Mismarking Fraud in Mutual Funds

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Abstract

We study potential fraudulent net asset value (NAV) and return inflation in mutual funds that invest in structured products. We design a filter to identify funds that likely mismark odd lot and two classes of round lot structured products. Applied to structured product-oriented funds launched after January 2010, our filter identifies 12 highly questionable funds managing $75 billion. The performance of these funds matches closely the predicted pattern of mismarking: extremely high alpha and skewness, particularly immediately after launch. We show that structured-product mismarking can seriously inflate return-since-inception metrics and cause material losses to later investor cohorts.

Keywords: mutual fund performance, structured products, odd lot, mismarking
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Executive Summary

How should a prospective investor regard a mutual fund that reports too-good-to-be-true returns? If the fund holds substantial positions in structured products like asset-backed securities and private-label collateralized mortgage obligations, we say "with suspicion."

We develop a filter to identify funds that likely mismark certain structured products and thus inflate their net asset value (NAV) and returns. Applied to all structured product-oriented funds launched between January 2010 and March 2017, our filter identifies 12 highly questionable funds whose performance matches closely the predicted pattern of mismarking: extremely high alpha and skewness, particularly immediately after launch.

Mismarking can seriously inflate return-since-inception metrics. During the first three months after launch, the 12 highly questionable funds report annualized mean net-of-benchmark returns that are more than +18% per year higher than our baseline funds.

The performance inflation caused by mismarking benefits the managers. The average initial 3-year Morningstar Rating for the nine of the identified funds receiving their initial 3-year Morningstar Rating within our sample period was 4.7 out of 5 – 1.3 stars higher than those of other funds. Moreover, their corresponding growth in assets averaged $1 billion a year more than the other funds.

As of March 31, 2017, the 12 funds managed a combined $75 billion and received management fees of about $450 million per year. About $26 billion (35%) of the assets were held in mismarking-prone positions. We estimate that these mismarking-prone holdings include over $600 million in "ghost assets" via inflated position marks. Because all fund share issuance and redemption occurs at the stated fund NAV, mark inflation causes significant losses to later investor cohorts.

Our analysis of the mutual fund performance reporting ecosystem leads to five specific recommendations encompassing:

(1) SEC sanctions against mismarking funds;
(2) best practices for auditors of mutual funds purchasing mismarking-prone securities;
(3) best practices for pricing vendors;
(4) Financial Industry Regulatory Authority (FINRA) structured product transaction report dissemination; and
(5) authenticity protocols that fund rating services and fund consultants should require of structured product funds.

1. Introduction

Academic research in finance not only aims to accurately describe and understand financial markets, but also seeks to improve their role and function. Academics enhance markets through introducing and evaluating new products, contracts, and strategies. For example, researchers have developed new valuation tools for complex contracts and securities (e.g., Black-Scholes, 1973), designed new incentive-based compensation schemes (e.g., Jensen and Murphy, 1990), and provided the theoretical foundations for new investment strategies (e.g., Fama, 1970).

In addition to guiding innovation, researchers also contribute to the regulation of markets by (1) identifying questionable practices by market participants; (2) measuring the impact of such practices on other users; and (3) developing policy recommendations aimed to improve regulation and protect market integrity. For example, Christie and Schultz (1994) interpret the lower frequency of odd-eight quotes as evidence of collusion among NASDAQ dealers. Carhart *et al*. (2002) identify mutual fund trading activity around calendar quarter ends that is designed to temporarily inflate the value of existing fund holdings and reported returns. Lie (2005) finds irregularities in stock returns around executive option grant dates and argues that many of these option grants were fraudulently backdated. These studies resulted in regulatory actions and significant changes in industry policies. Our study follows in their footsteps by producing evidence of potential mismarking fraud by open-end mutual funds that invest heavily in structured products.

The prospect that some mutual funds inflate the marks on newly purchased securities is quite plausible, as previous academic research has uncovered various manager misdeeds across the industry. For example, Chalmers, Edelen, and Kadlec (2001) analyzed how opportunistic traders can exploit mutual fund net asset value (NAV) affected by stale security prices. In 2003, two years after publication, prosecutors uncovered that this exploitive practice was widespread and proved that multiple mutual fund families had operated on a double standard by allowing certain clients to benefit from short-term market timing strategies and illegal after-hours trading to the detriment of other investors (see Zitzewitz, 2003 and Houge and Wellman, 2005).

We contribute to this literature by considering mismarking of structured products as a channel through which managers may inflate mutual fund NAV and returns. Structured products, complex

securities that trade in opaque, illiquid markets, are a convenient raw material for mismarking fraud by an opportunistic fund manager. Previous SEC enforcement actions address a particular mismarking strategy that involves managers purchasing illiquid "odd lot" (less than $1 million) structured product positions at discounted prices and immediately marking them at the higher prices provided by third-party pricing vendors applicable to much more liquid round lot sizes. Yet the odd lot stratagem is but *one* example of a general class of mismarking strategies that involve capturing a difference between the purchase price of a structured product and its end-of day mark. A manager could inflate reported investment performance by identifying and purchasing a new position (odd lot or round lot) in *any* security for which the fund's pricing source applies a higher-than-purchase-price mark. In such a case, the fund manager perverts traditional value-oriented security selection criteria by choosing investments solely to exploit knowledge of its pricing vendor's valuation mistakes.

Unlike the SEC, we cannot access individual mutual fund trading records to make direct trade-price-to-mark comparisons. Instead, our investigation of the open-end mutual fund industry looks for indirect evidence of mismarking-based schemes. We design a filter appropriate for an initial investigation of mismarking fraud and find that "buy, mismark, and hold" performance-inflating strategies are likely prevalent in the full universe of structured product-oriented US mutual funds. We confirm the existence of the previously identified odd lot stratagem but also uncover two *new* types of mismarking strategies applicable across a wide range of round lot (greater than $1 million) trades: "High-mark" and "Single-fund" positions. Both of these round lot strategies become especially useful after fund assets grow so large that the available odd lot supply no longer moves the performance-inflation needle.

"High-mark" round lot positions are those that a fund purchases and then marks in the top 25th percentile of all available marks contributed by all funds for the same security on the same date. New purchases of such positions may represent an investment aimed solely at gaming marking errors of the fund's pricing vendor. The manager simply targets securities that the fund's pricing vendor overvalues. "Single-fund" round lot positions are those in securities that are purchased and held by just one mutual fund. Such positions include special small-pool positions encompassing the entirety of a securitized set of loans. These securities are illiquid by definition because no bond dealer or other investor has access to the security. We conjecture that such single-fund round lots are likely valued at a discount to otherwise

comparable, but liquid, securities that a pricing vendor might use as valuation benchmarks. Such single-fund round lot positions are ripe for purchase and mismarking by an opportunistic fund.

Funds committing new purchase mismarking fraud need to deploy a material percentage of fund capital toward new purchases of mismarking-prone positions and also buy these positions at prices below their end-of-day marks. We analyze holdings and returns of open-end mutual funds that invest significantly in structured products and estimate the magnitudes of each fund's new mismarking-prone purchases in a given period as a percentage of its reported assets. We show that many of the 142 funds launched after January 2010 deploy a substantial fraction of their assets in one or more of our three types of mismarking-prone positions. We next identify a subset of 33 *Questionable* newly launched funds (about 25% of the total) displaying statistically significant contemporaneous positive correlations between new purchases of mismarking-prone positions and fund returns (i.e., funds that show patterns satisfying the necessary conditions for mismarking fraud). Within these, we also identify a group of 12 *Highly Questionable* funds making unusually large purchases of mismarking-prone structured products.

We analyze the daily return patterns of both *Highly Questionable* and *Questionable* funds relative to other structured product funds and a control sample pulled from the funds that have never invested in structured products. We find economically large and statistically significant differences in mean net-of-benchmark returns between the 12 *Highly Questionable* funds and their peers. During the first three months after launch, the *Highly Questionable* funds report annualized mean net-of-benchmark returns that are more than +18% per year higher than our baseline funds. Such a premium is more than three times the equity risk premium estimated by Campbell (2008).

The 12 *Highly Questionable* funds also show significantly positive skewness in their daily returns. We know of no equilibrium model capable of predicting the +18% per year return premium that our *Highly Questionable* funds report for their first three months after launch, particularly when combined with positive return skewness. Indeed, such a positive alpha/positive skewness pattern within the 12 *Highly Questionable* funds contradicts previous results for equity markets from Amaya *et al.* (2015), who find strong evidence of a negative cross-sectional relation between realized skewness and future returns. Moreover, both Conrad, Dittmar, and Ghysels (2013) and Bali and Murray (2013) report equity option market evidence consistent with a negative relation between expected returns and skewness. These

previous findings confirm a preference for positive skewness (Kraus and Litzenberger, 1976) and imply that, all else equal, assets with positively skewed returns should be priced to deliver lower-than-average returns. Thus, both theory and prior empirical research support our categorization of positive alpha/positive skewness findings as an anomalous pattern that is hard to justify by *any* appeal to unobserved equilibrium factors.

The combination of large alpha, positive skewness, and return sensitivity to new purchases exactly fits the predicted pattern of mismarking funds generated by a simulation model. We interpret our results as strong evidence that at least some of the 12 *Highly Questionable* funds realize immediate gains from mark inflation by capturing a positive difference between the end-of-day mark and the purchase price. We also compare the average sensitivities of reported monthly returns to new purchases of mismarking-prone assets of the *Highly Questionable* and *Questionable* funds relative to other structured product funds. The *Highly Questionable* funds have an order of magnitude higher sensitivity to new odd lot and single-fund round lot purchases, and similar coefficients on the high-mark round lot purchases.

Mismarking patterns evolve throughout a fund's life. Because the mark inflation on odd lots may be substantially higher than on high-mark and single-fund round lots, a performance-inflating manager will most likely start off buying odd lot positions aggressively just after launch, but later concentrate on buying high-mark and single-fund round lots after new inflows cause the fund to outgrow the available supply of odd lots. By mismarking high-mark and single-fund round lot purchases, the manager can still inflate NAV and reported returns even at fund sizes above $1 billion.

A fund might argue that an "inflated" (i.e., greater than the price just paid) mark makes sense if that mark equals the fund's expected exit price in a timely liquidation. To justify this stance for odd lots, a fund would need to be able to aggregate multiple odd lot purchases into round lot size with reasonable certainty. Yet, we show that the 12 *Highly Questionable* funds manage to successfully aggregate a mere 1.7% (7.9%) within three months (two years) after initial purchase. Moreover, we find that structured product round lot position liquidation rates for the 12 *Highly Questionable* funds are lower than those for 130 other newly launched structured product funds even though these same dozen funds liquidate non-structured product round lots faster than do the other funds. Thus, we see no reasonable basis to expect that the inflated marks approximate timely exit prices for mismarking-prone positions. Finally, we

provide statistical evidence rejecting an alternative explanation – that these patterns are driven by purchases of securities in primary offerings, a perfectly legal (when shared *pro rata* with all funds in the same family), although potentially unsustainable, way to boost returns.

In his investigation of the 2003 mutual fund scandal, then New York Attorney General Elliot Spitzer compared late trading to ''betting on a horse race after the horses have crossed the finish line.'' Today, fund managers committing mismarking fraud instead get an unfair early advantage, breaking quickly from the gate in the multi-billion dollar purse race to win a Five-Star Morningstar Rating. Nine of the 12 *Highly Questionable* funds received their initial 3-year Morningstar Rating within our sample period. The average initial 3-year Morningstar Rating for these nine funds was 4.65 Stars, 1.34 Stars higher than the average 3.31-Star initial rating for 46 other structured product funds. The annual change in assets of the nine ranked *Highly Questionable* funds averaged $1.26 billion versus just $0.20 billion for the other rated structured product funds.

Fund NAV inflations directly affect every mutual fund investor. We use a stylized model to show that such practices result in significant wealth transfers from later to early investors (including insiders). Investors entering near the end of the game are disadvantaged because fund inflows and outflows are valued at artificially high NAVs. The early investors win by selling participation in the existing mismarked portfolio at artificially high NAVs as well as by any continued participation in the mismarking of new positions purchased with new monies contributed by subsequent investors.

By March 31, 2017, the 12 *Highly Questionable* funds had grown to manage a combined $75 billion of assets and hold about $26 billion in mismarking-prone positions. We estimate that the reported $26 billion in mismarking-prone holdings generate more than $600 million in "ghost assets" via inflated position marks. As of March 31, 2017, the 526 funds in our initial sample held $149 billion in mismarking-prone assets. Absent reforms, we anticipate that the current problems in the structured product mutual fund space will only get worse as more managers are tempted to adopt the winning buy, mismark, and hold strategy.

While our forensic evidence on structured product funds stands on its own as an independent contribution to the mutual fund literature, we believe our analysis makes three broad contributions to the asset management literature. First, the positive alpha/positive skewness validation test is of general use

for any investment performance analysis. Evidence of positive alpha/positive skewness should be treated as a red flag. Thus, institutional investors, investment consultants, and auditors should employ a positive alpha/positive skewness validation test for all manager and sub-manager evaluations. Any "too-good-to-be-true" performance identified by such a test warrants further investigation for potential fraud.

Second, mismarking exacerbates the concerns of Goldstein, Jiang, and Ng (2017) that open-end funds holding illiquid assets may be fragile. In open-end funds, redemptions at NAV provide liquidity for redeeming investors, but cause transaction costs and negative externalities for remaining investors, especially when the fund experiences large outflows and must sell illiquid securities. The first-mover advantage of early redeeming investors exposes funds with illiquid holdings to the risk of a redemption cascade, i.e., an investor "run." For structured product funds, the mismatch between the illiquidity of the securities that may not trade for years and the daily liquidity of fund shares may be especially severe. Now, if a significant fraction of structured products held by funds are marked at inflated values, the negative externalities of redemptions will be even larger.

Third, our analysis of mismarking by growing funds suggests that the current practice of reporting mutual fund returns as time-weighted averages is prone to abuse by opportunistic mutual fund families. For example, families with access to even a small dollar amount of heavily discounted odd lots can launch an arbitrarily small fund that invests a large percentage of its assets in such positions. Thus, a small dollar amount of mismarking can be amplified into exceptional percentage gains in the first few months after launch. These early exceptional returns on small asset base contribute as much to time-weighted measures like compound annual return since inception (CAR) as returns after the fund has grown large. Furthermore, as we will show, a fund will preserve a large part of the excess return from mismarking that was "earned" when the fund was small and growing even if the regulator forces the fund to eventually revalue its mismarked assets.

2. The setting

Structured product investments by mutual funds receive scant attention within the otherwise voluminous literature on fund performance. A corresponding dearth of academic research in the market microstructure of structured products, especially for credit loss-exposed non-agency securities, no doubt

inhibits inquiry in this sector. Yet, agency pass-through mortgage-backed securities (MBS) and agency collateralized mortgage obligations (CMO) represent a meaningful proportion of the US debt market. Other less transparent and liquid structured products such as private-label residential MBS, private-label CMOs, commercial mortgage-backed securities (CMBS), and asset-backed securities (ABS) have transformed the financing landscape (for good and ill) since the turn of this century.

Bessembinder, Maxwell, and Venkataraman (2013) examine proprietary FINRA data on all secondary market trades in structured products for a year-and-one-half period and find that execution costs averaged 24 basis points when trades occurred. Such costs were considerably higher for products with a greater proportion of retail-size trades. Similarly, Atanasov, Merrick, and Schuster (2017) find that trading costs are an order of magnitude higher for smaller compared to larger large sizes. They find significant price discounts on customer buy trades of less than $50,000 relative to round lot sell trades in agency MBS, the most liquid structured products. Other structured products trade in more opaque markets that impede the ability of pricing vendors to provide fair position marks. Thus, corresponding odd lot price discounts should also be expected for buy trades in some agency CMOs and all non-agency structured products for trade sizes up to $1 million in current face value.

Structured product fund managers have motive, means, and opportunity for entering mismarking fraud via a buy, mismark, and hold strategy. The extra gains from inflating fund performance provide the motive. For example, the immediate fictitious capital gain generated by mismarking a newly purchased odd lot structured product simultaneously inflates the mutual fund's reported NAV and return for that day. This one-day inflation in return will also boost any performance metric spanning that day such as fund CAR. CARs are used by advisory services such as Morningstar to evaluate and rate funds for prospective investors. Investment inflows and outflows are sensitive to Morningstar Ratings, and a Five-Star Morningstar Rating is a highly valued status symbol that managers promote when reporting to existing and marketing to new investors.

The means for entering odd lot mismarking fraud is a mere sin of omission. Securities and Exchange Commission (2016b) quotes Section 2(a)(41)(B) of the Investment Company Act as the foundation for its actions against PIMCO:

> *Under Section 2(a)(41)(B) of the Investment Company Act, registered investment companies must value their portfolio assets by using: (1) market values for securities with readily available*

> *market quotations; and (2) fair value for all other portfolio assets, as determined in good faith by the board of directors. The fair value of securities for which market quotations are not readily available is the* ***exit price the fund would reasonably expect to receive for the securities*** (emphasis added).

The fund manager executes the strategy by simply buying a discounted odd lot position and valuing this new holding at a round lot mark to produce an overnight capital gain. Any mark appropriate for valuing a round lot position overstates the value of an odd lot position in the same security and violates the SEC rule requiring security marks to be based upon "exit" prices. Note that the fair valuation of this new position would entail deducting the appropriate discount from a vendor-supplied round lot mark.

The U. S. Securities and Exchange Commission (SEC) settlement of administrative and cease-and-desist proceedings against Pacific Investment Management Company (PIMCO) for mismarking new purchases of odd lot structured products in order to inflate the NAV and reported returns of its PIMCO Active Bond Exchange-Traded Fund (Ticker: BOND) during the first four months after launch provides an example of how such mismarking fraud might work (SEC, 2016a and 2016b). As detailed in this settlement, BOND's reported return-since-inception of 6.27% dwarfed the 1.50% earned by its benchmark over the same post-launch four-month period during which PIMCO purchased 43 positions that were, on average, approximately 9% lower than its end-of-day marks.[1]

The opportunity for such fraud exists for any mutual fund manager. No specific market edge or investment skill is required. Because the dollar amount of relevant securities available for purchase at any time in odd lot size is limited, managers desiring to inflate performance through intense use of the odd lot mismarking stratagem should do so while their fund is relatively small. Related schemes of buying certain mismarking-prone round lots, however, can be done at any fund size.

2.1 Related literature

In addition to the market timing/late trading literature, previous academic studies have analyzed fund NAV and returns manipulation under three other themes: "painting the tape," general returns

[1] The SEC also settled administrative and cease-and-desist proceedings against hedge fund manager Visium Asset Management LP for using sham broker quotes to inflate the value of securities held by funds for which Visium acted as investment adviser (SEC, 2018a). Most recently, the SEC filed a complaint against Premium Point Investments LP, its chief executive officer, and individual traders for engaging in a fraudulent scheme to inflate the value of securities, including non-agency mortgage-backed securities, held by several private investment funds that Premium Point advised (SEC, 2018b).

smoothing, and strategic performance transfers. Table 1 summarizes various contributions within all four main lines of inquiry.

Regarding painting the tape, Carhart *et al.* (2002) and Bernhardt and Davies (2005) show that managers inflate quarter-end portfolio prices with last-minute marketplace purchases of stocks already held.[2] Such trades cause stock exchange prices for the affected stocks to close the quarter at artificially high levels, which then directly feed into higher marks for the affected fund positions. Note that the fund does not inflate its marks directly since it and/or its pricing vendor apply observable exchange-determined prices to all positions. We categorize these manipulations as reflecting a "trade-based, market price" method that produce a transitory NAV effects with no positive impact on either fund alpha or skewness (i.e., the effect should reverse the next day when the manager's buying pressure is absent).

Other researchers find strong evidence that both mutual fund and hedge fund managers succeed in smoothing fund returns and imply related inflation of risk-adjusted performance metrics such as Sharpe ratios. For example, Cici, Gibson, and Merrick (2011), Getmansky, Lo, and Makarov (2004), and Cassar and Gerakos (2011) show that reported returns for funds with illiquid assets and no explicit marking policies tend to be smoother than true economic returns. In a similar vein, Bollen and Pool (2009) find a significant discontinuity in the pooled distribution of monthly hedge fund returns where the number of small gains far exceeds the number of small losses. Their evidence suggests that hedge fund managers strategically distort the month-end position marks to avoid small losses. We categorize these examples as reflecting "mark-based" manipulation methods that produce transitory NAV effects with no positive impact on either fund alpha or skewness (i.e., the effect should reverse once the manager's reporting pressure is absent).

