIMING^j} \\ &= \overline{FIXED} + \overline{TIMING} \end{aligned} \tag{8}$$

This TIMING is the same as in equation (5). The variable *FIXED* is *FIXWEIGHT* minus the return on portfolio K, and shows the differential return from holding the K different portfolios in fixed weights rather than just holding portfolio K. *FIXED* shows the contribution of average returns to the left hand side variable. The left hand side variable, $\overline{R}^M - \overline{R}^K$, is the benefit in terms of average returns of including portfolios 1 through K-1 in the market portfolio using value weights. If this number is negative, it shows that excluding the candidate portfolios raises average returns.

Thus excluding the candidate portfolios has two effects on average returns. The first is that the candidate may have average returns that are different from the non-candidate. The second is that by excluding the candidate, one is no longer involved in a strategy that changes the weight of the candidate over time. The timing component is the focus of this paper.

B. Relation to other approaches

The approach here is somewhat different from related work. Another way of understanding the timing contribution is to see its relation to standard forecasting regressions. For candidate j, average timing is $\operatorname{cov}(w^j, R^j - R^K)$. If one runs a forecasting regression of $R^j - R^K$ on w^j (which is in the information set at time t-1), the coefficient in this regression is $\operatorname{cov}(w^j, R^j - R^K) / \operatorname{var}(w^j)$. Thus the timing component is just a rescaled coefficient from a predictive regression. The difference from other forecasting regressions is that this regression coefficient has a special interpretation. It reflects not some arbitrary forecasting variable, but the specific choices made by the market. The rescaled regression coefficient is measured in meaningful units that show the economic size of the forecasting relation.

The goal of this paper is to understand market weights and their dynamic properties. The goal is not estimate optimal weights, optimal dynamic strategies, or the conditional mean-variance frontier. The optimal weights are of course interesting objects to study (as is done for example by Pastor and Stambaugh (2000) for the cross-section of stocks and by Barberis (2000) for the time series of stocks vs. bonds). Yet another approach is to look at the portfolios chosen by specific subsets of agents, for example individual vs. institutions (as is done in Barber and Odean (2001)). In contrast, the focus here is on value weights coming from the market, representing the net positions of all equity investors.

II. New Lists

This paper examines new lists, defined as firms that newly appear in the Center for Research in Security Prices (CRSP) database. Stocks are added to the CRSP database when they first list on a major exchange. This definition follows Fama and French (2001) in identifying a historically long and broad sample of new lists. New lists proxy for, but are not identical to, IPOs. After 1973, most new lists are IPOs; prior to 1973, most new lists are stocks that were previously traded over the counter before being added to the New York Stock Exchange.

I examine new lists for three reasons. First, new lists are interesting in their own right. They are similar to IPOS since listing reflects decisions made by firms based on market conditions. Dharan and Ikenberry (1995) find that new lists earn low returns. Second, one can construct a long time series of new lists going back to 1929. More data is always a good thing to have for testing hypotheses: one wants more observations, and one wants samples in which the independent variable has lots of variance. In the specific case of examining timing, one wants to be able to observe periods in which the market weight in new lists varies a lot. As shown later, it turns out that due to a wave of new lists in the late 1920's, the 1920's are a particularly important and informative time. Third, the goal of this paper is to decompose the market returns as commonly measured using the CRSP value weighted aggregate. To do this, one has to focus on stocks that are in the CRSP database. Gompers and Lerner (2001) report that it is rare for recent IPOs to list on the New York Stock Exchange (NYSE) in the period 1935-1972, and to study IPOs in the pre-1973 era they are forced to collect return data by hand since recent IPOs are not in CRSP (since they do not study the 1920's it is unclear how many of that wave of new lists were IPOs). Since the goal of this paper is to decompose CRSP returns, it is obvious that recent IPOs can have no effect on CRSP returns if they are not in CRSP.

In general, then, new lists are a proxy for IPOs and IPO-like stocks. Before 1973 they are mostly not IPOs but are similar to IPOs in that they have not previously traded on major exchanges, and have done well enough to be added to the exchange. The decision to list on a major exchange, like the decision to do an IPO, is a corporate event reflecting both the information possessed by firm management and market conditions.

A. The sample

The sample includes everything that gets into the CRSP value weighted return series, namely all securities on CRSP except American Depository Receipts. All stocks fall into two categories: they are either new lists or old lists. Thus

$$R_t^M = \left(1 - w_t^{LIST}\right) R_t^{OLD} + w_t^{LIST} R_t^{LIST} \tag{9}$$

A new list is any stock whose CRSP identifier PERMCO appears for the first time in CRSP, for the first 36 months of its appearance, and which is not added as the result of a distribution of some existing CRSP stock. Thus new lists include IPOs, carve-outs, and publicly traded firms that move onto an exchange covered by CRSP, but exclude spin-offs. Any stock that is not a new list is an old list. NYSE first appears in CRSP in December 1925, American Stock Exchange (AMEX) in August 1962, and NASDAQ in January 1973; all stocks that enter in these months on these exchanges are classified as old lists.

The sample period is January 1929 to December 2001. The top part of Table I shows summary statistics for new lists in the 876 months of the sample. On average, new lists are about five percent of the total value of the market, varying over time between one and 15 percent. Figure 1 shows the time-series behavior of the new list weight. It is clear that 1929/1930 and 1999/2000 were unusual historical episodes (the two peaks are May 1930 and March 2000).

Researchers have studied waves of IPOs for many years. Ibbotson and Jaffe (1975) show "hot" IPO markets, defined as periods with high initial returns from buying at the offer price, are accompanied by a large number of new issues. In contrast, my interest is in waves that significantly affect the composition of the market portfolio, and returns using market prices not offer prices.

Looking at returns after the initial day, Ritter (1991) and Loughran and Ritter (1995, 2000) find that IPO underperformance is larger when the number of IPOs is high. They interpret this finding as consistent with windows of opportunity, where corporate insiders go public when equity is overpriced (as would be predicted by Stein (1996), for example). Other evidence is consistent with this hypothesis. Corporate managers certainly say they are trying to time the market (Graham and Harvey (2001)). Contemporary observers also describe the waves as opportunistic behavior by firms and underwriters. Benjamin Graham described the wave in 1929 as "a wholesale and disastrous relaxation of the standard of safety previously observed by the reputable houses of issue" (Graham and Dodd (1934) p 9) and the smaller wave in 1968-69 as "unprecedented outpouring of issues of lowest quality, sold to the public at absurdly high offering prices and in many cases pushed much higher by heedless speculation…the familiar combination of greed, folly, and irresponsibility..." (Graham (1973) p. 142). These comments may resonate for those who lived through the events of 1999/2000.

B. Results for new lists

The average returns in Table I show the main results of this paper. In the language of Section I, the candidate portfolio is new lists. The total effect of including new lists on average market returns is shown by the average value of R^M - R^{OLD}. New lists cause the average return to fall by 1.7 basis points per month.[2] The t-statistic on this difference is 2.4. Another way of saying this result is that a portfolio of old lists significantly outperforms the market by 1.7 basis points per month. This result tells us that excluding the candidate, new lists, has a statistically significant effect on the average market return.

Is 1.7 basis points per month big or small? There are several ways of interpreting the magnitude of the effect. First, since the average excess return on the market is about 61 basis points per month, 1.7 basis points is three percent of the whole equity risk premium (similarly, Section III shows that Sharpe ratios rise about four percent by holding only old lists). Considering that new lists are only five percent of the market on average, a three percent reduction in excess returns is sizeable. Second, it is useful to compare with pre-existing results and a world of fixed weights. Ritter (1991) reports cumulative abnormal returns (IPO returns minus matched firm returns) of -29 percent over 36 months. Under constant weights of 0.046, the total effect on $R^M - R^{OLD}$ would be -3.7 basis points per month. So of the total, controversial amount of 3.7 basis points per month, I find about half when value weighting. Third, one can compare the magnitude of this effect with other celebrated asset pricing patterns. Section V looks at value and growth firms, and finds total effects (timing plus fixed weight) of 4.5 basis points for value and 7.6 basis points for growth. Thus the new list effect has the same order of magnitude as value or growth, though is somewhat smaller (due largely to the fact that new lists are a smaller fraction of the market). In sum, then, 1.7 basis points does not look small.

