The Value of Payment Innovation to Households: Evidence from a FinTech Platform

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Abstract

Many recent payment innovations feature embedding payment functionality into non-deposit assets. Leveraging a unique administrative dataset on payment-integrated money market fund products from Alipay, a digital payment provider in China, this paper examines the value of such innovation to households and the underlying mechanism. Using a structural demand model that accounts for both fund-level characteristics and investor-level heterogeneity, we estimate that households are, on average, willing to pay approximately 40 basis points annually to access integrated payment services. Valuation is higher among wealthy individuals and young males. We show that this heterogeneity is primarily driven by differences in consumption risk, suggesting that the primary source of value lies in the liquidity option value, rather than direct usage convenience.

Keywords: Digital payment, Money market funds, Demand estimation.

JEL Codes: D14, G11, G23, G50.

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1 Introduction

Over the past decade, the payment industry has undergone rapid transformation and expansion. Recognizing the value of payment flows in credit provision, deposit competition, and client retention (Puri et al., 2017; Mester et al., 2007; Hau et al., 2019; Ghosh et al., 2022), both traditional financial institutions (e.g., banks) and FinTech firms (e.g., PayPal, Stripe, AliPay) actively innovate and compete in providing payment services (Parlour et al., 2022). A key frontier in payment innovations is the integration of payment function with investment value, a leading example of which is cryptocurrencies and tokens. Being able to be used for transactions, these non-deposit assets offer viable alternatives to traditional money (Cong et al. 2023), raising important questions about their implications for the financial system (Allen and Walther 2024). Assessing their economic impacts requires estimating household adoption, which in turn hinges on understanding how much households value the payment feature embedded in an investment asset.

A similar payment innovation can be found in China's money market fund (MMF) industry, where a subset of MMFs offer their investors payment services, providing a valuable empirical setting to study how much households value embedded payment functionality.[1] Specifically, we leverage a unique administrative dataset on payment-integrated MMF products from Alipay, a leading digital payment service provider in China, to estimate the value of such innovation to households and the underlying mechanism. These payment-integrated MMF products on Alipay's platform are categorized as Yu'ebao.[2] Yu'ebao MMFs enable investors to make real-time payments and peer-to-peer transactions directly from their investments, while still offering investment returns similar to regular MMFs. However, they typically charge higher fees and offer lower net returns. This trade-off, together with information on demographics and consumption behaviors, allows us to estimate households' willingness to pay (WTP) for embedded payment feature and uncover the underlying mechanisms driving the valuation.

[1] PayPal and other digital payment providers have introduced similar products, while the one in China remains the largest and most widely adopted example of this innovation. For example, according to the 2018 annual report of Tianhong Yu'ebao MMF, a leading payment-integrated MMF with 99.97% retail ownership, had over 588 million accounts, reflecting its wide adoption.

[2] Additional details on the product are provided in Section 2. Throughout the paper, we use the terms payment-integrated MMFs and Yu'ebao MMFs interchangeably.

Given the clear trade-off, it is tempting to estimate the valuation of this payment feature using a reduced-form framework by directly comparing yield and fee differences between the payment-integrated and regular MMFs. However, this approach risks conflating investor preferences with supply-side distortions. Retail investors' demand does not entirely determine the returns of MMFs, which largely depend on conditions in the money market, in which banks and other institutional investors play an important role. In addition, market competition may limit the extent to which fund sponsors can capitalize on the payment feature by raising fees. A naive reduced-form approach is unlikely to accurately capture the valuation.

Considering these unique features of the MMF industry, we employ a structural demand model that takes into account both fund-level characteristics and investor-level heterogeneity. More specifically, we model investors' fund selection as a discrete-choice problem over MMF products. In each month, investors choose one MMF, from a set that includes both payment-integrated and regular MMFs, that yields the highest indirect utility, or opt for an outside alternative (e.g., cash, bank deposits, or other investments). Their utility depends on the fund's payment feature and other attributes, such as fund age, fund family size, etc. Crucially, our model allows preferences for the payment feature to vary systematically with investor characteristics such as age, gender, wealth, and consumption behavior. This structure enables us to study heterogeneity in valuation across investors, leveraging the richness of our disaggregated data. We obtain three main results.

First, the average household is willing to pay approximately 40 basis points (bps) per year in additional fees to gain payment functionality offered by an MMF product. We confirm that return-based motivations do not drive this valuation by controlling for fund excess expected returns. To put this figure into perspective, this WTP amounts to nearly two-thirds of the typical MMF fees, which in our sample range from 50 to 60 bps. With a monthly investment of 7000 RMB (approximately 1,000 USD), this translates to an equivalent valuation of roughly 2.3 RMB (approximately 0.3 USD) per month. Our estimated valuation of the embedded payment feature is comparable to the findings of Cipriani and La Spada (2021), who document a 20 bps premium for information insensitivity among retail investors using the US MMF data. Their estimate captures the safety dimension of money-like assets, while ours isolates the value of the payment feature.

Second, our micro-level framework enables us to uncover the substantial heterogeneity in this valuation across investor types. Following Petrin (2002), by incorporating investor-level micro-moments conditions — conditional expectations of demographic attributes among payment-integrated fund investors — into the structural demand model, we are able to recover individual valuations as a function of demographic and behavioral characteristics. We find that males place greater value on the payment feature offered by Yu'ebao MMFs, and this gender difference is entirely coming from the younger generation below 45 years old. Additionally, individuals with greater financial wealth and higher consumption levels tend to place a higher value on the embedded payment feature.

Third, to investigate the source of valuation, we conduct a decomposition analysis. We focus on two conceptually distinct components: utilization value and option value. Utilization value refers to the direct utility gained from actively using Yu'ebao to make payments, which is proportional to the payment usage intensity. While option value represents the precautionary liquidity benefit. Even when not used for transactions, holding funds in payment-integrated MMFs allows users to instantly convert savings into spending power, offering a form of precautionary insurance. This decomposition echoes a long-standing observation in household finance: individuals often forgo higher returns in favor of liquidity and ease of access (Gross and Souleles, 2002; Telyukova, 2013), which aligns with the precautionary saving literature (Carroll and Samwick, 1998; D'Acunto et al., 2020). The results suggest that the dominant driver of investor demand for embedded payment functionality is the precautionary liquidity value, that is, the flexibility to instantly access savings in response to unpredictable consumption needs, rather than the direct convenience of usage.

In more detail, we implement this decomposition using two empirical proxies. For utilization value, we construct a binary indicator for whether the individual used the payment-integrated fund for transactions in the past three months. For option value, we follow Blundell et al. (2008) and Catherine et al. (2024) to construct an individual-level measure of consumption risk, defined as the volatility of unexpected consumption shocks to nondurable consumption. The logic is that individuals facing greater uncertainty in consumption needs derive more value from maintaining frictionless access to funds, hence are expected to have higher precautionary liquidity needs. The decomposition reveals that nearly two-thirds of the

average valuation is attributable to consumption risk, while only about 10% can be explained by direct payment usage.

Our paper builds on and extends prior work that uses aggregate market-level data (Chen and Jiang, 2024). While aggregate data offer important insights into the overall valuation, our micro-level data set gives us significant advantages in cleanly estimating the valuation attributable to the embedded payment feature, and more importantly, enables a deeper exploration of heterogeneity in valuation across investor types, as well as the underlying mechanisms driving the valuation. First, by focusing on investors who actively select among available alternatives, we mitigate potential biases from limited product awareness, such as users who are not aware of MMFs other than Yu'ebao funds, leading to a smaller average valuation (40 bps with micro-level data versus 80 bps with aggregate market share).[3] Second, by leveraging individual data on both investment and consumption choices, we are able to uncover heterogeneity across investors. Third, our structural demand model separately identifies the option value (from liquidity access) from the utilization value (from actual transaction use), allowing a cleaner interpretation of the WTP.

Other Related Literature. Our paper contributes to several strands of literature. First, our paper contributes to the growing literature on money-like assets in a digitalized financial system. The proliferation of money-like assets, such as cryptocurrencies and stablecoins, has prompted new frameworks for comparing public and private monies (Brunnermeier and Niepelt, 2019; Adrian and Mancini-Griffoli, 2021), with potential implications for currency competition (Cong and Mayer, 2025), autonomy in payments (Berg et al., 2024), monetary policy transmission (Garratt et al., 2022), and financial stability (Greenwood et al., 2015; Ahnert et al., 2023). On the demand side, investors increasingly treat short-term government debt and shadow banking instruments as close substitutes for money (Krishnamurthy and Vissing-Jorgensen, 2012; Sunderam, 2015; Nagel, 2016; Cipriani and La Spada, 2021; Krishnamurthy and Li, 2023; Li, 2023), due to their information-insensitivity. Our paper contributes to this literature by quantifying the payment feature, from the household's perspective, of

[3]Inflows from investors unaware of regular MMF products, and thus facing a restricted choice set, can introduce biases in the estimation. This challenge is particularly difficult to address using market-level data, where individual awareness and choice sets are unobservable and often assumed to be homogeneous. See Section 3 for further discussion on the possibility of limited product awareness.

money-like assets. Given Alipay's widespread use in retail transactions, our quantification offers valuable inputs in estimating household adoption of digital money.

Second, our work relates to the literature on FinTech innovation and financial inclusion. A broad range of studies have shown that new financial technologies can improve household welfare, for example, by reducing transaction costs and encouraging savings (Bachas et al., 2018), improving risk-sharing (Jack and Suri, 2014; Riley, 2018; Breza et al., 2020), reducing disparities in access to finance (Erel and Liebersohn, 2022), improving market participation and portfolio efficiency (D'Acunto et al., 2019; Hong et al., 2020), and facilitating small business lending (Beaumont et al., 2021; Gopal and Schnabl, 2022). However, these benefits may not be uniformly distributed (Jiang et al., 2022; Hyun-Soo Choi, 2023). Notably, Buchak et al. (2021) highlights that Yu'ebao and similar FinTech products stimulate interest rate liberalization that forces banks to raise deposit rates or launch competing high-yield products, hence benefiting depositors. We show that Yu'ebao, as a FinTech innovation that removes traditional barriers between investing and spending, particularly benefits elderly households and those facing higher consumption risk.

Our paper also contributes to a large body of research on the adoption and impacts of digital payments. The convenience of digital payment increases consumer spending (Agarwal et al., 2024), boosts business creation and entrepreneurship (Agarwal et al., 2019, 2020). The adoption of digital payment also improves credit access (Puri et al., 2017; Buchak et al., 2018; Berg et al., 2020; Ouyang, 2021; Ghosh et al., 2022; Alok et al., 2024; Ahnert et al., 2025), changes the landscape of banking competition (Sarkisyan, 2023; Lu et al., 2024), and intensifies monetary transmission by reducing the market power of banks (Liang et al., 2025). Also using data from Alipay, Bian et al. (2023) show that payment-integrated credit products, such as Buy-Now-Pay-Later (BNPL), can spur consumption and short-term borrowing. Our analysis shows that for payment-integrated saving products, the liquidity option value, rather than the direct convenience of usage, is the major driver of household adoption.

The rest of the paper proceeds as follows. Section 2 describes the institutional background of the Alipay payment system and the Yu'ebao product. Section 3 presents a set of stylized facts on Yu'ebao investment and motivates our empirical strategy. Section 4 presents the demand model setup. Section 5 presents the individual dataset from Alipay and money

market funds data, as well as summary statistics. Section 6 presents the estimation and identification strategy. Section 7 reports the empirical estimation results on heterogeneous valuation and mechanism analysis. We conclude in Section 8 with a brief summary.

