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John M.R.Chalmers
Roger Edelen
Gregory B. Kadlec

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The Wharton School
University of Pennsylvania

The Rodney L. White Center for Financial Research

The Wharton School
University of Pennsylvania
3254 Steinberg Hall-Dietrich Hall
3620 Locust Walk
Philadelphia, PA 19104-6367

(215) 898-7616
(215) 573-8084 Fax
http://finance.wharton.upenn.edu/~rlwctr

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Predictable Changes in NAV: The Wildcard Option in Transacting Mutual-fund Shares[*]

John M.R. Chalmers
Lundquist College of Business
1208 University of Oregon
Eugene, OR 97403-1208
jchalmer@oregon.uoregon.edu

Roger M. Edelen
The Wharton School
University of Pennsylvania
Philadelphia, PA 19104-6367
edelen@wharton.upenn.edu

Gregory B. Kadlec
Pamplin College of Business
Virginia Tech
Blacksburg, VA 24060-0221
kadlec@vt.edu

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Abstract

Economic distortions can arise when financial claims trade at prices set by an intermediary rather than by direct negotiation between principals. We demonstrate the problem in a specific context, the exchange of open-end mutual fund shares. Mutual funds typically set the price at which fund shares are exchanged (NAV) using an algorithm that fails to account for nonsynchronous trading in the fund's underlying securities. This results in predictable changes in fund share prices, which lead to exploitable trading opportunities of 0.8% per trade at international and small-cap domestic equity funds. A simple modification to the pricing algorithm suggested by nonsynchronous trading theory eliminates much of this predictability. However, one can never rule out the possibility of distortions that arise from other unknown sources when intermediaries set prices.

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1. Introduction

The exchange of financial securities usually involves an intermediary. In many cases the intermediary acts merely as an administrative conduit, with the terms of trade set by the transacting principals. But there are important instances where the intermediary sets the terms at which one or both principals commits to trade. For example, in primary security offerings an investment bank typically sets the issue price; in exchanges of mutual fund shares fund management sets the price; and in certain cases involving secondary market transactions a specialist sets the price.[1] Our study is about problems that can arise when intermediaries are cast into a central role in the pricing of financial securities.

When an intermediary has the information and incentives to set prices that would obtain had the principals transacted directly, there is relatively little concern for economic inefficiency. It is only when the intermediary's information or incentives are weak that problems arise. Consider the preceding examples. When a specialist sets the price at which a secondary-market transaction occurs, he has substantial information about the market's concurrent reservation price. Moreover, his reputation is based entirely on his performance in the trading and pricing of securities. By contrast, when a mutual fund manager sets the price of fund shares, he does not have current information about the value of each security in the portfolio. Generally, he relies on historical transaction prices. Moreover, his incentives to arrive at an accurate price are weak. His reputation is based almost entirely on portfolio management, not on the details of determining fund share price. An intermediate case is that of the investment banker who sets the price of a primary offering. The investment banker uses indications of interest from prospective buyers to set the offer price. However, indications of interest are imperfect estimates of demand

[1] For example when crossing two electronic market orders or in the opening auction the price must fall between the best limit buy and the best limit sell, however, the specialist has some discretion regarding the transaction price.

as evidenced by the common occurrence of oversubscribed and failed offerings. This mispricing occurs despite strong incentives to satisfy the investment bank's clients on both sides of the transaction.

To demonstrate the nature and magnitude of problems that can arise when intermediaries set prices, we examine the case of open-end mutual funds. We first describe the source of the problem – a failure to account for nonsynchronous trading effects in setting NAV – and then document economically important and readily exploitable pricing errors.

U.S. domiciled mutual funds typically offer an exchange of shares once per day, at 4:00 p.m. ET at a price referred to as net asset value (NAV). The most common algorithm used by mutual funds to set NAV values each asset in the fund at its closing price. The closing price of an asset is the price of the last trade before the close of that asset's principal market. Because closing prices are often determined long before 4:00 p.m. ET, they often fail to reflect the value of the fund's assets at the time of the exchange.

This stale price issue is particularly apparent in the case of a U.S. domiciled Asian-market fund, where the underlying assets' market closes at least 13 hours prior to the exchange of fund shares. Yet even in the case of domestic-equity funds, where the close of the markets and the exchange of fund shares are simultaneous, the closing-price algorithm is problematic. There are often material delays between a stock's last trade and the close of the market, particularly in small capitalization firms. These delays cause returns of portfolios computed from closing prices to be predictable. This predictability has been noted in papers dating back as far as Fisher (1966), but it is generally regarded as an illusion in the data since a hypothetical trade occurring at the 4:00 p.m. close would not necessarily occur at the asset's last trade price. However, the predictability becomes real when a mutual fund uses closing prices to set the price at which fund shares trade.

Bhargava, Bose, and Dubofsky (1998) were the first to examine the fund-pricing problem in the context of five foreign equity funds. They show that predictability in foreign equity fund share prices allow trading strategies that earn large abnormal returns. We document that the fund-pricing problem is much more general, affecting domestic equity funds as well. For example, using a simple filter-rule that restricts attention to those days in which the ex ante opportunity for exploitation are in the 95th percentile, produces an average one-day excess return of .84% at high beta, small-cap domestic equity funds, and .87% at foreign equity funds. Recent working papers by Zitzewitz (2000) and Boudoukh, Richardson, Subrahmanyam, and Whitelaw (2000) also show that mutual fund return predictability allows profitable trading strategies in both foreign and domestic equity funds. Additionally, Zitzewitz (2000) finds profitable trading strategies in high-yield domestic bond funds.

Given the apparent profit opportunities, it is likely that predictable fund returns cause economic distortions. Greene and Hodges (2000) and Goetzmann, Ivkovi• and Rouwenhorst (2000) report that a substantial volume of trade in fund shares is attributable to attempts to exploit predictable fund returns. Edelen (1999) shows that increased flow causes funds to trade more frequently, resulting in lower fund returns. Thus, "excessive" trade induced by fund-pricing errors results in a dead-weight loss, borne by all fund investors. Moreover, trade that exploits predictable fund returns results in a direct transfer of wealth from buy-and-hold fund investors to active fund traders.[2]

These problems associated with fund-pricing errors are not lost on fund managers in setting their corporate policies. Indeed, we find that most funds have policies in place that directly or indirectly address the pricing problem. While we cannot divine the intent of these policies; load fees, transaction fees, and transaction restrictions all inhibit the exploitation of predictable fund returns. However these policies are inefficient solutions to the pricing problem because they impose costs on all fund holders, not just those attempting to exploit the pricing errors, and furthermore, they do not eliminate opportunities for exploitation.

A more efficient solution to the fund-pricing problem would be to modify the pricing algorithm to eliminate the opportunity for exploitation. We provide evidence that nonsynchronous trading is a primary source of the predictability in fund returns. Guided by this result, we construct an algorithm that immunizes fund prices from the effects of nonsynchronous trading. In a simulation of the pricing of a small-cap domestic equity fund, this algorithm eliminates much of the predictability in fund returns. These results show that the pricing algorithm currently used by funds can be substantially improved. However, nonsynchronous trading effects are but one source of NAV pricing error. As long as the task of setting the terms of trade falls on an intermediary with inadequate incentives or information, the potential for economic inefficiency remains.

The remainder of this paper is organized as follows. Section 2 develops the link between nonsynchronous trading and mutual fund return predictability. Section 3 presents our data and documents predictability in daily fund returns. Section 4 examines the impact that frictions imposed by funds have on the ability of traders to exploit predictable fund returns. Section 5 experiments with alternative fund-pricing algorithms that attempt to remove the effects of nonsynchronous trading on fund returns. Section 6 concludes.

[2] For an accounting of this wealth transfer, see Greene and Hodges (2000).

2. Nonsynchronous trading and mutual fund return predictability

Closing prices reflect the last trade price of the day for a security. Across a portfolio of stocks, the last trade generally occurs at different times, generating nonsynchronous-trading effects. For example, when valuing a U.S. equity portfolio at the 4:00 p.m. ET close, some of the assets may have traded as recently as 4:00 p.m. while other assets may not have traded since 2:00 p.m. The trade prices of the assets that last traded at 2:00 p.m. do not reflect information that arrives after 2:00 p.m. To the extent that asset prices are influenced by common factors, the prices of recently traded assets will tend to forecast the next-trade prices of assets that have not recently traded. This induces predictability in the returns to portfolios computed from closing prices. This source of predictability in the close-to-close returns of equity portfolios is analyzed extensively in the finance literature.[3]

The logic behind mutual fund return predictability follows directly, as mutual funds value their portfolios using the closing prices of the underlying assets. What is novel and economically meaningful about mutual fund return predictability, versus the well-known phenomenon of portfolio return predictability, is that it can be exploited. In the context of most portfolios, predictability caused by nonsynchronous trading is an illusion. To exploit it, one must be able to trade the underlying assets at their last-trade prices. This is not generally possible because attempts to trade stale priced assets will mark the assets' prices to market, thus refreshing the prices to their appropriate level. Mutual funds, however, use last-trade prices to set NAV, the price at which fund investors purchase and redeem shares. In effect mutual funds allow fund investors to trade the underlying assets at their last-trade prices. As a result, the illusory predictability caused by nonsynchronous trading becomes a reality.

