DO INVESTORS' GAINS AND LOSSES FROM SECURITIES FRAUD EQUAL OUT OVER TIME? SOME PRELIMINARY EVIDENCE

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ABSTRACT

The prevailing view in the academy is that providing compensation for securities fraud losses is inefficient. Under this view, because diversified investors that are active traders are as likely to gain from trading in fraud-tainted stocks as they are to be harmed by doing so, these investors should have no (or negligible) net losses from fraud. The preliminary evidence provided in this Article suggests that this view may be wrong. Using observational data on fraud occurrences and computer simulation techniques to model the trading behavior of 16 investor prototypes, I find that not only the individual investor prototypes, which hold few stocks and trade relatively infrequently, but also large numbers of actively trading, diversified institutional investor prototypes, suffer significant net losses from securities fraud over an eleven-year period. These results call into question the claims of fraud compensation opponents who assert that (i) an institutional investor suffers no (or negligible) net harm from fraud over the long-term and (ii) an individual investor can protect herself from fraud-related net harm through proper diversification or investing indirectly through a mutual fund or other intermediary.

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1. Introduction

The conventional wisdom among securities regulation scholars is that diversified investors that actively trade are hedged against the risk of secondary market securities fraud. The view is not merely that securities fraud risk is idiosyncratic and thus diversifiable like many other risks businesses face (Davis Evans 2007).[1] Rather, it is that, for an actively trading diversified investor, gains[2] and losses from secondary market fraud are approximately equal over time. This view appears to have taken hold following the publication of a well-known article by Easterbrook and Fischel in 1985. In this piece, Easterbrook and Fischel (1985, 641) state the following:

> Diversified investors act substantially as if risk neutral…An investor with a diversified portfolio will be the hidden gainer in a transaction [tainted by fraud] as often as he will be a loser. Every losing buyer … is matched with a gaining seller. Over the long run, any reasonably diversified investor will be a buyer half the time and a seller half the time. Such an investor perceives little good in a legal rule that forces his winning self to compensate his losing self over and over.[3]

In an influential article published 11 years later, Alexander (1996, 1502), in connection with a proposal that would eliminate securities litigation and compensation to investors who suffered losses from securities fraud, states:

> The chance of being on the losing or winning side of a transaction when the stock price is distorted by a securities violation can be assumed to be random. The more trades investors make, the more likely that, in the aggregate, their gains from trading while material facts are withheld will equal their losses.

Similarly, Don Langevoort (1996, 646) writes, "[A]ctive traders with large, diversified portfolios have roughly the same chance of being winners as losers from securities fraud, and over time these gains and losses will tend to net out toward zero . . ." Adam Pritchard (1999, 939-940) further suggests that secondary market fraud has no social cost:[4]

> The [securities fraud] victim's loss is also the measure of damages in fraud on the market cases, but here that measure does not correlate with the social costs of the fraud. In fraud on the market, for every shareholder who bought at a fraudulently inflated price, another shareholder has sold: The buyer's individual loss is offset by the seller's gain. Assuming all traders are ignorant of the fraud, over time they will come out winners as often as losers from fraudulently distorted prices. And if the corporation has not been trading in its own securities, the corporation has no gain, and,

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[1] One contrary example is Booth (2007, 13), who asserts, "[t]he risk of simple securities fraud is like any other ordinary business risk."

[2] One does not typically think of any innocent investor as one that benefits from securities fraud. However, the basic premise is that the investor that buys a stock on the open market before fraud causes the stock price to be artificially inflated, but then sells such stock at a time when the price is artificially inflated receives an improper gain on the transaction equal to the amount of the inflation. Thus, this investor unknowingly "benefits" from the commission of securities fraud. The price also could be artificially deflated in the case of "good news" fraud. See Booth (2007) for a brief discussion of good news fraud.

[3] Ultimately, Easterbrook and Fischel caution that eliminating compensation for victims of securities fraud altogether could lead to allocative efficiency losses. Easterbrook and Fischel (1985, 641) state, "[T]he optimal damages in [secondary market fraud] cases are [not] zero just because most gains and losses net out. There will be the usual net harms of the costs of guarding against and litigating about the wrong, and there will be an allocative efficiency loss if transactions of a particular sort create uncompensated risk. The larger the transfer among investors, the more they will spend guarding against the problem." They, however, do go on to argue that any compensation should be significantly less than "the gross transfer of wealth" (641-42).

[4] Pritchard (1999) does note, however, that investors lose in the aggregate in the presence of insider trading.

> therefore, no incentive to spend real resources in executing the fraud. Thus, shareholders would not spend resources to avoid fraud on the market, and corporations would not spend resources to commit it. If these assumptions hold, shareholders should have no expected loss from fraud on the market if the fraud is perfectly concealed until disclosure. (citations omitted)

The subtext (though sometimes stated explicitly) in statements that espouse this view on the netting of gains and losses from fraud is that investors can most inexpensively protect themselves from the risk of fraud by simply diversifying; providing a mechanism for compensation is inefficient. The following statement by Richard Booth (2007, 10-11) is representative of this view:

> In most [securities fraud class actions], diversified investors as a group suffer no financial harm as a direct result of the fraud. Simple securities fraud is a zero-sum event. For every investor who buys and suffers a loss, there is another investor who sells and effectively enjoys a gain (by avoiding a loss). Gains equal losses among traders. In short, most securities fraud class actions amount to a zero-sum redistribution of wealth.
>
> Admittedly, both diversified and undiversified investors may suffer some harm from securities fraud. An undiversified investor who picks a single stock can lose her entire investment. But it does not follow that an undiversified investor should have a remedy if she voluntarily assumes the unnecessary risk that goes with failure to diversify. Again, *it is irrational for a passive investor not to diversify*. Securities law should protect only reasonable investors. A diversified investor is equally likely to be on the winning side of a trade as on the losing side. While a diversified investor with many different portfolio stocks may still suffer harm from an individual trade, the harm is likely to be small. *More important, gains and losses will net out over time. Such investors are fully protected from simple securities fraud through diversification.* They need no remedy (citations omitted, emphasis supplied).

The prevailing view on the netting of gains and losses from securities fraud has significant policy implications. Essentially, the view of Booth and others is that, since it is “irrational” not to diversify, the law should make no effort to provide a remedy (i.e., compensation for securities fraud losses) to those who fail to act reasonably.

For 20 years, the view of Easterbrook and Fischel (2005) was espoused without any empirical data to support or refute it, due in all likelihood to the unavailability of detailed trading data for substantial numbers of institutional and retail investors. In 2005, Thakor et al. published the first piece, to my knowledge, that provides some evidence on the question of whether diversified investors are net losers from securities fraud. The study captured the attention of journalists in the mainstream media (see Glater 2005, Lehn 2006), thus reflecting the importance of this issue to the public more broadly.

In the piece, which was commissioned by the U.S. Chamber of Commerce, a vocal opponent of securities class actions, the authors find that, though undiversified investors can suffer great harm from securities fraud, on average, large, diversified investors essentially break even with respect to fraud-related gains and losses. According to the authors, over a ten-year period, large institutional investors suffer an average (median) net loss of $5 million ($0.25 million). Declaring that the average loss is trivial, the authors conclude that, as a group, large, diversified investors suffer virtually no net harm from secondary market securities fraud and are overcompensated when one factors in recoveries from class actions. There are some instances of extreme outliers in the study, however, and they primarily involve large losses. Of the 2,596 investors in the study, only one investor had a net gain of over $200 million, but 18 investors had net losses in excess of $200 million. Indeed, eight of these 18 investors had losses of over $500 million, and one had a net loss of over $1 billion. Thus, the results of the Thakor et al. study appear to confirm the conventional wisdom: Though there are a few outliers with substantial losses, on average, institutional investors are break even with respect to fraud-related gains and losses.

There are a few features of the Thakor et al. study that should give one pause, however. The universe of institutional investors used in the Thakor et al. study included investment managers with $100 million or more under discretionary management. Such investors are required to file with the Securities and Exchange Commission Form 13F statements that disclose their quarterly investment holdings. The Thakor et al. study uses the quarterly changes in the investment holdings disclosures to infer quarterly stock trades made by large institutions. Though it cannot be avoided given the lack of publicly available information on the trading behavior of institutional investors, one of the limitations of the Thakor et al. study is that Form 13F's on which the study relies aggregate data for fund families without providing any data at the level of any individual fund. Fund families generally contain several funds that pursue a number of strategies and hold a broad swath of the market.[5]

Thus, though the Thakor et al. study represents a tremendous step forward in understanding whether fraud-related gains and losses are equal over time, the study's results cannot, in fairness, be described as representative of the fraud-related gains and losses any individual investor would have experienced over the ten-year study period. Individuals invest in funds, not fund families, and the performance of different funds within a fund family is tracked separately.[6] Therefore, to understand whether any one fund is likely to suffer a net loss from securities fraud, one must somehow isolate the trades for that fund – something that is not possible with currently available public data. Moreover, because the Thakor et al. study relies on the quarterly data provided on Form 13F's, the authors do not have information on the timing of trades by the fund families under study.[7]

This study contributes to this literature by providing information on the effects of fraud on investment returns by using observational data to the extent possible, supplemented by data derived from simulated daily trading behavior, to better understand how investors with different trading strategies fare with respect to fraud. Because of the use of simulation techniques, I am able, despite the previously described data limitations, to offer evidence on the fraud-related gains and losses of investors that trade with different frequencies and hold portfolios of varying sizes. Also, because individual investors are often advised to invest in index funds as a means of inexpensive diversification, this study provides evidence, using only observational data, on the gains and losses of an investor whose trades tracked the changes in the S&P 500 over an eleven-year period.

Using available data on the trading behavior of mutual funds and individual investors, I give each of the 16 investor prototypes characteristics consistent with real-world investors. In a 2,000 iteration simulation over an eleven-year period, I find that though a number of investors enjoy significant net gains from fraud-related trading, many (indeed, more) investors incur substantial net losses. Though broadly diversified investors fare better than investors with less complete diversification, these results call into question the claims of investor compensation opponents who assert that institutional investors should

[5] For example, the 13F filed by Janus reflects the holdings of the entire family of Janus funds, not just a single fund. According to Janus' website (ww4.janus.com, last viewed on November 1, 2007), Janus offers retail investors 19 equity funds and three asset allocation funds (with portfolios that contain a mix of stock and other securities) that follow a variety of investment strategies and invest in stocks of companies of various sizes. It is likely that when aggregating all of the holdings of these 22 funds, a large portion of the market is included.

[6] According to a survey of institutional investors by Cox and Thomas (2005), investment managers sometimes place recoveries from securities class actions in their general fund, rather than allocating such recoveries to the specific fund portfolio that held the stock and suffered the loss. To the extent that this practice occurs with some frequency, analyzing net gains and losses on a fund family basis may be worthwhile.

[7] The authors assume, in three different analyses, that changes in holdings between quarters are made either at the end of the quarter, the middle of the quarter or in proportion to observed trading volume during the quarter.

suffer no net harm from fraud over the long-term and that individual investors could protect themselves from fraud by more complete diversification or investing through mutual funds or other intermediaries. However, the evidence in this study, does suggest that had an investor mimicked the behavior of the S&P 500 over an eleven-year period, it would have been essentially break even with respect to gains and losses from fraud.

The Article proceeds as follows. Section 2 describes the data, sample used, and simulation methodology of the study and presents preliminary results. Section 3 concludes and briefly considers the policy implications of this study's findings.

2. Data Sources, Sample, Methodology and Results of Analysis

2.1 Data and Sample

The period of this study is January 1, 1996 – December 31, 2006. This project requires a sample of stocks whose prices are inflated by fraud. To generate this sample, I begin with the list of all post-Private Securities Litigation Reform Act (PSLRA) class action settlements from 1996 – 2006 alleging common stock price inflation due to fraud, as reported by Cornerstone Research and identified in Institutional Shareholder Services' Securities Class Action Services (SCAS) database.[8] From this list of 827 settlements, I exclude stocks with class action periods of fewer than three days,[9] stocks where the alleged fraud did not affect secondary market trading prices, and stocks with class action periods that did not overlap with the study period.[10] I also add to the sample additional class action settlements for firms with multiple suits during the study period. Following these adjustments, a sample of 818 settlements remains. From this list of 818 settlements, I exclude 14 firms for whom the Center for Research & Security Prices (CRSP) has no stock price data and 151 settlements in which there was less than a 5% stock price decline of the defendant corporation at the end of the class action period.[11] This leaves me with a final sample consisting of 653 settlements.

Instances of "fraud" are assumed to be only those cases where a class action lawsuit for fraud was settled. This, of course, is an imperfect proxy for the incidence of fraud. For sure, there are instances where no fraud occurs, but a corporation settles a suit without merit to avoid the time and expense of protracted litigation. Conversely, there are instances where fraud occurs, but no suit is brought because the fraud cannot be proven or because the potential recovery is not high enough to attract the attention of a plaintiffs' lawyer.[12] In the context of this study, this is of little concern because I am calculating both

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[8] Laura E. Simmons & Ellen M. Ryan, Cornerstone Research, Securities Class Action Settlements, 2006 Review and Analysis 6 (2007), available at http://www.cornerstone.com/pdf/practice_securities/2006Settlements.pdf.

[9] A meaningful inflation ribbon cannot be computed for a class action period of such short duration.

[10] Since my hypothetical traders all purchase their initial portfolios on January 1, 1996, there would be no chance of the traders buying such stocks at inflated prices.

[11] This exclusion is consistent with the approach taken by Thakor et al. (2005). Thakor et al. write:

> An end-of-period stock price decline of less than 5.0 percent for a defendant company suggested to us a set of circumstances in which the constant inflation ribbon method would not produce an inflation estimate that was generally consistent with the claims made in the class action litigation (app. I, 3).

In addition to the reason for the exclusion set forth by Thakor et al., there are some firms in the sample for which a series of corrective disclosures were made before the end of the class action period, with only the "final truth" coming to light at the end of the class action period. In this case, it is possible that no discernible stock price decline will be observed at the end of the class action period.

[12] It is also possible that a suit is brought, but there is insufficient evidence of fraud for the case to make it past the motion to dismiss, thus ending any hope of the plaintiffs reaching a settlement with the defendants.

gains and losses from fraud, so the fact that my sample of fraud case is over- or underinclusive should not affect these calculations.