2 Institutional Background

2.1 Overview of Alipay and Yu'ebao

Alipay started in 2004 as a secure payment solution for Alibaba's e-commerce platforms. Over time, Alipay evolved from an escrow service to China's leading digital payment service provider. It is widely accepted by online and offline merchants, small businesses, service providers, and peer-to-peer transfers.

In addition, Alipay is also China's largest fund distributor, according to the statistics from the Asset Management Association of China.[4] It offers users convenient access to a wide range of investment products, including mutual funds, money market funds, and structured financial instruments. As of mid-2020, Alipay had partnered with approximately 170 asset management institutions, including almost all major mutual fund companies in China, and offered more than 6,000 financial products on its wealth management platform.[5]

Launched in 2013, Yu'ebao was Alipay's flagship wealth management product. As a payment-integrated MMF product, money invested in Yu'ebao is allocated to one of the underlying MMFs that accrues interest like a regular MMF, while remaining available for real-time payments, including peer-to-peer transfers, retail purchases (online and offline), and utility payments.

Figure 1 shows user interface screenshots that illustrate Yu'ebao's dual functionality. The "My Yu'ebao" page (left panel) shows the Yu'ebao's underlying investment interface, including fund performance and an extended link to the detailed fund profile. Users can switch the underlying MMF product by clicking "change product." At any given time, a user may only choose one underlying fund, selected from a designated pool of Yu'ebao MMFs. The middle and right panels show the payment function of Yu'ebao. When initiating transfers or making payments, users can choose to use funds in their Yu'ebao balance, linked debit

[4] https://www.amac.org.cn/sjtj/datastatistics/fundsalesindustrydata/

[5] Statistical numbers are obtained from *ANT GROUP IPO prospectus* in 2020.

cards, and Alipay's cash wallet. Credit cards and consumer loan facilities are also available for purchase transactions. This setup allows users to treat their payment-integrated MMF investment as an on-demand transaction account.

[Figure 1 about here]

While regular (non-Yu'ebao) MMFs are also available for investment through Alipay, they do not offer integrated payment functionality. To use them for transactions, users must first redeem their investment into their bank account. Although regular MMFs generally support relatively quick redemption, the associated operational frictions and delays prevent them from serving as real-time payment instruments in practice. On the Alipay platform, each MMF is designated as either a regular MMF or a Yu'ebao MMF, but not both. As such, when investors choose among available MMFs, they are effectively trading off different product attributes, including their ability to serve as payment tools via Yu'ebao integration and fees.

2.2 Yu'ebao's Evolution

Yu'ebao was initially exclusively associated with only one MMF, namely the Tianhong Yu'ebao MMF (henceforth Tianhong MMF). Tianhong MMF quickly grew to become one of the largest MMFs in the world by assets under management. At the end of 2017, it managed over 1579 billion RMB (about 240 billion USD), according to the fund's annual report. The unprecedented scale raised growing concerns about market concentration and systemic risks.

Beginning in 2018, the People's Bank of China (PBoC) and the China Securities Regulatory Commission (CSRC) encouraged Yu'ebao to expand to a multi-fund architecture, allowing multiple asset managers to offer independently managed MMFs through the same payment interface. Under this structure, users can choose to invest in a single fund from a list of eligible MMFs integrated with the Yu'ebao interface.[6] To accelerate the transition to a multi-fund structure, Tianhong MMF imposed a daily fund-level cap on new inflows, allocated on a first-come first-served basis, between February 2018 and April 2019. By 2020, the number of Yu'ebao MMFs had grown to around 30.

[6] Measures introduced during the financial regulatory reforms also included restrictions on investment caps, lowering the limit from 1 million RMB to 100,000 RMB per user, and placing a daily withdrawal limit of 10,000 RMB.

During the same time, China's MMF sector expanded dramatically. Figure 2 illustrates the growth trajectory of China's MMF sector in parallel with the rise of Yu'ebao. In 2012, before Yu'ebao's introduction, total MMF assets stood at approximately 0.5 trillion RMB. Over the subsequent decade, MMF assets expanded dramatically, reaching approximately 10 trillion RMB.

Note that other digital payment providers, such as WeChat Pay and several commercial banks (e.g., China Merchants Bank), have also introduced similar payment-integrated MMF products. In Figure 2, assets invested in such MMFs outside Alipay are included in the individual shares of non-Yu'ebao MMFs. The presence of multiple distribution platforms, along with the possibility that the same MMF may be offered with or without the embedded payment feature depending on the platform,[7] complicates the identification of payment functionality at the fund level. Using platform-level data helps mitigate potential measurement errors and provides additional advantages in estimating the value of the payment feature, as we discuss below in Section 3.

[Figure 2 about here]

3 Stylized Facts and the Necessity of Micro-data

Before proceeding to our empirical framework and estimation, we present a set of stylized facts based on aggregate market-level data from Wind Information Inc.[8] and survey evidence. We then discuss the necessity of micro-data in estimating the value of the payment feature.

We begin by examining the aggregate response to Yu'ebao inclusion at the fund level. Figure 3 presents an event study of average quarterly inflows into MMFs before and after their inclusion in the Yu'ebao. The x-axis denotes event time in quarters relative to inclusion (with 0 marking the quarter of inclusion), and the y-axis denotes average inflows in billions of RMB. The figure reveals that MMF inflows rise sharply in the quarter of inclusion, followed by sustained high inflows in subsequent quarters. This pattern suggests that inclusion in Yu'ebao

[7] For example, the shares of a single-class MMF Guotai-Lishibao (fund code: 003515) are available for purchase both via Yu'ebao and other fund distributors that do not provide payment service, e.g., Shanghai Tiantian Fund Sales, the third largest fund distributor in China.

[8] Wind is a leading provider of financial information services in China, serving numerous China's financial institutions and Qualified Foreign Institutional Investors (QFII) operating in China.

is associated with a substantial and persistent increase in investor demand, consistent with prior findings in the literature that use market-level fund flows to infer the liquidity premium (Chen and Jiang, 2024).

[Figure 3 about here]

While these stylized facts suggest the value of the embedded payment functionality to individuals, the aggregate flows can be confounded by several other factors that complicate the task of estimating this valuation. For example, the high visibility of Yu'ebao, due to the platform's disproportionate promotion activities, may drive many individuals to invest in Yu'ebao without fully understanding its MMF nature and considering alternative MMF products. This limited product awareness can lead investors to make *uninformed* decisions. Consequently, along with the measurement issues we discussed in Section 2.2, aggregate inflows may overstate the extent to which households actively value the payment feature of Yu'ebao.

To assess whether the concern of limited product awareness is material, we turn to the 2019 Chinese Household Finance Survey (CHFS), which includes questions on households' online investment behavior. Figure 4 displays the distribution of Yu'ebao holders across different types of financial investment experience. Strikingly, 64% of Yu'ebao holders have no other financial investment experience (e.g., mutual funds, stocks, bonds, structured products), and 98% do not invest in any regular MMFs outside of Yu'ebao. While the low participation in regular MMFs may reflect investors' optimal decisions, it is also potentially influenced by limited awareness of regular MMFs, which is likely to correlate with low financial literacy.

[Figure 4 about here]

The socioeconomic characteristics of different investor groups lend further support to the concern about limited product awareness. Table 1 shows that individuals who hold only Yu'ebao MMFs exhibit significantly lower education, wealth, income, and consumption than those who hold Yu'ebao along with other financial instruments. Since education and wealth are common proxies for financial sophistication, this aligns with concerns that Yu'ebao-only investors are more prone to making marketing-driven allocations or investment decisions without being fully informed of alternative options.

[Table 1 about here]

The evidence above underscores the importance of using individual-level investment data where fund-level payment integration is clearly indicated, to precisely isolate the value households assign to embedded payment functionality. On one hand, using micro-level data allows us to focus on a sample of investors who are likely aware of both payment-integrated and regular MMFs, thereby reducing bias from limited product awareness. On the other hand, it enables us to uncover the distribution of valuation across different types of users. For these reasons, we rely on micro-level data to provide a more accurate and behaviorally grounded estimate of households' WTP for the embedded payment feature. We present details on the dataset in Section 5.

4 Structural Demand Model

We rely on a structural model to estimate individual investors' valuation for the embedded payment feature. We model the investment behavior of individual investors as a multinomial discrete choice problem. In each period t, investor i chooses to invest in a MMF $j \in \mathcal{J}_t$ from the set of available MMFs $\mathcal{J}_t = \{1, 2, ..., J_t\}$, or not invest. The outside option of not investing in any of the MMFs is denoted $j = 0$. Practically, one can think of it as a choice that represents depositing in banks, or investing in other products (e.g., wealth management products) instead of the ones we consider. The indirect utility that investor i derives from investing each unit of capital in fund j at time t is given by:

$$u_{ijt} = -\alpha f_{jt} + \beta_{it} P_{jt} + X'_{jt}\Theta + \xi_{jt} + \epsilon_{ijt}. \tag{1}$$

Investors experience a disutility of $-\alpha f_{jt}$ from paying the expense ratio f_{jt}, which includes management fees, custodian fees, and sales service fees. The indicator variable P_{jt} equals to 1 if investments in fund j can be used for payment at time t, and 0 otherwise. The coefficient β_{it} measures investor i's preference for MMF's payment feature, which varies across investors and time depending on their demographic characteristics with details given below. X_{jt} is a vector of other observed fund characteristics, including fund age and the number of MMFs in the same fund family. The term $X'_{jt}\Theta$ captures the utility derived from these characteristics. ξ_{jt}

captures unobserved fund-time-specific attributes (e.g., marketing and promotion intensity). In the baseline specification and most of the other specifications, we decompose ξ_{jt} further to include time fixed effects (η_t), in which case ξ_{jt} can be written as $\xi_{jt} = \Delta\xi_{jt} + \eta_t$. The individual-fund-time residual ϵ_{ijt} is an i.i.d. error term assumed to follow a Type I Extreme Value distribution. It accounts for unobserved demand shocks to investor i for fund j at time t, allowing for individual-specific disagreement on which fund is the best choice. The utility from the outside option is normalized to zero for identification.

Given the challenge of accurately approximating investors' expectations of future returns using past returns (Lynch and Musto 2003; Afrouzi et al. 2023), we exclude return-related variables from our baseline specification. Instead, any influence of past returns is captured by the unobserved fund-time demand shock ξ_{jt} for average expectations and by the idiosyncratic term ϵ_{ijt} for individual-level deviations. In Section 7.2, we explicitly address expected return effects by incorporating a constructed proxy into the estimation.

A key feature of our framework is that preferences for payment functionality vary across investors. Specifically, we model investor-specific taste for payment functionality as:

$$\beta_{it} = \beta + \Pi(D_{it} - \bar{D}), \tag{2}$$

where β represents the average utility derived from the embedded payment feature, D_{it} is a column vector of individual observable characteristics (e.g., age, gender, wealth level), and Π is a row vector of coefficients capturing how deviations in individual characteristics from their averages ($\bar{D}$) translate into variations in individual preferences relative to β.[9]

Following Baker et al. (2024), we use the expense ratio f_{jt} as our numeraire to express the valuation in units of equivalent fees. Given the utility specification, and holding other fund characteristics constant, investor i is willing to pay β_{it}/α higher expense ratio for a MMF with the payment feature. This implied individual valuation of the payment feature,

[9] A more general specification that includes random coefficients for unobserved characteristics would substantially increase computational complexity and raise issues in identifying random coefficients. For these reasons, and in line with the suggestion of Hortaçsu and Joo (2023, pp. 65), we adopt a more stable and tractable specification to focus specifically on understanding systematic variation driven by observable investor attributes.

expressed in terms of the expense ratio, is:

$$v_{it} = \frac{\beta}{\alpha} + \frac{\Pi(D_{it} - \bar{D})}{\alpha}, \tag{3}$$

where β/α is the average valuation across all investors, and $\Pi(D_{it} - \bar{D})/\alpha$ captures the individual deviation in valuation driven by their characteristics.