[3] See for example, Atchison, Butler, and Simonds (1987), Lo and MacKinlay (1990), Boudoukh, Richardson, and Whitelaw (1994), and Kadlec and Patterson (1999).

As discussed earlier, an extreme case of the effects of nonsynchronous trading occurs when mutual funds value portfolios of foreign assets using last-trade prices. However, there is reason to believe that the effects of nonsynchronous trading are also important when mutual funds value domestic assets using last trade prices. Boudoukh, Richardson, and Whitelaw (1994) and Kadlec and Patterson (1999) show that nonsynchronous trading accounts for much of the predictability in short-horizon returns of domestic stock portfolios. For example, Kadlec and Patterson (1999) find nonsynchronous trading is capable of generating autocorrelations of 0.28 in daily returns of domestic small-capitalization portfolios.

Nonsynchronous trading is not the only potential source of predictability in mutual fund returns. For example, price-adjustment delays can cause predictability in portfolio returns in the same manner as nonsynchronous trading.[4] We focus on nonsynchronous trading because it is a primary source of portfolio return predictability and can be explicitly linked to mutual fund pricing methods.

3. Predictability in mutual fund returns

3.1 Data

The sample includes 943 mutual funds over the period February 2, 1998 through March 31, 2000. Daily returns data are obtained from TrimTabs.com of Santa Rosa, California. We restrict attention to funds with at least 100 daily return observations during the sample period, which eliminates 25 funds from the sample. The remaining sample includes 484 domestic equity funds,

[4]Cohen et al. (1983) note that there can be information delays in transaction prices due to frictions in the trading process. For example, specialists or dealers may impede the adjustment of price quotations because of exchange stabilization obligations or inventory imbalances (Hasbrouck and Sofianos (1993)). Also, with transaction costs, it is optimal for investors to accumulate news until the collective value of the news exceeds the cost of transacting (Goldman and Sosin (1979)). Mech (1993) examines the impact of price-adjustment delays on portfolio return predictability.

139 foreign equity funds and 295 bond funds as classified by the CRSP mutual-fund database.[5] In the appendix we describe data filters used to ensure that data errors and outliers do not influence the results.

Table 1 presents descriptive statistics. The median domestic equity fund in our sample is larger (with assets of $478 million) than the median domestic equity fund in the CRSP mutual fund database ($99 million).[6] The foreign equity and bond funds in our sample are also large relative to the funds in their respective categories in the CRSP database. The sample foreign equity funds have median assets of $123 million versus $73 million for the foreign equity funds in the CRSP database. The sample bond funds have median assets of $284 million versus $75 million for bond funds in the CRSP database.

Our analysis of mutual fund returns requires a market index to predict next-day fund returns and to benchmark returns earned from fund-trading strategies. Boudoukh, Richardson, and Whitelaw (1994) argue that index-futures prices tend to reflect information on a timelier basis than spot index values. Thus, futures returns should provide greater predictive power than spot index returns, and they should provide the sharpest measure of concurrent market (benchmark) returns. Accordingly, we use index futures data for the S&P 500 and 5-year T-Note from Tick Data as market indices.

3.2 Evidence of mutual fund return predictability

If fund NAVs are set using all information available in the capital markets, daily fund returns should have the same autocorrelation as their underlying assets (i.e., the corresponding futures contract). Excess autocorrelation is evidence of fund-pricing errors. From table 2, the

[5] Funds with more than 50% invested in U.S. stocks are classified as domestic equity, funds with more than 50% invested in foreign stocks are classified as foreign equity, and funds with more than 50% invested in government, corporate, or municipal fixed-income securities are classified as bond funds.

[6] We exclude funds with less than $10 million in assets from the CRSP data set for use in these comparisons.

average autocorrelation of daily fund returns is 8% for domestic equity funds, 18% for foreign equity funds, and 11% for bond funds. By contrast, the autocorrelation of the S&P 500 futures return is -5% while the autocorrelation of the 5-year T-Note futures return is 12%. That equity fund return autocorrelations are greater than equity index-futures return autocorrelations is consistent with the hypothesis that equity fund values are calculated from nonsynchronous closing prices. In contrast, bond fund returns exhibit nearly identical autocorrelation to 5-year T-Note future returns, suggesting that nonsynchronous pricing is not as widespread an issue at bond funds.

Autocorrelations do not reflect exploitable predictability because fund returns are not observable until after the deadline for placing orders has passed (4:00 p.m. ET). To document exploitable predictability in fund returns we regress fund returns on lagged daily index-futures returns computed to 3:55 p.m. ET, which is five minutes before most funds stop accepting purchase and redemption orders. From table 2, the average adjusted-R^2 from regressions of fund returns on lagged S&P 500 futures returns is 0.8% for domestic-equity funds and 10.8% for foreign-equity funds. The average adjusted-R^2 from regressions of bond fund returns on lagged 5-year T-Note future returns is 1.3%.

The nonsynchronous trading hypothesis has implications concerning the nature of the predictability of mutual fund returns. First, assuming securities trade at least once a day, fund return predictability should be confined to next-day fund returns. In results not tabulated, the average adjusted-R^2 from regressions of equity fund returns on lagged S&P 500 futures returns are virtually identical when additional lags out to lag 5 are added to the regressions. Thus, predictability in equity fund returns appears to be confined to next-day returns. However, in regressions of bond fund returns on lagged 5-year T-Note futures returns, the average adjusted-

R^2 increases when additional lags are added out to lag 3. This suggests, that either some bonds trade less frequently than once a day or there are other factors besides nonsynchronous trading contributing to bond fund return predictability.

A second implication of the nonsynchronous trading hypothesis concerns the non-trading and risk characteristics of the assets held by the fund. The predictability of an asset's closing return is greater where there is greater delay between the time of last trade and market close, and greater systematic risk. These implications follow from the fact that the valuation effects of market movements occurring since an asset's last trade are greater the longer the time delay and the greater the asset's sensitivity to market movements. Because data for characterizing the non-trading tendencies of funds' assets is readily available only for domestic equity funds, our analysis of this implication is confined to our sample of domestic equity funds.

A stock's market capitalization is often used as a proxy for non-trading tendencies (see i.e., Foerster and Keim (1993)). We use Morningstar's market capitalization classifications of funds' holdings to assign funds to large-cap, mid-cap, and small-cap categories. We estimate each fund's systematic risk (beta) by regressing monthly fund returns on the monthly returns of CRSP's value-weighted index of NYSE, ASE, and NASDAQ stocks over the period 1996-1998. We then assign funds to one of three beta categories: low beta (< 0.8), medium beta (0.8 - 1.2), and high beta (> 1.2).

Table 3 reports the average daily return autocorrelation for funds in each cell of a three-by-three partition of funds formed on beta and market capitalization of stocks held. The rows correspond to the beta categories while the columns correspond to the market-capitalization categories. Consistent with the nonsynchronous-trading hypothesis, the autocorrelation of fund returns is increasing in fund beta. From the "beta only" column, the average autocorrelation of daily returns is 6% for funds in the low-beta category, 7% for funds in the medium-beta category, and 15% for funds in the high-beta category. Also consistent with the nonsynchronous-trading hypothesis, the autocorrelation of fund returns is inversely related to the market capitalization of stocks held. From the "size only" row, the average autocorrelation of daily returns is 5% for funds in the large-cap category, 12% for funds in the mid-cap category, and 20% for funds in the small-cap category.

Kadlec and Patterson (1999) find that the average NYSE stock trades within one hour of the close. Given this fact, the nonsynchronous-trading hypothesis implies that domestic equity fund returns are likely to be more predictable using market returns over the later part of the day. This is because a late-day return interval corresponds more closely to the non-trading period of domestic stocks. Table 3 reports domestic-equity fund return predictability using full-day returns (previous day's close to 3:55) and last two-hour returns (from 1:55 to 3:55) to the S&P 500 index futures. The average adjusted-R^2 is higher using the two-hour return interval for all but one of the cells in the three-by-three partition. In addition, the difference is greatest in funds that are most susceptible to nonsynchronous trading. For example, the average adjusted-R^2 of regressions of high-beta small-cap fund returns on lagged futures returns increases from 3.3% for the full-day return to 5.2% for the last two-hour return. These results are consistent with the hypothesis that nonsynchronous closing prices contribute to the predictability of fund returns.