I acquire several additional types of data from a variety of sources. I secure split-adjusted closing stock prices and shares outstanding data from the CRSP database. Data on the composition of the S&P 500 at the beginning of the study period (January 2, 1996), as well as that which details changes in the composition of the S&P 500 from 1996-1999, are from Standard & Poor's Index Services. Data on composition changes from 2000 – 2006 are from the Standard & Poor's website (www.standardandpoors.com). I obtain data on class action periods directly from SCAS. The universe of stocks included in the simulation (serving as a proxy for the overall market) consists of every common stock (15,235) appearing in the CRSP database during the 11-year study period. Data on mutual fund characteristics was taken from the Morningstar database.

In the simulation, I analyze fraud by type. Specifically, I consider fraud-related gains and losses from frauds that purportedly affected only secondary market trading prices ("secondary market frauds"), as well as gains and losses from all frauds because these frauds still affected secondary market prices until the fraud was uncovered. I read the class action allegations for each of the 827 settlements considered for this study and coded each settlement by type of fraud ((1) fraud affecting secondary market prices only, (2) secondary market combination (that is, frauds that affected secondary market prices, as well as some other transaction such as a primary offering of securities), (3) fraud in connection with primary market offerings, and (4) fraudulent statements issued in connection with mergers and acquisitions transactions). I obtain the class action allegations from the SCAS database or from the Stanford Securities Class Action Clearinghouse or press reports when the SCAS database description of the allegations made it difficult to code the type of fraud with confidence.

2.2 Methodology

2.2.1 Investor Types

In this study, I simulate the trading behavior of 16 investor types. Table 1 describes the characteristics of these investor types. Each investor type differs based on the following characteristics: (1) trading strategy, (2) initial capital invested and percentage of capital invested held in cash, (3) number of stocks in the portfolio and (4) number of trades per year and over the course of the simulation.

Trading Strategy

I employ three types of trading strategies in the simulation: (1) random selection, (2) random selection of "popular stocks" only and (3) S&P 500 parallel. Investors employing the random selection strategy begin with a computer-generated random initial portfolio of stocks. The computer program, developed specifically for this project, also randomly selects stocks for these investors to buy and sell.[13] The investor employing the random selection of popular stocks strategy makes random buy decisions from a universe comprised only of the 25 most actively traded stocks in a given year. The investor following the S&P 500 parallel strategy purchases, on the first trading day of the simulation (January 2, 1996), all 500 stocks comprising the S&P 500 on that date in the proportions each stock represents of the S&P 500. Throughout the simulation, this investor sells stocks in its portfolio when such stocks are removed from the S&P 500 and purchases stocks that are added to the S&P 500 on the dates such stocks are removed or

[13] There is one exception to this general rule. When a stock held in an investor's portfolio ceases trading (e.g., because it files for bankruptcy or is acquired), the investor sells that stock on its last trading date and then re-invests the proceeds in another randomly selected stock.

added. In addition, this investor rebalances its portfolio once a quarter to maintain relative weightings, by market capitalization, of the stocks in its portfolio.[14]

Initial Capital Invested and Cash Reserves

"Initial Capital Invested" represents the amount of cash an investor has available to purchase stocks during the simulation period. At the beginning of the simulation, the investor purchases stocks with total dollar values equal to, as near as possible, the amount of initial capital invested. Throughout the simulation, when the investor sells a stock, it purchases shares of another stock as quickly as possible in an amount equal, as near as possible, to the amount of proceeds it received for the sold stock. In some cases, certain investor types do not invest 100% of their available assets, but rather hold a certain percentage in cash. These amounts are "cash reserves." Typically, mutual funds hold some small percentage of assets in cash or other highly liquid securities to meet shareholder redemption demand.

Number of Stocks in the Portfolio

At the beginning of the simulation, each investor begins with a portfolio consisting of a pre-set number of stocks, and this number of stocks generally does not vary during the simulation.[15]

Number of Trades per Year and Over the Course of the Simulation

In the simulation, a "trade" is a simultaneous (or near simultaneous) sale and purchase of a stock. During the simulation, most investors execute a pre-set number of trades each year in equal intervals of trading days over the course of the year. Multiplying this yearly total by 11 yields the total number of trades during the simulation period. However, the investor mimicking the S&P 500 trades on the dates stocks are added to, or removed from, the S&P 500.

Investor Type Characteristic Selection

The investor characteristics used in this simulation are consistent with characteristics observed among actual investors. Investor types 1, 2, 3, 4, 5 and 6 share characteristics with actively traded mutual funds. To obtain information on the trading behavior of large, diversified institutional investors, I performed a search in the Morningstar database for information on all domestic equity mutual funds in the United States.[16] Appendix A describes the search parameters. In the simulation, I use prototypes that are representative of the typical mutual fund (average and median), as well as those at both extremes (that is, mutual funds that hold portfolios with the highest and lowest number of stocks and those that trade most and least frequently). For the 333 funds in the search results, the average fund has total assets of

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[14] As is the case with the S&P 500 Equal Weight Index (see Standard & Poor's 2006 at 6), in this simulation, rebalancings occur on the third Friday of each month that ends a calendar-year quarter (March, June, September and December). If a stock is purchased in the middle of a quarter, it takes on the weight of the stock it replaces. The S&P 500 index, on which Investor 16 is modeled, does not rebalance on a fixed schedule. However, replicating the schedule of rebalancing in the context of this study is not practicable given data acquisition costs.

[15] The number of stocks held by the investor mimicking the S&P 500 may not always total 500 because the S&P 500, on occasion and for very brief periods, is comprised of fewer than 500 stocks.

[16] I performed the search after the market close on July 19, 2007. Though these observed characteristics apply only to domestic equity mutual funds, they are representative of actively trading institutional investors overall. It should be noted that available evidence does suggest that mutual funds generally trade more actively than pension funds (see figures in Davis Evans 2007, app. 2). In addition, it should be noted that the characteristics simulated are those of mutual funds today. The portfolio composition and trading frequency of investors during the study period (1996-2006) could differ significantly from today's investor characteristics. That said, since this is a simulation that attempts to demonstrate how investors of varying types would have fared with respect to fraud, and not an attempt to specify how any particular investor fared during the study period, this is of limited concern.

approximately $547 million, with 3.5% in cash reserves, 89 stocks in its portfolio, and 81% turnover.[17] Investor 1 in the simulation is modeled on this investor type. The median fund has total assets of $109 million, with 1.5% in cash reserves, 60 stocks in its portfolio, and 59% turnover and provides the parameters for Investor 2 in the simulation. The average fund in the top decile (by diversification), represented by Investor 3 in the simulation, has total assets of approximately $1.1 billion, with 2.5% in cash reserves, 300 stocks in its portfolio, and 97% turnover. The average fund in the top decile (by trading frequency) has total assets of approximately $325 million, with 1.9% in cash reserves, 120 stocks in its portfolio, and 263% turnover and provides the parameters for the simulation's Investor 4. The average fund in the bottom decile (by diversification) has total assets of approximately $532 million, with 7.1% in cash reserves, 24 stocks in its portfolio, and 45% turnover. Investor 5 in the simulation is modeled on this investor type. Finally, Investor 6 is modeled on the average fund in the bottom decile (by trading frequency), which has total assets of approximately $1.1 billion, with 4.4% in cash reserves, 76 stocks in its portfolio, and 9% turnover.

Investor types 7, 8, 9, 10, 11, 12, 13, 14 and 15 share characteristics with individual investors. According to survey data produced by the Investment Company Institute and the Securities Industry Association ("ICI/SIA"), in 2005, of 744 retail investors surveyed, the average (median) investor owned eight (four) stocks and had individual stock assets of $199,400 ($35,000) outside of employer retirement plans (Equity Ownership in America Appendices, 7, fig. E.4). According to a survey of 2,187 individual investors, 60% of these investors did not engage in any trades in 2004 (Equity Ownership in America, 25, fig. 34). Of the 40% that did trade, 57% traded five or fewer times during the year, and 79% traded 12 or fewer times during the year (Equity Ownership in America, 25, fig. 34).[18] In the simulation, Investor types 7 – 12 reflect the average and median stock ownership attributes described above and either trade 0 times per year, five times per year, or 12 times per year.

According to Meir Statman (2004), though a portfolio consisting of approximately 300 stocks is optimal for diversification today, in prior periods, according to researchers, portfolios consisting of 20 stocks or 30 stocks could afford sufficient, or even optimal, diversification. In the simulation, Investor type 13 holds a portfolio of 20 stocks, and Investor type 14 holds a 30-stock portfolio. Barber and Odean (2000) find that the average retail investor (household) portfolio has 75% turnover. Therefore, to model this trading behavior, in the simulation, Investor types 13 and 14 have a 75% turnover rate. Their total assets for investment are $200,000, approximately equal to the invested assets of the average individual investor surveyed by the ICI/SIA.

Investor 15 also has $200,000 available for investment, but holds a 10-stock portfolio. It chooses its investments from among a group of "popular stocks." "Popular stocks," for the purpose of the simulation, are the 25 most actively traded stocks (excluding exchange-traded funds) in a given year.[19] Barber and Odean (forthcoming) find that individual investors are attracted to stocks that capture their attention, for a number of reasons including large price moves, abnormally high trading volume and media coverage. Investor type 15 is designed to mimic an investor that trades only attention-grabbing stocks.

Investor type 16 mimics the behavior of an S&P 500 index fund and thus holds 500 stocks and buys and sells stocks when such stocks are added or deleted, respectively, from the S&P 500. Investor 16 begins with an initial portfolio of $361.5 million, an amount equal to the invested assets of the median S&P 500

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[17] Morningstar, consistent with general practice, defines turnover as the lesser of the amount of purchases or sales of securities during a year divided by average monthly net assets. In the simulation, the turnover statistics were translated into a number of trades per year.

[18] Note: The study defines an equity trade as either the sale or purchase of a corporate stock or shares in a mutual fund. Thus, the numbers used in the simulation likely overstate the level of trading activity by individual investors.

[19] Volume data is derived from CRSP.

Index Fund, according to the results of a Morningstar database search of S&P 500 index funds (n=38) as of December 17, 2007.

To facilitate comparisons among investor types, in a separate set of simulations, I hold portfolio assets and cash reserves constant at $1 million and 0.0%, respectively, for all investors.

2.2.2 Calculating Gains and Losses from Fraud

Consistent with the approach taken by Thakor et al. (2005), I calculate an investor's loss (gain) from fraud as the amount by which the price of the stock is inflated because of the fraud, multiplied by the number of shares purchased (sold) while the fraud is ongoing (that is, during the reported class action period). The amount of inflation per share is equal to the difference between the stock price one trading day before the end of the class action period and the price on the trading day after the class action period ends.[20] As Thakor et al. explain, this is the constant inflation ribbon method, which assumes that the decline in the company's stock price at the end of the class action period (purportedly when the bad news is disclosed) reflects the amount by which the price was inflated because of prior misrepresentations. This level of inflation is assumed to be constant throughout the class period.[21]

I recognize, as noted by Thakor et al., that the price drop upon disclosure is not a consistently reliable way to measure the level of inflation in a stock due to fraud. Moreover, assuming the amount of inflation stays constant throughout the study period also is not realistic. However, just as in the Thakor et al. study, since I use the same method, albeit flawed, to compute both gains and losses from fraud, the results should not be biased and should provide a rough approximation of how investors benefit and lose from fraud.[22]

I perform these calculations for gains and losses from all types of fraud, as well as for gains and losses exclusively from fraud coded as Type 1 (that which affects secondary market prices only).

2.3 Study Limitations

When interpreting this study's results, one must be mindful of certain limitations. First, except with respect to Investor 16, which mimics the S&P 500, the trading decisions of all investor types are guided by random selection. Thus, the results for the investor types profiled in this study may not be representative of the results an investor that follows a particular strategy (e.g., buying only large cap stocks, growth stocks or healthcare stocks) would achieve. In addition, because there are innumerable potential combinations of stock selections,[23] this study, through its use of 2,000 trials per investor type, provides a narrow view of the potential outcomes that any investor could expect. However, 2,000

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[20] Similar to the approach taken by Thakor et al. (2005), in this simulation, with respect to the gain or loss for any one investor, the amount of gain or loss is limited by the price at which the investor buys or sells the stock. For example, if the amount of inflation in a fraud-tainted stock is assumed to be $8 per share, and an investor purchases the stock during the class action period for $7 per share, the investor's loss from fraud is equal only to $7, not $8 per share. This investor is not permitted to "lose" a greater amount than its initial investment in the firm.

[21] As noted in Section 2.1 above, stocks that experienced a price decline of less than 5% at the end of the class action period are excluded from the study.

[22] Similarly, the gains and losses from fraud are not inflation- or market-adjusted. Therefore, the gains and losses in the late 1990's during the tech bubble are likely to be large relative to gains and losses in, for example, 1996. However, since I am calculating both gains and losses, the difference in the likely dollar value of gains and losses over the years should not bias the overall conclusion with respect to whether investors are on the winning side of trades tainted by fraud as often as they are on the losing side. Indeed, this is the way investors actually would experience gains and losses.

[23] Recall that there are 15,235 potential stocks to choose over an 11-year period.

iterations represents a sufficiently large sample to give some comfort as to a reasonable mean outcome and to assess the range of potential outcomes.

Second, this study assumes that the amount of inflation in a stock is the amount of gain to an investor who unknowingly sells while fraud is ongoing and the amount of loss to the investor that buys while the fraud is ongoing. However, as I discuss elsewhere (Davis Evans 2007), in reality, there is a fundamental asymmetry between purported gains and losses. When fraud is revealed, the firm's stock price usually does not decline only to the price that should prevail in the absence of fraud. Instead, the price typically declines by an additional amount to account for the uncertainty surrounding what additional negative disclosures may be forthcoming or what effect the legal process, in the form of lawsuits and government investigations, will have on the company going forward. Therefore, because this study assumes that gains and losses from fraud are equal, it, in all likelihood, underestimates the extent of net losses from fraud. That said, since the basic results, as described below, demonstrate that, on average, all types of investors are net losers from fraud, were I to adjust the net loss/gain calculation to account for the asymmetry described above, this would only further support the principal conclusions of this Article.

