# Between Attention and Portfolio Adjustment: Insights from Machine Learning-based Risk Preference Assessment

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# Between Attention and Portfolio Adjustment: Insights from Machine Learning-based Risk Preference Assessment

*Completed Research Paper*

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## Abstract

*Financial firms recommend products to customers, intending to gain their attention and change their portfolios. Based on behavioral decision-making theory, we argue attention's effect on portfolio adjustment is through the risk deviation between portfolio risk and their risk preference. Thus, to fully understand the adjustment process, it is necessary to assess customers' risk preferences. In this study, we use machine learning methods to measure customers' risk preferences. Then, we build a dynamic adjustment model and find that attention's impact on portfolio adjustment speed is stronger when customers' risk preference is higher than portfolio risk (which needs an upward adjustment) and when customers' risk preference is within historical portfolio risk experience. We conducted a field experiment and found that directing customers' attention to products addressing the risk deviation would lead to more portfolio adjustment activities. Our study illustrates the role of machine learning in enhancing our understanding of financial decision-making.*

**Keywords:** Risk Preference; Portfolio Adjustment; Machine Learning; Attention; FinTech

## Introduction

It is a common practice for financial firms to approach customers and promote products, intending to gain their attention and change their portfolios. However, the current approach to recommending financial products is not always effective. Financial marketing activities need a more theoretical understanding of the process between attention and portfolio adjustment by customers.

In this study, we investigate customer portfolio adjustment based on the behavioral decision-making theory, which includes three stages: deviation, search, and action (Simon, 1957). We argue that portfolio adjustment is rooted in the risk deviation between portfolio risk and risk preference, which could be resolved through searching followed by portfolio adjustment. Meanwhile, the search process is bounded by human's attention (Cyert & March, 1963;March & Simon, 1958). More attention allows for a thorough search, which in turn impacts the likelihood of resolving risk deviation. Therefore, we argue that the effect of attention on portfolio adjustment would depend on the risk deviation between portfolio risk and risk preference.

The alignment between customers' risk preferences and portfolios is well-recognized in finance. While risk-seeking investors tend to have higher-risk portfolios (Corter & Chen, 2006; Dohmen et al., 2011), customers' risk preferences and portfolios can be misaligned as customers do not always adjust their portfolios (Abel et al., 2013). Eliciting customers' risk preferences is a major challenge to investigating this deviation (Pedroni et al., 2017). Most financial firms survey their customers to ascertain risk preferences, which cannot be conducted frequently due to customers' aversion to such surveys (Haeffel & Howard, 2016). Moreover, the CFA Institute posits that the "current practice of using questionnaires to identify investor risk profiles is inadequate and unreliable" (Klement, 2015). Without reliable methods for assessing risk preferences, it is difficult to gauge the risk deviation between risk preferences and portfolio risk.

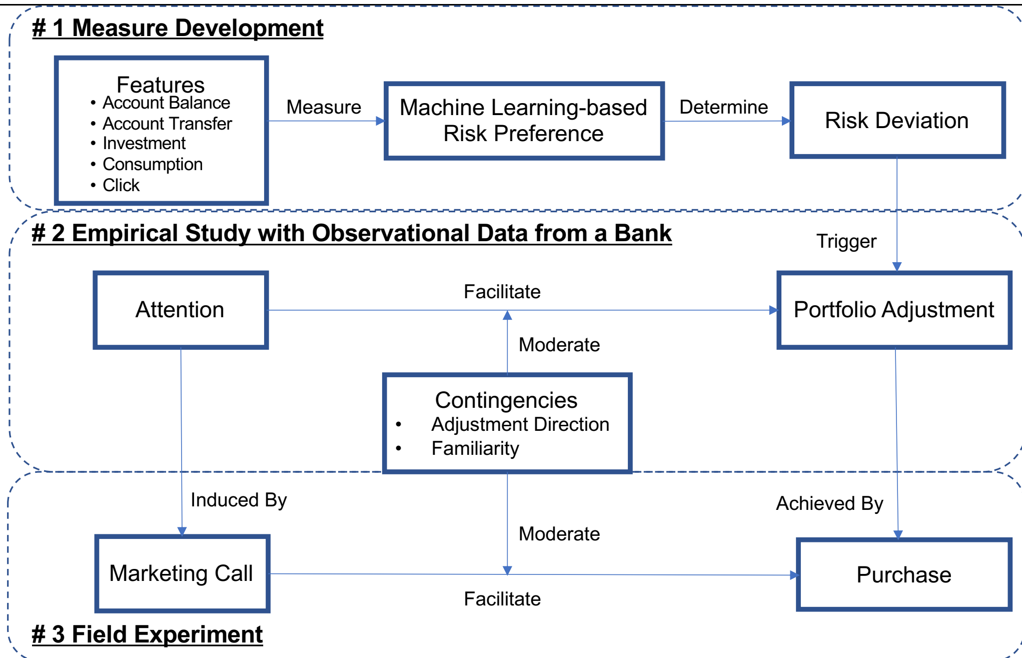


**Figure 1. Research Scheme**

To overcome this challenge, we employed machine learning techniques to measure risk preferences. Our research scheme, as illustrated in Figure 1, includes three steps: measure development, empirical study with observational data, and field experiment. First, in the measure development stage, this paper leverages a commercial bank setting and proposes to predict customers' risk preference based on their online behaviors, including account transactions (e.g., transfers, investments, payments, and credit or debit card purchases) and e-banking interactions (e.g., log-ins, clicks, and browsing). These data would allow us to estimate risk preferences for the theoretical understanding of portfolio adjustment.

Second, we conducted an empirical study with observational data from a large bank to evaluate a dynamic adjustment model on how attention impacts portfolio adjustment. Moreover, we investigated how the characteristics of risk deviation moderate this process. Specifically, we examined adjustment direction (i.e., if risk preference is higher or lower than portfolio risk) and familiarity (i.e., if risk preference is within vs. beyond historical portfolio experience). We measured customers' attention through their clicking behavior on financial products-related pages. After addressing the endogeneity concerns with instrument variables, our results show that attention has a stronger impact on portfolio adjustment when the adjustment is upward and when the target portfolio risk is within the customer's historical experience.

