What Makes Structured Products Popular? Evidence from China's Structured Funds

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PRELIMINARY DRAFT (DO NOT CIRCULATE)

Abstract

Why do investors buy complicated financial products? Using detailed account-level data from a large brokerage firm in China, we study the demand side of structured financial products by examining entry decisions into AB funds, a type of structured financial products that became immensely popular during the 2014-15 Chinese market bubble. Our analysis suggests that experience and extrapolation are two key determinants. Investors with prior exposure to other financial products such as warrants are more likely to trade AB funds. Additionally, extrapolators are more likely to trade AB funds, especially after recent positive market returns.

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1 Introduction

Structured financial products are financial products whose payoffs vary non-linearly with some underlying assets. The market for these products is massive. While the European retail market for structured financial market only dates back to the early 2000s, its size grew to 770 billion dollars in 2012, or 3% of all European financial savings. The size of structured financial products is also massive in the United States. In 2015, retail structured products assets under management was over 400 billion dollars (Célérier and Vallée 2017).

Despite the tremendous growth in market size over the last decade, it remains unclear what mechanisms are driving the popularity of structured financial products. The traditional framework suggests that institutions design structured financial products to meet investors' demand for hedging against various risks. Recent work, however, suggests a less benevolent motive: the primary purpose of structured financial products is for sophisticated issuers to extract rents from naive investors. Indeed, structured financial products appear to have highly negative risk-adjusted expected values (Vokata 2018). Moreover, they appear to shroud risk and extract rents from unsuspecting consumers (Henderson and Pearson 2011; Célérier and Vallée 2017; Vokata 2018). The overwhelming evidence suggests that investors seem to be worse off by investing in these structured financial products.

The desire from the supply side to sell overpriced assets and extract rents is straightforward. However, the demand side of this story is largely missing: why do investors buy these products in the first place? They have complex payoff structures that require some financial literacy to comprehend, and this could very well push investors away (Carlin et al. 2013). Their ex-post returns are extremely low and do not compensate for the embedded risks at all (Vokata 2018). If investors dislike complexity and returns are quite poor, what appeals to investors about these structured financial products?

In this paper, we offer evidence on the demand for retail structured financial products in a unique setting of Chinese markets. In particular, we focus on A and B funds from the Chinese market. They are similar in nature to Primes and Scores from the U.S. market (Jarrow and O'Hara 1989). Essentially, a regular fund's payoffs are sliced into two tranches: A funds payoffs are a fixed fraction, dividend-like, of the underlying assets while B funds claim the residual and resemble leveraged positions in the underlying assets. The popularity of these financial products mimics the enormous popularity of all retail structured financial products. For example, about 130,000 investors, or 7% of the active investor population in our sample, traded B funds in June 2015.

Our demand-based approach is enabled by detailed, account-level data from a large Chinese brokerage. This data includes all exchange-based trades made by Chinese investors through this brokerage from 2004 through 2016. Importantly, since we have individuals' trading histories, we are able to identify individual-level characteristics. We then link these characteristics to their decisions to trade AB funds.

Our empirical analysis highlights two key determinants: experience and extrapolation. First, we find that individuals, who have purchased warrants in the past, another popular complex financial product from the beginning part of our sample, are far more likely to trade complex financial products. This suggests there is a strong individual fixed effect that drives the demand for these products.

Second, we find that an individual's degree of extrapolation is a strong determinant of the decision to trade A and B funds. An individual with a trading history that indicates a high degree of extrapolation is much more likely to purchase B funds, especially after high recent market returns. This suggests that extrapolative beliefs are an important factor to consider in understanding why investors demand these costly structured financial products.

Related literature. Traditionally, risk-sharing motives were thought to explain the existence of structured financial products (Allen et al. 1994; Duffie and Rahi 1995). That is, structured financial products were created to help investors hedge risk. Recent theoretical work, however, suggests that many financial products are not designed for risk-sharing purposes, but rather to confuse investors and extract rents. Carlin (2009) develops a model where firms increase complexity in order to make customers unsophisticated and ensure the ability to extract rents. Similarly, Carlin and Manso (2010) develop a model that suggests mutual funds may increase complexity in order to increase the share of unsophisticated investors and maintain rents in a competitive market.

On the empirical front, a number of empirical papers provide evidence for institutions' rent-seeking motives. Coval et al. (2009) show that senior CDO tranches were significantly overpriced. Griffin et al. (2014) suggest and provide evidence that underwriters will produce overpriced complex assets. Analyzing 64 issues of a popular retail structured equity product, Henderson and Pearson (2011) show that structured equity products are overpriced. Ghent et al. (2017) find that complexity for financial products rose substantially during the financial crisis and that the more complex deals saw lower realized returns. Vokata (2018) shows that banks extract significant rents by charging significant fees on yield enhancement products. Amromin et al. (2018) find evidence that complexity shrouds the true risk-return payoff and lowers expected returns for purchasers of complex financial products. Specifically, they find that, even after a wide range of controls, complex mortgage borrowers have delinquency rates twice as high as those with vanilla fixed-rate contracts do.

For institutions to be able to extract rents from individuals through complex financial products, there must be a demand for complexity in the first place. But the puzzle is: why are complex financial products so widespread and popular? What deepens this puzzle is the evidence from Carlin et al. (2013): they experimentally test the impact of complexity on asset trading and find that complexity leads investors to be less inclined to trade.

One potential reconciliation is that many complex financial products appeal to individuals' behavioral biases. For example, Bordalo et al. (2016) suggest that banks popularize high-yield products by hiding the riskiness of the product and making salient the headline rate. Célérier and Vallée (2017) offer evidence for this hypothesis by analyzing retail structured products sold in Europe. They find that more complex products tend to earn lower risk-adjusted returns especially when interest rates are low, and therefore caters to yield-seeking investors. Egan (2018) offers evidence that brokers convince investors to buy dominated convertible bonds. Nearly all existing work focuses on the sell-side of these structured financial products, and evidence for buy-side determinants has been indirect. We extend this research area by measuring investors' behavioral biases and seeing how well they explain investors' decisions to trade complex financial products.

2 Institutional Background

The SEC, in rule 434, defines structured products as "securities whose cash flow characteristics depend upon one or more indices or that have embedded forwards or options or securities where an investor's investment return and the issuer's payment obligations are contingent on, or highly sensitive to, changes in the value of underlying assets, indices, interest rates or cash flows." According to this definition, AB funds represent a structured product that slices the payoffs of a regular mutual fund (Parent; P for brevity) into two separate products, a dividend-based product (A) and an appreciation-based product (B). More specifically, investors of A funds receive their payoffs based on the principle value (typically set at one) and a pre-specified dividend rate (e.g., the prevailing market interest rate plus a premium). Investors of B funds have the residual claim on the underlying assets and receive whatever is left after paying off A investors. In this regard, B funds are essentially levered and financed by A investors, where the interest rate is A's dividend rate and the leverage ratio is determined by their NAVs.