3.3 The wildcard strategy of transacting mutual fund shares

Mutual funds typically accept orders to purchase or redeem fund shares up to 4:00 p.m. With a telephone or Internet transfer, fund investors can make their trading decisions as late as, say, 3:55 P.M. At 3:55 many of the assets held by the fund have long-since experienced their last transaction of the day, and thus, their closing price does not fully reflect the day's market news. As a result, fund investors who defer their investment/redemption decision to the end of the day possess an option to trade some of the underlying assets of the fund at stale prices. We refer to this option as the mutual fund wildcard option.[7]

The basic trading strategy that exploits the mutual fund wildcard option involves switching between cash and fund shares. Because many mutual funds limit investors to 4-6 round-trip transactions in fund shares per year, we consider strategies that require a minimal amount of trading. For example, consider an investor with a position in cash. When the predicted next-day fund return is "high", he exercises a wildcard call by moving cash into fund shares. Each day thereafter he reevaluates his position continuing to hold fund shares until the predicted next-day fund return is "low", at which point he exercises a wildcard put by redeeming fund shares and moving the proceeds to cash. This trading strategy allows the trader to capture two wildcard exercises for each round-trip transaction in fund shares. However, it leads to stochastic market exposure. This can be offset by holding a futures position designed to match the fund exposure when out of the fund (if the trader targets fully invested exposure), or designed to offset the fund's market exposure when in the fund (if the trader targets zero market exposure). In other words, each investor can tailor a hedged strategy to have the desired risk characteristics.

3.3.1 Average one-day wildcard-option exercise value

The wildcard strategy we depict above involves maintaining a position in either cash or fund shares for several days between each wildcard exercise. However, the nonsynchronous-trading hypothesis and results of section 3.2 imply that wildcard exercise value is confined to the

[7]The term wildcard option is borrowed from the Treasury-bond futures market and the S&P 100 index options market because it is descriptive of options that allow exercise at stale prices. See Kane and Marcus (1986) and Harvey and Whaley (1992). To complete the option analogy, the underlying asset of the mutual-fund wildcard option is the portfolio of assets held by the mutual fund. The exercise price of the option is the portfolio-weighted price of the last trade in each asset held by the fund. The option expires at 4:00 P.M and it regenerates daily. Investors who currently hold fund shares possess both a wildcard-put and a wildcard-call, whereas all potential mutual fund investors possess a wildcard-call.

next-day fund return. Thus, a one-day return window -- the day after the fund trade is made -- is likely to provide the most precise inferences regarding the value of each exercise of the wildcard option.[8] Table 4 reports estimates of the average next-day return earned from exercising the wildcard option in domestic equity, foreign equity, and bond funds. Specifically, we calculate

$$\overline{R}_{t+1} = \frac{1}{\sum_{t=1}^{T} \left| I_t \right|} \sum_{t=1}^{T} I_t \times \left(\sum_{i=1}^{N} \frac{R_{i,t+1} - r_t}{N} \right)_t \tag{1}$$

where $R_{i,t+1}$ is the return to fund i on day $t+1$, r_t is the daily return to a cash position, T is the total days in the sample period, N is the number of funds in the sample, and I_t is an indicator variable equal to 1 on days where the trading signal is a buy, -1 on days where the trading signal is a sell, and 0 otherwise. $\overline{R}_{t+1}$ is the average next-day return that one earns from holding funds relative to cash for wildcard calls $(R_{t+1} - r_t)$, and from holding cash relative to funds for wildcard puts $(r_t - R_{t+1})$.

As previously mentioned, mutual funds often limit investors to 4-6 round-trip transactions per year. Thus, traders are likely to reserve wildcard option exercise for days when the expected value is large – days with extreme market returns. To incorporate this element into our analysis, we choose an *ex ante* wildcard exercise trigger, I_t , that allows an expected 6 round-trip transactions or 12 total trades per year. Conditioning on 5% of the return distribution leads to an expected exercise frequency of about 12 trades per year. Thus, for equity funds we define I_t using the upper and lower critical values from the 2.5% tails of the empirical distribution of daily S&P 500 futures returns over the 30 months preceding the sample period. For bond funds we

[8] Brown and Warner (1985) show that the power to reject the null, of no abnormal performance when abnormal performance is artificially introduced, is far greater when the event-day can be identified precisely.

define I_t using the upper and lower critical values from the 2.5% tails of the empirical distribution of daily 5-year T-Note futures over the 30 months preceding the sample period.

To isolate the exercise value of the wildcard option from market movements, we also report the average exercise value of the wildcard option net of the next-day market return:

$$Hedged\ \overline{R}_{t+1} = \frac{1}{\sum_{t=1}^{T}\left|I_t\right|}\sum_{t=1}^{T} I_t \times \left(\sum_{i=1}^{N}\frac{R_{i,t+1} - r_t - R_{Futures,t+1}}{N}\right)_t , \qquad (2)$$

where $R_{futures,t+1}$ is the percentage change in the settlement price of the futures contract on day t+1, and $R_{i,t+1}$, r, and I_t are as defined in Eq. (1). For wildcard calls, $Hedged\ \overline{R}_{t+1}$ is the average next-day return that one earns from holding fund shares and shorting futures relative to holding cash $(R_{t+1} - r_t - R_{futures,t+1})$. For wildcard puts, $Hedged\ \overline{R}_{t+1}$ is the average next-day return that one earns from holding cash and buying futures relative to holding fund shares $(r_t + R_{futures,t+1} - R_{t+1})$. Thus, $Hedged\ \overline{R}_{t+1}$ can be interpreted as the average next-day market-adjusted return earned from a wildcard-option exercise. The associated t-statistics are calculated by first computing the average return across all funds on the day-after each observed trigger. This produces a time-series of next-day return estimates, from which the sample t-statistic is calculated.

It is important to emphasize that $\overline{R}_{t+1}$ and $Hedged\ \overline{R}_{t+1}$ are average returns earned on the day after a wildcard exercise as opposed to average daily returns earned over the time the wildcard strategy is implemented. Furthermore, because implementing the wildcard strategy typically requires maintaining a position in fund shares for several days between exercises, the return to a wildcard trading strategy will have considerably more volatility than the one-day returns examined here. We focus on one-day returns because they provide the most precise estimate of the value of each exercise of the wildcard option. We will consider the returns earned from implementing the wildcard strategy over longer horizons in section 3.3.2.

From table 4, the average exercise value of the wildcard option at equity funds is large, both economically and statistically.[9] First, consider the next-day fund return using the full-day trigger, which conditions exercise on futures returns from the previous days close to 3:55 p.m. on the exercise day. For domestic-equity funds, each exercise of the wildcard option yields an average next-day raw return, $\overline{R}_{t+1}$, of 29 basis points and a next-day hedged return, $Hedged\ \overline{R}_{t+1}$, of 23 basis points.[10] The wildcard option exercise value is almost three times as large at foreign-equity funds, where each exercise has an average next-day return of over 80 basis points, raw or hedged. The average wildcard exercise value at bond funds is insignificant when using the 5-year T-Note futures return as the trigger.

In table 3 we observed that next-day domestic-equity fund returns are more correlated with the last two-hour market return than the full-day market return. Thus, it is of interest to examine wildcard exercise values using the shorter trigger interval. From table 4, the shorter trigger interval leads to larger average next-day returns at domestic-equity funds and smaller average next-day returns at foreign-equity funds. This is consistent with the fact that the delay in last-trade prices for domestic equity is substantially less than one day while the delay in last-trade prices for foreign equity is closer to a full day.

Finally, we examine wildcard-option exercise values for domestic-equity funds partitioned on beta and average market capitalization of stocks held. Substantial cross-sectional variation in wildcard exercise value is captured by these nonsynchronous-trading factors. From table 5, the

[9] In results not presented, separate estimates for the next-day return following a buy trigger and a sell trigger were statistically indistinguishable.

average wildcard exercise value at large-cap funds is 27 basis points versus 50 basis points for small-cap funds. The observed cross-sectional variation with respect to beta is even greater, ranging from 18 basis points for low-beta funds to 66 basis points for high-beta funds. When these two partitions are both applied, the cross sectional variation is even more dramatic. Large-cap, low beta funds have an average exercise value of 17 basis points, where small-cap, high-beta funds have an average exercise value of 84 basis points. Note that the next-day returns at small cap, high beta domestic-equity funds are as large as those at foreign-equity funds. From this we infer that nonsynchronous trading *within* markets can create pricing errors as large as those due to nonsynchronous trading *across* markets.[11]

3.3.2 Annual return performance of wildcard-option strategies

From table 4, the average hedged next-day return at domestic equity funds is 23 basis points. A simple estimate of the annualized excess return of the wildcard strategy at domestic equity funds is 2.8% ($1.0023^{12\text{exercises}}$) with 6 round-trip trades per year. Similarly, a simple estimate of the annualized excess return of the wildcard strategy at foreign equity funds is 10.4% ($1.0083^{12\text{exercises}}$). In this section we directly estimate the profitability of implementing the wildcard strategy over an annual period. While an analysis focusing on next-day returns provides the most precise estimate of the value of each exercise of the wildcard option, longer horizon results are useful in understanding the complexities of exploiting the wildcard option in practice.

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[10]This figure does not include futures transaction costs. The round-trip transaction costs (brokerage commission, bid-ask spread, exchange fees) associated with an S&P 500 futures hedge currently ranges from 1 to 3 basis points (see. i.e., Chance (2000)).