2.4 Results

2.4.1 All Frauds – Institutional Investors

The results of this simulation allow one to test the assertions of those who argue that compensation for fraud losses is unnecessary for large, diversified investors. Tables 2, 3 and 4 present the results for simulations that calculate gains and losses from all four types of fraud. First, Investor 16, whose trades follow actual changes in the S&P 500 index, encounters fraud-tainted stocks during the simulation. As shown in Table 2, the average or median institutional investor prototypes and those that are in the top decile by diversification or trading frequency are almost certain to buy or sell a stock tainted by fraud over an extended period. In all or almost all of the 2,000 iterations performed in the simulation, Investors 1, 2, 3 and 4 traded at least one stock whose price was inflated because of misrepresentations. However, Investors 5 and 6, representing the institutions that hold the fewest stocks and trade the least, only encounter a fraud-tainted stock 65% or 66%, respectively, of the time. This result is consistent with the intuition that the more stocks one holds and the more frequently one trades, the more likely one is to trade a fraud-tainted stock.

The results of this study reveal that Investor 16, which mimics the S&P 500, enjoys a net fraud-related gain of $311,539, which represents 0.086% of initial capital invested. For the eleven-year period of this study, the S&P prototype investor is essentially breakeven with respect to fraud-related trading, thus giving some credence to the arguments of the anti-compensation camp. Investor 16 is a highly diversified investor (indeed, it essentially holds the market portfolio) that trades fairly frequently.

However, the results of this study suggest that the breakeven outcome achieved by the S&P 500 prototype is not likely for most institutional investors. Though the compensation critics argue that, over time, gains and losses from fraud will be approximately zero, this simulation demonstrates that, on average, the large institutional investor prototypes are net losers from fraud over an 11-year period.[24] Investor 1, which begins the simulation with $547 million in invested capital, suffers a mean net loss over the course of 2,000 simulation iterations of $4.9 million. Similarly, Investor 2, which begins the simulation with $109

[24] With one exception, this result is statistically significantly different from zero. The 95% confidence intervals for the mean gain/loss for all investors, except Investors 1 and 3, contain only negative numbers and do not include the value "0," which suggests that the mean gains and losses for almost all the investor prototypes are negative and statistically significantly different from zero. In a 10,000 iteration simulation run for Investor 1, the 95% confidence interval includes only negative numbers and does not include the value "0." With respect to Investor 3, the most diversified investor in the simulation, I cannot reject the null hypothesis that over time the average investor's gains and losses from fraud will be zero.

million in invested capital, suffers a mean net loss of $1.5 million. Investor 3, with an initial $1.1 billion portfolio, experiences an average net loss of $8.2 million, while Investor 4, which begins the simulation with $325 million in capital, experiences an average net loss of $6.8 million. Investors 5 and 6, which have initial capital of $532 million and $1.1 billion, respectively, suffer average net losses of $19.7 million and $11.8 million, respectively.

Though the institutional investor prototypes, on average, suffer net losses from fraud-related trading, on a percentage basis relative to initial capital, the net losses are small. For example, the percentage of initial capital represented by the average net losses of Investors 1, 2, 3, 4, 5 and 6 are 0.9%, 1.4%, 0.8%, 2.1%, 3.7%, and 1.1%, respectively. These net losses seem even smaller when put in context because they occur over an 11-year period. However, there is a competitive marketplace for investor assets, so even large institutions generally are not indifferent to seemingly small differences in losses that can have an economically significant effect on returns and the ability to attract or retain investors. That said, given the relatively small average net losses of the simulated investor prototypes, the arguments of the anti-compensation camp appear to be correct with respect to what institutional investors might experience on average.

However, the results of the simulation provide a more nuanced view of how institutional investors fare that can go beyond a mere assessment of average net gains and losses. The results demonstrate that it is possible for investors to experience significant fraud-related losses or gains. The average mutual fund prototype, Investor 1, has simulated results that reveal a maximum net loss of $9.4 billion and a maximum net gain of $9.4 billion.[25] Both the maximum net loss and gain are 17 times as large as the investor's initial capital amount. Similarly, Investor 2, the median mutual fund prototype, has a maximum net loss of $206.7 million and a net gain of $231.1 million, both approximately twice as much as this investor's initial capital. For Investor 3, the highly diversified institutional investor prototype, the maximum net loss is $6.5 billion (more than six times initial capital), and its maximum net gain is $10 billion (more than nine times initial capital). Investor 4, the highly active trading institutional investor prototype, has a maximum net loss of $3.2 billion (almost 10 times initial capital), and its maximum net gain is $2.1 billion (more than six times initial capital). The investors with low diversification, Investor 5, and low trading frequency, Investor 6, have maximum net losses of $857.1 million (1.6 times initial capital) and $1.2 billion (1.1 times initial capital), respectively. Their maximum net gains are $378.9 million (0.7 times initial capital) and $900.2 million (0.8 million times initial capital), respectively. Both Investors 5 and 6 have highs and lows that, relative to initial capital amounts, are much lower than those of Investors 1-4. However, no investment manager would consider even these figures trivial.

One could argue that these are figures at the extreme and not necessarily typical of what an investor would be likely to experience. However, the results of this simulation demonstrate that investor loss amounts steadily decrease or increase to very large values and thus, an investor's gain/loss experience could take on any number of plausible values, including very large negative ones. The anti-compensation critics generally argue that, though there may be some outliers (at either the positive or negative extreme), generally, fraud-related gains and losses will net out over the long term, putting almost all diversified investors at the "0" location on the distribution curve. Consider the following statement by Alexander (1996, 1502, n.58):

> Of course, the offsetting of gains against losses reflects statistical probabilities; some individual investors will be net gainers or net losers. The more trades that are made and the more diversified the investments, however, the more an individual's experience is likely to approach the statistical mean.

[25] It is possible for an investor to have a net loss or gain that exceeds its initial capital investment because over the 11-year period, the value of the investment portfolio grows significantly, thereby exposing investors to the risk (opportunity) of large net losses (gains).

The evidence in this simulation suggests that this view does not apply to the experience of the typical institutional investor. What we might expect to see if this view were correct would be several gain/loss figures clustered near a mean of zero or almost zero, with a few outlier values on either side. However, in this simulation, what is observed instead appears in Figures 1a, 2a, 3a, 4a, 5a, and 6a. Figures 1a, 2a, 3a, 4a, 5a, and 6a show histograms of winsorized (at the 10% level at the top and bottom of the distribution) average gain and loss values for Investors 1 – 6. Note that though the modal gain or loss hovers near zero in all cases, there is not near universal clustering of gains/losses near zero.

The histograms in Figures 1a, 2a, 3a, 4a, 5a, and 6a show winsorized values for the top and bottom of the distribution so the reader may more clearly see the values of the gains and losses for 80% of the investors in a particular simulation. Because of the large dispersion of values (i.e., the extreme values on either end), the differences in the middle 80% are lost due to the scaling of the graph. Reviewing the histograms reveals that the distribution of gains and losses for Investors 1 – 4 (the most diversified and active traders of the mutual fund prototypes) are almost "normal" distributions, contrary to the conventional wisdom. However, the histograms of Investors 5 and 6 show more variability than that of Investors 1 – 4, likely due to Investor 5 and 6's low level of diversification or trading.

Figures 1b, 2b, 3b, 4b, 5b and 6b show scatter plots of all the values in the winsorized tail that fall at the bottom 10% of the distribution (i.e., the greatest losses).[26] What becomes apparent after reviewing the histograms in connection with the scatter plots is that, unlike the prediction seemingly made by Alexander (1996) which suggests that though there will be "some" outliers, almost all institutional investor net gains/losses will hover around zero, the simulated net loss values steadily progress from a negligible amount almost to the maximum loss value for an investor prototype. For example, in Figure 1b, one is able to see that there is a continuous stream of points all the way to a $959.6 billion net loss before the line "breaks" immediately before what could be considered the values of outliers. Values up to the "break" represent a net loss of up to 175.4% of Investor 1's initial capital invested. Similar "breakpoint" values for Investors 2, 3, 4, 5 and 6 are $59.8 million (54.9% of initial investment) as seen in Figure 2b, $1.5 billion (142.3% of initial capital) as seen in Figure 3b, $393 million (120.9% of initial capital) as seen in Figure 4b, $325.2 million (61.2% of initial capital) as seen in Figure 5b, and $137.3 million (12.6% of initial investment) as seen in Figure 6b, respectively.

2.4.2 All Frauds – Individual Investors

The results for the basic individual investor types (Investors 7 – 14) generally conform to the expectations of researchers. Investors with small portfolios who trade infrequently rarely purchase stocks tainted by fraud. Indeed, Investor 10, with a four-stock portfolio that she never trades, does not buy a fraud-tainted stock in any of the 2,000 iterations performed. Investor 7, who has a portfolio consisting of eight stocks and who also never trades, buys a fraud-tainted stock only 0.1% of the time. In the two instances when Investor 7, who begins the simulation with initial capital of $199,400, does buy a fraud-tainted stock, she suffers a net loss of $24,916 and $24,920. Investor 7, of course, cannot enjoy any gains from fraud because she does not sell any of the stocks in her portfolio during the simulation. Thus, buy and hold investors (in the most literal sense of the phrase) can only be net losers from fraud if they encounter a fraud-tainted stock (see Davis Evans 2007).

Investors 8, 9, 11, 12, 13, and 14, because they trade during the simulation, encounter at least one fraud-tainted stock far more frequently (in 36.0%, 68.7%, 37.2%, 69.0%, 74.1%, and 87.4%, respectively, of the iterations) than Investors 7 and 10. Moreover, in an average of 88.6% of the iterations for each of these

[26] I only provide scatter plots for the values at the bottom of the distribution in this piece. However, scatter plots for values at the top of the distribution (i.e., the largest gains) reveal a similar pattern to the graphs shown in this Article.

investor types, the investor is a net loser. In addition, in all these cases, the investors, on average, experience fraud-related net losses. Though the average net losses appear to be relatively modest ($18,535, $21,320, $6,037, $7,115, $10,129, and $6,073 for Investors 8, 9, 11, 12, 13, and 14, respectively), as a percentage of initial invested capital, they can be substantial as they range from 3% (for Investor 14, the most diversified individual investor (30 stocks)) to 20.3% (for Investor 12, one of the least diversified investors (4 stocks)).

In addition, there are extreme outliers. Though the highest recorded net gain in an iteration for Investors 8 and 9 (portfolio of 8 stocks, $199,400 of initial capital) is $70,688 and $263,918, respectively, the highest net loss is $248,289 and $495,636, respectively. Similarly, the highest recorded net gain in an iteration for Investors 11 and 12 (portfolio of 4 stocks, $35,000 of initial capital) is $49,825 and $37,354, respectively, and the highest net loss is approximately $67,215 and $154,295, respectively. Moreover, the highest recorded net gain in an iteration for Investors 13 and 14 (portfolio of 20 or 30 stocks, $200,000 of initial capital) is $267,756 and $132,574, respectively, and the highest net loss is approximately $331,272 and $618,466, respectively. As a percentage of initial capital, the maximum net gain for these investors ranges from 35.5% (for Investor 8 with eight stocks and moderate turnover) to 142.4% (for Investor 11, one of the least diversified investors (4 stocks) with relatively moderately high turnover). However, the maximum net loss for this group of investors ranges from 124.5% (for Investor 8) to 440.8% (for Investor 12, one of the least diversified investors (4 stocks) with high turnover). Overall, these results suggest that the typical retail investor is almost certain to find herself on the losing side of trades tainted by fraud more than on the winning side, and such losses can be substantial.

Investor 15 (10-stock portfolio, $200,000 in initial capital, high turnover, and ownership of only popular stocks) encountered fraud in 99.2% of the iterations – a higher percentage than any of the other individual investor prototypes.[27] Investor 15 was a net loser in 67.8% of the iterations, with an average net loss of $8,482 (4.2% of initial invested capital). The highest recorded net gain for Investor 15 was $133,005, and the highest net loss was $118,032.

2.4.3 All Frauds – Relative Results

To better understand the relative performance of investors, I performed simulations in which all investor characteristics were identical to the ones described in Section 2.2.1 above, with two key exceptions: the initial capital was held constant at $1 million and no investor held any cash reserves. Table 3 contains the results of this simulation. The results generally are qualitatively similar to the results described in Sections 2.4.1 and 2.4.2, but they allow the researcher to make some comparisons across investor strategy. As Table 4, which displays the results from Table 3 sorted by average net trading gain/loss, reveals, Investor 16, the S&P 500 index fund prototype, fared the best in the simulation, with a small net gain, and was followed by Investor 3, the mutual fund prototype with a high level of diversification (300 stocks), which, on average, suffered a modest net loss. Investor 4, the mutual fund prototype that trades the most frequently (turnover of 263%), follows Investors 16 and 3. This result is not surprising, as one might expect an investor with a large portfolio that actively trades to suffer the least, on a net basis, from securities fraud. Similarly, at the other end of the spectrum, Investors 11, 12 and 10, the least diversified investors, all with only four-stock portfolios, fared the worst in the simulation.

The ranking in the middle is perhaps a bit more surprising. For example, four individual investor prototypes (Investors 14, 7, 13, and 15 with portfolios consisting of 30, 8, 20 and 10 stocks, respectively) fared better, on average, than the average mutual fund prototype (Investor 1, with an 89-stock portfolio) and the median mutual fund prototype (Investor 2, with a 60-stock portfolio). Ignoring Investor 7, who

[27] This is understandable given Investor 15's strategy of only purchasing the 25 most active stocks – stocks of large companies with heavy trading volume are, all else being equal, attractive targets of securities fraud litigation.

never trades and only encounters fraud in one iteration, thus making it hard to generalize about an investor of this type's likely experience, all the other individual investor prototypes (Investors 14, 13, and 15) have higher turnover rates than Investor 2, and turnover rates that exceed or rival Investor 1. These results suggest that number of stocks in a portfolio may be most influential in determining net losses or gains, but that the level of trading also plays a substantial role.[28]

The performance of Investors 5 and 6 is puzzling. Investor 6, the mutual fund prototype with the lowest turnover (9%), but a reasonably diversified portfolio (76 stocks), fares better than Investors 1 and 2, both of which trade far more frequently than Investor 6. In addition, Investor 6 has slightly fewer stocks in its portfolio than Investor 1 (76 stocks versus 89 stocks). Investor 5, the mutual fund prototype with the lowest level of diversification (24 stocks) and moderate turnover (45%), fares better than Investors 1 and 2, both of which are more diversified than, and trade far more frequently than, Investor 5. More study is required to explain this apparent anomaly.