Regarding strategic performance transfers, Gaspar, Massa, and Matvos (2006) and Massa, Reuter, and Zitzewitz (2010) argue that mutual fund families allocate their scarce underpriced initial public offering (IPO) allotments to benefit "high family value" funds (e.g., high fee funds, young funds, high past performers, and single-manager funds) at the expense of "low value" funds. Similarly, Cici, Gibson, and Moussavi (2010) find that asset management companies operating both mutual and hedge funds often

[2] Another large literature examines "window dressing" by managers who buy winners and sell losers near the end of a reporting period (see Agarwal, Gay, and Ling, 2014, for a recent example).

cannibalize the mutual funds to benefit the hedge funds. These three papers promote disproportionate allocation of underpriced IPOs as the main mechanism to transfer benefits towards high family value funds. Finally, Agarwal *et al.* (2018) show that similar transfers of benefits can be achieved through disproportionate allocations of stakes in private companies in anticipation of upcoming investment rounds.[3]

In all performance transfers cases, the fund acquiring the discounted positions via its family's internal allocation decision immediately marks the new positions up to their fair market values. These examples reflect "trade-based, discounted price" manipulation methods that produce permanent NAV effects with positive impacts on both fund alpha and skewness for the funds to which the discounted positions have been steered. These effects will not reverse themselves after the allocation event because the beneficiary fund marks its positions at fair market values. Because the (cheaply) acquired positions are carried at fair market value, they entail no expected loss upon a potential future sale. Indeed, a beneficiary fund might even flip some of its underpriced IPO allotments immediately at a profit (i.e., so that they are never even seen in holdings reports).

In contrast to the above, the structured product manipulation strategy we study is a "trade-based, inflated mark" method and offers the possibility to generate large and permanent alpha at no cost for other funds in the same family. While this method is trade-based, all of the relevant new positions are purchased at market prices and the associated performance artificiality is generated by marking these new purchases at inappropriate inflated values supplied by external pricing vendors. Such mark inflation is not undertaken to avoid losses, but instead to accelerate gains via immediate positive jumps in NAV. Note that this "passive" type of mark inflation differs from the active mismarking on previously acquired holdings in the smoothing/small loss avoidance literatures. Rather than treat an overvalued position as a "store of value" to be actively drawn upon to bolster returns during a subsequent month of poor performance, the passive structured product mark inflation we study is never undone as long as the mismarked positions remain in the fund portfolio.

Because these (fairly) acquired structured product positions are carried at inflated market values, they entail expected losses upon any future sale. Thus, managers face the risk of reporting return reversals

[3] Evans (2010) examines incubation effects as another channel through which fund families game fund performance records.

if they are forced to either sell their overvalued structured product positions or receive heavy unscheduled principal repayments. In light of these risks, the success of these strategies in permanently inflating fund NAV and reported performance depends critically on attracting sufficiently large inflows. In contrast, the traditional performance transfer strategies based on IPO or private equity allocations do not require inflows because all gains can be fully realized by selling the now fairly marked securities.

Absent investor liquidation pressures, a buy, mismark, and hold manager will avoid selling any overvalued security so positive jumps in NAV (and daily return) will not be matched by negative jumps. Thus, the asymmetric effects predicted by this "trade-based, inflated mark" method manipulation should necessarily result in positively skewed reported returns. A simple test of the skewness of reported returns provides a useful filter for potential mismarking fraud. While this filter has been developed to study fraud related to structured product mutual funds, it is applicable in any other setting where mismarking is most likely to occur at position initiation. For example, privately placed offerings of shares in public companies are often done at discounts to the price of the publicly traded shares. Mutual funds participating in such offerings can realize immediate gains if they use the public prices for their marks. Furthermore, we note that the performance transfer papers can also benefit from using tests of skewness restrictions. Each paper studies non-price processes for allocating scarce discounted securities positions among related funds. Funds chosen to be the "winners" in each allocation event should see positive skewness-inducing NAV/return spikes due to the built-in capital gains. Such gains will not be offset by future losses since winners mark their new holdings at fair market values.

2.2 Detecting mismarking from reported holdings and returns

The opportunity for structured product fund managers to inflate performance metrics can be understood by extending the framework of Atanasov, Merrick, and Schuster (2017). They argue that discounts on odd lot trades in agency MBS are driven by two novel market frictions affecting dealers – a fundamental impediment to aggregating small positions and a suitability restriction against making recommendations to retail customers – in a setting where fixed per position holding costs eventually make amortizing structured products uneconomical for institutional investors. The effects of these frictions should be even more important in agency CMOs and non-agency structured products because these products are ineligible for the two main supra-security mechanisms used to help institutional investors

manage position size decay in agency MBS – the highly successful "to be announced" (TBA) forward contract market and security aggregation facilities sponsored by the issuing agencies (e.g., Fannie Mae's "megapools").

New purchase fraud generates overnight accounting gains because the purchase price of the security is lower than the inappropriate end-of-day mark applied to the position. A newly launched fund that deploys its entire capital in odd lot structured products at a 6% discount to the round lot end-of-day mark will inflate its end-of-day NAV and show a first-day gain of 6.38% (= .06/.94). If the fund receives no further cash inflows over the rest of the month, the fund will report a 0% net-of-benchmark return for each remaining day. A regression of daily net-of-benchmark percentage returns on daily percent new purchases in odd lots would produce a slope coefficient of 6.38 and an R-squared of 100%. Cumulative purchases of fairly marked assets should have no positive relation to same-day reported returns.

In practice, we do not observe daily purchases because funds do not report purchases at all and end-of-period holdings at best on a monthly but typically on a quarterly basis. Nevertheless, we can infer that a fund has made new purchases of a particular security any time that security appears as a holding in the current period but not in the previous period. Because all purchases executed below the marks result in overnight positive returns, the cumulative purchases of mismarked assets made within a reporting period should correlate positively with same-period reported returns as calculated by compounding daily returns.

2.3 Simulation results

Appendix A presents simulation analysis highlighting the differences in performance patterns caused by two concurrent fund policies. The first policy determines the size of investment in mismarking-prone securities. Funds choose to be "high usage," "low usage," or "zero usage." The second policy determines whether or not funds inflate the marks on their new purchases. The combinations of these two policies produce five distinct fund groups: (1) "zero usage" funds that never purchase mismarking-prone securities; (2) "fair-marking low usage" funds that purchase a limited amount of mismarking-prone securities and mark them fairly; (3) "fair-marking high usage" funds that purchase the maximum available amount of mismarking-prone securities and mark them fairly; (4) "mismarking low usage" funds that purchase and mismark a limited amount of mismarking-prone securities; and (5) "mismarking high

usage" funds that purchase and mismark the maximum available amount of mismarking-prone securities. We use a simulation to compare return patterns for each of four positive-usage fund types versus the baseline zero-usage funds. The return distributions of zero-usage funds are unaffected by odd lot purchases and/or mismarking by definition.

Mismarking funds should show high alpha relative to zero-usage funds especially because of the immediate fictitious capital gains from marking odd lot purchases at higher round lot prices. Mismarking funds should also exhibit high net-of-benchmark return skewness relative to zero usage funds. High skewness is a signature of mismarking because fund NAV will show a positive jump each day that a manager buys and mismarks new structured product positions. Thus, a fund making concentrated purchases of mismarked assets will generate both positive alpha and positive skewness.

The columns of Table A.1 compare regressions for fund alpha and skewness that each include (i) an intercept term; (ii) fund age indicators for each fund's first four post-launch quarters; and (iii) fund type-age interaction terms. The results show that mismarking high usage funds outperform all other categories, especially during the first three months after launch when they post a statistically and economically significant differential alpha versus the baseline zero-usage funds. This differential alpha falls rapidly over subsequent months, but the intercept coefficient implies differential net-of-benchmark returns even after the first year. As conjectured, mismarking high usage also exhibit significant positive skewness throughout and even beyond the first year.

The simulation analysis also examines whether a filter based on a regression of monthly net-of-benchmark fund returns on fund purchases of mismarking-prone securities (scaled as a percentage of assets) can correctly identity mismarking funds. The results presented in Table A.2 show that a t-test for a statistically significant positive estimated slope coefficient correctly identifies 99.5% or more of the mismarking funds (i.e., the test has high power). These striking differences between mismarking and fair-marking funds suggest that a statistically significant slope coefficient on contemporaneous new purchases of mismarking-prone positions in such a regression is a strong necessary condition for identifying mismarking funds. The mean slope estimates for mismarking high usage funds with significant t-statistics

in our base case (Panel A of Table A.2) are quite close to the simulation's assumed parameter value.

The combination of large alpha, positive skewness, and positive return sensitivity to new purchases exactly fits the predicted pattern of mismarking funds generated by a simulation model and is otherwise difficult to explain in equilibrium terms. However, t-tests for these simulated data also identify some fair-marking funds as mismarkers (i.e., the test produces "false positives"). The frequency of false positives is above the expected 2.5% rate of false positives given the chosen 5% size of the two-tailed test. Thus, we will first use the significant t-statistic filter in combination with evidence of high usage to identify *Highly Questionable* funds – i.e., funds that mismark with high probability. We will then assess the incidence of false positives within this group by testing whether the slope coefficients, net-of-benchmark returns, and skewness of this group are much higher than those of the remaining funds. Should this occur, we would conclude that this group exhibits all signature patterns of mismarking funds and that the problem of false positives is immaterial.

3. Data

We start by downloading holding reports, total returns, assets under management, and fund characteristics for the full Morningstar universe of United States mutual funds (including inactive funds) for the period from January 2010 until April 2017. This exercise yields returns for 42,248 individual share classes belonging to 10,585 funds and holding reports for 10,447 funds. As in Pástor, Stambaugh, and Taylor (2015), we weight returns of the individual share classes by their relative assets under management to aggregate to a fund-level return. For each fund, we download the returns of its Morningstar-assigned benchmark index.[4] We next merge monthly returns, assets, and holdings data. We define a security as a holding with non-missing CUSIP. We exclude all 144A non-structured product bonds and all TBA contract positions. We follow Pástor, Stambaugh, and Taylor (2017) and eliminate observations in which the sum of the market values of all holdings reported in Morningstar is either less than one-half or more

[4] We use Morningstar's Analyst Assigned Benchmark when available, and the MPT Benchmark otherwise. The Analyst Assigned Benchmark is a more specific index assignment based on research and editorial feedback. The MPT Benchmark is Morningstar's general index assignment based on broad asset class (for example, the Bloomberg Barclays US Aggregate Bond Index is used for Taxable Bond funds).

than twice the fund's total assets. We also download data on turnover ratios and net expense ratios from Morningstar on a fiscal-year basis. We assign both variables to all months of the fiscal year and again aggregate the share-class data to the fund level by weighting with assets under management.

Finally, using the Morningstar-supplied holding type to differentiate between structured products and other securities, we limit our analysis to two samples of funds. The first includes all funds that hold on average at least 25% of their assets in structured products. This sample includes 526 mutual funds. The second includes funds launched after January 2010 that never held any structured products during our entire sample period (2,951 funds).

We examine the sequence of available holding reports to construct a new positions indicator. A position is classified as a new position if it has not been in the fund's portfolio on the previous report but appears in its current holdings. Typically, holdings are reported on a quarterly basis, but a significant number of funds additionally report on a monthly basis. We use a monthly frequency for these funds and employ a monthly mapping of (excess) returns to newly acquired positions. For funds that report only quarterly, we adapt to a monthly frequency by distributing the value of the new positions equally among the months that are between the previous and current report. If there are, however, more than three months between successive reports, we eliminate the observation entirely from the sample.

Table 2 analyzes the distribution of average fund holdings by security type over our sample period. We group all security holdings into one of two broad categories: structured products and non-structured products. Based upon the security category identifiers provided by Morningstar, we further define five structured products types and five non-structured products types. The five structured products types are Agency Pass-Through MBS, Agency CMO and Other, CMBS, ABS, and Private-label CMO and Other. The five non-structured products types are Cash and Equivalents, Corporates, Treasuries, Municipals, and Other. For each fund and each security type, a percent of fixed income holdings variable is calculated as the sum of market values of positive holdings divided by the sum of the positive holdings in all fixed income security types in a given reporting period. To calculate summary statistics, we first average the percentage holdings over the total observation period on a per-fund level.

Table 2 also presents summary statistics calculated from per-fund average values across the 142 funds launched after January 1, 2010 and the 384 funds launched before January 1, 2010. The newer

funds invest much less intensely than the pre-2010 funds in transparent and liquid Agency MBS. Conversely, the newer funds invest much more heavily than do the pre-2010 funds in opaque and less liquid ABS and Private-Label CMOs. The average fund investment intensity for the newer funds was 21.9% in ABS and 12.4% in Private-Label CMOs (versus just 8.4% and 6.1%, respectively for the pre-2010 funds). At the extreme, the maximum average fund investment intensities for the newer funds were 95.8% in ABS and 94.9% in Private-Label CMOs (versus just 56.4% and 43.8%, respectively for the pre-2010 funds).

For each security type, we define the critical size distinguishing odd lot and round lot positions. For all but Agency MBS Pass-Through, we follow a general industry guideline by classifying round lot positions as $1 million and above in size. This choice is consistent with the guidance given by the commercial pricing vendor referenced in SEC (2016b). Atanasov, Merrick, and Schuster (2017) find that price discounts for customer buy trades rarely occur in standard agency MBS for trade sizes greater than $50,000. Thus, for Agency MBS Pass-Through, we size round lot position at $50,000 and above.

We study the distribution of marks that funds place on their positions. For each fund and each reporting period, the Morningstar mutual fund holdings database reports the market and par values of all security positions. We calculate the mark for security *i* held by fund *k* at date *t* by dividing the reported market value of that bond holding by the reported par value of the holding and then multiplying by one hundred.[5] This expresses the reported mark as percent of par value. Table 3 presents summary data for the number of funds reporting marks on structured product positions for the same security on the same report date. We report results for four mark count categories: 1, 2, 3-5, and 6 or more ("6+"). We further distinguish single-mark observations on structured product positions held by only one fund throughout the sample ("single-fund positions") with an asterisk. The remaining single-mark observations represent positions in securities that are held by multiple funds that do not share reporting dates. For the pooled sample of fund positions as well as within five broad security types, we present the number and percent of reported positions across mark categories. For the pooled sample, 33% of fund positions have 6+ comparable marks on a given report date. CMBS (68%) and ABS (50%) have much larger than average representation by percentage in the 6+ category. Indeed, ABS have almost as many 6+ mark positions by

[5] Following Cici *et al.* (2011), we drop all marks on any positions smaller than $10,000 in par value.

raw count as the much larger Agency Pass-Through MBS market. Among security types, Agency Pass-Through MBS have the most single-fund positions in both raw count and percentage terms (24%). Single-fund positions account for 17% of Agency CMO. In Private Label CMO, the least transparent security type, single-fund positions account for just 8% of all positions.

For positions held by three or more funds, we categorize the mark placed on by each fund as either "High," "Medium," or "Low" in relation to the cross-fund distribution of marks for that same security on that same report date. In this exercise, we compare marks on all positions across all 10,447 funds in the full Morningstar U.S. mutual funds universe. If only one or two funds hold the same security i on date t, we term the position as *"Unranked."* For each security i, we compute the median mark ($Median_{i,t}$) and the interquartile range of marks ($IR_{i,t}$) on each date t. We term fund k's mark ($M^k_{i,t}$) for individual security i on date t to be:

"High" if $M^k_{i,t} \geq Median_{i,t} + .5 * IR_{i,t}$;

"Medium" if $M^k_{i,t} > Median_{i,t} - .5 * IR_{i,t}$ and $M^k_{i,t} < Median_{i,t} + .5 * IR_{i,t}$;

"Low" if $M^k_{i,t} \leq Median_{i,t} - .5 * IR_{i,t}$.

Define a high-mark position's "markup" as the difference between the mark used by a given fund and the median mark across all funds for that same security on that same report date. Table 4 presents results for the distribution of markups on high-mark positions broken down by broad security type and mark count categories. These results lead to three main conclusions. First, in all cases, the mean markup is at least double and sometimes five-times as high the median markup. Indeed, the values associated with the 75th, 95th, and 99th percentiles of the markup distribution show some funds valuing positions at extreme markups (e.g., a markup of 11.09 for the 99th-percentile for Private-Label CMO versus the median of 0.32). Second, regardless of security type, the mean markup is higher when the number of comparable fund marks is lower (i.e., when the security is less widely held). Across all of these high-mark positions, the average markup for positions with 3-5 comparable marks is 0.17 higher (about +42%) than that for positions with 6+ comparable marks. Third, Private-Label CMO and ABS show the highest mean, median, and right-hand tail percentile markup values among the five broad security types.

Last, it is possible that funds are able to purchase securities in the primary market at a discount to the market value (see, e.g., Weinstein, 1978). We therefore download data on the issue date from

Thomson Reuters Eikon for all 165,668 structured product and 211,727 non-structured product securities purchased by a fund during our observation period. We define a purchase as a primary market purchase if the security was issued between the previous reporting date and the reporting date at which the security first appears in the fund's portfolio. We then assign the value of the new purchase to the issue month.

3.1 Are new security purchases related to fund returns?

Appendix B presents preliminary evidence regarding whether any fund returns are indeed enhanced by the mere act of purchasing new securities. Table A.3 presents panel regression models across our entire sample and a subsample of funds launched after January 1, 2010. We find that new purchases of odd lot structured product positions have statistically significant positive effects on benchmark-adjusted fund excess returns. These results strongly reject the hypothesis that all funds fairly mark their new purchases of odd lot structured products.

The slope estimates for aggregate new purchases of round lot structured products from Table A.3 also show evidence of statistically significant impacts for both fund samples. The magnitudes of the round lot purchase impacts for the newly launched funds subsample are roughly double those for the full sample (and the t-statistics are 50% higher). In contrast to their structured product counterparts, both new odd lot and round lot purchases of non-structured products generate no statistically significant effects on returns. Regressions on disaggregated round lot data show consistent and statistically significant fund return impacts to emanate mainly from new purchases of high mark round lot and single-fund round lot structured products. The coefficients and t-statistics are larger for the subsample of newly launched funds.

Taken altogether, the Table A.3 results focus our attention on potential performance inflation by mutual funds via mismarking of new purchases of odd lot positions and both high-mark and single-fund round lot positions in structured products.

4. Identifying likely mismarking funds

Guided by our simulation results, we identify *Questionable* funds by searching for a statistically significant positive relation between net-of-benchmark returns and purchases of mismarking-prone positions in individual fund regressions. Among the *Questionable* funds, we next identify *Highly Questionable* funds as those associated with the largest new purchases of structured product positions in

the first three months after launch. Finally, we compare the net-of-benchmark return averages, skewness, and regression slopes across the *Highly Questionable*, *Questionable*, and remaining funds.

4.1 Using regressions to identify potential mismarking funds

We focus our regression tests on the subset of funds launched after January 1, 2010, because the effects of mismarking will be strongest if it is initiated immediately after launch. We estimate models explaining individual fund net-of-benchmark returns as a function of odd lot or high-mark round lot or single-fund position purchases (expressing each as a percentage of end-of-period assets). Our fund identification strategy rests importantly on the t-statistics for the estimated slope coefficients in the individual net-of-benchmark fund return regressions.

Table 5 summarizes the estimated t-statistics for the fund-by-fund regressions. The results show that the panel regressions reported in Table A.3 mask substantial heterogeneity across funds regarding the contemporaneous relation between net-of-benchmark returns and the key new purchases variables. We partition the fund sample into two groups based upon the results of these t-tests: statistically significant at the 5% level versus non-significant. Twenty-five (18%) of the funds show significant positive correlations between net-of-benchmark returns and new purchases of odd lot structured product positions. Thirteen (9%) of the funds show significant positive correlations between net-of-benchmark returns and new purchases of high-mark round lot structured product positions. Fifteen (11%) of the funds show significant positive correlations between net-of-benchmark returns and new purchases of single-fund round lot structured product positions.

Our bad news for mutual fund investors is that mark inflation of new purchases of structured products appears to be widespread: 33 funds among the 142 funds examined have statistically significant correlations between at least one of the new mismarking-prone purchases variables and net-of-benchmark fund returns. We do not challenge the reported performance records of the 109 structured product funds with insignificant t-statistics. However, the 33 associated with statistically significant correlations between at least one of the new purchases variables and net-of-benchmark fund returns – about one in four funds – exhibit evidence of possible fraud that warrants further investigation.