We use a simple example to illustrate their payoff structures. Suppose that with a total NAV of \$100, P issues 50 shares of A and 50 shares of B, all with a per-share NAV of \$1. The dividend is set at an annual rate of 5%. Under this contract, B investors essentially takes a 1:1 leverage with an interest rate of 5%. Table 1 shows the NAVs for A and B under different return scenarios after one year. Notice that, while the leverage ratio is initially set at 1:1, it changes over time depending on stock prices: when prices are high, B's NAV rises, reducing leverage; when prices are low, B's NAV drops, increasing leverage.

A is not entirely risk-free: in theory, if stock prices drop more than 50%, A's value also drops. In order to reduce this downside risk, a protection term is embedded. Under this protection term, once the NAV per unit of B falls below a certain threshold (0.25 RMB for most funds), it is restructured. It is also restructured when the NAV per unit of the parent fund rises above a certain threshold (1.5 RMB for most funds). During the restructuring, the total investment units are cut short so that the NAVs per share return back to one for A, B and P, and the additional units are converted back to units of P. Such mechanism is

Table 1: An example of A-B fund payoffs

NAV_P	NAV_A	NAV_B	ΔNAV_P	ΔNAV_B	Leverage
1.25	1.05	1.45	0.25	0.45	0.72:1
1.15	1.05	1.25	0.15	0.25	0.84:1
1.05	1.05	1.05	0.05	0.05	1:1
0.95	1.05	0.85	-0.05	-0.15	1.26:1
0.85	1.05	0.65	-0.15	-0.35	1.62:1

designed to protect the benefit of investors by lowering the leverage of B when its NAV falls and raising the leverage of B when its NAV rises.

Like a standard mutual fund product, P can be purchased or redeemed at its NAV in the primary market. However, in some cases, P is also listed on the exchange and traded on the second market, and investors and buy or sell P shares directly. Similar to closed-end funds, this potentially creates a difference between a fund's price and its NAV. Different from closed-end funds, this mispricing can be traded subject to transaction costs and timing risks: for instance, suppose that P is currently traded above its NAV, an investor can first purchase a share from her broker, and then sell it on the market. Unlike P, A and B can be traded on the stock market but *cannot* be purchased or redeemed individually. As a result, even when the prices of A and B exhibit significant deviations from their NAVs, investors can't trade on such mispricing directly. However, investors can buy both A and B on the second market according to the fixed contracted ratio, synthesize them into P, and sell it on the primary market. Investors can also purchase P on the primary market, convert it into A and B, and sell these shares on the second market.

In the US market, similar financial products, called primes and scores, were introduced and traded for a short period of time in the 1980s. Primes, scores, and units respectively represent As, Bs, and Ps in our setting. While primes and scores later disappeared in the US market, AB funds experienced tremendous growth in Chinese markets. The first AB fund was introduced in China by UBS SDIC Fund Management Company. In 2015, AB funds, especially Bs, became increasingly popular among Chinese individual investors. To see this, Figure 1 shows the popularity of various financial products introduced to the Chinese capital market. In our sample, in June 2015 alone, more than 130,000 traded B, accounting for almost 7% of the active investor population. As were significantly less popular: even at the peak, less than 20,000 accounts traded A. For comparison, we also plot the popularity of various warrant products, which were introduced to around 2006 and became hugely popular from 2006 and 2008 (Xiong and Yu, 2011). According to these numbers, in 2015, AB funds were as popular as warrants back in 2006-2008. Our empirical analysis aims to understand why AB funds became so popular.

3 Data and Variables

3.1 Data

Our account-level transaction data is from a large national brokerage firm in China. The company has branches in almost all of China's provincial-districts and are market leaders in several regions. Moreover, this brokerage firm provides comprehensive capital market service to its clients, making all exchange-listed securities available in terms of trading. This enables us to observe the trades of all exchange-listed assets, namely stocks, warrants, equity and bond ETFs, and various listed funds. Our dataset includes investors' every transaction record from 2006 to 2016, which covers two prominent episodes of structure product boom in China's financial market. The structure of the dataset is similar to the one used by Odean (1998): each observation specifies the account, date, time, price, quantity, and security code. The portfolio holdings are then derived from the transactions records by assuming that their initial positions are all zero. Based on the transaction and holdings datasets, we construct the measures that comprehensively depict investors' trading behavior and portfolio characteristics.

We present summary statistics about our brokerage data in Table 2. The brokerage sample includes almost 2 million active investors, where an active investor is defined by having traded at least once in the sample period. These investors, on average, make 6.5 trades per month (median is 2.7) with a monthly turnover of more than 300% (median is

100%). Such findings are consistent with the extant literature that retail investors trade excessively in Chinese A Shares market. Investors are largely under-diversified: the average (median) number of stocks in the portfolio is 3.2 (2.4), whereas the average (median) portfolio balance is around 250,000 RMB (30,000 RMB). Overall, the distribution is very much skewed to the right: in all cases, the average is substantially greater than the median.

In this version of the paper, due to computation constraints, our subsequent analysis is restricted to a subsample of 50,000 investors, which are randomly selected [ALLEN: FILL IN THE DETAILS]. Their summary statistics are reported in Panel B. These summary statistics are very close in Panel A, suggesting that even the 50K sample can to some extent represent the behavior of the population.

3.2 Variables

Behavioral biases. Our analysis concerns entry decisions into complicated financial products. A focus of our analysis is which psychological factors propel investors into complicated financial products. To this end, we consider behavioral biases that have been studied extensively in the literature. Specifically, we consider extrapolative beliefs, skewness preferences, experience, and the disposition effect, .

The first behavioral bias we consider is return extrapolation, or the idea that investors form beliefs about future stock returns based on past stock returns. Odean (1999) shows that investors tend to buy stocks with positive returns over the past two years. Using a number of different surveys, Greenwood and Shleifer (2014) find significant evidence that investors' beliefs regarding future stock returns are positively correlated with past returns. Liao and Peng (2018) document evidence of extrapolation among investors in the Chinese stock market. Ertan et al. (2019) document evidence of individual investor over-extrapolation around earnings announcements.

We next consider skewness preferences, or the desire of investors to hold assets with a positively-skewed distribution. Kumar (2009) finds that individual investors prefer stock with lottery features and that this demand increases during economic downturns. There is evidence that this skewness preference is particularly evident before earnings announcements (Liu et al. 2017). Dorn et al. (2014) find that the relationship between traditional lottery prize amounts and retail stock market activity is negative. Cookson (2018) finds that prize-linked savings accounts, or accounts that make lottery-like payments instead of interest payments, reduces investors desire to gamble at casinos.

The third individual characteristic we consider is experience. There are a number of papers showing the importance of experience in financial decision making. Malmendier and Nagel (2011) find that individuals' experience with macroeconomic shocks can help us understand individuals' risk-taking decisions, and Malmendier and Nagel (2015) find that investors tend to overweight inflation experienced during their lifetimes when forming expectations regarding future inflation. Kaustia and Knüpfer (2008) find that investors tend to overweight their personal experiences when subscribing to an IPO. Finally, Chernenko et al. (2016) show that firsthand experience played a role in mutual fund manager's investment decision during the 2003-2007 mortgage boom. Specifically, we consider two dimensions of experience: total time length of trading and whether an investor has traded other new financial products before.

