Getting Better or Feeling Better? How Equity Investors Respond to Investment Experiences

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Abstract

Using a large representative sample of Indian retail equity investors, many of them new to the stock market, we show that recent investment experiences affect portfolio composition. Because investors are imperfectly diversified, cross-sectional variation in their investment experiences allows us to identify such feedback effects. As investors spend more time in the market, they generally adopt style tilts and trading behaviors that are more consistent with the advice of financial economists; however, good account performance slows down this transition. Investors who experience a high return to an equity style trade to reduce their style tilt in the short run but increase it in the longer run, possibly reflecting the offsetting effects of disposition bias and style chasing. We find little evidence to support the view that investors are rationally learning about their investment skill.

It's a little better all the time. (It can't get no worse.)

Lennon and McCartney, "Getting Better," 1967.

And I do anything to just feel better, Any little thing that just feel better.

Santana, "Just Feel Better," 2005.

1 Introduction

The large historical equity premium has led both financial planners and academic economists to recommend substantial equity allocations for households accumulating financial assets (Campbell and Viceira 2002, Campbell 2006, Siegel 2007, Gomes and Michaelides 2008). However, households can lose much of the benefit of stock market participation by choosing inefficient equity portfolios that have a high proportion of uncompensated idiosyncratic risk (Calvet et al. 2007) or negatively compensated style tilts. For example, households may reduce their returns by holding growth stocks in a market with a value premium, or by adopting a short-term contrarian investment strategy in a market with momentum where outperforming stocks continue to outperform for a period of time. These style tilts are inefficient unless they hedge other risks faced by households.

Because the benefits of equity investing can only be realized through efficient portfolio construction, it is important to understand how households learn to perform this function. In this paper we show that households' recent investment experiences have an important influence on the composition of their equity portfolios. We are motivated by the recent finding of Malmendier and Nagel (2011, 2014) that adverse macroeconomic experiences affect household willingness to participate in the stock market. Malmendier and Nagel interpret this effect as the result of reinforcement learning, in which directly experienced events have a more powerful effect on decisions than events that are public information but not directly experienced.

We adopt a novel strategy to measure cross-sectional variation in experiences and identify reinforcement learning effects on portfolio composition. For Malmendier and Nagel, all households alive at a point of time share a common macroeconomic experience, so cross-sectional variation in households' experiences arises only from differences in their birth years (cohorts) and hence the events they have lived through. Experiences of this sort have impacts that can only be identified if one is willing to restrict cohort effects on behavior; and they accumulate only slowly over time, so Malmendier and Nagel need a long sample period to measure reinforcement learning and distinguish it from age effects. We instead measure idiosyncratic variation in experienced returns that results from imperfect portfolio diversification, an approach used earlier by Calvet et al. (2009) to identify inertia in asset allocation. This idiosyncratic variation exists at high frequencies, so we can measure its effects even controlling for individual fixed effects and over a much shorter sample period; and it exists both in a household's overall portfolio, generating positive or negative returns relative to the market, and within equity style categories.

To illustrate the latter point, consider the fact that in each month investors receive feedback on the desirability of a portfolio style tilt, for example towards value, from the differences in the returns of stocks *that they hold* which are positively style-tilted (value stocks), and those which are negatively style-tilted (growth stocks). Thus, the fact that investors hold different stocks within the broad categories of value and growth helps us to identify the impacts of this source of style-specific feedback on future value and growth tilts. The distinction between the directly experienced feedback that we measure (returns on the value stocks that households own) and hypothetically observed feedback (the aggregate returns on broad portfolios of value stocks) is analogous to the distinction in Malmendier and Nagel (2011) between macroeconomic disasters that households live through, and those that they read about in history books.

We implement our approach using new data on direct ownership of equities in India. This dataset has several characteristics that make it ideally suited to our analysis. First, India has electronic registration of equity ownership, allowing us to track the complete ownership and trading history of listed Indian stocks over a decade. Our data are monthly, and this allows us to measure feedback effects at a relatively high frequency. Second, mutual funds account for a relatively small value share of Indian households' equity exposure, so the composition of directly held stock portfolios gives a meaningful picture of the diversification and style tilts of overall household equity portfolios. This is not true in the datasets that have been used in previous work on household equity ownership.[2] Finally, India is an emerging market whose capitalization and investor base have been growing rapidly. In such a population of relatively new investors, reinforcement learning may be stronger and easier to detect than in better established equity markets.

The Indian data do have one important limitation: we observe investment accounts but we have almost no information about the demographic characteristics of account owners. Thus we cannot follow the strategies, common in household finance, of proxying financial sophistication using information about investors' age, education, and occupation (Calvet et al. 2007, 2009a, Betermier et al. 2013), their IQ test scores (Grinblatt and Keloharju 2011), or survey evidence about their financial literacy (Lusardi and Mitchell 2007). Instead, we use investor fixed effects to control for inherent levels of sophistication and all other time-invariant household characteristics. And we use account age (the length of time that an account has been investing in equities) to capture the effect of time in the market on investor behavior.

We find that households' investment experiences do influence equity portfolio composition. Good overall account performance encourages underdiversification, and accumulation of large, growth, and high-momentum stocks. Strong performance of style-representative stocks within investors' portfolios induces short-run decumulation (likely a manifestation of the disposition effect) but encourages longer-run accumulation of these styles. This is consistent with the "style chasing" model of Barberis and Shleifer (2000).

Time in the market has mixed effects on portfolio composition. Diversification does not improve as accounts age, but longer-established accounts have a tendency to accumulate

[2] Much previous research uses a US dataset on accounts at a single discount brokerage following Odean (1998, 1999). To the extent that US investors have other brokerage, mutual fund, or retirement accounts, this data does not give a complete picture of household equity exposure. Other work has used Scandinavian data. Grinblatt and Keloharju (2000, 2001, 2011) and Linnainmaa (2011) use Finnish data on direct ownership of Finnish stocks, but these data exclude mutual funds which are relatively important in Finland. Calvet et al. (2007, 2009) and Betermier et al. (2013) use Swedish data on all components of wealth, including mutual funds, but these data are available only at a lower annual frequency.

small stocks and value stocks. Thus overall account performance and account age have opposite effects on these two tilts, with high performance slowing down the general tendency to move towards smaller stocks and value stocks.

Responses to feedback from investment experience can be rationalized if investors are learning about their skill either as equity investors in general (Seru et al. 2010, Linnainmaa 2011), or as investors within a particular equity style. In this case high returns encourage further active investing in the market as a whole and greater allocation to an equity style. To explore this possibility, we aggregate the total portfolios held by investors with higher past returns, and the style portfolios held by investors who are predicted to increase their style tilts most aggressively, and compare them with the portfolios held by investors with lower past returns or investors who are predicted to reduce their style tilts. We find little evidence that past returns in general, or returns that encourage style tilts, predict high returns going forward.

We do however find some evidence that time in the market affects the performance of Indian equity portfolios. Longer-established Indian investors appear to have substantially higher returns than novice investors, although this result is imprecisely estimated. Longer-established Indian investors also tend to tilt their portfolios towards types of stocks which are commonly thought to have higher returns: small stocks, stocks with low turnover, and stocks held by institutions. Finally, these investors are more likely to avoid large, attention-grabbing initial public offerings.

While the main focus of this paper is on portfolio composition, we also present some evidence on trading behavior. Here we follow a large literature that documents the tendency of households to trade ineffectively, incurring high transactions costs by churning their portfolios (Odean 1999, Barber and Odean 2000), or accelerating the payment of taxes through the tendency (known as the disposition effect) to sell winning investments and hold losing investments (Shefrin and Statman 1985, Odean 1998, Grinblatt and Keloharju 2001). Trading behavior has been the focus of previous research because it is possible to measure even in datasets that do not give a complete picture of equity portfolio composition.

In the Indian data, we find that both feedback and time in the market affect trading behavior. Overall account performance encourages both higher turnover and a stronger disposition effect. Good performance of recent trading decisions has a significant and highly persistent impact on turnover, but there is little evidence that the performance of recent losing stocks sold relative to winning stocks sold has any influence on the strength of the disposition effect. Both turnover and the disposition effect decline substantially with account age. Thus in this context too, account performance and account age have opposite effects on investor behavior.

Taken together, our results show that strong investment performance encourages style tilts and trading behaviors that have potentially deleterious longer-run consequences, perhaps on account of investors simply "feeling better" in response to positive feedback and repeating the actions they associate with positive investment results. However we also find that longer-established Indian retail investors generally behave in a manner more consistent with the recommendations of finance theory, "getting better" over time.

The organization of the paper is as follows. Section 2 presents a brief literature review, focused on recent empirical research. Section 3 explains our methodology for estimating the effects of feedback on portfolio composition and trading behavior. Section 4 describes our data, and defines the empirical proxies we use to measure portfolio composition and trading behavior. Section 5 discusses our results on the impacts of feedback on portfolio composition. Section 6 relates portfolio composition to account performance, and evaluates the performance of portfolios aggregated from the holdings of different types of accounts. Section 7 discusses trading behavior, and Section 8 concludes.

2 Literature Review

Our paper contributes to a recent empirical literature on household decisionmaking in equity markets. This research can be grouped into two broad categories. The smaller part of the literature looks at total household portfolios, using relatively low-frequency data. Calvet et al. (2007, 2009) use comprehensive data on Swedish investors' total wealth to shed light on stock-market participation and portfolio rebalancing, and a recent study by Betermier et al.

(2013) examines the value tilt of Swedish investors, finding a tendency for this tilt to increase over the life cycle. The life-cycle effect on value investing could be consistent with models in which growth stocks hedge intertemporal fluctuations in expected stock returns (Campbell and Vuolteenaho 2004) or technological progress that erodes the value of human capital (Gârleanu, Kogan, and Panageas 2012), thereby appealing to younger investors with longer horizons and greater human capital; however, it could also be consistent with a behavioral bias of young investors towards future-oriented growth stocks, or with households learning about the value premium as they spend more time participating in the stock market. The Swedish data have an annual frequency and so cannot be used to measure higher-frequency feedback effects, making our results complementary to those of Betermier et al.

Several recent papers ask whether households use undiversified equity holdings to hedge their specific labor income risks. Massa and Simonov (2006), using Swedish data, and Døskeland and Hvide (2011), using Norwegian data, find that if anything households hold stocks that have a more positive correlation with their labor income than average, indicating a tendency to "anti-hedge". Massa and Simonov attribute this to superior information that households have about the industries in which they are employed, but Døskeland and Hvide find no evidence for superior performance of anti-hedging investments.

The larger part of the literature studies the determinants and performance of equity trades, rather than equity portfolio composition, using higher-frequency data that do not reveal the composition of total household portfolios. The focus has been on household-level determinants of turnover and the disposition effect, building on the work of Odean (1999) and Barber and Odean (2000) on turnover, and of Odean (1998) and Grinblatt and Keloharju (2001) on the disposition effect.

One set of papers, including Feng and Seasholes (2005), Dhar and Zhu (2006), and Korniotis and Kumar (2011), relates trading intensity and the disposition effect to time in the market and investors' demographic characteristics. A second set of papers, including Nicolosi et al. (2009), Seru et al. (2010), and Linnainmaa (2011), studies the effect of trading performance on trading intensity. The finding of these papers that good performance predicts trading intensity is consistent with a model in which investors learn from their performance about their trading skill, and cease trading if they conclude that they lack skill. These studies address econometric problems caused by exit decisions, which are much less serious in our context because investors rarely exit equity portfolio ownership even if they do cease active trading. Our use of overall account performance as a feedback variable is consistent with the approach of these papers.

Within the trading literature Huang (2014) is the closest paper to ours. Using the US discount brokerage dataset, Huang shows that good past performance of the stocks that an investor holds within an industry increases the probability that the investor will purchase stocks in that industry. She does not find any such effect on value or size tilts, contrary to our results.

Other papers have documented household reinforcement learning in other settings, such as 401(k) savings rates (Choi et al 2009), investment in IPOs (Kaustia and Knüpfer 2008, Chiang et al. 2011), and household choice of credit cards (Agarwal et al., 2006, 2008). Agarwal et al. (2008) find that households learn how best to reduce fees on their credit card bills, and estimate that knowledge depreciates by roughly 10% per month, i.e., they find evidence that households learn and subsequently forget. In a similar spirit our empirical specification allows us to compare the short- and long-run effects of investment performance feedback on household investment decisions.

Finally, there is a parallel literature measuring the effects of experience and feedback on the decisions of professional investors. Greenwood and Nagel (2009) document trend following, particularly by younger mutual fund managers, during the technology boom. Kempf, Manconi, and Spalt (2013) show that managers perform better in industries where they have more years of investment experience. Institutional investors' feedback trading behavior has been studied by Froot, O'Connell, and Seasholes (2001), Froot and Teo (2008), and Campbell, Ramadorai, and Schwartz (2009) among others. Our analysis is distinguished from these papers by our use of cross-sectional variation in the directly experienced performance of styles rather than the use of aggregate style returns. As aggregate style returns are potentially correlated with a range of unobserved time-series variables, our use of investor-specific variation in style returns allows for sharper identification.