Under the assumptions above, the probability of investor i selects fund $j \in \mathcal{J}_t \bigcup \{0\}$ at time t is:

$$s_{ijt} = \frac{exp(-\alpha f_{jt} + \beta_{it} P_{jt} + X'_{jt}\Theta + \xi_{jt})}{1 + \sum_{k \in \mathcal{J}_t} exp(-\alpha f_{kt} + \beta_{it} P_{kt} + X'_{kt}\Theta + \xi_{kt})}, \quad j \in \mathcal{J}_t, \tag{4}$$

$$s_{i0t} = 1 - \sum_{k \in \mathcal{J}_t} s_{ijt}, \quad j = 0. \tag{5}$$

Given the individual choice probability, we can calculate the market share of fund j for each time period t as:

$$s_{jt} = \frac{1}{N} \sum_{i}^{N} s_{ijt}, \tag{6}$$

where N is the total number of investors. These predicted choice probabilities and market shares form the core of our empirical estimation strategy described in Section 6.

5 Data and Summary Statistics

5.1 Alipay Administrative Records

Our primary dataset is an individual-month level administrative panel from Alipay, covering a sample of one hundred thousand users from January 2018 to December 2021. To ensure that our sample captures informed investors who are meaningfully exposed to the full range of MMF products, we impose a filtering criterion before random selection. Specifically, we retain only users who, at least once between 2018 and 2021, held both Yu'ebao MMFs and regular MMFs. This restriction guarantees that all sampled investors are highly likely to be aware of both types of funds. As a result, variation in observed investment choices within this filtered sample is more likely to reflect genuine preferences over payment integration and other fund characteristics, rather than differences arising from limited product awareness or

asymmetric exposure to the platform's offerings.

The data provide detailed information along three key dimensions: demographic information, investments, and consumption. The demographic information includes essential characteristics such as users' age, gender, and city of residence. The investment data provides detailed records of users' month-end balances and transaction flows across a variety of financial assets, including Yu'ebao and non-Yu'ebao MMFs, mutual funds, and other structured products available on the platform. The consumption data records monthly spending amounts and frequencies across predefined categories. It also includes monthly payment flows through different payment methods, including Balance, Yu'ebao, Debit cards, Credit cards, and Buy-Now-Pay-Later (BNPL).

Table 2 presents the summary statistics of users' characteristics. Of the users in the sample, 56% are male, and the average age is 36. The average financial wealth, defined as total investment on the platform, is approximately 90,000 RMB. Of the amount invested, 49% is invested in risky asset classes, including mutual funds and other structured products, while the remaining 51% is held in Yu'ebao and regular MMFs. The average monthly active inflow into Yu'ebao is approximately 8,000 RMB, with the distribution very positively skewed. The average monthly consumption per user is 6,700 RMB, with the majority of the expenditure allocated to non-durables, including food, clothing, household supplies, and transportation. Among total consumption via Alipay, 23% of spending is processed through Yu'ebao. Payment methods are further distributed as follows: 22% via credit cards, 14% via debit cards, 34% through BNPL online credit.

[Table 2 about here]

At the individual level, consumption through Yu'ebao mildly crowds out credit card and debit card usage. By implementing a simple event study design, we show in Figure 5 that, following first-time adoption of Yu'ebao, defined as the first active investment in Yu'ebao after at least five consecutive months of zero balance in our sample, the share of consumption transacted via Yu'ebao increases sharply and remains elevated over time. This increase primarily crowds out debit card and credit card usage, with minimal impact on online credit (BNPL). This pattern confirms that Yu'ebao functioned not only as a savings vehicle but also as an integrated payment solution. Further details on the event study design and implementation

are provided in Appendix Section A.

[Figure 5 about here]

Data Access and Privacy Compliance This study was remotely conducted on the Ant Open Research Laboratory[10] in an Ant Group Environment. All data was sampled and desensitized, and was analyzed on the Ant Open Research Laboratory. The laboratory is a sandbox environment where the authors can only remotely conduct empirical analysis and individual observations are invisible. The main regression variables include basic variables, investment variables, and consumption variables.[11]

5.2 Product Universe and Market Share Construction

To make sure our results are not driven by a few Yu'ebao MMFs, our empirical analysis focuses on the period from 2019 to 2021, a phase characterized by regulatory stabilization and a relatively broad selection of funds available within Yu'ebao. To define the relevant product universe, we restrict attention to the 60 largest MMFs on the Alipay platform, ranked by the number of holding investors.[12] An investor is considered to hold fund j if their holdings exceed 100 RMB. We exclude Tianhong MMF, the original and largest fund linked to Yu'ebao, from our estimation sample, as its share rationing (described in Section 2.2) makes it impossible to distinguish investors' active choices from product unavailability. All remaining investments outside the top 60 are treated as part of the outside option, which aggregates other investment opportunities within or outside the platform (e.g., deposits, other funds, or wealth management products). After applying these selection criteria, our sample includes 28 Yu'ebao MMFs and 29 regular MMFs.[13]

Given this definition of the relevant product universe and the individual-level investor data, we construct market shares s_{jt} based on each investor's primary active fund purchase,

[10] https://www.deor.org.cn/labstore/laboratory

[11] This section is included as required by the data provider for regulatory compliance.

[12] As argued by An et al. (2023), restricting attention to large funds alleviates search frictions that limit investors' knowledge of product availability (Hortascu and Syverson, 2004). Since the number of funds linked to Yu'ebao is around 30, we focus on the top 60 funds to ensure a comparable number of regular MMFs in our sample.

[13] The final sample includes fewer than 60 funds because three regular MMFs, though held by some investors in 2018, received no inflows in our sample between 2019 and 2021 and are therefore excluded.

as described below. We define the fund market share s_{jt} at time t as the number of investors *actively*[14] purchasing fund j in month t divided by the total number of investors in the market at that time:

$$s_{jt} = \frac{\text{Number of investors whose primary purchased MMF is } j \text{ at time } t}{\text{Total number of investors at time } t} \tag{7}$$

This definition is directly consistent with the model's discrete-choice framework, where each investor selects a single product from a choice set in each period, and the platform-level market share reflects the proportion of investors making that choice. Empirically, we define an investor's "choice" as the fund to which they actively allocate their largest active investment in a given month. As shown in Figure 6, the vast majority of investors in our sample make zero or only one purchase in MMF in any given month. For those who make investments in multiple funds, we retain only the fund with the highest monthly flow, reflecting the most meaningful investment decision. As of January 2019, Yu'ebao MMFs have an average market share of 2.1%, while regular MMFs average 0.2%.

[Figure 6 about here]

This participation-based market share differs from those used in prior studies, such as fund assets under management relative to the total market size (Roussanov et al., 2021) or monetary fund flows (**?**Baker et al., 2024). In settings without individual-level data, researchers often use capital-weighted market shares, effectively equating individual-level decisions with per-dollar decisions. Imposing this assumption in our setting may disproportionately lead the market share to reflect the behavior of a few high-wealth individuals and bias demand estimates towards them, which is detrimental to uncovering investor preference and its heterogeneity. As our investor-level data allows us to observe each individual's choice directly, we construct market shares based on equal weighting across investors, in line with the discrete choice model.

[14] Active purchases are inflows that exclude recurring subscriptions and passive (automatic) transfers from account balance.

5.3 Fund-level Data

To complement the user-level data, we integrate information on MMF characteristics from Wind. This supplementary dataset offers comprehensive coverage of fund attributes, including registration details, fees, asset allocations, and performance. We match this data to funds offered through the Alipay platform during the study period.

Table 3 presents summary statistics for the MMFs in our sample, disaggregated by Yu'ebao MMFs versus regular MMFs. Several distinct patterns emerge between the two fund categories. First, Yu'ebao MMFs tend to be older and larger than their non-linked counterparts. They also have a more retail-oriented investor base: on average, 99% of shares in Yu'ebao MMFs are held by individual investors, compared to 90% for regular MMFs. Second, Yu'ebao MMFs charge higher total fees. The average total expense ratio for Yu'ebao funds is 0.63%, compared to 0.47% for non-Yu'ebao MMFs. Higher operational costs could drive this difference in fees, as Yu'ebao MMFs accommodate more frequent purchases and redemptions to provide the payment service. The difference in fees partly explains why Yu'ebao MMFs tend to have lower average yields compared to regular MMFs (2.25% vs. 2.46%). Third, the asset allocation strategies of Yu'ebao MMFs are more conservative. They allocate a slightly larger share of assets to deposits (39% vs. 32%), potentially reflecting the need to maintain larger cash buffers to meet investors' transaction needs. Differences in asset allocation may also contribute to the yield gap between Yu'ebao and regular MMFs. Finally, we find minimal differences in fund manager characteristics, such as tenure and educational background, between Yu'ebao MMFs and regular MMFs.

[Table 3 about here]

6 Estimation and Identification

6.1 Estimation Procedure

A key challenge in estimating v_{it} from observed choices is the potential endogeneity of the unobserved fund-time characteristics ξ_{jt}, which may be correlated with fund fees. A potential approach is to use the Maximum Likelihood Estimation method, together with a control function that explicitly models ξ_{jt}. However, this approach requires (strong) functional form

assumptions on ξ_{jt}, which is not trivial a priori. To remain agnostic, we follow the BLP framework (Berry, 1994; Berry et al., 1995) by inverting the observed market shares (within our sample) to recover ξ_{jt}, and implement a two-stage Generalized Method of Moments (GMM) procedure to estimate the structural parameters $(\alpha, \beta, \Theta, \Pi)$. Our identification leverages two sources of variation: (1) platform-level fund market shares (aggregate moments), and (2) investor-level information on the correlation between demographics and choice patterns (micro-moments) as in (Petrin, 2002; Berry et al., 2004). Our estimation approach builds on recent advances in the literature (Conlon and Gortmaker, 2020, 2025) and uses the PyBLP package developed by them.

Micro-moments

Following Petrin (2002) and Berry et al. (2004), we construct micro-moment conditions to align model predictions with observed demographic patterns. Specifically, we require that model-implied conditional expectations of investor demographics among those selecting payment-integrated funds ($E[D_{it}|\mathbf{1}_{it}\{P_{jt} = 1\} = 1]^{\text{model}}$) match the empirical sample counterparts ($E[D_{it}|\mathbf{1}_{it}\{P_{jt} = 1\} = 1]^{\text{data}}$), where $\mathbf{1}_{it}\{P_{jt} = 1\}$ is an indicator equal to 1 if investor i chooses a payment-integrated fund in month t. The model expectation integrates over predicted choice probabilities s_{ijt}, interacted with the payment functionality indicator P_{jt}:

$$\hat{m}(D_i) = \frac{\sum_t^T \sum_i^N \sum_{j=0}^{J_t} D_{it} \cdot \hat{s}_{ijt} \cdot P_{jt}}{\sum_t^T \sum_i^N \sum_{j=0}^{J_t} \hat{s}_{ijt} \cdot P_{jt}}, \tag{8}$$

where $\hat{s}_{ijt}$ are the predicted choice probabilities based on model parameters. The empirical average of any investor characteristic D_i among investors selecting payment-integrated funds is:

$$m(D_i) = \frac{\sum_t^T \sum_i^N D_{it} \cdot \mathbf{1}_{it}\{P_{jt} = 1\}}{\sum_t^T \sum_i^N \mathbf{1}_{it}\{P_{jt} = 1\}}. \tag{9}$$

The resulting micro-moment condition is thus given by

$$\hat{g}_m(D_i) = m(D_i) - \hat{m}(D_i). \tag{10}$$

Intuitively, these moment conditions incorporate information on the covariance of investors' demographics and fund payment functionality (P_{jt}), which enables the identification of Π.