Finally, we also consider the disposition effect. There is a long literature on the disposition effect, that is, the tendency for investors to sell at a gain and avoid sales at a loss. Shefrin and Statman (1985) use a theoretical framework to motivate prospect theory. Odean (1998), using a data set of 10,000 trading accounts from a large discount brokerage, documents this aversion to realizing losses. Genesove and Mayer (2001) find evidence for this tendency in the downtown Boston housing market. Hartzmark and Solomon (2012) look at a set of NFL betting contracts at Tradesports.com and uncover evidence consistent with the disposition effect. Kelly (2018) finds that company insiders exhibit the disposition effect.

Variable construction. We create two extrapolation measures based on different horizons. The first measure, degree of extrapolation (DOX), is defined based on the past returns of past purchases. Specifically, it equals the weighted-average, based on purchase sizes, past X-month return for all purchases. We consider $X = 1, 3, 6, 12$, but primarily use $X = 1$ given the short extrapolation horizon shown in Liao and Peng (2018). Our dataset starts in 2006, which means that we do not observe their transactions prior to 2006. This motivates our second extrapolation measure, modified extrapolation. This measure assumes that the individual purchased the associated stock at the previous day's closing price if a stock appears for the first time in an individual's holdings in January of 2006. These two measures produce almost identical results. In the remainder of the paper, we only report results using the first measure.

Similar to our extrapolation measure, our preference for skewness measure is defined based on the skewness of past purchases. Specifically, it equals the weighted-average, based on purchase sizes, past skewness for all purchases, where past skewness is calculated based on the daily returns over the last 12 months. Given that high volatility stocks also exhibit high skewness, we also construct a preference for volatility measure based on the volatility of past purchases, where volatility is calculated based on the daily returns over the last 12 months.

Next, we construct a set of variables for experience. The first measure is the total number of months since the first transaction, which measures the length of trading experience in the stock market. The second measure is a dummy variable that measures whether they have traded warrants before, a non-traditional financial product that became immensely popular from 2006 to 2008 and later disappeared.

Finally, following Odean (1998), we measure the disposition effect with $PGR - PLR$, where PGR is short for Proportion of Gains Realized and is defined by dividing the total number of gains sold to the total number of positions on a selling days, and PLR is short for Proportion of Losses Realized and is similarly defined. In particular, when defining gains and losses, we use the value-weighted purchase price based on all prior purchases and sales.

Other controls. We calculate portfolio returns based on the equity holdings data. We calculate the daily return for each stock in each account by looking at the profits from unchanged holdings, purchases, and sales of the associated stock divided by the quantity of the dollar size of the unchanged position plus the dollar size of purchases plus the dollar size of sales of the associated stock. We then take the weighted-average, based on the quantity of the dollar size of the unchanged position plus the dollar size of purchases plus the dollar size of sales, daily return of all stocks across the account to determine the daily return of the account. We then compute our portfolio return measure based on the historical weighted-average, based on the quantity of the dollar size of the unchanged position of all stocks on a given day plus the dollar size of all purchases on a given day plus the dollar size of all sales on a given day, daily account return since inception. We also compute a monthly portfolio return based on the weighted-average, computed the same way, daily account return over the associated month.

Other account-level variables include: number of trades, which is based on the total number of transactions including both buys and sells; average balance, defined by the average monthly balance in RMB; turnover, calculated by diving total trading volume in RMB to average balance; and HHI (Herfindahl–Hirschman Index), which is defined as the sum of the squares of each stock's portfolio weight and measures the degree of diversification.

3.3 Summary Statistics

We report summary statistics in Table 3. Panel A reports the summary statistics for end-of-sample account characteristics. That is, each investor represents one observation, and account characteristics are calculated based on the entire trading history. A number of observations are worth nothing. First, the sample is relatively balanced in gender: 53% are male, and 47% are female. Second, in terms of participation into other financial products, 1.3% of investors have traded A and 8.0% of investors have traded B. These numbers are roughly consistent with the numbers in Figure 1. In comparison, 18.2% of investors in our sample have traded warrants: this is a result of our 50K sample covering early investors. Third, in terms of performance, the average returns from equities are positive while the average returns for A and B are both negative, suggesting underperformance in these more sophisticated financial products. Fourth, consistent with prior literature, Chinese individual investors exhibit a strong extrapolative tendency:given the 25th-percentile is 0.07, more than 75% investors tend to buy stocks with positive one-month returns. Similarly, they exhibit a strong tendency to display the disposition effect: more than 75% of them display a disposition effect. Fifth, turnover is very high for Chinese investors: on average, the monthly turnover rate is around 1, which means that investors completely change their portfolios once per month. Finally, the average HHI is 0.64, suggesting significant under-diversification: an investor on average holds less than 2 stocks.

Panel B reports the summary statistics for up-to-date account characteristics. Specifically, in each month, we calculate each account's characteristics based on its transaction history so far, and this gives us a panel of observations at the investor-month level. Later in our regression analysis, we primarily use these up-to-date characteristics. The distribution of these variables are roughly similar and consistent with Panel A.

4 Empirical Results

In this section, we analyze the behavioral determinants of entry into A funds and B funds – two structured financial products. A funds and B funds are components of a parent AB fund. We first analyze the determinants of entry into A funds and then we discuss the determinants of entry into B funds.

4.1 Overview

We start by comparing end-of-sample characteristics across four groups of investors: those who have traded both A and B, those who have traded only A, those who have traded only B, and those who have traded neither. The summary statistics are reported in Table 4. In terms of performance in the equity market, the four groups seem to be rather similar. However, they exhibit rather different performances in AB returns: A-only investors perform substantially better than AB-both investors in A markets, whereas B-only investors perform substantially worse than AB-both investors in B markets. This is consistent with the anecdote that A fund investors are more sophisticated.

In terms of other variables, a few patterns immediately stand out. First, from the top to the bottom row, there is a monotonic increase in their prior participation in warrants: investors who trade A and B are more likely to have traded warrants before. Second, investors who trade B exhibit a higher degree of extrapolation than others. Third, there is a similar monotonic increase in number of transactions and turnover: investors who trade A and B appear to be more frequent traders. In the next section, we explore in detail the determinants of entrance into A and B funds.

4.2 A Funds

We first consider entry decisions into A funds from January 2005 until December 2016. We estimate regressions of the following form for individuals i that have not purchased A funds as of month $m-1$:

$$Dummy^{A}_{i,m} = \alpha + \Theta Determinants_{i,m-1} + FE_m + \epsilon_{i,m}, \tag{1}$$

where $Dummy^{A}_{i,m}$ equals 1 if i trades A in month m and 0 otherwise, and $Determinants_{i,m-1}$ represent various account characteristics based on transactions made up to month $m-1$. We consider a number of different determinants rooted in various psychological theories. In particular, we focus on history trading complicated financial products, degree of extrapolation, and disposition effect.