3 Estimating Feedback Effects

Variation in portfolios across investors generates cross-sectional variation in investors' experienced returns. We measure feedback using two types of specific experiences that each investor has in the market. The first, which we term "account performance feedback" is the historical performance of the investor's total stock portfolio relative to the market. The coefficients on account performance feedback capture the effects on the outcome variables of interest (behavior and style demands) of the investor performing relatively well or relatively poorly over a period of time. The second is "behavior-specific" or "style-specific" feedback. We measure this source of feedback using historical experienced returns attributable specifically to the past behavior or style tilt of the investor which we seek to explain. For example, when forecasting an investor's net demand for value stocks, the style-specific feedback is measured as the recent return difference between the value stocks and the growth stocks actually held in the investor's portfolio.

To estimate feedback effects, we proceed as follows. Consider the following model of style demands, behavior, or account performance, represented generically as an outcome Y_{it} below:

$$Y_{it} = s_i + \delta_t + \gamma X_{it} + \beta A_{it} + \varepsilon_{it}. \tag{1}$$

In equation (1), s_i is an investor fixed effect, which we might think of as capturing the inherent sophistication or investment ability of investor i. Note that this subsumes all fixed investor attributes, such as gender, education, occupation, or birth cohort. δ_t represents an unobserved time fixed effect, and X_{it} is a predictor variable, which contains, most importantly for our purposes, the feedback experienced by investor i at time t. A_{it} is a measure of the age of account i at time t, which we use to capture the effect of time in the market on investor behavior.

We can cross-sectionally demean equation (1) and rewrite it as:

$$Y_{it} - Y_t = (s_i - s_t) + \gamma(X_{it} - X_t) + \beta(A_{it} - A_t) + \varepsilon_{it}, \tag{2}$$

where s_t is the cross-sectional average fixed effect of investors in the market at time t. In an unbalanced panel, as investors enter and exit the market, s_t can in general vary over time.

The fatal drawback of equations (1) and (2) is that the age effect is not identified on account of perfect collinearity. This is the usual problem with any specification containing a linear transformation of unrestricted age effects, unrestricted cohort or individual effects, and unrestricted time effects (Ameriks and Zeldes 2004, Guiso and Sodini 2013).

To estimate our model, we therefore restrict s_t in equation (2). The simplest restriction we employ is that $s_t = 0$, which requires the average ability or inherent sophistication of investors in the market to be time-invariant. It is important to note that our panel is unbalanced due to substantial entry and some exit of Indian retail investors over time. In a balanced panel, the average ability or inherent sophistication of investors (i.e. average investor fixed effect) would already be constant over time, so a different restriction would be required to identify equation (2).

Applying this restriction, we arrive at our baseline specification:

$$Y_{it} - Y_t = s_i + \gamma(X_{it} - X_t) + \beta(A_{it} - A_t) + \varepsilon_{it}. \tag{3}$$

This baseline specification is vulnerable to two econometric difficulties, and so in the internet appendix we consider alternatives to address the following concerns.

Changing average sophistication

First, it is possible that, contrary to the identifying restriction, the average inherent sophistication of Indian investors has been changing over time as market participation expands. To address this possibility, we model these changes in the internet appendix using the cross-sectional average of a set of investor attributes, i.e., by estimating:

$$Y_{it} - Y_t = (s_i - \alpha C_t) + \gamma(X_{it} - X_t) + \beta(A_{it} - A_t) + \varepsilon_{it} \tag{4}$$

where C_t includes the cross-sectional average of investor initial log account value and investor initial number of equity positions, as well as the income and literacy rates of the states in which investors are located, and the share of the investor population residing in rural and urban areas. Put differently, specification (4) simply attempts to fit cross-sectional average sophistication with the set C_t of cross-sectional average investor attributes. This specification remains identified as long as the dimension of the set C_t is less than the number of cross-sections.

We find that none of our inferences about feedback coefficients γ, and only a few of our inferences about time-in-the-market coefficients β, are affected by the introduction of these variables C_t. Estimated feedback effects are particularly robust to the modeling of average investor fixed effects since feedback variables have a great deal of high-frequency cross-sectional variation.

Failure of strict exogeneity

Second, panel estimation with fixed effects can deliver biased estimates when explanatory variables are not strictly exogenous. Intuitively, if the time dimension of the panel is short, and if high values of Y_i early in the sample predict high future values of X_i, then relative to its sample mean Y_i must be low later in the sample. As a result, Y_i will spuriously appear to be negatively predicted by X_i. This is a particular problem if we use account size as an explanatory variable to predict returns, since account size is mechanically driven in part by past returns. Similar issues may arise when we use investment behaviors or style tilts as explanatory variables, if their prevalence is behaviorally influenced by past returns.

Even the use of account age as a control variable may suffer from this problem if the disposition effect – the tendency of investors to sell gains rather than losses – leads to disproportionate exit of investors who have been lucky, as reported by Calvet et al. (2009a). In this case, the surviving, long-established investors may disproportionately be investors who had poor returns when they were novices. In the presence of investor fixed effects, this can produce an upward bias in the estimated effect of account age on portfolio returns. This bias can also exist in age effects in our behavior and style regressions to the extent that behaviors are also influenced by returns.

Fortunately violations of strict exogeneity are less serious in our application than in many panel estimation exercises because our panel has a relatively long time dimension, and the outcomes we study are generally not strong predictors of subsequent control variables. Furthermore, in the internet appendix we respond to the problem by estimating an alternative specification:

$$Y_{it} - Y_t = \theta(C_i - C_t) + \gamma(X_{it} - X_t) + \beta(A_{it} - A_t) + \varepsilon_{it} \tag{5}$$

This specification restricts the individual fixed effects used in (3), modeling them using the same set of investor attributes C described above. By eliminating the use of sample mean Y_i to estimate fixed effects, the specification protects against the bias discussed above. The appendix shows that our inferences about the impact of feedback, for which we might be concerned about bias arising from violations of strict exogeneity, are unaffected in this new specification.

With regard to the specific issue of luck-driven account exit, in the internet appendix we model the relationship of account exit and investor behaviors to past returns and use this to simulate survival bias in account age effects using our primary specification. We find that while account exit does tend to follow good past returns, the account exit rate is too modest and too weakly related to past returns for our inferences to be affected significantly.

Other econometric issues

We conclude with a few notes on estimation. First, all our regressions, except account returns, include log account size as a control variable. Second, when predicting investment behaviors we also include lagged behavior, Y_{it-1}, as a regressor. The inclusion of a lagged outcome variable makes the model one in which there is partial adjustment to a target which depends on the investor's feedback, as well as on account age. Feedback is almost entirely transitory, so we report the impulse response function, that is, the effect of lagged feedback on behavior taking into account the endogenous response of lagged behavior and its effect on current behavior. Since changes in account age are permanent, we report the impact of account age on the target level of behavior.

We estimate panel regressions applying equal weight to each cross-section. Standard errors are computed by bootstrapping months of data. This procedure makes standard errors robust to cross-correlations in the residual which may emerge, for example, if individuals act in herds. This estimation methodology is in the spirit of the well-known Fama-Macbeth regression method (since it gives each time period equal weights, and assumes errors are cross-sectionally correlated within each period but uncorrelated across periods), although ours differs in its inclusion of account fixed effects.

4 Data

4.1 Electronic stock ownership records

Our data come from India's National Securities Depository Limited (NSDL), with the approval of the Securities and Exchange Board of India (SEBI), the apex capital markets regulator in India. NSDL was established in 1996 to promote dematerialization, that is, the transition of equity ownership from physical stock certificates to electronic records of ownership. It is the older of the two depositories in India, and has a significantly larger market share (in terms of total assets tracked, roughly 80%, and in terms of the number of accounts, roughly 60%) than the other depository, namely, Central Depository Services Limited (CDSL). NSDL's share of individual accounts by state tends to be slightly greater in wealthier urban states, but has the majority of the depository market in most areas.

While equity securities in India can be held in both dematerialized and physical form, settlement of all market trades in listed securities in dematerialized form is compulsory.[3] We do not observe data on the derivatives transactions of Indian investors, including their participation in single-stock futures markets (in which open interest and trading volume are both larger than the stock index futures market, see, for example, Vashishtha and Kumar 2010). However, there is evidence that trading volume on Indian stock futures is very highly correlated with trading volume in the corresponding underlying equity security (Martins,

[3]To facilitate the transition from the physical holding of securities, the stock exchanges do provide an additional trading window, which gives a one time facility for small investors to sell up to 500 physical shares; however the buyer of these shares has to dematerialize such shares before selling them again, thus ensuring their eventual dematerialization. Statistics from the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) highlight that virtually all stock transactions take place in dematerialized form.

Singh, and Bhattacharya 2012), suggesting that the patterns that we uncover will not be greatly affected by the absence of these data. Note also that single-stock futures volume is likely to be concentrated in a minority of accounts, and may not be important for the majority of Indian equity investors.

The sensitive nature of our data mean that there are certain limitations on the demographic information provided to us. While we are able to identify monthly stock holdings and transactions records at the account level in all equity securities on the Indian markets, we have sparse demographic information on the account holders. The information we do have includes the state in which the investor is located, whether the investor is located in an urban, rural, or semi-urban part of the state, and the type of investor. We use investor type to classify accounts as beneficial owners, domestic financial institutions, domestic non-financial institutions, foreign institutions, foreign nationals, government, and individual accounts.[4] This paper studies only the category of individual accounts.

A single investor can hold multiple accounts on NSDL; however, a requirement for account opening is that the investor provides a Permanent Account Number (PAN) with each account. The PAN is a unique identifier issued to all taxpayers by the Income Tax Department of India. NSDL provided us with a mapping from PANs to accounts, so in our empirical work, we aggregate all individual accounts associated with a single PAN. PAN aggregation reduces the total number of individual accounts in our database from about 13.7 million to 11.6 million. [5]

Table 1 summarizes the coverage of the NSDL dataset. The first two columns report

[4]We classify any account which holds greater than 5% of an stock with market capitalization above 500 million Rs (approximately $10 million) as a beneficial owner account if that account would otherwise be classified as a trust, "body corporate,"or individual account. This separates accounts with significant control rights from standard investment accounts. Otherwise our account classifications are many-to-one mappings based on the detailed investor types we observe.

[5]It is worth noting here that PAN aggregation may not always correspond to household aggregation if a household has several PAN numbers, for example, if children or spouses have separate PANs. In addition it is possible that there may be households in our NSDL data who also have depository accounts with CDSL, which we do not observe. Conversations with our data provider suggest, however, that the fraction of retail investors with such multiple depository relationships is small, and that depository relationships tend to be persistent. Moreover, in the absence of the unlikely scenarios of substantial negative correlation in trading in cross-depository accounts, or movement of trading activity from one depository account to the other conditional on experience or feedback, we would not expect this issue to importantly affect our inferences.

the total number of securities (unique International Securities Identification Numbers or ISIN) and the total number of Indian equities reported in each year. Securities coverage grows considerably over time from just 12,350 in 2004 to almost 23,000 in 2011, as does the number of unique Indian equities covered. Starting at 4,533 in 2004, the number of equities reaches a peak of 7,735 in 2012. When we match these data to price, returns, and corporate finance information from various datasets, we are able to match between 96% and 98% of the market capitalization of these equities, and roughly the same fraction of the individual investor ownership share each year. The third column shows the market capitalization of the BSE at the end of each year. The dramatic variation in the series reflects both an Indian boom in the mid-2000s, and the impact of the global financial crisis in 2008.

The fourth column of Table 1 shows the fraction of Indian equity market capitalization that is held in NSDL accounts. The NSDL share grows from just above 50% at the beginning of our sample period to about 70% at the end. The fifth column reports the fraction of NSDL market capitalization that is held in individual accounts. The individual share starts at about 18% in 2004, but declines to just below 10% in 2012, reflecting changes in NSDL coverage of institutions, as well as an increase in institutional investment over our sample period. The sixth column shows the mutual fund share of total equities, which accounts for a little over 3.5% of total assets in the NSDL data in 2004, growing to a maximum of 4.72% in 2006, and declining to 3.97% by 2012. While comparing the fifth and sixth columns of Table 1 demonstrates the magnitude of direct household equity ownership relative to mutual funds, this simple comparison would lead to an overestimate of mutual fund ownership by households. SEBI data in 2010 show that roughly 60% of mutual funds in India are held by corporations.[6] In the internet appendix (Campbell, Ramadorai, and Ranish 2014), we estimate that individuals' indirect equity holdings through mutual funds, unit trusts, and unit-linked insurance plans were between 6% and 19% of total household equity holdings over the sample period. We note also that a 2009 SEBI survey found that about 65% of Indian households owning individual stocks did not own any bonds or mutual funds.