As can be noted in equation (4), the construction of $\hat{s}_{ijt}$ also requires aggregate parameters $(\alpha, \beta, \Theta, \xi_{jt})$, which we discuss below.

Aggregate moments

For each month t, we observe the market share of fund j in our sample as:

$$s_{jt} = \frac{1}{N} \sum_{i}^{N} \mathbf{1}_{ijt}, \tag{11}$$

where $\mathbf{1}_{ijt}$ indicates whether investor i selects fund j at month t. Under the model, the predicted share is:

$$\hat{s}_{jt}(\delta_{jt}, \Pi) = \frac{1}{N} \sum_{i}^{N} \frac{exp(\delta_{jt} + \Pi D_i)}{1 + \sum_{k \in \mathcal{J}_t} exp(\delta_{kt} + \Pi D_i)}, \forall j \in \mathcal{J}_t \tag{12}$$

where

$$\delta_{jt} = -\alpha f_{jt} + \beta P_{jt} + X'_{jt}\Theta + \xi_{jt}$$

is the average utility from fund j across investors. By matching $\hat{s}_{jt}$ to observed s_{jt}, we invert the system to recover δ_{jt}, following the contraction mapping algorithm in Berry (1994). Once δ_{jt} is recovered, we estimate the parameters (α, β, Θ) using a linear IV-GMM procedure:

$$\xi_{jt} = \delta_{jt} - (-\alpha f_{jt} + \beta P_{jt} + X'_{jt}\Theta).$$

The corresponding moment condition is:

$$\hat{g}_A = \sum_{t=1}^{T} \sum_{j \in \mathcal{J}_t} \hat{\xi}_{jt} z_{jt} \tag{13}$$

where Z_{jt} are instruments assumed to be orthogonal to ξ_{jt}. We discuss the choice of instruments in Section 6.2.

GMM Esitmation

Stacking the aggregate and micro-moments into $g = (g_A, g_m)$, we iterate the above procedure and search for the parameters $(\alpha, \beta, \Theta, \Pi)$ that solve:

$$\min_{\alpha,\beta,\Theta,\Pi} \ \hat{g}' W \hat{g}, \tag{14}$$

where W is the optimal (block-diagonal) weighting matrix.

6.2 Instrumental Variable Strategy

We employ two classes of instrumental variables to address the potential endogeneity of fund fees arising from the correlation between unobserved product quality ξ_{jt} and pricing decisions. First, following (Hausman et al., 1994; Nevo, 2001), we use average fees charged by the same sponsor on other MMFs at time t as an instrument for fund j's fee. When there is no other MMF in the same family, we use the average of all other MMFs. The exclusion restriction assumes that the idiosyncratic demand shock ξ_{jt} is uncorrelated with the fund sponsor's pricing decisions for other funds.[15] While similar instruments have been widely used in differentiated product demand estimation, it may still be subject to endogeneity concerns arising from cross-fund pricing strategies employed by fund sponsors.

To address these limitations and reinforce identification, we complement the sponsor-based instrument with a second class of instruments that exploit product differentiation, following the strategy proposed by Gandhi and Houde (2019). These instruments are designed to capture the degree of horizontal differentiation between products, under the idea that competitive pressure depends on the distance of a product relative to other alternatives in product characteristics space. For each fund characteristic k (except fees), we define the differentiation measure as:

$$z_{jtk}^{\text{Diff}} = \sum_{j' \in \mathcal{J}_t \setminus \{j\}} 1(|x_{jkt} - x_{j'kt}| < \text{SD}_k), \tag{15}$$

[15] Our instrument is slightly different from the classical Hausman instrument, which uses prices of the same product in other markets and relies on cross-market independence of product costs. The challenge of applying such a construction in our context lies in identifying distinct markets for MMFs, as these funds exhibit limited variation in geographical availability and investment strategies (unlike equity funds).

where $\mathcal{J}_t \setminus \{j\}$ denotes the set of funds available at time t, excluding fund j. SD_k is the standard deviation of pairwise differences in characteristic k computed across all periods. $1(|x_{jkt} - x_{j'kt}| < \text{SD}_k)$ indicates whether products j and j' are close to each other in terms of characteristic k. These instruments capture how "differentiated" a fund is relative to other products. They capture local competitive intensity in product space, which restricts the fees that a sponsor can charge, and hence are less likely to be correlated with unobserved demand shocks, thereby strengthening the instrument set.

6.3 Assessing Selection into Yu'ebao

A potential concern is that investors may interpret payment integration as a positive signal of fund quality. Although we cannot fully rule out this possibility, we test whether Alipay selects funds based on observable characteristics. A null result, particularly for fund performance, would lend support to treating payment integration as independent of perceived quality. More specifically, we conduct predictive regressions to see which funds are more likely to be linked to Yu'ebao. The dependent variable is a binary indicator of whether fund j is linked to Yu'ebao at time t, and the independent variables are lagged predictors, measured as the past 6-month averages of key fund characteristics, including total shares, the ratio of individual shares to total shares, fees, portfolio allocations across different asset classes, and annualized returns. Additionally, we include fund age and the number of MMFs within the same fund family as explanatory variables. To avoid contamination of predictors, a fund is excluded from the sample once it is linked to Yu'ebao.

Table 4 presents the regression results using Probit and Logit models. The sample covers January 2018 to December 2019, the expansion phase of Yu'ebao's underlying funds. Tianhong MMF, the original and sole fund before 2018, is excluded to focus on funds added during the expansion. The results in Table 4 are consistent across both models and across the sample of all MMFs as well as the subsample of funds targeting retail investors[16]. Both fund age and the number of MMFs in the same fund family significantly and positively predict the likelihood of a fund being included as an underlying fund for Yu'ebao, while fund portfolio allocations and past performance do not show any significant predicting power. Funds with

[16] A fund is defined as a retail-oriented fund if its minimum subscription amount is smaller than 1.

a higher individual investor share are also more likely to be linked to Yu'ebao. However, the effect of the management fee and individual investor share diminishes when focusing on retail-oriented funds, which suggests that the observed influence of individual shares and fees is primarily due to the fact that retail-oriented funds are generally more likely to be included in Yu'ebao. As our demand estimation is performed within the Alipay platform, where the universe of product set is retail-oriented, this correlation is less likely to be a concern.

To account for the potential selection effect, we include fund age and the number of MMFs in the same family as fund characteristics into our demand estimations.

[Table 4 about here]

7 Empirical Results

7.1 Baseline Estimates

We begin by estimating the structural demand model described in Section 4. Table 5 and Table 6 present results from three model specifications. Column (1) reports estimates from an IV logit model that relies solely on platform-level market share data and observed fund-time characteristics, without accounting for demographic heterogeneity. Column (2) reports our preferred specification, which estimates the baseline model Equation (1) with investor demographics, including wealth and consumption levels, age, and gender. As a robustness check, Column (3) re-estimates the baseline model using a restricted sample that includes only investors who had prior experience with regular MMFs before the start of the estimation period (January 2019). This restriction ensures that all individuals in the sample are aware of both Yu'ebao MMFs and regular MMFs from the beginning. In all specifications, we control for time fixed effects.

Across all three specifications in Table 5, we observe a negative and significant coefficient on fees: investors are sensitive to fund expenses, and the estimated marginal disutility of fees ranges from -12.4 to -13.7 across specifications. The coefficient on the payment feature is positive and significant, ranging from 5.02 to 5.17, highlighting a strong revealed preference for the integrated payment functionality. To translate these utility coefficients into economic terms, we scale the payment coefficient by the price coefficient (α), yielding an implied

average valuation of approximately 37.8 to 41 bps in annual fees for access to the payment functionality. Other fund characteristics also exhibit intuitive patterns: older funds and those affiliated with larger fund families are more likely to be chosen.

The average expense ratio for MMFs typically ranges from 50 to 60 bps in our sample. A valuation of 40 bps indicates that investors are willing to pay two-thirds more in fees to access the availability of using their investment as a payment instrument. Given that the average monthly Yu'ebao inflow is approximately 8,500 RMB (approximately 1214 USD), this WTP corresponds to an average per-user valuation of about 2.83 RMB (0.4 USD) per month. From the fund perspective, the total size of MMFs by the end of 2022 is about 11.3 trillion RMB (1.4 trillion USD).[17] If all MMFs offered embedded payment functionality, our valuation implies a potential annual revenue of 45.2 billion RMB (5.65 billion USD) from integrated payment services.

[Table 5 about here]

Table 6 reports the estimation coefficients on investor characteristics that correspond to Columns (2) and (3) in Table 5. The results reveal substantial and robust heterogeneity in the valuation of Yu'ebao's payment functionality across both the full and restricted samples. First, we find that investors with higher consumption levels and greater financial wealth (observed on the Alipay platform) exhibit higher WTP for the embedded payment feature. Second, we observe pronounced heterogeneity by age and gender. To better present the pattern, we compute group-specific valuations and visualize them in Figure 7. In this figure, blue lines represent male investors and orange lines represent female investors. Male investors consistently place a higher value on the payment feature, with the gender gap most evident among younger cohorts under the age of 45. Among older investors, the gender difference largely disappears. In Section 7.3, we further examine the drivers of this heterogeneity by analyzing group-level consumption patterns and demonstrate that differences in consumption risk explain a substantial portion of the variation in payment valuation.

[Table 6 about here]

[Figure 7 about here]

[17] According to Wind data.

Using the estimates from our baseline model specification, we compute individual-specific valuations of the payment feature, as defined in Equation (3). Figure 8 presents the resulting cross-sectional distribution of these valuations. The distribution exhibits substantial heterogeneity, with implied WTP ranging from approximately 20 to over 45 bps. This variation highlights the importance of incorporating individual-level heterogeneity when assessing the demand for payment-integrated financial products.

[Figure 8 about here]

7.2 Controlling for Return Expectations

We now investigate how return considerations influence MMF choices. In particular, we expect that investors' demands for a fund increase with their expectations of fund returns. To capture this effect, we extend the baseline utility specification to incorporate both the overall level of expected MMF returns and funds' excess expected returns relative to the average level. The modified model specification is given by:

$$u_{ijt} = -\alpha f_{jt} + \beta_{it} P_{jt} + \gamma(r_{jt} - \bar{r}_t) + \omega \bar{r}_t + X'_{jt}\Theta + \xi_{jt} + \epsilon_{ijt}, \tag{16}$$

where r_{jt} is the expected return of fund j at time t. To estimate each MMF's expected return, we adopt a linear model that captures its exposure to short-term interest rates. Specifically, we assume that a fund's return is exposed to three short-term interest rates: the overnight repo rate (FR001), the 1-week SHIBOR, and the 3-month China's T-bill rate, reflecting its portfolio allocation across three key asset classes: repos, bank deposits, and fixed income assets.[18] The fund-specific interest rate loadings are estimated via rolling regressions on historical weekly returns, as detailed in Appendix Section B. $\bar{r}_t$ represents the average of r_{jt} across all focal MMFs at time t, capturing shifts in the overall MMFs yield. $r_{jt} - \bar{r}_t$ captures the excess expected return of fund j relative to the average level. While these constructs may not fully coincide with investors' beliefs, they offer a meaningful and transparent benchmark.