[11]In fact, nonsynchronous trading *within* foreign markets almost surely occurs to a greater degree than in U.S. markets. The fact that foreign equity fund returns have higher autocorrelations than domestic equity fund returns supports this conjecture. Thus, at 4:00 p.m. ET when foreign-equity funds are priced, the closing-price algorithm not only fails to incorporate the information in the US market, but also certain information available *within* the foreign market as well.

We consider two wildcard-option strategies. The cash-based strategy attempts to maintain a position with zero systematic risk. The investor holds cash until a wildcard call (buy) trigger occurs, at which point he goes long fund shares and short a futures position. He continues to hold this position until a wildcard put (redeem) trigger occurs, at which point he redeems the fund shares and unwinds the futures position. This process is repeated over the sample period and constrained to a maximum of 6 round-trip transactions in fund shares per year.

The fully invested strategy attempts to maintain a position with systematic risk equal to that of the mutual fund. The investor begins holding fund shares. When a wildcard put trigger occurs she redeems the fund shares and goes long a futures position. She maintains the futures position until a wildcard call trigger occurs, at which point she purchases fund shares and unwinds the futures position. This process is repeated over the sample period and constrained to a maximum of 6 round-trip transactions in fund shares per year.

Each of these two strategies captures 12 one-day wildcard exercise values. The performance of the strategies may differ from the simple extrapolations of next-day returns for two reasons. First, despite there being no theoretical reason to expect it, the one-day return that we document may reverse in subsequent days. Second, the random tracking error of the futures hedge is likely to cause the wildcard-strategy returns to be different than their benchmark. We find that there is no apparent return reversal, although tracking error does affect the precision of these estimates.

To assess the annual performance of the wildcard strategies we first tailor a hedge portfolio to each fund in the sample. Hedge ratios are determined for each fund by regressing the fund's weekly return on three futures contract returns (S&P 500, NASDAQ 100, Russell 2000) over the three years prior to the sample period. We then compute returns to each strategy over the sample period. Finally, we estimate the alpha of each strategy from a regression of weekly strategy returns on the three indices used in the hedge, which are intended to capture factor returns.

For domestic equity funds, the average annual alpha of the cash-based strategy is 3.8% (*t*-statistic=2.4). The average annual alpha for the fully-invested strategy is 3.9% (t-statistic=2.3). By comparison, the average annual alpha for a buy-and-hold strategy in fund shares is 0.7% (*t*-statistic=0.2). The difference in the alphas of the fully-invested wildcard strategy versus the buy-and-hold strategy is 3.2%. Though not statistically significant (t-statistic=1.3), the magnitude is very similar to the simple extrapolation of next-day wildcard exercise values calculated above. This suggests that there is no tendency for returns to reverse after wildcard exercise.

For foreign equity funds, the average annual alpha is 15.0% (t-statistic=3.2) for the cash-based strategy and 15.9% (t-statistic=3.3) for the fully-invested strategy. This compares favorably to the alpha of a buy-and-hold strategy, 9.9% (t-statistic=1.43). The foreign-equity alphas must be interpreted with caution, however, because they are estimated using nonsynchronous returns on U.S. indices as factors. The annual alphas for the bond strategies are insignificant.

Statistical inferences of the annual alphas from the wildcard strategy are relatively imprecise vis à vis the next-day returns. While the annual alpha of the cash-based strategy is statistically significant, the difference in annual alphas between the fully-invested and buy-and-hold strategy is not significant. The source of imprecision in these annual estimates is the approximately 20 days of tracking-error between each wildcard exercise. This suggests that the wildcard strategy is not a pure arbitrage.

4. Mutual fund trading frictions

Many mutual funds impose load fees, transaction fees, and various trade restrictions on investors. In this section we consider whether wildcard strategies are profitable in spite of these frictions.

Table 6 presents load fees, transaction fees and trade restrictions for 868 of our sample of 918 sample funds. These data are collected from Morningstar, from funds' 1999 prospectuses, and through phone calls to funds' investor service departments. A large percentage of sample funds have load fees. From table 6, 55% of domestic equity funds, 62% of foreign equity funds, and 73% of bond funds have either a front-end or back-end load. Among the funds that have loads, the average load ranges from 4% to 5.3%.

The magnitude of most load fees exceeds the average exercise value of the wildcard option, which would appear to eliminate the profitability of wildcard strategies. However, load fees typically apply only once, upon entry or exit into a fund family. Within that family, investors can make exchanges between funds at no cost.[12] In fact, investors can often exit the family altogether and return within 60-90 days without paying a load. Thus, excluding all load funds overstates the restriction on wildcard exercise imposed by loads. We exclude these funds, nonetheless, and find nearly identical results.

Among funds that do not charge load fees, we examine transaction fees and trade restrictions. Transaction fees are different from load fees because they are assessed with each transaction, not just upon entry (or exit) to the fund family. Moreover, the proceeds from transaction fees are added to the assets of the fund. In our sample, transaction fees are rarely used. Of domestic-equity funds without load fees, 3.3% impose an average transaction fee of 1.4%. Transaction fees are more prevalent in foreign-equity funds with 24.5% of the no-load sample imposing an average transaction fee of 1.8%. No-load bond funds impose transaction fees in 6.8% of the funds and average 1.2%.

Finally, we examine limits on the number of transactions that investors are allowed within a fund. Among the sample of no-load funds, 41% of domestic equity, 48% of foreign equity, and 45% of bond funds place explicit limits on the number of transactions.[13] Among those funds that have limits, the average limit is eight round-trip transactions and the median limit is four round-trip trades per year. Additionally, nearly every fund prospectus states that the fund reserves the right to exclude investors who engage in market timing strategies. However, our discussions with customer service representatives suggest that these limits are seldom enforced when investors limit their trades to less than $1,000,000. Given the evidence on fund restrictions, we feel that it is conservative to suggest that six round-trip wildcard exercises per year are available to investors in a substantial number of funds.

To examine the robustness of our estimates of wildcard exercise value with respect to trading frictions, we repeat the analysis of table 5 excluding funds with loads and transaction fees. The wildcard estimates for funds without loads or transaction fees are nearly identical to those of the full sample. For example, from table 7 the average raw next-day return of domestic equity funds without loads and transaction fees is .33% vs. .34% for the full sample of domestic equity funds. The remaining values in the three-by-three partitions of tables 7 and 5 are nearly identical, suggesting that while fees and restrictions may impede fund investors from exercising the wildcard option, their incidence is not concentrated in funds where the problem is

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[12] We checked the prospectus of 100 load funds and found this to be explicitly stated in over 90% of the cases.

[13] Since there are typically no costs to exchanges within a load family, load funds also impose transaction restrictions. The frequency of transaction restrictions in a sample of 100 load funds, 31 out of 100, roughly matches that of the of no-load sample funds.

particularly severe. Thus, table 7 shows that there are ample opportunities to exploit the wildcard option at funds with no loads or transaction fees.

To further address the question of whether funds that exhibit predictable returns impose frictions to mitigate exploitation, we estimate a cross-sectional regression of fund return predictability on transaction frictions. For each fund the dependent variable is the adjusted-R^2 from a regression of fund returns on the lagged S&P futures return up to 3:55 p.m. As independent variables we include the magnitude of front-end and back-end loads, transaction fees, and number of roundtrip transactions allowed per year. For funds with no explicit limit on roundtrip transactions we set the variable equal to 50. We exclude bond funds from this analysis to maintain a consistent predictor variable leaving 586 sample funds. Coefficient estimates with t-statistics (in parentheses) are reported below[14]:

Predictability	Intercept	Domestic Eq Dummy	Front-end Load	Back-end Load	Transaction Fees	Transaction Limits
Coefficient	11%	-10%	-.03%	-.12%	1.18%	.01%
(t-statistic)	(26.4)	(-31.0)	(-.53)	(-1.6)	(2.8)	(.77)

Consistent with Zitzewitz (2000), we find some evidence that funds are aware of return predictability. In particular, transaction fees are positively associated with fund return predictability. There is, however, no association between transaction limits and fund return predictability.

5. Solutions to the Fund-Pricing Problem

While transaction fees and trade restrictions can be used to reduce the profitability of wildcard strategies they impose costs on all fund investors, not just those engaging in wildcard strategies. Further, transaction fees and trade restrictions offer no relief to the implicit cost of

[14]The inferences we draw from this regression are identical when we exclude load funds, estimate predictability using the last two hours of the S&P index, use a limit of 100 trades per year instead of 50 and use the log of the limits on transactions variable. The 586 observations reflect missing transaction fees and transaction limits data.

trading assets at the wrong price. A more efficient solution to the fund-pricing problem is the direct solution, to set NAV using all available information up to the time of the exchange in fund shares. The following section considers alternative fund-pricing methodologies designed to address the nonsynchronous pricing issue in the context of domestic-equity funds.[15]

5.1 Alternative approaches to computing NAV

We consider two alternatives to using closing prices for determining NAV. Each approach could be implemented with a standardized system using readily available data. The first approach uses the midpoint of each stock's closing bid and ask quotes to compute NAV. A number of studies argue that specialists or dealers continually update their bid and ask quotes to reflect new information even in the absence of trade. The second approach updates each stock's closing price to reflect the return on a relevant benchmark over the interval from the time of last trade to close. We refer to the latter as market-updated prices.