4.3 New purchase intensities of odd lot, high-mark round lot, and single-fund round lot positions

Table 6 presents summary statistics of percent new odd lot, percent new high-mark round lot, and percent new single-fund round lot positions purchased by funds during the first four quarters after inception for the sample of 142 structured product funds launched after January 1, 2010. We calculate the quarterly percentage of each type of mismarking-prone position purchases as the sum of monthly purchases scaled by end-of-month fund assets made during each of the three months in the quarter.

The results in Panel A show that the median value (50th percentile) of new purchases of odd lot structured products during the first three months after fund launch equals 16.22% of fund assets. The percentage of new odd lot purchases for the median fund subsequently falls off quickly to just 1.63% by the final period. The results also show that some funds initiate much higher odd lot purchase intensities and maintain them well beyond the first three months. The 95th percentile of new odd lot purchases percentage is 82.06% during the first three months after fund launch, more than five times the median fund's value. The 95th percentile of new odd lot purchases percentage is still 11.48% by the final period, seven times the corresponding value for the median fund.

The median fund buys no high-mark round lots (0%) at any time during the first year after launch (Panel B). Again, the results also show substantial heterogeneity among funds. The 95th percentile of the new high-mark round lot purchases percentage is 8.92% during the first three months after launch. The 95th percentile of the new high-mark round lot purchases percentage is still 4.72% by the fourth three-month period, showing only a fraction of the drop off associated with odd lots. The median fund in Panel C buys no single-fund round lots (0%) at any time during its first year. The 95th percentile of the single-fund round lot position purchases percentage is 27.83% during the first three months after fund launch. The 95th percentile of the new single-fund round lot purchases percentage is still 7.99% by the fourth three-month period.

Taken altogether, the positively skewed strategy usage intensities suggest that a select set of funds specializes in buying odd lots and high-mark and single-fund round lots. Purchases of these mismarking-prone securities are largest during the first three months of fund life, but persist for a select set of funds beyond the first post-launch quarter.

4.4 Highly Questionable funds

We identify *Highly Questionable* funds as funds that have both a higher than 1.96 t-statistic on one of the filtering regressions and a corresponding high mismarking-prone position purchase intensity across its first three months after launch. We define high initial mismarking-prone position purchase intensity as one of the following: 1) the sum of percent new odd lot structured product purchases across the first three months to be greater than 50% of assets; 2) the sum of percent high-mark round lot structured product purchases across the first three months to be greater than 5% of assets; and 3) the sum of percent single-fund round lot structured product purchases across the first three months to be greater than 20% of assets. These cutoffs values are approximately the 90th percentile of usage of each type of mismarking-prone position in the first three months since fund launch, as reported in Table 6.

The critical levels applied for t-statistics and purchase intensities for each of the three types of mismarking-prone positions identify nine funds that have high t-stats and high initial usage of odd lots, two additional funds with high t-stats and high initial usage of high-mark round lots, and one final fund with high t-stats and high initial usage of single-fund round lots. Thus, our filters produce a combined set of 12 funds whose heavy purchases of new mismarking-prone positions have statistically significant correlations with their benchmark-adjusted reported returns.

4.5 The Highly Questionable funds exhibit the signatures of mismarking

We first study daily net-of-benchmark fund returns defined as the difference between the fund daily return minus the daily return on its benchmark. We use these daily data to estimate fund *Alpha* at a monthly frequency by computing the average daily net-of-benchmark return during successive, non-overlapping 30-calendar-day periods ("months") that begin at fund launch and continue throughout the sample. We create a companion fund *Skewness* measure as the skewness of net-of-benchmark daily returns for these same successive periods.

Table 7 presents regressions examining the differential post-launch patterns in measured *Alpha* and *Skewness* across groups of funds. We compare four fund groups: the 12 *Highly Questionable* structured product funds (statistically significant purchase-return correlations and high usage rates); 21 *Questionable* structured product funds (significant purchase-return correlations but lower usage rates); 109 *Unchallenged* structured product funds (insignificant purchase-return correlations), and the baseline

group of 2,951 funds that never invested in structured products. The regressions for *Alpha* and *Skewness* each include (i) an intercept term (interpreted as "*Months 13+*"); (ii) four fund age indicators; and (iii) terms that interact the *Highly Questionable*, *Questionable,* and *Unchallenged* fund-type indicator variables with the intercept and four fund age indicators.

The *Alpha* regression shows that the *Highly Questionable* funds have 7.4 basis points per day—more than +18% per year—higher mean net-of-benchmark returns during the first three months after launch. This coefficient is highly statistically significant (p-value of the associated t-test is less than .0001). For both *Questionable* and *Unchallenged Funds*, the coefficient estimate of the differential *Alpha* effect over the first three months is not significantly different from zero. The baseline, non-structured product funds show a statistically significant but small negative effect over the first three months (-0.2 basis points per day).

The regression's estimated intercept, a measure of long-run alpha for the baseline non-structured product funds, is a statistically significant -0.6 basis points per day (about -1.5% per year). In contrast, the differential long-run alpha estimates for all three structured product fund groups are positive and statistically significant for the *Highly Questionable* and *Unchallenged* Funds. The differential long-run alpha estimates for the 21 *Questionable* funds (0.47) and 109 *Unchallenged* funds (0.92*)* are reasonably similar. The average estimate of 0.85 basis points per day across all 130 of these funds implies special *Months 13+* net-of-benchmark return benefits of about +2.2% per year during our sample period.

But our 12 *Highly Questionable* funds show a differential long-run alpha estimate of 1.55 basis points per day (about +4.0% per year) that is almost *twice* that of their 130-fund peer group. An F-test that the *Alpha* regression's long-run coefficient for *Highly Questionable* funds is different from that of the *Unchallenged* funds has an F-statistic of 12.3 (p-value < .0001). Thus, our estimates show that the 12 *Highly Questionable* funds also report extraordinary *long-run* performance relative to both presumed fair marking peers and all non-structured product funds. This matches the pattern of our simulation results in Table A.1 for funds that continue to conduct mismarking fraud beyond their first year of existence.

The *Skewness* regression shows *Highly Questionable* funds to be associated with a positive differential effect over the first three months that is highly statistically significant (p-value < .0001). In fact, the estimated positive differential effect lasts beyond the first three months. Four of the five fund-age

interaction terms (including that for the long run) are statistically significant. The marginal *Skewness* effects over the first three months for *Questionable* and *Unchallenged* funds are not statistically significant. The baseline, non-structured product funds show a statistically significant negative effect on skewness over the first three months.

The simulation in Appendix A highlights stark divergences for high usage mismarking funds versus both high and low usage fair-marking funds regarding the distribution of the estimated slope coefficient from a regression of monthly returns on new purchases of a mismarking-prone asset (interpreted in Table A.2 as odd lot structured products, but applicable to any such asset). High usage mismarking funds should be associated with a much larger estimated slope coefficient than that for fair-marking funds.

We test this prediction in Table 8 using two sets of monthly fund return panel regressions. The first two columns use net-of-benchmark returns as the dependent variable. Columns 3 and 4 use net-of-T-bill returns as the dependent variable but add the excess return on the benchmark as an explanatory variable. For both dependent variables, we estimate two specifications. The first focuses on new mismarking-prone position purchase effects for the odd lot, high-mark round lot, and single-fund round lot categories and allow for interaction effects with our *Highly Questionable*, *Questionable*, and *Unchallenged* fund type indicator variables. To allow for a possible alternative explanation of the observed return patterns, the second specification includes *Primary Security Purchases* (scaled as a percentage of assets) for both structured products and non-structured products as additional explanatory variables. Funds purchasing securities in the primary market at a discount (see, e.g., Weinstein, 1978) and marking them (fairly) at the higher secondary market price will outperform their benchmarks. Moreover, such purchases when scaled as a percentage of assets could be more material early in the life of a fund. All regressions include fund-specific control variables: monthly fund flows (i.e., the percentage change in net assets after adjusting for fund returns), annual turnover, net expense ratios, and family assets.

The first three rows of the table focus on slope effects of odd lot purchases. Consistent with the expectation that the *Highly Questionable* mismark odd lot positions, we find that their slope coefficient is 3.4 to 3.5 points higher than the one for *Unchallenged* funds. This difference is statistically significant at a p-value < .0001. Rows 4 through 6 of the table focus on slope effects of high-mark positions. We find

that the high-mark slope coefficients of *Highly Questionable* funds are not significantly different from those of the *Unchallenged* funds. Rows 7 through 9 of the table focus on slope effects of single-fund positions. Consistent with the expectation that *Highly Questionable* funds also mismark single-fund positions, we find that their slope coefficient is 2.9 to 4.1 points higher than that for *Unchallenged* funds and that this difference is statistically significant at a p-value < .05. The inclusion of the Primary Security Purchases variables has little impact on the estimated coefficients measuring the differential impacts of the *Highly Questionable* funds.

In sum, the results from Tables 7 and 8 show that the 12 *Highly Questionable* funds behave the same way as the simulated high usage mismarking funds in terms of differential net-of-benchmark return mean, skewness, slope, and intercept patterns. We find no evidence supporting a competing equilibrium explanation that return patterns result from benefits tied to allocations of "cheap" primary market securities or are driven by other fund characteristics.

5. Are there valid reasons for recognizing immediate gains when purchasing mismarking-prone positions?

We investigate the possibility that round lot marks for odd lot positions are justifiable for funds that purchase and subsequently aggregate multiple odd lot purchases in the same security into round lot-sized positions. Panel A of Table 9 presents statistics on the percentage of positions that funds aggregate to round lot size within various time horizons (i.e., 3-months, 6-months, 1-year, and 2-years) after their initial odd lot purchase. We compare results for the 12 *Highly Questionable* funds with those for the 130 other structured product funds launched after January 1, 2010. We present statistics for both structured product and non-structured product securities.

Panel A of Table 9 shows that the baseline group of 130 funds rarely succeeds in aggregating odd lot structured products into round lot size. Their aggregation success percentage is 1.2% within a 3-month period and rises to only 4.19% within two years. The group of 12 *Highly Questionable* funds experiences slightly better aggregation outcomes: 1.72% within a 3-month period rising to 7.92% within two years. Funds have a strong incentive to aggregate odd lot structured products into round lot size, but little incentive to aggregate odd lot non-structured product positions. Yet, 2-year odd lot structured product

aggregation success rates for both fund groups are only about half those for non-structured products. Thus, structured product aggregation is much less effective than that for non-structured products even though these funds have incentives to achieve the former but not the latter. The rare odd lot aggregation in the structured product space is consistent with the SEC's stance that funds have no reasonable basis for valuing odd lot positions at round lot prices.

In *Revisions of Guidelines to Form N-1A*, SEC Release No. 33-6927, March 20, 1992, the SEC has designated that an open-end fund registered under the 1940 Act can invest no more than 15% of its assets in "illiquid securities." From *Acquisition and Valuation of Certain Portfolio Instruments by Registered Investment Companies*, SEC Release No. IC-14983, March 17, 1986, the "term 'illiquid security' generally includes any security which cannot be disposed of promptly and in the ordinary course of business without taking a reduced price. A security is considered illiquid if a fund cannot receive the amount at which it values the instrument within seven days."[6] The evidence in Panel A of Table 9 that the group of 12 *Highly Questionable* funds successfully aggregates only 1.72% of their odd lot positions to a sell-at-the-mark round lot size even after three months indicates that those new purchases should be categorized as illiquid.

For high-mark and single-fund round lot structured product positions, a fund's ability to sell such positions at the pricing vendor's marks would be the relevant criteria for justifying immediate use of those marks under the SEC's exit price standard.[7] We do not have the access to internal fund trade ticket data for those high-mark and single-fund round lot structured product positions sold by funds within our sample. However, we analyze a related non-price metric: the percentage of round lot positions liquidated (i.e., either sold or paid off) within various time horizons. Our focus on this metric exploits the proposition that funds using inflated marks will be biased against selling such positions at (lower) market prices. Funds that fairly mark their round lot structured product positions will exhibit no such bias.

Panel B of Table 9 presents statistics on the percentage of round lot positions that funds successfully liquidate within alternative 3-month, 6-month, 1-year, and 2-year horizons after initial purchase. In line with the conjectured bias against selling structured product positions that have been

[6] Last accessed on July 25, 2018 at http://www.sec.gov/rules/final/1986/ic-14983.pdf and http://www.sec.gov/rules/other/1992/33-6927.pdf.

[7] The SEC found that PIMCO did not have a reasonable basis for valuing odd lot structured product positions at round lot prices because BOND sold its structured product odd lots at prices averaging 3.81% below the marks (SEC, 2016b).

valued at inflated marks, Panel B of Table 9 shows the structured product liquidation rates for the 12 *Highly Questionable* funds to be generally lower than those for the baseline group of structured product funds. The liquidation rate difference for single-fund round lot positions is especially large—the 12 *Highly Questionable* funds only liquidate about 50% as much as the baseline funds at any horizon.[8] In contrast, the 12 *Highly Questionable* funds liquidate non-structured product round lots at a *faster* rate than do the 130 baseline funds. These results are in line with the prediction of relatively slow liquidation for mark-inflated structured products under the presumptions that (i) the 12 *Highly Questionable* funds inflate the marks on certain structured products and (ii) non-structured products are fairly marked by all funds.

Taken together, the absence of meaningful odd-lot-to-round-lot aggregation opportunities and the relatively slow liquidation of mismarking-prone round lot securities offer no evidence against interpreting the extraordinary reported performance of the 12 *Highly Questionable* funds to be the product of mismarking fraud.

6. Effects of mismarking on fund managers and investors

Mutual fund mismarking fraud affects both fund managers and investors. Managers benefit because fund advisory services and other investment consultants may attribute any artificial boost to fund track records to "manager skill." Such false attributions would enhance manager reputation, fund ranking, and possibly attract undeserved inflows from investors.[9] Investors not only overweight undeserving funds in their portfolios, but may also suffer direct harm by purchasing fund shares at inflated NAVs. The actual harm caused to any specific investor will depend on the degree of NAV artificiality due to position mismarking existing at the investor's share entry and exit dates. In this section, we provide evidence that the post-launch performance inflation we observe for *Highly Questionable* funds has rewarded these funds with extraordinarily high Morningstar Ratings and net inflows. We then develop a stylized model to show significant wealth transfers from late to early investors.

[8] One mildly surprising result is that the 12 *Highly Questionable* funds' liquidation rate on other structured product positions (34.05% at the 2-year horizon) is lower than the corresponding high-mark round lot value (54.93%).

[9] As concisely stated in SEC (2016a) upon settlement of the PIMCO case, "*PIMCO misled investors about the true long-term impact of its odd lot strategy and denied them the opportunity to make fully informed investment decisions about the Total Return ETF. Investment advisers must accurately describe the significant sources of performance and the strategies being used.*"

6.1 Effects on fund managers

Risk-adjusted relative performance is the main criteria by which advisory services such as Morningstar rate funds for prospective investors. Fund managers understand that investment inflows and outflows are sensitive to a fund's Morningstar Rating. Thus, a manager has a clear incentive to artificially boost reported performance in the race for the top Five-Star Rating. Nine of the 12 *Highly Questionable* funds received their initial 3-year Morningstar Rating within our sample period. The average initial 3-year Morningstar Rating for these nine funds was 4.65 Stars. This 4.65-Star Rating was 1.34 Stars higher than the average 3.31-Star Rating of the 46 other structured product funds obtaining initial 3-year Morningstar Ratings within the same period.

We examine the effects of the exceptional performance on asset gathering success by comparing the average annual change in assets of the nine Morningstar-ranked *Highly Questionable* funds with that of the 46 other ranked structured product funds. Each inception-year cohort (i.e., launched in 2010, 2011, 2012, and 2013) among the nine ranked *Highly Questionable* funds generated much larger average changes in assets than those experienced by other structured product funds. Across all cohorts, the annual change in assets of the nine ranked *Highly Questionable* funds averaged $1.26 billion versus $202 million for the 46 other ranked structured product funds.

As of March 31, 2017, the 12 *Highly Questionable* funds have grown to manage a combined $75 billion of assets. These include holdings of $26 billion in mismarking-prone securities. Based upon fund holdings across the three categories of mismarking-prone assets and our estimated inflation factors, the $26 billion in mismarking-prone securities overstates fair asset value by about $629 million.

In sum, the *Highly Questionable* funds report both extraordinarily high average net-of-benchmark returns as well as extraordinary positive skewness over their first three months after launch. While their relative performance declines sharply afterwards, we find no evidence to contradict the interpretation that their initial fast break from the gate ensures that Morningstar will reward these funds with extraordinarily high ratings that lead investors to disproportionately reward the fund managers with undeserved capital inflows. Such inflows result in misallocated investor resources and undeserved manager fees.

6.2 Effects on fund investors

In an open-end mutual fund, there will be different investors entering and exiting at various dates. Depending on the timing of their entry and exit, investors will gain or lose different amounts when trading at inflated NAVs caused by position mismarking. Note that the distortions created under mutual fund NAV-inflation fraud differ from other trade-at-false-price market manipulations because of the specific form of the order placed by an open-end mutual fund investor. A customer's buy order specifies the *dollar* value of the shares to be purchased at the open-end mutual fund's end-of-day NAV as distinct from a specific *number of shares*. Compare a new buyer investing $10,000 in a mutual fund whose manager has caused inflated net asset value (NAV_t^{mis}) to an otherwise identical buyer in a fund whose manager fairly marked all assets at a counterfactual fair net asset value $\left(NAV_t^{cf}\right)$. The buyer of the inflated NAV fund receives fewer shares and therefore owns proportionately less of fund assets than the buyer of the fair NAV fund (i.e., $\frac{\$10,000}{NAV_t^{mis}} < \frac{\$10,000}{NAV_t^{cf}}$). This impact on the number of shares transacted means that the economic distortions of NAV inflation carries on through time reflecting future revaluations and cash flows due to the shortfall in number of shares initially credited to the buyer.

Appendix C presents an analysis of the impact of mismarked structured product purchases on NAVs, reported fund returns, CAR, and investor wealth. We measure these distortions by comparing results for an archetypical mismarking fund with those of an otherwise identical fund with a counterfactual fair-marking manager. We find that mismarking schemes can seriously inflate the officially reported time-weighted return performance records mandated by the SEC.

To construct net investor flows, holdings, and returns for an archetypical mismarking fund, we use the average assets under management and average purchase intensities for odd lot structured products, high-mark round lots, and single-fund round lots of the 12 *Highly Questionable* funds during their first 36 months as inputs. We further assume that the assets of each fund yield a monthly return of 0.25% and that structured products are repaid at a monthly rate of 2.5%.

Finally, the model requires estimates for the mark inflations of odd lot, high-mark round lots, and single-fund round lots structured products. We can estimate the inflation effect for high-mark purchases directly from the distribution of marks in the Morningstar holdings data. Assuming that purchases are made at the median mark, we calculate the percentage inflation for each of the 12 *Highly Questionable*

funds' high mark new purchases as the reported mark minus the median mark divided by the median. We calculate the market-value-weighted-average of the inflation to be 0.4 percentage points and we use this parameter in the model. We employ regression analysis, presented in Table 10, to estimate the mark inflation of new purchases of odd lot and single-fund positions. We estimate regressions for both the net-of-benchmark and net-of-T-bill return variables with and without the control variables from Table 8. We estimate four additional regressions in which the dependent variables are first adjusted for the presumed impact of high-mark round lot purchases. We calculate the adjusted dependent variables as the difference between each fund monthly return and 0.004 times the corresponding fund monthly new purchases of high-mark round lots scaled as a percentage of assets.

The slope coefficient for odd lot purchases ranges from 4.37 to 5.11 percentage points depending upon the model (average estimate of 4.79). The corresponding slope coefficient for single-fund purchases ranges from 3.04 to 3.48 points for single-fund purchases (average estimate of 3.25). We transform these average slope coefficients into percentage discounts of 4.6% (= .0479/1.0479) for odd lot and 3.1% (= .0325/1.0325) for single-fund purchases.