One can split this 1.7 basis point effect into two components using equation (8). The average value of FIXED is $\overline{w}^{LIST}\left(\overline{R}^{LIST}-\overline{R}^{OLD}\right)$ and the average value of TIMING is $\operatorname{cov}\left(w^{LIST},R^{LIST}-R^{OLD}\right)$. Table I shows that 1.1 basis points are due to timing while 0.6 basis points are due to fixed weights. Thus more than half the effect comes from timing. The timing component has a t-statistic of about 3, while the fixed weight component is insignificant at conventional levels.

This result, that timing is significantly negative and accounts for most of the decrease in market return, is the main contribution of this paper. The previous literature has focused on the average value of FIXED, that is, whether new lists and old lists have different average returns (after risk-adjusting). Table I shows only weak evidence that FIXED is negative (the next table shows that risk-adjusting using multifactor models also gives weak evidence for FIXED). Table I shows that most of the economic significance of new lists comes not from FIXED, but from TIMING. To understand how an investor holding the market is hurt by new lists, one must understand the dynamic way in which the market weights new lists. TIMING is strongly negative, and as shown in the next two tables, is robust to different ways of measuring and risk adjusting.

The bottom part of Table I shows correlations. The correlation between the new list weight and differential returns on new minus old lists is -0.13. This negative correlation is another measure of the negative covariation that drives the mean value of TIMING. As it turns out, the new list weight is also negatively correlated with excess returns on new lists and on old lists. Thus when new lists are a large fraction of the market, both new and old lists subsequently have low returns, with new lists having lower returns than old.

C. Why different measures give different results

Different ways of posing the question lead to different results. The traditional approach has been to look at the return on a portfolio of new lists and risk-adjust using matching firms, using market returns, or using factor regressions. This subsection discusses why market-adjusting fails to capture timing. Later, section III.B discusses the issues involving α.

Table I shows that market adjusting new lists give weak results. New lists do not significantly underperform the market on average, since the t-statistic on R^{LIST} - R^{M} is only 1.2

(similarly, Fama and French (2001) find that market-adjusted new list returns are not significantly different from zero).[3]

Why do R^{LIST} - R^{M} and R^{M} – R^{OLD} give such different answers? The effect of subtracting the market return from the candidate portfolio is straightforward:

(10) $$R_t^{LIST} - R_t^{M} = \left(1 - w_t^{LIST}\right)\left(R_t^{LIST} - R_t^{OLD}\right)$$

(11) $$\overline{R}^{LIST} - \overline{R}^{M} = \frac{1-\overline{w}^{LIST}}{\overline{w}^{LIST}}\overline{FIXED} - \overline{TIMING}$$

Market-adjusting the candidate just combines the two components in a different way. First, when w is small it gives greater weight to the fixed weight component. Second, it gives the two effects the opposite sign, so they tend to cancel out. Thus market-adjusted returns cannot tell the whole story.

The fact that the fixed weight return and market-adjusted return on new lists are insignificantly different from zero, but the timing component is not, shows the importance of looking at new lists in the context of the market. Part of the debate over how to measure the economic relevance of an asset class involves which methodology is most relevant for actual investors. For example, Lyon, Barber, and Tsai (1999) argue that one should use buy-and-hold returns (rather than monthly returns) because they "precisely measure investor experience." However, Table I gives a different insight on investor experience, since the net equity position of all investors is the market. Looking at new lists in isolation, they have a mean return that is certainly higher than t-bills and a healthy Sharpe ratio similar to the market. But looking at R^{M} – R^{OLD}, it is clear an investor would be better (in terms of mean returns) by shunning new lists. Previous results have looked at new list returns in the context of the whole market by either market adjusting or by running CAPM regressions and showing α and β. But these techniques do not evaluate the dynamic strategy pursued by the market, and thus don't put new list returns in proper context.

D. Regression results

Table II contains regression results for new lists. For clarity it shows several different ways of expressing the basic point, although as a result some columns contain redundant information. Table II shows α from various factor models, showing risk adjusted returns. The first model is the CAPM. The second is the Fama and French (1993) three-factor model, which includes the excess market return, SMB (the return on small stocks minus big stocks) and the HML (the return of high book-market stocks minus low book-market stocks). The last is a four-factor model as in Carhart (1997) which adds a price momentum factor, UMD (the return of stocks with high prior year returns minus stocks with low prior year returns).[4] The table shows α for the CAPM and the three-factor models, and shows the complete regression results for the four-factor model. Table II also shows results splitting the sample approximately in half before and after August 1962 (the date when AMEX firms enter CRSP).

Column's (1) and (2) are traditional excess returns on the portfolio of old and new lists. Column (1) shows that old lists have a positive α with respect to the market, the three-factor model, and the four-factor model. The table shows these positive α's are stable and significant both before and after 1962. This is one way of seeing the basic result that one would be better off shunning new lists. Shunning new lists is not a difficult strategy to pursue: it does not require any costly information gathering or frequent trading. Investors just need to refrain from buying new lists until 36 months have passed.

Column (2) shows excess returns for new lists. New lists have negative α's, but only strongly significant for the four-factor model. Based on these results alone, one would not think there is strong evidence that new lists are mispriced. It turns out, as shown in section III.B, that α can reflect dynamic portfolio weights in unexpected ways. Looking at the factor loadings, it appears that new list returns behave like small growth stocks with positive price momentum. Column (5) shows market-adjusted returns on new lists. Since the market return is already on the right hand side in all regressions, α in column (5) is identical to α in column (2). Again, the market-adjusted raw return of -12 basis points is far from significant. In summary, by most measures the underperformance of new lists is insignificant.

Column (3) shows the difference between market and old lists return. This statistically significant difference of 1.7 basis points is the central measure of the cost of holding new lists using market weights, and is the number that is decomposed in columns (6) and (7). The α's is of course identical to column (1), and show that the 1.7 basis point number is basically unaffected by various risk corrections.

Column (4) shows the differential return approach of subtracting old lists from new lists. This return differential of 14 basis points per month is insignificantly different from zero, although the CAPM and four-factor α's are more than two standard errors from zero.

Column (6) shows the timing component of column (3). In terms of mean return, the timing component is 1.1 basis points per month, and the full samples α's range from 1.2 to 0.9, all significant. The strength of the timing results (the t-statistics are around three) contrasts with the weakness of the fixed weight component shown in column (7) (the estimates in column (7) are simply five percent of the estimates in column (4)). The robustness of TIMING shows that the central result of this paper is not caused by measurable risk exposure or by a specific sample period.

In summary, Table II shows that there is a significant cost to holding new lists, to the tune of 1.7 basis points per month for the investor holding the market. More than half of this cost comes from the timing feature of holding new lists. The timing component is mispriced by the CAPM, and three- and four-factor models, and is present in both halves of the sample period.

E. Robustness tests

Table III shows robustness tests. First, it looks at only common stock as is typical in previous work. In calculating the two components, non-common stock gets discarded and does not appear in the return series or in the weights (the right-hand-side factors are all calculated in the regular way, however). This change has no effect. The main body of the paper includes non-common stock because the point is to decompose the standard market return, which includes non-common stock. Further, it is not clear why one would want to arbitrarily exclude other classes of stock, such as closed end funds, from the analysis. If one is interested in the hypothesis that new issues appear in response to mispricing, closed-end funds are valuable evidence to examine. Indeed, relative mispricings, such as those found in closed end funds or intercorporate holdings (as in Lamont and Thaler (2001)) are one of the few ex ante ways of knowing whether an IPO is overpriced.[5]

Table III also looks at equal weighting instead of value weighting in calculating the decomposition. Here the analysis decomposes returns for the equal weighted CRSP return instead of the value weighted return, and the waves are in the number of new lists instead of the market value of new lists. As is usual, equal weighting makes the effects bigger.

Table III next looks at a definition of timing that could be implemented in real time. The timing portfolio previously used involves the average weights over the entire 1929-2001 sample period, a number that could not be known in 1929. “Real timing” replaces the average weight calculated over the entire period with a backward looking weight that uses the sample average up to month t (thus the number of observations used to compute this weight grows over time). This series starts in 1934, so that a minimum of five years is available. The table shows that this change has little effect, lowering mean timing from 1.1 to 0.8 basis points.

The last part of Table III shows the effect of different sample periods (in addition to the subperiods shown in Tables II). First, it shows the effect of starting in 1973, when NASDAQ firms get added to CRSP. After this date, most new lists are IPOs. The table shows that this change makes mean TIMING higher, rising to 1.6 basis points (although standard errors also rise substantially). Figure 2 is helpful in understanding the different periods. It shows that the timing returns are highly variable at the beginning and end of the 1929-2001 period (not surprisingly, given the higher portfolio weights at these points). The 1999/2000 period is particularly volatile, and helps explain why the standard errors rise so much. In terms of the three-factor model, Ritter and Welch (2002) find that the 1999/2000 period has an extreme effect on three-factor regressions, and argue that one should be especially wary of three-factor α's in this period.