We present the full-sample results in Table 5. Standard errors are double-clustered at the account and monthly levels. We first examine previous history trading complicated financial products. In Column (1) of Table 5, we show that having traded warrants in the past is associated with 0.013% higher chance of purchasing an A fund this month. This is economically significant. As a benchmark, the total participation of A funds is 1.32% over a 12-year horizon, which suggests a monthly entry rate of around 0.009%. Therefore, if one has traded warrants in the past, she is more than twice as likely to purchase A funds in the next month. In Column (2), we further decompose warrant experiences into call warrants and put warrants, and we find that most of the explanatory power comes from call warrants.

Second, we examine whether stock investment performance affects their entry decisions into A. In Column (3), we regress past cumulative stock returns on next period's entry into A and find no significant results. Therefore, it seems that prior performance itself does not seem to predict entry into A. In Column (4), we further decompose returns into a stock-picking component and a market-timing component, and again find that neither can explain their entry decisions.

Third, we find that extrapolative beliefs are associated with a *lower* probability of purchasing A funds. Specifically, in column (5) we see that a one-standard deviation increase in *DOX* is associated with a decrease in the probability of purchasing A funds by about

0.001% when the past 1-month return on the market was zero. This is intuitive: those who have chased high returns in the equity markets – what our extrapolation measure is based off of – will be less keen to chase the more stable returns of A funds.

In Column (6), we further control for market returns (which means that we have to drop month fixed effects). Two observations are worth noting. First, high market returns encourage entry into A funds, which is consistent with overall enthusiasm. Second, the interaction between market returns and *DOX* is negative and significant with a large magnitude. Consistent with before, when market returns are high, extrapolators are much less likely to enter A: it is the contrarians who like to buy A.

Finally, in Columns (7) and (8), we include all determinants as regressors in two slightly different specifications: Column (7) includes month fixed effects but not market returns while Column (8) the opposite. Both columns see that those with a greater disposition effect are less likely to purchase A funds. The economic significance is similar to the economic significance of extrapolation. A one-standard deviation in the disposition effect is associated with a decrease in the probability of purchasing an A fund by about 0.001%. Turnover positively correlates with entry into A, suggesting that frequent traders are more likely to buy A funds.

We repeat the same regression using transactions in different periods. Results are reported in Table 6. Most of the results are driven by the crash. This suggests that when recent market returns are negative, investors seek safety in the stable returns of A funds.

4.3 B Funds

We next consider entry decisions into B funds from January 2005 until December 2016. We estimate regressions of the following form for individuals i that have not purchased B funds as of month $m-1$:

$$Dummy^{B}_{i,m} = \alpha + \Theta Determinants_{i,m-1} + \epsilon_{i,m}, \tag{2}$$

where $Dummy^{B}_{i,m}$ equals 1 if i trades B in month m and 0 otherwise, and $Determinants_{i,m-1}$ represent various account characteristics based on transactions made up to month $m-1$.

We present the results in Table 7. Again, we consider a number of different determinants rooted in different psychological theories. In particular, we find that the individual's previous history trading complicated financial products, degree of extrapolation, and disposition effect are important determinants of the decision to purchase B funds.

We first examine an individual's history trading complicated financial products. In column (1) of Table 7, we show that having traded warrants in the past is associated with 0.058% higher chance of purchasing a B fund this month. This is economically significant. Specifically, if you have purchased warrants in the past you are almost twice as likely to purchase B funds in the associated month.

In contrast to our findings with A funds, we find that extrapolative beliefs are associated with a higher probability of purchasing B funds. Specifically, in column (5) we see that a one-standard-deviation increase in the degree of extrapolation, or *DOX*, is associated with an increase in the probability of purchasing B funds by about 0.008% when the past 1-month return on the market was zero. This is intuitive as those who have chased high returns in the equity markets – what our extrapolation measure is based off of – will be keen to chase the more levered returns of B funds. When we look at entry decisions during different sub-periods, we find even stronger evidence that *DOX* is a strong determinant of B fund entry.

We present the results from the run-up period, or the period from October 2014 to May 2015, in Table 9. In the first column, we show that a one-standard-deviation increase in *DOX* is associated with a 0.14% increase in the probability to purchase B funds. In Column (3), we show that extrapolation is especially important when past market returns are high. This is intuitive as extrapolative investors are likely keen to purchase an asset when past returns are high. To the extent that B returns are correlated with market returns, we would expect investors to purchase B funds after market returns are high. We find that a one-standard increase in *DOX* is associated with a 0.004% decrease in the probability to trade B funds when past month market returns are zero. However, when past market returns are one-standard-deviation above their mean, we find that a one-standard deviation increase in *DOX* is associated with a 0.11% increase in the probability of purchasing B funds. In summary, we find that *DOX* is a strong determinant of the decision to purchase B funds during the periods of greatest B holdings.

5 Conclusion

Using detailed account-level data from a large brokerage firm in China, we study the demand side of structured financial products. We examining entry decisions into AB funds, a type of structured financial product that became immensely popular during the 2014-15 Chinese market bubble. Our analysis suggests that experience and extrapolation are two key determinants of entrance into AB funds. Investors with prior exposure to other financial products such as warrants are more likely to trade AB funds. Additionally, extrapolators are more likely to trade AB funds, especially after the market has gone up recently. Our paper complements prior literature by focusing on the demand side of structured financial products.

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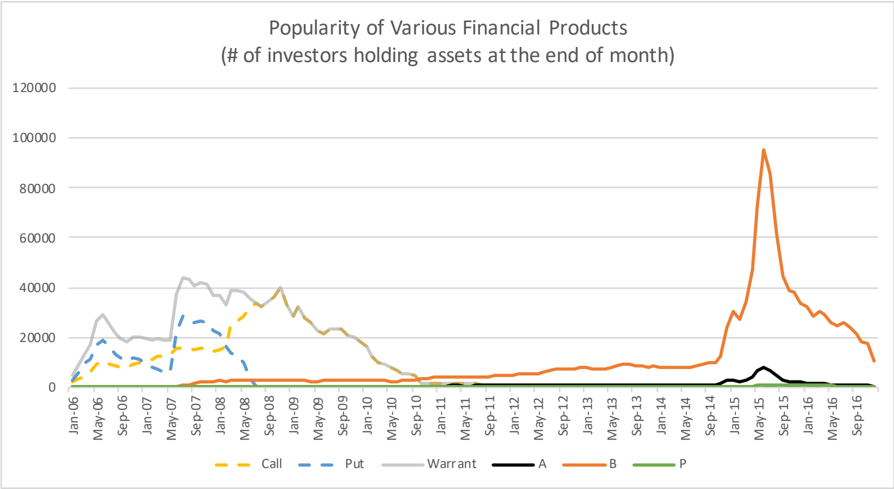
Figure 1: Popularity of various financial products

This figure plots the total number of accounts trading and holding a particular type of asset from 2006:01 to 2016:12. Figure a is based on month-end portfolio holdings, and Figure b is based on all the transactions in a given month. The six lines correspond to: call warrants, put warrants, all warrants, A funds, B funds, and parent funds.