[18] FR001 is the most commonly used overnight repo fixing rate in China's money market, derived from transaction data in the interbank repo market, and reflecting the short-term market liquidity. SHIBOR stands for Shanghai Interbank Offered Rate, based on quotes submitted by a panel of designated commercial banks in China. It is the Chinese counterpart of the former LIBOR. All the rate data are from China's National Interbank Funding Center (NIFC).

Similar to the baseline specification, deviations in investors' beliefs from this benchmark are captured by ξ_{jt} and ϵ_{ijt}.

The coefficient ω captures how much utility is affected by the level of MMFs' average returns. A positive estimate of ω implies that higher average yields increase the attractiveness of MMFs as an asset class, encouraging substitution away from outside options such as deposits. The coefficient γ measures how much utility investors derive from a fund's relative performance compared to the average MMFs' return. A positive γ indicates investors actively substitute toward relatively higher-yield funds.

The estimation results of Equation (16) are reported in Table 7. The average valuation of the payment feature remains robust across all specifications, ranging from 43.8 to 45.5 bps, suggesting that our estimation of investors' preference for payment integration is not confounded by return-based considerations. If anything, incorporating expected returns slightly increases the estimated valuation, consistent with the observation that Yu'ebao MMFs tend to offer lower realized returns on average. Regarding return sensitivity, we find that the coefficient on the average MMFs' return is 6.592 and statistically significant, which suggest that higher market-wide yields on money market instruments increase the overall attractiveness of MMFs relative to the outside option, such as bank deposit. The coefficient on relative return $r_{jt} - \bar{r}_t$ is positive, suggesting that, on average, investors prefer funds offering higher yields within the MMF asset class.

[Table 7 about here]

7.3 Value Decomposition

The previous section documents substantial heterogeneity in households' WTP for the embedded payment functionality, raising the natural question: why do investors value this feature, and what mechanisms underlie this variation? To better understand what drives household demand for payment-integrated MMFs, we turn to a decomposition of the estimated valuation.

Specifically, we separate the overall valuation into two conceptually distinct components: utilization value and option value. Utilization value refers to the direct utility gained from actively using payment-integrated MMFs to make payments, which is proportional to the

payment usage intensity. In contrast, option value represents the precautionary liquidity benefit. Even when not used for transactions, holding funds in payment-integrated MMFs allows users to instantly convert savings into spending power at no additional cost, offering a form of precautionary insurance. In this sense, Yu'ebao embeds a real option to convert savings into payments on demand, which carries time value even if it is not exercised frequently.

This distinction is particularly interesting because, given the lower average returns of Yu'ebao MMFs compared to regular MMFs, if investors derive utility only from actual payment, investing in Yu'ebao MMFs without using them for spending would suggest suboptimal behaviors. In our sample, we observe a significant share of investors who actively invest in payment-integrated MMFs, but only rarely use it for consumption. This empirical pattern is analogous to the "credit card debt puzzle", where households simultaneously borrow on high-interest credit cards while holding liquid assets in low-return accounts (Gross and Souleles, 2002). By holding cash (or keeping a credit line unused), they insure against unforeseen needs, even if it means incurring interest costs (Telyukova, 2013).[19] Such coexistence of realized use and precautionary value suggests that the embedded payment feature provides utility beyond direct usage, potentially due to the flexibility or psychological reassurance of having immediate access to funds.

To implement this decomposition empirically, we use two proxies to capture households' utilization value and option value when investing in Yu'ebao MMFs. To measure utilization value, we use a binary indicator capturing whether the individual actively used Yu'ebao for consumption payments in the past three months. To capture investors' need for the liquidity option, we use their consumption risk. Individuals with higher unexpected consumption shocks are expected to exert higher precautionary liquidity needs.

Our measure of individual-level consumption risk is constructed in two steps. First, we estimate the unexpected consumption shock for each individual. Second, we sort individuals by $age \times gender$ group as in our demographic micro-moments, and compute the cross-sectional standard deviation of the unexpected consumption shocks for each group and month. Our

[19]Similar value decomposition can be found in health insurance purchase (Finkelstein and McGarry, 2006), where two types of people are expected to buy long-term care insurance: high-risk individuals who expect to use benefits, and high risk-averse individuals who may never make claims but strongly value the available to use protection. As well as in durable goods adoption (Dubin and McFadden, 1984), which separates the ownership decision from usage intensity.

methodology largely follows Blundell et al. (2008) and Catherine et al. (2024). To ensure that the consumption data from Alipay meaningfully reflect individual spending behavior, we restrict our sample to users who spent at least 100 RMB per month consistently throughout the sample period. More details on consumption risk measurement are given in Appendix Section C. Figure 9 displays the estimated consumption risk for each *age* × *gender* group. Males exhibit higher consumption risk than females, with the gender gap particularly pronounced among younger individuals. This pattern mirrors the heterogeneity in valuation observed in our baseline results, suggesting that consumption risk may be a key driver of the cross-sectional differences in households' WTP for embedded payment features.

[Figure 9 about here]

We then decompose the utility flow from the payment feature β_{it} into four components:

$$\beta_{it} = \beta_1 \log(\text{consumption})_{i,t-1} + \beta_2 \log(\text{wealth})_{i,t-1} \tag{17}$$

$$+ \beta_3 \text{Consumption risk}_{i,t} + \beta_4 \text{Payment utilization}_{i,t}. \tag{18}$$

Each term represents a distinct channel contributing to investors' utility from payment integration. The total average valuation can then be decomposed accordingly. The contribution from consumption risk is calculated by multiplying the average consumption risk by β_3/α. Contributions from other components can be calculated similarly.

Table 8 presents the value decomposition results. Among the four components, consumption risk emerges as the dominant driver of payment valuation. With estimated β_3 (4.179) and α (15.72), consumption risk (with an average value of 0.92) accounts for 24.42 bps, nearly two-thirds of the total average valuation of 38.41 bps. Payment utilization, which reflects realized transactions that Yu'ebao facilitates, contributes an additional 5.4 bps. Taken together, these results offer a clear decomposition of the utility investors derive from the embedded payment feature of Yu'ebao MMFs. While it offers both transactional convenience and liquidity flexibility, the latter plays a more important role in the revealed valuation. A caveat of using consumption risk as a proxy is that, while strongly linked to liquidity needs, consumption risk may not fully capture the source of option value that investors place on the payment integration, such as the psychological value of liquidity (e.g., peace of mind),

which remains unobservable. This limitation may also explain part of the decrease in the total average valuation.

[Table 8 about here]

8 Conclusion

This paper provides a novel quantification of the value of embedded payment functionality in financial assets from the perspective of household demand. Leveraging detailed administrative data from Alipay, a dominant digital payment platform in China, we examine individual investment in a class of MMFs with built-in payment features, known as Yu'ebao MMFs. Using a structural demand model, we estimate both average and heterogeneous valuations: households are willing to pay approximately 40 bps annually for the payment feature offered by Yu'ebao, with large heterogeneity across demographic groups. Importantly, this valuation is primarily driven by households' precautionary liquidity needs rather than actual usage. We provide revealed-preference estimates of household WTP for such payment innovations and highlight the underlying drivers of this valuation.

Our research contributes to the growing literature on household finance, digital payments, and FinTech innovation. It complements prior research that emphasizes the macro-level implications of MMFs and payment technologies by shifting the lens toward individual-level demand and mechanisms. Given that households have access to other payment tools, such as debit and credit cards, they still assign significant value to financial products that integrate payment functionality. Our quantitative valuation can serve as an input to study households' adoption of other money-like assets such as cryptocurrencies and stablecoins, and their impact on household portfolio allocation and liquidity management, and more broadly, the monetary system in the digital era.

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Table 1: Yu'ebao Users Summary Statistics from CHFS

		High school	log(total asset)	log(total income)	Cmp(per cap.)
Only Yu'ebao	Mean	0.61	13.74	11.45	35,836
	s.d.	0.49	1.23	1.26	35,303
Yu'ebao & other Fin inv	Mean	0.77	14.69	11.93	48,197
	s.d.	0.42	1.01	1.10	37,782
Yu'ebao & MMFs or Mutual funds	Mean	0.84	14.85	12.18	59,844
	s.d.	0.37	1.06	0.92	51,081
Yu'ebao & MMF	Mean	0.90	14.95	12.31	66,586
	s.d.	0.30	0.95	0.89	57,448

Note: This table presents summary statistics of key demographic and financial variables across different groups or subgroups of Yu'ebao investors using data from the 2019 Chinese Household Finance Survey (CHFS). For each group, we report the mean and standard deviation (s.d.) of the following characteristics: High school completed, log of total assets, log of total income, and per capita consumption (in RMB).

Table 2: Summary Statistics of Alipay Users

	Mean	SD	25%	50%	75%
A. Demographics					
Age	35.90	8.51	30.00	24.00	41.00
Male	0.56	0.50	0.00	1.00	1.00
B. Wealth Allocation					
Financial Wealth	90,356.04	151,316.80	8,329.24	33,519.10	100,632.40
Yu'ebao Share	0.41	0.37	0.06	0.30	0.77
Other MMF Share	0.10	0.21	0.00	0.00	0.06
Mutual Fund Share	0.43	0.37	0.01	0.40	0.80
Other Share	0.06	0.14	0.00	0.00	0.03
Monthly Yu'ebao Flows	8,519.44	18,919.92	0.00	0.00	8,045.03
C. Consumption					
Monthly Total Consumption	6,742.87	11,657.95	1,146.40	2,974.70	7,240.48
Share of Non-durable Spending	0.76	0.28	0.62	0.87	0.98
Share of Durable Spending	0.11	0.19	0.00	0.02	0.12
Payment Share through Yu'ebao	0.23	0.02	0.21	0.23	0.24
Payment Share through Debit Card	0.14	0.01	0.14	0.14	0.15
Payment Share through Credit Card	0.22	0.04	0.19	0.21	0.24
Payment Share through BNPL	0.34	0.03	0.33	0.34	0.36
Other Payment Methods	0.07	0.02	0.05	0.06	0.06

Note: This table reports summary statistics for the Alipay user sample in our study. Panel A presents demographic characteristics measured at the individual level in January 2019. Panels B and C report user-month-level statistics over the estimation period of 2019-2021 on wealth allocation and consumption, respectively. "Financial Wealth" refers to the total balance of financial assets held on the Alipay platform, including Yu'ebao, other money market funds (MMFs), mutual funds, and other investment products. "Monthly Yu'ebao Flows" is the monthly inflows associated with Yu'ebao. "Monthly Total Consumption" captures the total value of consumption transactions processed through Alipay. Payment shares represent the proportion of monthly consumption paid using each method, aggregated at the platform level.