To see whether the late 1990's are driving the results, the last rows of Table III show the effect of looking at 1973-1998. Here mean TIMING drops from 1.6 to 1.0, while the standard error drops in half as the highly variable end period is excluded. Timing is strongly significant in this subperiod as well.

In summary, the average value of the timing component of new lists is robust to alternate sample periods and alternate methods of calculation.

F. Predictive ability of portfolio weights for returns

This subsection examines more traditional regression evidence on the predictive power of new list portfolio weights for subsequent returns. As shown in Table I, both market excess returns and differential returns between new and old lists are negatively correlated with the new list weight. To understand how this covariation is related to the timing component, it is important to recognize that average TIMING is only non-zero if the portfolio weight covaries with the *differential* between the two classes of stock. One can look at the two separate components of timing:

$$(12) \qquad \overline{TIMING} = \operatorname{cov}\left(w^{LIST}, R^{LIST} - R^{OLD}\right) = \operatorname{cov}\left(w^{LIST}, R^{LIST} - R^{F}\right) - \operatorname{cov}\left(w^{LIST}, R^{OLD} - R^{F}\right)$$

The fact that the average value of timing is the difference between these two covariances reflects the fact that this timing component is not about timing the whole market. Rather, timing reflects the ability of the weights to forecast differential returns. Put differently, timing can only be non-zero if the weights have different forecasting ability for excess returns on new and old lists.

The timing component thus reflects the fact that when holding the market, one has to sell old lists in order to buy new lists. Since (as shown in Table I) returns on both old and new lists are negatively correlated with the new list weight, these two covariances tend to offset each other as in equation (12). The fact that one is buying new lists when they have low returns is offset by the fact that one is selling old lists when they too have low returns. This effect makes it harder to reject the null hypothesis that TIMING has mean zero.

The first column of Table IV examines the covariance between portfolio weights and subsequent differential portfolio returns. It shows that the new list weight negatively forecasts subsequent returns of new lists minus old lists.[6] This regression coefficient is just a rescaled TIMING average, as discussed in Section I.B. The rest of the columns in Table IV show how the portfolio weights predict aggregate returns. This predictive power is logically distinct from the predictive power for differential returns between new and old lists. The table shows that the new list weight is a powerful forecaster of future returns, even in the presence of other variables such as scaled aggregate prices.

The first aggregate return regression shows that the new list weight is a significant predictor of excess returns on the market. The next column shows a forecasting regression with market excess returns on the left-hand-side and the price/dividend (P/D) ratio on the right hand side, along with the T-bill yield. The P/D ratio does not do well, mostly because the last few years of the sample were not kind to the forecasting relation. The second column shows that the ratio of price to the last 10 years earnings, P/E10, does somewhat better (both these scaled price variables come from Shiller's web page).

The next two columns add the new list weight. This variable comes in strongly negative, and drives the P/E10 variable out of significance. The results show that when the market is overweight in new lists, market excess returns are subsequently low. These results suggest that firms issue equity when expected returns on equity are low (or when equity prices are high).

The last two columns in Table IV look at annual forecasting regressions for market excess returns. These regressions include the variable SHARE from Baker and Wurgler (2000). Baker and Wurgler (2000) show that aggregate equity issuance negatively forecasts aggregate stock returns, which they interpret as managers issuing equity when it is overpriced. Their variable is the ratio of gross equity issues to the sum of gross equity issues and gross debt issues. SHARE is a similar variable to the portfolio weights; both use the dollar amount of new issues scaled by some other variable. They differ in that the portfolio weight scales by the value of the market where SHARE scales by the value of financing (SHARE also uses issues for a single year rather than the last three years). The first annual regression shows that both measures come in negative and significant. The second shows that with the addition of P/E10 and the T-bill yield, the coefficient on the new list portfolio weight falls and is less than two standard errors away from zero. Thus it appears that the new list weight combines information in the price level and in SHARE, but does not add much new information (the new list weight has an annual correlation of 0.39 with P/E10 and 0.20 with SHARE).

III. An investment perspective on new lists and market timing

A. Benefits of shunning new lists

Tables I-II show that holding new lists results in lower mean returns, and that the difference in returns (between the market and a portfolio that shuns new issue lists) has a negative α. How much would a mean-variance investor benefit by shunning new lists? This question cannot be answered by α because α is not designed to describe dynamic strategies.

Table V shows an investment perspective on new lists. This perspective examines various different portfolios that investors might want to hold, instead of holding the market. The top part of Table V shows some simple portfolio strategies, while the bottom part shows the result from textbook portfolio optimization techniques. The first row in Table V shows that the Sharpe ratio for the market during this period was 0.109 using monthly excess returns. The next row shows that by substituting old for new lists, an investor can raise his mean return and lower his standard deviation. In this sense, one can meaningfully say that a mean-variance optimizing investor would be better off by doing the substitution. New lists are inferior to old lists.

A further question one could ask is: are new lists inferior to T-bills? The answer is yes. The next row shows the result one would get by replacing new lists in the market with T-bills. Again, this is dynamic strategy that holds different weights at different times. Table V shows that an investor could boost his Sharpe ratio 7.3 percent higher than the market, using this simple strategy. By doing the substitution, one is engaged in a contrarian strategy that underweights the market when new issues are booming. It is bearish during waves of IPOs. The improved Sharpe ratio reflects the fact that w^{LIST} forecasts negative returns on both old and new issues.

The next row shows the effect of substituting cash for new lists. Cash is defined as non-interest-bearing currency that has return zero. Even this primitive form of investment is superior to new lists from the perspective of a mean-variance investor who is currently holding the market. Thus it seems that by any reasonable benchmark, "investing in firms issuing stock is hazardous to your wealth" as claimed by Loughran and Ritter (1995), at least for investors looking to maximize their Sharpe ratios. To explain these low returns in a rational risk-based equilibrium framework, one would need to find some reason that new issues are "safer" than currency or are providing insurance to investors.

B. Understanding optimal portfolios

Although it is not immediately apparent, the dynamic nature of market weights is a pervasive issue in empirical finance. An example is standard portfolio analysis when both the market and other equity portfolios are being considered. Whenever one calculates optimal portfolios weights for mean variance efficiency where one of the constituent portfolios is a subset of another, one is implicitly constructing a dynamic strategy. The bottom part of Table V shows portfolio weights generated using standard mean variance calculations based on the sample period means, variances, and covariances,

Consider the meaning of the α of -0.197 for new lists versus the market, reported in Table II. A well-known result from portfolio theory is that a negative α implies that one can construct a portfolio with a higher Sharpe ratio than the market by combining a long position in the market with a short position in the left hand side portfolio. Table V shows that this optimal combination of new lists and the market happens to be 200 percent long in the market and 100 percent short in new lists. Call these weights the "apparent" weights. This combination results in a higher

Sharpe ratio of 0.128. On the face of it, this optimal portfolio looks like a static combination of two portfolios. In fact, this portfolio is a dynamic strategy with a peculiar constraint. Since the market is a weighted combination of old and new lists as in equation (9), the implied weights on new and old lists are a function of the apparent weights. The constraint is that if the apparent weight on new lists is a constant x, the implied weight on new lists must be x + (1-x) w_t^{LIST}.
Since x is 100 percent in this case, the implied weights are -1 + 2 w_t^{LIST}, and based on the fact that average w_t^{LIST} is five percent, this portfolio has an average weight of -91 percent in new lists. In order to get a constant of negative one in the implied weight, the optimizer is forced to put a positive two in front of w_t^{LIST}. Thus instead of following a contrarian strategy of underweighting new lists when they are a large fraction of the market, it is constrained to dynamically overweight them. Thus a simple α actually embodies a convoluted compromise between (productive) average underweighting and (counterproductive) timing.

The next row in Table V shows the optimal combination of old and new lists, without using the market as one of the constituent portfolios. Here the optimizer is able to achieve a constant weight of -92 percent in new lists, similar to the average weight before, but without being forced to engage in a counterproductive timing strategy. Consequently, the Sharpe ratio rises slightly.