To assess the relative merits of these alternative fund-pricing methodologies we compare the properties of a synthetic fund's returns computed from closing prices, closing quotes, and market-updated prices. To construct a synthetic fund we obtain portfolio holdings data for an actual small company growth fund with assets over $100 million and a high daily return autocorrelation (potential for pricing improvements) from CDA Spectrum. This particular fund has a 1% front-end load fee and allows unlimited free exchanges within the fund complex. Thus, other than the one-time 1% fee, this fund is a legitimate target for unrestricted exploitation with the wildcard strategy. We obtain closing prices, closing quotes, and time of last trade for each stock in the fund's portfolio on each trading day during the period January 1998 through

[15]We restrict our analysis to domestic equity funds because transactions data are more readily available for domestic equity securities. Similar methods could be used to price foreign equity funds and bond funds. For example, Burns, Engle and Mezrich (1998) also propose a method to synchronize foreign asset prices using an Asynchronous GARCH model.

November 1999 from the TAQ database. With these data we compute the synthetic fund's daily NAV using closing prices, closing quotes and market-updated prices. To compute market-updated prices we multiply each stock's last trade price by one plus the product of the fund's beta times the minute-to-minute return on an equity index futures contract from the time of last trade to close.[16] The fund's daily returns are then calculated using the NAVs computed from closing prices, closing quotes, and market-updated prices.

In the prior section we used the S&P 500 futures contract to examine equity fund return predictability and the associated profitability of wildcard strategies. The choice of this particular futures contract was guided by the fact that the S&P 500 index is representative of most equity funds' holdings (see e.g. Falkenstein (1996)). However, for the small-cap fund under consideration here, the Russell 2000 index is more representative, and thus, may be more relevant for updating prices. Unfortunately, the Russell 2000 futures is not as actively traded as the S&P 500 futures and, thus, may not reflect as current information. Therefore, as a practical matter, the choice of index futures used to update last-trade prices involves tradeoffs. We report results using both Russell 2000 index futures and S&P 500 index futures to examine the ramifications of this trade-off. As it turns out, NAVs computed from Russell 2000 futures updated prices exhibit somewhat less predictability than those using S&P 500 index futures.

Table 8 reports descriptive statistics for the synthetic fund's three return series. For purposes of comparison, we also report descriptive statistics for the actual fund's returns. The synthetic fund's closing returns are very similar to the actual fund's returns. The synthetic fund's closing returns have a correlation of .97 with the actual fund's returns and nearly identical

[16]We use the fund's estimated beta as opposed to estimates of each underlying stocks' beta due to the inherent noise in estimates of individual stock betas (See for example, Black, Jensen, Scholes (1972)).

mean and standard deviation. The synthetic fund's closing return autocorrelation is .32 where the actual fund's return autocorrelation is 0.33. The R^2 of regressions of fund returns on lagged Russell 2000 futures returns is 7.2% using the synthetic fund's closing returns and 7.8% using the actual fund's returns. These results are consistent with the actual fund's reliance on closing prices for computing NAV and establish that the synthetic fund is a reasonable representation of an actual mutual fund.

Table 8 also provides information to evaluate the alternative methods of computing NAV. The autocorrelation and predictability of the synthetic fund's returns computed from closing quotes are nearly identical to those of returns computed from closing prices. The autocorrelation of fund returns computed from both closing quotes and closing prices is 0.33. Similarly, the R^2 of regressions of fund returns on lagged Russell 2000 futures returns is 7.2% using returns computed from both closing quotes and closing prices. Thus, surprisingly, closing quotes do not appear to offer any improvement over closing prices. Market-updated prices, however, show a marked improvement over closing prices. The autocorrelation of fund returns computed from market-updated prices is 0.15, as compared to 0.33 for returns computed from closing prices. Similarly the R-square of regressions of fund returns on lagged Russell 2000 futures returns is 1.9% using returns computed from market-updated prices as compared to 7.2% using returns computed from closing prices. Given that market-updated prices correct only for the effects of nonsynchronous trading, this result confirms that nonsynchronous trading is a primary source of autocorrelation in daily fund returns.[17]

Finally, we compare the profitability of the wildcard strategy as applied to the synthetic fund's three return series (calculated from closing prices, closing quotes, and market-updated

[17]This result is consistent with Kadlec and Patterson (1999), which reports that nonsynchronous trading, accounts for roughly 50% of the autocorrelation in daily portfolio returns.

prices). We use a trigger of (<-1.7% or > +1.7%) returns of the Russell 2000 futures prior to 3:55 p.m. The average hedged wildcard exercise value is 45 b.p., 44 b.p., and 20 b.p. using synthetic fund returns computed from closing prices, closing quotes, and market-updated prices, respectively. By way of comparison, the actual fund's average wildcard exercise value over the same period, same strategy, is 40 b.p.. Thus, market-updated prices cut the profitability of the wildcard strategy in half, whereas prices set from closing quotes offer no improvement.[18]

5.2 Implementation issues

The market-updated pricing algorithm represents an operationally feasible alternative to the closing-price algorithm. But it may have limitations of its own. First and foremost, it is a mechanical algorithm. The potential always exists that a loophole could be found to exploit it. Second, the feasibility from a legal and regulatory point of view must be addressed.

Ogden and O'Hagan (1997) describe the extant SEC rules (Section 2(a)(41) of the Investment Company Act of 1940) on determining NAV as follows:

> The definition essentially divides the capital markets into two categories. First, if "market quotations are readily available" for a security, the security should be valued at "current market value." Second where market quotation are not "readily available," the security should be valued at "fair value" as determined in good faith by the [fund's] board of directors.

Thus, mutual fund's legal pricing objective is to price shares using the most current information available. The previous section suggests that market-updated pricing achieves this objective better than closing prices. Furthermore, market-updated pricing appears to fit under the rubric of "fair value pricing". However, fair value pricing requires that fund investors accept the valuation of fund shares on faith. Therefore, the objectivity of the pricing algorithm is of

[18]We performed the above fund-pricing analysis on a second small company growth fund. The results are very similar. The autocorrelation and predictability of the fund returns computed from market-updated prices are less than half that of fund returns computed from closing prices.

paramount concern. For example, large price adjustments might be met with skepticism by fund investors and resistance by regulators. We examine the adjustments made to closing prices by the two alternative fair-value pricing techniques, closing quotes and market-updated prices, to assess the likelihood that these concerns are material.

Table 9 reports descriptive statistics of the difference between closing prices and closing quotes and the difference between closing prices and market-updated prices. Because of the relative success of market-updated prices we focus our discussion on comparisons of closing prices to market-updated prices. From table 9, the mean absolute adjustment to a stock's price using the market-updated price approach is less than 5 cents, the median adjustment is 3 cents, and 90 percent of the adjustments are less than 12 cents. Thus, the adjustments using this approach are relatively minor in comparison to the typical bid-ask spread.

While our analysis of fund-pricing methodologies is restricted to domestic equity funds, market-updated prices could be used to price foreign equity funds and bond funds as well. Goetzmann, Ivkovi• , and Rouwenhorst (2000) propose an alternative method to correct stale pricing in foreign equity funds. In contrast to market-updated prices where adjustments are made on a security-by-security basis, their approach adjusts the fund's NAV at a portfolio level. The market- updated price approach has several virtues. First, the market-updated price approach relies on a single parameter estimate, beta, with a well-established literature on estimation.[19] Perhaps more importantly, market-updated prices address both stale price issues associated with pricing foreign equity funds. Recall that, in the context of foreign equity funds there are two components to the stale price problem, asynchronous trading across markets and asynchronous trading within markets. Adjustments made at a portfolio level do not necessarily address the problem of nonsynchronous trading within markets. Given the evidence regarding the effects of nonsynchronous trading in U.S. equity markets, which are the worlds most active, the effects of nonsynchronous trading are likely to be even greater in foreign markets.

6. Conclusions

Open-end mutual funds are an example where investors commit to trade a financial claim without knowing the terms and instead allow the price to be set by an intermediary. In 1999 over $1.3 trillion of mutual fund share purchases and $1 trillion of mutual fund share redemptions were transacted in this fashion (Investment Company Institute). This paper demonstrates problems that can arise when an intermediary's role extends to that of pricing financial claims. We document economically important and readily exploitable pricing errors in the case of open-end mutual fund shares.[20]

The exchange of mutual fund shares is not the only case in which an intermediary sets security prices. For example, in primary security offerings the investment bank sets the offer price. Similar to the pricing of mutual funds, it appears that the pricing of seasoned equity offerings is closely linked to historical closing prices (see Loderer, Sheehan, Kadlec (1991)). As in the case of mutual funds, the pricing mechanism tends to cause distortions. For example, Kadlec, Loderer, and Sheehan (1997) provide evidence of price manipulation prior to seasoned equity offerings. In response to allegations of price manipulation, the SEC adopted rule 10b-21 in 1988, which prohibits covering short sales with stock from a public offering.