Figure 1 shows the archetypical mismarking fund's implied evolution of month-end holdings in mismarking-prone positions. The share of odd lots in the fund's portfolio declines steadily from 33.71% to 10.12% during the first three years of its life as the fund grows and becomes unable to locate a sufficient number of discounted odd lot positions. At the same time, the shares of high-mark and single-fund positions increase from 4.29% and 11.61% to 9.08% and 15.86%, respectively. The purchase of mismarking-prone positions continues throughout the average *Highly Questionable* fund's life. This fund reaches its three-year anniversary with mismarking-prone holdings averaging about 35% of assets. Because our evidence indicates that these positions are marked at inflated values that could not be realized upon an attempted sale, this archetypical mismarking fund violates the SEC's 15% limitation on holdings of illiquid assets throughout its entire life.

Figure 2 compares the future value paths of an initial $10,000 originally invested in three different funds over a 3-year horizon. We compare our archetypical mismarking fund with a counterfactual fund that experiences the same inflows and makes the same investments, but always marks its positions at fair exit prices. A third benchmark fund invests all proceeds in non-mismarking prone

round lot positions. After three years, the mismarking fund reports that an initial $10,000 investment is valued at $11,851, implying a 5.82% three-year CAR. The fair-marking counterfactual fund reports the same investment to be worth $11,082, implying a 3.48% three-year CAR. Finally, the three-year-horizon value of an initial $10,000 investment in the benchmark round lot fund is just $10,941, implying a 3.04% CAR. Due to its fundamental advantage of buying securities at a discount, the fair-marking specialist fund outperforms the round lot benchmark fund over time. But the fair-marking fund's 44-basis point CAR advantage over the benchmark pales in comparison to the 278-basis point pick-up reported by the mismarking fund, which is more than 230 basis points higher. Mismarking works wonders for a manager's reported track record.

Moreover, a full revaluation to fair marks can at most lead to a one-time loss equal to the magnitude of the mark inflation (for a fund that is 100% invested in mismarked securities). For example, at the end of three years, our archetypical mismarking fund holds 10.12% of its assets in odd lots, 9.08% in high-mark round lots, and 15.86% in single-fund round lots. If the fund were forced to remark these positions using the three inflation parameters (4.6%, 0.4%, and 3.1%), its ending NAV would drop by 1.0%. Such a reevaluation would lead to a reduction of the mismarking fund's CAR from 5.82% to a still large 5.47%. So even if an auditor/regulator compels a fund to change its marking policy and properly revalue its assets at the 3-year horizon, fund management still captures the majority of the implied marketing benefits of "outperformance" from previous fraudulent inflation of reported returns since inception. The reason a fund keeps a large fraction of its excess returns after a correction is the standard return calculation as a time-weighted average. This scheme places the same weight on the fund's first monthly return on a relatively small asset base and the 36th month with assets that have grown by a factor of about 70 for our archetypical mismarking fund.

Depending on the timing of their entry and exit, mutual fund investors will gain or lose different amounts when trading at the artificial fund NAVs caused by position mismarking. For a given intensity of mismarked purchases, the actual impact on any investor depends on the exact NAV artificiality at the time of entry as well as the distribution of future fund inflows and redemptions (as determined by the behavior of other investors).

We employ the framework presented in Appendix C to calculate the relative gains and losses of different investor cohorts in the archetypical fund that mismarks and is eventually forced to remark positions to fair values. We assume investors redeem their funds monthly at the 36% average annual bond fund redemption rate from ICI (2017) and that all redemptions occur on a first in, first out basis. We also assume that the fund liquidates after three years. At that time, all holdings are sold at fair market values and the proceeds are distributed to investors. Analytically, this produces the same outcomes as if an audit after its first three years forced the fund to employ fair marks in its NAV accounting.

Figure 3 displays percentage and absolute gains and losses of the seed investors (Cohort 0) and the 36 cohorts that invest in the fund from month 1 to 36 relative to the same investment in the counterfactual fund. Seed investors (Cohort 0) extract wealth from the later cohorts. The seed money investors are the clear winners; but also note that their 4.04% percentage gain is larger than the 1.97% return that the fund reports immediately after its initial round of investments. The added benefit for the seed money investors works through sharing gains from the fund manager's ability to raise new monies at inflated NAVs from successive cohorts and both purchase and mismark additional new positions. Investors in the next 18 monthly cohorts profit from the fund's mismarking scheme; investors in cohort 19 just about break-even; and then the final 17 cohorts of investors lose. For our representative mismarking fund, losses for the later investor cohorts total about $23 million. The resulting wealth transfers will be even larger if the fund invests in more slowly repaying securities or if the overall redemption rate is higher.

7. Conclusions and recommendations

Our empirical findings suggest that some, if not all, of the *Highly Questionable* funds have engineered artificial outperformance by inflating the marks on new purchases of both odd lot and some round lot structured product positions. Performance inflation of this type is especially meaningful for new funds that use the mismarking strategy intensely and succeed in attracting significant subsequent investment inflows. Post-launch fund inflows and redemptions interact with position mismarking to generate wealth transfers among investor cohorts.

The success of twelve funds in inflating their reported historical returns sufficiently to attract new inflows that grew aggregate assets to $75 billion suggests serious weaknesses in the mutual fund performance reporting ecosystem. Appendix D presents our analysis of this ecosystem and the interactions among its constituents: fund boards, fund managers, securities dealers, pricing vendors, independent auditors, investment consultants, the FINRA, the SEC, the Public Company Accounting Oversight Board (PCAOB), and investors. Our analysis leads to five policy recommendations to help restore the integrity of commingled investment vehicles investing in structured products.

First, in addition to monetary sanctions, any SEC disciplinary actions against a mismarking fund should also require restatement of historical NAVs and returns using adjusted position marks that conform to the SEC's exit price valuation standard, or at least force funds to expunge all mismarking-tainted performance records from any fund marketing materials. Second, independent auditors examining funds with significant investments in structured products should incorporate trade price versus end-of-day mark comparisons for all new purchases of mismarking-prone securities as a routine component of every audit. Third, pricing vendors should develop appropriate schedules for odd lot discounts by structured product type and security characteristics and reassess their current valuation methodology for securities that tend to appear in mutual fund portfolios as single-fund round lots. Fourth, FINRA should expand public dissemination of structured product transaction reporting (trade date, time, price, and quantity) by its TRACE system. Finally, fund rating services (e.g., Morningstar) and fund consultants should proactively investigate "too-good-to-be-true" (high alpha combined with positive skewness) performance of structured product funds, especially immediately after launch. Ideally, ratings services and consultants should require structured product funds to provide evidence that their performance records are not overstated. The most convincing evidence would be histories of all new purchase trade prices on mismarking-prone positions matched against end-of-day position marks as validated by their independent auditors.

Appendix A. Simulation results: signatures of mismarking funds

We employ simulation analysis to study the difference in performance patterns caused by two fund policies. The first policy determines the size of investment in mismarking-prone securities. Funds choose to be "high usage," "low usage," or "zero usage." The second policy determines whether or not funds inflate the marks on their new purchases. The combinations of these two policies produce five distinct fund groups: (1) "zero usage" funds that never purchase mismarking-prone securities; (2) "fair-marking low usage" funds that purchase a limited amount of mismarking-prone securities and mark them fairly; (3) "fair-marking high usage" funds that purchase the maximum available amount of mismarking-prone securities and mark them fairly; (4) "mismarking low usage" funds that purchase and mismark a limited amount of mismarking-prone securities; and (5) "mismarking high usage" funds that purchase and mismark the maximum available amount of mismarking-prone securities.

We perform 100 simulation runs. In each simulation run, we create 125 funds split equally across the five groups. Funds receive new inflows calibrated so that the funds grow by a factor of 60 over their first two years of life. Inflows are immediately used to buy new securities. Low-usage funds receive inflows in two separate installments observed on two random days during the month. We label the mismarking-prone positions to be "odd lots," but the analysis applies to other assets that can be purchased at a price below the end-of-day marks. Each low-usage fund manager uses the first inflow installment to buy discounted odd lot positions and the second installment to buy non-mismarking prone round lot positions. The relative size of the installment invested into odd-lot positions is drawn from a uniform distribution between 0% and 100%. The order in which the monthly odd lot versus round lot purchases are made is random, but all odd lot positions are purchased at a 6% discount to the prevailing round lot price. Zero-usage funds have only one inflow installment per month that they invest in round lot positions. High-usage funds also have only one inflow installment per month that they invest in odd lot positions. All principal payments are reinvested in round lot positions.

The main challenge when simulating returns of structured product funds that invest in discounted positions is modeling the joint effect of underlying asset returns and prepayments on fund returns. We jointly draw historical prepayments and underlying asset returns from the historical distributions of FNMA 6% prepayments and the Bloomberg Barclays MBS Index returns. We first draw a realized

monthly prepayment from historical calendar month data for FNMA 6% during our sample period. We then create the daily returns of round lot holdings for that simulated month by using the daily return history of the Bloomberg Barclays MBS index associated with the same calendar month. Because the portfolio of a fund manager typically does not exactly mirror that of a market index, we add a normally distributed tracking error when calculating the daily returns of a fund that buys and holds round lots. In different simulations, we set the standard deviation of the tracking error to equal 35%, 50%, or 65% of the standard deviation of the benchmark return. These tracking error values result in the benchmark explaining between 70% and 90% of the excess returns of the zero-usage funds, R-squared values typical for the zero-usage structured product funds in our sample.

We use the simulation to compare return patterns for each of four positive-usage fund types versus the baseline zero-usage funds. The return distributions of zero-usage funds are unaffected by odd lot purchases and/or mismarking by definition. Mismarking funds will show high alpha relative to zero-usage funds especially because of the immediate fictitious capital gains from marking odd lot purchases at higher round lot prices. Fair-marking funds will also generate positive alpha relative to zero-usage (pure round lot) funds, though this extra relative return will be earned gradually over the life of their odd lot holdings as cash flows are received.

Mismarking funds will also exhibit high net-of-benchmark return skewness relative to zero usage funds. High skewness is a signature of mismarking because fund NAV will show a positive jump each day that a manager buys and mismarks new structured product positions. Absent investor liquidation pressures, a buy, mismark, and hold manager will avoid selling that same mismarked security so positive jumps in NAV (and daily return) will not be matched by negative jumps.[10] Thus, a fund that periodically makes concentrated purchases of mismarked assets will tend to generate both positive alpha and positive skewness.

Fair-marking funds will also exhibit positive net-of-benchmark return skewness. Since principal repayments occur at par, a fund that correctly marks odd lot positions at a discount will benefit from a small return boost relative to a round lot fund benchmark whenever principal is repaid. These occasional

[10] Selling that same security would generate an offsetting reported loss because the selling price would reflect a market-determined price below the fund's inflated mark.

boosts are not offset by similarly sized negative returns leaving the fair-marking fund's net-of-benchmark returns with positive skew.

Table A.1 presents results for our comparative study of 60 months of simulated net-of-benchmark fund return distributions. *Fair-Marking Low Usage Funds*, *Fair-Marking High Usage Funds*, *Mismarking Low Usage Funds*, and *Mismarking High Usage* are alternative zero/one indicator variables for fund category. Zero-usage funds define the baseline category. *Months 1-3, Months 4-6, Months 7-9, and Months 10-12* are zero/one fund age indicator variables useful for estimating differential alpha and skewness effects over four consecutive three-month intervals after fund launch. *Months 13+* is an indicator variable for months beyond a fund's first year.

The columns of Table A.1 compare regressions for fund alpha and skewness that each include (i) an intercept term (interpreted as "*Months 13+*"); (ii) the four fund age indicators; and (iii) interaction terms for four fund type indicator variables with the intercept and four fund age indicators. The results show that *Mismarking High Usage Funds* outperform all other categories, especially during the first three months after launch when they post a statistically significant differential alpha of 21 basis points *per day*—implying a 52.5% per year advantage versus the baseline zero-usage funds. This extreme differential alpha falls rapidly over subsequent months, but the coefficient for *Months 13+* of 0.44 basis points per day implies differential net-of-benchmark returns of 1.10% per year even after the first year. As conjectured, *Mismarking High Usage Funds* also exhibit significant positive skewness throughout and even beyond the first year.

Mismarking Low Usage Funds also outperform the baseline zero-usage funds. Across the board, the degree of outperformance for each interval is just roughly one-half to two-thirds that of *Mismarking High Usage Funds.* During the first three months after launch the *Mismarking Low Usage Funds* post a statistically significant differential alpha of 14 basis points per day, implying differential net-of-benchmark returns of 35% per year. Their long-run alpha from the coefficient for *Months 13+* of 0.22 basis points per day implies differential net-of-benchmark returns of 0.55% per year after the first year. As conjectured, *Mismarking Low Usage Funds* also exhibit statistically significant positive skewness throughout and beyond the first year.

Fair-Marking High Usage Funds also outperform the baseline funds during the first year. However, the outperformance of just 0.3 basis points per day (0.75% per year) is much more consistent over time. The long-run differential alpha from the coefficient for *Months 13+* of about 0.5 basis points per day implies differential net-of-benchmark returns of 1.25% per year after the first year. As conjectured, *Fair-Marking High Usage Funds* also exhibit statistically significant positive skewness, though the skew generated by these funds during the first year is much lower than that observed for their mismarking counterparts.

Finally, *Fair-Marking Low Usage Funds* outperform the baseline funds too. Again, the measured outperformance is small and consistent over time. The long-run differential alpha from the coefficient for *Months 13+* of 0.2 basis points per day implies average net-of-benchmark returns of 0.58% after one year. Our tests fail to detect any statistically significant positive skewness for *Fair-Marking Low Usage Funds*.

The simulation allows us to examine whether a filter based on a regression of monthly net-of-benchmark fund returns on fund purchases of mismarking-prone securities (scaled as a percentage of assets) can correctly identity mismarking funds. Table A.2 presents results analyzing the relation between simulated net-of-benchmark returns and contemporaneous odd lot purchases across the four fund marking status/usage categories via estimation of three alternative filtering regressions. The dependent variables for all three forms of the filtering regression are simulated fund net-of-benchmark returns defined as the difference between fund returns and matched returns on the benchmark index fund. We pool the 25 funds of each type from the 100 simulation runs so that we have in total 2,500 funds in each group. Panel A of Table A.2 presents results for univariate regressions using simulated contemporaneous new purchases of odd lot positions as a percentage of current fund assets as the independent variable. Panel B presents results for univariate regressions using simulated contemporaneous new purchases of odd lot positions as a percentage of lagged fund assets as the independent variable. Panel C presents results for bivariate regressions using the simulated contemporaneous new purchases of odd lot positions as a percentage of current fund assets as well as lagged total odd lot holdings as a percentage of current fund assets as an additional control.

Each panel lists the number of funds in each category that show a statistically significant positive estimated slope coefficient (i.e., estimated t-statistic >1.96) as well as the mean and median of the significant slope estimates across the four different fund marking status/usage categories for the three different tracking error values—"Low" (.35), "Medium" (.50), and "High" (.65). For each form of the regression, the results show that a t-test for a statistically significant positive estimated slope coefficient correctly identifies 99.5% or more of the mismarking funds (i.e., the test has high power). These striking differences between mismarking and fair-marking funds lead us to conclude that a statistically significant slope coefficient on contemporaneous new purchases of mismarking-prone positions in such a filtering regression is a strong necessary condition for identifying mismarking funds.

However, the t-test also identifies some fair-marking funds as mismarkers, especially for funds with low tracking error (i.e., the test produces "false positives"). The frequency of false positives for the Panel A regressions ranges from 3.4% for the low usage, high tracking error case to 6.8% for the high usage, low tracking error case. These outcomes are above the expected 2.5% rate of false positives given the chosen 5% size of the two-tailed test.

The results for the alternative regression forms in Panels B and C offer no improvement in this regard. In fact, scaling by lagged rather than current assets (Panel B) raises the rates of false positives to between 4.2% and 7.6%. Likewise, adding the lagged holdings variable (Panel C) raises the rates of false positives to between 4.4% and 10.1%. Therefore, we proceed with the Panel A specification.

The mean slope estimates for mismarking high usage funds with significant t-statistics in Panel A equal 6.32 or 6.33 in all cases (close to the idealized parameter value of 6.38 discussed above). The mean slope estimates for mismarking low usage funds with significant t-stats are slightly larger at 7.62. In contrast, the mean slope estimates for fair-marking high usage funds that are falsely identified as mismarkers by their significant t-statistics are much smaller, ranging from 0.46 (for the 169 funds "caught" in the low standard error case) to 0.82 (for 87 funds in the high standard error case). The mean slope estimates for the fair-marking low usage funds with significant t-statistics range from 0.87 (for 127 funds in the low standard error case) to 1.64 (for 86 funds in the low standard error case). Thus, in the low tracking error cases, the mean slope estimates for mismarking funds will be 9 to 14 times the size of their fair-marking counterparts. Even for high tracking error cases, the mean and median slope estimates for

mismarking funds will be 5 to 8 times those of corresponding fair-marking funds tagged by the significant t-test. These additional signatures suggest that relative slope estimates may provide insight when evaluating individual cases for possible "false positive" results.

Appendix B. Panel regressions relating fund returns to new purchases

Table A.3 presents panel regression models across the full sample of structured product funds as well as a subsample of funds launched after January 1, 2010. These regressions test whether any fund returns are indeed enhanced by the mere act of purchasing new securities. We present regressions with two definitions of monthly fund return performance. First, we define net-of-benchmark fund return as the reported monthly fund return minus the monthly return on the Morningstar-assigned fund benchmark. Second, we define the excess return ("net-of-T-bill") on a fund as the difference between the return on the fund and the contemporaneous return on a one-month U.S. Treasury Bill.

We define four new purchase categories based upon interacting two broad security types, structured products ("SP") and non-structured products ("NonSP"), with two broad position types, odd lot and round lot. The regressions in Panel A employ these four key new purchases variables each scaled by the level of end-of-month fund assets: *New Odd Lot SP/Assets*, *New Odd Lot NonSP/Assets*, *New Round Lot SP/Assets,* and *New Round Lot NonSP/Assets*. We estimate three specifications across the two samples (all funds and newly launched funds) and the two dependent variables (net-of-benchmark and net-of-T-bill monthly returns) for a total of 12 regressions. All regressions include fund-specific control variables: monthly fund flows (i.e., the percentage change in net assets after adjusting for fund returns), annual turnover, net expense ratios, and family assets.

From SEC (2016b) and Atanasov, Merrick, and Schuster (2017), we know that odd lot discounts do exist in structured product markets. If some funds inflate their marks on new odd lot purchases, regression estimates should uncover positive excess return impacts for new odd lot structured product positions acquired in a particular month. Tests based on the three other new purchase variables can be interpreted as placebo tests that all round lot positions and/or odd lot positions in non-structured product assets do not generate excess returns.

Across all 12 Panel A regressions, we find *New Odd Lot SP/Assets* to have statistically significant effects on benchmark-adjusted fund excess returns. All slope coefficients on purchases of odd lot

structured products have values between 2.4 and 2.7, and t-statistics larger than 4.0 (p-values < 0.0002). These results strongly reject the hypothesis that all funds fairly mark their new purchases of odd lot structured products.

The slope estimates for new purchases of round lot structured products show evidence of statistically significant impacts for both fund samples. The magnitudes of the impacts for the newly launched funds subsample are roughly double those for the full sample (and the t-statistics are 50% higher). In contrast to their structured product counterparts, both new odd lot and round lot purchases of non-structured products generate no statistically significant effects on returns.

Panel B of Table A.3 presents additional regression estimates of fund return impacts after disaggregating the original fund new round lot ("RL") structured product purchases variable into four separate variables based upon mark status. $High\ Mark\ New\ RL\ SP/Assets$ counts only those purchases of new round lot structured products associated with position marks classified as "*High*." $Medium\ Mark\ New\ RL\ SP/Assets$ counts only those purchases of new round lot structured products associated with position marks classified as "*Medium*." $Low\ Mark\ New\ RL\ SP/Assets$ counts only those purchases of new round lot structured products associated with position marks classified as "*Low*." $Unranked\ Mark\ New\ RL\ SP/Assets$ counts only those purchases of new round lot structured products associated with position marks classified as "*Unranked*."

The Panel B results show consistent and highly statistically significant fund return impacts from new purchases of high-mark round lot structured products across all 12 regressions, with the coefficients and t-statistics larger for the subsample of newly launched funds. No such effects are found for new round lot structured product purchases across purchases within the medium or low mark categories. Note that if randomly assigned marks are the cause for the statistical significance of the positive signed coefficients on high-mark round lots, then the corresponding coefficients on low mark round lots should be negative signed and statistically significant. They are not.

Interestingly, the results from regressions for net-of-T-bill returns show a statistically significant fund return impact from new round lot purchases of unranked structured products.
We study such purchases in more detail in Panel C which presents estimates of fund return impacts of unranked round lot purchases after disaggregating this variable into three separate mark status variables.