The last row of Table V shows the optimal combination of three portfolios: the market, old lists, and new lists. The optimizer now has two parameters (instead of one) to choose, and consequently it can engineer a strategy that has both a low average weight in new lists and a contrarian weighting during waves of new lists. The average weighting in new lists is -39 percent. The huge contrarian coefficient of -40.56 on the weight on new lists implies that when new lists reach their peak of 15 percent of the market, the strategy has a weight of -460 percent in new lists. When new lists reach their low of one percent of the market, the strategy has a weight of 107 percent in new lists. This ability to engage in productive timing boosts the Sharpe ratio of this strategy to 0.156.

Thus the conclusions from Table V are that the market is far from the optimal portfolio combining new and old lists. Going from the market to the optimal combination, the Sharpe ratio increases from 0.109 to 0.156. As before, most of the benefit comes not from avoiding the average underperformance but rather from avoiding (or doing the opposite of) the waves of new lists. A static combination alone raises Sharpe ratios to only 0.128. To get the full benefit of the optimal strategy, dynamic weightings are necessary.

IV. Net corporate issuance

This section broadens the analysis to examine more generally all corporate events that affect the composition of the market, not just new lists. An investor who is holding the market portfolio has to respond to any event that changes the number of shares outstanding of a particular old list stock. For example, he has to buy in response to seasoned equity offerings (SEOs) and sell in response to repurchases. Ikenberry, Lakonishok, and Vermaelen (1995) find that firms repurchasing their own stock have high subsequent returns. Loughran and Ritter (1995) find that firms doing SEOs have low subsequent returns. This evidence is consistent with the idea that firms take advantage of overpricing to sell stock, and take advantage of underpricing to buy stock back.

This section jointly examines these actions by looking at net new issues by corporations. Net new issues are events that change the number of (split-adjusted) shares of the firm. In addition to IPOs and new lists, share increasing events include SEOs, stock-financed acquisitions, and exercise of stock options. Share decreasing events include open market repurchases and tender offers. All these events reflect conscious choices by firms, and might be considered economically equivalent. For example, the number of shares increases when an executive exercises options. Although this event does not involve the firm selling shares to the public, it is economically equivalent to the case where the firm sells equity, gives the proceeds to the executive, and the executive buys stock. In both cases value is being transferred from existing shareholders to the executive, and in both cases the existing shareholders have their stake diluted.

A. Change in the number of shares

The total capitalization of the market at any period t is the sum of listed stocks that were not in the market 36 months ago, plus the sum of listed stocks that were. So far I have been focusing on this distinction. I now further subdivide the market capitalization of old lists into three portfolios: the market equity of old lists in proportion to their shares outstanding 36 months (portfolio LAG), plus the market equity of firms in proportion to their newly added shares over the past 36 months (portfolio PLUS), minus the market equity of firms in proportion to their decrease in shares over the past 36 months (portfolio MINUS). Let there be N old lists with split adjusted shares outstanding of Q. Let ADD be a dummy variable equal to 1 if the number of shares outstanding increases between t-36 and t. Then the entire market equity of old lists is:

$$
\begin{aligned}
\mathrm{ME}_t^{OLD} &= \sum_{i=1}^{N_t} P_t^i Q_t^i = \sum_{i=1}^{N_t} P_t^i Q_{t-36}^i + \sum_{i=1}^{N_t} P_t^i \left(Q_t^i - Q_{t-36}^i\right) \\
&= \sum_{i=1}^{N_t} P_t^i Q_{t-36}^i + \sum_{i=1}^{N_t} P_t^i \left(Q_t^i - Q_{t-36}^i\right) \mathrm{ADD}_t + \sum_{i=1}^{N_t} P_t^i \left(Q_t^i - Q_{t-36}^i\right)\left(1-\mathrm{ADD}_t\right) \\
&= \mathrm{ME}_t^{LAG} + \mathrm{ME}_t^{PLUS} + \mathrm{ME}_t^{MINUS}
\end{aligned}
\tag{13}
$$

The same stocks appear in both LAG and either PLUS or MINUS. $\mathrm{ME}^{\mathrm{MINUS}}$ is a negative number that shows how much the total market equity of old lists has decreased due to repurchases and other share decreasing events.

Using these three portfolios, one can now decompose the market into four portfolios: LIST, PLUS, MINUS, and LAG. The first three are the candidate portfolios that are collectively net new issues. Thus the difference between market returns and returns on LAG are:

$$R_t^{M} - R_t^{LAG} = w_t^{PLUS}\left(R_t^{PLUS} - R_t^{LAG}\right) + w_t^{MINUS}\left(R_t^{MINUS} - R_t^{LAG}\right) + w_t^{LIST}\left(R_t^{LIST} - R_t^{LAG}\right) \tag{14}$$

Thus w^{PLUS} is the percent by which the total dollar value of the market is higher due to share increases, while w^{MINUS} is the percent by which it is lower due to share decreases (Daniel and Titman (2001) study a related variable).

And one can decompose this further into three fixed weight returns and three timing returns. The timing and fixed weight components for new lists is the same as before, except now using portfolio LAG instead of portfolio OLD in the calculation. Portfolio LAG and OLD contain exactly the same set of old lists, but using slightly different portfolio weights.

The returns in equation (14) are somewhat different from what one would calculate using the traditional approach. A traditional value weighted calendar time return from a portfolio of SEOs, for example, would consist of the same firms as PLUS, but with different portfolio weights. The traditional return would weight each SEO firm according to its market equity. Instead, PLUS weights each firm according to its market equity times the percent of the firm that is newly issued. Thus a \$1 billion stock that doubles its number of shares gets ten times the weight of a \$1 billion stock that issues ten percent more shares.

As with new lists, there are costs and benefits from using only CRSP share data to identify net issuance, rather than traditional databases of SEOs and repurchases. The benefit is that one can construct a very long time series going back to 1929. One cost is that one is forced to lump together various different corporate events. Another cost is that this method might be particularly prone to errors in the CRSP database. There is no doubt that shares outstanding data from CRSP contains numerous errors. In the course of this study I discovered numerous errors (now corrected) in number of shares, mostly occurring in months surrounding stock splits or distributions. Of course, this type of error affects any study involving market capitalization or value weighting.

B. Empirical results

Net new issues are nine percent of the market on average, ranging from two percent to 27 percent. This number is the percent of the market that is new lists, plus the percent that has been added by old lists, minus the percent that has been subtracted by old lists. Looking within net new issues, the PLUS and LIST portfolio are both around five percent of the market on average, with the MINUS portfolio about one percent of the market on average. Figure 3 shows the portfolio weights of PLUS and MINUS. Comparing figures 1 and 3, it is clear that new lists and additional shares issued by old lists have weights that move together over time, both peaking at the end of the 1920's and 1990's (the correlation is 0.56). Similarly, Loughran and Ritter (1995) show that the number of SEOs and the number of IPOs are positively correlated in the period 1970-1990. Reductions in shares are negligible until the 1980s (as documented by Bagwell and Shoven (1989), repurchases became popular then).

Table VI show the timing and fixed weight components for net new issues and its three parts. The total effect of net new issues is shown by $R^M - R^{LAG}$. The timing component for net new issues is the sum of the three timing components for LIST, PLUS, and MINUS components, and similarly for the fixed weight component.

Overall, shunning net new issues would increase mean returns by 3.5 basis points per month, and this quantity is not substantially changed by risk adjustment using the various factor models. Operationally, holding LAG rather than the market is easy to do and places low informational demands on investors. Just hold all stocks in proportion to the shares outstanding 36 months ago, rather than in proportion to shares outstanding today.

Of the 3.5 basis points, 2.2 are due to the fixed weight component and 1.3 are due to the timing component. Most of this timing component comes from new lists, with the PLUS and MINUS contributing almost nothing to the mean of the timing component. The timing component is statistically indistinguishable from zero for PLUS and MINUS. Thus timing appears important only for new lists, not for old lists doing net issuance. Similarly, Mitchell and Stafford (2000) do not find much evidence in favor of a timing effect for SEOs, acquisitions, and stock repurchases. In contrast, Loughran and Ritter (1995, 2000) find that underperformance of SEOs is larger when the number of SEOs is high.

The PLUS and MINUS fixed weight components are statistically different from zero, with the expected result that both types of corporate events reduce market returns. In terms of fixed weight returns, all three portfolios contribute to lower market returns, with new lists contributing seven basis points, share increases contributing 11 basis points, and share decreases contributing three basis points. The fixed weight component is not much affected by the various factor models and is stable over the two subperiods.

