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On the perils of security pricing by financial intermediaries: the case of open-end mutual funds*

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Abstract

There are many instances where financial claims trade at prices set by intermediaries. Pricing by an intermediary introduces the potential for economic distortions from innumerable sources. As one example, we show that nonsynchronous-trading generates predictable, readily exploitable, changes in mutual fund-share prices (NAV). The exploitation of predictable changes in mutual fund NAVs involves a wealth transfer from buy-and-hold fund investors to active fund traders and is costly to all fund investors. A simple modification to the mutual fund pricing algorithm eliminates much of this predictability, but nonsynchronous trading is just one of the issues intermediaries face when setting prices.

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1. Introduction

There are many instances where financial claims trade at prices set by an intermediary. For example, corporate debt and equity are typically issued at prices set by an underwriter. Exchanges in open-end mutual funds are another example. In 1999 over $1 trillion in mutual fund shares were exchanged at prices set by the fund manager.[1] This paper points out economic distortions that can arise when intermediaries set security prices by documenting economically important pricing errors that occur in the case of open-end mutual funds.

Most U.S. domiciled mutual funds 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 is to value each asset in the fund portfolio at its closing price. The closing price of an asset is the price of the last trade posted before the close of trading in that asset's primary market. Because closing prices are often determined long before 4:00 p.m. ET, they often fail to reflect the value of the asset at the time of the exchange. The problem is particularly clear in the case of a U.S. domiciled Asian-market fund, where the underlying assets' last trade is about 13 hours prior to the setting of NAV and exchange of fund shares. Yet even in the case of domestic-equity funds, where the exchange of fund shares and the closing of the asset market 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 the case of small capitalization firms. These delays give rise to the well-known tendency for close-to-close portfolio returns to appear to be predictable. This predictability is generally regarded as an illusion in the data since a hypothetical trade occurring at the 4:00 p.m. close would not

[1]Source: Investment Company Institute 2000 fact book (1999 sales were $1.3 Trillion and redemptions were $1.02 Trillion. For comparison, the annual trading volume on the NYSE is about $9 trillion (www.NYSE.com.).

necessarily occur at the last trade price. But the illusion becomes real when an intermediary uses a closing-price algorithm to set mutual fund share prices.

The issue of whether or not the closing-price algorithm used to set fund NAVs is problematic can only be resolved empirically. We document that for many funds, both domestic and international, the closing-price algorithm results in predictable next-day returns that are readily exploitable.[2] For example, a simple filter-rule produces an average market-adjusted one-day return of .82% at high beta, small-cap domestic equity funds, and .83% at international equity funds.

It is likely that predictable fund returns cause economic distortions. For example, Greene and Hodges (2000) show 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 share 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.[3]

These problems 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 redemption restrictions all inhibit the exploitation of predictable fund returns. However these

[2]The predictability in foreign equity fund returns due to asynchronous trading *across* markets is examined in Bhargava, Bose, and Dubofsky (1998), Bhargava and Dubofsky (1999), and other recent working papers including Boudoukh, Richardson, Subrahmanyam, and Whitelaw (BRSW) (2000), Greene and Hodges (2000), Goetzmann Ivkovic, and Rouwenhorst (2000), and Zitzewitz (2000)). Zitzewitz (2000), and BRSW (2000), also demonstrate that mutual fund return predictability due to nonsynchronous trading *within* markets is economically large.

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

policies are inefficient solutions to the pricing problem, because they impose costs on all fund holders, not just those attempting to exploit the intermediary's pricing algorithm.

A more efficient solution to the pricing problem would be to improve the pricing algorithm. We construct a pricing algorithm that immunizes fund returns from the effects of nonsynchronous trading. In simulating the pricing of a small-cap domestic equity fund, this algorithm eliminates much of the predictability in fund returns. While this alternative-pricing algorithm may have unknown shortcomings, the simulation results imply that the pricing algorithm currently used by funds can be substantially improved. A more general implication of the simulation results is that mutual fund return predictability is a function of the price-setting algorithm, and therefore illustrates one of the many potential shortcomings of intermediary-based pricing.