(a) total number of accounts holding a particular asset at month-end



(b) total number of accounts trading a particular asset during a month

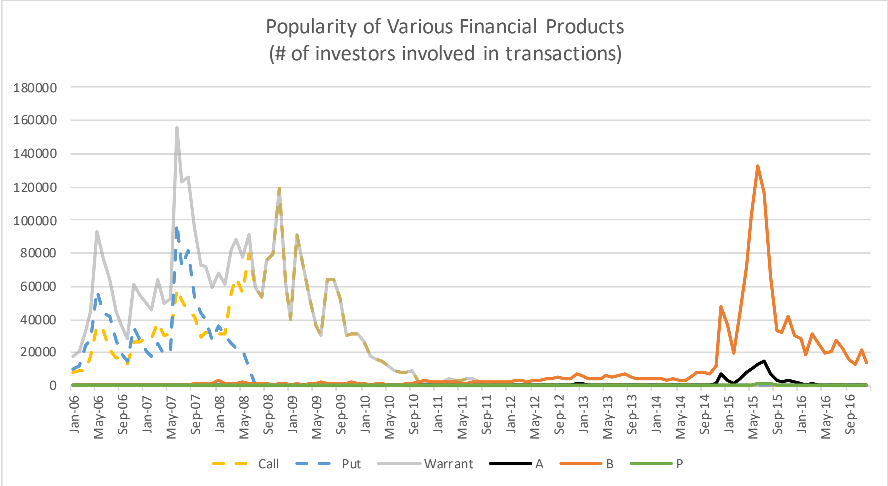


Table 2: Summary statistics for the full sample and 50K sample

This table shows the descriptive statistics for stock market transaction and holding datasets. Stock market trading records come from a large national brokerage firm in China. Panel A presents the summary statistics for investors' holding and trading characteristics for the full sample. Turnover is calculated as sum of transaction value divided by average of position value at the beginning and end of the day. Holding period is in trading day terms. Panel B presents the same summary statistics for the 50,000 investors sample.

	Panel A: full sample					
	Average	Std.	25%	Median	75%	Obs.
Number of Trades (Monthly)	6.48	59.07	1.13	2.67	6.06	1,996,821
Number of Unique Stocks Ever Traded	26.32	36.31	6	15	33	1,996,821
Turnover (Monthly)	367%	34660%	46%	104%	206%	1,996,821
Number of Stocks in Portfolio (Month End)	3.17	3.57	1.62	2.44	3.77	1,996,821
Portfolio Size (Month End)	252,190	19,110,691	9,972	29,919	89,763	1,996,821
Holding Period (Days)	17.29	41.17	1	4	8	1,996,821
	Panel B: 50K sample					
	Average	Std.	25%	Median	75%	Obs.
Number of Trades (Monthly)	6.31	14.16	1.19	2.75	6.36	18,511
Number of Unique Stocks Ever Traded	41.83	49.58	11	27	54	18,511
Turnover (Monthly)	387%	27624%	40%	87%	174%	18,511
Number of Stocks in Portfolio (Month End)	3.72	3.30	1.88	2.82	4.43	18,511
Portfolio Size (Month End)	138,725	742,555	13,787	38,851	105,798	18,511
Holding Period (Days)	14.66	33.08	3	6	11	18,511

Table 3: Summary statistics for account-level variables

This table shows the summary statistics for account-level characteristics. Panel A presents account characteristics based on an account's entire transaction history, and Panel B presents the cumulative characteristics based on transactions up to a given month. Ret^E, Ret^A, and Ret^B denote the return rate from equity, A, and B, where the return rate is calculated by dividing total RMB return to average RMB balance. DM^A, DM^B, and DM^W are dummy variables for whether an account has traded A, B, and warrants before. DE denotes the disposition effect, measured by the different between the proportion of gains realized and the proportion of losses realized on selling days. DOX, VOL and $SKEW$ denotes the degree of extrapolation, preference for volatility, and preference for skewness. They are constructed as the weighted-average, based on purchase sizes, past one-month return, past 12-month volatility, and past 12-month skewness for all purchases, where volatility and skewness is calculated based on the daily returns. N^{Trade} is the total number of transactions. BAL denotes average account balanced in million RMB, and TN is calculated as sum of transaction value divided by average account balance. HHI is calculated as the sum of the squares of each stock's portfolio weight.

	Male	Ret^E (%)	Ret^A (%)	DM^A (%)	Ret^B (%)	DM^B (%)	DM^W (%)	DE	DOX	VOL	$SKEW$	N^{Trade}	BAL (million)	TN	HHI
								Panel A: end-of-sample account characteristics							
min	0	-0.69	-8.49	0	-6.38	0	0	-1.00	-0.45	0.01	-2.76	2	0.00	0.00	0.00
p25	0	-0.07	-0.53	0	-0.69	0	0	0.07	0.07	0.03	0.18	64	0.01	0.16	0.46
p50	1	0.01	-0.05	0	-0.04	0	0	0.16	0.13	0.04	0.37	192	0.04	0.45	0.66
p75	1	0.07	0.08	0	0.35	0	0	0.25	0.19	0.04	0.64	502	0.10	1.10	0.86
max	1	0.79	1.18	100	6.59	100	100	1.00	2.11	1.48	13.99	33838	46.06	15.29	1.00
mean	0.53	0.01	-0.67	1.32	-0.16	8.04	18.23	0.16	0.13	0.04	0.51	467.66	0.14	0.92	0.64
sd	0.50	0.21	1.78	11.41	1.80	27.20	38.61	0.18	0.11	0.03	0.69	919.14	0.79	1.38	0.25
N	18,511	18,511	244	18,511	1,489	18,511	18,511	16,933	17,641	17,691	17,691	17,466	18,511	18,511	18,511
								Panel B: up-to-date account characteristics							
min	0	-0.69	-8.49	0	-6.38	0	0	-1.00	-0.48	0.00	-6.23	2	0.00	0.00	0.00
p25	0	-0.09	-0.44	0	-0.57	0	0	0.07	0.07	0.04	0.16	101	0.01	0.16	0.38
p50	1	0.00	-0.05	0	-0.06	0	0	0.17	0.13	0.04	0.40	264	0.03	0.45	0.58
p75	1	0.09	0.05	0	0.32	0	0	0.28	0.19	0.05	0.77	626	0.09	1.10	0.80
max	1	0.79	1.18	100	6.59	100	100	1.00	4.32	1.57	14.18	33838	55.79	17.48	1.00
mean	0.52	0.01	-0.57	0.35	-0.15	2.44	18.71	0.18	0.14	0.04	0.60	571.61	0.12	0.91	0.58
sd	0.50	0.23	1.58	5.92	1.61	15.42	39.00	0.21	0.11	0.02	0.81	1033.59	0.63	1.33	0.28
N	1,774,924	1,774,924	6,242	1,774,924	43,246	1,774,924	1,774,924	1,560,401	1,669,309	1,677,815	1,677,815	1,615,111	1,774,924	1,774,924	1,774,924