Table 3: Summary Statistics of Money Market Funds

	Yu'ebao MMFs		**Regular MMFs**	
	Mean	SD	Mean	SD
A. Fund Basics				
Fund Age (in number of months)	106.80	52.76	61.18	33.86
Total Shares (Billion of RMB)	53.91	48.73	15.37	29.84
Individual Shares (%)	99.31	1.73	89.77	18.17
Number of MMFs in the Family	9.50	4.98	11.97	5.90
B. Fund Fees				
Total Fees (%)	0.63	0.06	0.47	0.10
Management Fee (%)	0.30	0.04	0.21	0.07
Custodian Fee (%)	0.08	0.02	0.06	0.02
Sales Service Fee (%)	0.25	0.01	0.22	0.07
C. Asset Allocation				
Share of Deposits (%)	39.16	11.72	31.91	15.01
Share of Fixed Income (%)	38.76	13.30	48.86	12.70
Share of Repos (%)	21.64	9.77	18.47	10.53
D. Fund Performance				
Yield (%)	2.25	0.36	2.46	0.43
E. Fund Managers' Characteristics				
Experience (in number of years)	7.78	2.63	7.91	2.97
Education Level	1.82	0.36	1.97	0.36
Term (in number of months)	82.64	26.27	70.62	18.52
Number of Manager	1.73	0.73	1.54	0.60

Note: This table reports summary statistics for MMFs offered on the Alipay platform, comparing Yu'ebao MMFs (columns 1–2) and other regular MMFs not linked to Yu'ebao (columns 4–5).Panel A presents basic fund characteristics, including age, size (measured by total shares outstanding), investor composition, and the number of MMFs within the same fund family. Panel B reports fee structures, including total fees and their components: management, custodian, and sales service fees (all expressed as annual percentages). Panel C shows the average portfolio allocation across major asset classes: deposits, fixed income securities, and repurchase agreements. Panel D summarizes fund performance, including average yield and volatility. Panel E describes fund manager characteristics, including average years of experience, education level (coded as 1 for undergraduate, 2 for master's, and 3 for doctoral degrees), managerial tenure (in months), and the number of managers per fund.

Table 4: Yu'ebao Inclusion Predictability

	All Funds		**Retail Funds**	
	(1) Probit	(2) Logit	(3) Probit	(4) Logit
log of Fund Age	0.246	0.779	0.297	0.937
	(1.99)	(1.96)	(2.24)	(2.18)
log of Fund Number in the Family	0.185	0.530	0.150	0.414
	(2.34)	(2.27)	(1.95)	(1.86)
log of Average Total Shares	0.011	0.035	0.016	0.047
	(0.73)	(0.86)	(0.98)	(1.09)
Average of Individual Shares Ratio	0.007	0.020	0.005	0.016
	(2.22)	(2.11)	(1.72)	(1.60)
Average Custodian Fee	-5.192	-16.283	-4.799	-15.636
	(-1.20)	(-1.25)	(-1.09)	(-1.16)
Average Management Fee	4.245	12.479	3.800	11.173
	(2.30)	(2.13)	(2.06)	(1.88)
Average Sales Service Fee	1.957	6.551	1.278	4.137
	(1.69)	(1.60)	(1.01)	(0.98)
Average Deposit Share	-0.002	-0.009	-0.013	-0.036
	(-0.15)	(-0.20)	(-0.54)	(-0.54)
Average Fixed Income Share	0.010	0.029	-0.001	0.003
	(0.60)	(0.60)	(-0.02)	(0.04)
Average Repo Share	-0.001	-0.003	-0.010	-0.027
	(-0.06)	(-0.05)	(-0.40)	(-0.38)
Average Annualized Return	0.073	0.200	0.101	0.276
	(0.83)	(0.78)	(1.08)	(1.03)
Observations	13,504	13,504	8,422	8,422
Pseudo R^2	0.135	0.135	0.096	0.097

Note: This table presents the results of Probit and Logit predictive regressions. The dependent variable is a binary indicator equal to one if the fund is included in the Yu'ebao platform. Independent variables include the log of fund age, the log of the number of funds within the same fund family, the log of average fund-level characteristics computed over the preceding six months, including total shares outstanding, the ratio of individual shares to total shares, annualized management, custodian, and sales service fees, asset allocation shares (deposits, fixed income, and repos), and gross annualized return. Columns (1) and (2) use the full sample of MMFs, while Columns (3) and (4) restrict the sample to retail-oriented MMFs with no minimum purchase threshold. Standard errors are clustered at the fund level, and corresponding t-statistics are reported in parentheses.

Table 5: Baseline Demand Estimation

	IV Logit (1)	Baseline (2)	Subsample (3)
	Panel A. Price Coefficient		
Fees	-12.418	-12.416	-13.67
	(-4.55)	(-4.545)	(-5.082)
	Panel B. Base Coefficients		
Payment	5.087	5.021	5.17
	(16.036)	(16.793)	(17.466)
log(Fund Age)	0.839	0.838	0.9
	(4.54)	(4.530)	(5.000)
log(Fund Number in the Family)	0.800	0.8	0.79
	(10.56)	(10.526)	(10.260)
Time FE	Y	Y	Y
Observation	1590	1590	1590
Average valuation(bps)	40.9	40.4	37.8

Note: This table reports results from demand estimations. All specifications include fund characteristics: fees, a Yu'ebao integration indicator, log fund age, and log number of MMFs within the same fund family. We use Hausman and differentiation instruments for fees. Column (1) reports the results of IV Logit without user demographics. Column (2) reports the results of the baseline model Equation (1) with micro-moments on user demographics. Column (3) restricts the sample to investors with prior experience investing in MMFs before the estimation window. Robust t-stats are reported in parentheses.

Table 6: Baseline Demand Estimation (Cont.)

	Panel C. Micro-moments Coefficients			
	(2)		(3)	
log(cmp)	0.14		0.14	
	(19.71)		(19.86)	
log(wealth)	0.11		0.11	
	(27.75)		(22.40)	
	Female	Male	Female	Male
<25	0.109	0.410	0.112	0.419
	(1.603)	(7.321)	(1.493)	(6.758)
25-29	-0.036	0.252	-0.042	0.249
	(-1.029)	(7.875)	(-1.135)	(7.324)
30-34	-0.201	0.113	-0.202	0.108
	(-6.484)	(3.767)	(-6.121)	(3.484)
35-39	-0.204	0.047	-0.197	0.046
	(-6.000)	(1.469)	(-5.472)	(1.353)
40-44	-0.076	0.075	-0.076	0.077
	(-1.900)	(2.083)	(-1.767)	(1.974)
45-49	0.106	0.111	0.111	0.112
	(2.304)	(2.581)	(2.220)	(2.435)
50-54	0.219	0.171	0.213	0.182
	(3.650)	(2.948)	(3.277)	(2.935)
>55	0.236	0.269	0.229	0.260
	(3.420)	(4.203)	(3.137)	(3.881)

Note: This table reports the estimated coefficients for age-gender-specific micro-moments from the structural demand models presented in Columns (2) and (3) of Table 5. Each column shows separate estimates for female and male users across age groups. The coefficients represent deviations in β_{it} relative to the sample mean. Consumption and Wealth are the past three-month moving averages of the consumption amount and total financial wealth on Alipay's platform, respectively. Column (2) corresponds to the baseline model, and Column (3) restricts the sample to users with prior MMF investment experience. Robust t-statistics are reported in parentheses.

Table 7: Money Market Fund Expected Returns

	(1)	(2)
	Panel A. Price Coefficient	
Fees	-11.367	-11.572
	(-3.75)	(-3.72)
	Panel B. Base Coefficients	
Payment	5.117	5.065
	(17.89)	(18.22)
$r_{jt} - \bar{r}_t$	18.026	12.9
	(2.28)	(1.47)
$\bar{r}_t$	6.592	
	(3.27)	
Other fund characteristics	Y	Y
Other micro-moments on demographics	Y	Y
Time FE	N	Y
Average valuation(bps)	45.5	43.8

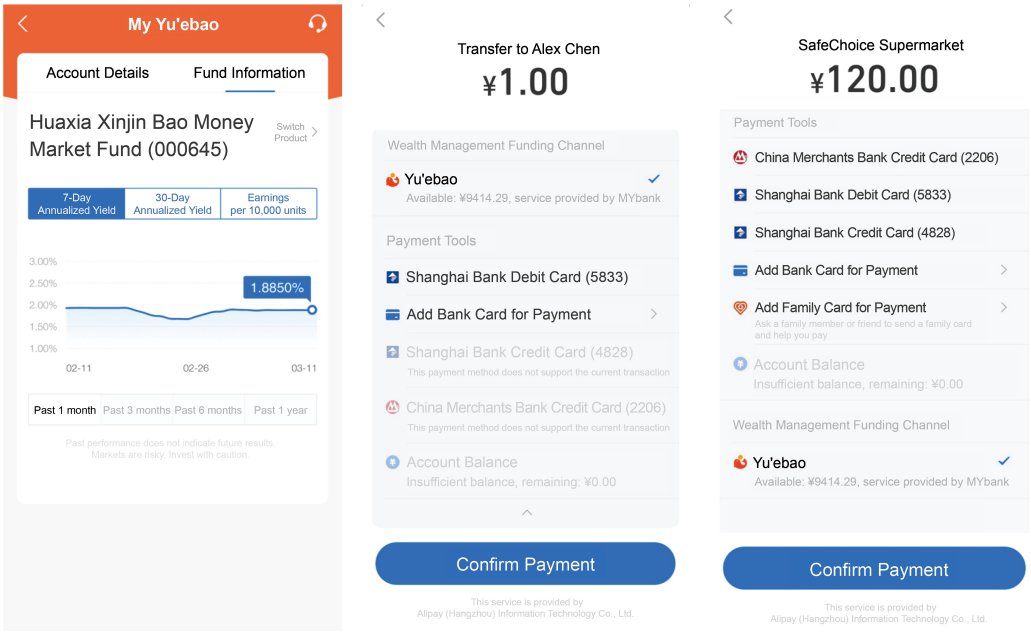
Note: This table reports estimates from demand models examining the role of expected returns in household preferences for money market funds (MMFs). The variable $r_{jt} - \bar{r}_t$ captures the deviation of fund j's expected return from the cross-sectional average in month t, while $\bar{r}_t$ represents the average expected return across all funds. All specifications include other fund characteristics and user-level micro-moments, consistent with the baseline specification in Table 5. Robust t-statistics are reported in parentheses.

Table 8: Contribution of Consumption Risk to Yu'ebao Valuation

	Coefficient		
Fees	-15.72 (-6.96)		
		Mean value	Contribution (bps)
$\log(\text{Consumption})_{t-1}$	0.042 (4.246)	8.33	2.22
$\log(\text{wealth})_{t-1}$	0.106 (22.28)	10.01	6.42
Consumption Risk	4.179 (12.15)	0.92	24.42
Payment Utilization	1.04 (38.5)	0.817	5.4
Other fund characteristics	Y		
Time FE	Y		
Average valuation(bps)			38.41

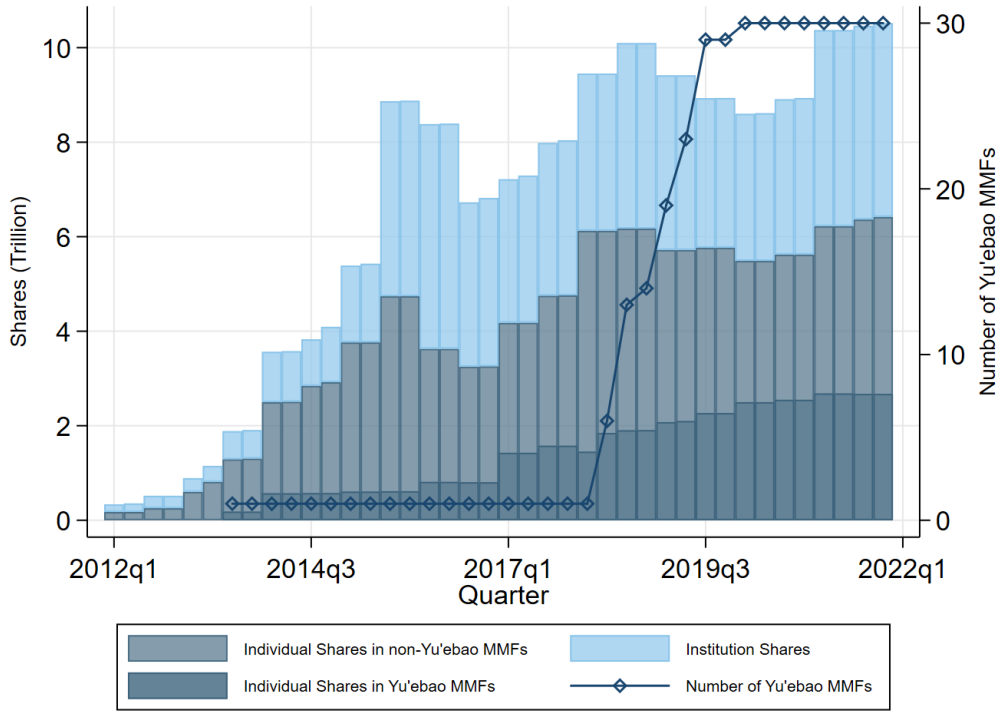
Note: This table reports the demand estimation results for the value decomposition. Price coefficient and base coefficients in Equation (17) are reported. The column "Mean value" reports the sample average of each variable, and the "Contribution" column reports the contribution in bps from each of the components, calculated as the product of the base coefficient and the sample average, scaled by the price coefficient. All specifications include observed fund characteristics and time fixed effect. Robust t-statistics are reported in parentheses.