Finally, we conducted a field experiment for further causal identification. We collaborated with a branch of the bank and brought customers' attention to two types of financial products (based on popularity and based on their risk preferences) through phone calls. This experimental design complements our earlier empirical study by directly manipulating customers' attention. The results show that more portfolio adjustments happen when customers' attention is drawn to the products related to risk deviation, which confirms our findings from the empirical study.

The contributions of this paper are two-fold. First, the findings enhance our comprehension of financial decision-making. We provide theoretical insights into the relationship between attention and portfolio adjustments. We found that attention's impact on portfolio adjustment is conditional on the deviation between customer portfolio risk and risk preference. Second, we employed a machine learning approach to measure customers' risk preferences for the study, which illustrates the role of data analysis in business research. Moreover, this approach can be easily implemented and generalized in practice for risk preference assessment. Our findings indicate that financial firms need to leverage data analysis to better understand customers' risk preferences and provide tailored financial products that meet their evolving needs, which aligns with the trend that is transforming financial services (Goldstein et al., 2019; Hendershott et al., 2021).

## Theoretical Development and Hypotheses

### *Risk Preference and Portfolio Risk*

The classic financial theory proposes that an investor's risk preference influences the asset choices in their portfolio (Markowitz, 1952). Risk-seeking investors tend to prefer and can sustain higher-risk assets, which may offer a higher expected return. Empirical evidence suggests that more risk-seeking investors tend to hold high-risk assets (Dorn & Huberman, 2005) and choose higher-risk portfolios (Corter & Chen, 2006; Dohmen et al., 2011). However, some studies have reported a misalignment between portfolio risk and risk preference. For example, using data from the Survey of Consumer Finances, Jianakoplos (2002) found that investors who declare themselves more risk-averse hold unexpectedly large risky assets. Similarly, Ehm et al. (2014) discovered that investors act inconsistently with their risk attitude.

An increasing number of studies have focused on the misalignment between portfolio risk and risk preference. On the one hand, this misalignment can be attributed to the dynamic nature of risk preference, which has been empirically examined in some studies. For example, Chuang and Schechter (2015) found that experimental measures of risk preferences are not stable over time, possibly due to external shocks that cause risk preferences to change. Guiso et al. (2018) further supported this argument through surveys of risk preferences before and after the 2008 financial crisis, finding that investors became more risk-averse after the crisis, which cannot be explained by changes in wealth or expected income. On the other hand, the misalignment can also be due to the delayed response of investors to changes in their risk preferences. Investors often show inertia in portfolio allocation and slowly rebalance their portfolios in response to capital gains and losses (Brunnermeier & Nagel, 2008).

### *Attention, Risk Deviation, and Portfolio Adjustment*

We argue the risk deviation between portfolio risk and risk preference is part of the portfolio adjustment process, as illustrated in the middle part of Figure 1. This model adopts the behavioral decision-making paradigm, which consists of three stages: deviation, search, and action (Simon, 1957). From a behavioral perspective, when there is a deviation between current and desired levels, decision-makers engage in a search process to find solutions, and once a satisfactory solution is found, they take action. Accordingly, we argue that the portfolio adjustment starts from the risk deviation between risk preferences and portfolio risk and after customers' search and finding of appropriate financial products.

For customers, the search process is bounded to their attention (Cyert & March, 1963; March & Simon, 1958). By allocating more attention, customers may be able to process and integrate new information more effectively, which can lead to quicker learning and adjustment. Allocating attention can help customers evaluate more alternatives and compare them more effectively, thus facilitating their decision-making processes and ultimately leading to faster adjustment. Thus, we argue that attention will affect portfolio adjustment which is rooted in risk deviation. Specifically, if we view portfolio adjustment as a dynamic process, where portfolio risks change following risk preference, attention's impact will be reflected in customer's portfolio adjustment speed. Therefore, we hypothesize:

*H1. Attention is positively related to portfolio adjustment speed.*

Moreover, the fundamental reason for portfolio adjustment, i.e., the risk deviation between portfolio risk and risk preference, would also affect how attention is involved in portfolio adjustment. In this study, we focus on two aspects: the adjustment direction (upward vs. downward) and familiarity (within vs. beyond experience). According to dual system theories (Evans 2008; Evans and Stanovich 2013; Kahneman 2011), attention's effect on portfolio adjustment would be different in these situations.

For adjustment direction, when customers' risk preferences are higher than their portfolio risks, they need to adjust their portfolio "upward." Upward adjustments often involve the purchase of high-risk financial products, necessitating a broader comparison of investment options to close the risk deviation. This wider range of choices inherently requires more calculation and, thus, a higher level of analytical thinking. Additionally, the increased risk associated with upward adjustments makes customers more cautious, aligning with the dual-system theory's premise that higher cognitive demand triggers greater analytical thinking (Evans & Stanovich 2013). Consequently, attention plays a more significant role in the decision-making process during upward adjustments. On the other hand, when customers opt for "downward" adjustments to align with lower risk preferences, the cognitive demand generally decreases. These customers often have prior experience with lower-risk products, reducing the need for extensive comparisons or calculations. As a result, the influence of attention on the decision-making process tends to weaken during downward adjustments. Therefore, we hypothesize:

*H2a. The effect of attention on portfolio adjustment speed is stronger when the risk preference is higher than portfolio risk (i.e., upward adjustment is needed).*

For familiarity, we compare customers' risk preferences with their historical portfolio risk, where a risk level beyond historical experience is "unfamiliar." When customers face a familiar problem (within historical experience), they hold financial literacy and know what financial products could help them close the risk deviation. Therefore, they do not need to allocate much attention to finding the solution. However, if customers face a risk level beyond experience, they need to search for more information and compare to find a satisfactory solution. In this case, allocating more attention would facilitate their search for a solution and speed up the adjustment process. Thus, we hypothesize:

*H2b. The effect of attention on portfolio adjustment speed is stronger when the risk preference is beyond the customer's historical experience (into an unfamiliar zone).*

## Research Context

Our research was conducted at a top-10 joint-stock commercial bank in China. The bank allows customers to open investment accounts and conduct investment transactions. The bank has customer data on balances, investments, transactions, and webpage access along within e-banking or mobile banking. The transactions include not only balance transfers and investment activities, but also consumptions (such as debit or credit card payment records), with the date, amount, channel, etc. Such data, to our knowledge, are often available in other commercial banks. We obtained access to a random sample of about 10 thousand customers in the bank, covering their activities from January 2018 to October 2018.