Table 4: Summary statistics for cumulative variables across investor groups

This table shows the summary statistics for average cumulative characteristics across four groups of investors: those who have traded neither A or B, those who have traded only A, those who have only traded B, and those who have traded both. Ret^E, Ret^A, and Ret^B denote the return rate from equity, A, and B, where the return rate is calculated by dividing total RMB return to average RMB balance. DM^W is a dummy variable for whether an account has traded warrants before. DE denotes the disposition effect, measured by the different between the proportion of gains realized and the proportion of losses realized on selling days. DOX, VOL and $SKEW$ denotes the degree of extrapolation, preference for volatility, and preference for skewness. They are constructed as the weighted-average, based on purchase sizes, past one-month return, past 12-month volatility, and past 12-month skewness for all purchases, where volatility and skewness is calculated based on the daily returns. N^{Trade} is the total number of transactions. BAL denotes average account balanced in million RMB, and TN is calculated as sum of transaction value divided by average account balance. HHI is calculated as the sum of the squares of each stock's portfolio weight. EXP measures the total number of months since account opened.

	Ret^E (%)	Ret^A (%)	Ret^B (%)	DM^W	DE	DOX	VOL
Neither	0.01	.	.	0.17	0.17	0.13	0.04
A only	0.01	-0.19	.	0.22	0.14	0.12	0.04
B only	0.00	.	-0.23	0.28	0.15	0.14	0.04
Both	0.01	-0.79	0.32	0.36	0.13	0.11	0.04
Total	0.01	-0.67	-0.16	0.18	0.16	0.13	0.04

	$SKEW$	N^{Trade}	TN	BAL (millions)	HHI	Male	EXP (months)
Neither	0.52	3.98	0.87	0.17	0.65	0.54	93.40
A only	0.46	10.82	1.13	0.18	0.52	0.45	120.02
B only	0.45	10.26	1.38	0.24	0.56	0.50	116.07
Both	0.44	13.58	1.73	0.29	0.54	0.56	120.15
Total	0.52	4.57	0.92	0.18	0.64	0.53	95.33

Table 5: Entry decisions into A funds

This table shows the regression results by regressing entry decisions into A on cumulative account characteristics. All regressions use observations from 2005:01 to 2016:12. $Dummy_m^A$ denotes whether an account trades A in month m. All regressors use transactions up to month $m-1$ (indicated by the subscripted $m-1$) and represent an account's cumulative characteristics. $Dummy_{m-1}^W$, $Dummy_{m-1}^{CW}$, and $Dummy_{m-1}^{PW}$ denote the whether an account has traded warrants, call warrants, and put warrants. Ret_{m-1}^E denote the return rate from equity investment, where the return rate is calculated by dividing total RMB return to average RMB balance. $Ret_{m-1}^{StockPicking}$ and $Ret_{m-1}^{MarketTiming}$ decompose Ret_{m-1}^E into a part driven by stock picking and a part driven by market timing. DOX_{m-1}, VOL_{m-1} and $SKEW_{m-1}$ denotes the degree of extrapolation, preference for volatility, and preference for skewness. They are constructed as the weighted-average, based on purchase sizes, past one-month return, past 12-month volatility, and past 12-month skewness for all purchases, where volatility and skewness is calculated based on the daily returns. DE_{m-1} denotes the disposition effect, measured by the different between the proportion of gains realized and the proportion of losses realized on selling days. N_{m-1}^{Trade} is the total number of transactions. BAL_{m-1} denotes average account balanced in million RMB, and TN_{m-1} is calculated as sum of transaction value divided by average account balance. HHI_{m-1} is calculated as the sum of the squares of each stock's portfolio weight. EXP_{m-1} measures the total number of months since account opened.

	$Dummy_m^A$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dummy_{m-1}^W$	0.013***						0.008**	0.005
	(0.004)						(0.003)	(0.003)
$Dummy_{m-1}^{CW}$		0.017***						
		(0.006)						
$Dummy_{m-1}^{PW}$		-0.002						
		(0.003)						
Ret_{m-1}			0.001				0.013*	0.007
			(0.003)				(0.007)	(0.007)
$Ret_{m-1}^{StockPicking}$				0.006				
				(0.023)				
$Ret_{m-1}^{MarketTiming}$				0.273				
				(0.480)				
DOX_{m-1}					-0.012*	-0.002***	-0.009	-0.002
					(0.006)	(0.001)	(0.007)	(0.009)
$MktRet_{m-1}$						0.001*		0.001*
						(0.001)		(0.001)
$DOX_{m-1} \times MktRet_{m-1}$					-0.001	-0.013*	-0.001	-0.002**
					(0.001)	(0.006)	(0.001)	(0.001)
$(PGR-PLR)_{m-1}$							-0.006**	-0.008**
							(0.003)	(0.003)
VOL_{m-1}							-0.145***	-0.195***
							(0.053)	(0.070)
$SKEW_{m-1}$							0.003**	0.004***
							(0.001)	(0.002)
N_{m-1}^{Trade}							0.002**	0.002**
							(0.001)	(0.001)
TN_{m-1}							0.003*	0.004**
							(0.002)	(0.002)
BAL_{m-1}							0.002	0.002
							(0.001)	(0.001)
HHI_{m-1}							-0.005	-0.004
							(0.004)	(0.004)
EXP_{m-1}							-0.000	0.000***
							(0.000)	(0.000)
Gender							YES	YES
Constant	0.012***	0.012***	0.014***	0.014***	0.017***	0.016***	0.027***	-0.008
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.004)	(0.008)	(0.005)
Observations	1,753,538	1,753,538	1,753,538	1,753,538	1,647,660	1,645,670	1,537,467	1,537,467
R-squared	0.001	0.001	0.001	0.001	0.001	0.000	0.002	0.000

Table 6: Entry decisions into A funds, by periods

This table shows the regression results by regressing entry decisions into A on cumulative account characteristics. $Dummy_m^A$ denotes whether an account trades A in month m. The first column uses observations from 2005:01 to 2014: 09, the second column from 2014:10 to 2015:05, the third column from 2015:06 to 2015:08, and the last column from 2015:09 to 2016:12. All regressors use transactions up to month $m-1$ (indicated by the subscripted $m-1$) and represent an account's cumulative characteristics. $Dummy_{m-1}^{W}$, $Dummy_{m-1}^{CW}$, and $Dummy_{m-1}^{PW}$ denote the whether an account has traded warrants, call warrants, and put warrants . Ret_{m-1}^{E} denote the return rate from equity investment, where the return rate is calculated by dividing total RMB return to average RMB balance. $Ret_{m-1}^{StockPicking}$ and $Ret_{m-1}^{MarketTiming}$ decompose Ret_{m-1}^{E} into a part driven by stock picking and a part driven by market timing. DOX_{m-1}, VOL_{m-1} and $SKEW_{m-1}$ denotes the degree of extrapolation, preference for volatility, and preference for skewness. They are constructed as the weighted-average, based on purchase sizes, past one-month return, past 12-month volatility, and past 12-month skewness for all purchases, where volatility and skewness is calculated based on the daily returns. DE_{m-1} denotes the disposition effect, measured by the different between the proportion of gains realized and the proportion of losses realized on selling days. N_{m-1}^{Trade} is the total number of transactions. BAL_{m-1} denotes average account balanced in million RMB, and TN_{m-1} is calculated as sum of transaction value divided by average account balance. HHI_{m-1} is calculated as the sum of the squares of each stock's portfolio weight. EXP_{m-1} measures the total number of months since account opened.