[6]See the SEBI website, http://www.sebi.gov.in/mf/unithold.html.

From the beginning to the end of our sample period, the number of individual NSDL accounts grew from 2.7 million to roughly 6.1 million, that is, by 125%. Our results are estimated from a stratified random sample of 143,359 accounts. This sample is constructed by drawing 5,000 individual accounts from each Indian state with more than 5,000 accounts, and all accounts from states with fewer than 5,000 accounts. From this sample, we use the 118,929 accounts which opened after January 2002 and hold stocks at some point. For accounts opened earlier, we do not observe the full investing history, do not know when the account first invested in stocks, and do not observe the initial account characteristics. In our internet appendix, we show that our results are qualitatively unchanged when we perform our analyses with all individual accounts after making assumptions required to make use of the additional older accounts. The internet appendix also shows that, as expected, state participation rates are highly correlated with per-capita state income. Our return regressions are estimated using about 4.2 million account months of data spanning January 2004 through January 2012, and our regressions of account behaviors and style tilts use somewhat fewer observations, as these measures cannot be defined for as many account months. In these regressions, within each cross-section, we use appropriate weights to account for the sampling strategy.

4.2 Characteristics of individual accounts

Table 2 describes some basic characteristics of Indian individual accounts, summarizing our panel dataset in two ways. The first set of three columns reports time-series moments of cross-sectional means. The first column is the time-series mean of the cross-sectional means, which gives equal weight to each month regardless of the number of accounts active in that month. The second and third columns are the time-series maximum and minimum of the cross-sectional mean, showing the extreme extent of time-variation in cross-sectional average account behavior. The second set of three columns reports cross-sectional moments of time-series means calculated for each account over its active life, giving equal weight to each account for which the given characteristic can be measured in at least twelve months. Since the cross-sectional dimension of the dataset is much larger than the time-series dimension, we report the 10th percentile, median, and 90th percentile of the cross-sectional distribution.

Account size, number of stocks held, and location

In the first panel of Table 2, we begin by reporting account sizes both in rupees (using Indian conventions for comma placement), and in US dollars, both corrected for inflation to a January 2012 basis. Given our focus on household finance questions, as opposed to the determination of Indian asset prices, we equally weight accounts in our empirical analysis as advocated by Campbell (2006). The table shows that the cross-sectional median account size is small, at $1,327, and even the 90th percentile account size is only $10,815, reflecting positive skewness in the distribution of account sizes. However, bear in mind that per-capita GDP in India is only about three percent of that in the U.S., and the median (wealthiest) deciles of Indian households had average total asset values of about $3,000 ($35,000) in 2003 (Subramanian and Jayaraj 2008), so these amounts likely represent a non-trivial share of wealth for many of the investors.

Turning to the number of stocks held in each account, we find that the median account holds only 3.4 stocks on average over its life. The 10th percentile account holds a single stock, while the 90th percentile account holds 14.3 stocks. The next row shows that around 56% of individual accounts are associated with urban account addresses, 32% with rural addresses, and 12% with semi-urban addresses.[7]

4.3 Portfolio composition and trading behavior

The remainder of Table 2 presents summary statistics for portfolio composition, performance, and trading behavior.

Underdiversification

The idiosyncratic share of portfolio variance is calculated from estimates of each stock's beta and idiosyncratic risk, using a market model with the value-weighted universe of Indian

[7] The internet appendix describes the method used to classify accounts into location-based categories.

stocks as the market portfolio, using a procedure very similar to that employed in Calvet et al. (2007).[8] The average idiosyncratic share is about 45% in both the time-series and cross-sectional moments, though there is considerable variation over time (from 25% to 55%) and across accounts (from 24% at the 10th percentile to 68% at the 90th percentile).

Style tilts

Table 2 also reports individual accounts' market betas and style (small, value, and momentum) tilts.

We construct account-level betas with the Indian market by estimating stock-level betas as described earlier, and then value-weighting them within each account. The average beta over time or across accounts is very slightly greater than one at 1.03. There is relatively little variation across either dimension as we estimate betas close to one for most large Indian stocks.

To represent portfolios tilts for each style, we first calculate the difference in value-weighted average style percentile between the account and the market. Then, we scale this by the difference in value-weighted style percentiles between style-sorted portfolios formed in the manner of Fama and French (1993). For example, a 10% small tilt means that the portfolios' small (i.e. inverse market capitalization) tilt can be replicated by a portfolio consisting of the market, plus a long position of 10% in the small-stock portfolio and a short position of 10% in the large-stock portfolio.

In US data, individual investors overweight small stocks and institutional investors overweight large stocks (Falkenstein 1996, Gompers and Metrick 2001, Kovtunenko and Sosner 2004). The average individual investor's portfolio has size percentile equivalent to the market plus a long position in the small stock portfolio (and equivalent short position in the

[8] In order to reduce noise in estimated stock-level betas, however, we do not use realized stock-level betas but instead use fitted values from a panel regression whose explanatory variables include stock-level realized betas (in monthly data over the past two years), realized betas on four portfolios of similar stocks (formed based on industry, and size, value, and momentum quintiles), and a dummy for stocks that are less than two years from their initial listing. To reduce noise in the estimate of idiosyncratic risk, we estimate idiosyncratic variance from a GARCH(1,1) model using parameters set to the median GARCH parameters selected across stocks in an initial round of GARCH estimation.

large stock portfolio) ranging in magnitude between 5.82% and 12.84% over time. The tilt is skewed across accounts: the 10th percentile account has a roughly a 6% large tilt while the 90th percentile account has a 34% small tilt. Individual Indian investors also have a modest average tilt towards value stocks, averaging about 11% over time, though with significant fluctuations. There are also very large differences across accounts in their tilt towards growth or value, with a spread of about 80% between the 10th and 90th percentiles of accounts. Finally, individual investors have a contrarian, or anti-momentum tilt. Both the time-series mean and cross-sectional median momentum tilts are about -8%. This pattern is consistent with results reported for US data by Cohen et al. (2002), and with short-term effects of past returns on institutional equity purchases estimated by Campbell et al. (2009).

Account performance

Table 2 reports monthly account returns, calculated from beginning-of-month stock positions and monthly returns on Indian stocks. These returns are those that an account will experience if it does not trade during a given month; in the language of Calvet et al. (2009a), it is a "passive return." It captures the properties of stocks held, but will not be a perfectly accurate measure of return for an account that trades within a month.[9]

The table shows that on average, individual accounts have slightly underperformed the Indian market (proxied by a value-weighted index that we have calculated ourselves). There is considerable variation over time in the cross-sectional average, with individual accounts underperforming in their worst months by as much as 4.8% or overperforming in their best months by as much as 10.2%. There is also dramatic variation across investors in their time-series average performance, with the 10th percentile account underperforming by 1.75% per month and the 90th percentile account outperforming by 1.52% per month.

Turnover

We measure turnover by averaging sales turnover and purchase turnover. Sales turnover

[9]The internet appendix provides details on our procedures for calculating Indian stock returns. The appendix also shows that our results are robust to consideration of "active" returns from intra-month trading.

equals the value of last month's holdings (at last month's prices) that were sold in the current month divided by the geometric average of the value of last month's holdings and the current month's holdings. This value is winsorized at 100%. Purchase turnover equals the value of the current month's holdings (at current prices) that were bought in the current month, divided by the same denominator and also winsorized at 100%.[10] Our measure of turnover is not particularly high on average for Indian individual accounts. The time-series mean of the cross-sectional mean is 5.7% per month (or about 68% per year), and the cross-sectional median turnover is only 2.6% (or 31% per year). Turnover this low should not create large differences between the passive return we calculate for accounts and the true return that takes account of intra-month trading. Once again, however, there is important variation over time and particularly across accounts. The 10th percentile account has no turnover at all (holding the same stocks throughout its active life), while the 90th percentile account has a turnover of 16.3% per month (196% per year).[11]

Disposition effect

In India, capital gains on equities are realized tax-free if the position is held at least twelve months and sold through a recognized stock exchange. Thus, it is usually costly to favor the sale of gains within a year of the purchase, even though this short period accounts for over 80% of gains realizations. Although there is not as strong of an argument about the harm of the disposition effect at longer holding periods, we measure the effect across all holding periods. First, measurement of the disposition effect over longer holding periods is necessary to measure the disposition effect for investors that trade infrequently. Second, we present evidence in the internet appendix that the relative tendency to sell gains and losses does not change around the twelve-month threshold defining long-term capital losses and

[10] We use a common denominator for sales and purchase turnover so that the related measures of style demand and supply we introduce can be properly netted against each other. However, the value of the last and current month's holdings are generally quite close, so this assumption is not quantitatively important.

[11] Following Odean (1999), we have compared the returns on stocks sold by individual Indian investors to the returns on stocks bought by the same group of investors over the four months following the purchase or sale. In India, the former exceeds the latter by 2.41%, which makes it more difficult to argue that trading by individuals is not economically harmful. At a one year horizon following the purchase or sale, we find that stocks sold outperform stocks bought by 4.36%.

gains. This suggests that incentives to minimize tax liability do not play a large role in this setting.

We calculate the disposition effect using the log difference of the proportion of gains realized (PGR) and the proportion of losses realized (PLR), with these proportions both winsorized at 0.01.[12] This is a modification of the previous literature which often looks at the simple difference between PGR and PLR. By calculating a log difference, we eliminate any mechanical relation between the level of turnover and our measure of the disposition effect. PGR and PLR are measured within each month where the account executes a sale as follows: Gains and losses on each stock are determined relative to the cost basis of the position, which is observed whenever the position was established after the account was opened. In the remaining 35% of cases we use the median month-end price over the 12 months prior to NSDL registry as the cost basis. We only count sales where a position is fully sold, as partial sales could be driven by account re-balancing. Both the assumption about unobserved cost basis and convention of only counting complete sales make little difference to the properties of the measure.

The disposition effect is important for Indian individual accounts. On average across months, the cross-sectional mean proportion of gains realized is 1.23 log points or 242% larger than the proportion of losses realized, while the median account has a PGR that is 286% larger than its PLR. While both time-series and cross-sectional variation in the disposition effect are substantial, it is worth noting that over 90% of accounts in the sample with 12 or more months with sales exhibit this effect.[13]

[12] Our results are robust to reasonable variation in this winsorization threshold.

[13] In the internet appendix, we compare the disposition effect in our Indian data with US results reported by Odean (1998). Specifically, we plot the mean ratio of PGR and PLR aggregated across accounts by calendar month, a series that can be compared with Odean's numbers. The Indian disposition effect is considerably stronger on average than the US effect, and in both India and the US, the disposition effect is weaker towards the end of the tax year (calendar Q4 in the US, and calendar Q1 in India).

5 Equity Portfolio Composition

In this section we use the methodology of Section 3 to estimate feedback and time in the market effects on equity portfolio composition. Our panel regressions are summarized in Table 3, which has four columns corresponding to regressions predicting the idiosyncratic share of portfolio variance and three measures of net demands for different equity styles. The effects of feedback and account age are modeled in a relatively unrestricted way, and are presented graphically. All regressions also include the log of account value and a lagged dependent variable, whose coefficients are reported.

5.1 The idiosyncratic variance share

The first column of Table 3 shows that as accounts become larger, they tend to become better diversified. In addition, the idiosyncratic variance share is quite persistent, with a coefficient of 0.776 on the lagged dependent variable.

Time in the market

The solid lines in Figure 1 represent point estimates of account age and performance feedback effects on the idiosyncratic variance share, and the dotted lines indicate the 95% confidence intervals of the estimates (a convention we follow in subsequent figures as well).

The top panel of Figure 1 shows that the idiosyncratic share of portfolio variance changes little with account age, after controlling for account size. Longer-established Indian investors do not seem to diversify their portfolios better except insofar as their accounts grow in value over time.

Account performance feedback

The bottom panel of Figure 1 shows that account outperformance leads investors to make larger idiosyncratic bets, especially over the first quarter following an increase in performance. The estimated coefficient implies that the idiosyncratic share of portfolio variance becomes about 22% higher than the mean idiosyncratic share for an account that has recently outperformed the market by 100%. This may be because past outperformance encourages investors to assess their investing skills more optimistically, in turn leading them to increase their idiosyncratic bets.

One might be concerned that there could be a mechanical effect of account performance on the idiosyncratic variance share. However, the presence of the lagged idiosyncratic variance share in the regression controls for any mechanical impact (given less than complete rebalancing within the month) of the return to an undiversified account on the end-of-month idiosyncratic variance share of the account. That is, we measure account return during the month leading up to the measurement date for the lagged idiosyncratic variance share, not the month following that measurement date. In this way we guarantee that the effects we estimate are behavioral and do not result mechanically from imperfect rebalancing.