To summarize, almost all of the timing contribution comes from new lists. For share increases and decreases, there is little evidence for timing, but ample evidence for fixed weight returns causing a lower market return.

V. Comparison to growth, value, and size

This section briefly examines growth, value, and size using the framework of this paper. Setting aside the topic of new issues, it measures the impact of the market's dynamic weighting of stocks sorted into various categories. This measurement is useful both for comparing to new lists, and for testing whether these portfolios have time-varying expected returns. Before discussing the specific results, it is useful to lay out what might be expected for the timing component. If there are time-varying expected returns (perhaps due to temporary mispricing) on different categories of assets, the timing effect should be negative. For example, by holding growth stocks using market weights, investors are giving low weight to growth when it is cheap, and high weight when it is expensive. According to this view, by leaning against the wind and holding growth stocks in fixed weights one can earn higher return.

Table VII first looks at the effect of excluding growth stocks, defined as stocks in the bottom 30 percent of book-market (B/M) using NYSE breakpoints. Book values come from an updated version of the data in Davis, Fama, and French (2000), generously supplied by Ken French. Growth stocks are 49 percent of the market on average. Excluding these stocks has a surprisingly small effect. The portfolio excluding growth stocks has mean returns that are 8 basis points higher than the market. Neither this effect nor its timing and fixed weight components are statistically distinguishable from zero. There is no evidence that the timing component is different from zero using the various factor models.

Looking at value (the top 30 percent of B/M) rather than growth, there is again little evidence for timing ability. Value stock are 17 percent of the market on average. They have returns that are significantly higher than non-value stock returns. Last, looking at small stocks (defined as firms in the bottom 30 percent of market capitalization using NYSE breakpoints), there is a bit of evidence for timing in mean returns but not much after risk-adjusting using the CAPM or the factor models.

In summary, although growth, value, and small firms all have timing components with the expected negative sign, none of the timing effects are strongly significant. It appears that statistically significant timing is confined to new lists. Of course, this analysis uses no conditioning information other than value weights. Other variables (for example the ratio of market weights to book weights as in Cohen, Polk, and Vuolteenaho (2001)) might produce different results.

VI. Conclusions

This paper presents a framework for understanding the contribution of particular asset classes to market returns. The framework decomposes market returns into the returns due to the average performance of asset classes and their average weight in the market, and the returns due to the implicit dynamic strategy that the market takes in different asset classes. This framework can be used for any asset classes with fluctuating weights. One cause of fluctuating weights is waves of corporate events. For the specific case of new lists, the results show that waves of new lists are negatively correlated with differential returns on new minus old lists. Most of the effect of new lists on the total market comes from this timing component. Unlike other phenomena, such as value, growth, or new share issues by existing firms, for new lists the timing component is a central part of the story.

There are several benefits to this framework. First, it connects various disparate pieces of information (such as average underperformance, waves, and predictive regressions for returns) and shows how they fit together to affect the market portfolio. Second, it provides a measure of the economic significance (as opposed to statistical significance) of timing. Third, it reveals the perils of studying asset pricing phenomena in isolation. Looked at in isolation, the underperformance of new lists is not terribly strong. Only in the context of the overall market can one see the true costs of holding new lists. This context is necessary because it is not always obvious how the dynamic nature of the market changes inferences about asset pricing.

A. *Interpretation of results*

The fact that issuances are negatively correlated with future returns does not, by itself, say much about the rationality of stock prices. If expected returns on equities fall relative to other assets, one would expect to see firms issuing equity whether or not the stock market is rational. This statement holds true for both differential returns and aggregate returns. Not only do new lists do poorly when the market heavily weights new lists; old lists also do poorly.

It turns out that the portfolio weight that the market puts in new lists is a powerful forecaster of aggregate market returns. One possible explanation is that when expected returns fall, firms issue equity in order to invest in physical capital; consistent with this story, Lamont (2000) shows that investment plans by corporations predict future excess stock returns. This relation could reflect mispricing due to cognitive errors or sentiment. It could reflect changes in rational risk premia. It could also have nothing to do with either mispricing or risk – perhaps liquidity, taxes, or some other force is at work.

For example, suppose for some reason equities become more liquid. In that case, equities will have a lower required rate of return (the illiquidity premium falls), and companies should rationally respond by issuing more equity (replacing illiquid debt, perhaps). This paper provides some support for this explanation, since new lists as a percent of the market in 1929-2001 corresponds to patterns of liquidity and turnover presented in Jones (2002) and Chordia, Roll, and Subrahmanyam (2001). On the other hand, section III shows that from a Sharpe ratio perspective investors would be better off holding currency, the most liquid of all assets, rather than IPOs, so a liquidity explanation may be implausible. And of course, new issues could still be overpriced even if they are more liquid (Baker and Stein (2001) provide a model where liquidity and mispricing go together.)

Thus additional evidence is necessary to discriminate between rational and irrational stories. Various pieces of circumstantial evidence from the period 1999/2000 hint at a mispricing explanation, particularly for technology IPOs. As shown in Figure 1, the period 1999/2000 was an important episode in financial history, and it is useful to study it closely because it is a very well documented case of alleged mispricing. First, Lamont and Thaler (2001) show that there were several technology IPOs in the period that were blatantly overpriced relative to other securities, but that short sale constraints prevented arbitrageurs from correcting this overpricing. Second, Ofek and Richardson (2002) show that various IPO-related anomalies, such as predictable declines in prices around the ending of lockups and predictable rises around the ending of the quiet period, were more severe for internet IPOs in this period. These predictable returns are consistent with mispricing. Third, Loughran and Ritter (2002) document that during this period, average first day IPO returns exceeded 60 percent, far higher than the historical mean. It is not clear exactly how this fact fits in, but it is clear that one way for IPOs to get overpriced is for their price to rise in the first day. Fourth, various hard-to-quantify phenomena occurred in the IPO market during this period that seem best described by words such as “mania,””irrational,”or “sentiment.” In February 2000, chaos erupted in the street of Hong Kong. Huge crowds gathered around 10 different banks. The police were called in to maintain order. Some branches closed their doors, while others extended their hours to accommodate the impatient mob. A bank run? Sort of. But instead of fighting to get their money out, these people were fighting to get their money in. They were applying to subscribe to the IPO of a new Internet company. It seems unlikely these investors thought that the IPO had a low expected return but were willing to hold it due to its high liquidity or low risk.

Any complete explanation for the timing phenomenon needs to address the comovement of several variables. Aggregate issuance, the level of aggregate stock prices, and aggregate volume are all positively correlated over time. All three things peak in the late 1920's and late 1990's (with perhaps a lower middle peak in the late 1960's). All three things are negatively related to subsequent aggregate stock returns.

Footnotes

[1] See Barber and Lyon (1997), Brav (2000), Brav, Geczy and Gompers (2000), Brav and Gompers (1997), Fama (1998), Ikenberry, Lakonishok, and Vermaelen (1995), Kothari and Warner (1997), Lyon, Barber, and Tsai (1999), Mitchell and Stafford (2000).

[2] Average continuously compounded (log) returns for R^M - R^{OLD} are -0.019 with a t-statistic of 2.64, so this change makes the effect slightly stronger.

[3] Here the definition of a new list is a firm newly listed in the past three years, where Fama and French (2001) look at the first three years separately. Their approach has the drawback of producing portfolios that contain very few stocks in some months, creating high volatility and high standard errors.

[4] The four factors come from Ken French's web page. The momentum factor, UMD for up minus down, is created by French and is slightly different from the one used by Carhart (1997).

[5] Weiss (1989) and Peavey (1990) find that closed-end funds do poorly after their IPO. This finding is consistent with the fact that they typically sell at a premium to their net asset value initially (Klibanoff, Lamont, and Wizman (1998) mention an extreme example of the 92 percent premium for the Taiwan fund two months after its inception). A piece of time series evidence suggests another connection between IPOs and closed end funds: Lee, Shleifer and Thaler (1991) find that IPO waves by operating companies correspond to times when closed end fund prices are atypically high relative to NAV.

[6] A concern in this regression (and more generally in the TIMING measure) is spurious predictability. Shultz (2001) discusses the possibility of "pseudo market timing" creating spurious predictability of returns using waves of issuance. A well known small sample bias, discussed in Stambaugh (1999), exists in this situation due to persistence in the independent

variable and covariance of shocks to new lists weights and new list returns. Using the formula on page 273 of Campbell, Lo, and Mackinlay (1997), the bias is only -0.26, which is small compared to the actual coefficient of 16.35.