It is interesting to note that though, in general, the institutional investor prototypes fare better than the individual investor prototypes in this simulation, the variability of possible outcomes for the institutional investors is significantly greater, as shown by the coefficients of variation of the prototypes (ranging from 2.0 – 12.1, and averaging 7, for the mutual fund prototypes and ranging from 1.2 – 4.8 and averaging 2 for the individual investor prototypes). Thus, the results of this simulation suggest that institutions will have a greater chance of being large net losers and net gainers than individual investors.

2.4.4 Secondary Market Frauds Only

Tables 5, 6 and 7 show the results of a repeat the simulations described above with one key exception – the only instances of fraud recognized are those frauds affecting only secondary market trading prices. With few exceptions (including a negligible loss for Investor 16, the S&P 500 prototype, rather than a slight gain), the gain/loss results are qualitatively identical to the ones described above, and there is a slight reordering of the investor types' relative fraud-related performance, as shown in Table 7. Thus, considering the effects of fraud that only affects secondary market prices does not affect meaningfully the analysis in this piece.

3. Discussion and Conclusion

Twenty-three years ago, Easterbrook and Fischel (1985) observed that the loss one innocent investor suffers from buying a fraud-tainted stock is offset by the gain another innocent shareholder receives from selling the stock while the fraud is ongoing. Thus, the scholars asserted, for an actively trading diversified investor, over the long term, gains and losses from fraud should be approximately equal. Until recently, there was no empirical evidence to support or refute that assertion. However, in a piece published in 2005, Thakor et al., on the basis of aggregated institutional ownership data, conclude that large, diversified investors do break even from fraud and are in fact "overcompensated" for any losses when recoveries from securities class actions are considered.

The results of this study as they relate to Investor 16 (the S&P 500 index prototype) appear to support the assertion of the compensation critics: it is possible for a large, broadly diversified investor to be essentially economically neutral with respect to gains and losses from fraud. It may appear something of a puzzle as to why Investor 16 fared better than the actively traded mutual fund prototypes. One generally thinks of index funds as buy-and-hold investors. However, in five of the 11 years of the study period, the level of trading by Investor 16 rivals or exceeds that of Investor 2 (see Table 1, note e). During the late 1990's, at the height of the tech bubble, there was an exceptionally high amount of index

[28] A preliminary, unreported regression analysis confirms this intuition.

composition turnover.[29] In addition to being an active trader for much of the simulation, Investor 16 invests in a portfolio of stocks that represents approximately 75% of the U.S. equities market (Standard & Poor's 2007). Thus, Investor 16 is more broadly diversified than any of the mutual fund prototypes.

The number of stocks in the portfolio and hence the level of diversification likely plays a significant role in the returns of any particular investor type. Meir Statman (2004) states that, under mean-variance portfolio theory, the optimal level of diversification requires holding over 300 stocks.[30] Though apparently designed as a guide for retail investors, as it compares the decrease in risk with the costs of obtaining the additional diversification, the insight is the same -- larger numbers of stocks in a portfolio will decrease, all things equal, the standard deviation of returns. Therefore, Investor 16, with a 500-stock portfolio representing the broad market, has a better chance of being on the winning side of trades tainted by fraud as often as it is on the losing side.

However, despite the outcome for Investor 16, overall, the results of this simulation provide a view that differs from the conventional wisdom in significant ways. Every investor type in this simulation, on average, suffers a net loss from fraud. This is true whether the investor type is mimicking the behavior of a large, actively traded mutual fund or that of a buy-and-hold retail investor. The results for the retail investor prototypes are not surprising. For the prototypical retail investor that holds a small portfolio and trades infrequently, these simulation results confirm the intuition of many and the findings of Thakor et al. (2005). An undiversified investor, if she encounters a fraud-tainted stock, is highly likely to be a net loser from fraud, and the loss is likely to be significant. This piece makes a related and, to my knowledge, unique contribution to the literature. The results of the simulation demonstrate that an investor with a small portfolio that never trades rarely will encounter a fraud-tainted stock. However, individuals that hold small portfolios and trade with some frequency are likely to encounter a fraud-tainted stock over an extended period. For example, the simulation results suggest that 37% of investors with a small portfolio of only four stocks that make five trades a year (such as Investor 11) can expect, over an 11-year period, to trade a stock with a price artificially inflated by fraud. This is a significant figure[31] and demonstrates that securities fraud has the potential to affect a large number of investors – both institutional and individual.

The results for the mutual fund prototypes do not lead to clear-cut policy prescriptions. Though, on average, every institutional investor prototype is a net loser from fraud, the average net loss is modest in relation to each prototype's initial capital investment. So, if one were concerned only with overall social welfare, one might argue that, on average, no investor suffers net losses and providing compensation to them is inefficient. Indeed, because it is difficult for an investor to know ex ante whether it will be a net loser or net gainer from fraud, its expected loss from fraud is zero. However, as Figures 1-6 (a &b) reveal, though the average net loss is close to zero, there are a substantial number of investors, not just a few outliers, that suffer net losses from fraud that can rival or substantially exceed an investor's initial

[29] In 1998, 1999 and 2000, the S&P 500's composition changed an average of 46 times. At the other extreme, in 2003, the composition changed only nine times. In extended periods with relatively few composition changes (trades), the net fraud losses observed may be significantly different from the results reported in this study.

[30] Staman (2004, 46) describes mean-variance portfolio theory and its relationship to optimal diversification as follows: "In mean–variance portfolio theory, the optimal level of diversification is determined by marginal analysis; that is, diversification should be increased as long as its marginal benefits exceed its marginal costs. The benefits of diversification in mean–variance portfolio theory are in the reduction of risk; the costs are transaction and holding costs. Risk is measured by the standard deviation of portfolio returns."

[31] This figure is also likely understated as a practical matter because, as explained previously, this simulation does not capture all fraud – only fraud lawsuits that resulted in settlements.

capital investment. Those concerned with corrective justice likely would find the potential for uncompensated losses of the magnitude revealed to be possible by this simulation troubling.[32]

Another relevant consideration relates to the potential effect of uncompensated fraud losses on allocative efficiency. Because an investment manager does not know ex ante where she may fall on the distribution, she has an incentive to guard against the risk of fraud. As I argue elsewhere (see Davis Evans 2007), investors are likely to take precautions to minimize their downside exposure. This can lead to allocative inefficiencies, as argued by Easterbrook and Fischel (1985), that result from investors expending energy to ferret out fraud risk rather than focusing on company fundamentals.

Even investors that suffer modest net losses, on an absolute basis, may be inclined to take excessive precautions. As mentioned previously, even seemingly small losses can be economically significant to mutual funds, which are extraordinarily focused on returns. Morningstar's highly influential mutual fund rating system gives the top 10% of mutual funds 5-star ratings, the next 22.5% 4-star ratings, the next 35% 3-star ratings, the next 22.5% 2-star ratings, and the bottom 10% 1-star ratings. Researchers generally find that individual investors flock to 5-star and 4-star funds and sell funds if they fall to 3-star status. According to Morningstar (2007), in 2004, funds rated 4-star outperformed funds rated 3-star, with respect to one-year total return, by only 49 basis points (0.49%).[33] Thus, it is possible that what some may view as modest net losses from fraud could have an economically significant influence on a fund's inflows and outflows if losses from fraud caused a fund to move from one star rating to another. Institutional investment managers are likely to care a great deal about these losses.

One suggestion made previously is for compensation to be eliminated only for large institutions, but maintained for undiversified individual investors. As I argue elsewhere (see Davis Evans 2007), changing the law in this regard could inadvertently provide incentives for individuals not to invest in mutual funds due to a sense of being "better protected" from fraud and could lead to such investors suffering more non-fraud-related losses. However, beyond this, there is another reason to question whether undiversified investors are truly more deserving of compensation than large institutions. Though the preliminary data in this study do appear to confirm the hypothesis that investors that are more diversified and trade more frequently fare better, on average, with respect to fraud-related gains and losses than investors that hold few stocks and rarely trade, the data also reveal that institutional investors may have a higher likelihood of experiencing extreme net losses than individual investors.[34] Institutions generally trade more frequently and hold more stocks than individuals. This activity makes it more likely for them to experience extreme highs and lows. Because of the potential for significant outsize losses, one could argue that institutions, because of the higher potential for catastrophic losses, need compensation as much as, if not more than, individuals.

This study, which demonstrates that retail investors and institutional investors alike can suffer significant harm from securities fraud, provides previously unavailable data that can be useful in shaping future discussions regarding compensation for securities fraud losses. The evidence presented in this Article, though preliminary, should give pause to those who call for the elimination of compensation from our securities regulation regime because it is unnecessary.

[32] Corrective justice adherents also would not be moved, in all likelihood, by claims that some investors enjoy significant net gains from fraud.

[33] This was an ex post look at how funds rated by Morningstar fared with respect to returns, not an ex ante input to the formula that determined the rating (though returns are an important part of the rating formula). However, it does demonstrate that small differences in return can separate mutual funds in the minds of investors in meaningful ways.

[34] See Section 2.4.3.

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Table 1
Investor Characteristics

Investor No.	Trading Strategy	Prototypical Investor Type
1	Random Selection	Actively Managed Domestic Equity Mutual Fund - Average Assets, Diversification and Trading
2	Random Selection	Actively Managed Domestic Equity Mutual Fund - Median Assets, Diversification and Trading
3	Random Selection	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Diversification
4	Random Selection	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Trading
5	Random Selection	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Diversification
6	Random Selection	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Trading
7	Random Selection	Individual Investor - Average Assets and Diversification, No Trades (a)
8	Random Selection	Individual Investor - Average Assets and Diversification, Moderate Turnover (a)
9	Random Selection	Individual Investor - Average Assets and Diversification, High Turnover (a)
10	Random Selection	Individual Investor - Median Assets and Diversification, No Trades (a)
11	Random Selection	Individual Investor - Median Assets and Diversification, Moderate Turnover (a)
12	Random Selection	Individual Investor - Median Assets and Diversification, High Turnover (a)
13	Random Selection	Individual Investor - Average Assets, Modest Diversification, High Turnover (b)
14	Random Selection	Individual Investor - Average Assets, Modest Diversification, High Turnover (b)
15	Random Selection - Most Popular Stocks (c)	Individual Investor - Average Assets, Low Diversification, High Turnover (b)
16	S&P 500	S&P 500 Index Fund

Investor No.	Initial Capital	Cash Reserve	No. Stocks in Portfolio	Turnover	No. Trades per Year (d)	No. Trades during Simulation
1	$547,057,057	3.5%	89	81%	70	770
2	$109,000,000	1.5%	60	59%	35	385
3	$1,069,424,242	2.5%	300	97%	283	3,113
4	$325,121,212	1.9%	120	263%	310	3,410
5	$531,636,364	7.1%	24	45%	10	110
6	$1,094,393,939	4.4%	76	9%	6	66
7	$199,400	0.0%	8	0%	0	0
8	$199,400	0.0%	8	62.5%	5	55
9	$199,400	0.0%	8	150%	12	132
10	$35,000	0.0%	4	0%	0	0
11	$35,000	0.0%	4	125%	5	55
12	$35,000	0.0%	4	300%	12	132
13	$200,000	0.0%	20	75%	15	165
14	$200,000	0.0%	30	75%	23	253
15	$200,000	0.0%	10	100%	10	110
16	$361,500,000	0.0%	500	5.8%	29 (e)	315

(a) Characterizations based on Investment Company Institute/Securities Industry Association survey results and are intended to reflect relative, not absolute behavior of individual investors. According to the ICI/SIA survey, 60% of investors surveyed made no trades during the year in question, approximately 22.8% made 1 - 5 trades during the year, 8.8% made 6-12 trades, and 8.4% made more than 13 trades.

(b) Characterization of assets held as "average" relates to ICI/SIA survey described in note (c) above. Level of diversification is characterized as "modest" if it conforms to prior research on number of stocks that can be held for sufficient diversification (20 or 30 stocks, depending on researcher and year of study).

(c) Investor makes random buy decisions from a limited universe of "popular stocks." "Popular stocks" are defined as the 25 most actively traded stocks (excluding exchange-traded funds) in any given year.

(d) A "trade" is defined as a simultaneous (or near simultaneous) sale and purchase of a stock.

(e) Average (rounded) yearly trades. Trades by year in 1996-2006, respectively, are: 21; 27; 41; 41; 56; 30; 22; 9; 19; 18; 31. Note: Last sale of 1999 is accompanied by buy at the beginning of 2000. Figures may not reflect number of additions/deletions to the index in any given year because trade total excludes deletions/additions that merely reflect a name change, merger or other reorganization that does not require a sale and subsequent purchase of stock. Three such trades are excluded from 1996 total and one such trade is excluded from 2006 total.