5.2 Style demand and supply

The right-hand three columns of Table 3 summarize regressions predicting measures of style demand and supply. Style demand is defined as the cross-sectionally demeaned percentile of the portfolio of stocks bought by the investor multiplied by the purchase turnover of that investor. Thus, demand for value can be high when an investor buys a sizable amount of stocks with a modest value tilt or a modest amount of stocks with a sizable value tilt. As with our measures of style tilt in Table 2, we scale style demand by the difference in style percentiles between style-sorted portfolios constructed in the manner of Fama and French (1993). Then, value demand of 1% has equivalent impact on the value percentile of the investor's portfolio as would a shift of 1% of the portfolio's value from the Fama-French growth portfolio to the Fama-French value portfolio. Style supply is defined similarly, but for the investor's sales. We are especially interested in net style demand, which is the difference between style demand and style supply. The internet appendix provides separate results for style demand and supply.

Net style demand does not translate directly into a change in the style characteristics of an investor's portfolio. Because the style characteristics of any individual stock tend to regress towards the mean (with value stocks becoming more expensive relative to book value and growth stocks becoming cheaper, for example), a style-tilted portfolio requires some net style demand just to maintain its current style tilt. This effect is more important for large style tilts, so for example an investor who wishes to maintain an extreme value tilt must continually sell those stocks in the portfolio that have lost their extreme value characteristics, and replace them with the cheapest stocks available in the market.

In Table 3 we report the coefficients on log account value and lagged style tilts. The table shows that as accounts become larger, they have a greater tendency to accumulate small stocks and growth stocks. For each log unit increase in account value, the increase in net demand for small and growth stocks has equivalent impact on portfolio tilts as a monthly shift of 0.077% of the portfolio from large to small stocks, and 0.117% from value to growth stocks. The table also shows that all net style demands are negatively related to lagged style tilts, capturing a tendency for investors to trade in a way that moves their portfolios towards the average style characteristics of stocks in the Indian market.

Time in the market

The three panels of Figure 2 show how time in the market influences net demands for small market cap, value, and momentum. The top panel shows that the net small demand of an investor with eight years of experience exceeds that of a new investor by about 0.45% per month. The middle panel indicates that net value demand increases even more with account age, increasing by a total of about 1.8% over the first eight years. Our finding here is consistent with the results reported by Betermier et al. (2013) for older investors in Sweden, although it is important to keep in mind that Betermier et al. work with the age of underlying investors, not our measure of account age.

The internet appendix shows that these coefficients on account age are driven by the effects of time in the market on both style demand and style supply. However, the increasing net demand for small stocks is driven more by intensifying purchases of small stocks, whereas the increasing net demand for value stocks is primarily due to a reduction in the tendency to sell value stocks.

The bottom panel of Figure 2 demonstrates a modest U-shaped effect of account age on the accumulation of momentum stocks: one cannot reject the hypothesis that eight-year-old accounts have momentum tilts that are comparable to those of novice investors, with a minimum rate of accumulation of winners at the five-year age mark. This is due to the fact that novices setting up their portfolios disproportionately purchase well known stocks that have recently appreciated, then via the disposition effect they disproportionately sell their winners, which have higher momentum. As the disposition effect fades for longer-established accounts (a result discussed in the next section), net momentum demand shifts upward again.

Account performance feedback

Figure 3 illustrates the impacts of an account's overall market-relative performance on the investor's net style demands. The three panels in the left column of the figure show the impact of account performance on net style demands as a function of the time elapsed since the performance was realized. The three panels in the right column of the figure integrate these responses to show the cumulative impacts of feedback on the investor's trading behavior. The two panels in the top row of the figure show the impact on net small-cap demand, the two panels in the second row show the impact on net value demand, and the two panels in the third row show the impact on net momentum demand.

Impacts of overall account performance on net style demands are substantial, persistent, and highly statistically significant, with outperformance predicting higher net demands for large, growth, and momentum stocks. Even four years after a 100% outperformance by an account, net demand for small stocks is about 25 basis points per month lower, net demand for value stocks is about 1% per month lower, and net demand for momentum stocks is about 40 basis points per month higher. The cumulative effect on net style demand at the four-year mark is over 10% lower for small stocks, over 60% lower for value stocks, and over 25% higher for momentum stocks.

The internet appendix shows that the positive effect of account outperformance on net style demand for large, growth, and momentum stocks comes mostly from reduced investor sales of these styles. One possible interpretation is that large, growth, and momentum stocks have similar characteristics to the best performing stocks among investors' current and recent holdings. The disposition effect implies that investors tend to sell their specific winners, but when their overall account performance has been good this tendency may be weaker, and they may also seek to replace these winners with other stocks that have similar characteristics at the date of sale. It is also likely that outperformance increases overconfidence, as suggested by Daniel, Hirshleifer, and Subrahmanyam (1998), Gervais and Odean (2001), Statman, Thorley, and Vorkink (2006), and Kruger (2013). However, while overconfidence might explain a preference for growth stocks it is not clear that it should generate tilts towards large-cap or momentum stocks.

Style-specific feedback

Figure 4 has the same structure as Figure 3, but it illustrates the impact of style-specific feedback on investors' net style demands. This style-specific feedback is constructed by taking the total returns on the sub-portfolio of stocks held by the investor that are ranked above the cross-sectional average of all stocks in the same period on the given style (i.e., smallness, value, and momentum) minus the total returns on the sub-portfolio of stocks held by the investor ranked below average in the given style. In cases in which the investor does not own stocks ranked above or below the average for a given style, value-weighted market returns are substituted for the type of stocks that the investor does not own (e.g. growth, if an investor holds only value stocks).

The left column of Figure 4 shows that there are two distinct impacts of style-specific feedback. The first is a more precisely estimated short-term effect, in which the investor decumulates the style that has outperformed. The internet appendix shows that this short-term effect is due to a spike in supply of the outperforming style, suggesting this relates to the disposition effect. However, for all three of the styles, the far longer-lived effect is a tendency to continue to accumulate styles in which the investor has experienced positive returns. This "style chasing" behavior is consistent with the theoretical model of Barberis and Shleifer (2003). For all three cases, the cumulative net demand is positive, indicating that style chasing ultimately more than offsets the initial decumulation. The positive cumulative demand is statistically significant at the 5% level for value at horizons of two, three, and four years and marginally significant for momentum at the four-year horizon.

Interactions between time in the market and feedback

We have also considered the possibility that there are interaction effects between time in the market and feedback. Such effects might arise if account age influences the attention that investors pay to the stock market, as reinforcement learning should have a stronger effect when investors are following their portfolio performance more closely. Despite the theoretical plausibility of these effects, we have not found statistically significant or economically meaningful interactions. To save space we report these specifications only in the internet appendix.

6 Account Performance

In the previous section we showed that both feedback from investment experiences and time in the market affect the composition of Indian equity portfolios. How do these effects influence overall performance? In this section we analyze the impact of time in the market and feedback on investor portfolio returns.

Performance is inherently difficult to measure because account returns are subject both to considerable idiosyncratic volatility and to common shocks resulting from our measured style tilts and other systematic tilts. Accordingly we look at performance using two alternative approaches. First we measure performance directly at the account level. Second, we analyze the returns on portfolios of stocks held by different types of investors: long-established and novice investors, and investors demonstrating particular style tilts and investment behaviors. Additionally, in the internet appendix we predict the returns on individual Indian stocks using the characteristics of the investor base as well as characteristics of the stocks and companies themselves.

Finally, we ask whether the patterns in performance are consistent with the view that investors respond to feedback because they are rationally learning about their own investment skill.

6.1 Time in the market and account performance

The top plot of Figure 5 shows the impact of account age on account performance estimated from a piecewise linear model. While the reported age effects have substantial economic magnitudes (roughly 100 basis points a month higher for an eight-year investor relative to a novice), they are imprecisely estimated and only barely significant at the five percent level at seven years. The internet appendix reports more comprehensive results, showing that the account age effect remains economically meaningful but statistically insignificant when it is restricted to be linear. When we add measures of investor behavior and style tilts as explanatory variables, we find that changes in these behaviors with experience account for about one-third of the age effect on returns.

These performance results do not account for transactions costs. In India one-way levies and fees (primarily in the form of a securities transaction tax) of about 20 basis points plus brokerage fees of around 10-30 basis points result in an estimate of direct trading costs of 30 to 50 basis points each way. In the next section of the paper we estimate that the average difference in monthly (two-way) turnover between the oldest and newest quintile of accounts is just under 5%. Combining these facts leads to the estimate that increased turnover reduces after-cost returns of the newest quintile of accounts relative to the oldest by about 3 to 5 basis points per month, strengthening the return to time in the market illustrated in Figure 5.

6.2 Aggregated account-age portfolios

We form representative stock portfolios for individual investors sorted by account-age quintile. The representative long-established account has a stratified-sample-weighted average of the portfolio weights of accounts in the top quintile of account age, while the representative novice account is formed in the same way from accounts in the bottom quintile of account age. The bottom plot of Figure 5 illustrates the cumulative excess returns (relative to the Indian short rate) to the established-investor and novice-investor portfolios, along with the overall excess return of the Indian equity market, over the period January 2004–January 2012. By the end of this period the cumulative excess return on the established-investor portfolio was 89%, while the cumulative excess return on the Indian market index was 79%, and the cumulative excess return on the novice-investor portfolio was only 10%. In the internet appendix, we also plot an exponentially weighted moving average of the difference in returns on the long-established and novice portfolios. This shows that the novice portfolio outperformed only in 2004, late 2007, and during the surge in stock prices in the spring of 2009.

We next form a zero-cost portfolio that goes long the representative long-established account and short the representative novice account. The first column of Table 4 reports results for this portfolio. The second and third columns decompose it into long-short portfolios formed between the long-established and average (i.e. middle-quintile) representative investor and between the average and novice representative investor.

In the first column of Table 4, we regress the portfolio weights in the long-established minus novice zero-cost portfolio onto a vector of stock characteristics, to see what characteristics are preferred or avoided by long-established investors relative to novice investors. The second and third columns of the table do the same for the long-established minus average and average minus novice portfolios respectively. In the bottom of the table, we show how the returns on the zero-cost portfolios can be attributed into unconditional and timing effects related to either stock characteristic tilts or a residual that we call "selectivity" following Wermers (2000). This decomposition is described in our internet appendix.

The table shows that relative to novice investors, the longest-established Indian investors tilt their portfolios towards small stocks, value stocks, stocks with low turnover, stocks without large beneficial ownership, and stocks held by institutions. Long-established investors also avoid large, attention-grabbing initial public offerings. This last result is unsurprising considering that such IPOs are one of the main routes to initial investor participation in the Indian stock market.

While these portfolio tilts of long-established investors seem sensible given evidence from developed stock markets, in our Indian dataset the stock characteristics of long-established investors explain only 9 basis points out of a total outperformance relative to novice investors of 38 basis points per month. The remainder is not explained by characteristic timing, which makes an insignificant but negative contribution of 10 basis points. The performance differential is attributable mainly to stock timing effects (27 basis points) and non-characteristic related stock selection (13 basis points). Most of these differences are preserved when looking at the difference between average-aged and novice accounts, implying that the initial mistakes made by inexperienced investors ("rookie mistakes") contribute to the performance differential between long-established and novice accounts.

In the first column of Table 5 we evaluate the long-established minus novice zero-cost portfolio in a different way, by regressing its return on six factors commonly used in the asset pricing literature: the market return, small minus big (SMB) return, value minus growth (HML) return, momentum (UMD) return, and factor portfolios capturing short-term reversals and illiquidity as measured by turnover. We find that the portfolio has a negative loading on HML, despite its slight tilt towards value characteristics, and has a significantly positive six-factor alpha. It appears that long-established investors add value not by taking compensated factor exposures, but by finding outperforming stocks whose factor exposures are generally poorly compensated. To the extent that this is the case, the results of Coval et al. (2005) that following high-performing individual investors' trades generates high abnormal returns should also apply to a strategy of emulating long-established investors' equity holdings.

6.3 Alternative account-based portfolio sorts

The remaining columns of Table 5 repeat this exercise using zero-cost portfolios that go long stocks held by investors with high levels of past performance, idiosyncratic variance, or style tilts, and short stocks held by investors with unusually low levels of these attributes.

The second column shows that there is little evidence of account performance persistence in the Indian data. A portfolio that is long stocks held by investors with high average past performance, and short stocks held by investors with low average past performance, has a raw return of only 7 basis points per month, and a negative six-factor alpha. The portfolio unsurprisingly tilts towards momentum and away from short-term reversal, since high-performing accounts will tend to hold stocks that are past winners both in the medium term (positive momentum) and in the shorter term (negative reversal).

The third column reports weak evidence that undiversified accounts perform well. A portfolio that is long stocks held by undiversified investors, and short stocks held by diversified investors, has a positive average return of 27 basis points per month and a positive six-factor alpha of 31 basis points per month. Such outperformance is consistent with the suggestion of Ivkovic et al. (2008) that underdiversification may in some cases result from stock-specific information possessed by sophisticated investors – they find that individual trader performance improves as the number of stock holdings decreases, holding other determinants of performance constant. However, in our dataset neither the raw return not the six-factor alpha of the undiversified-account portfolio is statistically significant.