The bank provides multiple types of financial products with different risks, such as savings, mutual funds, bonds, gold, bank wealth-management products, and insurance. According to industry standards, the bank assigns each product a risk level from 1 to 5. While banks control the highest risk level a customer can purchase, customers decide the risk level of their portfolio by purchasing different products. From time to time, customers can proactively change investment targets.

The bank provides online banking services through PCs and apps, which enable customers to conduct transactions and, in the meanwhile, access financial product information. The website provides rich information on financial products (e.g., risk level, minimum purchase amount, past performance reports, etc.). Customers may deliberately read such information or accidentally view such information by clicking on ads, coupons, or other promotional materials. Viewing the financial product information would increase customers' knowledge and may influence their portfolio adjustment. The bank keeps the clickstream data on webpage browsing time and channel.

The bank also provides us with interaction records between managers and customers through the customer service call center, which is the major channel other than e-banking/mobile banking where the bank is in contact with customers. The call center records include who initiates the calls (managers or customers) and time duration of the phone calls. Customers may be presented with financial product information through phone calls. Customers may also access financial product information through other channels, such as in-store interactions, which were not observable to us.

Overall, our sample includes 106,993 customer-month observations. Table 1 shows the summary statistics of the entire dataset. On average, the customers are 42 years old and stay with the bank for about 10 years. As we can see, the customers make active transactions in terms of investments, transfers, and consumption. They also frequently use online banking services. On average, customers spend approximately 40 minutes on online-banking webpages browsing in a month. The customers' engagement with the bank provides us with sufficient information to elicit their risk preferences.

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| Age | 42.309 | 10.763 | 16 | 90 |
| Tenure (years) | 9.965 | 5.380 | 0 | 30 |
| Ln (Total asset) | 12.509 | 1.727 | 0 | 18.451 |
| # Purchasing transactions | 0.738 | 1.563 | 0 | 70 |
| # Redeeming transactions | 0.424 | 2.331 | 0 | 288 |
| # Transferring transactions | 2.665 | 6.305 | 0 | 461 |
| # Debit card payments | 14.310 | 143.007 | 0 | 15042 |
| # Credit card payments | 6.827 | 8.284 | 0 | 32 |
| Time spent on webpage browsing | 39.953 | 57.534 | 0 | 2247. 433 |
| # Clicks on all webpages | 136.447 | 181.137 | 1 | 10,036 |

**Table 1. Summary Statistics of the Sample**

## Machine Learning-based Measure for Risk Preference

### *Existing Risk Preference Elicitation Methods*

Most financial firms use questionnaires to collect customers' risk preferences. This approach is straightforward and inexpensive but has received criticism for potential self-serving biases that may cause customers to distort their reports (Camerer et al., 1999). Additionally, some researchers argue that self-reported risk preferences may be little more than "cheap talk" (Beshears et al., 2008). Moreover, this approach measures risk preference at an ordinal level, making it challenging to extrapolate. Increasing the frequency of elicitation may increase customers' cognitive load and reduce satisfaction (Haeffel & Howard, 2016).

Another approach is to use portfolio risk (PR) as a proxy for risk preference (Ehm et al., 2014; Weber et al., 2012). This approach infers customers' risk preferences from their investment behavior. However, customers must actively participate in investment transactions to update their observed PR (OPR). Otherwise, the OPR may deviate from their risk preferences, making timely assessment difficult. Even if customers proactively report risk preferences through investment transactions, their updated OPR is delayed, making intervention by financial firms difficult.

Researchers have also used experiments, such as lottery games, to elicit subjects' risk preferences (Crosetto & Filippin, 2013; Holt & Laury, 2002). However, this approach is time-consuming and difficult to scale (Charness et al., 2018), and different elicitation methods may generate conflicting results with low coherence (Pedroni et al., 2017). Strict experimental conditions also limit the applicability of this method to real-world contexts.

## *Machine Learning Approach*

The primary objective of our study is to develop a method for continuously assessing customers' risk preferences. As shown in Figure 2, customers' risk preferences are dynamic and can change over time. They may be aligned with the observed portfolio risk (OPR) when they buy or sell financial products. However, when their portfolios remain static, their risk preferences may diverge from their portfolios' risk levels. To address this, we define customers' OPR at the points with adjustment (i.e., proactively buying or selling financial products) as their risk preferences. In the meanwhile, we consider customers' risk preferences at these time points are correlated and thus can be predicted by customers' characteristics and behaviors (such as credit card payments, account transfers, interactions with the bank through online banking, etc.). So, we use the portfolio risk when customers adjust their portfolio as the learning target (dependent variable) and use customers' behavioral data (before portfolio adjustment) as features to build the risk preference prediction model. After training a model on time points with adjustment, we could predict risk preference between portfolio adjustments. By doing so, we would construct a timely measure of risk preference.