Table 2
Simulation Results - All Frauds

Investor No.	Prototypical Investor Type	Initial Capital	No. Iterations	No. Iterations Fraud Encountered
1	Actively Managed Domestic Equity Mutual Fund - Average Assets, Diversification and Trading	$547,057,057	2,000	1,998
2	Actively Managed Domestic Equity Mutual Fund - Median Assets, Diversification and Trading	$109,000,000	2,000	1,918
3	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Diversification	$1,069,424,242	2,000	2,000
4	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Trading	$325,121,212	2,000	2,000
5	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Diversification	$531,636,364	2,000	1,298
6	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Trading	$1,094,393,939	2,000	1,328
7	Individual Investor - Average Assets and Diversification, No Trades	$199,400	2,000	2
8	Individual Investor - Average Assets and Diversification, Moderate Turnover	$199,400	2,000	719
9	Individual Investor - Average Assets and Diversification, High Turnover	$199,400	2,000	1,374
10	Individual Investor - Median Assets and Diversification, No Trades	$35,000	2,000	0
11	Individual Investor - Median Assets and Diversification, Moderate Turnover	$35,000	2,000	743
12	Individual Investor - Median Assets and Diversification, High Turnover	$35,000	2,000	1,379
13	Individual Investor - Average Assets, Modest Diversification, High Turnover	$200,000	2,000	1,482
14	Individual Investor - Average Assets, Modest Diversification, High Turnover	$200,000	2,000	1,748
15	Individual Investor - Average Assets, Low Diversification, High Turnover (Most Popular Stocks)	$200,000	2,000	1,984
16	S&P 500 Index Fund	$361,500,000	1	1

		Of Those Affected by Fraud								
Investor No.	% Iterations	Net Gainers	%	Net Losers	%	Avg. Trading Gain (Loss)	Median Trading Gain (Loss)	Std. Dev. Trading Gain (Loss)	High Trading Gain (Loss)	Low Trading Gain (Loss)
1	99.90%	917	45.8959%	1081	54.1041%	($4,906,473)	($1,190,512)	$320,133,643	$9,370,369,663	($9,429,577,904)
2	95.90%	690	35.9750%	1,228	64.0250%	($1,493,709)	($564,019)	$15,939,222	$231,166,891	($206,723,479)
3	100.00%	800	40.0000%	1,200	60.0000%	($8,194,963)	($3,748,577)	$347,505,270	$10,015,789,654	($6,488,353,546)
4	100.00%	789	39.4500%	1,211	60.5500%	($6,755,419)	($2,194,855)	$129,680,185	$2,076,551,470	($3,202,295,574)
5	64.90%	186	14.3297%	1,112	85.6703%	($19,710,310)	($5,374,146)	$63,404,642	$378,870,284	($857,062,377)
6	66.40%	269	20.2560%	1,059	79.7440%	($11,763,983)	($2,817,544)	$72,393,814	$900,206,092	($1,183,224,798)
7	0.10%	0	0.0000%	2	100.0000%	($24,918)	($24,918)	$3	($24,916)	($24,920)
8	35.95%	48	6.6759%	671	93.3241%	($18,535)	($7,116)	$31,630	$70,688	($248,289)
9	68.70%	129	9.3886%	1,245	90.6114%	($21,320)	($8,589)	$42,469	$263,918	($495,636)
10	0.00%	N.M.	N.M.	N.M.	N.M.	N.M.	N.M.	N.M.	N.M.	N.M.
11	37.15%	27	3.6339%	716	96.3661%	($6,037)	($2,487)	$8,841	$49,825	($67,215)
12	68.95%	70	5.0761%	1,309	94.9239%	($7,115)	($2,740)	$11,397	$37,354	($154,295)
13	74.10%	232	15.6545%	1,250	84.3455%	($10,129)	($3,739)	$30,548	$267,756	($331,272)
14	87.40%	437	25.0000%	1,311	75.0000%	($6,073)	($1,679)	$29,464	$132,574	($618,466)
15	99.20%	638	32.1573%	1,346	67.8427%	($8,482)	($5,415)	$24,989	$133,005	($118,032)
16	100.00%	1	100.0000%	0	0.0000%	$311,539	$311,539	N.M.	$311,539	$311,539

Table 3
Simulation Results - All Frauds
Standardized Initial Capital and Cash Reserves

Investor No.	Prototypical Investor Type (a)	Initial Capital	Cash Reserve	No. Iterations	No. Iterations Fraud Encountered
1	Actively Managed Domestic Equity Mutual Fund - Average Assets, Diversification and Trading	$1,000,000	0%	2,000	1,988
2	Actively Managed Domestic Equity Mutual Fund - Median Assets, Diversification and Trading	$1,000,000	0%	2,000	1,923
3	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Diversification	$1,000,000	0%	2,000	2,000
4	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Trading	$1,000,000	0%	2,000	2,000
5	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Diversification	$1,000,000	0%	2,000	1,234
6	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Trading	$1,000,000	0%	2,000	1,305
7	Individual Investor - Average Assets and Diversification, No Trades	$1,000,000	0%	2,000	1
8	Individual Investor - Average Assets and Diversification, Moderate Turnover	$1,000,000	0%	2,000	779
9	Individual Investor - Average Assets and Diversification, High Turnover	$1,000,000	0%	2,000	1,340
10	Individual Investor - Median Assets and Diversification, No Trades	$1,000,000	0%	2,000	2
11	Individual Investor - Median Assets and Diversification, Moderate Turnover	$1,000,000	0%	2,000	750
12	Individual Investor - Median Assets and Diversification, High Turnover	$1,000,000	0%	2,000	1,372
13	Individual Investor - Average Assets, Modest Diversification, High Turnover	$1,000,000	0%	2,000	1,499
14	Individual Investor - Average Assets, Modest Diversification, High Turnover	$1,000,000	0%	2,000	1,758
15	Individual Investor - Average Assets, Low Diversification, High Turnover (Most Popular Stocks)	$1,000,000	0%	2,000	1,983
16	S&P 500 Index Fund	$1,000,000	0%	1	1

		Of Those Affected by Fraud								
Investor No.	% Iterations	Net Gainers	%	Net Losers	%	Avg. Trading Gain (Loss)	Median Trading Gain (Loss)	Std. Dev. Trading Gain (Loss)	High Trading Gain (Loss)	Low Trading Gain (Loss)
1	99.40%	616	30.9859%	1372	69.0141%	($85,689)	($29,389)	$1,038,382	$17,509,468	($32,244,399)
2	96.15%	413	21.4769%	1,510	78.5231%	($100,575)	($31,847)	$291,337	$2,891,836	($2,954,771)
3	100.00%	804	40.2000%	1,196	59.8000%	($4,069)	($4,482)	$34,023	$202,904	($664,748)
4	100.00%	813	40.6500%	1,187	59.3500%	($8,362)	($8,176)	$82,474	$993,987	($950,183)
5	61.70%	222	17.9903%	1,012	82.0097%	($17,326)	($8,175)	$34,474	$113,075	($499,918)
6	65.25%	282	21.6092%	1,023	78.3908%	($10,237)	($2,942)	$89,446	$1,264,441	($1,277,492)
7	0.05%	0	0.0000%	1	100.0000%	($35,911)	($35,911)	N.M.	($35,911)	($35,911)
8	38.95%	54	6.9320%	725	93.0680%	($102,694)	($36,999)	$182,109	$441,100	($1,939,337)
9	67.00%	111	8.2836%	1,229	91.7164%	($102,701)	($39,110)	$192,075	$689,729	($1,838,424)
10	0.10%	0	0.0000%	2	100.0000%	($135,108)	($135,108)	$162,475	($20,221)	($249,995)
11	37.50%	23	3.0667%	727	96.9333%	($198,763)	($102,728)	$274,442	$299,726	($2,033,227)
12	68.60%	70	5.1020%	1,302	94.8980%	($196,044)	($81,701)	$286,042	$486,390	($2,214,999)
13	74.95%	249	16.6111%	1,250	83.3889%	($42,292)	($12,845)	$134,052	$645,043	($2,264,186)
14	87.90%	440	25.0284%	1,318	74.9716%	($31,634)	($10,188)	$151,222	$1,713,191	($2,159,461)
15	99.15%	639	32.2239%	1,344	67.7761%	($47,730)	($26,533)	$122,525	$413,831	($723,945)
16	100.00%	1	100.0000%	0	0.0000%	$8,559	$8,559	N.M.	$8,559	$8,559

(a) Descriptions based on characteristics used in earlier versions of the simulation. See Table 1. The initial capital amounts and cash reserve percentages are held constant across investor prototypes in this simulation.

Table 4
Simulation Results - All Frauds
Standardized Initial Capital and Cash Reserves
Sorted by Average Trading Gain (Loss)

Investor No.	Prototypical Investor Type (a)	Initial Capital	Cash Reserve	No. Iterations	No. Iterations Fraud Encountered
16	S&P 500 Index Fund	$1,000,000	0%	1	1
3	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Diversification	$1,000,000	0%	2,000	2,000
4	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Trading	$1,000,000	0%	2,000	2,000
6	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Trading	$1,000,000	0%	2,000	1,305
5	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Diversification	$1,000,000	0%	2,000	1,234
14	Individual Investor - Average Assets, Modest Diversification, High Turnover	$1,000,000	0%	2,000	1,758
7	Individual Investor - Average Assets and Diversification, No Trades	$1,000,000	0%	2,000	1
13	Individual Investor - Average Assets, Modest Diversification, High Turnover	$1,000,000	0%	2,000	1,499
15	Individual Investor - Average Assets, Low Diversification, High Turnover (Most Popular Stocks)	$1,000,000	0%	2,000	1,983
1	Actively Managed Domestic Equity Mutual Fund - Average Assets, Diversification and Trading	$1,000,000	0%	2,000	1,988
2	Actively Managed Domestic Equity Mutual Fund - Median Assets, Diversification and Trading	$1,000,000	0%	2,000	1,923
8	Individual Investor - Average Assets and Diversification, Moderate Turnover	$1,000,000	0%	2,000	779
9	Individual Investor - Average Assets and Diversification, High Turnover	$1,000,000	0%	2,000	1,340
10	Individual Investor - Median Assets and Diversification, No Trades	$1,000,000	0%	2,000	2
12	Individual Investor - Median Assets and Diversification, High Turnover	$1,000,000	0%	2,000	1,372
11	Individual Investor - Median Assets and Diversification, Moderate Turnover	$1,000,000	0%	2,000	750

		Of Those Affected by Fraud								
Investor No.	**% Iterations**	**Net Gainers**	**%**	**Net Losers**	**%**	**Avg. Trading Gain (Loss)**	**Median Trading Gain (Loss)**	**Std. Dev. Trading Gain (Loss)**	**High Trading Gain (Loss)**	**Low Trading Gain (Loss)**
16	100.00%	1	100.0000%	0	0.0000%	$8,559	$8,559	N.M.	$8,559	$8,559
3	100.00%	804	40.2000%	1,196	59.8000%	($4,069)	($4,482)	$34,023	$202,904	($664,748)
4	100.00%	813	40.6500%	1,187	59.3500%	($8,362)	($8,176)	$82,474	$993,987	($950,183)
6	65.25%	282	21.6092%	1,023	78.3908%	($10,237)	($2,942)	$89,446	$1,264,441	($1,277,492)
5	61.70%	222	17.9903%	1,012	82.0097%	($17,326)	($8,175)	$34,474	$113,075	($499,918)
14	87.90%	440	25.0284%	1,318	74.9716%	($31,634)	($10,188)	$151,222	$1,713,191	($2,159,461)
7	0.05%	0	0.0000%	1	100.0000%	($35,911)	($35,911)	N.M.	($35,911)	($35,911)
13	74.95%	249	16.6111%	1,250	83.3889%	($42,292)	($12,845)	$134,052	$645,043	($2,264,186)
15	99.15%	639	32.2239%	1,344	67.7761%	($47,730)	($26,533)	$122,525	$413,831	($723,945)
1	99.40%	616	30.9859%	1372	69.0141%	($85,689)	($29,389)	$1,038,382	$17,509,468	($32,244,399)
2	96.15%	413	21.4769%	1,510	78.5231%	($100,575)	($31,847)	$291,337	$2,891,836	($2,954,771)
8	38.95%	54	6.9320%	725	93.0680%	($102,694)	($36,999)	$182,109	$441,100	($1,939,337)
9	67.00%	111	8.2836%	1,229	91.7164%	($102,701)	($39,110)	$192,075	$689,729	($1,838,424)
10	0.10%	0	0.0000%	2	100.0000%	($135,108)	($135,108)	$162,475	($20,221)	($249,995)
12	68.60%	70	5.1020%	1,302	94.8980%	($196,044)	($81,701)	$286,042	$486,390	($2,214,999)
11	37.50%	23	3.0667%	727	96.9333%	($198,763)	($102,728)	$274,442	$299,726	($2,033,227)

(a) Descriptions based on characteristics used in earlier versions of the simulation. See Table 1. The initial capital amounts and cash reserve percentages are held constant across investor prototypes in this simulation.

Table 5
Simulation Results - Secondary Market Frauds Only

Investor No.	Prototypical Investor Type	Initial Capital	No. Iterations	No. Iterations Fraud Encountered
1	Actively Managed Domestic Equity Mutual Fund - Average Assets, Diversification and Trading	$547,057,057	2,000	1,997
2	Actively Managed Domestic Equity Mutual Fund - Median Assets, Diversification and Trading	$109,000,000	2,000	1,881
3	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Diversification	$1,069,424,242	2,000	2,000
4	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Trading	$325,121,212	2,000	2,000
5	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Diversification	$531,636,364	2,000	1,219
6	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Trading	$1,094,393,939	2,000	1,282
7	Individual Investor - Average Assets and Diversification, No Trades	$199,400	2,000	2
8	Individual Investor - Average Assets and Diversification, Moderate Turnover	$199,400	2,000	683
9	Individual Investor - Average Assets and Diversification, High Turnover	$199,400	2,000	1,289
10	Individual Investor - Median Assets and Diversification, No Trades	$35,000	2,000	0
11	Individual Investor - Median Assets and Diversification, Moderate Turnover	$35,000	2,000	702
12	Individual Investor - Median Assets and Diversification, High Turnover	$35,000	2,000	1,293
13	Individual Investor - Average Assets, Modest Diversification, High Turnover	$200,000	2,000	1,413
14	Individual Investor - Average Assets, Modest Diversification, High Turnover	$200,000	2,000	1,693
15	Individual Investor - Average Assets, Low Diversification, High Turnover (Most Popular Stocks)	$200,000	2,000	1,984
16	S&P 500 Index Fund	$361,500,000	1	1

		Of Those Affected by Fraud								
Investor No.	**% Iterations**	**Net Gainers**	**%**	**Net Losers**	**%**	**Avg. Trading Gain (Loss)**	**Median Trading Gain (Loss)**	**Std. Dev. Trading Gain (Loss)**	**High Trading Gain (Loss)**	**Low Trading Gain (Loss)**
1	99.85%	912	45.6685%	1,085	54.3315%	($3,566,161)	($1,016,107)	$318,210,112	$9,370,369,663	($9,434,780,814)
2	94.05%	679	36.0978%	1,202	63.9022%	($1,302,243)	($498,818)	$15,672,725	$233,296,815	($206,723,479)
3	100.00%	820	41.0000%	1,180	59.0000%	($6,791,919)	($3,250,781)	$344,640,715	$9,976,242,776	($6,488,353,546)
4	100.00%	801	40.0500%	1,199	59.9500%	($6,035,594)	($1,902,179)	$102,140,476	$2,076,551,470	($2,547,130,017)
5	60.95%	175	14.3560%	1,044	85.6440%	($19,166,876)	($5,060,336)	$60,896,561	$258,173,030	($857,062,377)
6	64.10%	259	20.2028%	1,023	79.7972%	($11,756,618)	($2,624,875)	$73,556,454	$900,473,401	($1,183,224,798)
7	0.10%	0	0.0000%	2	100.0000%	($24,918)	($24,918)	$3	($24,916)	($24,920)
8	34.15%	51	7.4671%	632	92.5329%	($18,021)	($6,693)	$31,105	$70,688	($248,289)
9	64.45%	128	9.9302%	1,161	90.0698%	($20,831)	($8,089)	$42,289	$263,918	($495,636)
10	0.00%	N.M.	N.M.	N.M.	N.M.	N.M.	N.M.	N.M.	N.M.	N.M.
11	35.10%	25	3.5613%	677	96.4387%	($5,966)	($2,380)	$8,825	$49,825	($67,215)
12	64.65%	69	5.3364%	1,224	94.6636%	($6,842)	($2,392)	$11,254	$37,354	($154,295)
13	70.65%	230	16.2774%	1,183	83.7226%	($9,396)	($3,102)	$27,878	$267,756	($331,272)
14	84.65%	437	25.8122%	1,256	74.1878%	($5,932)	($1,542)	$29,467	$113,469	($618,466)
15	99.20%	638	32.1573%	1,346	67.8427%	($8,476)	($5,408)	$24,989	$133,005	($118,032)
16	100.00%	0	0.0000%	1	100.0000%	($50,144)	($50,144)	N.M.	($50,144)	($50,144)