$Single\ Fund\ New\ RL\ SP/Assets$ counts only those purchases of new round lot structured products associated with positions held by just one fund throughout the entire sample period. $One\ Mark\ New\ RL\ SP/Assets$ counts purchases of new round lot structured product positions associated with just one mark exists on a given report date even though the same security is held by two or more funds (each reporting on a different date). $Two\ Mark\ New\ RL\ SP/Assets$ counts only those new round lot purchases of structured product positions for which only two marks exist on a given report date. We also define corresponding variables for non-structured product positions.

The estimates for all regressions show consistent and statistically significant fund return impacts from new purchases of single-fund round lot structured products. No net-of-benchmark return effects are found for new round lot structured product purchases across the one-mark or two-mark categories. For net-of-T-bill returns, we find some evidence of positive excess return impacts for new purchases of two-mark round lots by newly launched funds.

Taken altogether, the Table A.3 return regression results focus our attention on potential performance inflation by mutual funds via mismarking of new purchases of odd lot positions and both high-mark and single-fund round lot positions in structured products.

Appendix C. Modeling the impact of mismarking on returns and investor wealth

C.1 Return impact of the mismarking strategy

We compare fund returns from an archetypical mismarking fund (*mis*) with counterfactual (*cf*) returns from an otherwise identical fair-marking fund. The returns that a mismarking fund would report, r_t^{mis}, are the product of two components: r_t^{assets}, the return on $A_{t-1}^{\text{month end}}$, the fund's asset holdings valued at fair discount-adjusted prices at the end of the previous month, and r_t^{NewDiscP}, a return attributable to the mismarking of new purchases of discounted positions in month t, $NewDiscP_t$. Given a discount d and net new cash flows F_t, the mismarking fund's returns can be calculated as follows:[11]

$$1 + r_t^{mis} = (1 + r_t^{\text{assets}}) \cdot \left(1 + r_t^{\text{NewDiscP}}\right)$$

[11] For simplicity, we focus in this section on one type of mismarking-prone security.

$$= \frac{A_t^{\text{before cash flows}}}{A_{t-1}^{\text{month end}}} \cdot \frac{A_t^{\text{month end}}}{A_t^{\text{before cash flows}} + F_t}, \tag{A.1}$$

$$A_t^{\text{month end}} = A_t^{\text{before cash flows}} + F_t + NewDiscP_t \cdot d. \tag{A.2}$$

Equations (A.1) and (A.2) assume the following:

i. The realized return r_t^{assets} on the fund's asset holdings as at the end of the previous month $A_{t-1}^{\text{month end}}$ combines to generate a new month end pre-inflow/outflow asset value, $A_t^{\text{before cash flows}}$. The asset return r_t^{assets} include any fees or other expenses.

ii. After the realization of $A_t^{\text{before cash flows}}$, the fund receives new net flows F_t (inflows and/or redemptions) and new shares are issued or redeemed. New cash flows are used to purchase new assets (with or without discount) at month-end.

iii. $NewDiscP_t$ represents the reported value of all new mismarking-prone positions purchased at the end of month t. Since the fund reports these new positions at inflated values, the actual change in $A_t^{\text{month end}}$ described in Equation (A.2) includes all gains from the immediate mismarking of new purchases in month t. Because the fund manager only paid $NewDiscP_t \cdot (1-d)$ for these new positions, the gains from mismarking equal $NewDiscP_t \cdot d$. For example, assume an odd lot discount of 6% and a fund that employs \$2,000,000 of inflows to purchase \$1,060,000 in round lots and \$940,000 in odd lots. The fund immediately mismarks the new \$940,000 odd lot position at its corresponding \$1,000,000 round lot value. As per Equation (A.2), month-end (reported) assets increase by \$2,060,000 = \$2,000,000 + \$60,000 ($= F_t + NewDiscP_t \cdot d$).

Note that inflows and redemptions in (ii) occur at a share price reflecting the asset value before new cash flows, $NAV_t^{\text{before cash flows}}$. This share price differs from the month end value and we have $NAV_t^{\text{before cash flows}} = NAV_{t-1}^{\text{month end}} \cdot (1 + r_t^{\text{assets}})$ and $NAV_t^{\text{month end}} = NAV_t^{\text{before cash flows}} \cdot (1 + r_t^{\text{NewDiscP}})$. In each period t, the number of newly issued shares is calculated as $S_t^{mis} = \frac{F_t}{NAV_t^{\text{before cash flows}}}$, leading to a total number of shares $TotS_t^{mis} = TotS_{t-1}^{mis} + S_t^{mis}$.

Equations (A.3) and (A.4) present expressions for mismarking-prone and not mismarking-prone positions, respectively:

$$TotDiscP_t^{month\ end} = TotDiscP_{t-1}^{\text{month end}} \cdot (1 - PctDiscP_t) \cdot (1 + r_t^{\text{assets}}) + NewDiscP_t, \tag{A.3}$$

$$TotNotDiscP_t^{\text{month end}} = A_t^{\text{month end}} - TotDiscP_t^{\text{month end}}, \tag{A.4}$$

where $PctDiscP_t$ is the percentage change of existing mismarking-prone positions during month t, for example due to principal repayments. Note that repayments of discounted mismarking-prone positions are identical to those for a not mismarking-prone security and lead to relative valuation gains for the counterfactual fund. Returns from changes in mismarking-prone positions are calculated as:

$$r_t^{\text{DiscP change}} = PctDiscP_t \cdot \frac{TotDiscP_{t-1}^{\text{month end}}(1-d)}{TotNotDiscP_{t-1}^{\text{month end}} + TotDiscP_{t-1}^{\text{month end}}(1-d)} \cdot \frac{d}{1-d}. \tag{A.5}$$

We can now calculate the returns of the properly marked counterfactual fund as

$$1 + r_t^{cf} = (1 + r_t^{\text{assets}}) \cdot \left(1 + r_t^{\text{DiscP change}}\right). \tag{A.6}$$

Investors enter and exit the counterfactual fund at the share price, $NAV_t^{cf,\text{month end}} = NAV_{t-1}^{cf,\text{month end}} \cdot (1 + r_t^{cf})$ and we can calculate the number of new shares as $S_t^{cf} = \frac{F_t}{NAV_t^{cf,\text{month end}}}$, leading to a total number of shares $TotS_t^{cf} = TotS_{t-1}^{cf} + S_t^{cf}$.

We compute compound annual returns (CAR) for the two funds $f \in \{mis, cf\}$ as:

$$CAR^f = \left(\prod_{t=0}^{T} 1 + r_t^f\right)^{\frac{1}{T/12}} - 1. \tag{A.7}$$

For the analysis in Section 6, we calibrate the model so that $A_t^{\text{month end}}$ equals the reported average assets under management of the 12 *Highly Questionable* funds. Moreover, we use the average purchase intensities of new discounted positions, i.e., $\frac{NewDiscP_t}{A_t^{\text{month end}}}$ of these 12 funds. Together with assumptions on the discount d, principal repayments $PctDiscP_t$, and asset return r_t^{assets}, the model is fully specified.

C.2 Wealth transfers between investor cohorts

To calculate gains and losses for different investor cohorts, we need to separate monthly net cash flows F_t into inflows I_t and outflows/redemptions O_t, i.e., $F_t = I_t - O_t$. We calculate outflows $O_t = \left(1 - (1 - redR)^{1/12}\right) \cdot A_{t-1}^{\text{month end}}$ with $redR$ as a constant annual redemption rate. We then assume that there is one investor cohort per observation months t and that this cohort holds all shares issued by the fund in return for the inflows I_t. The shares redeemed $shRed_{t,s}^{\text{f}}$ for each cohort t in period s for the mismarking fund ($f = mis$) and the counterfactual fund ($f = cf$) can be calculated using the assumption that outflows occur on a *first in, first out* basis (alternatively, redemptions could also be pro rata or based on individual investors' portfolio data).

We can now calculate the final wealth F_t^f of each cohort t when investing in the mismarking fund or in the counterfactual fund as

$$F_t^f = \sum_{s=t+1}^{T} \left[\left(\prod_{\tau=s+1}^{T} 1 + r_\tau^{\text{assets}} \right) \cdot NAV_s^f \cdot shRed_{t,s}^f \right]. \tag{A.8}$$

Note that $NAV_s^{cf} = NAV_s^{cf,\text{month end}}$ for the counterfactual fund and $NAV_s^{mis} = NAV_s^{before\ cash\ flows}$ for the mismarking fund. For Figure 3, we further assume that the fund is liquidated at the final date T at its current market value $A_T^{\text{liquidation}} = A_T^{\text{month end}} - d \cdot TotDiscP_T^{\text{month end}}$. The net asset value in the final period, NAV_T^{mis}, reflects the liquidation value of the fund. Finally, cash flows from early redemptions occur at different time periods. To make these cash flows comparable to the cash flows from the fund's liquidation in T, we assume that the investor is able to find a comparable investment opportunity that yields the same asset returns. We therefore multiply cash flows that occur in period s by $\prod_{\tau=s+1}^{T} 1 + r_\tau^{\text{assets}}$ in Equation (A.8). We then define wealth transfers W_t for each cohort t as the gain/loss of the cohort from the mismarking policy, i.e.,

$$W_t = F_t^{mis} - F_t^{cf}. \tag{A.9}$$

For all cohorts combined, wealth transfers sum up to 0.

Appendix D. Mutual Fund Organization and the Performance Reporting Ecosystem

A fund's sponsor typically is a prospective investment adviser, administrator, or distributor and usually provides personnel to manage and operate the fund, including officers and affiliated directors (Schonfeld and Kerwin, 1993). The sponsor is typically the first shareholder, providing seed capital in exchange for the initial issue of shares. The sponsor also recruits independent directors to fill out the board. Independent directors must be "uninterested persons," a requirement that eliminates anyone directly affiliated with the fund's investment adviser, principal underwriter, or any broker or dealer. The most important duties of independent directors include approving the fund's investment advisory arrangements and monitoring the fund's relationships with the investment adviser and other insiders.

Fund directors monitor the fund's investment performance, review and approve agreements with other service providers such as a third-party pricing vendor, select the fund's independent auditor, review the allocation of the fund's brokerage and affiliated brokerage transactions, supervise the administration of the fund's legal compliance program and code of ethics, and set policies to value investments for which market prices are not readily available (Schonfeld and Kerwin, 1993). The fund and the board are subject to regulation by the SEC under the Investment Company Act of 1940, which places important fund adviser oversight responsibilities on the fund's directors. The fund adviser ("fund manager") is subject to regulation by the SEC under the Investment Advisers Act of 1940.

An audit committee consisting solely of independent directors typically meets with the fund's independent auditors to review the fund's financial statements and discuss its internal procedures. Majorities of both the independent directors and the board as a whole must approve the initial underwriting contract with the fund's distributor, who is registered with the SEC as a broker-dealer under the Securities Exchange Act of 1934. The distributor purchases and resells the fund's shares to the public.

The fund manager makes all investment and financing (if leverage is allowed) decisions, subject to an investment policy approved by the board, and transacts fund business with securities dealers. The manager's investment and financing decisions result in fund positions that must be marked at fair exit

value to determine the fund's Net Asset Value (NAV). All share issuance and redemption transactions are priced at the fund's end-of-day NAV.

The final end-of-day fund marks on all positions are determined by the fund. The fund's board is responsible both for determining marking policies and also supervising their implementation to assure that the marks used to determine the fund's NAV represent SEC-compliant fair exit values. To assist in this process, the fund typically hires a pricing vendor to develop appropriate evaluated marks for fund holdings. Evaluated prices are market-based measurements processed through a rules-based pricing application and represent the vendor's good faith determination as to what the holder may receive in an orderly transaction (for an institutional round lot position typically of $1 million or greater current value) under current market conditions.[12] For example, ICE Data Services generates mark evaluations for more than 1,000,000 U.S. agency pass-through issues (FHLMC, FNMA, GNMA, and SBA pools) and more than 200,000 U.S. agency and non-agency collateralized mortgage obligations, approximately 17,000 asset-backed securities, and 11,000 commercial mortgage-backed securities.

The pricing vendor's evaluation process is hampered by inadequate inputs from both FINRA's TRACE system and securities dealers. FINRA sees the whole market, but does not disseminate individual transaction reports for round lot trades in structured products. For such trades, FINRA provides only market-level aggregated by broad security categories (e.g., non-agency CMOs). Dealers can provide indications for specific securities in round lot sizes, but they see only the narrow range of securities that they have traded within a given period.

The independent auditor hired by the board evaluates the fund's financial statements, NAV calculation methods, and historical performance data. The Public Company Accounting Oversight Board (PCAOB) sets standards for auditing and related professional practice standards for registered public accounting firms to follow in the preparation of audit reports for public companies. Under Section 10A of

[12] See the discussion in https://www.theice.com/market-data/pricing-and-evaluations/evaluated-pricing.

the Securities Exchange Act of 1934, an independent auditor has certain reporting obligations if, during the course of an audit, he or she becomes aware of a possible "illegal act" – defined as "an act or omission that violates any law, or any rule or regulation." Furthermore, Section 10A requires a report to be submitted to the SEC when the independent auditor detects a likely illegal act that could have a material effect on a company's financial statements and if management or the board does not take appropriate action to remedy the situation.

Investors evaluate funds on the basis of standard past performance metrics such as net-of-benchmark returns. The role of investment advisory services such as Morningstar is also important in this regard. Investment inflows and outflows are sensitive to Morningstar Ratings, and a Five-Star Morningstar Rating is a highly valued status symbol that funds and fund managers promote when reporting to existing and marketing to new investors. Morningstar and other consultants evaluate and rate funds primarily upon their relative reported risk and return performance histories.

D.1 Fund Conflicts of Interest

Fund sponsors and managers earn income from fees paid by investors on assets under management. Thus, sponsors and managers have incentives to inflate fund returns in order to attract new inflows from investors. There is also an incentive to inflate returns in order to manipulate a fund's initial Morningstar rating, which is conferred three years after launch. One particular mark inflation strategy highlighted in previous SEC enforcement actions involves fund purchases of discounted illiquid odd lot (less than $1 million) structured product positions and immediately marking them at the higher prices applicable to more liquid round lot sizes produced by third-party pricing vendors such as ICE Data Services.

As the initial shareholder, the fund sponsor is directly conflicted because high marks on any fund holding purchased with the sponsor's seed capital inflates fund NAV. Additional shares sold to public investors are then issued at an inflated NAV. These transactions advantage the sponsor's position as the initiating shareholder by leaving the sponsor with an unfairly high percentage ownership of the now

larger fund. Fund board members and the fund's manager would likely also benefit by choosing to be "early" investors (see the analysis of Section 6.2).

But the more important conflicts for the fund's sponsor and manager arise from the positive impact on fees arising from any new money inflows pouring in from investors induced by inflated past performance records. A fund that inflates its performance record in a way that results in an artificially high initial 3-year Morningstar rating may benefit the most. Section 6.1 provides evidence that the annual change in assets of the nine Morningstar-rated *Highly Questionable* funds averaged $1.26 billion versus just $202 million for 46 other ranked structured product funds.

D.2 Failures among Gatekeepers

None of the standard gatekeepers in the performance reporting ecosystem may be informed enough to detect opportunistic behavior within structured product mutual funds. The reason is simple: many structured products are complex securities that trade infrequently in opaque markets. Thus, pricing vendors, independent auditors, and fund consultants such as Morningstar operate at a clear disadvantage to fund insiders.

Because FINRA does not disseminate transaction reports for round lot structured product trades, pricing vendors cannot access the detailed security-by-security price and quantity trade histories that are typically available for other securities like corporate bonds or agency debentures. Pricing vendors preparing evaluated marks on individual securities are clearly handicapped by this data restriction. For example, analysis of complete structured product transaction histories for both odd and round lot trades occurring at the same time would allow pricing vendors to accurately assess odd lot discounts for specific securities. Moreover, in the absence of round lot TRACE data, pricing vendors must rely solely on dealer indications for many securities. Worse yet for valuation clarity, in many cases there may only be one dealer in contact with a security – the dealer who placed the entire issue with a single buyer (e.g., a "single-fund" position).

Likewise, independent auditors applying methods useful for typical bond and equity funds face similar challenges regarding security complexity and market data paucity when confronting structured product funds. Independent auditors with practices spanning a wide set of clients may gain useful insights by constructing their own pricing databases by aggregating individual client trade records. Independent auditors with smaller practices would appear to be disadvantaged regarding this data generation dimension. In any case, given the hundreds of thousands of individual structured product CUSIPs, any auditor or pricing vendor attempting to apply discounted cash flow valuation models will most likely leave certain niches of securities systematically overvalued or undervalued. Such valuation errors are ripe for opportunistic fund managers to exploit in buy, mismark, and hold strategies.

Finally, investment consultants such as Morningstar face direct challenges because audited reported fund return histories are the main inputs for their fund ratings schemes. Return inflations of the type modeled in Section 6.2 (e.g., the archetype mismarking fund generates a compound annual net-of-benchmark return that is 230 basis points per year higher than that of the otherwise identical fair-marking fund over its initial three years of operation) clearly imply that a mismarking fund will easily shoot to the top of the ratings scheme (e.g., "Five-star").

In some respects, the problems faced by mutual fund gatekeepers are similar to those faced by credit ratings organizations (CROs) in their attempts to rate the various new subprime real estate-related structured products issued during the boom 2004-2007 period. The CROs had years of experience doing standard corporate credit analysis on the basis of both financial statement data and professional judgments concerning management teams and organizational quality. But faced with the complexities of the new subprime mortgaged-based tranches of securities issued by stand-alone trusts, the CRO's ratings procedures devolved rather quickly away from holistic due diligence towards pure model-driven risk rating schemes that were calibrated against abbreviated, unrepresentative historical sample data.[13]

[13] Moreover, by sharing the models with would-be security structurers, the CROs allowed their ratings to be gamed. Such cooperation delivered huge short-run profits for both security structurers and the CROs, but later led to massive losses for affected investors.

D.3 Policy Recommendations

Analysis of the structured products mutual fund performance-reporting ecosystem leads us to five important policy recommendations.

First, we recommend that, in addition to monetary sanctions, any SEC disciplinary actions against a mismarking fund should also require restatement of historical NAVs and returns using adjusted position marks that conform to the SEC's exit price valuation standard. Such restatements would permit fund investors to more easily assess the damages they incurred while transacting at inflated NAVs. In the absence of proper restatements, the SEC should at least force funds to expunge all performance records for mismarking-tainted periods from any fund marketing materials. Otherwise, fund management will continue to benefit from its "outperformance" record and inflated Morningstar Ratings by earning excess investment inflows and asset management fees.

Second, independent auditors examining funds with significant investments in structured products should incorporate trade price versus end-of-day mark comparisons for all new purchases of mismarking-prone securities as a routine component of every audit. Independent auditors should revisit all prior years since inception, conduct tests for mark inflation on structured product purchases, and then either affirm or restate fund financials to produce accurate NAV and return-since-inception histories for investors.

Third, by providing just a single mark for each structured product, pricing vendors currently act as enablers for mark inflation of odd lot positions. Those vendors who go forward providing just a single mark for each security should revamp their client messaging to specifically note that this mark is suitable only for round lot positions. A better approach would be for pricing vendors to develop appropriate schedules for odd lot discounts by security or by structured product type and security characteristics (e.g., credit rating, coupon, maturity, etc.). Such schedules would help independent auditors as well because generally accepted auditing standards favor external confirmations (see AU-C 505 of the Auditing Standards Board, 2018). Creation of discount schedules for odd lots would also change mark inflation by managers from a passive sin of omission to a sin of commission, no doubt lessening its likelihood.

We also recommend that pricing vendors reassess their current valuation methodology for securities that routinely appear in mutual fund portfolios as single-fund round lots. Our regression

evidence indicates that pricing vendors systematically overvalue these securities. Public dissemination by FINRA's TRACE system of structured product transaction-level data, even if delayed, would no doubt help correct these errors. Bessembinder, Maxwell, and Venkataraman (2013) argue that an additional benefit of such trade price dissemination would be a substantial decrease of trade execution costs. We believe that expanded transaction reporting would also help restore the integrity of commingled investment vehicles investing in structured products.