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 capitalize on 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. Nonsynchronous trading and mutual fund return predictability

Closing prices are 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 portfolio at 4:00 p.m. 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 return to portfolios containing assets that have not recently traded. This source of portfolio return predictability is analyzed extensively in the finance literature.[4]

Two implications of nonsynchronous trading theory are that the predictability of portfolio returns is greater where there is 1) greater disparity between the time of last trade and market closure, and 2) 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.

The logic behind mutual fund return predictability follows directly: 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.

[4]See i.e., 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 more than 50% of the predictability found in short-horizon returns of domestic stock portfolios. For example, Kadlec and Paterson (1999) find that daily returns to domestic portfolios of small-capitalization stocks have an autocorrelation coefficient on the order of 30%.

Finally, nonsynchronous trading is not the only potential source of predictability in mutual fund returns. For example, price-adjustment delays cause predictability in portfolio returns in the same manner as nonsynchronous trading.[5] 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

In this section we document mutual fund return predictability and provide evidence on nonsynchronous trading as an explanation for this predictability.

[5]Cohen et al. (1983, 1986) note that there can be price-adjustment 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.

3.1 Data

The sample includes 943 mutual funds over the period February 2, 1998 through March 31, 2000. These data are from TrimTabs.com of Santa Rosa, California. We restrict attention to funds with more than 100 daily return observations during the sample period, which eliminates 25 funds from the sample. Using investment objectives from the CRSP mutual-fund database, our sample includes 484 domestic equity funds, 139 foreign equity funds and 295 bond funds.[6] 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 dataset ($99 million).[7] The foreign equity and bond funds in our sample are also large relative to the CRSP sample in their respective categories. The sample foreign equity funds have median assets of $123 million versus $73 million for the universe of foreign equity funds on the CRSP dataset, while the bond sample funds have median assets of $284 million versus $75 million for the universe of bond funds.

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. Index-futures prices tend to reflect more timely information than spot index values (Boudoukh, Richardson, and Whitelaw (1994)). Thus, futures returns should provide greater predictive power than spot index returns, and they should provide the sharpest measure of concurrent market (benchmark) returns.

[6] 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.

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

Accordingly, we use index futures data for the S&P 500 and 5-year T-Note from Tick Data as our market indices.

3.2 Evidence of mutual fund return predictability

Given that fund returns are not observable during the trading day, own-fund returns cannot be used to implement trading strategies. Nonetheless fund return autocorrelation can provide evidence of fund-pricing errors. 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). From table 2, the average autocorrelation of daily fund returns is 8% for domestic equity funds, 18% for foreign equity funds, and 11% for bond funds.[8] By contrast, the autocorrelation of the S&P 500 futures is a statistically insignificant -5% while the autocorrelation of the 5-year T-Note futures is a statistically significant 12%. That equity fund autocorrelations are greater than equity index-futures autocorrelations is consistent with the hypothesis that equity fund values are calculated from nonsynchronous closing asset prices. By 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.

To assess predictability in mutual fund returns, lagged daily index-futures returns are computed at 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%. While overall the adjusted-R^2s appear small, there are good reasons to

[8]The autocorrelation coefficient is positive for 88% of domestic equity funds, 100% of foreign equity funds, and 78% of bond funds.

believe that these R^2s understate return predictability. First, the estimates are unconditional. We show below that subsets of funds identified by various *ex-ante* factors have dramatically higher adjusted-R^2s. Second, we have not maximized predictability through our choice of predictive variables. For example, in unreported results, the adjusted-R^2 of regressions using NYSE index futures is higher for both domestic-equity and foreign-equity funds.

If fund-return predictability is caused by nonsynchronous trading, it should be related to the systematic risk and non-trading tendencies of the funds' assets. Because data for characterizing the nontrading tendencies of funds' assets is readily available for domestic equity funds only, our analysis focuses on this sub-sample of funds.

We estimate each fund's systematic risk (beta) using monthly fund returns and 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). A stock's market capitalization is often used as a proxy for non-trading tendencies (see i.e., Foerster and Keim (1993)). To characterize the market capitalization of funds' holdings, we use Morningstar's classifications of funds' holdings to assign funds to large-cap, mid-cap, and small-cap categories.