Table 6
Simulation Results - Secondary Market Frauds Only
Standardized Initial Capital and Cash Reserves

Investor No.	Prototypical Investor Type (a)	Initial Capital	Cash Reserve	No. Iterations	No. Iterations Fraud Encountered
1	Actively Managed Domestic Equity Mutual Fund - Average Assets, Diversification and Trading	$1,000,000	0%	2,000	1,971
2	Actively Managed Domestic Equity Mutual Fund - Median Assets, Diversification and Trading	$1,000,000	0%	2,000	1,876
3	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Diversification	$1,000,000	0%	2,000	2,000
4	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Trading	$1,000,000	0%	2,000	2,000
5	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Diversification	$1,000,000	0%	2,000	1,173
6	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Trading	$1,000,000	0%	2,000	1,248
7	Individual Investor - Average Assets and Diversification, No Trades	$1,000,000	0%	2,000	1
8	Individual Investor - Average Assets and Diversification, Moderate Turnover	$1,000,000	0%	2,000	738
9	Individual Investor - Average Assets and Diversification, High Turnover	$1,000,000	0%	2,000	1,262
10	Individual Investor - Median Assets and Diversification, No Trades	$1,000,000	0%	2,000	1
11	Individual Investor - Median Assets and Diversification, Moderate Turnover	$1,000,000	0%	2,000	704
12	Individual Investor - Median Assets and Diversification, High Turnover	$1,000,000	0%	2,000	1,294
13	Individual Investor - Average Assets, Modest Diversification, High Turnover	$1,000,000	0%	2,000	1,425
14	Individual Investor - Average Assets, Modest Diversification, High Turnover	$1,000,000	0%	2,000	1,709
15	Individual Investor - Average Assets, Low Diversification, High Turnover (Most Popular Stocks)	$1,000,000	0%	2,000	1,983
16	S&P 500 Index Fund	$1,000,000	0%	1	1

		Of Those Affected by Fraud								
Investor No.	% Iterations	Net Gainers	%	Net Losers	%	Avg. Trading Gain (Loss)	Median Trading Gain (Loss)	Std. Dev. Trading Gain (Loss)	High Trading Gain (Loss)	Low Trading Gain (Loss)
1	98.55%	639	32.4201%	1332	67.5799%	($90,651)	($23,053)	$913,058	$10,140,187	($32,244,399)
2	93.80%	443	23.6141%	1,433	76.3859%	($87,044)	($25,960)	$274,259	$2,914,011	($2,954,771)
3	100.00%	820	41.0000%	1,180	59.0000%	($2,986)	($3,416)	$29,265	$205,892	($346,457)
4	100.00%	824	41.2000%	1,176	58.8000%	($6,516)	($6,581)	$78,350	$994,939	($878,497)
5	58.65%	222	18.9258%	951	81.0742%	($16,694)	($7,085)	$34,668	$113,075	($489,115)
6	62.40%	275	22.0353%	973	77.9647%	($10,768)	($2,507)	$86,820	$1,264,441	($1,277,492)
7	0.05%	0	0.0000%	1	100.0000%	($35,911)	($35,911)	N.M.	($35,911)	($35,911)
8	36.90%	51	6.9106%	687	93.0894%	($100,676)	($36,111)	$171,342	$441,100	($1,356,278)
9	63.10%	112	8.8748%	1,150	91.1252%	($101,729)	($38,070)	$191,450	$689,729	($1,838,424)
10	0.05%	0	0.0000%	1	100.0000%	($249,995)	($249,995)	N.M.	($249,995)	($249,995)
11	35.20%	25	3.5511%	679	96.4489%	($195,253)	($101,206)	$269,769	$299,726	($2,033,227)
12	64.70%	76	5.8733%	1,218	94.1267%	($191,609)	($77,909)	$281,295	$486,390	($2,214,999)
13	71.25%	248	17.4035%	1,177	82.5965%	($41,003)	($11,460)	$133,769	$645,043	($2,264,186)
14	85.45%	431	25.2194%	1,278	74.7806%	($30,376)	($8,911)	$150,469	$1,713,191	($2,159,461)
15	99.15%	639	32.2239%	1,344	67.7761%	($47,695)	($26,533)	$122,553	$413,831	($723,945)
16	100.00%	0	0.0000%	1	100.0000%	($1,418)	($1,418)	N.M.	($1,418)	($1,418)

(a) Descriptions based on characteristics used in earlier versions of the simulation. See Table 1. The initial capital amounts and cash reserve percentages are held constant across investor prototypes in this simulation.

Table 7
Simulation Results - Secondary Market Frauds Only
Standardized Initial Capital and Cash Reserves
Sorted by Average Trading Gain (Loss)

Investor No.	Prototypical Investor Type (a)	Initial Capital	Cash Reserve	No. Iterations	No. Iterations Fraud Encountered
16	S&P 500 Index Fund	$1,000,000	0%	1	1
3	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Diversification	$1,000,000	0%	2,000	2,000
4	Actively Managed Domestic Equity Mutual Fund - Average among Top Decile by Trading	$1,000,000	0%	2,000	2,000
6	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Trading	$1,000,000	0%	2,000	1,248
5	Actively Managed Domestic Equity Mutual Fund - Average among Bottom Decile by Diversification	$1,000,000	0%	2,000	1,173
14	Individual Investor - Average Assets, Modest Diversification, High Turnover	$1,000,000	0%	2,000	1,709
7	Individual Investor - Average Assets and Diversification, No Trades	$1,000,000	0%	2,000	1
13	Individual Investor - Average Assets, Modest Diversification, High Turnover	$1,000,000	0%	2,000	1,425
15	Individual Investor - Average Assets, Low Diversification, High Turnover (Most Popular Stocks)	$1,000,000	0%	2,000	1,983
2	Actively Managed Domestic Equity Mutual Fund - Median Assets, Diversification and Trading	$1,000,000	0%	2,000	1,876
1	Actively Managed Domestic Equity Mutual Fund - Average Assets, Diversification and Trading	$1,000,000	0%	2,000	1,971
8	Individual Investor - Average Assets and Diversification, Moderate Turnover	$1,000,000	0%	2,000	738
9	Individual Investor - Average Assets and Diversification, High Turnover	$1,000,000	0%	2,000	1,262
12	Individual Investor - Median Assets and Diversification, High Turnover	$1,000,000	0%	2,000	1,294
11	Individual Investor - Median Assets and Diversification, Moderate Turnover	$1,000,000	0%	2,000	704
10	Individual Investor - Median Assets and Diversification, No Trades	$1,000,000	0%	2,000	1

		Of Those Affected by Fraud								
Investor No.	% Iterations	Net Gainers	%	Net Losers	%	Avg. Trading Gain (Loss)	Median Trading Gain (Loss)	Std. Dev. Trading Gain (Loss)	High Trading Gain (Loss)	Low Trading Gain (Loss)
16	100.00%	0	0.0000%	1	100.0000%	($1,418)	($1,418)	N.M.	($1,418)	($1,418)
3	100.00%	820	41.0000%	1,180	59.0000%	($2,986)	($3,416)	$29,265	$205,892	($346,457)
4	100.00%	824	41.2000%	1,176	58.8000%	($6,516)	($6,581)	$78,350	$994,939	($878,497)
6	62.40%	275	22.0353%	973	77.9647%	($10,768)	($2,507)	$86,820	$1,264,441	($1,277,492)
5	58.65%	222	18.9258%	951	81.0742%	($16,694)	($7,085)	$34,668	$113,075	($489,115)
14	85.45%	431	25.2194%	1,278	74.7806%	($30,376)	($8,911)	$150,469	$1,713,191	($2,159,461)
7	0.05%	0	0.0000%	1	100.0000%	($35,911)	($35,911)	N.M.	($35,911)	($35,911)
13	71.25%	248	17.4035%	1,177	82.5965%	($41,003)	($11,460)	$133,769	$645,043	($2,264,186)
15	99.15%	639	32.2239%	1,344	67.7761%	($47,695)	($26,533)	$122,553	$413,831	($723,945)
2	93.80%	443	23.6141%	1,433	76.3859%	($87,044)	($25,960)	$274,259	$2,914,011	($2,954,771)
1	98.55%	639	32.4201%	1332	67.5799%	($90,651)	($23,053)	$913,058	$10,140,187	($32,244,399)
8	36.90%	51	6.9106%	687	93.0894%	($100,676)	($36,111)	$171,342	$441,100	($1,356,278)
9	63.10%	112	8.8748%	1,150	91.1252%	($101,729)	($38,070)	$191,450	$689,729	($1,838,424)
12	64.70%	76	5.8733%	1,218	94.1267%	($191,609)	($77,909)	$281,295	$486,390	($2,214,999)
11	35.20%	25	3.5511%	679	96.4489%	($195,253)	($101,206)	$269,769	$299,726	($2,033,227)
10	0.05%	0	0.0000%	1	100.0000%	($249,995)	($249,995)	N.M.	($249,995)	($249,995)

(a) Descriptions based on characteristics used in earlier versions of the simulation. See Table 1. The initial capital amounts and cash reserve percentages are held constant across investor prototypes in this simulation.

Figure 1a – Histogram of Middle 80% of Trials for Investor 1 (Both tails winsorized at 10%)

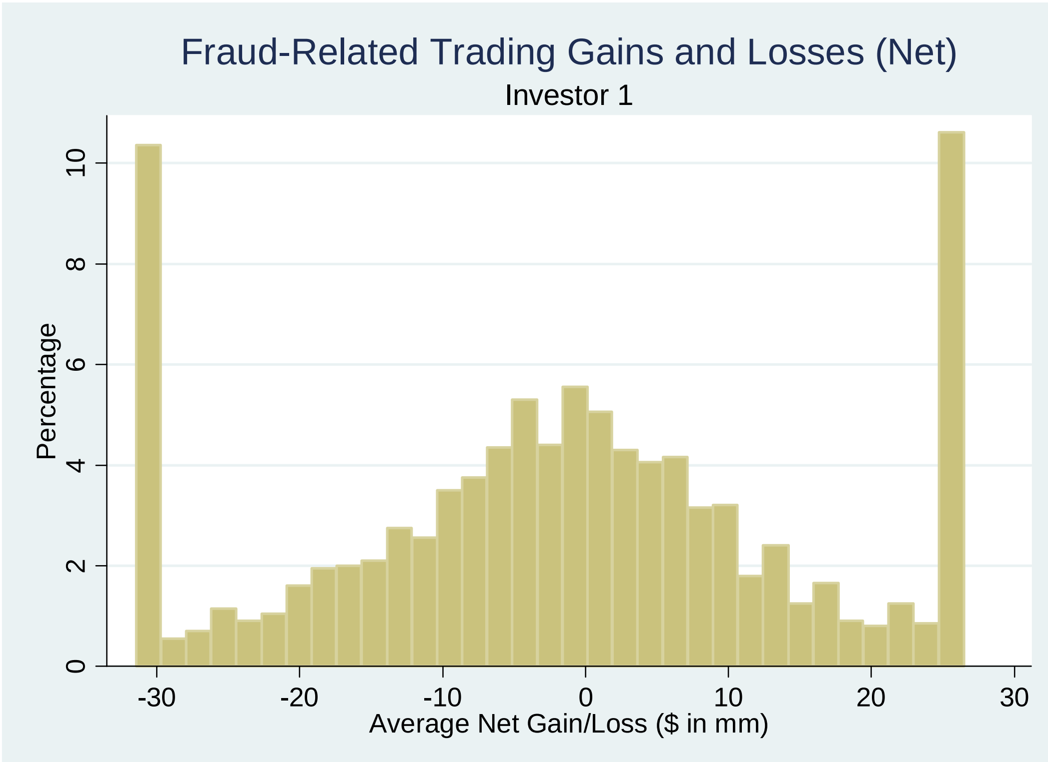


Figure 1b – Scatter Plot of Bottom 10% of the Distribution for Investor 1

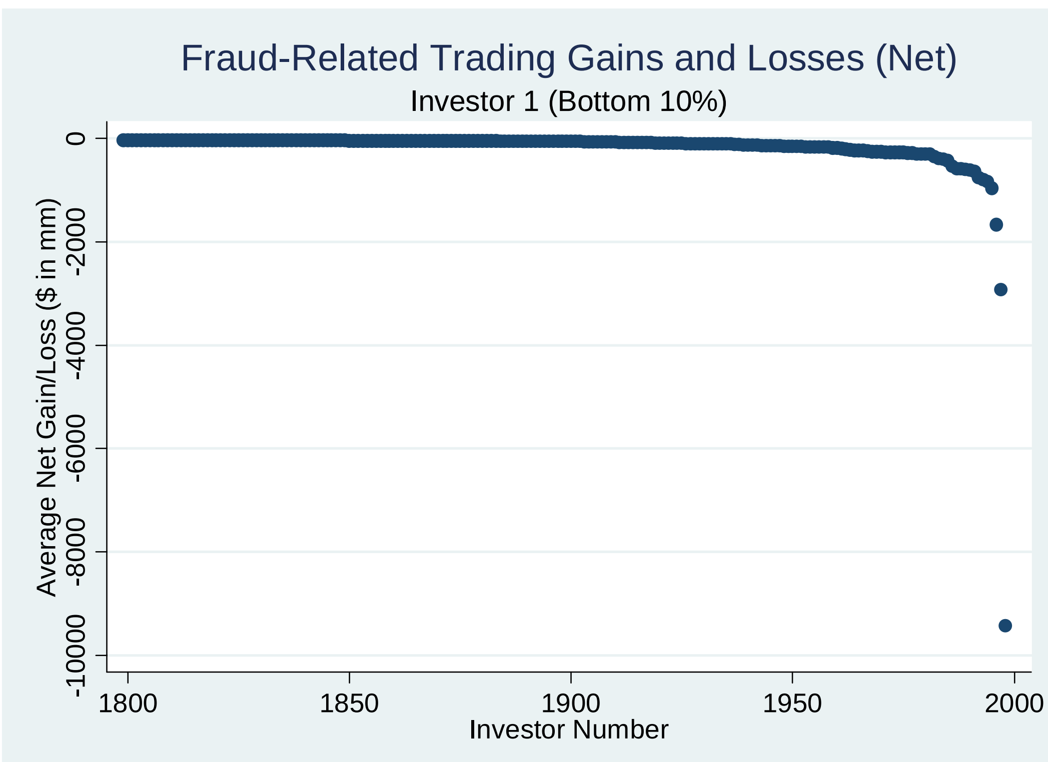


Figure 2a – Histogram of Middle 80% of Trials for Investor 2 (Both tails winsorized at 10%)