Figure 1: Dual Functionality of Yu'ebao



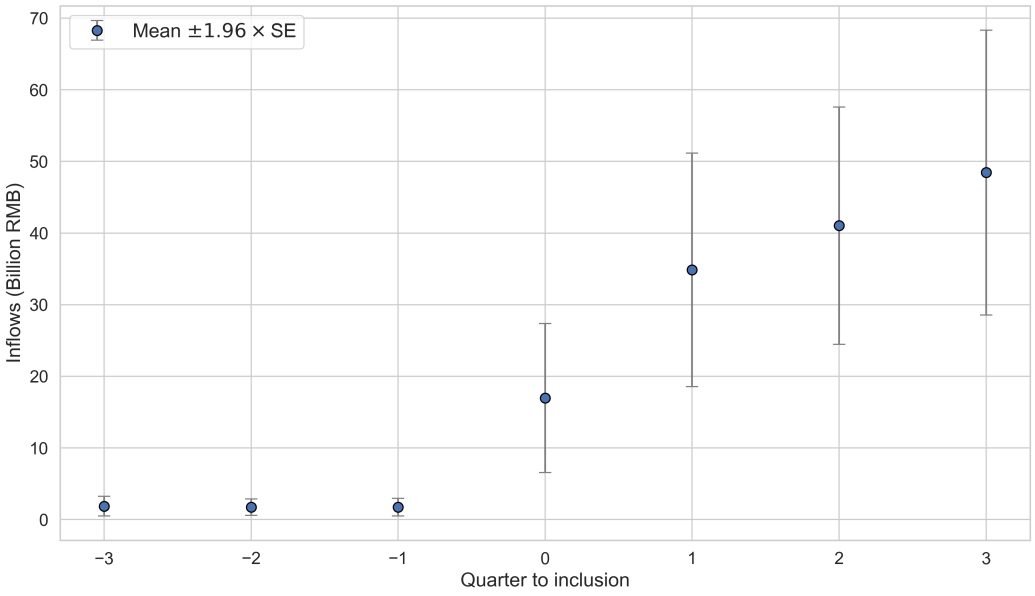
Notes: This figure illustrates the dual functionality of Yu'ebao as both an investment product and a payment tool. The left panel shows the "My Yu'ebao" interface, where users can view detailed information about their underlying money market fund of Yu'ebao. The middle panel shows the interface for making peer-to-peer transfers. Users can choose Yu'ebao as the funding source, alongside a list of linked debit cards. Credit cards and other consumer finance options are not available for transfer transactions. The right panel presents the payment interface for a merchant transaction. In this context, users can select from a wider range of payment tools, including Yu'ebao, debit cards, credit cards, and linked financing services.

Figure 2: Growth and Investor Composition of China's Money Market Funds



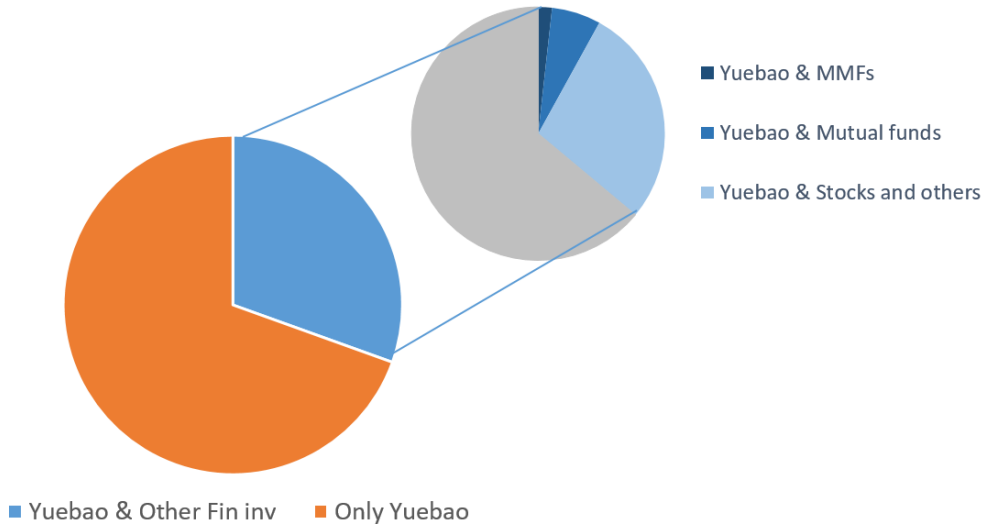
Notes: This figure presents the evolution of China's money market fund (MMF) market from 2012Q1 to 2021Q4, with a focus on investor composition. The stacked bars display the total outstanding MMF shares (in trillions of RMB), disaggregated by investor type: institutional investors (light blue), individual investors in regular MMFs (medium blue), and individual investors in Yu'ebao MMFs (dark blue). The line with diamond markers, plotted on the right vertical axis, indicates the number of Yu'ebao MMFs over time.

Figure 3: Fund Inflows Around Yu'ebao Inclusion



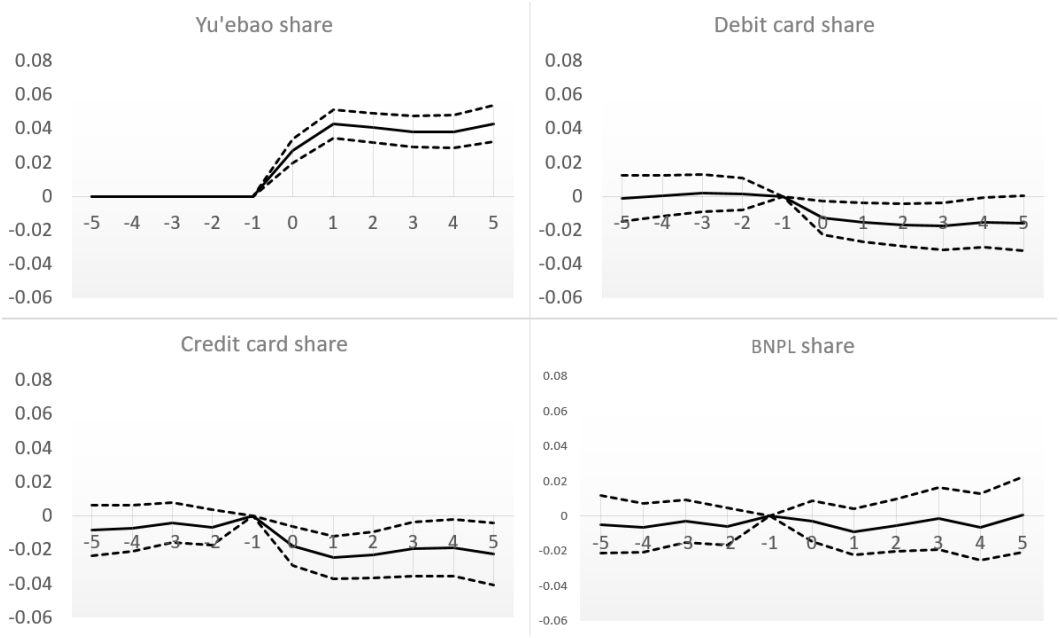
Notes: This figure presents the average fund inflows before and after inclusion in the Yu'ebao platform. The x-axis measures time relative to the quarter of inclusion (quarter 0), while the y-axis reports average quarterly inflows in billions of RMB. Each data point corresponds to the cross-sectional mean inflow among newly included funds in a given event quarter.

Figure 4: Financial Diversification Among Yu'ebao Users



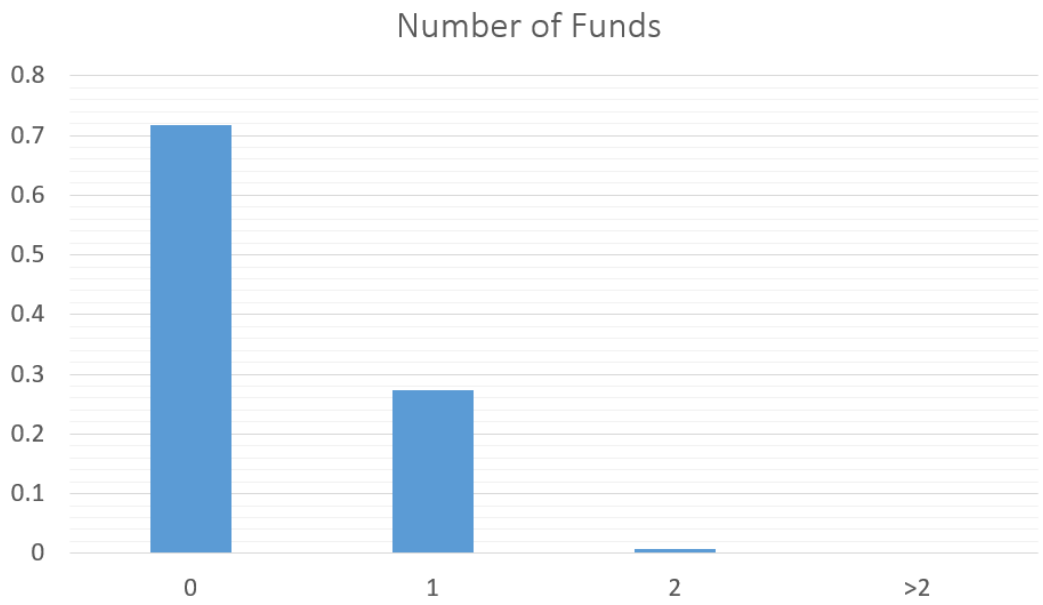
Notes: This pie chart presents the distribution of Yu'ebao users by investment diversification, based on data from the 2019 wave of the Chinese Household Finance Survey (CHFS). Respondents are grouped into two main categories: those who exclusively hold Yu'ebao ("Only Yu'ebao"), and those who hold Yu'ebao in combination with other financial products. Among the latter group, we further distinguish three subgroups: (1) Households holding both Yu'ebao and other MMFs ("Yu'ebao & MMF"); (2) Households holding both Yu'ebao and mutual funds ("Yu'ebao & Mutual Funds"); and (3) Households holding both Yu'ebao and other non-fund assets, including stocks, bonds, and structured products ("Yu'ebao & Other Fin Inv").