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 average market capitalization of funds' holdings. The rows correspond to the beta categories while the columns correspond to the market capitalization categories. Consistent with the nonsynchronous-trading hypotheses, the autocorrelation of fund returns is increasing in the systematic risk of funds' holdings. 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 market capitalization of holdings. 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.

The nonsynchronous-trading hypothesis predicts that returns to the market index over the later part of the day are a better predictor of domestic fund returns than full-day market returns, as a shorter return interval corresponds more closely to the non-trading period of domestic stocks. In table 3, we test this by predicting next-day fund returns using the returns to the S&P 500 index futures from 1:55 to 3:55, and from the previous day’s close to 3:55. The average adjusted-R^2 is higher using the two-hour return interval for funds in all but one of the cells in the three-by-three partition. In addition, the biggest difference is found in funds 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 profitability of trading strategies that exploit mutual fund predictability

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 feasibly make their trading decisions as late as, say, 3:55 P.M. At 3:55 many of the underlying assets held by the fund have long-since experienced their last transaction of the day, and thus, their last transaction 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 at least some of the underlying assets of the fund at stale prices. We refer to this option as the mutual fund wildcard option.[9]

The strategy to exploit mutual fund return predictability is straightforward. Buy fund shares (or exercise a wildcard call) on days when the predicted next-day fund return is positive; redeem fund shares (or exercise the wildcard put) on days when the predicted next-day fund return is negative. Because many mutual funds limit fund holders to 4-6 round-trip transactions per year, traders are likely to reserve exercise for days when the value is relatively high – days with extreme positive or negative market returns. To incorporate this element into the analysis, we choose an *ex ante* daily return trigger using data from the 30 months preceding the sample period. Conditioning on 5% of the return distribution leads to an expected exercise frequency of about 12 trades per year. Thus, for equity funds we use a trigger that takes the 2.5% tails of the empirical distribution of daily S&P 500 futures returns. The trigger for bond funds is set using the 2.5% tails for the distribution of 5-year T-Note futures returns.

Table 4 reports estimates of wildcard-option exercise value for domestic equity, foreign equity, and bond funds. Defining $R_{i,t+1}$ as the return to fund i on day t+1 and $R_{futures,t+1}$ as the futures return, the average exercise value to the wildcard strategy is

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

[9]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.

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 to the wildcard strategy as

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

The associated t-statistics are similarly calculated from the time-series of cross-sectional average next-day returns (or hedged returns).[10]

The hedge serves two purposes. First, it isolates the source of the abnormal returns. Absent a hedge, the next-day fund return is substantially affected by the realization of the random market factor, compromising inferences about the value of the trading strategy. Second, the hedged returns mimic the returns to a strategy that maintains the investor's current exposure to the market, making it meaningful to compare to a buy-and-hold return. For example, consider a trader who holds shares in the ABC-equity fund and observes a sell signal. The hedged return mimics the return for this trader if she sells ABC fund and simultaneously buys an S&P 500 futures contract, thus maintaining her exposure to the equity market until a buy signal is observed.[11] This obviates the need for an immediate (next-day) reversal of the wildcard-option exercise.

From table 4, the average exercise value of the mutual-fund wildcard option at equity funds is large, both economically and statistically. Consider the full-day futures return 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

[10] Separate estimates of the exercise values of wildcard calls and puts are within one standard error of each other.
[11] 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 based on a $7 brokerage commission, $50-$200 bid-ask spread, and $2 exchange fee per $750,000 S&P 500 contract. (see. i.e., Chance (2000)).

raw return of 29 basis points and a hedged return of 23 basis points. This implies a 3.5% ($1.0029^{12 exercises}$ –1) excess raw return and 2.75% hedged excess return over a buy-and-hold strategy with only six round-trips per year. The wildcard option exercise value averages almost three times as much at foreign-equity funds, where each exercise has an average next-day return of over 80 basis points, hedged or unhedged. This implies a compounded excess return of more than 10% per year over a buy and hold strategy with only six round trips per year. Finally, on average, the wildcard option appears to have no value at bond funds when using the full-day 5-year T-Note futures return as the trigger.