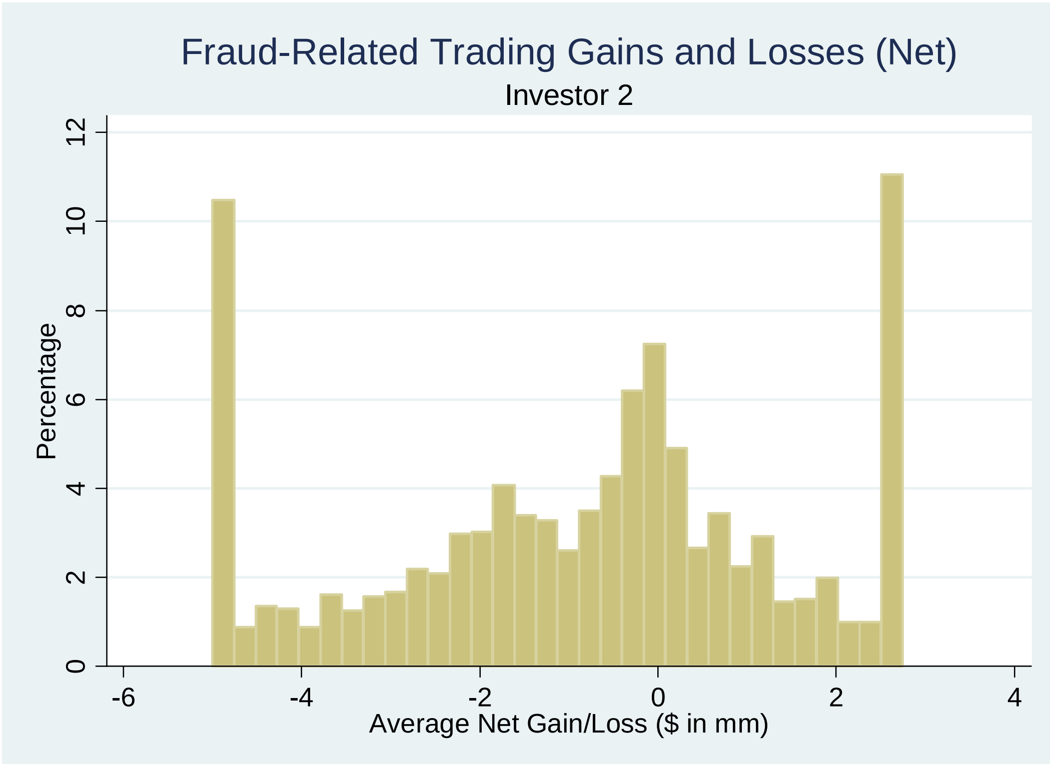


Figure 2b – Scatter Plot of Bottom 10% of the Distribution for Investor 2

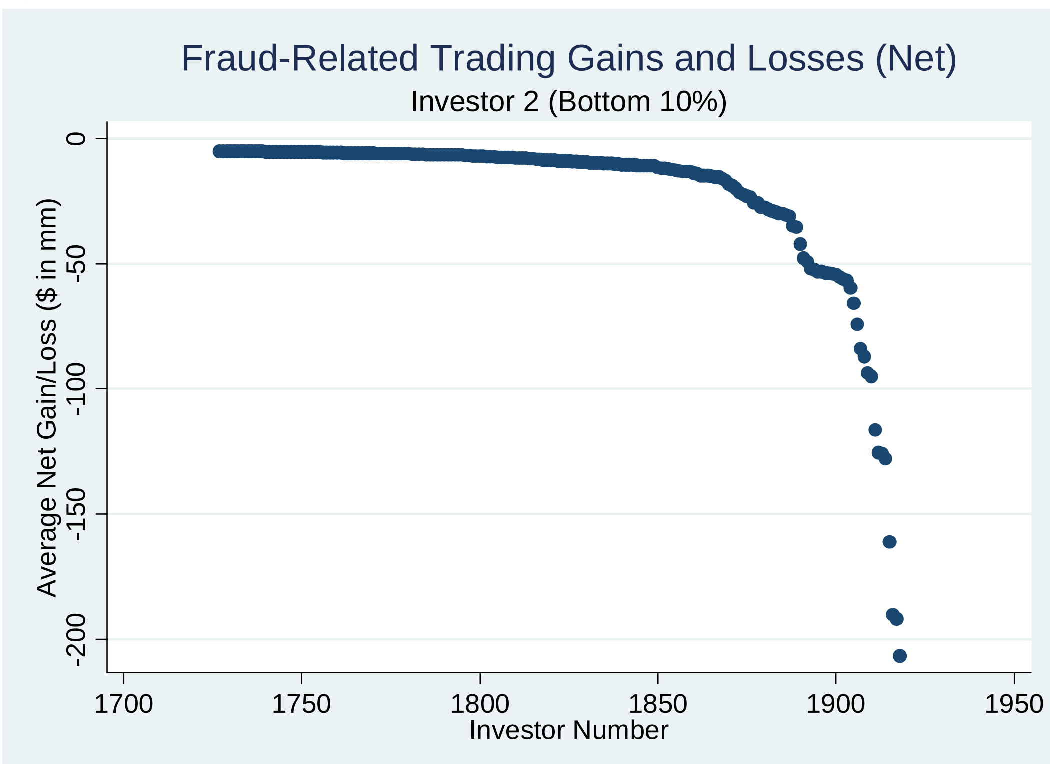


Figure 3a – Histogram of Middle 80% of Trials for Investor 3 (Both tails winsorized at 10%)

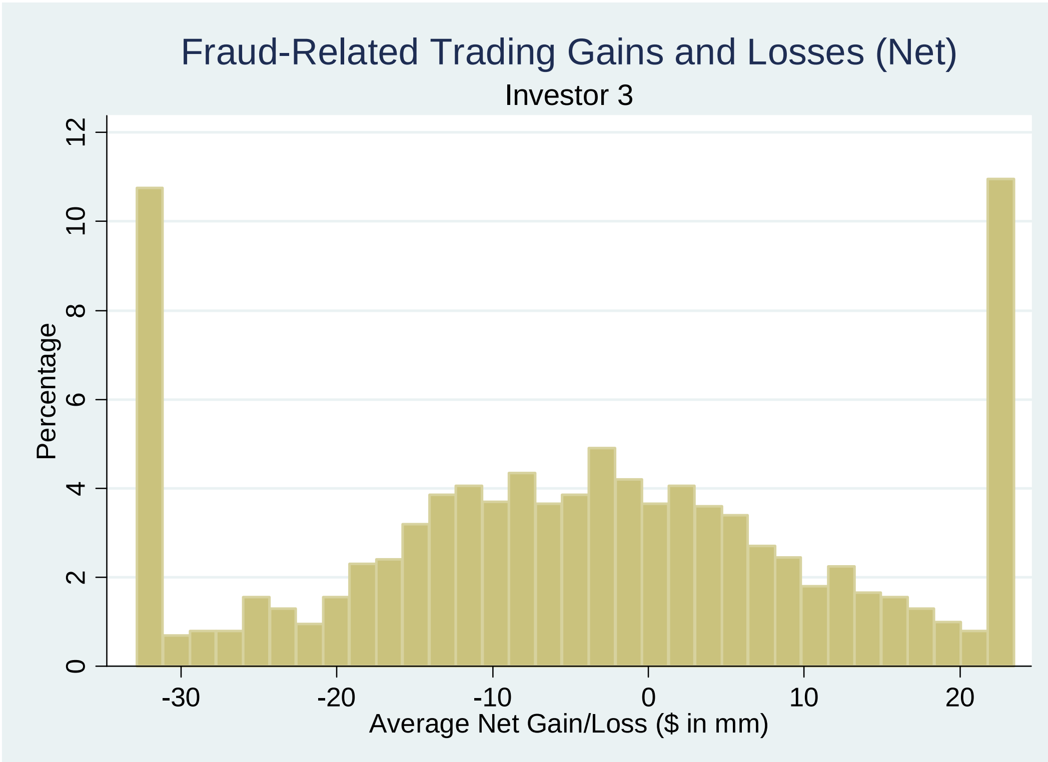


Figure 3b – Scatter Plot of Bottom 10% of the Distribution for Investor 3

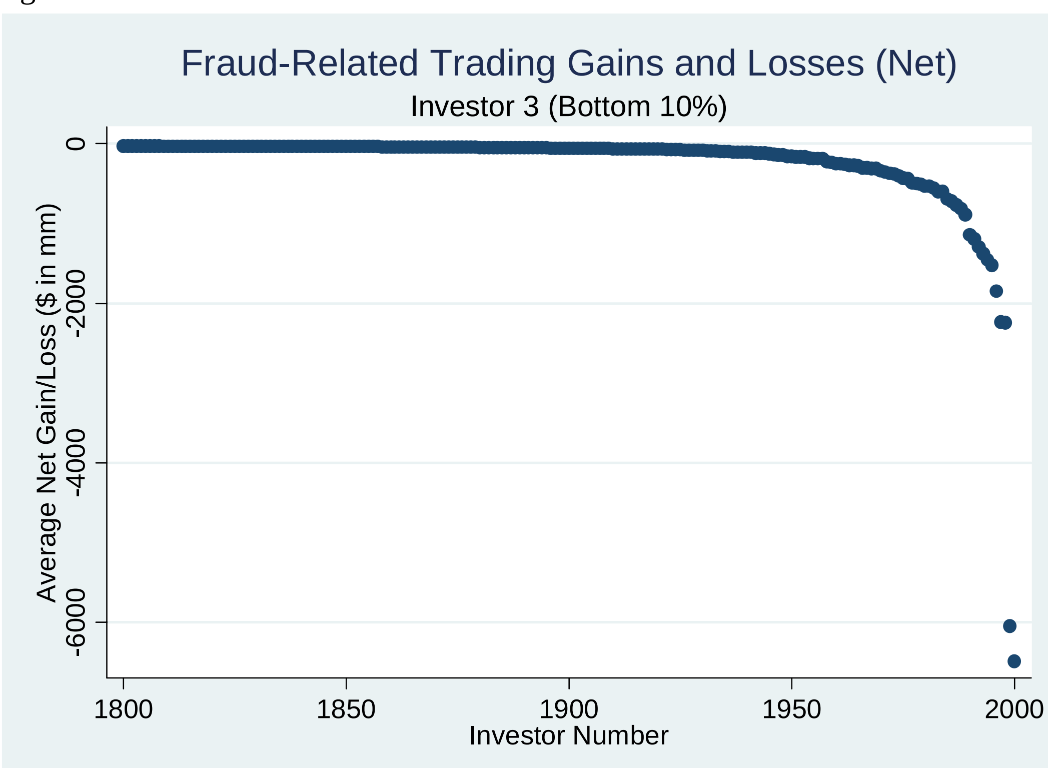


Figure 4a – Histogram of Middle 80% of Trials for Investor 4 (Both tails winsorized at 10%)