The next three columns look at portfolios of stocks favored by accounts with extreme style tilts. The most interesting results are in the fourth column, which analyzes the return to a portfolio that is long stocks held by small-stock investors, and short stocks held by large-stock investors. Unsurprisingly this portfolio has a strong loading on the SMB factor; it also has a positive loading on HML and a negative loading on UMD. The raw return on the portfolio is close to zero, but its six-factor alpha is significantly negative at -100 basis points per month. It appears that Indian retail investors who favor small stocks do not earn the appropriate compensation for their style tilts. Results are also disappointing for the momentum tilt in the sixth column, but better for the value tilt in the fifth column; however there are no statistically significant returns (positive or negative) in these columns.

6.4 Are investors learning about their skill?

One possible interpretation of feedback effects on portfolio composition is that investors are learning about their investment skill, either as active equity investors in general or as specialists in a particular equity style. According to this view, strong past account performance reduces diversification because investors rationally anticipate good future performance when they pick stocks; and strong past returns within a particular style increase the tilt to that style (in the longer run) because investors rationally anticipate stock-picking success within that style. This view applies to portfolio composition the arguments about learning to trade made in Nicolosi et al. (2009), Seru et al. (2010), and Linnainmaa (2011).

For this explanation to be correct, past performance should predict future performance.[14] In Table 6 we ask whether this is the case, both for overall and style-specific performance, and both for holdings and new purchases. Like Table 5, the table reports both raw returns and six-factor alphas for long-short portfolios, along with the estimated factor loadings from the six-factor model.

The first two columns of the table form portfolios of stocks either held (first column) or purchased (second column) by accounts in the top quintile of past performance (held long) or the bottom quintile of past performance (held short). The first column repeats the evidence of Table 5 that there is little performance persistence in our data. The second column shows that past returns do not predict future performance of new purchases either, so the weak results in the first column are not just the result of inertia in equity holdings.

The remaining columns of Table 6 sort investors by their predicted response to style feedback (weighting very recent past style returns negatively and longer-term past style returns positively, as in Figure 4). Portfolios are formed that go long stocks held or purchased by investors who are predicted to increase their allocation to ("chase") a style, and go short stocks held or purchased by investors who are predicted to reduce their allocation to ("exit")

[14] Berk and Green (2004) present a model of investment skill among mutual fund managers in which good past performance reveals skill, but generates inflows that expand assets under management to offset any effect on future performance. The insights of this model do not apply to our context, since Indian retail accounts are too small for diminishing returns to scale to be relevant, and retail investors are not subject to flows in the same way as professional investors.

the style. The raw returns to these portfolios are consistently positive, but very imprecisely estimated, while the six-factor alphas have mixed signs. In the internet appendix we show similar results when we condition only on the longer-term portion of the predicted style allocation that is driven by positive past performance.

Overall, these results offer little support to the view that portfolio composition responds to feedback because investors learn rationally about their investment skill.

7 Trading Behavior

In this section we use our Indian data to explore investors' trading behavior. Table 7, which has the same structure as Table 3, summarizes regressions predicting turnover and disposition bias at the account level. Figure 6 shows the impacts of time in the market and feedback on these two behaviors (in rows), with the three columns showing, respectively, the impacts of account age, past total account performance relative to the market, and past behavior-specific feedback. In these plots, we scale variables by the time-series average of their cross-sectional means reported in Table 2.

The first column of Figure 6 shows that account age effects on trading behavior are large in economic magnitude. Over the course of five years, monthly turnover declines by a statistically significant 75% of the mean, with this number becoming an even larger 98% for an eight-year old account relative to a novice account. The disposition effect declines by 42% for a five-year account relative to a novice, although the internet appendix shows that much of this effect may actually be attributable to the fact that early cohorts appear more sophisticated along the dimension of the disposition effect.

It is tempting to interpret the effects of account age on turnover and disposition bias as an effect of time in the market on individuals' investment skill. We note however that the reduced turnover for longer-established accounts could also reflect diminished interest in stock trading, rather than any increase in skill per se.

The second column of Figure 6 shows the ability of account performance to predict turnover and the disposition effect. Account performance has a significant but short-lived effect on both behaviors, with a 100% outperformance increasing turnover by over 70% and the disposition effect by about 80% relative to the cross-sectional means of these variables.

The third column of Figure 6 looks at more specific measures of feedback based on the performance generated by each trading behavior. For turnover, we measure an account's past trading success. Turnover-specific feedback from a given month is the difference between actual returns in that month and the returns that would have obtained if the investor had not traded in the previous three months. This variable strongly predicts turnover, implying that trading profits strengthen the tendency to trade stocks frequently.[15] Specifically, a return of 100% from recent trading initially increases turnover by over 100% of its cross-sectional mean. Even after several years, the effect remains statistically significant and economically important at about 30% of the cross-sectional mean.

It should be noted that the effects of recent account performance and trading profits on turnover may result in part from the disposition effect. If recent trading is profitable, then an account has tended to purchase winners, and these are more likely to be sold if the investor has a disposition bias. Such sales, and subsequent purchases of replacement stocks, increase turnover. However, the stronger response of turnover to trading profits than to account performance, and the persistence of the response to trading profits, suggest that the disposition effect is not the only factor driving turnover.

Finally, we consider a specific measure of feedback related to the disposition effect. We calculate excess returns relative to the market index on stocks that each account sold, during the three month period following each sale, and compare the excess returns to losers sold relative to winners sold, weighting by the value of each sale. This feedback measure could be positive if the account holds mean-reverting stocks, or negative if the account holds stocks that display momentum. This variable predicts the future disposition effect with the expected positive sign, but the effect is not statistically significant.[16]

Trading behaviors, like style tilts, could respond rationally to feedback if investors learn

[15] This result is consistent with the findings of Linnainmaa (2011), who employs information on a set of high-frequency traders from Finland.

[16] Consistent with this result, Ranguelova (2001) finds that the disposition effect is attenuated among investors who hold small US stocks with greater momentum in their returns.

about their own skill. For example, skilled traders might learn from their trading profits that they have the skill needed to justify continued trading (Seru et al. 2010, Linnainmaa 2011). Similarly, certain investors might specialize in holding mean-reverting stocks for which realizing gains and holding losses is a systematically profitable strategy; and past disposition-effect profits might tell these investors about their skill at implementing this strategy. However, the last two columns of Table 5 suggest that this explanation is not correct. In the Indian data, turnover and disposition bias are associated with lower, not higher returns in aggregated portfolios. The negative effect of turnover on returns is economically large and statistically significant both for raw returns and for six-factor alphas.

8 Conclusion

In this paper we have studied how individual investors adjust the composition of their equity portfolios in response to feedback from experienced equity returns. This requires comprehensive high-frequency data on equity holdings, which we obtain from India over the period from 2004 to 2012. To identify investors' responses, we exploit the fact that their portfolios are imperfectly diversified, which generates cross-sectional variation in experienced returns both at the overall portfolio level and within equity styles. We have also explored the effect of time spent in the equity market on portfolio composition, and have additionally considered two trading measures, turnover and disposition bias, that most previous papers—lacking our ability to measure overall portfolio composition—have concentrated upon. Our results can be summarized in two main categories.

First, we find offsetting effects of overall investment performance and time in the market on portfolio composition and trading behavior. Strong investment performance relative to the aggregate market reduces diversification, pushes investors towards large growth stocks, and increases turnover and disposition bias. This implies that high experienced returns encourage what we might characterize as "bad" investment behavior through a reinforcement learning or "feeling better" effect. Offsetting this effect, however, the propensity to invest in large growth stocks, turnover, and disposition bias all decline with account age. It appears that with greater time spent in the market, Indian investors increasingly avoid style tilts and trading behavior that are generally thought to reduce performance. In this sense they are "getting better" over time, through some combination of increased investment skill and reduced interest in naïve equity trading strategies.

Second, we find feedback effects from specific experienced returns to portfolio composition and trading behavior. Returns to style tilts within investors' portfolios, which vary idiosyncratically with the particular style stocks held, have short-term negative effects on net style demand—probably a manifestation of the disposition effect, as investors sell winning positions—but longer-term persistent positive effects that are consistent with theories of "style chasing". In the case of value, the cumulative effect is positive and statistically significant over a two- to four-year time horizon. In addition, returns to recent trading activity encourage turnover, and this effect is highly persistent.

We have considered the possibility that these feedback effects reflect rational learning by investors about their own investment skill, either in the equity market generally or within specific styles. However we do not find the sort of performance persistence that would be necessary to support this explanation. While there is some evidence that long-established accounts tend to outperform novice accounts, particularly after risk adjustment in a six-factor model, there is little evidence that past account-level or style-specific performance predicts future performance of either stocks held or stocks purchased. And in our data turnover is quite strongly associated with lower future returns.

India is a natural laboratory in which to study investor responses to feedback, given the rapid development of its financial system and the availability of high-frequency administrative data on directly held equity portfolios, which represent the great majority of Indian equity investments. The effects of feedback on portfolio composition and trading behavior that we discover in Indian data are broadly consistent with fragmentary evidence from other countries, and are likely to reflect general patterns of investor behavior. Thus we believe our findings are of interest beyond the particular Indian context in which we have obtained them.

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Table 1: Summary Statistics for NSDL Database

The percentages below are computed for each monthly cross-section, and the average of these monthly percentages within each year appear in the table. The number of unique securities and equities are determined by the average number of unique ISIN appearing in the NSDL database in each month in the given year. Individual accounts exclude beneficial owners. BSE market capitalization (from the World Federation of Exchanges), is from the end of each year and represents the market capitalization of all equities listed on the BSE, representing the vast majority of Indian equities.

	Number of Unique Securities	Number of Unique (Indian) Equities	Market Capitalization of BSE (Billions of US$)	% of Indian Equity Market Capitalization in NSDL Accounts	% of NSDL Equity Value in Individual Accounts	% of NSDL Equity Value in Mutual Funds
2004	12,350	4,533	$386.3	51.02%	17.50%	3.51%
2005	13,613	4,844	$553.1	57.71%	15.78%	3.73%
2006	15,408	5,150	$818.9	63.12%	14.94%	4.72%
2007	17,262	5,516	$1,819.1	66.06%	12.81%	4.55%
2008	17,417	5,988	$647.2	64.60%	11.89%	4.46%
2009	17,592	6,398	$1,306.5	64.01%	11.22%	4.56%
2010	19,681	6,897	$1,631.8	66.82%	10.78%	4.35%
2011	22,794	7,493	$1,007.2	67.73%	10.12%	4.00%
2012	21,431	7,735	$1,263.3	68.55%	9.91%	3.97%

Table 2: Summary Statistics for Individual NSDL Accounts

Statistics are computed on the basis of individuals' account months used in the regression models. Sampling weights are used to reflect the state-stratified manner in which the random sample was drawn. Time-series means of the variables are computed only for accounts where the given data are observed in at least 12 months. Styles of holdings are measured as the difference in account and market style percentiles divided by the difference in the corresponding Fama-French style portfolios.

	Time Variation in Cross-Sectional Means			Cross-Sectional Variation in Time-Series Means		
	Mean	**Min**	**Max**	**10th**	**50th**	**90th**
Account Value, Jan 2012 Rs	Rs 12,63,311	Rs 2,50,767	Rs 33,73,772	Rs 7,288	Rs 67,684	Rs 5,51,585
Account Value, Jan 2012 US$	$24,771	$4,917	$66,152	$143	$1,327	$10,815
Number of Equity Positions	6.88	4.75	8.02	1.00	3.42	14.27
Urban Accounts	55.84%	54.60%	57.54%	0	1	1
Semi-Urban Accounts	12.31%	11.86%	12.79%	0	0	1
Rural Accounts	31.85%	30.05%	33.05%	0	0	1
Idiosyncratic Share of Portfolio Variance	0.45	0.25	0.55	0.24	0.46	0.68
Stock Portfolio Beta	1.03	0.95	1.09	0.95	1.02	1.13
Style of Holdings Minus Market:						
Small	8.54%	5.82%	12.84%	-5.92%	2.93%	33.77%
Value	10.97%	-14.58%	73.61%	-22.07%	7.58%	61.97%
Momentum	-8.49%	-25.59%	10.64%	-32.87%	-8.70%	6.52%
Monthly Account Stock Return Minus Market	-0.03%	-4.80%	10.21%	-1.75%	-0.12%	1.52%
Monthly Turnover	5.72%	2.09%	12.28%	0.00%	2.57%	16.30%
Disposition Effect	1.23	-1.26	2.40	0.25	1.35	2.38

Table 3: Individual Investors Portfolio Composition Regressions

Regressions follow Equation (3) using account-months for which the variables used in the regression are defined. Idiosyncratic share of portfolio variance is scaled by the time-series average of its cross-sectional mean. Investor net style demands are scaled by the spread in percentiles between the Fama French long and short portfolios based on the corresponding styles. Account value is winsorized below at Rs. 10,000 (approximately $200 US). Panel regressions are run using weights that account for sampling probability and further apply equal weight to each cross-section (month). Standard errors in ( ) are computed from bootstraps of monthly data. Coefficients that are significant at a five percent level are in bold type.