	$Dummy_m^A$			
	(1)	(2)	(3)	(4)
$Dummy_{m-1}^{W}$	0.002	0.061	0.061	0.001
	(0.002)	(0.041)	(0.039)	(0.007)
Ret_{m-1}	0.003	0.088	0.245	-0.007
	(0.003)	(0.132)	(0.291)	(0.026)
DOX_{m-1}	-0.016***	0.005	-1.697**	-0.025
	(0.005)	(0.077)	(0.338)	(0.025)
$MktRet_{m-1}$	0.000**	0.013***	0.054***	0.000
	(0.000)	(0.002)	(0.002)	(0.000)
$DOX_{m-1} \times MktRet_{m-1}$	-0.001*	0.002	-0.137*	0.001
	(0.000)	(0.011)	(0.038)	(0.002)
$(PGR-PLR)_{m-1}$	-0.005*	-0.025	-0.009	-0.022**
	(0.003)	(0.033)	(0.059)	(0.008)
$Volatility_{m-1}$	-0.041**	-0.695	-3.275	-0.273**
	(0.016)	(0.594)	(2.653)	(0.109)
$Skewness_{m-1}$	0.001	0.011	0.074	0.001
	(0.001)	(0.011)	(0.038)	(0.002)
$\#ofTrades_{m-1}$	0.000*	0.007	-0.003	-0.000
	(0.000)	(0.004)	(0.002)	(0.000)
$Turnover_{m-1}$	0.001	0.025	0.079	0.008
	(0.001)	(0.018)	(0.057)	(0.005)
$AvgBalance_{m-1}$	0.000	0.012	-0.002	0.003
	(0.001)	(0.012)	(0.003)	(0.004)
$AvgHHI_{m-1}$	-0.001	-0.033	-0.167	-0.005
	(0.002)	(0.032)	(0.149)	(0.009)
Exp_{m-1}	0.000***	0.000	-0.001	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)
Gender	YES	YES	YES	YES
Constant	0.003	-0.062	1.008*	0.054**
	(0.003)	(0.093)	(0.245)	(0.023)
Observations	1,222,935	99,370	35,349	167,749
R-squared	0.000	0.001	0.002	0.000

Table 7: Entry decisions into B funds

This table shows the regression results by regressing entry decisions into B on cumulative account characteristics. $Dummy_m^B$ denotes whether an account trades B in month m. All regressors use transactions up to month $m-1$ (indicated by the subscripted $m-1$) and represent an account's cumulative characteristics. $Dummy_{m-1}^W$, $Dummy_{m-1}^{CW}$, and $Dummy_{m-1}^{PW}$ denote the whether an account has traded warrants, call warrants, and put warrants . Ret_{m-1}^E denote the return rate from equity investment, where the return rate is calculated by dividing total RMB return to average RMB balance. $Ret_{m-1}^{StockPicking}$ and $Ret_{m-1}^{MarketTiming}$ decompose Ret_{m-1}^E into a part driven by stock picking and a part driven by market timing. DOX_{m-1}, VOL_{m-1} and $SKEW_{m-1}$ denotes the degree of extrapolation, preference for volatility, and preference for skewness. They are constructed as the weighted-average, based on purchase sizes, past one-month return, past 12-month volatility, and past 12-month skewness for all purchases, where volatility and skewness is calculated based on the daily returns. DE_{m-1} denotes the disposition effect, measured by the different between the proportion of gains realized and the proportion of losses realized on selling days. N_{m-1}^{Trade} is the total number of transactions. BAL_{m-1} denotes average account balanced in million RMB, and TN_{m-1} is calculated as sum of transaction value divided by average account balance. HHI_{m-1} is calculated as the sum of the squares of each stock's portfolio weight. EXP_{m-1} measures the total number of months since account opened.

	$Dummy_m^B$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dummy_{m-1}^W$	0.058***						0.045***	0.021**
	(0.011)						(0.010)	(0.008)
$Dummy_{m-1}^{Call}$		0.052***						
		(0.011)						
$Dummy_{m-1}^{Put}$		0.024**						
		(0.011)						
Ret_{m-1}			-0.031***				0.038**	-0.002
			(0.010)				(0.017)	(0.025)
$Ret_{m-1}^{StockPicking}$				-0.078				
				(0.101)				
$Ret_{m-1}^{MarketTiming}$				-0.749				
				(1.496)				
DOX_{m-1}					0.007	-0.004	0.039	0.075
					(0.029)	(0.038)	(0.044)	(0.063)
$MktRet_{m-1}$						0.005*		0.005*
						(0.003)		(0.003)
$DOX_{m-1} \times MktRet_{m-1}$					0.007*	-0.000	0.010*	0.004
					(0.004)	(0.004)	(0.005)	(0.005)
$(PGR-PLR)_{m-1}$							-0.022*	-0.034**
							(0.012)	(0.014)
$Volatility_{m-1}$							-0.352*	-0.575**
							(0.200)	(0.289)
$Skewness_{m-1}$							0.007*	0.014**
							(0.004)	(0.006)
$\#ofTrades_{m-1}$							0.008***	0.007***
							(0.003)	(0.002)
$Turnover_{m-1}$							0.014***	0.019***
							(0.004)	(0.005)
$AvgBalance_{m-1}$							0.015*	0.015*
							(0.008)	(0.009)
$AvgHHI_{m-1}$							0.009	0.020**
							(0.009)	(0.009)
Exp_{m-1}							-0.002***	0.002***
							(0.001)	(0.001)
Gender							YES	YES
Constant	0.076***	0.076***	0.087***	0.085***	0.090***	0.088***	0.180***	-0.079***
	(0.002)	(0.002)	(0.000)	(0.002)	(0.004)	(0.016)	(0.033)	(0.030)
Observations	1,717,779	1,717,779	1,717,779	1,717,779	1,611,917	1,609,927	1,501,806	1,501,806
R-squared	0.007	0.007	0.007	0.007	0.007	0.000	0.007	0.001