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Table I
Summary statistics for new lists

R^M is the CRSP market return. R^F is the t-bill portfolio return. R^{OLD} is the return on old lists not newly appearing in CRSP in the last 36 months. R^{LIST} is the return on new lists newly appearing in CRSP in the last 36 months. All returns are value weighted, monthly, in percent. w^{LIST} is the portfolio weight of the market in newly listed stocks, and has average value of $\overline{w}^{LIST}$ over the entire sample period. FIXED is $\overline{w}^{LIST}\left(R_t^{LIST}-R_t^{OLD}\right)$ and TIMING is $\left(w_t^{LIST}-\overline{w}^{LIST}\right)\left(R_t^{LIST}-R_t^{OLD}\right)$. The sample period is January 1929 to December 2001.

Variable	Mean	t-stat on mean	Std. Dev.	Min	Max
R^M - R^F	0.606	3.22	5.567	-29.003	38.174
R^{OLD} - R^F	0.623	3.34	5.531	-28.441	38.057
R^{LIST} - R^F	0.487	2.08	6.940	-33.264	43.679
R^M - R^{OLD}	-0.017	-2.37	0.216	-2.279	1.833
R^{LIST} - R^{OLD}	-0.137	-1.25	3.231	-22.038	21.743
R^{LIST} - R^M	-0.119	-1.16	3.039	-20.300	20.128
TIMING	-0.011	-3.05	0.107	-1.382	0.934
FIXED	-0.006	-1.25	0.149	-1.016	1.002
w^{LIST}	0.046	52.46	0.026	0.009	0.147

Correlations

	R^M - R^F	R^{OLD} - R^F	R^{LIST} - R^F	R^M - R^{OLD}	R^{LIST} -R^{OLD}	R^{LIST} - R^M	TIMING	FIXED
R^{OLD} - R^F	0.999							
R^{LIST} - R^F	0.905	0.890						
R^M - R^{OLD}	0.186	0.148	0.533					
R^{LIST} - R^{OLD}	0.233	0.200	0.625	0.893				
R^{LIST} - R^M	0.234	0.202	0.626	0.878	1.000			
TIMING	0.052	0.022	0.209	0.779	0.412	0.383		
FIXED	0.233	0.200	0.625	0.893	1.000	1.000	0.412	
w^{LIST}	-0.127	-0.121	-0.158	-0.174	-0.132	-0.128	-0.168	-0.132

Table II
Regression results for new lists

	R^{OLD} - R^{F} (1)	R^{LIST} - R^{F} (2)	R^{M} - R^{OLD} (3)	R^{LIST}-R^{OLD} (4)	R^{LIST} - R^{M} (5)	TIMING (6)	FIXED (7)
Mean return	0.623	0.487	-0.017	-0.137	-0.119	-0.011	-0.006
	(0.187)	(0.234)	(0.007)	(0.109)	(0.103)	(0.004)	(0.005)
pre-62	0.520	0.374	-0.019	-0.146	-0.126	-0.013	-0.007
	(0.202)	(0.312)	(0.012)	(0.178)	(0.167)	(0.006)	(0.008)
post-62	0.745	0.619	-0.015	-0.126	-0.111	-0.009	-0.006
	(0.330)	(0.354)	(0.006)	(0.113)	(0.108)	(0.004)	(0.005)
CAPM α	0.022	-0.197	-0.022	-0.219	-0.197	-0.012	-0.010
	(0.007)	(0.100)	(0.007)	(0.107)	(0.100)	(0.004)	(0.005)
3-factor α	0.016	-0.128	-0.016	-0.144	-0.128	-0.009	-0.007
	(0.006)	(0.074)	(0.006)	(0.078)	(0.074)	(0.003)	(0.004)
4-factor α	0.021	-0.199	-0.021	-0.219	-0.199	-0.010	-0.010
	(0.006)	(0.076)	(0.006)	(0.080)	(0.076)	(0.003)	(0.004)
R_M - R_F	0.995	1.088	0.005	0.093	0.088	0.001	0.004
	(0.001)	(0.015)	(0.001)	(0.015)	(0.015)	(0.001)	(0.001)
SMB	-0.033	0.502	0.033	0.535	0.502	0.008	0.025
	(0.002)	(0.023)	(0.002)	(0.024)	(0.023)	(0.001)	(0.001)
HML	0.024	-0.314	-0.024	-0.338	-0.314	-0.008	-0.016
	(0.002)	(0.022)	(0.002)	(0.023)	(0.022)	(0.001)	(0.001)
UMD	-0.004	0.065	0.004	0.069	0.065	0.001	0.003
	(0.001)	(0.018)	(0.001)	(0.019)	(0.018)	(0.001)	(0.001)
R-squared	0.999	0.904	0.451	0.504	0.499	0.146	0.504
4-factor α	0.018	-0.164	-0.018	-0.182	-0.164	-0.009	-0.008
pre-62	(0.008)	(0.103)	(0.008)	(0.109)	(0.103)	(0.005)	(0.005)
4-factor α	0.017	-0.192	-0.017	-0.209	-0.192	-0.007	-0.010
post-62	(0.006)	(0.099)	(0.006)	(0.103)	(0.099)	(0.004)	(0.005)

Table II
Notes

R^M is the CRSP market return. R^F is the t-bill portfolio return. R^{OLD} is the return on old lists not newly appearing in CRSP in the last 36 months. R^{LIST} is the return on new lists newly appearing in CRSP in the last 36 months. All returns are value weighted, monthly, in percent. w^{LIST} is the portfolio weight of the market in newly listed stocks, and has average value of $\overline{w}^{LIST}$ over the entire sample period. FIXED is $\overline{w}^{LIST}\left(R_t^{LIST} - R_t^{OLD}\right)$ and TIMING is $\left(w_t^{LIST} - \overline{w}^{LIST}\right)\left(R_t^{LIST} - R_t^{OLD}\right)$. The CAPM α is the intercept term from a regression on R^M - R^F. The three-factor α is the intercept term from a regression on the three variables of Fama and French (1993), including the excess market return, SMB (the return on small stocks minus big stocks) and the HML (the return of high B/M stocks minus low B/M stocks). The four-factor model adds UMD, a momentum factor reflecting the return of stocks with high prior year returns minus stocks with low prior year returns. Pre-1962 is prior to August 1962. Post-1962 is after July 1962. The table shows four-factor loadings as well as α. The sample period is January 1929 to December 2001. Standard errors in parentheses.

Table III
Robustness tests for timing

The table shows the average value of TIMING and its α's for different specifications and time periods. R^M is the CRSP market return. R^F is the t-bill portfolio return. R^{OLD} is the return on old lists not newly appearing in CRSP in the last 36 months. R^{LIST} is the return on new lists newly appearing in CRSP in the last 36 months. All returns are value weighted, monthly, in percent. w^{LIST} is the portfolio weight of the market in newly listed stocks, and has average value of $\overline{w}^{LIST}$ over the entire sample period. TIMING is $\left(w_t^{LIST} - \overline{w}^{LIST}\right)\left(R_t^{LIST} - R_t^{OLD}\right)$. The CAPM α is the intercept term from a regression on R^M - R^F. The three-factor α is the intercept term from a regression on the three variables of Fama and French (1993), including the excess market return, SMB (the return on small stocks minus big stocks) and the HML (the return of high B/M stocks minus low B/M stocks). The four-factor model adds UMD, a momentum factor reflecting the return of stocks with high prior year returns minus stocks with low prior year returns. "Common stock only" uses only stock with CRSP share code 10 or 11 in the calculation of the old and new list portfolios returns and weights. "Equal weighted" replaces all value weights with equal weights. "Real timing" uses average weights calculated as the average of all weights up to month t, provided at least 5 years of data are available. For common stock only and equal weighted, the sample period is January 1929 to December 2001. For all regressions, the factors on the right hand side are calculated in the regular way. Standard errors in parentheses.