Dependent Variable:	Idiosyncratic Share of Portfolio Variance	Net Small Demand	Net Value Demand	Net Momentum Demand
Number of Observations:	3,444,690	3,599,452	3,599,452	3,599,452
Account Age, Piecewise Linear Form	-------*See Figure 1*-------	------------------------------------*See Figure 2*------------------------------------		
Account Performance Feedback, by Time Since Event		------------------------------------*See Figure 3*------------------------------------		
Style-Specific Feedback, by Time Since Event		------------------------------------*See Figure 4*------------------------------------		
Log Account Value	**-0.015**	**0.077%**	**-0.117%**	0.019%
	(0.001)	*(0.018%)*	*(0.031%)*	*(0.026%)*
Lagged Dependent Variable	**0.776**	**-0.078%**	**-0.118%**	**-0.052%**
	(0.008)	*(0.005%)*	*(0.006%)*	*(0.003%)*

Table 4: Decomposition of the Difference in Returns on Old and New Accounts

Over our sample period, we form zero cost portfolios as differences in average portfolio weights between the cohorts (determined by quintile rankings on age) of investors mentioned in the column headers (e.g., oldest minus average (middle quintile)). These weights pertain to 2,677 stocks with market capitalization of at least Rs. 500 million (approximately $10 million US). In the top panel of the table, we relate these portfolio weights to stock characteristics listed below using Fama MacBeth regressions, where all characteristics used except market beta, stock age, and the IPO control are measured in rank-normalized form, and coefficients are multiplied by 1000. The bottom panel decomposes total returns into timing and selection effects -- Section 6.2 of the paper provides details. Standard errors in ( ) are computed by bootstrap, and statistically significant coefficients at the five and ten percent level are indicated by bold and italicized type respectively.

Number of Observations (Stock-Months): 103,509

Zero-Cost Portfolios:	Oldest minus Newest	Oldest minus Average	Average minus Newest
Portfolio Tilts	[1]	[2]	[3]
Market Beta	-0.547	*-0.393*	-0.154
	(0.568)	*(0.224)*	*(0.428)*
1 / Market Capitalization	0.318	**0.448**	-0.130
	(0.233)	*(0.185)*	*(0.272)*
Book-Market	0.171	0.100	0.071
	(0.143)	*(0.095)*	*(0.179)*
Momentum (Lagged) Returns	-0.003	0.113	-0.116
	(0.340)	*(0.255)*	*(0.175)*
Stock Turnover	**-0.908**	-0.237	*-0.671*
	(0.262)	*(0.306)*	*(0.396)*
Beneficial Ownership	*-0.604*	**-0.457**	-0.147
	(0.367)	*(0.192)*	*(0.246)*
Institutional Ownership	**0.919**	**0.447**	0.472
	(0.356)	*(0.162)*	*(0.438)*
Log (1 + Stock Age)	0.010	*0.216*	**-0.207**
	(0.075)	*(0.118)*	*(0.104)*
Large IPOs (Market Cap if Age<One Year)	**-13.358**	**-0.733**	**-12.625**
	(3.723)	*(0.358)*	*(3.625)*
Return Decomposition			
Stock Characteristic Selection	8.52	3.37	5.15
	(5.54)	*(2.34)*	*(3.54)*
Additional Stock Selection	12.90	4.72	8.19
	(14.55)	*(5.97)*	*(11.15)*
Stock Characteristic Timing	-9.63	1.16	-10.79
	(11.13)	*(5.73)*	*(7.17)*
Additional Stock Timing	26.60	-0.41	27.02
	(21.24)	*(7.35)*	*(21.53)*
Total Difference in Returns	38.40	8.83	29.56
	(28.34)	*(10.87)*	*(24.42)*

Table 5: Performance Evaluation of Portfolios Based on Account Age, Past Returns, and Investor Behavior

The zero-cost portfolios evaluated below are the differences in representative individual portfolios of accounts ranked in the highest and lowest quintiles by [1] account age (the first column of Table 4), [2] returns, [3]-[6] portfolio composition, and [7]-[8] trading behavior. Investor level portfolio composition and trading behaviors are measured as the lagged cumulative average of their cross-sectionally de-meaned values. Returns on the portfolios are adjusted using a six factor model, where the factor returns (except Illiq) are constructed in an analogous way to the factor returns from Ken French's website. The yield on three-month Indian Treasury bills is used as the risk free rate. The illiquidity factor (Illiq) is constructed from a independent double sort on size and turnover over the past 12 months, Illiq=0.5 x (Small, Low Turnover-Small, High Turnover)+0.5 x (Large, Low Turnover-Large, High Turnover). All standard errors are computed using a Newey West adjustment for serial correlation (with three lags).

Investor Characteristic Sort	Account Age [1]	Portfolio Returns [2]	Idiosyncratic Share of Portfolio Variance [3]	Small Tilt [4]	Value Tilt [5]	Momentum Tilt [6]	Turnover [7]	Disposition Effect [8]
Raw Return	*0.38%*	0.07%	0.27%	-0.02%	*0.74%*	-0.09%	**-0.84%**	*-0.34%*
	(0.23%)	*(0.41%)*	*(0.35%)*	*(0.50%)*	*(0.41%)*	*(0.41%)*	*(0.31%)*	*(0.19%)*
Monthly Alpha	**1.11%**	-0.32%	0.31%	**-1.00%**	0.36%	-0.29%	**-1.31%**	-0.12%
	(0.33%)	*(0.36%)*	*(0.39%)*	*(0.37%)*	*(0.48%)*	*(0.48%)*	*(0.29%)*	*(0.17%)*
Factor Loadings								
Market Beta	*-0.10*	*0.09*	*0.08*	**0.10**	0.04	0.04	*0.08*	*-0.05*
	(0.06)	*(0.05)*	*(0.04)*	*(0.04)*	*(0.06)*	*(0.07)*	*(0.04)*	*(0.03)*
SMB	*0.07*	-0.06	**0.17**	**0.49**	**0.28**	-0.08	**0.12**	0.04
	(0.04)	*(0.05)*	*(0.05)*	*(0.07)*	*(0.07)*	*(0.07)*	*(0.04)*	*(0.04)*
HML	**-0.20**	-0.03	0.10	**0.34**	0.14	-0.09	**0.22**	0.01
	(0.07)	*(0.09)*	*(0.07)*	*(0.09)*	*(0.11)*	*(0.10)*	*(0.05)*	*(0.05)*
UMD	0.03	**0.47**	**-0.22**	**-0.21**	**-0.16**	**0.42**	**-0.17**	**-0.13**
	(0.05)	*(0.07)*	*(0.04)*	*(0.05)*	*(0.06)*	*(0.09)*	*(0.04)*	*(0.04)*
Short Term	-0.10	**-0.18**	0.05	0.00	0.05	0.00	0.01	0.03
Reversals	*(0.07)*	*(0.07)*	*(0.04)*	*(0.06)*	*(0.07)*	*(0.11)*	*(0.05)*	*(0.03)*
Illiq (Based	-0.14	0.02	-0.20	0.03	0.00	-0.03	-0.01	-0.08
on Turnover)	*(0.13)*	*(0.12)*	*(0.15)*	*(0.12)*	*(0.16)*	*(0.15)*	*(0.09)*	*(0.06)*

Table 6: Performance Evaluation of Portfolios of Holdings and Purchases Based on Account-Level Past Returns and Estimated Style Feedback Response

The zero-cost portfolios evaluated below in columns [1] and [2] represent the holdings (column [1]) or purchases (column [2]) of the quintile of accounts with the highest past returns minus the quintile of accounts with the lowest past returns, where past returns are measured by the cumulative average of past cross-sectionally demeaned returns. The zero-cost portfolios in columns [3] through [8] represent differences of zero-cost (long position in the style, short position in the opposite style) portfolios of stocks held or purchased between accounts in the highest quintile of style feedback minus accounts in the lowest quintile of style feedback. For example, column [3] represents [(small stocks held by accounts with good small minus large feedback)-(large stocks held by accounts with good small minus large feedback)]-[(small stocks held by accounts with poor small minus large feedback)-(large stocks held by accounts with poor small minus large feedback)]. Style feedback ranking is based on the predicted response of net style demand illustrated in Figure 4. Returns on the portfolios are adjusted using a six factor model as in Table 5. All standard errors are computed using a Newey West adjustment for serial correlation (with three lags).

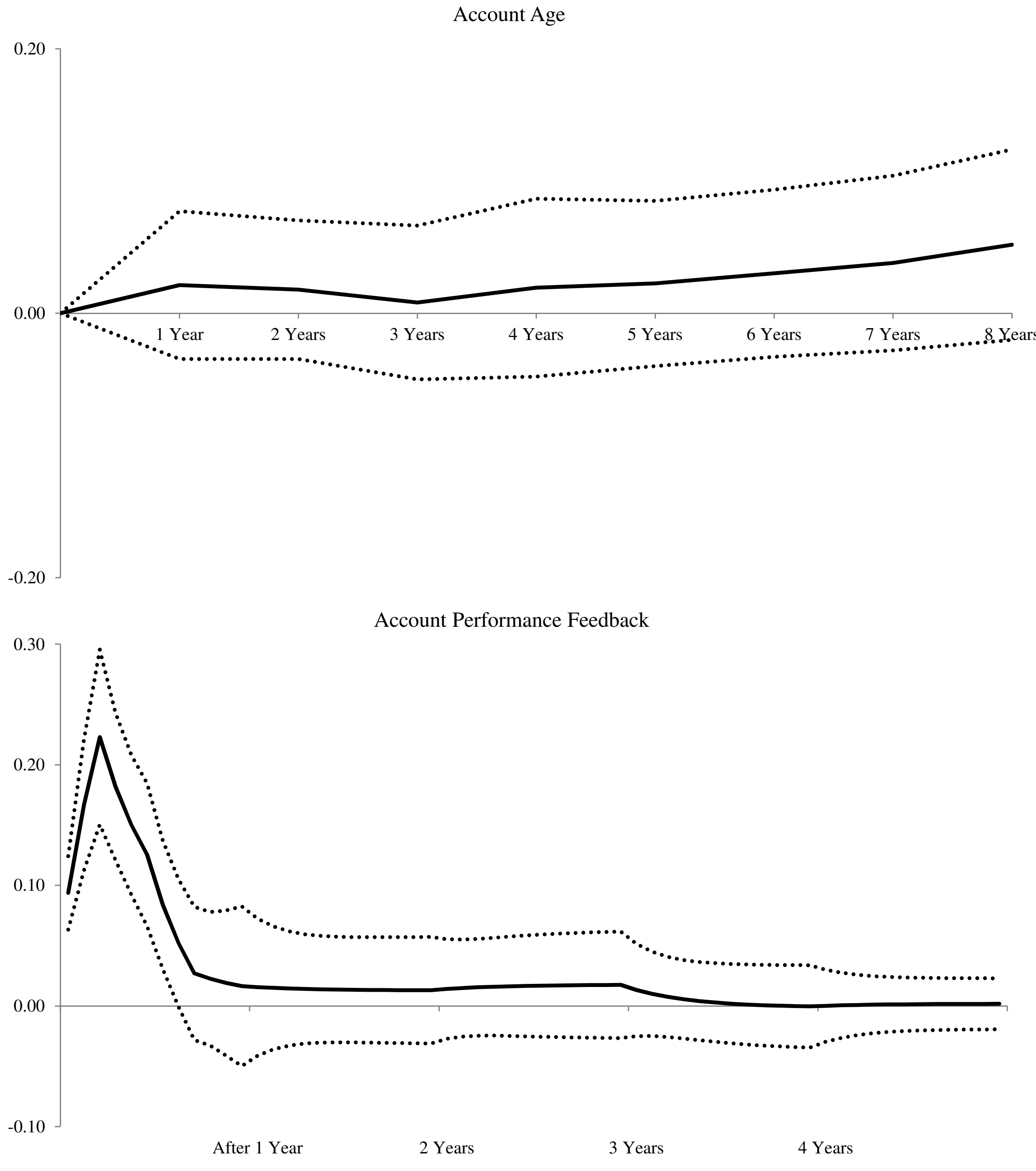
Sort	Average Past Return Outperformance		Predicted Response to Small Feedback		Predicted Response to Value Feedback		Predicted Response to Momentum Feedback	
Portfolio	Holdings	Purchases	Small Minus Large Holdings	Small Minus Large Purchases	Value Minus Growth Holdings	Value Minus Growth Purchases	High Minus Low Momentum Holdings	High Minus Low Momentum Purchases
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Raw Return	0.07%	0.19%	0.41%	0.13%	0.20%	0.18%	0.27%	0.00%
	(0.41%)	*(0.19%)*	*(0.57%)*	*(0.45%)*	*(0.32%)*	*(0.15%)*	*(0.21%)*	*(0.17%)*
Monthly Alpha	-0.32%	0.13%	-0.29%	0.61%	-0.13%	0.23%	0.10%	-0.30%
	(0.36%)	*(0.19%)*	*(0.55%)*	*(0.60%)*	*(0.34%)*	*(0.18%)*	*(0.27%)*	*(0.19%)*
Factor Loadings								
Market Beta	*0.09*	0.00	-0.07	0.03	-0.01	0.02	0.01	-0.01
	(0.05)	*(0.02)*	*(0.06)*	*(0.04)*	*(0.05)*	*(0.02)*	*(0.03)*	*(0.02)*
SMB	-0.06	-0.03	0.03	-0.09	**0.07**	-0.02	-0.02	**-0.04**
	(0.05)	*(0.02)*	*(0.09)*	*(0.07)*	*(0.03)*	*(0.02)*	*(0.03)*	*(0.02)*
HML	-0.03	-0.01	0.17	-0.20	0.03	-0.02	-0.09	**0.10**
	(0.09)	*(0.04)*	*(0.15)*	*(0.13)*	*(0.13)*	*(0.04)*	*(0.07)*	*(0.04)*
UMD	**0.47**	**0.19**	**-0.23**	-0.05	0.11	**-0.09**	0.09	0.03
	(0.07)	*(0.03)*	*(0.08)*	*(0.06)*	*(0.10)*	*(0.03)*	*(0.06)*	*(0.02)*
Short Term	**-0.18**	-0.04	**0.57**	*0.15*	0.20	0.02	**0.24**	**0.10**
Reversals	*(0.07)*	*(0.03)*	*(0.10)*	*(0.08)*	*(0.13)*	*(0.03)*	*(0.07)*	*(0.03)*
Illiq (Based	0.02	-0.05	0.19	-0.06	-0.01	0.05	0.07	0.02
on Turnover)	*(0.12)*	*(0.08)*	*(0.20)*	*(0.23)*	*(0.12)*	*(0.07)*	*(0.07)*	*(0.07)*