Enumerating all of the potential problems with intermediary-based pricing is beyond the scope of this paper and arguably misguided. Loopholes, manipulations, and distortions can appear when a third party sets the price of a security. Thus, it seems more fruitful to focus on

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[19] See e.g., Scholes and Williams (1977), Dimson (1979), Fowler and Rourke (1983), and Denis and Kadlec (1994).
[20] Another fund pricing problem with microstructure origins is studied in Carhart, Kaniel, Musto, and Reed (1999), which provides evidence that bid-ask bounce is used to influence fund's closing prices.

conditions that ultimately give rise to the problem. At least two factors are critical to the quality of an intermediary-determined price. First, the intermediaries must have strong incentives to arrive at an accurate price. Second, the intermediary must have good information concerning the price that clears investors' demands. The best way to address the loopholes, manipulations, and distortions that may arise with intermediary-based pricing is to address these factors.

Appendix

Filters. With hand-entered data such as TrimTabs', solitary typographical errors (e.g., NAV = 13.12, 13.17, 1**1.3**2, 13.15) are a concern. Visual inspection of the data (after searching for extreme cases) confirms that such errors are present. A solitary error in the level of NAV (or total assets) induces negative autocorrelation in the changes series. Since the autocorrelation of returns is a key statistic in this study, we want to ensure that the true processes, not data errors, drive inferences. Two filters are applied.

The first filter removes observations if the absolute value of the daily return is greater than five standard deviations, where the standard deviation is calculated on a fund by fund basis. A five standard-deviation move in the value-weighted NYSE-AMEX index has happened 14 times since 1965, implying that this a decidedly rare event in the true data. A similar five standard-deviation filter is applied to the daily change in total assets.

The second filter is designed to catch false reversals. It removes observations when a three standard deviation move is followed by a reversal to within 1.5 standard deviations of the original (two days prior) value. A three standard deviation move in the NYSE-AMEX index has happened 92 times over the past 33 years, or about three times a year. However, a subsequent reversal back to within 1.5 standard deviations of the original (two days prior) value has happened only 15 times. Thus, historically, this filter removes less than ¼% of true data. Nevertheless, the data that this filter removes is extremely negatively autocorrelated. Removing true extreme negative autocorrelation biases the remaining data toward positive autocorrelation. To offset this, we also apply a similar filter for continuations: remove if the observation is a three standard deviation move followed by a further 1.5 standard deviation move in the same direction the next day. This happened with the NYSE-AMEX index 26 times between 1965 and 1999.

The autocorrelation of daily returns of the value-weighted NYSE-AMEX index over the 1965 – 1999 period is 14% without filters and 15% with filters. Assuming that the index data are free from errors, this implies that the two filters do not materially distort true autocorrelation. On the other hand, they almost surely remove most data errors. If a data-entry error is present, e.g. a digit transposition, then it is likely to be greater than 3 or 5 standard deviations, or about 5%, in magnitude. For example, digit transpose in NAV is typically about a 10% error if it occurs in the cents' columns and far greater in the dollars columns.

In the sample fund data, the filters have a tremendous effect on the standard deviation and autocorrelation statistics. For example, the standard deviation of daily equity-fund returns without filtering is 20.7%, shown in Table 2. With filters, the standard deviation of daily equity-fund returns is 1.2%. By comparison, the standard deviation of the value-weighted NYSE-AMEX index returns over this period is 0.94% per day. This indicates data errors in the raw data, suggesting that the filtered data provide more reliable inferences. Throughout the paper we use filtered data.

References

Atchison, M., K. Butler, and R. Simonds, 1987, Nonsynchronous security trading and market index autocorrelation, *Journal of Finance* 42, 111-118.

Bhargava, R., A. Bose, and D.A. Dubofsky, 1998, Exploiting International Stock Market Correlations with Open-end International Mutual Funds, Journal of Business Finance and Accounting, 25, 765-773.

Bhargava, Rahul and David A. Dubofsky, 1999, A note on fair value pricing of mutual funds, *Journal of Banking and Finance*, forthcoming.

Black, F., M. Jensen, and M. Scholes, 1972, "The capital asset pricing model: Some empirical tests, in Jensen, M. (ed.) *Studies in the Theory of Capital Markets*, Praeger, New York.

Boudoukh, J., M. Richardson, and R. Whitelaw, 1994, A tale of three schools: Insights on autocorrelations of short-horizon returns, *Review of Financial Studies* 7, 539-573.

Boudoukh, J., M. Richardson, M. Subrahmanyam and R. Whitelaw, 2000, The last great arbitrage: Exploiting the buy-and-hold mutual fund investor, working paper, Stern School of Business.

Brown, S.J. and J. B. Warner, 1985, Using daily stock returns: The case of event studies, *Journal of Financial Economics*, 14, 3-31.

Burns, P., R. Engle, and J. Mezrich, 1998, Correlations and Volatilities of Asynchronous Data, Journal of Derivatives, Summer: 1-12.

Carhart, M., R. Kaniel, D.K. Musto, A. Reed, 1999, Mutual fund returns and market microstructure, Wharton working paper.

Chance, D., 2000, *An Introduction to Derivatives and Risk Management*, Harcourt Inc., New York, NY.

Cohen, K., G. Hawawini, S. Maier, R. Schwartz, and D. Whitcomb, 1983, Frictions in the trading process and the estimation of systematic risk, *Journal of Financial Economics* 12, 263-278.

Cowles, A., and H. Jones, 1937, Some a posteriori probabilities in stock market action, *Econometrica* 5, 280-294.

Denis, D., and G. Kadlec, 1994, Corporate events, trading activity, and the estimation of systematic risk, *Journal of Finance*, 49, 5, 1787-1811.

Dimson, E., 1983, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 14, 217-251.

Edelen, R., 1999. Investor flows and the assessed performance of open-end mutual funds, *Journal of Financial Economic*, 53, 439-466.

Falkenstein, E. G., 1996, Preferences for stock characteristics as revealed by mutual fund portfolio holdings, Journal of Finance, 51, 1, 111-135.

Fisher, L., 1966, Some new stock market indices, *Journal of Business* 39, 191-225.

Foerster, S., and D. Keim, 1993, Direct evidence of non-trading of NYSE and AMEX stocks, working paper, Wharton.

Fowler, D., and C. Rorke, 1983, Risk measurement when shares are subject to infrequent trading: Comment, *Journal of Financial Economics* 7, 279-283.

Goetzmann, W.N., Z. Ivkovi• , and G. Rouwenhorst, 2000, Day trading international mutual funds: evidence and policy solutions, working paper, Yale University.

Goldman, B., and H. Sosin, 1979, Information dissemination, market efficiency, and the frequency of transactions, *Journal of Financial Economics* 7, 29-61.

Greene, J.T. and C.W. Hodges, 2000, The dilution impact of daily fund flows on open-end mutual funds, working paper, Georgia State University.

Harvey and Whaley, 1992, Market volatility, prediction, and the efficiency of the S&P 100 index option market, *Journal of Financial Economics* 31 (1), 43-74.

Kadlec, G., and D. Patterson, 1999, A transactions data analysis of nonsynchronous trading, *Review of Financial Studies* 12 (3), 608-630.

Kadlec, G., C. Loderer, andD. Sheehan, 1997, Issue day effects for common stock offerings: causes and consequences, working paper, Virginia Tech.

Kane, A., and A. Marcus, 1986, Valuation and optimal exercise of the wild card option in the treasury bond futures market, *Journal of Finance* 41 (1), 195-208.

Lo, A., and A.C. MacKinlay, 1990a, An econometric analysis of nonsynchronous trading, *Journal of Econometrics* 45, 181-211.

Loderer, C., D. Sheehan, and G. Kadlec, 1991, The pricing of equity offerings, *Journal of Financial Economics* 29, 35-57.

Mech, T., 1993, Portfolio return autocorrelation, *Journal of Financial Economics* 34, 307-344.

Ogden, Thomas P. and Cindy J. O'Hagan, 1997, Mutual funds confront dilemmas in trying to value portfolios, The New York Law Journal, December 15, 1997.

Scholes, M., and J. Williams, 1977, Estimating betas from nonsynchronous data, *Journal of Financial Economics 5*, 309-327.

Zitzewitz, E., 2000, Daily mutual fund net asset value predictability and the associated trading profit opportunity, MIT working paper.

Table I: Sample fund characteristics

The sample includes all mutual funds with at least 100 daily returns available from Trimtabs.com over the period 2/1/1998 through 3/30/2000. Sample mutual funds are assigned to domestic equity, foreign equity, and bond fund categories using CRSP Mutual Fund database investment objective classifications. This table reports cross-sectional mean and median values for the number of daily observations, age, total assets at year-end 1998, and fraction invested in equity. Fund age, total assets, and fraction invested in equity are obtained from the CRSP mutual fund database. For comparison, we report age, total assets, and percent invested in equity for funds in the 1998 CRSP Mutual Fund database with greater than $10 million in assets and greater than 50% in their associated asset class. Bond funds do not include money market funds.