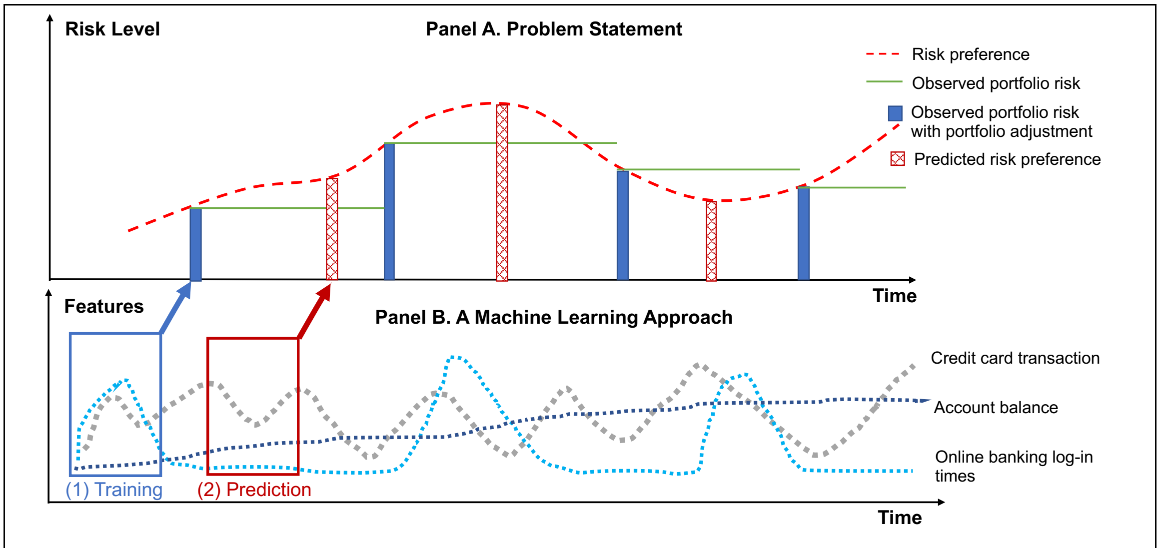


**Figure 2. Operation of the Machine Learning Approach**

Specifically, the learning target (dependent variable) of the model, portfolio risk (PR), is calculated as:

$$PR = (\sum Risk_k * Asset_k)/\sum Asset_k$$

where $Risk_k$ is the risk level of the (customers') $k$th asset, and $Asset_k$ is the value of the $k$th asset. The bank assigns a risk level for each asset class, where the risk level is 0 to 5, from low risk to high risk. Previous studies use similar measures to score portfolio risk (Corter & Chen, 2006).

Based on the five categories of data we have (account balance, transfer, investment history, consumption transactions, and click stream), we generate statistical measures at month level for each customer. Later, we use multiple month's features as prediction features to build a prediction model.

First, for account balance data, we include the monthly account balances for savings accounts, mutual funds, bonds, gold, bank wealth-management products, and insurance as features. We also consider the original amount and category ratio of each type of financial product. In addition, we incorporate the monthly portfolio and ratio of different risk levels.

Second, for account transfer, investment, and consumption transactions, we generate monthly statistics (sum, average, minimum, maximum, and standard deviation) and the frequency of transactions within the month. Specifically, for investment transactions, we differentiate between buying and selling financial products with different risk levels. For the consumption transactions, we incorporate both credit and debit card consumption transactions. In addition to the monthly statistics of overall transactions, we consider consumption categories in terms of clothing, food, housing, transportation, and third-party consumption. We also include the proportion and total number of consumption categories.

Third, for click stream data, we split a customer's clickstream into sessions, which are defined as active periods of using the system. We generate session-level features in terms of viewing time and the number of clicks, and page-level features in terms of viewing time, relative position of clicks, and click sequence patterns. We then generate monthly statistics of page-level viewing time and position. Finally, we use PageRank algorithms to generate importance scores for different web pages.

After the feature generation process, we end up with 425 monthly features.

### *Effectiveness of Risk Preference Prediction*

We use eXtreme Gradient Boosting (XGBoost), a popular gradient-boosting tree model (Chen & Guestrin, 2016), to connect behavior data with known risk preferences and build prediction models. XGBoost produces accurate models, includes regularization to prevent overfitting, and is widely used in various applications. Moreover, its tree-based structure enhances interpretability, which aligns with financial industry regulations. We also experimented with other methods that are allowed by the bank and regulation.

Before using the predicted risk preference in an empirical study, we need to assess its effectiveness. When building the model, we use three months of historical data to predict the next month's risk preference, resulting in a dataset of 74893 observations (customer-month). Among them, there are 28331 customer-months with portfolio adjustment, i.e., with trustworthy risk preference that can be used for evaluation. We randomly split these 28331 samples into a training set with 60% of the observations and a testing set with 40% of the observations. We performed feature selection using the XGBoost model before training any machine learning models. We then tuned the parameters using ten-fold cross-validation on the training set and evaluated the model on the test set using commonly used metrics. Because PR is a numerical measure, we computed the $R^2$, root mean square error (RMSE), and mean absolute error (MAE) for different models and algorithms.

| Algorithm Comparison | $R^2$ | RMSE | MAE |
|---|---|---|---|
| OPR | 0.565 | 0.517 | 0.261 |
| SVR | 0.626 | 0.480 | 0.278 |
| Decision tree | 0.618 | 0.485 | 0.279 |
| Random forest | 0.642 | 0.470 | 0.271 |
| XGBoost | 0.695 | 0.434 | 0.251 |

**Table 2. Prediction Performance**

Table 2 presents the prediction performance of different learning algorithms. The first row serves as a benchmark, assuming the OPR in the last period is the real risk preference, which is a natural solution used by banks. Our XGBoost model explains 69.5% of the variance in PR, which is approximately 23% higher than using OPR only (from 56.5% to 69.5%). We also compared model performance with different feature combinations, where we gradually added consumption, click, account balance, transfer, and investment features and inspected the use of different months of features. The results show that incorporating more features generally improves prediction performance.