	Mean return	CAPM α	3-factor α	4-factor α
Common Stock Only	-0.011	-0.012	-0.009	-0.011
	(0.004)	(0.004)	(0.004)	(0.004)
Equal weighted	-0.018	-0.023	-0.023	-0.022
	(0.006)	(0.006)	(0.006)	(0.006)
Real timing, 1934:2-2001:12	-0.008	-0.009	-0.004	-0.007
	(0.004)	(0.004)	(0.003)	(0.004)
Benchmark definition, 1973:1 - 2001:12	-0.016	-0.017	-0.005	-0.012
	(0.008)	(0.008)	(0.007)	(0.007)
Benchmark definition, 1973:1 - 1998:12	-0.010	-0.009	-0.007	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)

Table IV
Predictive power of new list portfolio weight for returns

Forecasting regressions of returns on portfolio weights. The dependent variable is $R^{LIST} - R^{OLD}$ in the first column and R^M - R^F in the other columns. R^{OLD} is the return on old lists, a portfolio of stocks that have not newly appeared in CRSP in the last 36 months. R^{LIST} is the return on new lists, a portfolio of stocks that have newly appeared in CRSP in the last 36 months. w^{LIST} is the portfolio weight of the market in newly listed stocks. R^M - R^F is the excess return on the CRSP value weighted market. P/D is the ratio of current price to past year dividends for the S&P Composite index. P/E10 is the market ratio of current price to average earnings per share over the past 10 years, for the S&P Composite index. BILLYIELD is the t-bill yield. SHARE is the equity share over the past year, calculated as gross equity issues divided by gross equity issues plus gross debt issues. All returns are value weighted, monthly, in percent. For monthly regressions the sample period is January 1929 to December 2001. For annual regressions (the last two columns only) the sample period is 1929 to 2000. Regressions include a constant term, not shown. Standard errors in parentheses.

	$R^{LIST} - R^{OLD}$	-------------------------------------			R^M - R^F		-------------------------------------	
							Annual	Annual
w^{LIST}	-16.353	-27.177			-25.577	-23.127	-250.853	-154.698
	(4.167)	(7.185)			(7.515)	(8.015)	(91.075)	(98.260)
P/D			-0.018		-0.004			
			(0.013)		(0.014)			
P/E10				-0.062		-0.025		-0.761
				(0.026)		(0.029)		(0.334)
BILLYIELD			-10.331	-12.100	-10.126	-10.807		-36.014
			(5.804)	(5.674)	(5.769)	(5.668)		(63.241)
SHARE							-63.343	-72.641
							(21.206)	(21.808)
R-squared	0.017	0.016	0.007	0.012	0.020	0.021	0.230	0.290

Table V
Sharpe ratios and portfolio weights

The table shows Sharpe ratios and portfolio weights for different portfolios. R^M is the CRSP market return. R^F is the t-bill portfolio return. R^{OLD} is the value weighted return on a portfolio of stocks that have not newly appeared in CRSP in the last 36 months. w^{LIST} is the portfolio weight of the market in newly listed stocks. "Substitute t-bills for new lists" is the return $(1- w^{LIST})(R^{OLD} - R^F)$. "Substitute t-bills for cash" is the return $(1- w^{LIST})R^{OLD} - R^F$. "Apparent weights" are (seemingly static) portfolio weights produced by a standard mean variance optimizer using means, variances, and covariances from the full sample period. "Implied weights" are the (possibly time-varying) portfolio weights in new and old lists implied by the apparent weights. The sample period is January 1929 to December 2001.

	Mean return	Std dev	Sharpe Ratio	-- Apparent Weights -- R^{OLD}	R^{LIST}	R^M	--------- Implied Weights --------- R^{OLD}	R^{LIST}
Simple portfolios								
$R^M - R^F$	0.606	5.567	0.109				$1-w_t^{LIST}$	w_t^{LIST}
$R^{OLD} - R^F$	0.623	5.531	0.113				1	0
Substitute t-bills for new lists	0.612	5.232	0.117				$1-w_t^{LIST}$	0
Substitute cash for new lists	0.597	5.233	0.114				$1-w_t^{LIST}$	0
Optimal portfolios								
R^{LIST}, R^M	0.726	5.688	0.128		-1.00	2.00	$2.00 - 2.00\, w_t^{LIST}$	$-1.00 + 2.00\, w_t^{LIST}$
R^{LIST}, R^{OLD}	0.748	5.728	0.131	1.92	-0.92		1.92	-0.92
R^{LIST}, R^{OLD}, R^M	1.124	7.194	0.156	40.08	1.48	-40.56	$-0.48 + 40.56\, w_t^{LIST}$	$1.48 - 40.56\, w_t^{LIST}$

Table VI
Regression results for net new issues

	$R^M - R^{LAG}$	--Net new issues-- TIM	FIXED	--PLUS-- TIM	FIXED	--MINUS-- TIM	FIXED	--LIST-- TIM	FIXED
Mean return	-0.035	-0.013	-0.022	-0.002	-0.011	0.001	-0.003	-0.011	-0.007
	(0.010)	(0.005)	(0.007)	(0.002)	(0.003)	(0.001)	(0.001)	(0.004)	(0.005)
pre-62	-0.043	-0.018	-0.025	-0.004	-0.013	0.000	-0.004	-0.013	-0.008
	(0.016)	(0.007)	(0.011)	(0.002)	(0.003)	(0.001)	(0.001)	(0.006)	(0.008)
post-62	-0.026	-0.008	-0.018	0.000	-0.009	0.001	-0.002	-0.009	-0.006
	(0.009)	(0.005)	(0.008)	(0.003)	(0.005)	(0.001)	(0.002)	(0.004)	(0.005)
CAPM α	-0.041	-0.014	-0.027	-0.002	-0.013	0.000	-0.003	-0.012	-0.011
	(0.010)	(0.005)	(0.007)	(0.002)	(0.003)	(0.001)	(0.001)	(0.004)	(0.005)
3-factor α	-0.033	-0.011	-0.022	-0.001	-0.013	0.000	-0.002	-0.010	-0.007
	(0.007)	(0.004)	(0.005)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.004)
4-factor α	-0.035	-0.012	-0.023	-0.001	-0.010	0.000	-0.002	-0.011	-0.011
	(0.008)	(0.005)	(0.005)	(0.002)	(0.003)	(0.001)	(0.001)	(0.004)	(0.004)
$R_M - R_F$	0.007	0.001	0.005	0.000	0.002	0.000	0.000	0.001	0.004
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
SMB	0.041	0.010	0.031	0.000	0.008	0.002	-0.002	0.008	0.025
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
HML	-0.034	-0.011	-0.023	-0.003	-0.005	0.000	-0.002	-0.009	-0.016
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
UMD	0.002	0.001	0.001	0.000	-0.002	0.000	0.000	0.001	0.003
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
R-squared	0.439	0.147	0.471	0.066	0.188	0.123	0.137	0.148	0.505
4-factor α	-0.035	-0.011	-0.024	-0.002	-0.012	0.000	-0.002	-0.010	-0.009
pre-62	(0.011)	(0.007)	(0.007)	(0.002)	(0.003)	(0.001)	(0.001)	(0.005)	(0.005)
4-factor α	-0.027	-0.007	-0.020	0.000	-0.009	0.000	-0.001	-0.008	-0.010
post-62	(0.008)	(0.006)	(0.007)	(0.003)	(0.005)	(0.001)	(0.002)	(0.004)	(0.005)

Table VI
Notes

R^M is the CRSP market return. R^F is the t-bill portfolio return. R^{LAG} is the return on a portfolio of stocks not newly appearing in CRSP in the last 36 months, using value weights calculated with the number of shares outstanding 36 months ago. R^{LIST} is the return on new lists, a portfolio of stocks newly appearing in CRSP in the last 36 months. R^{PLUS} is the return on shares added in the last 36 months by firms that were on CRSP 36 months ago, using value weights calculated with the number of shares that have been added. R^{MINUS} is the return on shares subtracted in the last 36 months by firms that were on CRSP 36 months ago, using value weights calculated with the number of shares that have been subtracted. All returns are value weighted, monthly, in percent. All calculations using shares are split-adjusted. w^{LIST} is the portfolio weight of the market in newly listed stocks, and has average value of $\overline{w}^{LIST}$ over the entire sample period. For new lists, FIXED is $\overline{w}^{LIST}\left(R_t^{LIST}-R_t^{LAG}\right)$ and TIMING is $\left(w_t^{LIST}-\overline{w}^{LIST}\right)\left(R_t^{LIST}-R_t^{LAG}\right)$. The weights, fixed weight returns, and timing returns are calculated similarly for PLUS and MINUS. For "net new issues," the FIXED component is the sum of the three LIST, PLUS, and MINUS components, and similarly for TIMING. The CAPM α is the intercept term from a regression on R^M - R^F. The three-factor α is the intercept term from a regression on the three variables of Fama and French (1993), including the excess market return, SMB (the return on small stocks minus big stocks) and the HML (the return of high B/M stocks minus low B/M stocks). The four-factor model adds UMD, a momentum factor reflecting the return of stocks with high prior year returns minus stocks with low prior year returns. The table shows four-factor loadings as well as α. Pre-1962 is prior to August 1962. Post-1962 is after July 1962. The sample period is January 1929 to December 2001. Standard errors in parentheses.