		Sample Funds			**1998 CRSP Universe of Funds**		
		Domestic Equity	Foreign Equity	Bond	Domestic Equity	Foreign Equity	Bond
Number of Funds		484	139	295	3423	875	2427
Daily Obs / fund	Mean	426	416	402			
	Median	481	487	451			
Fund Age (in years to 1999)	Mean	16	8	11			
	Median	10	7	10			
Assets (millions)	Mean	1,134	486	526	706	405	292
	Median	478	123	284	99	73	75
Percent equity	Mean	88	92	3	90	92	2
	Median	94	95	0			

Table II: Sample fund returns

This table reports cross-sectional mean and median values of the mean time-series daily fund return, standard deviation of daily fund returns, and first-order autocorrelation coefficient of daily fund returns. Also reported are the mean adjusted R^2 from regressions of each fund's day-T return on an intercept and day T-1 S&P 500 futures return measured from close to 3:55 p.m. E.T. and for bonds funds the 5-year T-Note futures which closes at 3:00 p.m. E.T.

		Sample Funds		
		Domestic Equity	Foreign Equity	Bond
Daily fund return	Mean	.06%	.08%	-.01%
	Median	.06%	.09%	-.01%
Standard Dev.	Mean	1.18%	1.15%	.20%
	Median	1.15%	1.11%	.18%
AR(1) coefficient	Mean	8.41%	18.22%	11.12%
	Median	6.80%	18.07%	10.46%
	% > 0	88%	100%	83%
Predictability				
S&P futures	Adj R^2	.78%	10.85%	
Bond futures	Adj R^2			1.27%

Table III. Mutual fund return predictability and fund characteristics

This table reports return predictability for domestic equity mutual funds sorted by beta and average market capitalization of holdings. Mean AR(1) is the mean first-order autocorrelation coefficient for daily fund returns. Mean Adj. R^2 is the mean adjusted R^2 from regressions of each fund's day-T return on an intercept and day T-1 S&P 500 futures return. We define full day S&P 500 futures returns as returns from close to 3:55 p.m. E.T., and last two hours are defined as returns from 1:55 p.m. to 3:55 p.m. The sample includes all domestic equity funds with at least 100 daily returns available from Trimtabs.com over the period the period 2/1/1998 through 3/30/2000. We assign funds to beta categories (low beta < 0.8, medium beta 0.8 < beta < 1.2, and high beta > 1.2) using beta estimates from regressions of monthly fund returns on monthly returns of the value-weighted NYSE composite index. Morningstar's classification of fund holdings defines the capitalization categories, small-cap, mid-cap, and large-cap.

	Small Cap less than 80^{th}	**Mid-Cap 80^{th} – 95^{th}**	**Large Cap Above 95^{th}**	**By Beta Only**
Low Beta (avg=.64)				
Mean AR(1)	15.72%	8.56%	3.81%	6.36%
Mean Adj. R^2				
Full day S&P futures	.69%	.87%	.78%	.79%
Last 2hr S&P futures	1.96%	1.27%	.86%	1.08%
N funds	14	25	75	114
Med Beta (avg=.98)				
Mean AR(1)	20.48%	11.29%	4.41%	7.12
Mean Adj. R^2				
Full day S&P futures	.96%	.54%	.20%	.33%
Last 2hr S&P futures	2.45%	1.25%	.30%	.67%
N funds	24	43	186	253
High Beta (avg=1.32)				
Mean AR(1)	21.34%	15.08%	9.84%	15.04
Mean Adj. R^2				
Full day S&P futures	3.33%	2.37%	.71%	2.08%
Last 2hr S&P futures	5.29%	3.29%	.63%	2.94%
N funds	21	36	27	84
By Size Only				**All Funds**
Mean AR(1)	19.67%	11.87%	4.77%	8.40%
Mean Adj. R^2				
Full day S&P futures	1.74%	1.26%	.40%	.77%
Last 2hr S&P futures	3.35%	1.96%	.48%	1.20%
N funds	59	104	288	451

Table IV. Wildcard option exercise value

Wildcard exercise values are reported for domestic equity, foreign equity, and bond funds. Defining $R_{i,t+1}$ as the return to fund *i* on day *t*+1, r_t as the daily return earned on cash, and $R_{futures,t+1}$ as the futures return, the average exercise value is defined as

$$\overline{R}_{t+1} = \frac{1}{\sum_{t=1}^{T} |I_t|} \sum_{t=1}^{T} I_t \times \left(\sum_{i=1}^{N} \frac{R_{i,t+1} - r_t}{N} \right)_t \qquad (1)$$

where T (N) is the total days (funds) in our sample and I_t is an indicator variable equal to 1 when the trading signal is a buy, -1 when the trading signal is a sell, and 0 otherwise. We calculate the average hedged exercise value of the mutual-fund wildcard option as

$$Hedged\ \overline{R}_{t+1} = \frac{1}{\sum_{t=1}^{T} |I_t|} \sum_{t=1}^{T} I_t \times \left(\sum_{i=1}^{N} \frac{R_{i,t+1} - r_t - R_{Futures,t+1}}{N} \right)_t . \qquad (2)$$

The associated t-statistics, in parentheses, are similarly calculated from the time-series of cross-sectional average next-day returns or hedged returns. For equity funds we use the S&P 500 index futures to trigger exercise and hedge returns. The trigger threshold return is 1.70% for the full day period (close of previous day – 3:55 p.m.), 0.94% for the last-two hour (1:55 p.m. – 3:55 p.m.) period. 1.70% is the cutoff value for the 5% tails of the empirical S&P 500 daily return distribution from 6/1/1995 to 1/31/1998. The partial-day cutoffs represent 1.70% scaled to the corresponding return interval (i.e., times the square root of: 2 hours / 6.5 hours, and 1 hour / 6.5 hours, respectively.) For bond funds we use the 5-year U.S. Treasury Note futures to trigger exercise and hedge returns. The trigger threshold return for the T-note futures is 0.39% for the full day, 0.17% for the last-two hour period (12:55 p.m. – 2:55 p.m.). The sample includes all mutual funds with at least 100 daily returns available from Trimtabs.com over the period the period 2/2/1998 through 3/31/2000. Units are percents (i.e., .01 is one basis point).

	Domestic Equity Funds	**Foreign Equity Funds**	**Bond Funds**
Trigger: Futures return (full day: prior day close - 3:55 p.m.)			
$\boldsymbol{R_{i,t+1}}$	0.29	0.87	0.02
	(2.6)	(9.4)	(0.8)
Hedged $\boldsymbol{R_{i,t+1}}$	0.23	0.83	-0.02
	(2.7)	(6.2)	(-1.6)
Trigger: Futures return (last 2 hours: 1:55p.m. - 3:55 p.m.)			
$\boldsymbol{R_{i,t+1}}$	0.34	0.65	0.06
	(2.7)	(5.7)	(1.7)
Hedged $\boldsymbol{R_{i,t+1}}$	0.33	0.62	-0.04
	(3.4)	(4.1)	(-1.3)

Table V: Wildcard option exercise value by fund characteristics

Wildcard exercise values are reported for domestic equity funds sorted by beta and average market capitalization of fund holding. We assign funds to beta categories (low beta < 0.8, medium beta 0.8 < beta < 1.2, and high beta > 1.2) using beta estimates from regressions of monthly fund returns on monthly returns of the value-weighted CRSP composite index. We assign funds to market capitalization categories (small-cap, mid-cap, large-cap) using Morningstar's classifications of fund holdings. Wildcard exercise values are reported for each classification. Defining $R_{i,t+1}$ as the return to fund i on day t+1, r_t daily return earned on cash, and $R_{futures,t+1}$ as the futures return, the average wildcard exercise value for each classification is defined as

$$\overline{R}_{t+1} = \frac{1}{\sum_{t=1}^{T} |I_t|} \sum_{t=1}^{T} I_t \times \left(\sum_{i=1}^{N} \frac{R_{i,t+1} - r_t}{N} \right)_t \tag{1}$$

where T (N) is the total days (funds) in our sample and I_t is an indicator variable equal to 1 when the trading signal is a buy, -1 when the trading signal is a sell, and 0 otherwise. We calculate the average hedged exercise value of the mutual-fund wildcard option as

$$Hedged\ \overline{R}_{t+1} = \frac{1}{\sum_{t=1}^{T} |I_t|} \sum_{t=1}^{T} I_t \times \left(\sum_{i=1}^{N} \frac{R_{i,t+1} - r_t - R_{Futures,t+1}}{N} \right)_t . \tag{2}$$

For equity funds we use the S&P 500 index futures to trigger exercise and hedge returns. The trigger threshold return is 1.70% for the full day period (close of previous day – 3:55 p.m.), 0.94% for the last-two hour (1:55 p.m. – 3:55 p.m.) period. 1.70% is the cutoff value for the 5% tails of the empirical S&P 500 daily return distribution from 6/1/1995 to 1/31/1998. The partial-day cutoffs represent 1.70% scaled to the corresponding return interval (i.e., times the square root of: 2 hours / 6.5 hours, and 1 hour / 6.5 hours, respectively.) The sample includes all domestic equity funds with a beta estimate, a market capitalization classification, and at least 100 daily returns available from Trimtabs.com over the period the period 2/2/1998 through 3/31/2000. Units are percents (i.e., .01 is one basis point). The associated t-statistics, in parentheses, are calculated from the time-series of cross-sectional average next-day returns or hedged returns.