## A Dynamic Adjustment Model to Understand Portfolio Adjustment

### *Econometric Model*

After obtaining a (predicted) measure of risk preference, our main interest is to explore how customers' attention affects the adjustment of portfolios. As illustrated in Figure 2, a risk deviation between portfolio risk and risk preference triggers customers' portfolio adjustments. However, the portfolio adjustment may not be prompt and may not fully fill the gap. The resulting adjustment is a function of the risk deviation, which is influenced by other factors. Our interest is in the role of attention in the adjustment process. We model customers' portfolio adjustments with a dynamic adjustment model as follows:

$$OPR_{i,t} - OPR_{i,t-1} = \lambda_{i,t}(PPR_{i,t} - OPR_{i,t-1}) + Ctrl_{i,t} + \theta_t + e_{i,t} \tag{2}$$

where $OPR_{i,t}$ is the observed portfolio risk for customer $i$ in time period $t$. $PPR_{i,t}$ is the predicted portfolio risk for customer $i$ in time period $t$. $\lambda_{i,t}$ is the adjustment speed, which indicates how quickly customers adjust their portfolio in response to the risk deviation between the observed portfolio risk (OPR) and adjustment target (PPR in our case). $Ctrl_{i,t}$ are the control variables, and $e_{i,t}$ is the random noise. $\theta_t$ controls for the time fixed effects, including the market trend. In the literature, the adjustment target is often modeled as the hidden variable, which can be estimated using regression (Calvet et al., 2009). Given that we already predicted PPR using machine learning, the setup of our problem can be framed as follows:

$$Adjust_{i,t} = \lambda_{i,t} * Dev_{i,t} + Ctrl_{i,t} + \theta_t + e_{i,t} \tag{3}$$

where $Adjust_{i,t} = OPR_{i,t} - OPR_{i,t-1}$, and $Dev_{i,t} = PPR_{i,t} - OPR_{i,t-1}$.

To test our hypotheses, we followed the previous dynamic adjustment model literature (Faulkender et al., 2012), modeling $\lambda_{i,t}$ as a function of our focal variable $Attention_{i,t}$.

$$\lambda_{i,t} = \alpha + \beta * Attention_{i,t} \tag{4}$$

where $Attention_{i,t}$ indicates the amount of information consumed by customers to make the portfolio adjustment decision. Substituting (4) into (3) gives the following estimable model:

$$Adjust_{i,t} = \alpha * Dev_{i,t} + \beta * Attention_{i,t} * Dev_{i,t} + Ctrl_{i,t} + \theta_t + \varepsilon_{i,t} \tag{5}$$

where our interest is focused on $\beta$, which reflects the impact of attention on adjustment speed.

We measured attention by counting the number of clicks customers make on financial product-related pages each month. In the behavioral finance literature, researchers have used the number of online brokerage account log-ins (Sicherman et al., 2016) and time spent on brokerage account websites (Gargano & Rossi, 2018) to represent investors' attention to financial information. Our measure aligns with these designs and represents the same nature of attention to financial information. Note that we only included clicks directly related to investment activities in our measure of attention while excluding clicks on other functional modules (e.g., payment, balance check, etc.).

We hypothesize that the role of attention in portfolio adjustment varies in different decision contexts. As explained earlier, we differentiated the direction of risk adjustment (i.e., upward or downward adjustment) and familiarity (i.e., within or beyond experience). We set the downward adjustment and within experience as the baseline and define two dummy variables $Upward_{i,t}$ and $Beyond_{i,t}$ to indicate upward adjustment and beyond experience situations. In particular, to operationalize experience, we define a customer's "experience" as the historical portfolio risk level at the 80% quantile. If the target portfolio risk is below this level, we consider it within experiences. If the target portfolio risk exceeds this level, we consider it beyond experience. We then included three-way interaction terms using the following models:

$$\begin{aligned} Adjust_{i,t} &= \alpha * Dev_{i.t} + \beta * Attention_{i,t} * Dev_{i,t} + \gamma_1 * Upward_{i,t} * Attention_{i,t} * Dev_{i,t} + \\ &\gamma_2 * Upward_{i,t} * Attention_{i,t} + \gamma_3 * Upward_{i,t} * Dev_{i,t} + \gamma_4 * Upward_{i,t} + Ctrl_{i,t} + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{6}$$

$$\begin{aligned} Adjust_{i,t} &= \alpha * Dev_{i.t} + \beta * Attention_{i,t} * Dev_{i,t} + \delta_1 * Beyond_{i,t} * Attention_{i,t} * Dev_{i,t} + \\ &\delta_2 * Beyond_{i,t} * Attention_{i,t} + \delta_3 * Beyond_{i,t} * Dev_{i,t} + \delta_4 * Beyond_{i,t} + Ctrl_{i,t} + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{7}$$

where our interests are $\gamma_1$ and $\delta_1$. We hypothesize that when customers adjust their portfolio to a higher level and when the target risk level is beyond experience, their need for cognition is higher, and the impact of attention is greater. Therefore, we expect that $\gamma_1$ and $\delta_1$ will be significantly positive.

## *Endogeneity*

Since we used predicted risk preference in the empirical study, to avoid reverse causality, we split the sample into two parts and used the first half (January 2018 to June 2018) to build a prediction model and applid the model to the second half of the data (July 2018 to October 2018) to predict customers' risk preferences.

To account for the potential influence of various factors on customers' investment decisions, we included two sets of control variables in our analysis. First, we considered customer demographics, previous risk exposure, and portfolio size, which have been identified in prior research as key drivers in financial decision-making (Barber & Odean, 2002; Korniotis & Kumar, 2011; Seru et al., 2010). Specifically, we controlled for the age, gender, and tenure of each customer with the bank, as well as for their previous portfolio risk exposure ($OPR_{i,t-1}$) and portfolio size ($PortfolioSize_{i,t-1}$) before they made investment decisions in month t.

Second, given that commercial banks often engage in various efforts to interact with customers, which may impact their investment choices, we also included control variables to account for bank–customer interactions. Specifically, we controlled for the number of phone calls initiated by customers ($CustCallTimes_{i,t}$) and managers ($MangCallTimes_{i,t}$), as well as the duration of these calls ($CustCallDuration_{i,t}$ and $MangCallDuration_{i,t}$). In addition, we differentiated between calls initiated by customers and those initiated by managers. To further capture the impact of managers' characteristics on customers' investment decisions, we also included manager tenure ($MangTenure_{i,t}$) and experience ($MangExperience_{i,t}$). We measured manager experience as the number of customers managed in month t.