Table VII
Value and size

R^{GROWTH} is the value weighted portfolio of all firms that are in the top 30 percent of stocks sorted on market/book ratios. R^{VALUE} is the value weighted portfolio of all firms that are in the bottom 30 percent of stocks sorted on market/book ratios. R^{SMALL} is a value weighted portfolio of all firms that are in the bottom 30 percent of stocks sorted on market capitalization. R^{EX_GROWTH}, R^{EX_VALUE}, and R^{EX_SMALL} are the complements. w^{GROWTH} is the portfolio weight of the market in firms in the top 30 percent sorted on market/book. $FIXED^{GROWTH}$ is $\overline{w}^{GROWTH}\left(R_t^{GROWTH} - R_t^{EX\_GROWTH}\right)$ and TIM^{GROWTH} is $\left(w_t^{GROWTH} - \overline{w}^{GROWTH}\right)\left(R_t^{GROWTH} - R_t^{EX\_GROWTH}\right)$, and similarly for value and small. The CAPM α is the intercept term from a regression on R^M - R^F. The three-factor α is the intercept term from a regression on the three variables of Fama and French (1993), including the excess market return, SMB (the return on small stocks minus big stocks) and the HML (the return of high B/M stocks minus low B/M stocks). The four-factor model adds UMD, a momentum factor reflecting the return of stocks with high prior year returns minus stocks with low prior year returns. The sample period is January 1929 to June 2001. Standard errors in parentheses.

	Mean return	Mean weight	CAPM α	3-factor α	4-factor α
$R^M - R^{EX\_GROWTH}$	-0.076	0.488	-0.045	0.056	0.065
	(0.046)		(0.045)	(0.026)	(0.027)
TIM^{GROWTH}	-0.014		-0.002	0.010	0.003
	(0.011)		(0.010)	(0.009)	(0.009)
$FIXED^{GROWTH}$	-0.062		-0.043	0.046	0.061
	(0.040)		(0.040)	(0.023)	(0.024)
$R^M - R^{EX\_VALUE}$	0.045	0.165	0.036	0.002	-0.005
	(0.015)		(0.015)	(0.008)	(0.009)
TIM^{VALUE}	-0.012		0.000	0.013	0.001
	(0.009)		(0.008)	(0.007)	(0.007)
$FIXED^{VALUE}$	0.057		0.036	-0.011	-0.006
	(0.019)		(0.018)	(0.006)	(0.007)
$R^M - R^{EX\_SMALL}$	0.005	0.038	0.001	-0.002	-0.004
	(0.005)		(0.005)	(0.003)	(0.003)
TIM^{SMALL}	-0.008		-0.003	0.003	-0.001
	(0.004)		(0.004)	(0.003)	(0.003)
$FIXED^{SMALL}$	0.013		0.004	-0.006	-0.003
	(0.006)		(0.006)	(0.002)	(0.002)

Figure 1
Fraction of market that is new list in past 36 months, 1929 - 2001

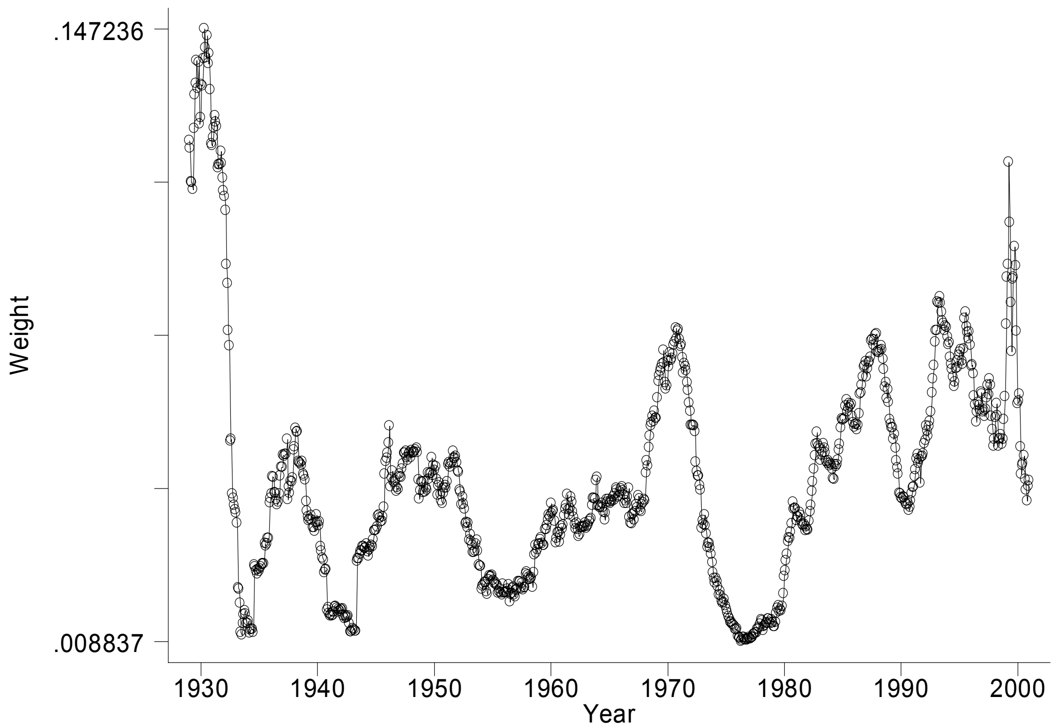

Figure 2: TIMING, 1929 – 2001

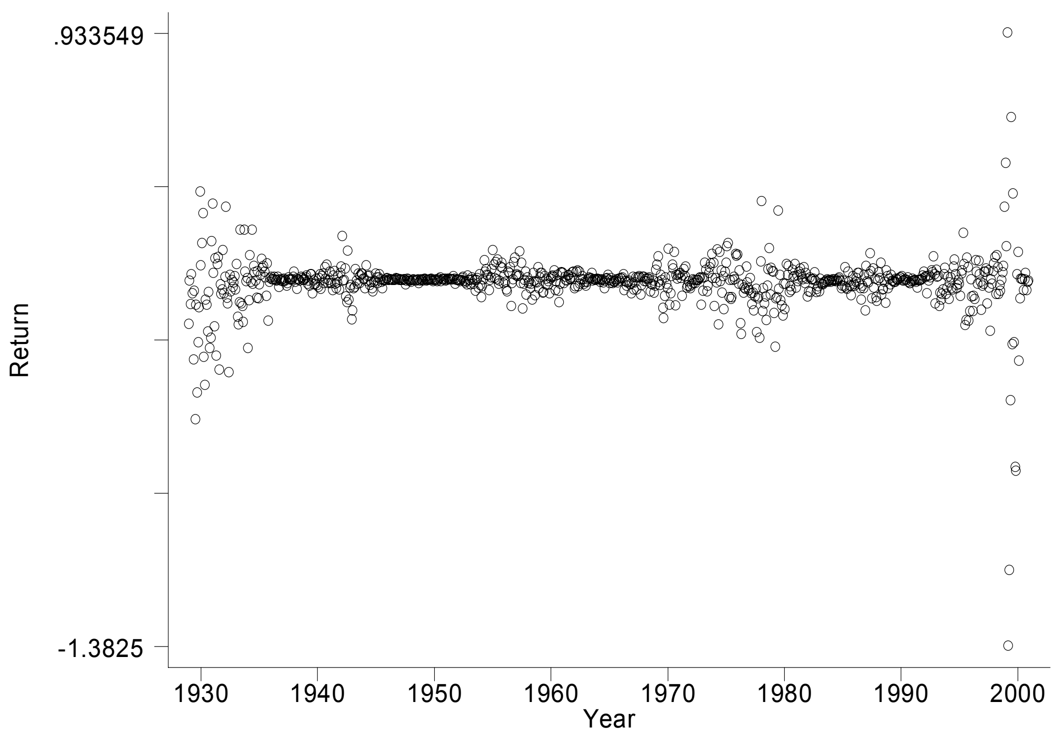

Figure 3: Fraction of market that is plus or minus in past 36 months, 1929- 2001