In reference to table 3 we observed that domestic-equity fund returns are more predictable using the last two-hour market return rather than full-day return. Thus, it is of interest to examine the profitability of the wildcard option strategy using the shorter market return interval as a trigger. From table 4, the shorter trigger interval increases the average exercise value of the wildcard option at domestic equity funds while it decreases the average exercise value at foreign equity funds. It is logical that wildcard profitability in foreign funds is greater with a longer trigger interval. The predictability in foreign fund returns using S&P 500 futures is the result of markets being open at different times, not nonsynchronous trading within a market. When using a domestic trigger for foreign funds the only consideration is obtaining the largest possible market move during the foreign market closure. This occurs with the full-day interval.

Table 5 presents estimates of wildcard exercise values for domestic-equity funds partitioned on beta and market capitalization of holdings. Substantial cross-sectional variation in wildcard exercise value is captured by these nonsynchronous-trading factors. From table 5, the 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 expected trading profits 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 distortions as large as those due to nonsynchronous trading *across* markets. [12]

4. Fund return predictability and 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 mutual fund 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. From table 6 the sample funds include a large number of load funds. Among the domestic equity fund, 55% of the funds have either a front-end or back-end load. This compares to 62% for foreign equity funds and 73% for bond funds. 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

[12] 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

make exchanges between funds at no cost.[13] In fact, investors can often exit the family altogether and return without paying a load within 60-90 days. Thus, excluding all load funds from the set of funds that are vulnerable to wildcard exercise overstates the restriction on wildcard exercise imposed by loads. We exclude these funds, nonetheless, and find practically identical results as we discuss below.

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 funds rather than leaving the fund. In our sample, transaction fees are rarely used. Of the domestic-equity funds without load fees, 3.3% impose an average transaction fee of 1.4%. Transaction fees are more prevalent in the 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%.

We also examine limits on the number of transactions that investors are allowed to make within a fund. Within 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.[14] The average limit is eight round-trip transactions, though the median and mode among funds that impose transaction limits is four round-trip trades per year. Although nearly every fund prospectus states that the fund reserves the right to exclude investors that engage in market timing strategies,

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only fails to incorporate the information in the US market, but also certain information available *within* the foreign market as well.

[13] We checked the prospectuses of 100 load funds from 23 fund families. In 95 funds and 20 families we found an explicit statement that no additional load charges accrue when transferring between funds in the family. We found no statement in the remaining 3 families and 5 funds.

[14] 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.

our discussions with customer service representatives suggest that these limitations are seldom enforced when traders 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 roundtrip wildcard exercises per year are available to investors in a substantial set of funds.

To examine the robustness of our estimates of wildcard-option exercise value with respect to trading frictions, we repeat the analysis of table 5 excluding funds with loads and transaction fees. The estimates for funds without loads or transaction fees are nearly identical to the wildcard exercise values found in the full sample. For example, from table 7 the average unadjusted next-day return of domestic equity funds without loads and transaction fees is .33% vs .34% for the full sample of domestic equity funds (table 4). 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 particularly severe.

To further address the question of whether funds that exhibit predictable returns take actions 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 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[15]:

[15] 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

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

Transaction fees are positively associated with fund return predictability. However, there is not a statistically reliable association between transaction limits and fund return predictability. Consistent with Zitzewitz (2000), we conclude that some funds behave in a manner that suggests awareness of return predictability. Table 7 shows, however, that there is ample opportunity to exploit the wildcard option at funds with no loads, transaction fees or restrictions.

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 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 intermediated trade 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.[16]

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

limits on transactions variable. Note that the 586 observations reflect missing transaction fees and transaction limits data.

[16]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. Burns, Engle and Mezrich (1998) also propose a method to synchronize foreign asset prices using an Asynchronous GARCH model.

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 from CDA Spectrum that has assets over $100 million and a high daily return autocorrelation (0.33). This choice of fund yields potential for pricing improvements. 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 November 1999 from the TAQ database. With these data we compute the synthetic fund's daily NAV using closing prices. We also compute a daily NAV using 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.[17] 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 index is not as actively traded as the S&P 500 futures contract, and thus, may not reflect as current information. Thus, 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. To facilitate discussion we focus on the results using Russell 2000 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 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 the 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

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[17]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. i.e, Black Jensen Scholes (1969)).