To strengthen our identification, we utilized an instrument variable (IV) approach in our estimations. Specifically, we introduced two IVs for $Attention_{i,t}$: $Attention_{i,t-1}$ and $AvgMangAttention_{i,t}$. The first IV is the focal customer's attention in month $t$-1 ($Attention_{i,t-1}$). Due to serial correlation, a customer's number of clicks on financial product pages in one month is often correlated with their number of clicks in previous months. However, since portfolio adjustment is based on the gap between the customer's preferred and actual portfolio, it is unlikely to be related to any clicks before the focal month. The second IV is the average attention of customers (excluding the focal customer $i$) served by the same account manager in month $t$ ($AvgMangAttention_{i,t}$). Since the customers of an account manager remained stable in our dataset, removing a focal customer from the overall attention of these customers and taking the average can be correlated with the attention of the focal customer. However, it is important to note that other customers' attention does not affect the focal customer's portfolio adjustment. By using these two IVs, we could reduce the potential bias in our estimates and obtain more accurate estimates of the causal effects of attention on portfolio adjustment.

## *Econometric Results*

Table 3 presents the descriptive statistics for the variables used in our empirical study, covering the period from June to October 2018. The results revealed that, on average, customers allocated similar levels of attention to both upward and downward adjustments, but the extent of attention allocation varied depending on their familiarity with the problem. Specifically, customers within their experience zone devoted more attention than those who needed to adjust beyond their experience zone. Additionally, our findings showed that customers tended to have a higher level of risk in their portfolios before making a downward adjustment compared to before making an upward adjustment.

Table 4 shows the main models estimated using the OLS and IV approaches. The results are generally consistent. Our research interest is in the impact of attention on adjustment speed, which is the coefficient $\beta$ of the interaction term of attention and risk deviation. In both Models 1 and 4, the coefficients are significantly positive. This implies that customers adjust their portfolio toward risk preference more efficiently if they browse more on financial products pages. Therefore, H1 is supported.

| | Full Sample | | Downward Adjustment | | Upward Adjustment | | Within Experience | | Beyond Experience | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variables | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Adjust | -0.008 | 0.419 | -0.089 | 0.416 | 0.105 | 0.396 | -0.011 | 0.451 | 0.003 | 0.296 |
| Risk deviation | -0.083 | 0.515 | -0.326 | 0.504 | 0.254 | 0.290 | -0.158 | 0.546 | 0.153 | 0.296 |
| Attention | 22.714 | 35.716 | 23.495 | 35.677 | 21.633 | 35.743 | 23.649 | 35.875 | 19.775 | 35.053 |
| Age | 42.521 | 10.828 | 42.644 | 11.167 | 42.350 | 10.338 | 42.658 | 11.106 | 42.090 | 9.890 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Tenure (years) | 9.912 | 5.417 | 9.574 | 5.410 | 10.379 | 5.391 | 9.655 | 5.438 | 10.721 | 5.269 |
| Male | 0.337 | 0.473 | 0.327 | 0.469 | 0. 351 | 0.477 | 0.320 | 0.467 | 0.390 | 0.488 |
| OPR | 1.709 | 1.120 | 2.319 | 0.983 | 0.867 | 0.654 | 1.979 | 1.081 | 0.861 | 0.758 |
| PortfolioSize | 12.617 | 1.648 | 12.618 | 1.603 | 12.616 | 1.709 | 12.608 | 1.643 | 12.647 | 1.666 |
| CustCallTimes | 0.076 | 0.859 | 0.076 | 0.840 | 0.074 | 0.885 | 0.075 | 0.818 | 0.078 | 0.976 |
| MangCallTimes | 0.390 | 2.183 | 0.415 | 2.398 | 0.356 | 1.844 | 0.398 | 2.322 | 0.366 | 1.671 |
| CustCallDuration | 0.090 | 1.345 | 0.092 | 1.419 | 0.087 | 1.236 | 0.087 | 1.298 | 0.100 | 1.484 |
| MangCallDuration | 0.465 | 2.852 | 0.502 | 3.205 | 0.414 | 2.276 | 0.473 | 3.036 | 0.437 | 2.176 |
| MangTenure (months) | 28.155 | 13.110 | 28.466 | 13.007 | 27.724 | 13.240 | 28.386 | 13.003 | 27.429 | 13.418 |
| MangExperience | 19.726 | 12.746 | 19.715 | 12.596 | 19.741 | 12.953 | 19.864 | 12.685 | 19.291 | 12.929 |

**Table 3. Descriptive Statistics of Variables**

| DV: $Adjust_{i,t}$ | (1) OLS | (2) OLS | (3) OLS | (4) IV | (5) IV | (6) IV |
|---|---|---|---|---|---|---|
| $Dev_{i,t}$ $\boldsymbol{\alpha}$ | 0.443*** | 0.236*** | 0.376*** | 0.386*** | 0.227*** | 0.382*** |
| | (0.019) | (0.016) | (0.015) | (0.015) | (0.017) | (0.015) |
| $Dev_{i,t} \times Attention_{,t}$ $\boldsymbol{\beta}$ | 0.110*** | 0.062*** | 0.098*** | 0.106*** | 0.062*** | 0.113*** |
| | (0.008) | (0.014) | (0.007) | (0.009) | (0.012) | (0.010) |
| $Dev_{i,t} \times Attention_{,t,t} \times Upward_{i,t}$ $\boldsymbol{\gamma_1}$ | | 0.063*** | | | 0.054*** | |
| | | (0.014) | | | (0.022) | |
| $Dev_{i,t} \times Attention_{,t,t} \times Beyond_{i,t}$ $\boldsymbol{\delta_1}$ | | | -0.024 | | | -0.064*** |
| | | | (0.016) | | | (0.023) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effect | Yes | Yes | Yes | Yes | Yes | Yes |
| # Observations | 28,106 | 28,106 | 28,106 | 27,552 | 27,552 | 27,552 |
| $R^2$ | 0.122 | 0.149 | 0.125 | 0.119 | 0.148 | 0.122 |
| Wald F statistic | | | | 3779 | 180.3 | 790.4 |
| Hansen J statistic | | | | 8.179 | 3.068 | 8.247 |