Finally, fund rating services (e.g., Morningstar) and fund consultants should proactively investigate "too-good-to-be-true" performance of structured product funds, especially immediately after launch. Performance attribution statements contained within annual shareholder reports are woefully inadequate to allow any analyst to determine whether unusually good returns match up well with their purported drivers or are instead the result of mismarking fraud. Ideally, ratings services and consultants should require structured product funds to provide evidence that their performance records are not overstated. The most convincing evidence would be histories of all new purchase trade prices on mismarking-prone positions matched against end-of-day position marks as validated by their independent auditors.

References

Agarwal, V., Barber, B., Cheng, S., Hameed, A., Yasuda, A., 2018. Private Company Valuations by Mutual Funds, working paper.

Agarwal, V., Gay, G., Ling, L., 2014, Window dressing in mutual funds, The Review of Financial Studies, 27 (11), 3133–3170.

Amaya, D., Christoffersen, P., Jacobs, K., Vasquez, A., 2015. Does realized skewness predict the cross section of equity returns? *Journal of Financial Economics* 118, 135–167.

Atanasov, V., Merrick, J., Schuster, P., 2017. Why do dealers buy high and sell low? An analysis of persistent crossing in extremely segmented markets, *Review of Finance*, 21, 719-760.

Auditing Standards Board (ASB), 2018, *Clarified Statements on Auditing Standards: External Confirmations AU-C 505*. https://www.aicpa.org/content/dam/aicpa/research/standards/auditattest/downloadabledocuments/au-c-00505.pdf.

Bali, T., Murray, S., 2013, Does risk-neutral skewness predict the cross section of equity option portfolio returns? *Journal of Financial and Quantitative Analysis* 48, 1145–1171.

Bernhardt, D., Davies, R.J., 2005. Painting the tape: aggregate evidence. *Economics Letters*, 89, 306-311.

Bessembinder, H., Maxwell, W. F., and Venkataraman, K. (2013). Trading activity and transaction costs in structured credit products. *Financial Analysts Journal*, *69*(6), 55-67.

Bhargava, R. , Bose, A. and Dubofsky, D., 1998. Exploiting international stock market correlations with open-end international mutual funds. *Journal of Business Finance & Accounting*, 25, 765-773.

Bhattacharyya, S., Nanda, V., 2013. Portfolio pumping, trading activity and fund performance, *Review of Finance*, 17 (3), 885–919.

Black, F., Scholes, M., 1973, The Pricing of Options and Corporate Liabilities, Journal of Political Economy, 81, 637-654.

Blume, M., Keim, D., 2006. Stale or sticky stock prices? Non-trading, predictability, and mutual fund returns, working paper.

Bollen, N., Pool, V., 2009. Do hedge fund managers misreport returns? Evidence from the pooled distribution, *Journal of Finance*, 64, 2257–2288.

Boudoukh, J., Richardson, M., Subrahmanyam, M., Whitelaw, R., 2002. Stale prices and strategies for trading mutual funds. *Financial Analysts Journal*, 58 (4), 53-71.

Campbell, J. Y., 2008. Estimating the equity premium. *Canadian Journal of Economics*, 41, 1–21.

Carhart, M., Kaniel, R., Musto, D., Reed, A., 2002. Leaning for the tape: evidence of gaming behavior in equity mutual funds. *Journal of Finance* 57, 661-693.

Cassar, G., Gerakos, J., 2011, Hedge funds: Pricing controls and the smoothing of self-reported returns, *Review of Financial Studies*, 24 (5), 1698-734.

Chalmers, J., Edelen, R., and Kadlec, G., 2001, On the perils of financial intermediaries setting security prices: the mutual fund wild card option. *The Journal of Finance,* 56 (6), 2209-2236.

Chandar, N., Bricker, R., 2002. Incentives, discretion, and asset valuation in closed-end mutual funds, *Journal of Accounting Research*, 40 (4), 1037-1070.

Christie, W., and P. Schultz, 1994, Why do NASDAQ marketmakers avoid odd-eighth quotes, *Journal of Finance*, 49, 1813-1840.

Cici, G., Gibson, S., Merrick, J., 2011. Missing the marks? Dispersion in corporate bond valuations across mutual funds, *Journal of Financial Economics*, 101 (1), 206-226.
Cici, G., Gibson, S., Moussawi, R., 2010. Mutual fund performance when parent firms simultaneously manage hedge funds, *Journal of Financial Intermediation,* 19, 169-187.
Conrad, J., Dittmar, R., Ghysels, E., 2013. Ex ante skewness and expected stock returns, *Journal of Finance*, 68 (1), 85-124.
Duong, T., and F. Meschke, 2016. The rise and fall of portfolio pumping among U.S. mutual funds, Working paper.
Evans, R., 2010. Mutual fund incubation, *Journal of Finance*, 65, 1581–1611.
Fama, E., 1970, Efficient capital markets: A review of theory and empirical work, *Journal of Finance* 25, 383–417.
Gaspar, J., Massa, M., Matos, P., 2006. Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization, *The Journal of Finance*, 61, 73-104.
Getmansky, M., Lo, A., Makarov, I., 2004. An econometric model of serial correlation and illiquidity in hedge fund returns, *Journal of Financial Economics*, 74, 529–609.
Goetzmann, W., Ivković, Z., Rouwenhorst, K. G., 2001. Day trading international mutual funds: Evidence and policy solutions. *Journal of Financial and Quantitative Analysis*, 36, (3), 287-309.
Goldstein, I., Jiang, H., Ng, D., 2017. Investor flows and fragility in corporate bond funds, *Journal of Financial Economics*, 126, 592–613.
Greene, J., Hodges, C., 2002. The dilution impact of daily fund flows on open-end mutual funds, *Journal of Financial Economics*, 65, 131-158.
Houge, T., Wellman, J., 2005, Fallout from the mutual fund trading scandal, *Journal of Business Ethics*, 62, 129–139.
Investment Company Institute (ICI), 2017, Investment Company Fact Book, https://www.ici.org/pdf/2017_factbook.pdf.
Jensen, M., Murphy, K., 1990, Performance pay and top-management incentives, *Journal of Political Economy*, 98 (2), 225-264.
Jorion, P., Schwarz, C., 2014. Are hedge fund managers systematically misreporting? Or not? *Journal of Financial Economics*, 111 (2), 311-327.
Kadlec, G., 2004. On solutions to the mutual fund timing problem, working paper.
Kraus, A. and Litzenberger, R., 1976, Skewness preference and the valuation of risk assets, *Journal of Finance*, 31 (4), 1085-1100.
Lie, E., 2005, On the timing of CEO stock option awards, *Management Science*, 51, 802-812.
Massa, M., Reuter, J., Zitzewitz, E., 2010. When should firms share credit with employees? Evidence from anonymously managed mutual funds, *Journal of Financial Economics*, 95, 400-424.
Pástor, L., Stambaugh, R., Taylor, L., 2015, Scale and skill in active management, *Journal of Financial Economics*, 116, 23-45.
Pástor, L., Stambaugh, R., Taylor, L., 2017, Fund tradeoffs, Working Paper.
Schonfeld, V., Kerwin, T., 1993, Organization of a mutual fund. *The Business Lawyer* 49, 107-161.
Securities and Exchange Commission, 1986, *Acquisition and Valuation of Certain Portfolio Instruments by Registered Investment Companies*, SEC Release No. IC-14983, March 17.
Securities and Exchange Commission, 1992, *Revisions of Guidelines to Form N-1A*, SEC Release No. 33-6927, March 20.

Securities and Exchange Commission, 2016a, Press Release 2016-252, "PIMCO settles charges of misleading investors about ETF performance," https://www.sec.gov/news/pressrelease/2016-252.html.

Securities and Exchange Commission, 2016b, *In the Matter of Pacific Investment Management Company LLC, Respondent*, Administrative and Cease-and-Desist Proceeding File No. 3-17701, https://www.sec.gov/litigation/admin/2016/ia-4577.pdf.

Securities and Exchange Commission, 2018a, *In the Matter of Visium Asset Management, LP, Respondent*, Administrative and Cease-and-Desist Proceeding File No. 3-18473, https://www.sec.gov/litigation/admin/2018/33-10494.pdf

Securities and Exchange Commission, 2018b, *Securities and Exchange Commission against Premium Point Investments LP, Anilesh Ahuja a/k/a Neil Ahuja, Amin Majidi, and Jeremy Shor, Defendants*, http://www.sec.gov/litigation/complaints/2018/comp-pr2018-83.pdf

Tufano, P., Quinn, M., Taliaferro, R., 2012. Insights: live prices and stale quantities: T+1 accounting and mutual fund mispricing. *Journal of Investment Management*, 10 (1), 5-15.

Weinstein, M. I., 1978. The Seasoning Process of New Corporate Bond Issues, *Journal of Finance*, 33, 1343–1354.

Zitzewitz, E., 2003. Who cares about shareholders? Arbitrage-proofing mutual funds, *Journal of Law Economics and Organization*, 19(2), 245–280.

Zitzewitz, E., 2006. How widespread was late trading in mutual funds? *American Economic Review: Papers and Proceedings*, 96 (2), 284-289.

Table 1. Summary of the academic literature on fund NAV manipulation by type, method, and associated impacts on fund return alpha, standard deviation, and skewness.

See discussion in Section 2.1.

Manipulation Type	**Paper**	**Manipulation Method**	**Alpha**	**Std. Dev.**	**Skewness**
Performance transfer	Gaspar, Massa, Matos (2006)	Trade-based, discounted price	Positive effect on alpha for select funds at expense of other funds	No	Do not examine, but should be positive
Performance transfer	Cici, Gibson, Moussawi (2010)	Trade-based, discounted price	Positive effect on alpha for select funds at expense of other funds	No	Do not examine, but should be positive
Performance transfer	Agarwal *et al*. (2018)	Trade-based, discounted price	Positive effect on alpha for select funds at expense of other funds	No	Do not examine, but should be positive
Performance transfer/Market Timing	Massa, Reuter, Zitzewitz (2010)	Trade-based, discounted price/stale price	Positive effect on alpha for select funds at expense of other funds	No	Do not examine, but should be positive
Market timing	Bhargava, Bose, Dubofsky (1998)	Trade-based, stale price	No direct effect. Second order negative effects through volatility of flows	No	No
Market timing	Chalmers *et al*. (2001)	Trade-based, stale price	No direct effect. Second order negative effects through volatility of flows	No	No
Market timing	Goetzmann, Ivković, Rowenhorst (2001)	Trade-based, stale price	No direct effect. Second order negative effects through volatility of flows	No	No
Market timing	Boudoukh *et al*. (2002)	Trade-based, stale price	No direct effect. Second order negative effects through volatility of flows	No	No
Market timing	Greene and Hodges (2002)	Trade-based, stale price	No direct effect. Second order negative effects through volatility of flows	No	No
Market timing	Zitzewitz (2003)	Trade-based, stale price	No direct effect. Second order negative effects through volatility of flows	No	No
Market timing	Kadlec (2004)	Trade-based, stale price	No direct effect. Second order negative effects through volatility of flows	No	No
Market timing	Blume and Keim (2006)	Trade-based, stale price	No direct effect. Second order negative effects through volatility of flows	No	No
Market timing	Zitzewitz (2006)	Trade-based, stale price	No direct effect. Second order negative effects through volatility of flows	No	No
Painting the tape	Carhart *et al*. (2002)	Trade-based, market price	No long-term, but could boost alpha for a specified period	Yes	No
Painting the tape	Bernhardt and Davies (2005)	Trade-based, market price	No long-term, but could boost alpha for a specified period	Yes	No
Painting the tape	Bhattacharyya and Nanda (2013)	Trade-based, market price	No long-term, but could boost alpha for a specified period	Yes	No
Painting the tape	Duong and Meschke (2016)	Trade-based, market price	No long-term, but could boost alpha for a specified period	Yes	No
Smoothing	Chandar and Bricker (2002)	Mark-based	Some evidence for mismarking to barely beat the benchmark long-term	Yes	Not studied

Manipulation Type	Paper	Manipulation Method	Alpha	Std. Dev.	Skewness
Smoothing	Getmansky, Lo, Makarov (2004)	Mark-based	No	Yes	Not studied
Smoothing	Bollen and Pool (2009)	Mark-based	No	Yes	Negative skewness for offenders, positive for non-offenders
Smoothing	Cassar and Gerakos (2011)	Mark-based	No relation between alpha and pricing sources	Yes	Not studied
Smoothing	Cici, Gibson, Merrick (2011)	Mark-based	No	Yes	Not studied
Smoothing	Jorion and Schwartz (2014)	Mark-based	No	Yes	Not studied
T+1 Position Accounting	Tufano, Quinn, Taliaferro (2012)		No	No	Examine but find none

Table 2. Distribution of fund holdings by security type.

We classify the 30+ fixed income security types identified in the Morningstar data into five types of structured products (SP) and five types of non-SP securities. The Non-SP Other category includes a handful of holdings in agency debentures, bonds from foreign governments or supranationals, or unclassified bonds. The Percent of Fixed Income Holdings variable is calculated as the sum of market values of positive holdings in a particular security type divided by the sum of the positive holdings in all fixed income security types in a given reporting period. The majority of funds in our sample report holdings on a quarterly basis. The remaining funds report on a monthly basis. To calculate summary statistics, we first average the percentage holdings over the total observation period at a per-fund level. The summary statistics are then calculated from these per-fund values across the 142 funds launched after Jan 1, 2010 and the 384 funds launched before Jan 1, 2010.

		Funds launched after Jan 2010			**Funds Launched before Jan 2010**		
Product Space	Security Type	Average Percent of Fixed Income Holdings	Median Percent of Fixed Income Holdings	Maximum Percent of Fixed Income Holdings	Average Percent of Fixed Income Holdings	Median Percent of Fixed Income Holdings	Maximum Percent of Fixed Income Holdings
Structured Products (SP)	Agency MBS Pass-Through	10.5	2.3	90.3	24.7	19.8	100.0
	Agency CMO+Other	7.7	4.0	75.4	10.0	5.0	69.9
	Commercial MBS	6.1	3.7	67.2	4.2	3.0	47.5
	Asset-Backed Securities	21.9	17.4	95.8	8.4	5.6	56.4
	Private-Label CMO+Other	12.4	7.7	94.9	6.1	4.4	43.8
Non-SP	Cash and Equivalents	0.0	0.0	0.8	0.1	0.0	15.3
	Treasuries	12.6	9.3	50.7	17.9	16.9	75.1
	Corporate Bonds	24.2	25.4	64.9	21.7	24.3	66.1
	Muni	1.7	0.2	45.2	1.4	0.5	23.4
	Other	2.8	0.5	54.5	5.5	2.5	55.8

Table 3. Positions by number of funds reporting marks on structured product positions for the same security on the same report date.

We report results for four mark count categories: 1, 2, 3-5, and 6 or more ("6+"). We further distinguish single-mark observations on security positions held by only one fund throughout the sample ("single-fund positions") with an asterisk ("1*"). The remaining single-mark observations represent positions in securities that are held by multiple funds that do not share reporting dates.

	All Structured Product Securities		Agency MBS Pass-Through		Agency CMO+Other		Commercial MBS		Asset-Backed Securities		Private-Label CMO+Other	
Mark count	Number	Percent	Number	Percent	Number	Percent	Number	Percent	Number	Percent	Number	Percent
1*	2,004,387	16%	1,530,702	24%	260,418	17%	13,802	1%	72,775	4%	126,691	8%
1	1,545,565	12%	1,086,146	17%	168,525	11%	27,184	3%	116,174	6%	147,537	9%
2	2,047,946	16%	1,265,510	20%	310,206	21%	47,238	5%	196,531	10%	228,461	14%
3-5	2,775,287	22%	1,334,800	21%	383,515	25%	164,930	17%	450,031	24%	442,011	27%
6+	4,138,157	33%	1,025,580	16%	312,743	21%	650,154	68%	957,924	50%	615,114	37%
Total	12,511,342		6,242,738		1,435,406		903,308		1,793,435		1,559,814	

Table 4. Distribution of markups on "high-mark" round lot structured products.

For round lot positions in each security *i* held by three or more funds, we compute the median mark ($Median_{i,t}$) and the interquartile range of marks ($IR_{i,t}$) placed by each fund on each date *t*. We term fund *k*'s mark ($M^k_{i,t}$) for a round lot on individual security *i* on date *t* to be: *"High"* if $M^k_{i,t} \geq Median_{i,t} + .5 * IR_{i,t}$. A fund's $Markup^k_{i,t}$ is defined as the difference between a fund's mark on a given high-mark round lot position in security *i* on a given date, $M^k_{i,t}$, and that same report date's median mark on round lot positions in that same security across all funds. The summary statistics for the distribution of markups on high-mark round lot positions are computed after disaggregating the observations by broad security type and mark count categories.

	Mark Category	Observations	Mean	Median	75th Percentile	95th Percentile	99th Percentile
Agency MBS Pass-Through	3-5 marks	201,578	0.50	0.09	0.33	1.34	3.32
	6+ marks	220,310	0.30	0.10	0.29	0.81	1.97
Agency CMO+Other	3-5 marks	11,494	0.45	0.11	0.39	1.76	4.35
	6+ marks	20,988	0.32	0.13	0.31	1.12	2.55
Commercial MBS	3-5 marks	11,239	0.50	0.18	0.43	1.72	5.41
	6+ marks	77,463	0.42	0.20	0.43	1.26	4.67
Asset-Backed Securities	3-5 marks	27,114	0.67	0.17	0.57	2.74	8.25
	6+ marks	102,156	0.50	0.10	0.33	2.09	6.82
Private-Label CMO+Other	3-5 marks	23,436	0.86	0.32	0.74	3.20	11.09
	6+ marks	61,247	0.58	0.24	0.48	2.19	6.82

Table 5. Number and percentage of funds with significant t-statistics for new purchases slope coefficients in univariate individual fund regressions of monthly net-of-benchmark returns on odd lot, high-mark round lot, and single-fund round lot new purchases variables (significance level = .05).

The dependent variable in all regressions is the net-of-benchmark monthly return. For each fund, we run three separate regressions -- one using percent new odd lot purchases, one using percent new high-mark round lot purchases, and one using percent new single-fund round lot purchases. The regressions are run only on the 142 structured product funds launched after Jan 1, 2010.

Slope t-Test Conclusion	**t-Statistic Range**	**Odd Lot**		**High-Mark Round Lot**		**Single-Fund Round Lot**	
Significant	> 1.96	**25**	**18%**	**13**	**9%**	**15**	**11%**
Not Significant	<= 1.96	101	71%	87	61%	87	61%
No usage		16	11%	42	30%	40	28%
Total Funds		142		142		142	

Table 6. Summary statistics of percent new odd lot, high-mark round lot, and single-fund round lot quarterly purchases during a fund's first year.

Sample includes only the 142 structured-product funds launched after Jan 1, 2010. We calculate the quarterly percentage of each type of mismarking-prone position purchases as the sum of monthly purchases scaled by end-of-month fund assets made during each of the three months in the quarter.

Panel A. Sum percent new odd lot purchases

Period	50th Percentile	75th Percentile	90th Percentile	95th Percentile
1-3 Months	16.22%	36.10%	58.66%	82.06%
4-6 Months	5.50%	11.38%	18.60%	21.54%
7-9 Months	2.98%	6.54%	12.60%	16.29%
10-12 Months	1.63%	5.35%	8.27%	11.48%

Panel B. Sum percent new high-mark round lot purchases

Period	50th Percentile	75th Percentile	90th Percentile	95th Percentile
1-3 Months	0.00%	0.47%	4.03%	8.92%
4-6 Months	0.00%	0.45%	3.65%	6.31%
7-9 Months	0.00%	0.43%	2.06%	4.33%
10-12 Months	0.00%	0.62%	2.08%	4.72%

Panel C. Sum percent new single-fund round lot purchases

Period	50th Percentile	75th Percentile	90th Percentile	95th Percentile
1-3 Months	0.00%	3.16%	19.63%	27.83%
4-6 Months	0.00%	1.03%	4.09%	10.49%
7-9 Months	0.00%	0.86%	4.64%	7.77%
10-12 Months	0.00%	0.98%	4.65%	7.99%

Table 7. Alpha and skewness of daily fund returns by time since inception.

Comparison of 12 structured product funds identified as having both statistically significant purchase-return correlations and high usage rates ("*Highly Questionable Funds*"), 21 funds having statistically significant purchase-return correlations but lower usage rates ("*Questionable Funds*"), 109 unchallenged structured product funds ("*Unchallenged SP-Funds*") associated with insignificant t-statistic results, and the baseline group of 2,951 non-structured product funds. Sample period: January 2010-April 2017. *Months 1-3*, *Months 4-6*, *Months 7-9*, and *Months 10-12* are zero/one fund age indicator variables corresponding to four consecutive three-month intervals after fund launch. *Months 13+* is an indicator variable for months beyond a fund's first year. We report t-statistics clustered on funds in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels. Significant results (at 5% or better) are in **boldface**.