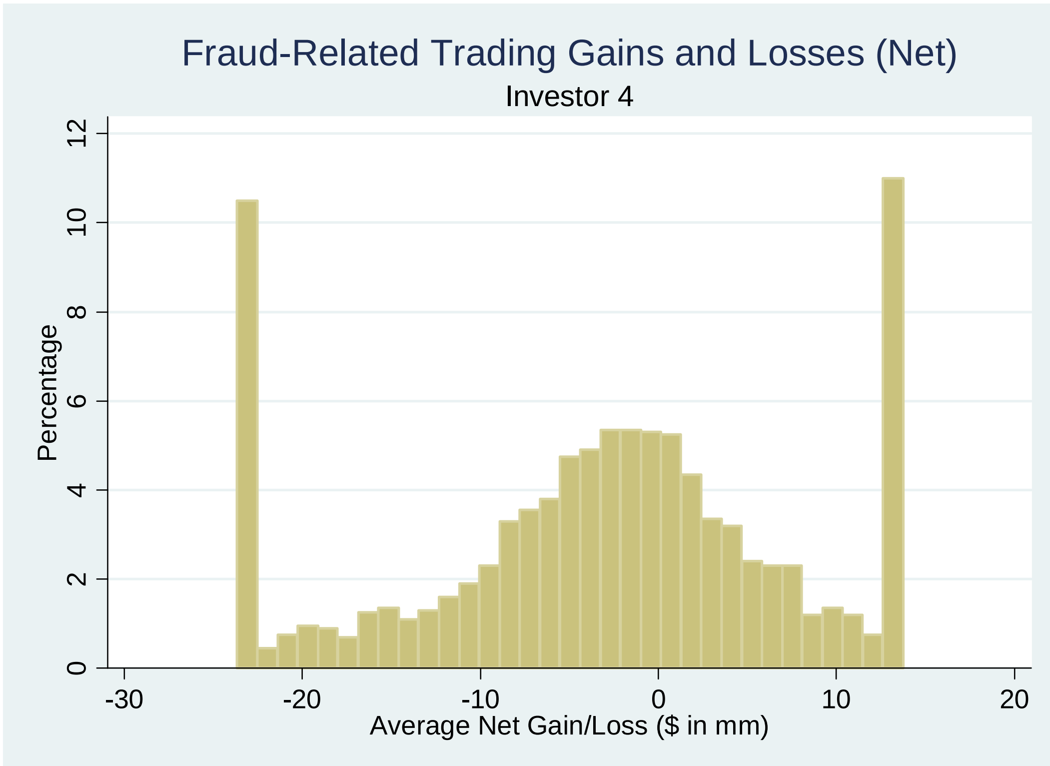


Figure 4b – Scatter Plot of Bottom 10% of the Distribution for Investor 4

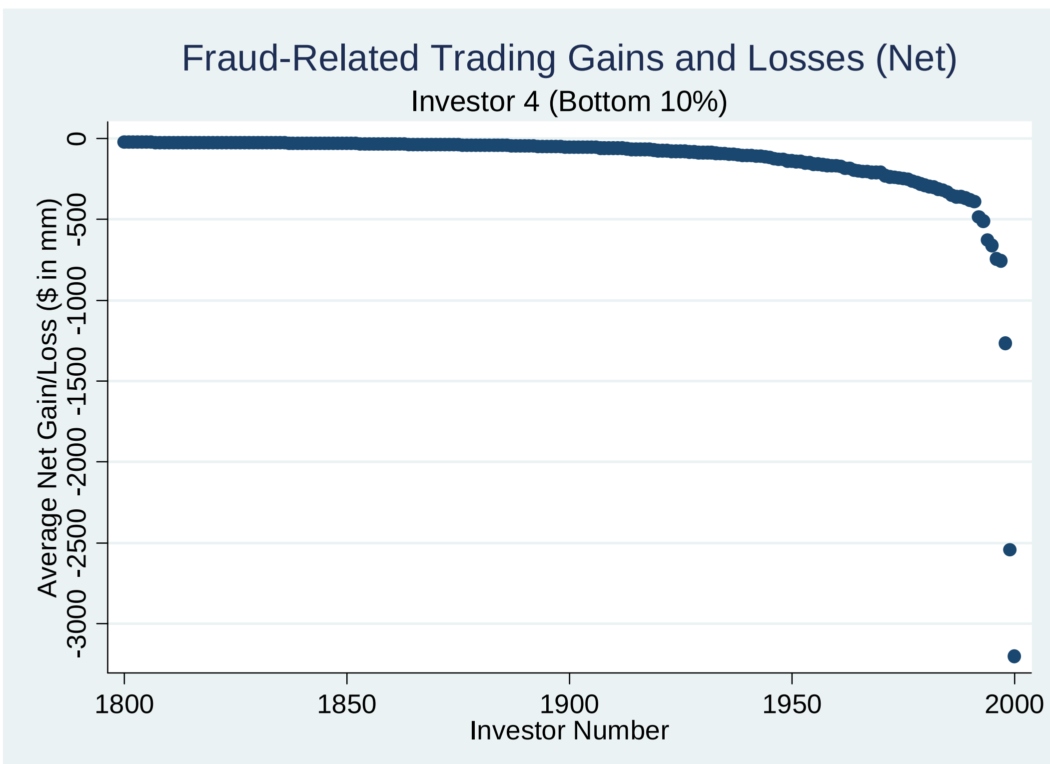


Figure 5a – Histogram of Middle 80% of Trials for Investor 5 (Both tails winsorized at 10%)

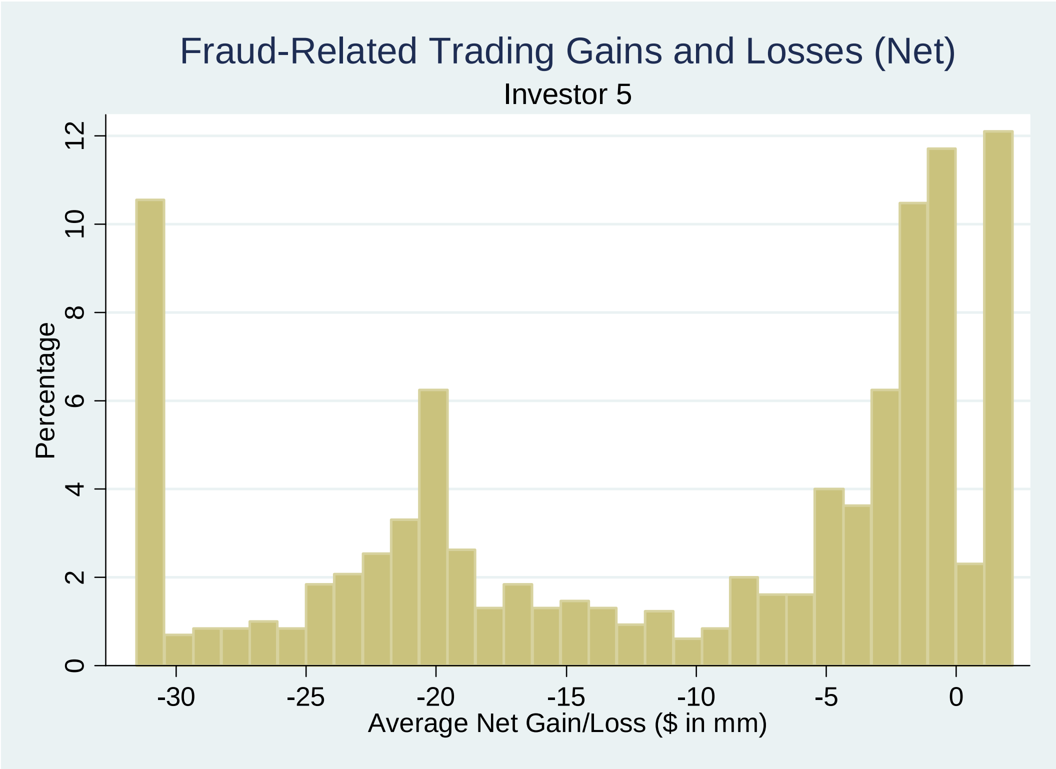


Figure 5b – Scatter Plot of Bottom 10% of the Distribution for Investor 5

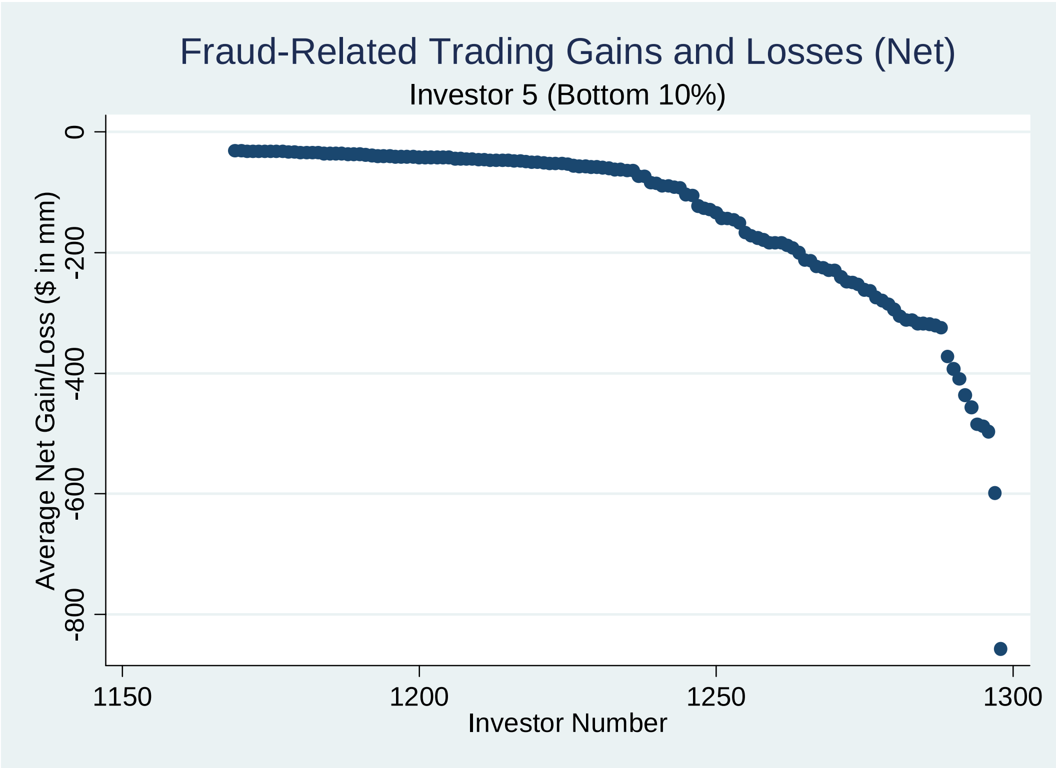


Figure 6a – Histogram of Middle 80% of Trials for Investor 6 (Both tails winsorized at 10%)

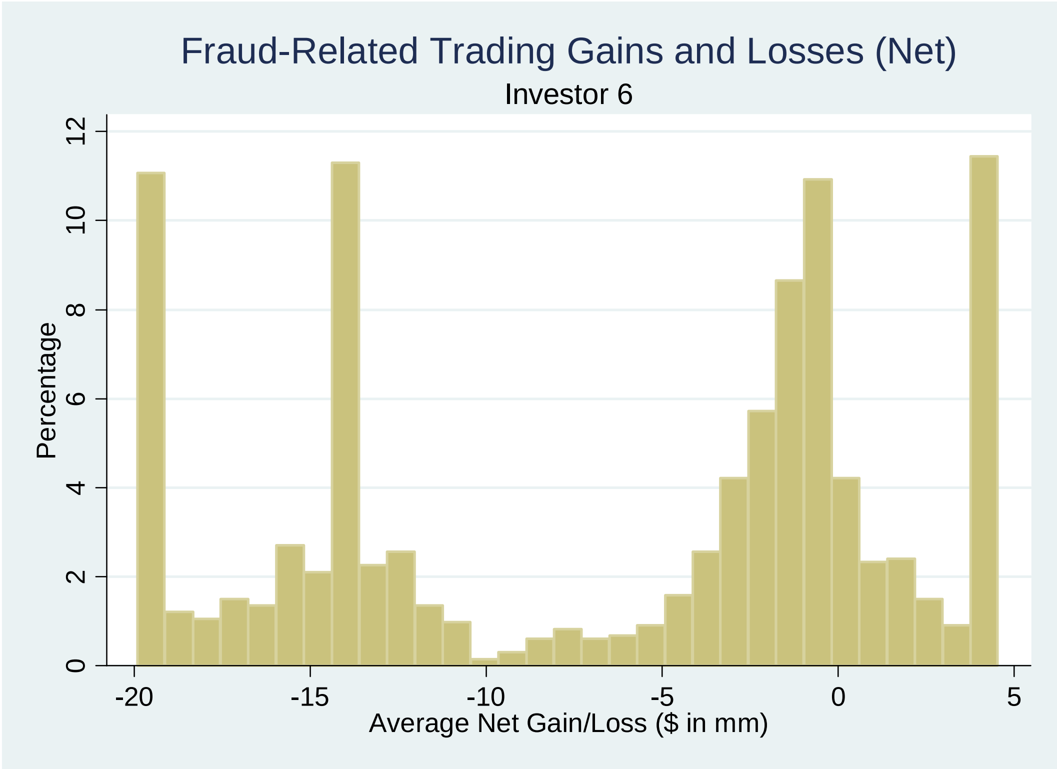
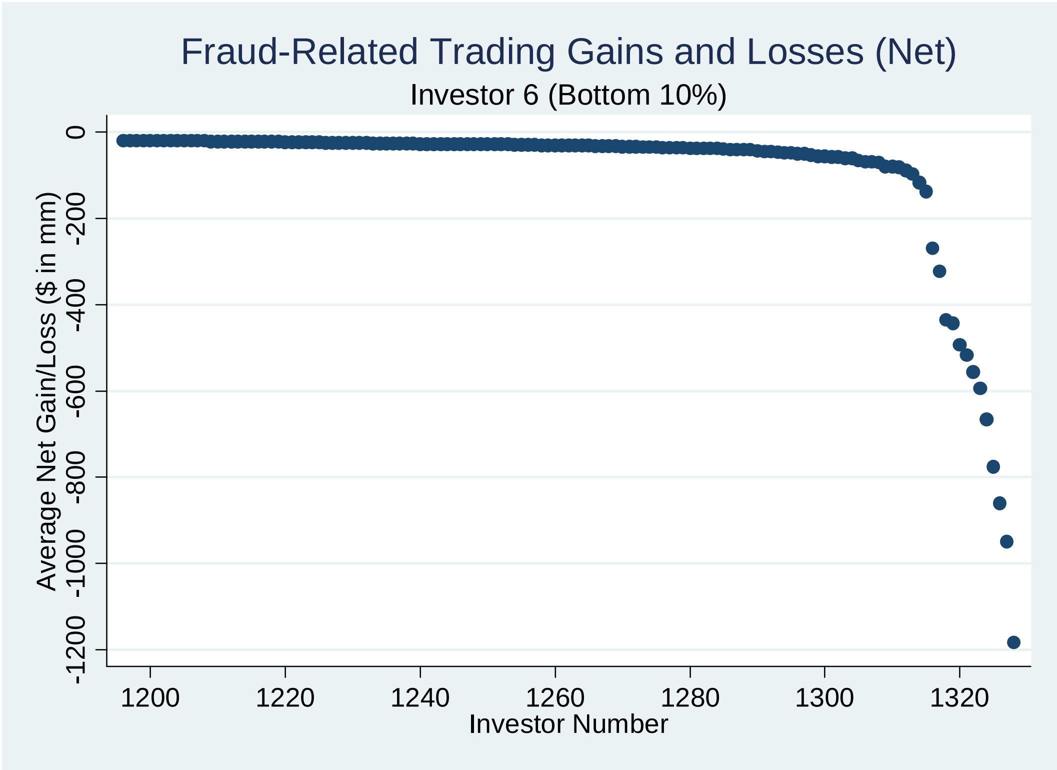


Figure 6b – Scatter Plot of Bottom 10% of the Distribution for Investor 6



Appendix A
Morningstar Mutual Fund Search Parameters

(% Bond = 0)
and (% Other = 0)
and (% Non-US Stock = 0)
and (% Cash not = 100)
and (Index Funds = No)
and (Enhanced Index Funds = No)
and (Fund of Funds = No)
and (Distinct Portfolio Only = Yes)

Number of funds: 333

The table above provides the search parameters used in the Morningstar mutual fund database search on July 19, 2007 to generate the sample of actively managed domestic stock mutual funds for inclusion in the "mutual fund" sample. The sample only includes 100% domestic stock funds (that is, funds with no securities other than stock of U.S. corporations). Index funds and funds of funds are excluded. To avoid double-counting, I ensure that I have a sample of unique funds, rather than different share classes of the same fund by searching