Table 7: Trading Behavior Regressions

Regressions follow Equation (3) using account-months for which the variables used in the regression are defined (disposition effect is defined only where a trade occurs and gains and losses both exist). Trading behaviors are scaled by the time-series average of their cross-sectional means. Account value is winsorized below at Rs. 10,000 (approximately $200 US). Panel regressions are run using weights that account for sampling probability and further apply equal weight to each cross-section (month). Standard errors in ( ) are computed from bootstraps of monthly data. Coefficients that are significant at a five percent level are in bold type.

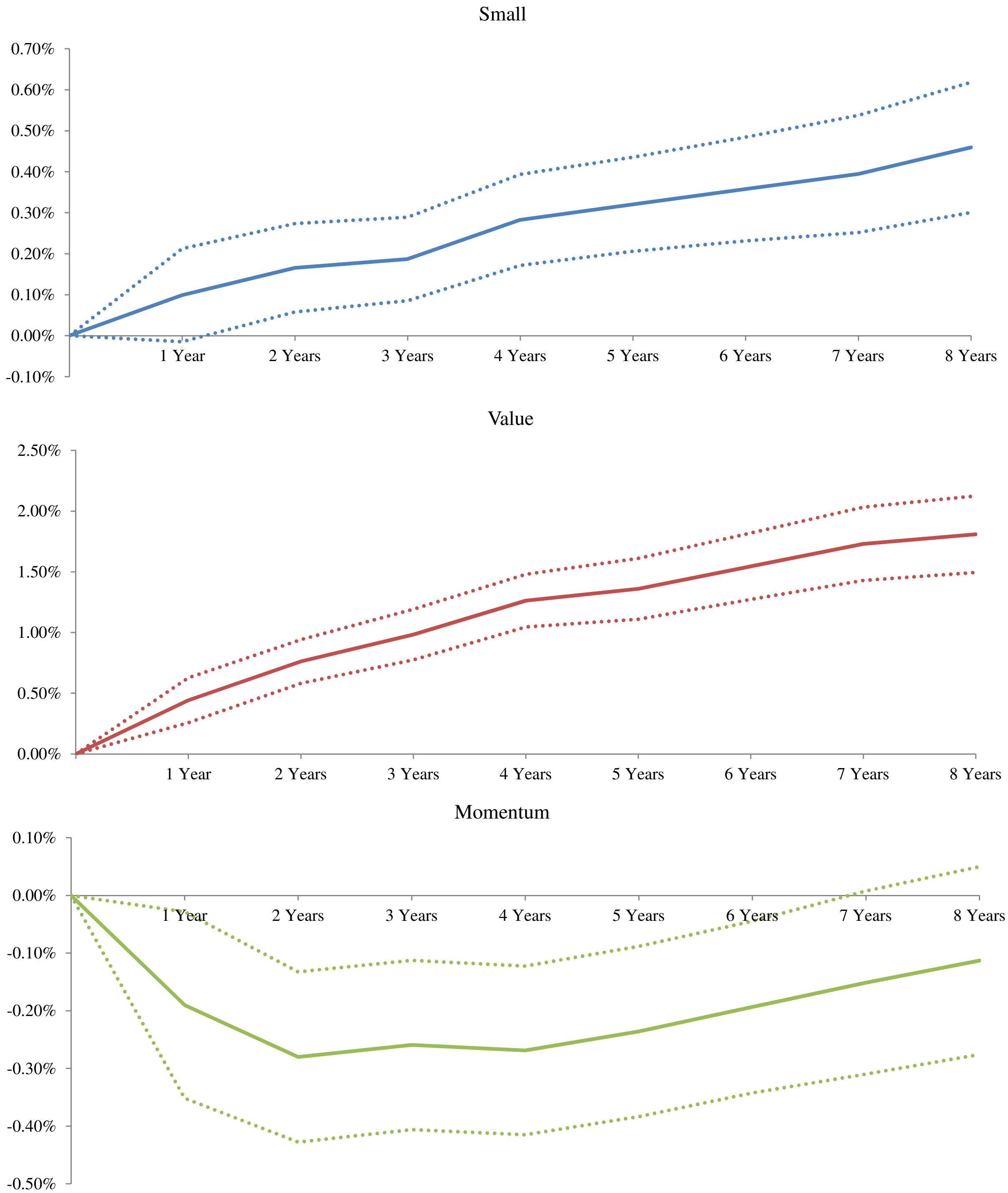
Dependent Variable:	Turnover	Disposition Effect
Number of Observations:	3,444,690	439,974
Account Age, Piecewise Linear Form	*See Figure 6*	*See Figure 6*
Account Performance Feedback, by Time Since Event	*See Figure 6*	*See Figure 6*
Behavior-Specific Feedback, by Time Since Event	*See Figure 6*	*See Figure 6*
Log Account Value	**0.126**	**-0.037**
	(0.013)	*(0.015)*
12-Month Average Lagged Trading Behavior	**0.369**	**-0.149**
	(0.018)	*(0.011)*

Figure 1: Effects on Portfolio Diversification (Idiosyncratic Share of Portfolio Variance)



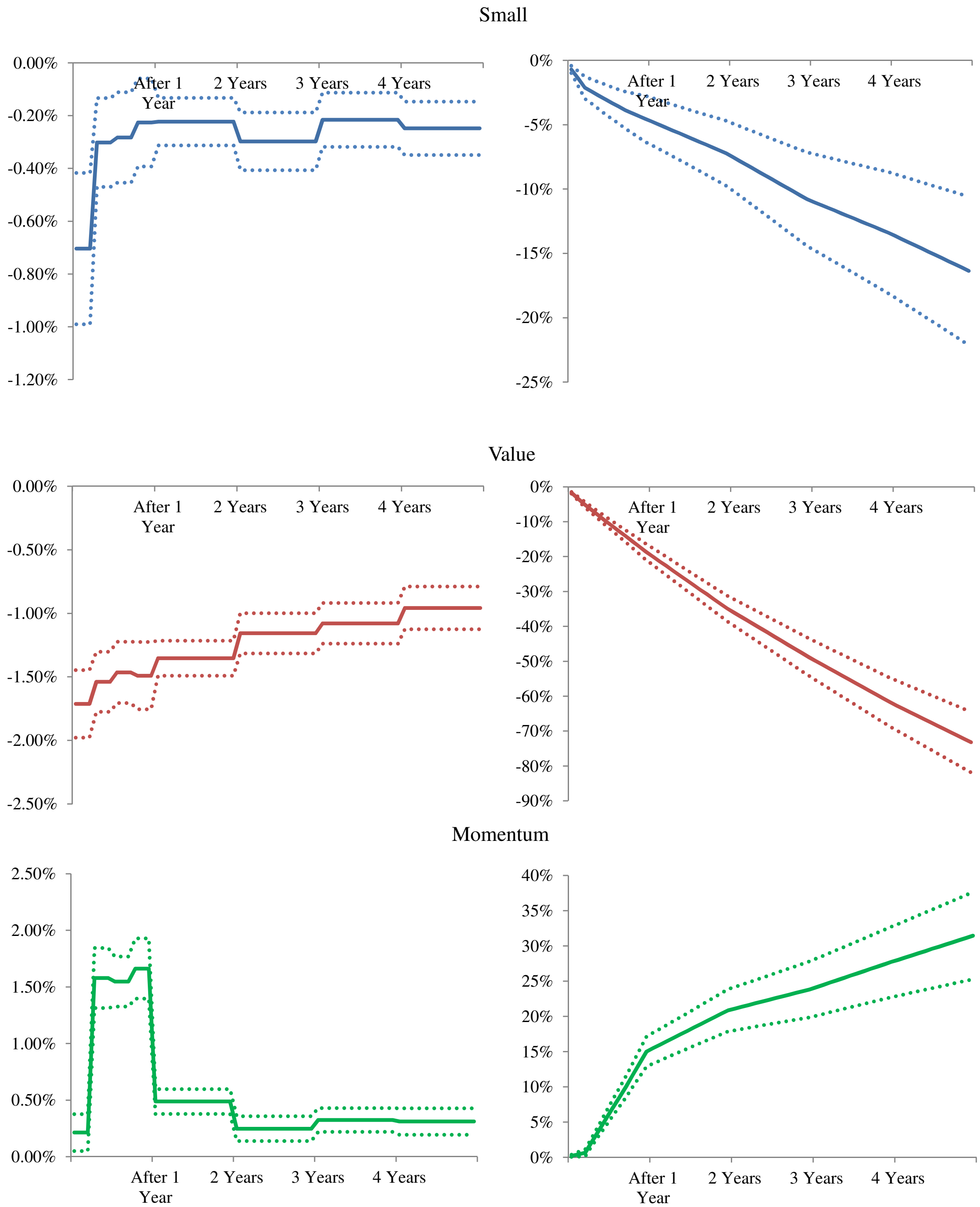
The plots above are produced from the regression of idiosyncratic share of portfolio variance in Table 3, where values are scaled relative to the mean idiosyncratic share. Values in the top plot are adjusted to represent the effect of age on the target idiosyncratic variance share. Specifically, point estimates given by the regression are divided by one minus the coefficient on the lagged dependent share. The bottom plot is an impulse responses to a unit (100%) shock to account performance feedback, making use of coefficients on both feedback and lagged behavior. Dotted lines represent 95% confidence intervals.

Figure 2: Account Age Effects on Net Style Demand



The plots above are produced from investor net style demand regressions in Table 3. Dotted lines represent 95% confidence intervals.