	Alpha	**Skewness**
*Highly Questionable Funds*Months 1-3*	**7.444*** **	**0.5430*** **
	(4.88)	**(4.01)**
*Highly Questionable Funds*Months 4-6*	0.711	**0.2958*** **
	(0.51)	**(3.48)**
*Highly Questionable Funds*Months 7-9*	0.124	0.0901
	(0.10)	(0.47)
*Highly Questionable Funds*Months 10-12*	0.777	**0.2934*** **
	(1.00)	**(2.65)**
*Highly Questionable Funds*Months 13+*	**1.552*** **	0.0732*
	(10.01)	(1.93)
*Questionable Funds*Months 1-3*	-1.059	-0.0033
	(-1.08)	(-0.02)
*Questionable Funds*Months 4-6*	-0.595	-0.0647
	(-0.62)	(-0.54)
*Questionable Funds*Months 7-9*	0.329	-0.0049
	(0.78)	(-0.05)
*Questionable Funds*Months 10-12*	**2.393*** **	0.0783
	(2.75)	(1.15)
*Questionable Funds*Months 13+*	0.468	0.0334
	(1.40)	(1.55)
*Unchallenged Funds*Months 1-3*	0.225	0.0499
	(1.02)	(0.96)
*Unchallenged Funds*Months 4-6*	0.062	0.0487
	(0.25)	(1.18)
*Unchallenged*Months 7-9*	-0.204	0.0108
	(-0.64)	(0.24)
*Unchallenged*Months 10-12*	-0.166	-0.0291
	(-0.57)	(-0.53)
*Unchallenged*Months 13+*	**0.935*** **	0.0268
	(8.87)	(1.48)
Months 1-3	**-0.198** **	**-0.0331*** **
	(-2.09)	**(-4.26)**
Months 4-6	0.078	0.0078
	(0.80)	(1.06)
Months 7-9	0.058	-0.0155
	(0.57)	(-2.09)
Months 10-12	-0.052	-0.0033
	(-0.50)	(-0.46)
Months 13+	**-0.584*** **	**0.0331*** **
	(-14.71)	**(10.42)**
No. Obs.	126,652	126,517

Table 8. Panel regressions to compare slopes of *Highly Questionable* and *Questionable* versus the *Unchallenged* funds baseline group.

Sample includes only the 142 structured-product funds launched after Jan 1, 2010. Sample period: January 2010-April 2017. The first column reports results using monthly fund net-of-benchmark returns as the dependent variable. The second column reports results using monthly fund net-of-T-Bill returns as the dependent variable, adding the excess return on the fund benchmark as a separate control variable. In both versions, we estimate new mismarking-prone position purchase effects using the odd lot, high-mark round lot, and single-fund round lot new purchases measures as explanatory variables. In the second and fourth regressions, we include primary purchases of structured and non-structured products as control variables. All new position purchase variables are scaled to be percentages of fund assets. The regressions allow for interaction effects with our *Highly Questionable* and *Questionable* fund type indicator variables. *Unchallenged* funds serve as the baseline group. Additional control variables include fund monthly flows, annual turnover, net expense ratio, and family assets. We report t-statistics clustered on date in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels. Significant results (at 5% or better) are in **boldface**.

	Net-of-Benchmark Returns		**Net-of-T-Bill Returns**	
Highly Questionable Funds*PctNewOddLotPurchases	**3.513*** **	**3.475*** **	**3.389*** **	**3.380*** **
	(4.887)	**(4.788)**	**(4.728)**	**(4.657)**
Questionable Funds*PctNewOddLotPurchases	1.395	1.380	2.105	2.188
	(0.901)	(0.869)	(0.961)	(1.006)
PctNewOddLotPurchases	0.277	0.328	0.453	0.459
	(0.695)	(0.792)	(1.247)	(1.199)
Highly Questionable Funds*PctNewHighMarkPurchases	7.404	7.181	4.161	4.136
	(1.572)	(1.491)	(0.936)	(0.922)
Questionable Funds*PctNewHighMarkPurchases	16.573	16.886*	11.823	11.887
	(1.642)	(1.689)	(1.395)	(1.403)
PctNewHighMarkPurchases	2.406	2.708	3.313*	3.356*
	(1.014)	(1.055)	(1.949)	(1.844)
Highly Questionable Funds*PctNewSingleFundPurchases	**4.086*** **	**4.001*** **	**2.923** **	**2.960** **
	(2.847)	**(2.777)**	**(2.230)**	**(2.261)**
Questionable Funds*PctNewSingleFundPurchases	2.487	2.503	0.757	0.821
	(0.597)	(0.599)	(0.217)	(0.236)
PctNewSingleFundPurchases	-0.538	-0.432	-0.017	-0.017
	(-0.709)	(-0.567)	(-0.031)	(-0.031)
Highly Questionable Funds	0.009	0.009	0.065	0.064
	(0.198)	(0.185)	(1.430)	(1.414)
Questionable Funds	-0.148*	-0.151*	-0.105	-0.106
	(-1.698)	(-1.724)	(-1.489)	(-1.496)
Intercept	**0.157*** **	**0.160*** **	**0.167*** **	**0.171*** **
	(4.070)	**(4.115)**	**(4.454)**	**(4.251)**
Benchmark Index Excess Return			**0.597*** **	**0.597*** **
			(8.262)	**(8.258)**
PctPrimaryPurchases_SP		-0.672		-0.066
		(-0.703)		(-0.083)
PctPrimaryPurchases_nonSP		0.020		-0.230
		(0.054)		(-0.478)
Additional control variables	Yes	Yes	Yes	Yes
Number of observations	4,522	4,522	4,522	4,522
R-squared	0.01	0.01	0.44	0.44

Table 9. Aggregation of odd lot positions to round lot size and liquidation of high-mark and single-fund positions.

We present statistics for the 12 *Highly Questionable* funds and the remaining 130 funds launched after Jan 1, 2010. Panel A shows the percentages of odd lot structured product (SP) and non-SP positions that are aggregated to round lot size 3 months, 6 months, 1 year, and 2 years after purchase. Panel B presents the percentages of positions of high mark round lot (RL) SPs, round lot SPs held only by a single fund (Single-Fund RL), all round lot SPs, and all round lot non-SPs that are liquidated (i.e., sold or matured and no longer in the fund's portfolio), after 3 months, 6 months, 1 year, and 2 years of purchase.

Panel A. Aggregation percentages of odd lot positions to round lot size

	12 Highly Questionable Funds				**130 Other Structured Product Funds Launched in or after 2010**			
	After 3 Months	After 6 Months	After 1 Year	After 2 Years	After 3 Months	After 6 Months	After 1 Year	After 2 Years
Odd Lot SPs	1.72%	3.12%	6.02%	7.92%	1.20%	2.05%	3.12%	4.19%
Odd Lot Non-SPs	5.73%	8.79%	12.52%	14.83%	2.81%	4.26%	5.96%	7.44%

Panel B. Liquidation percentages of high-mark and single-fund round lot positions

	12 Highly Questionable Funds				**130 Other Structured Product Funds Launched in or after 2010**			
	After 3 Months	After 6 Months	After 1 Year	After 2 Years	After 3 Months	After 6 Months	After 1 Year	After 2 Years
High Mark RL SPs	8.27%	16.65%	31.29%	54.93%	7.88%	16.11%	36.79%	69.99%
Single-Fund RL SPs	3.32%	6.63%	12.92%	23.48%	6.12%	12.63%	27.61%	45.67%
Other RL SPs	4.26%	8.94%	16.96%	34.05%	8.72%	15.81%	29.85%	54.30%
All RL Non-SPs	35.03%	54.55%	72.69%	86.84%	21.52%	34.79%	54.57%	75.56%

Table 10. Panel regressions to estimate the mark inflation for odd lot and single-fund purchases of the *Highly Questionable* funds.

Sample includes only the 12 *Highly Questionable* funds launched after Jan 1, 2010. Sample period: January 2010-April 2017. Columns 1-2 and 5-6 report results using monthly fund net-of-benchmark returns as the dependent variable. Columns 3-4 and 7-8 report results using monthly fund net-of-T-Bill returns as the dependent variable, adding the excess return on the fund benchmark as a separate control variable. The left half of the table (columns 1-4) reports results with unadjusted net-of-benchmark or net-of-T-Bill returns. The right half of the table (columns 5-8) uses returns that are adjusted for the average effect of high-mark round lot purchases on returns. The adjustment is done by subtracting from the monthly return measure for each fund *i* and each month *t* the product of $pctNewHighMarkPurchases_{i,t}$ and AverageHighMarkInflation, where AverageHighMarkInflation is calculated as the weighted average of the actual inflation relative to the median mark of each high-mark round lot purchase made by the *Highly Questionable* funds during the sample period. We estimate new mismarking-prone position purchase inflation effects using the odd lot and single-fund round lot new purchases measures as explanatory variables. We include primary purchases of structured and non-structured products as control variables. The new purchases variables are scaled to be percentages of fund assets. Additional control variables include fund monthly flows, annual turnover, net expense ratio, and family assets. We report t-statistics clustered on date in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels. Significant results (at 5% or better) are in **boldface.**

	Unadjusted for High-Mark Purchases				Adjusted for High-Mark Purchases			
	Net of Benchmark		Net of T-Bills		Net of Benchmark		Net of T-Bills	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PctNewOddLotPurchases	**5.107*** **	**4.941*** **	**4.770*** **	**4.373*** **	**5.100*** **	**4.938*** **	**4.763*** **	**4.370*** **
	(5.823)	**(5.756)**	**(5.434)**	**(5.216)**	**(5.813)**	**(5.741)**	**(5.433)**	**(5.220)**
PctNewSingleFundPurchases	**3.096*** **	**3.164*** **	**3.484*** **	**3.363*** **	**3.038*** **	**3.117*** **	**3.426*** **	**3.317*** **
	(3.302)	**(4.626)**	**(3.705)**	**(3.871)**	**(3.340)**	**(4.746)**	**(3.780)**	**(3.943)**
Benchmark Excess Return			**0.597*** **	**0.589*** **			**0.597*** **	**0.589*** **
			(5.962)	**(5.565)**			**(5.964)**	**(5.572)**
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	655	621	655	621	655	621	655	621
R-squared	0.21	0.23	0.41	0.42	0.21	0.23	0.41	0.42

Table A.1. Post-launch patterns in fund alpha and skewness of simulated daily fund returns.

The dependent variable in the first three columns (*Alpha*) of each panel is calculated as the average daily net of benchmark return (in basis points) calculated for each month. The dependent variable in the last three columns (*Skew*) is calculated as the skewness of daily net of benchmark returns for each month. In different simulation runs, we vary the standard deviation of the fund tracking error to equal 35%, 50%, or 65% of the standard deviation of the benchmark return. *AlphaLow* (*Med*, *High*) and *SkewnessLow* (*Med*, *High*) are from the 35% (50%, 65%) tracking error simulation. See Table 2 for more details on the simulation and the definitions of the fund categories *Mismarking High Usage, Mismarking Low Usage, Fair Marking High Usage,* and *Fair Marking Low Usage* funds. The baseline fund group does not purchase mismarking-prone securities. *Months 1-3*, *Months 4-6*, *Months 7-9*, and *Months 10-12* are fund age indicator variables corresponding to four consecutive three-month intervals after fund launch. *Months 13+* is an indicator variable for months beyond a fund's first year. The reported coefficients are averages from 100 simulation runs, each with 125 funds and 60 monthly observations. 100-simulation run average t-statistics are reported in parentheses.

	AlphaLow	*AlphaMed*	*AlphaHigh*	*SkewLow*	*SkewMed*	*SkewHigh*
*Mismarking High Usage Funds*Months 1-3*	21.160	21.156	21.153	3.659	3.836	3.915
	(113.44)	(79.41)	(61.08)	(33.14)	(34.71)	(35.40)
*Mismarking High Usage Funds*Months 4-6*	6.495	6.502	6.509	3.454	3.447	3.306
	(31.48)	(22.05)	(16.97)	(61.59)	(59.22)	(53.58)
*Mismarking High Usage Funds*Months 7-9*	3.495	3.487	3.479	3.101	2.817	2.425
	(17.44)	(12.18)	(9.35)	(51.92)	(41.67)	(31.64)
*Mismarking High Usage Funds*Months 10-12*	2.337	2.329	2.321	2.606	2.092	1.591
	(11.57)	(8.07)	(6.19)	(39.49)	(26.28)	(17.92)
Mismarking High Usage Funds Months 13+*	0.440	0.441	0.442	0.522	0.313	0.192
	(9.10)	(6.39)	(4.94)	(27.03)	(15.89)	(9.78)
*Mismarking Low Usage Funds*Months 1-3*	13.986	13.972	13.959	3.614	3.554	3.444
	(17.47)	(17.00)	(16.40)	(24.80)	(23.12)	(21.56)
*Mismarking Low Usage Funds*Months 4-6*	3.466	3.474	3.482	2.704	2.354	2.015
	(11.22)	(9.30)	(7.80)	(17.54)	(14.91)	(13.06)
*Mismarking Low Usage Funds*Months 7-9*	1.806	1.794	1.783	1.955	1.492	1.125
	(7.48)	(5.66)	(4.50)	(12.41)	(10.28)	(8.63)
*Mismarking Low Usage Funds*Months 10-12*	1.253	1.258	1.262	1.418	0.955	0.644
	(5.63)	(4.13)	(3.25)	(9.63)	(7.58)	(5.91)
Mismarking Low Usage Funds Months 13+*	0.226	0.224	0.223	0.211	0.110	0.062
	(4.65)	(3.26)	(2.50)	(9.79)	(5.52)	(3.20)
*Fair-Marking High Usage Funds*Months 1-3*	0.321	0.308	0.296	0.739	0.462	0.324
	(1.74)	(1.17)	(0.86)	(4.85)	(2.95)	(2.04)
*Fair-Marking High Usage Funds*Months 4-6*	0.285	0.264	0.243	0.390	0.188	0.103
	(1.41)	(0.91)	(0.65)	(4.47)	(2.27)	(1.28)
*Fair-Marking High Usage Funds*Months 7-9*	0.278	0.269	0.260	0.330	0.159	0.087
	(1.36)	(0.93)	(0.69)	(3.78)	(1.92)	(1.09)
*Fair-Marking High Usage Funds*Months 10-12*	0.312	0.318	0.325	0.330	0.162	0.090
	(1.54)	(1.09)	(0.86)	(3.85)	(1.96)	(1.09)
Fair-Marking High Usage Funds Months 13+*	0.456	0.455	0.455	0.200	0.085	0.043
	(9.34)	(6.54)	(5.03)	(10.27)	(4.50)	(2.30)
*Fair-Marking Low Usage Funds*Months 1-3*	0.179	0.181	0.182	0.218	0.117	0.076
	(0.97)	(0.69)	(0.54)	(1.51)	(0.82)	(0.54)
*Fair-Marking Low Usage Funds*Months 4-6*	0.170	0.172	0.173	0.094	0.039	0.019
	(0.83)	(0.59)	(0.45)	(1.14)	(0.49)	(0.25)
*Fair-Marking Low Usage Funds*Months 7-9*	0.150	0.150	0.150	0.074	0.026	0.009
	(0.73)	(0.51)	(0.39)	(0.90)	(0.32)	(0.11)
*Fair-Marking Low Usage Funds*Months 10-12*	0.119	0.106	0.093	0.085	0.037	0.018
	(0.59)	(0.37)	(0.25)	(1.03)	(0.45)	(0.23)
Fair-Marking Low Usage Funds Months 13+*	0.230	0.230	0.230	0.037	0.013	0.005
	(4.70)	(3.30)	(2.55)	(1.90)	(0.66)	(0.25)
Months 1-3	0.015	0.021	0.027	0.000	0.000	0.000
	(0.14)	(0.14)	(0.14)	(0.01)	(0.01)	(0.01)
Months 4-6	0.008	0.011	0.014	-0.001	-0.001	-0.001
	(0.07)	(0.07)	(0.07)	(0.01)	(0.01)	(0.01)
Months 7-9	0.014	0.020	0.026	0.000	0.000	0.000
	(0.09)	(0.09)	(0.09)	(-0.02)	(-0.02)	(-0.02)
Months 10-12	0.006	0.009	0.012	-0.001	-0.001	-0.001
	(0.05)	(0.05)	(0.05)	(-0.00)	(-0.00)	(-0.00)
Months 13+	0.000	0.000	0.000	0.002	0.002	0.002
	(-0.01)	(-0.01)	(-0.01)	(0.12)	(0.12)	(0.12)
Observations per run	7,500	7,500	7,500	7,500	7,500	7,500
Number of simulation runs	100	100	100	100	100	100

Table A.2. Using filtering regressions to identify mismarking funds: patterns in slope coefficient estimates across fund marking status/usage categories for alternative regressions of monthly net-of-benchmark returns versus contemporaneous odd lot purchases (simulation data).

Simulation sample for 10,000 positive-usage funds split equally across four categories: (1) "mismarking, high-usage" funds that purchase and mismark the maximum available amount of mismarking-prone securities; (2) "mismarking, low-usage" funds that purchase and mismark a limited amount of mismarking-prone securities; (3) "fair marking, high-usage" funds that purchase the maximum available amount of mismarking-prone securities but mark them fairly; and (4) "fair marking, low-usage" funds that purchase a limited amount of mismarking-prone securities but mark them fairly. Underlying asset returns and prepayments for a fund buying only round lots are simulated using a realized monthly prepayment drawn from historical calendar month data for FNMA 6%, the daily return history of the Barclays MBS index associated with the same calendar month, and a normally distributed tracking error. In different simulations we vary the standard deviation of the tracking error to equal 35%, 50%, or 65% of the standard deviation of the index return. In the first month, a fund starts with assets under management of $1,000. The fund receives new inflows that are calibrated so that the fund grows by a factor of 60 over its first two years of life. Inflows are immediately used to buy new securities. For both low-usage groups, inflows appear in two separate installments observed on two random days during the month. The fund manager uses one inflow installment to buy discounted odd lot positions and uses the other installment to buy round lot positions. The relative size of the installment invested into odd-lot positions is drawn from a uniform distribution between 0% and 100%. The order in which the monthly odd lot versus round lot purchases are made is random, but all odd lot positions are purchased at a 6% discount to the prevailing round lot price. High-usage funds also have only one inflow installment per month that they invest in odd lot positions. All principal payments are reinvested in round lot positions. The dependent variables for all regressions are simulated fund net-of-benchmark returns defined as the difference between fund returns and matched returns on the benchmark index fund. Panel A presents results for univariate regressions using simulated contemporaneous new purchases of odd lot positions as a percentage of current fund assets as the independent variable. Panel B presents results for univariate regressions using simulated contemporaneous new purchases of odd lot positions as a percentage of lagged fund assets as the independent variable. Panel C presents results for bivariate regressions using the lagged total odd lot holdings as a percentage of current fund assets as well as simulated contemporaneous new purchases of odd lot positions as a percentage of current fund assets as independent variables. A statistically significant estimated slope coefficient, ω_i, is indicated by a t-test statistic > 1.96 (5% critical value) and we calculate mean and median slopes for the significantly positive coefficients. Each panel's regression equation appears above its tabulated results.