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 adjusted-R^2 of regressions of fund returns on lagged Russell 2000 futures returns is 1.7% using returns computed from market-updated prices as compared to 6.9% 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 fund returns.[18] Nonsynchronous-trading effects are just an illusory artifact of the data to all except those who would set a fund's NAV – or the price of any other security – according to closing prices. This result establishes, therefore, that serious concerns about intermediary-based pricing exist not just in principle, but in fact.

We also compare the profitability of the wildcard strategy as applied to the synthetic fund's three return series (calculated from closing prices, closing spread-midpoints, and market-updated 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

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

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.[19]

5.2 Implementation issues

The market-updating pricing algorithm represents an operationally feasible alternative to the closing-price algorithm. But it may have limitations of its own. First and foremost, it remains an intermediary-based pricing algorithm. Like all such pricing techniques, 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 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

[19] 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.

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. The market-updated price approach has several virtues. First, it is acceptable under current SEC regulations. Fair value pricing requires funds' securities be valued on an individual basis as opposed to at a portfolio level. Second, the market-updated price approach does not rely on estimated parameters, and thus, is not subject to estimation error. Finally, 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

The exchange of mutual fund shares is a prominent example where an intermediary sets security prices, but it is not the only one. Underwritten-security offerings are another. 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 fact, in response to allegations of price manipulation, the SEC adopted rule 10b-21 in 1988 prohibiting covering short sales with stock from a public offerings.

In our study we find that intermediary-based pricing of fund shares results in predictable fund returns. Those who exploit this predictability stand to earn economically significant trading profits. Such opportunities introduce economically material distortions. For one, the exploitation results in a transfer of wealth from passive fund investors to active fund traders. Moreover, it implies excess trading in fund shares, which is costly to all fund investors (Edelen, 1999). Finally, economists have long held that a price that fails to reflect *all* current information lowers welfare, as it leads to inefficient consumption and investment decisions. In the $6.8 trillion[20] mutual fund market, where over $1 trillion in assets changes ownership every year, the importance of an efficient price is clear. Yet, as we demonstrate with the mutual fund example, it

[20] Including $1.6 trillion in money market funds the total value is $6.8 trillion for December 1999. Source Investment Company Institute, www.ici.org.

is perilously difficult for an intermediary to set a security's price such a way that all relevant information is assimilated.

It is important to recognize that the intermediary pricing problem is more general than nonsynchronous-trading effects. The underwritten-securities example points to a separate source of distortion in prices set by an intermediary. Other examples, similar to nonsynchronous trading in their microstructure origins, are bid-ask bounce, which also causes predictable close-to-close returns, and bid-ask manipulation of stocks' closing prices (see Carhart, Kaniel, Musto, Reed (1999)). Our intent is not to enumerate all possible concerns with intermediary-based pricing – such a task is both impossible and inconsistent with the general point of our paper: novel loopholes, manipulations, and distortions are always likely to appear when the price of a security is set by algorithm rather than by the direct, open clearing of supply and demand for that security.

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, A Profitable Trading Strategy Using International Open End 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.

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.

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.

Cohen, K., S. Maier, R. Schwartz, and D. Whitcomb, 1986, The microstructure of securities markets: Theory and implications, (Prentice-Hall, Englewood Cliffs, NJ).

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

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.

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, and D. 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.

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	Mean	16	8	11			
(in years to 1999)	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 80th	**Mid-Cap 80th – 95th**	**Large Cap Above 95th**	**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 and $R_{futures,t+1}$ as the futures return, the average exercise value is defined as

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

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

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

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 and $R_{futures,t+1}$ as the futures return, the average wildcard exercise value for each classification is defined as

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

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

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

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	25^{th} percentile	50^{th} percentile	75^{th} percentile	90^{th} percentile	95^{th} 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	25^{th} percentile	50^{th} percentile	75^{th} percentile	90^{th} percentile	95^{th} 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%