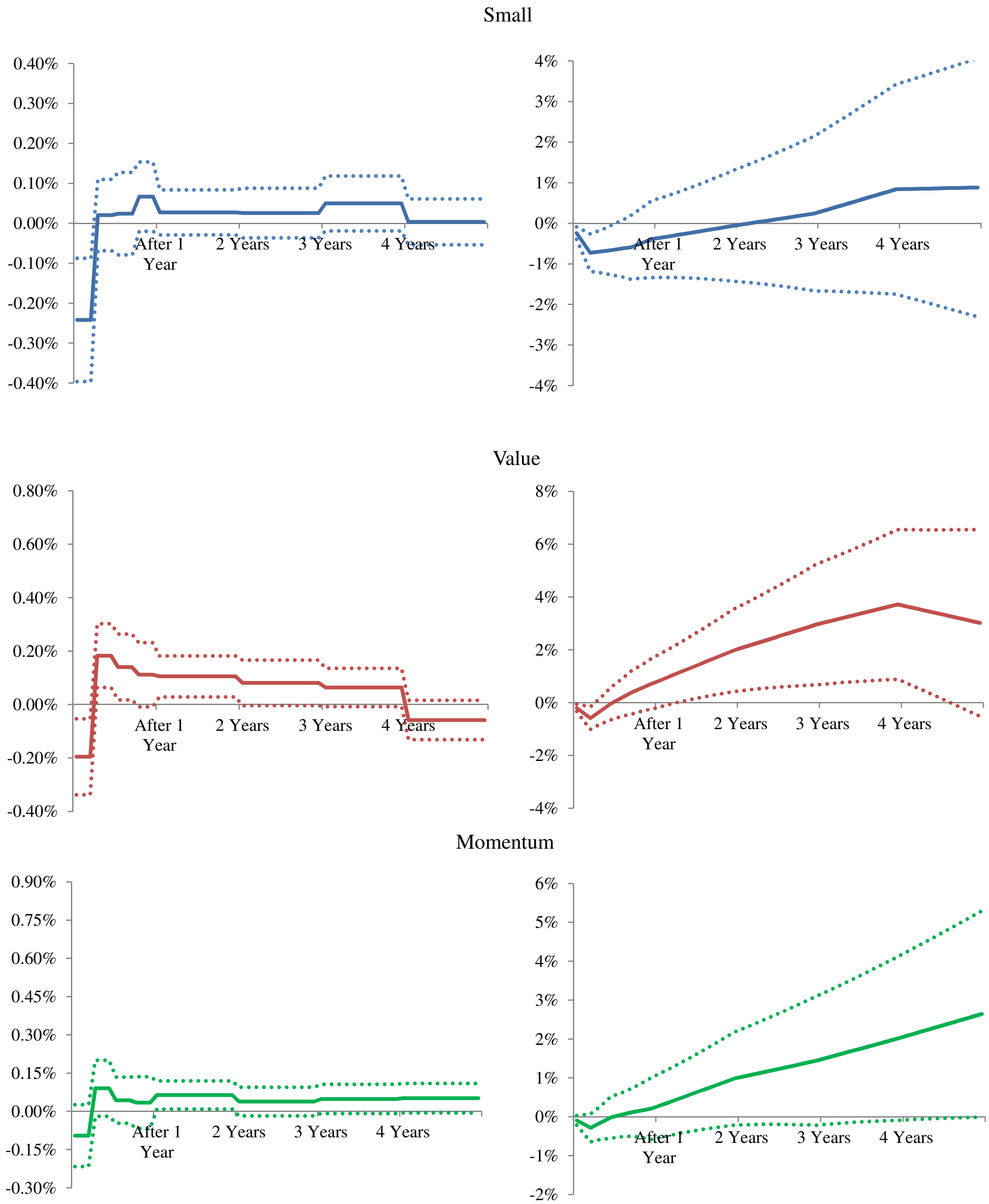
Figure 3: Account Performance Feedback Effect on Net Style Demand
Response (Left) and Cumulative Response (Right)



Plots are produced from investor net style demand regressions in Table 3. Dotted lines represent 95% confidence intervals.

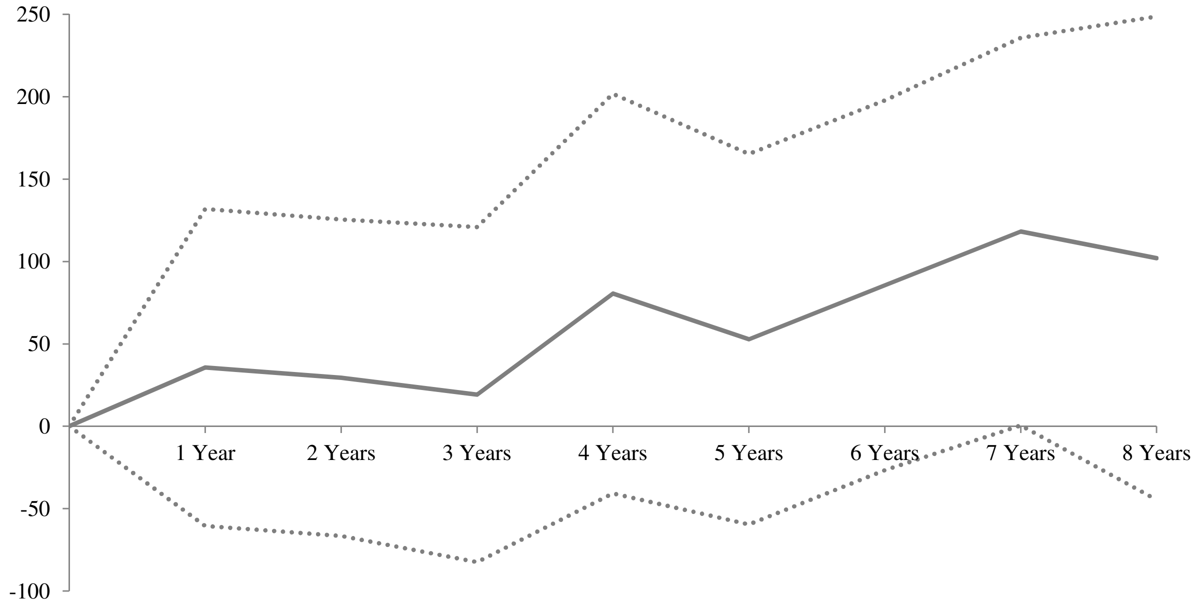
Figure 4: Style Feedback Effect on Net Style Demand

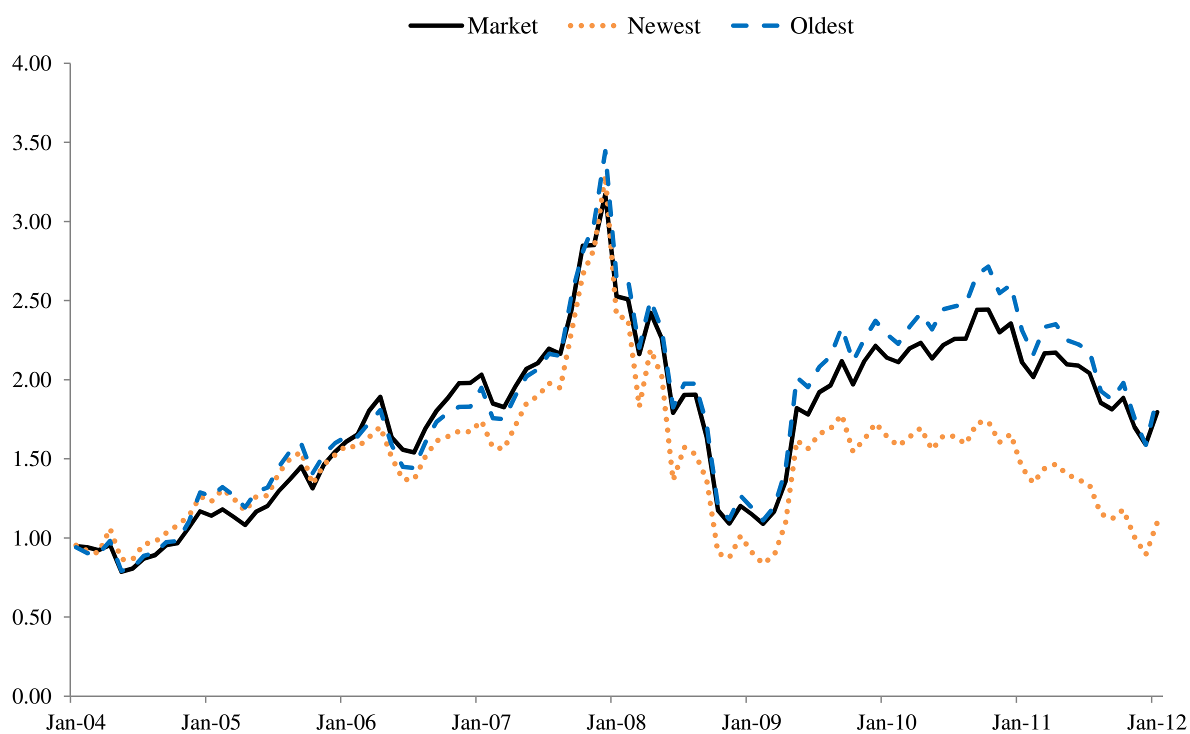
Response (Left) and Cumulative Response (Right)



Plots are produced from investor net style demand regressions in Table 3. Dotted lines represent 95% confidence intervals.

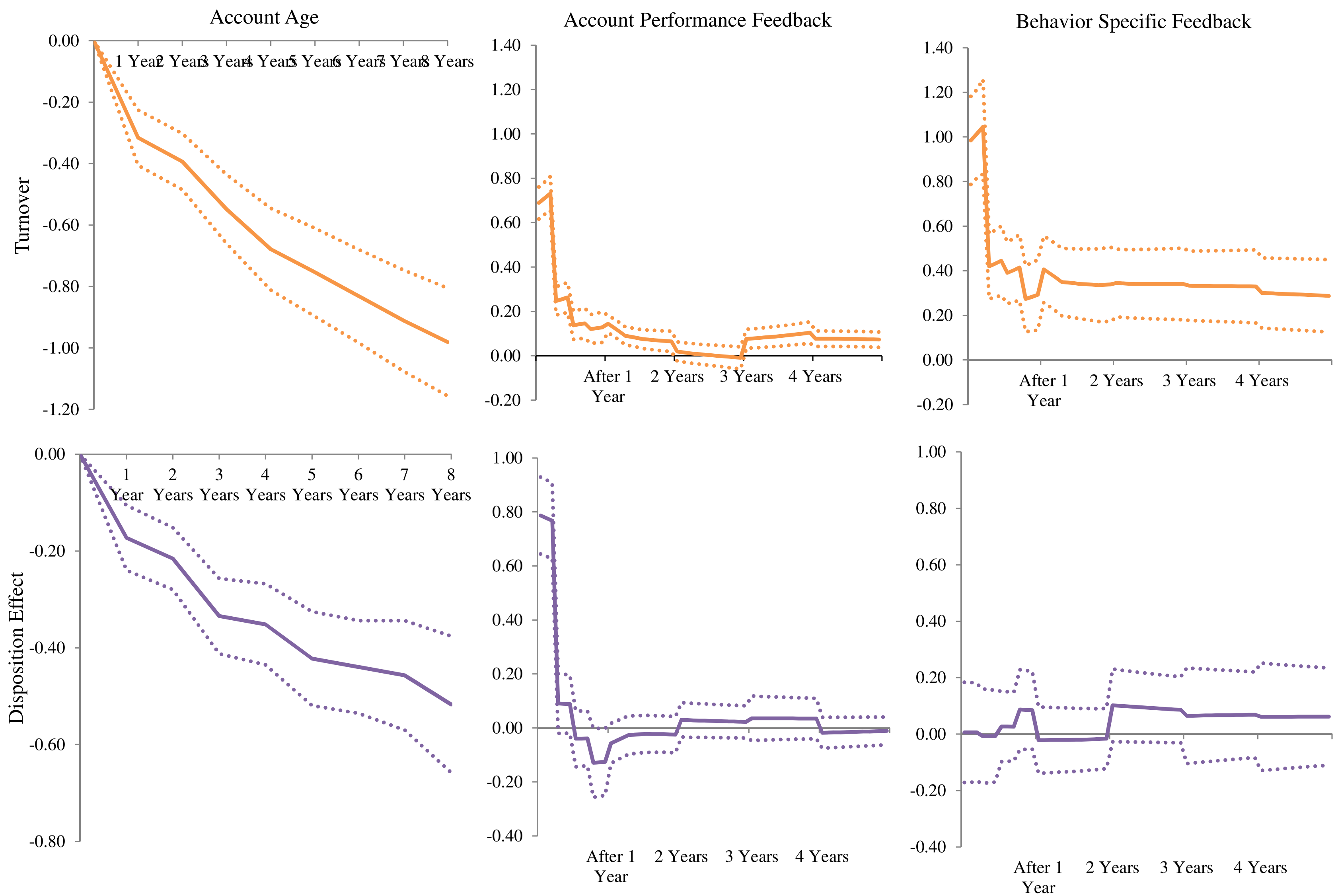
Figure 5: Top: Account Age Effects on Account Returns (bp/mo)
Bottom: Cumulative Excess Equity Returns to Old and New Accounts





Top: The plotted series represents piecewise linear age effects from the regression R_{it}-R_t=s_i+β(A_{it}-A_t)+ε_{it}, where the break-points in piecewise linear age occur at years one, two, three, four, five, and seven. Dotted lines represent the 95% confidence interval.
Bottom: Oldest and newest reflect representative portfolios of individual investors in the oldest and newest quintile of accounts present in the month. Excess returns are produced by subtracting the yield on three-month Indian Treasury bills from the portfolios.

Figure 6: Effects on Trading Behavior



The plots above are produced from trading behavior regressions in Table 7, with all values scaled by the mean level of the trading behavior. Values in the account age plot are adjusted to represent the effect of age on the target level of trading behavior. Specifically, point estimates given by the regression are divided by one minus the coefficient on the lagged dependent variable. Feedback effect plots are impulse responses of trading behavior to a unit (100%) shock to either performance feedback or behavior-specific feedback. Responses are generated using coefficients on both feedback and lagged behavior. Dotted lines represent 95% confidence intervals.