Table 8: Entry decisions into B funds, by periods

This table shows the regression results by regressing entry decisions into B on cumulative account characteristics. $Dummy_m^B$ denotes whether an account trades B in month m. The first column uses observations from 2005:01 to 2014: 09, the second column from 2014:10 to 2015:05, the third column from 2015:06 to 2015:08, and the last column from 2015:09 to 2016:12. All regressors use transactions up to month $m-1$ (indicated by the subscripted $m-1$) and represent an account's cumulative characteristics. $Dummy_{m-1}^W$, $Dummy_{m-1}^{CW}$, and $Dummy_{m-1}^{PW}$ denote the whether an account has traded warrants, call warrants, and put warrants . Ret_{m-1}^E denote the return rate from equity investment, where the return rate is calculated by dividing total RMB return to average RMB balance. $Ret_{m-1}^{StockPicking}$ and $Ret_{m-1}^{MarketTiming}$ decompose Ret_{m-1}^E into a part driven by stock picking and a part driven by market timing. DOX_{m-1}, VOL_{m-1} and $SKEW_{m-1}$ denotes the degree of extrapolation, preference for volatility, and preference for skewness. They are constructed as the weighted-average, based on purchase sizes, past one-month return, past 12-month volatility, and past 12-month skewness for all purchases, where volatility and skewness is calculated based on the daily returns. DE_{m-1} denotes the disposition effect, measured by the different between the proportion of gains realized and the proportion of losses realized on selling days. N_{m-1}^{Trade} is the total number of transactions. BAL_{m-1} denotes average account balanced in million RMB, and TN_{m-1} is calculated as sum of transaction value divided by average account balance. HHI_{m-1} is calculated as the sum of the squares of each stock's portfolio weight. EXP_{m-1} measures the total number of months since account opened.

	$Dummy_m^B$			
	(1)	(2)	(3)	(4)
$Dummy_{m-1}^W$	0.027***	0.182**	-0.046	0.055**
	(0.006)	(0.060)	(0.063)	(0.024)
Ret_{m-1}	-0.004	0.442	-0.131	0.120*
	(0.012)	(0.325)	(0.360)	(0.066)
DOX_{m-1}	-0.061***	-0.038	6.239***	-0.010
	(0.015)	(0.329)	(0.267)	(0.034)
$MktRet_{m-1}$	0.000	0.050***	0.087*	0.003**
	(0.001)	(0.008)	(0.024)	(0.001)
$DOX_{m-1} \times MktRet_{m-1}$	0.001	0.126***	0.448***	-0.003*
	(0.002)	(0.036)	(0.033)	(0.001)
$(PGR-PLR)_{m-1}$	-0.009	-0.125	-0.404	-0.020
	(0.005)	(0.158)	(0.355)	(0.030)
$Volatility_{m-1}$	0.050	-4.565***	-6.318	1.114
	(0.106)	(1.048)	(4.999)	(1.202)
$Skewness_{m-1}$	0.004*	0.049	0.016	-0.045*
	(0.002)	(0.039)	(0.047)	(0.021)
$\#ofTrades_{m-1}$	0.003**	0.023**	0.007	0.002
	(0.001)	(0.010)	(0.010)	(0.003)
$Turnover_{m-1}$	0.008***	0.083**	0.130	0.041**
	(0.003)	(0.034)	(0.091)	(0.018)
$AvgBalance_{m-1}$	0.003	0.017	0.442	0.019
	(0.005)	(0.025)	(0.326)	(0.015)
$AvgHHI_{m-1}$	-0.000	-0.029	-0.002	0.036
	(0.007)	(0.051)	(0.187)	(0.025)
Exp_{m-1}	0.000	-0.006	-0.006	-0.002**
	(0.000)	(0.004)	(0.009)	(0.001)
Gender	YES	YES	YES	YES
Constant	0.013	0.593	2.429	0.252**
	(0.009)	(0.400)	(1.287)	(0.088)
Observations	1,209,642	96,045	32,445	152,338
R-squared	0.000	0.004	0.006	0.001

Table 9: Entry decisions into B funds, the run-up period

This table shows the regression results by regressing entry decisions into B on cumulative account characteristics. $Dummy^B_m$ denotes whether an account trades B in month m. All columns use observations from 2014:10 to 2015:05. All regressors use transactions up to month $m-1$ (indicated by the subscripted $m-1$) and represent an account's cumulative characteristics. $Dummy^W_{m-1}$, $Dummy^{CW}_{m-1}$, and $Dummy^{PW}_{m-1}$ denote the whether an account has traded warrants, call warrants, and put warrants . Ret^E_{m-1} denote the return rate from equity investment, where the return rate is calculated by dividing total RMB return to average RMB balance. $Ret^{StockPicking}_{m-1}$ and $Ret^{MarketTiming}_{m-1}$ decompose Ret^E_{m-1} into a part driven by stock picking and a part driven by market timing. DOX_{m-1}, VOL_{m-1} and $SKEW_{m-1}$ denotes the degree of extrapolation, preference for volatility, and preference for skewness. They are constructed as the weighted-average, based on purchase sizes, past one-month return, past 12-month volatility, and past 12-month skewness for all purchases, where volatility and skewness is calculated based on the daily returns. DE_{m-1} denotes the disposition effect, measured by the different between the proportion of gains realized and the proportion of losses realized on selling days. N^{Trade}_{m-1} is the total number of transactions. BAL_{m-1} denotes average account balanced in million RMB, and TN_{m-1} is calculated as sum of transaction value divided by average account balance. HHI_{m-1} is calculated as the sum of the squares of each stock's portfolio weight. EXP_{m-1} measures the total number of months.

	$Dummy^B_m$		
	(1)	(2)	(3)
$Dummy^W_{m-1}$	0.153**	0.182**	0.182**
	(0.056)	(0.060)	(0.060)
Ret_{m-1}	0.787*	0.457	0.442
	(0.380)	(0.330)	(0.325)
DOX_{m-1}	1.285**	1.127**	-0.038
	(0.490)	(0.405)	(0.329)
$MktRet_{m-1}$		0.067***	0.050***
		(0.009)	(0.008)
$DOX_{m-1} \times MktRet_{m-1}$			0.126***
			(0.036)
$(PGR - PLR)_{m-1}$	-0.159	-0.124	-0.125
	(0.163)	(0.158)	(0.158)
$Volatility_{m-1}$	-5.009***	-4.652***	-4.565***
	(1.201)	(1.060)	(1.048)
$Skewness_{m-1}$	0.061	0.051	0.049
	(0.038)	(0.039)	(0.039)
$\#ofTrades_{m-1}$	0.022*	0.023**	0.023**
	(0.009)	(0.010)	(0.010)
$Turnover_{m-1}$	0.101**	0.084**	0.083**
	(0.029)	(0.034)	(0.034)
$AvgBalance_{m-1}$	0.017	0.017	0.017
	(0.025)	(0.026)	(0.025)
$AvgHHI_{m-1}$	0.009	-0.027	-0.029
	(0.039)	(0.049)	(0.051)
Exp_{m-1}	-0.003	-0.006	-0.006
	(0.004)	(0.004)	(0.004)
Constant	0.743	0.459	0.593
	(0.397)	(0.382)	(0.400)
Observations	96,045	96,045	96,045
R-squared	0.002	0.004	0.004