**Table 4. Model Estimation Results**

*Notes*. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Moreover, we found that the coefficient $\gamma_1$ of the three-way interaction was significantly positive in both Models 2 and 5, which indicated that the effect of attention was stronger when customers adjusted upward compared to downward. Therefore, H2a is supported. This result aligns with our previous discussion, as customers who need to adjust upward are more cautious and need to compare more products to find the right solution. Hence, the effect of attention is more pronounced in this case. However, when customers need to decrease their portfolio risk (i.e., sell high-risk products or buy low-risk products), they do not need to devote as much cognitive effort and rely more on their intuition.

Interestingly, we found a negative and significant coefficient $\boldsymbol{\delta_1}$ in Model 6, indicating that the accelerating effect of attention was amplified when customers adjusted risk within their experience range. Therefore, H2b is not supported. One possible explanation is that when customers face a new problem (i.e., adjusting their portfolio beyond their experience range), they rely more on their affective processes rather than on logical thinking (Roxanne I et al., 2015), and their attention has little impact on their risk adjustment behavior. This highlights the importance of considering decision context and experience range in studying the impact of attention on adjustment speed.

### *Robustness Check*

To ensure the robustness of our findings, we conducted several additional analyses. First, one may argue that the risk preference measure is correlated with attention because we also used clicks information to predict the risk preference. To alleviate the concern, we predicted PPR without click information and conducted the same analysis. Second, we defined experience risk level with different standards. Apart from the 80% quantile of historical OPR, we also defined historical high as the maximum and 90% quantile of historical OPR. Third, we employed alternative measures for attention. We incorporated the browsing time spent on financial products-related pages as a measure of attention and estimated the adjustment model. Overall, our results remained robust across all additional analyses. These findings support the robustness and reliability of our empirical results.

## Bring Needed Risk to Attention: A Field Experiment

To further validate our theoretical argument, we conducted a field experiment in which we brought products that can address customers' risk deviation between risk preference and portfolio risk to their attention. Through this experiment, we investigated how this solution would affect customers' purchasing behavior.

### *Experimental Design and Procedure*

We collaborated with a branch of the bank to promote financial products through phone calls. The field experiment was conducted with VIP customers who had a higher probability of purchasing financial products and were, therefore, worth the efforts of telemarketers. The subjects were randomly assigned to two groups. We distinguished between two types of personalized recommendations delivered through phone calls. The control group received calls promoting the most-viewed financial products (popularity group) by customers within a two-month period, which is the traditional marketing practice and unrelated to risk preference. The treatment group received phone calls promoting the financial products that help customers address the risk deviation between their risk preference and portfolio risk. Specifically, for each customer, we first predicted the customer's risk preferences for the next month as $PPR_{t+1}$. Then, we selected from the most-viewed products the ones that could reduce the difference between $PPR_{t+1}$ and $OPR_t$ if they were incorporated into the portfolio using the following formula:

$$Minimize\colon \left| PPR_{t+1} - \frac{\sum Risk_k * Amount_k + Risk_F * Amount_F}{\sum Amount_k + Amount_F} \right| \tag{8}$$

$$Subject\ to\colon\ Amount_F \geq minimum\ purchase\ amount\ of\ asset\ F$$

$$F \in \{most\ viewed\ products\}$$

where $Risk_k$ and $Amount_k$ indicate the risk level and amount of the assets in the portfolio at month $t$. $F$ indicates the feasible solution that could help customers reduce the gap between portfolio risk and risk preference. For instance, if two customers viewed financial products with risk levels 3 and 4, the feasible solution for a customer in an upward adjustment situation (i.e., OPR = 3, PPR = 3.5) could be products with a risk level of 4, while the feasible solution for a customer in a downward adjustment situation (i.e., OPR = 4, PPR = 3.5) could be products with a risk level of 3. We provided all feasible solutions to the telemarketers and instructed them to prioritize recommendations. For instance, we might say, "The customer is more likely to buy products with risk levels 4 and 5; please recommend these with priority."

### *Results*

The telemarketers called 355 customers during the one-month campaign period, with 177 in the treatment group and 178 in the control group. Table 5 shows the subject demographics of the different groups. As we can see, there was no significant difference between the treatment and control groups after randomization.

| | | Full Sample | | Downward Adjustment | | Upward Adjustment | | Within Experience | | Beyond Experience | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Age | T | 42.808 | 11.284 | 43.629 | 11.652 | 42.117 | 10.920 | 42.721 | 11.221 | 42.565 | 11.194 |
| | C | 44.528 | 12.253 | 44.290 | 13.515 | 44.382 | 11.410 | 44.891 | 12.757 | 43.854 | 11.674 |
| Tenure (years) | T | 6.774 | 2.098 | 6.484 | 2.231 | 6.937 | 2.010 | 6.798 | 2.083 | 6.739 | 2.133 |
| | C | 6.753 | 2.213 | 6.806 | 2.079 | 6.691 | 2.322 | 6.717 | 2.308 | 6.768 | 2.151 |
| Male | T | 0.260 | 0.440 | 0.258 | 0.441 | 0.261 | 0.441 | 0.260 | 0.441 | 0.261 | 0.442 |
| | C | 0.348 | 0.478 | 0.290 | 0.458 | 0.355 | 0.481 | 0.348 | 0.479 | 0.341 | 0.477 |
| Portfolio Size | T | 12.177 | 0.858 | 12.174 | 0.677 | 12.171 | 0.959 | 12.232 | 0.853 | 12.083 | 0.886 |
| | C | 12.117 | 0.595 | 12.106 | 0.333 | 12.128 | 0.711 | 12.174 | 0.579 | 12.072 | 0.619 |
| MangTenure (months) | T | 43.147 | 28.507 | 38.048 | 26.817 | 44.928 | 28.746 | 42.846 | 28.707 | 41.884 | 27.581 |
| | C | 39.584 | 29.298 | 36.129 | 30.082 | 39.864 | 28.178 | 39.196 | 29.397 | 39.598 | 29.578 |
| MangExperience | T | 8.983 | 3.874 | 9.532 | 3.903 | 8.676 | 3.855 | 9.212 | 4.009 | 8.638 | 3.686 |
| | C | 8.219 | 3.920 | 8.371 | 4.209 | 8.127 | 3.803 | 8.609 | 4.156 | 7.817 | 3.672 |