	Trigger S&P futures returns 1:55 to 3:55 ET 71 trigger days using +/- .94% over two hours			
All returns in %	**Small Cap less than 80th**	**Mid-Cap 80th – 95th**	**Large Cap Above 95th**	**By Beta Only**
Low Beta (avg=.64)				
$R_{i,t+1}$	.27	.20	.17	.18
	(3.57)	(2.62)	(1.96)	(2.34)
S&P Hedged $R_{i,t+1}$	.23	.17	.13	.15
	(1.66)	(1.42)	(1.28)	(1.37)
Med Beta (avg=.98)				
$R_{i,t+1}$	.32	.38	.30	.30
	(2.81)	(2.99)	(2.13)	(2.35)
S&P Hedged $R_{i,t+1}$	.28	.34	.27	.27
	(1.99)	(3.46)	(2.61)	(3.32)
High Beta (avg=1.32)				
$R_{i,t+1}$	.84	.72	.48	.66
	(4.70)	(3.66)	(2.34)	(3.64)
S&P Hedged $R_{i,t+1}$	.82	.70	.45	.63
	(4.52)	(4.72)	(2.72)	(4.62)
By Size Only				
$R_{i,t+1}$	.50	.46	.27	.33
	(4.20)	(3.59)	(2.09)	(2.78)
S&P Hedged $R_{i,t+1}$	.46	.43	.24	.30
	(3.45)	(4.20)	(2.53)	(3.39)

Table VI. Mutual fund fees and trade restrictions

Load fees, transaction fees, and transaction limits are reported for domestic equity, foreign equity, and bond funds. The data are obtained from 1999 fund prospectuses. The table averages are calculated using only those funds with a positive value of the indicated variable (i.e., load, transaction fee, or limits on the number of roundtrip transactions). The sample includes all mutual funds with at least 100 daily returns available from Trimtabs.com over the period the period 2/2/1998 through 3/31/2000.

Restrictions in 1999 Prospectuses	**Domestic Equity Funds**	**Foreign Equity Funds**	**Bond Funds**
Total Sample	484	139	295
less funds that were closed or missing	23	10	17
Net Sample	461	129	278
Front-end Loads			
% with front-end load	32.3%	32.6%	39.9%
if load: average front-end load	5.3%	5.3%	4.1%
Back-end Loads			
% with back-end load	22.6%	29.5%	34.2%
if load: average back-end load	4.1%	4.2%	4.0%
Number of funds with any Load	252	80	204
Net Sample for Fees and Limits (no loads)	209	49	74
Transaction Fees			
% with transaction fees	3.3%	24.5%	6.8%
If fee: average fee	1.4%	1.8%	1.2%
Limits on roundtrip trades			
% funds with limits	40.8%	47.9%	44.6%
If limit: average round-trips/year	8	9	9
If limit: mode round-trips/year	4	4	4

Table VII: Wildcard option exercise values for funds without load or transaction fees

We restrict the sample of domestic equity funds to those having no front-end load, back-end load or transaction fees (193 of the 451 domestic equity funds). Using this sample we replicate the analysis of table 5. The load fees and transaction fees are obtained from 1999 fund prospectuses.

	Trigger S&P futures returns 1:55 to 3:55 ET 71 trigger days using +/- .94% over two hours			
All returns in %	**Small Cap less than 80th**	**Mid-Cap 80th – 95th**	**Large Cap Above 95th**	**By Beta Only**
Low Beta (avg=.64)				
$R_{i,t+1}$	0.28	0.29	0.11	0.17
	(3.26)	(2.97)	(1.26)	(2.08)
S&P Hedged $R_{i,t+1}$	0.25	0.17	0.08	0.14
	(1.64)	(1.64)	(0.78)	(1.24)
Med Beta (avg=.98)				
$R_{i,t+1}$	0.35	0.40	0.28	0.29
	(2.82)	(3.16)	(1.99)	(2.28)
S&P Hedged $R_{i,t+1}$	0.31	0.36	0.25	0.26
	(2.08)	(3.42)	(2.28)	(3.14)
High Beta (avg=1.32)				
$R_{i,t+1}$	0.89	0.73	0.42	0.69
	(4.73)	(3.75)	(2.02)	(3.86)
S&P Hedged $R_{i,t+1}$	0.87	0.70	0.39	0.66
	(4.29)	(4.68)	(2.50)	(4.59)
By Size Only				All
$R_{i,t+1}$	0.51	0.50	0.25	0.34
	(4.35)	(3.61)	(1.88)	(2.79)
S&P Hedged $R_{i,t+1}$	0.47	0.47	0.22	0.31
	(3.46)	(4.27)	(2.19)	(3.39)

Table VIII. Properties of daily fund returns using various fund-pricing methodologies
This table presents the properties of a synthetic fund's returns computed from closing prices, closing quotes, and market-updated closing prices. To construct a synthetic fund, portfolio holdings data for a small company growth fund as of March 1998 are collected ed from CDA Spectrum. We obtain closing prices, closing bid and ask quotes, and time of last trade for each stock in the fund's portfolio on each trading day during the period January 1998 through November 1999 from the TAQ database. For each trading day we compute the fund's NAV using closing prices, the midpoint of closing quotes, and market-updated closing prices. To compute market-updated closing prices we multiply each stock's closing (last trade) price by one plus the minute-to-minute return on an equity index futures contract (Russell 2000 and S&P 500) from the time of last trade to close. The fund's daily returns are then calculated using the NAVs computed from closing prices, the midpoint of closing quotes, and market-updated prices. Panel A presents summary statistics, Panel B presents correlations between the returns to the various portfolios, and panel C provides evidence on the predictability and wildcard values of the various portfolios.

Panel A: Summary statistics

	N	**Mean**	**Std. Dev.**
Actual fund	480	-.04%	0.89%
Synthetic fund			
Closing prices	480	-.03%	1.00%
Closing quotes	480	-.04%	1.00%
Market-updated prices			
Russell 2000	480	-.04%	1.10%
S&P 500	480	-.04%	1.10%

Panel B: Correlations

	Actual Fund	Closing Prices	Closing Quotes	Market Updated R2000	Market Updated SP500
Actual fund	1	0.97	0.97	0.91	0.91
Closing prices		1	0.99	0.93	0.94
Closing quotes			1	0.93	0.94
Market-updated: R2000				1	0.93
Market updated: SP500					1

Panel C: Predictability and Wildcard Values

	Predictability			**Wildcard Value**	
	AR(1)	Adj. R^2 $R_{R2000, T-1}$	Adj. R^2 $R_{S\&P500, T-1}$	R_{t+1} 1.7% R2000 Trigger	R_{t+1} 1.7% SP500 Trigger
Actual fund	.32	7.7%	1.2%	.40%	.35%
Closing prices	.33	6.9%	1.1%	.45%	.37%
Closing quotes	.33	6.9%	1.1%	.44%	.36%
Market updated: R2000	.15	1.7%	-.2%	.20%	.16%
Market-updated: SP500	.16	3.4%	-.2%	.32%	.24 %

Table IX. Price-adjustments using various price updating methodologies

This table provides descriptive statistics of absolute differences between closing prices and closing quotes and closing prices and market-updated prices for a synthetic fund. To construct a synthetic fund, portfolio holdings data for a small company growth fund as of March 1998 are collected from CDA Spectrum. Closing prices, closing bid and ask quotes, and time of last trade for each stock in the fund's portfolio on each trading day during the period January 1998 through November 1999 come from the TAQ database. For each trading day we compute the fund's NAV using closing prices, the midpoint of closing quotes, and market-updated closing prices. To compute market-updated last trade prices we multiply each stock's closing (last trade) price by one plus the minute-to-minute return an index futures contract (Russell 2000 and S&P 500) from the time of last trade to close. Panel A reports average dollar changes in prices relative to each stocks' closing price. Panel B reports average percentage change in prices relative to each stocks' closing price.

Panel A: Absolute dollar difference between closing price and updated prices

Price updating method	Mean	Standard Deviation	25th percentile	50th percentile	75th percentile	90th percentile	95th percentile
Closing quotes	0.07	0.08	0.03	0.03	0.09	0.16	0.22
Market-updated: R2000	0.05	0.05	0.01	0.03	0.06	0.11	0.15
Market-updated: S&P500	0.05	0.06	0.01	0.03	0.06	0.11	0.15

Panel B: Absolute percent difference between closing price and updated prices

Price updating method	Mean	Standard Deviation	25th percentile	50th percentile	75th percentile	90th percentile	95th percentile
Closing quotes	0.60%	0.85%	0.15%	0.36%	0.75%	1.38%	2.00%
Market-updated: R2000	0.35%	0.34%	0.12%	0.27%	0.49%	0.76%	0.98%
Market-updated: S&P500	0.34%	0.36%	0.11%	0.24%	0.45%	0.76%	1.01%