Panel A:

$$Net\ of\ Benchmark_SIM_Return_{i,t} = \alpha_i + \omega_i \cdot \left(\frac{SIM_New\ Odd\ Lot\ SP}{SIM_Fund\ Assets}\right)_{i,t} + error_{i,t}$$

		Low Tracking Error			**Medium Tracking Error**			**High Tracking Error**		
Marking Status	Usage Rate	Number of funds with t-stat>1.96	Mean Slope	Median Slope	Number of funds with t-stat>1.96	Mean Slope	Median Slope	Number of funds with t-stat>1.96	Mean Slope	Median Slope
Mismarking	High	2,500	6.32	6.32	2,500	6.32	6.32	2,500	6.33	6.32
Mismarking	Low	2,498	7.62	7.00	2,496	7.62	7.08	2,494	7.62	7.14
Fair-Marking	High	169	0.46	0.45	100	0.65	0.64	87	0.82	0.8
Fair-Marking	Low	127	0.87	0.78	98	1.24	1.08	86	1.64	1.45

Table A.2. (Cont.)
Panel B:

$$Net\ of\ Benchmark_SIM_Return_{i,t} = \alpha_i + \omega_i \cdot \frac{SIM_New\ Odd\ Lot\ SP_{i,t}}{SIM_Fund\ Assets_{i,t-1}} + error_{i,t}$$

		Low Tracking Error			Medium Tracking Error			High Tracking Error		
Marking Status	Usage Rate	Number of funds with t-stat>1.96	Mean Slope	Median Slope	Number of funds with t-stat>1.96	Mean Slope	Median Slope	Number of funds with t-stat>1.96	Mean Slope	Median Slope
Mismarking	High	2,500	2.56	2.56	2,500	2.56	2.56	2,500	2.56	2.56
Mismarking	Low	2,496	3.65	3.19	2,493	3.66	3.19	2,488	3.66	3.17
Fair-Marking	High	189	0.23	0.22	146	0.32	0.31	120	0.42	0.4
Fair-Marking	Low	143	0.48	0.43	115	0.68	0.6	105	0.9	0.78

Panel C:

$$Net\ of\ Benchmark_SIM_Return_{i,t} = \alpha_i + \gamma_i \cdot \frac{SIM_All\ Odd\ Lot\ SP_{i,t-1}}{SIM_Fund\ Assets_{i,t}} + \omega_i \cdot \left(\frac{SIM_New\ Odd\ Lot\ SP}{SIM_Fund\ Assets}\right)_{i,t} + error_{i,t}$$

		Low Tracking Error			Medium Tracking Error			High Tracking Error		
Marking Status	Usage Rate	Number of funds with t-stat>1.96	Mean Slope	Median Slope	Number of funds with t-stat>1.96	Mean Slope	Median Slope	Mean Slope	Mean Slope	Number of funds with t-stat>1.96
Mismarking	High	2,500	6.31	6.30	2,500	6.31	6.30	6.30	6.30	2,500
Mismarking	Low	2,496	7.49	6.94	2,494	7.49	7.02	7.48	7.48	2,493
Fair-Marking	High	252	0.48	0.46	154	0.66	0.64	0.84	0.84	111
Fair-Marking	Low	151	0.91	0.78	124	1.29	1.08	1.69	1.69	109

Table A.3. Panel regression of fund returns on contemporaneous new position purchases disaggregated by security type, position size, and mark status.

The All SP Fund sample includes 526 structured product mutual funds. The New SP Funds subsample is the set of 142 SP funds launched after January 1, 2010. Panels A and B present regressions of monthly fund excess returns on contemporaneous new position purchases disaggregated by security type (structured product or non-SP), position size (Odd Lot or Round Lot), and mark status (High, Medium, Low, or Unranked). Panel C presents regressions of monthly fund excess returns on contemporaneous new position purchases after further disaggregation of unranked round lot (RL) positions into those that are: (i) only ever owned by a single fund (Single-Fund RL), (ii) owned by other funds but having only one available mark on a report date (1-Mark RL), or (iii) owned by other funds but having only two available marks on a report date (2-Mark RL). All new position purchase variables are scaled to be percentages of fund assets. The left-hand columns report results using monthly fund net-of-benchmark returns as the dependent variable. The right-hand columns report results using monthly fund net-of-T-Bill returns as the dependent variable (those regressions also add the excess return on the fund benchmark as a separate control variable). The control variables include monthly fund flows, annual turnover, net expense ratio, and family assets. We report t-statistics clustered by date in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels. Significant results (at 5% or better) are in **boldface**.

Panel A. Regressions based on security and position size types

	Net-of-Benchmark Returns						**Net-of-T-Bill Returns**					
	All SP Funds			New SP Funds			All SP Funds			New SP Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Odd Lot SP/Assets	**2.736*** **	**2.737*** **	**2.648*** **	**2.674*** **	**2.765*** **	**2.620*** **	**2.584*** **	**2.529*** **	**2.414*** **	**2.602*** **	**2.742*** **	**2.524*** **
	(6.012)	**(5.275)**	**(4.982)**	**(4.644)**	**(4.428)**	**(4.016)**	**(5.933)**	**(5.089)**	**(4.757)**	**(4.829)**	**(4.936)**	**(4.333)**
Odd Lot Non-SP/Assets		-0.002	0.029		-0.247	-0.218		0.125	0.167		-0.376	-0.326
		(-0.008)	(0.094)		(-0.589)	(-0.521)		(0.455)	(0.606)		(-1.131)	(-0.979)
Round Lot SP/Assets			0.356*			**0.713** **			**0.469*** **			**1.054*** **
			(1.718)			**(2.143)**			**(2.695)**			**(4.177)**
Round Lot Non-SP/Assets			-0.030			0.512			0.007			0.375
			(-0.216)			(1.182)			(0.050)			(0.811)
Benchmark Index Excess Return							**0.735*** **	**0.735*** **	**0.734*** **	**0.594*** **	**0.594*** **	**0.592*** **
							(30.323)	**(30.322)**	**(30.295)**	**(26.294)**	**(26.289)**	**(26.224)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	30,947	30,947	30,947	4,821	4,821	4,821	30,947	30,947	30,947	4,821	4,821	4,821
Adjusted R^2	0.0062	0.0061	0.0065	0.0117	0.0116	0.0133	0.5848	0.5848	0.5851	0.4283	0.4283	0.4309

Table A.3. (Cont.)

Panel B. Round lot regressions based upon position mark status

	Net-of-Benchmark Returns						**Net-of-T-Bill Returns**					
	All SP Funds			New SP Funds			All SP Funds			New SP Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
High Mark RL	**2.632*** **	**2.316** **	**2.324** **	**8.650*** **	**8.002*** **	**7.894*** **	**2.654*** **	**2.213** **	**2.215** **	**8.907*** **	**7.492*** **	**7.411*** **
SP/Assets	**(2.950)**	**(2.513)**	**(2.516)**	**(4.038)**	**(3.800)**	**(3.622)**	**(3.025)**	**(2.517)**	**(2.518)**	**(4.059)**	**(3.113)**	**(2.991)**
Medium Mark RL		0.303	0.322		-0.045	-0.280		0.282	0.286		0.201	0.025
SP/Assets		(0.924)	(0.962)		(-0.068)	(-0.409)		(0.985)	(0.979)		(0.363)	(0.043)
Low Mark RL		0.329	0.337		0.153	0.159		-0.326	-0.324		0.551	0.555
SP/Assets		(0.501)	(0.510)		(0.090)	(0.095)		(-0.545)	(-0.539)		(0.343)	(0.350)
Unranked RL		0.292	0.288		0.532	0.535		**0.603** **	**0.602** **		**0.993** **	**0.995** **
SP/Assets		(0.981)	(0.966)		(1.187)	(1.193)		**(2.236)**	**(2.232)**		**(2.277)**	**(2.281)**
Round Lot Non-			-0.066			0.477			-0.015			0.357
SP/Assets			(-0.470)			(1.157)			(-0.105)			(0.773)
Benchmark Index							**0.734*** **	**0.734*** **	**0.734*** **	**0.593*** **	**0.592*** **	**0.592*** **
Excess Return							**(30.272)**	**(30.283)**	**(30.272)**	**(26.414)**	**(26.300)**	**(26.331)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	30,947	30,947	30,947	4,821	4,821	4,821	30,947	30,947	30,947	4,821	4,821	4,821
Adjusted R^2	0.0011	0.0013	0.0013	0.0085	0.0082	0.0083	0.5827	0.5829	0.5829	0.4265	0.4271	0.4271

Panel C. Round lot regressions of disaggregated unranked (<3 marks) position types

	Net-of-Benchmark Returns						**Net-of-T-Bill Returns**					
	All SP Funds			New SP Funds			All SP Funds			New SP Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Single-Fund RL	**1.160** **	**1.182** **	**1.184** **	**2.110** **	**2.117** **	**2.135** **	**1.282*** **	**1.064** **	**1.066** **	**2.468** **	**2.036** **	**2.077** **
SP/Assets	**(2.451)**	**(2.446)**	**(2.449)**	**(2.456)**	**(2.159)**	**(2.165)**	**(2.680)**	**(2.264)**	**(2.268)**	**(2.532)**	**(2.022)**	**(2.037)**
1-Mark RL SP/Assets		-0.284	-0.287		-1.281	-1.421		0.465	0.458		0.446	0.145
		(-0.420)	(-0.424)		(-0.765)	(-0.828)		(0.838)	(0.824)		(0.293)	(0.094)
2-Mark RL SP/Assets		0.314	0.316		2.048	1.970		0.720	0.720		**2.392** **	2.224*
		(0.471)	(0.474)		(1.559)	(1.432)		(1.203)	(1.206)		**(2.023)**	(1.825)
Single-Fund RL Non-			-0.571			7.667			-0.651			**15.315** **
SP/Assets			(-0.783)			(1.133)			(-0.734)			**(1.999)**
1-Mark RL Non-			0.410			2.259			0.631			5.222
SP/Assets			(0.424)			(0.604)			(0.707)			(1.622)
2-Mark RL Non-			-0.112			0.916			-0.007			2.225
SP/Assets			(-0.098)			(0.148)			(-0.007)			(0.423)
Benchmark Index							**0.734*** **	**0.734*** **	**0.734*** **	**0.593*** **	**0.592*** **	**0.591*** **
Excess Return							**(30.270)**	**(30.299)**	**(30.302)**	**(26.235)**	**(26.278)**	**(25.787)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	30,947	30,947	30,947	4,821	4,821	4,821	30,947	30,947	30,947	4,821	4,821	4,821
Adjusted R^2	0.0007	0.0006	0.0005	0.0043	0.0042	0.004	0.5825	0.5825	0.5825	0.4235	0.4238	0.4247

Figure 1. Projected holdings of mismarking fund in (1) odd lots; (2) high-mark round lots; and (3) single-fund round lots throughout first 36 months after launch.

Post-launch paths for month-end holdings generated assuming initial $43.2 million fund that grows to final 36-month horizon value of $3 billion. Monthly returns on round lot positions assumed to equal 0.25%, the January 2010-April 2017 sample average return on Bloomberg Barclays MBS Index. Prepayments on all positions equal 2.5% per month, the sample average prepayment rate for FNMA 6% security during our sample period. Holdings derived from new purchases net of principal repayments. Assets under management and new purchase rates for all three types of positions calibrated using data from the 12 *Highly Questionable* funds.

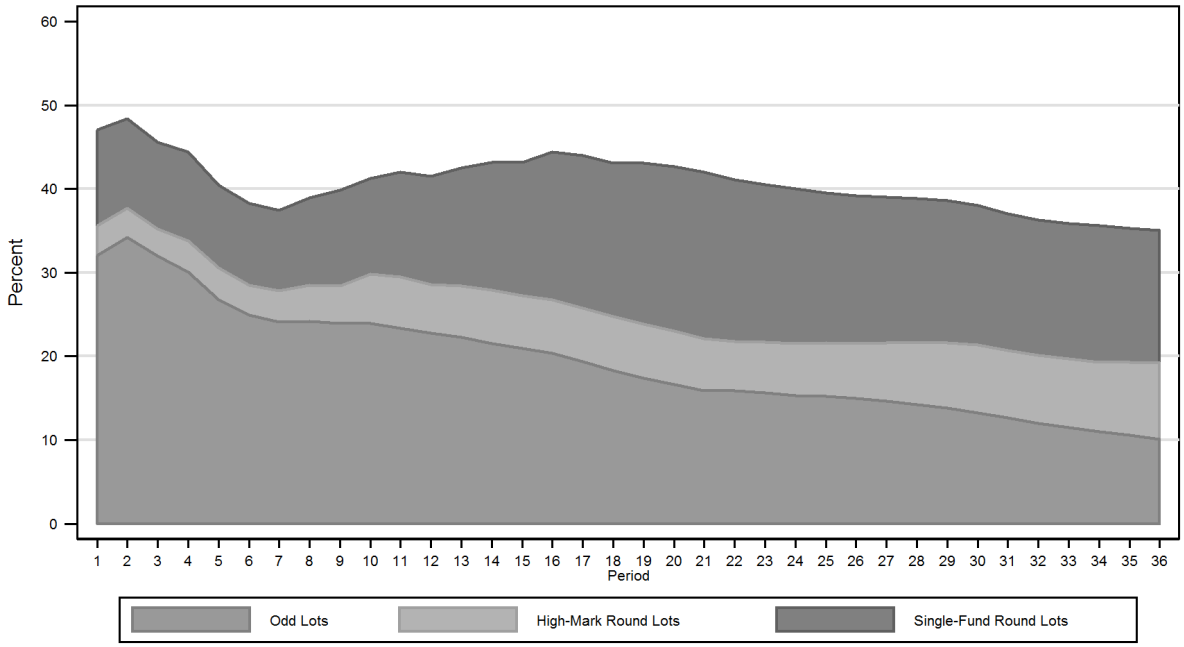


Figure 2. Mismarking and standard fund performance communication: 36-month paths for reported fund values and excess CAR.

Reported values of an initial $10,000 investment in a Mismarking Fund, a Fair Marking Fund, and a Benchmark Fund that invests only in non-mismarking prone round lots are plotted versus the primary (left) axis for the first 36 months after launch. Excess CAR expresses difference of reported Mismarking Fund versus Fair Marking Fund values as an annualized percentage return spread since inception and is plotted versus the secondary (right) axis. We assume a $43.2 million fund that grows to final 36-month horizon value of $3 billion. Monthly returns on round lot positions assumed to equal 0.25%, the January 2010-April 2017 sample average return on Bloomberg Barclays MBS Index. Prepayments on all positions equal 2.5% per month, the sample average prepayment rate for FNMA 6% security during our sample period. Assets under management and new purchase rates for all three types of positions calibrated using data from the 12 *Highly Questionable* funds.

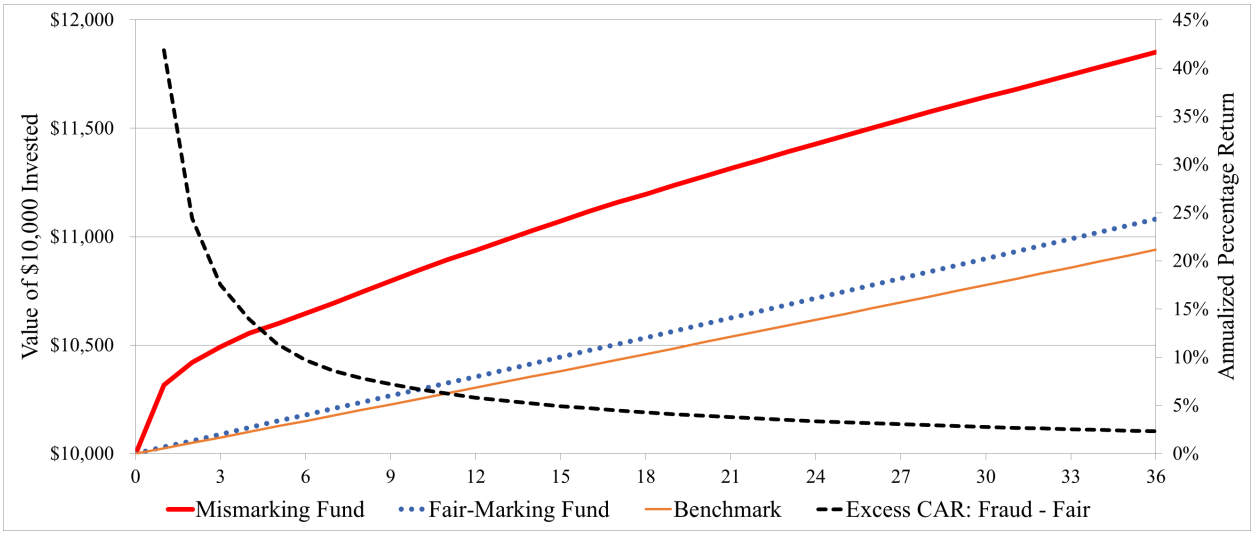
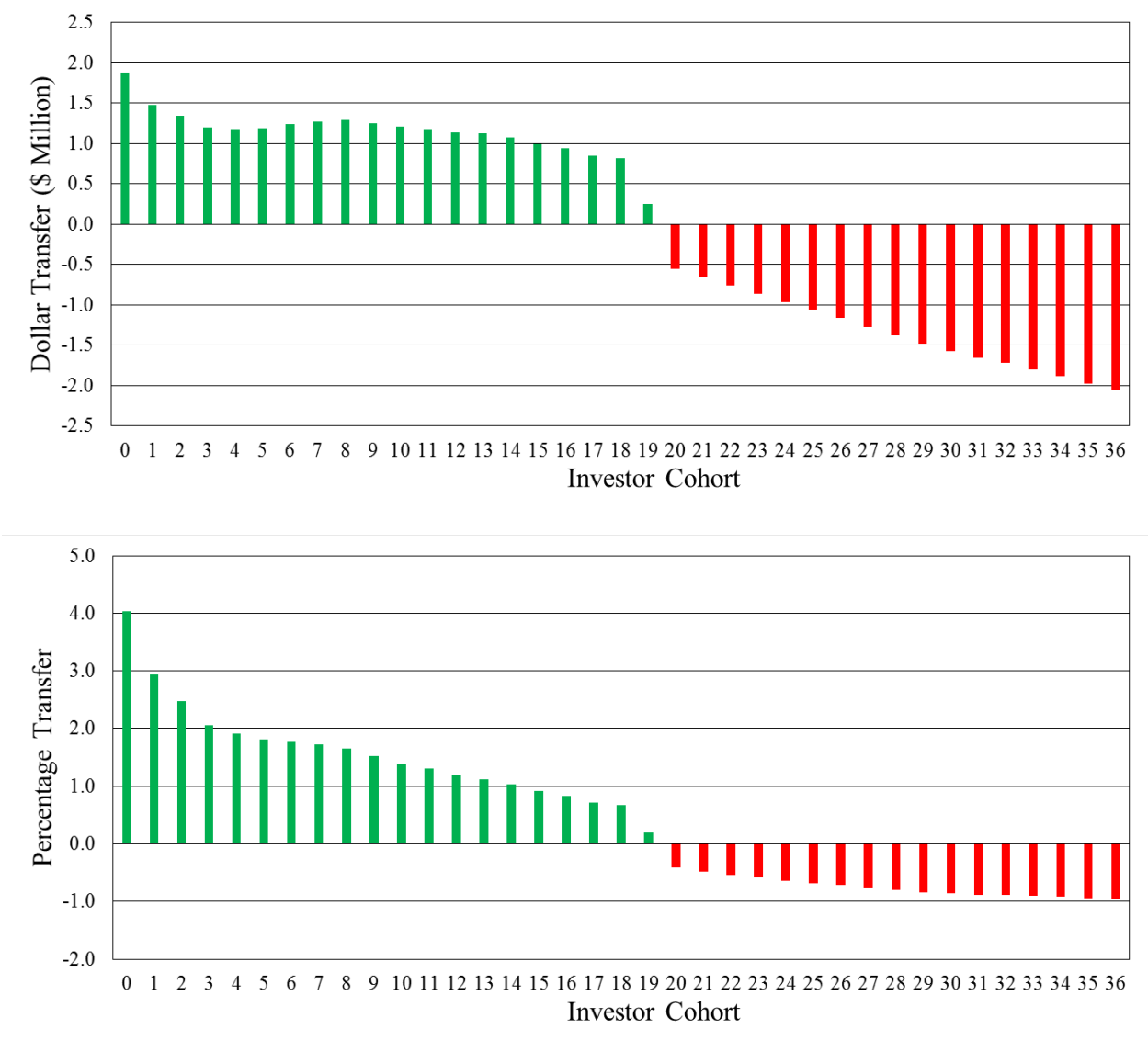


Figure 3. Wealth transfers among investor cohorts.

The calculated transfers assume an initial $43.2 million fund that grows to final 36-month horizon value of $3 billion. Monthly returns on round lot positions assumed to equal 0.25%, the January 2010-April 2017 sample average return on Bloomberg Barclays MBS Index. Prepayments on all positions equal 2.5% per month, the sample average prepayment rate for FNMA 6% security during our sample period. Assets under management and new purchase rates for all three types of positions calibrated using data from *Highly Questionable* funds. We assume an annual redemption rate of 36% (ICI, 2017). The top graph presents gains/losses in $ million of the seed investors (cohort 0) and the 36 investor-cohorts that enter the fund in months 1 to 36. The bottom graph shows percentage gains/losses.