**Table 5. Demographics of the Subjects**

We checked the customers' purchases (i.e., portfolio adjustments) within 10 days after the phone call, per the bank's suggestion, and provided customers with a few days to finalize the purchase. The results showed that the number of customers in the experimental group who made portfolio adjustments was 37, and that for the control group was 21. The chi-squared test results showed that the conversion rate was significantly higher for the treatment group than for the control group (20.90% vs. 11.80%; $\chi^2 = 5.38, p < 0.05$). Meanwhile, the experimental group's purchasing amount was 257 thousand RMB more than that of the control group (1498 vs. 1241).

We conducted logit regression to study how the effects of providing tailored solutions varied among different types of customers. Specifically, for customer i, we set the model as follows:

$$\Pr(Buy_i = 1) = \alpha + \beta * Treatment_i + \gamma * CallingWeek_i + \mathrm{Ctrl}_{\mathrm{i,t}} + \varepsilon_i$$

where $\Pr(Buy_i = 1)$ is the customers' propensity to purchase. $Treatment_i$ is a dummy variable indicating whether customers were in the treatment or control groups. $CallingWeek_i$ was used to control for the week fixed effect. The model was built on the three types of customers for analysis.

Table 6 shows the regression results, where Column 1 presents the effect for the full sample and Columns 2–5 show effects for different subsamples. Column 1 confirms the chi-squared test result that portfolio adjustment is stronger when customer attention is drawn to products that may address the risk deviation between risk preference and portfolio risk.

The results from Columns 2–5 confirm significant treatment effects for upward adjustments and within-experience situations. The finding on upward adjustments aligns with previous research, showing that customers allocate more cognitive resources when they need to increase portfolio risk, making tailored products more satisfying. The treatment effect was most distinct in this group of samples. We also found that providing solutions within customers' experience was significant, suggesting that persuasion is more effective when customers face a decision at a familiar risk level. For the other two customer types, the effect of attention was weaker, triggering fewer portfolio adjustments for these two groups. Overall, the experiment provided evidence of the interaction effect of attention and risk deviation on portfolio adjustment, confirming our finding on archival data.

| DV: $Buy_i$ | (1) Full Sample | (2) Downward Adjustment | (3) Upward Adjustment | (4) Within Experience | (5) Beyond Experience |
|---|---|---|---|---|---|
| Treatment | 0.666** | 0.507 | 0.779* | 0.859*** | 0.127 |
| | (0.305) | (0.473) | (0.434) | (0.388) | (0.542) |
| Constant | -4.074* | -0.509 | -7.521** | -4.478 | -0.816 |
| | (2.178) | (4.924) | (3.081) | (3.116) | (2.852) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Week Fixed Effect | Yes | Yes | Yes | Yes | Yes |
| Observations | 355 | 124 | 221 | 196 | 151 |
| Pseudo $R^2$ | 0.045 | 0.073 | 0.114 | 0.080 | 0.041 |

**Table 6. Experimental Results**

*Notes*. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Discussion

Our findings contribute to the understanding of the relationship between attention and portfolio adjustment in the financial context. Drawing on behavioral decision-making theory, we argue the fundamental reason for portfolio adjustment is the risk deviation between portfolio risk and risk preference, which is influenced by attention. To empirically evaluate this claim, we employed data analytics to measure customers' risk preferences from their behavior data. Enabled by this measurement approach, we showed that attention has a stronger impact on portfolio adjustment when the adjustment is upward to higher risk and within the customer's historical risk experience, which may be due to the greater need for analytical reasoning in these regions. We validated these findings through a field experiment that directed customers' attention to different types of products, which showed that the products that can address the risk deviation between risk preferences and portfolios lead to more portfolio adjustments.

Our study provides important theoretical insights into financial decision-making from a behavioral perspective. First, it contributes to understanding on the underlying mechanisms of the relationship between attention and portfolio adjustment. By explicating risk deviation (the problem), adjustment (the action), adjustment direction and familiarity (the contingencies), and how they relate, we provide a more nuanced understanding of portfolio adjustment. In doing so, we show the importance of employing a more nuanced approach to model the process from attention-seeking interventions to portfolio adjustments in financial decision-making.

Second, our study demonstrates the utility of data analytics in financial decision-making, particularly in measuring customers' risk preferences. Equipped with such approaches to measure risk preference, we can develop and test theories where individuals have different risk preferences, how these preferences evolve, the factors that induce changes in risk preference, and the economic consequences of shifts in risk preference (Einav and Levin 2014). To understand risk deviation and customers' needs, financial firms can leverage big data analytics to measure risk preference for a large population of customers over time and evaluate how they can better align their products and relationship management to meet the customers evolving risk preferences.

Future research can extend our study in different ways. From a contextual perspective, as our study was conducted in one commercial bank in China, the generalizability of the findings to other contexts will be useful to examine. From a methodology perspective, our risk preference estimation was based on mature models and feature engineering. Other methods such as deep learning and explainable AI models can be developed for risk preference assessment. From a theoretical perspective, our model integrated attention, risk deviation and portfolio adjustment, and the contingency of familiarity. Future work can investigate the role of different attention-shifting methods and contingencies pertaining to the type of financial products and the decision-maker.

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