Figure 5: Event Study of Payment Method Shares Around Yu'ebao Adoption



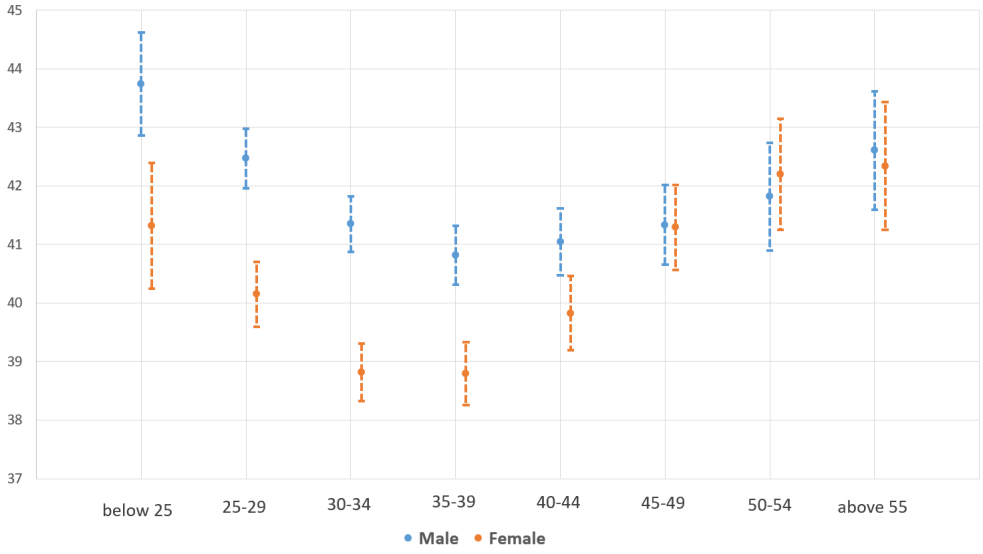
Notes: This figure presents an event-study analysis of changes in payment method usage around the initial adoption of Yu'ebao. Each panel displays estimated coefficients β_τ from Equation (19) for the five months before and after the first month of Yu'ebao adoption. The panels correspond to four payment methods: Yu'ebao (top left), debit card (top right), credit card (bottom left), and buy-now-pay-later (BNPL, bottom right). The dependent variable in each regression is the monthly share of consumption transactions conducted using the respective method. We control for individual fixed effects and time fixed effects, as well as the time-varying log of consumption and financial wealth. Solid lines connect the point estimates, and dashed lines indicate 95% confidence intervals.

Figure 6: Distribution of MMF Purchases per User per Month on Alipay



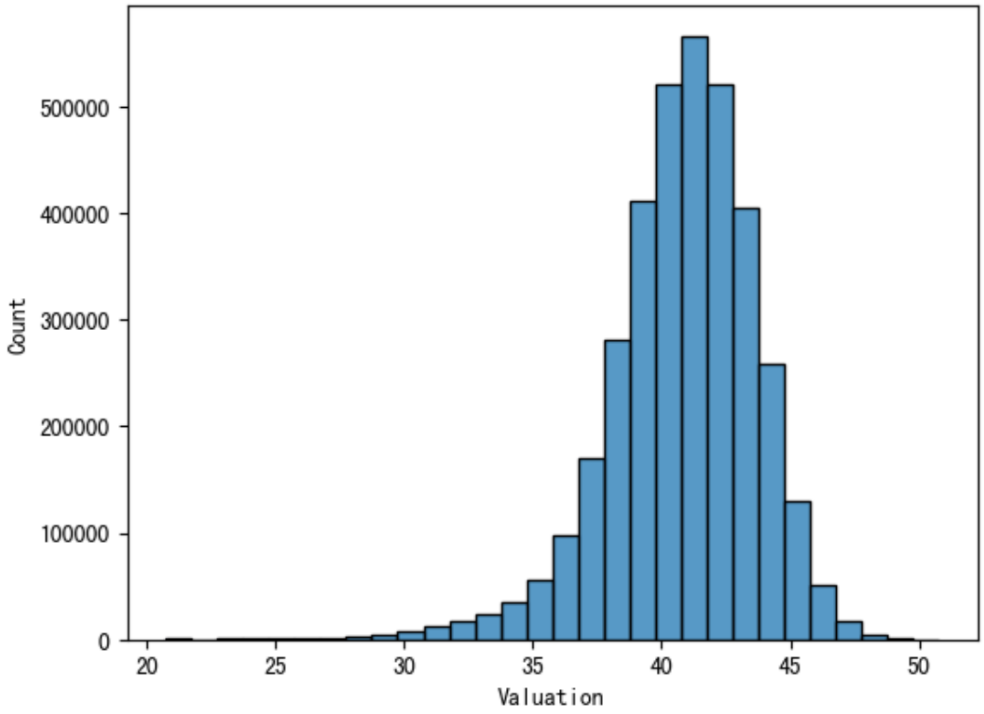
Notes: This figure displays the distribution of the number of distinct MMFs purchased by individual investors within a single month on the Alipay platform. The x-axis indicates the number of different MMFs purchased by a user, while the y-axis shows the proportion of users in each category. The majority of users do not purchase any MMF in a given month, and among those who do, nearly all limit their purchase to a single fund.

Figure 7: Estimated Valuation Heterogeneity by Age and Gender



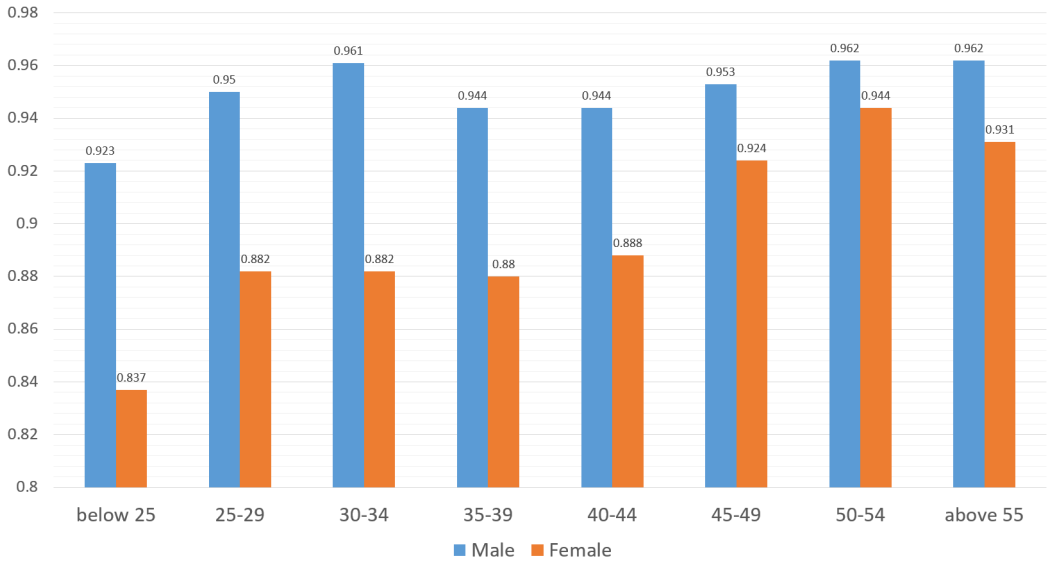
Notes: This figure visualizes the estimated heterogeneity in valuation across age and gender, corresponding to column (2) in Table 6. The blue lines represent estimates for male individuals, and the orange lines represent female individuals. For each age-gender group, we plot the point estimates of v_{it} and the 95% confidence intervals.

Figure 8: Distribution of Estimated Valuation



Notes: This figure shows the cross-sectional distribution of estimated individual-level valuations for Yu'ebao's integrated payment feature. The valuations are derived from the structural demand model reported in Column (2) of Table 5 and Table 6, which incorporate individual demographic characteristics to capture heterogeneity in preferences.

Figure 9: Distribution of Consumption Risk



Notes: This figure presents the distribution of estimated consumption risk for each *age* × *gender* group, following the methodology described in Section C. The value displayed above each bar denotes the group's average consumption risk over the sample period (36 months).

Appendix A Event-study of Yu'ebao Adoption

Our individual-level dataset allows us to track each user's monthly consumption activity disaggregated by four major payment methods: debit card, credit card, buy-now-pay-later (BNPL), and Yu'ebao. To examine how payment behavior evolves around the adoption of Yu'ebao's embedded payment functionality, we implement an event study framework that traces changes in the composition of payment methods before and after the adoption of Yu'ebao. We define Yu'ebao adoption at the user level as the first month in which the user's Yu'ebao balance becomes strictly positive following a sequence of zero balances in the preceding five months. We estimate the following event study specification:

$$Y_{it}^{m} = \sum_{\tau \neq -1} \beta_\tau \mathbb{1}_{E_{it}=\tau} + FE_i + FE_t + \varepsilon_{it}, \tag{19}$$

where Y_{it}^{m} denotes the share in total consumption by individual i in month t transacted through payment method $m \in \{Yu'ebao, debit, credit, BNPL\}$. The variable E_{it} is defined as the number of months relative to individual i's Yu'ebao activation month. We include indicators for each event month $\tau \in [-5, +5]$, omitting $\tau = -1$ as the baseline reference period. The coefficients β_τs capture dynamic changes in payment behavior. To control for confounding variation, we include individual fixed effects, which absorb time-invariant user characteristics. We also include time fixed effects, which account for macroeconomic shocks or seasonal spending patterns. We control for time-varying log of monthly total consumption and the log of financial wealth (measured by non-Yu'ebao holdings), to ensure that we isolate substitution across payment methods rather than changes in the overall scale of financial activity.

The estimated coefficients β_τs are presented graphically in Figure 5, which plots the dynamic response of each payment method around Yu'ebao adoption, enabling us to examine the substitution patterns among different payment methods following Yu'ebao adoption.

Appendix B MMF Expected Return

To estimate expected returns for each MMF, we adopt a linear model that captures the exposure of individual funds to short-term interest rates. The model for the expected return of fund j in month t is specified as follows:

$$r_{jt} = \alpha_{jt} + \beta_{jt}^{repo} r_t^{repo} + \beta_{jt}^{shibor} r_t^{shibor} + \beta_{jt}^{FI} r_t^{FI}, \tag{20}$$

where r_t^{repo}, r_t^{shibor}, and r_t^{FI} represent the monthly compounded returns of three benchmark interest rates: the overnight repo rate (FR001), the 1-week SHIBOR, and the 3-month China's T-bill rate, respectively. These rates serve as proxies for the short-term money market instruments that MMFs typically invest in, capturing the core components of the funds' income-generating portfolios. To estimate the fund-specific factor loadings — β_{jt}^{repo}, β_{jt}^{shibor}, and β_{jt}^{FI} — we conduct rolling-window regressions using a one-year historical window of weekly return data. Specifically, for each fund j and month t, we estimate the regression model using weekly returns from $t-12$ up to $t-1$ month. The fund's weekly return, as well as the three benchmark interest rates' weekly returns, are computed as the cumulative return over five trading days. Once the fund-specific intercept and factor loadings are estimated, we construct the expected monthly return $\hat{r}_{jt}$ for each fund by applying the estimated coefficients to the realized values of the three benchmark rates in month t:

$$\hat{r}_{jt} = \hat{\alpha}_{jt} + \hat{\beta}_{jt}^{repo} r_t^{repo} + \hat{\beta}_{jt}^{shibor} r_t^{shibor} + \hat{\beta}_{jt}^{FI} r_t^{FI}. \tag{21}$$

This estimated return serves as a forward-looking proxy for the expected return based on publicly available information about interest rate conditions and historical fund performance.

To ensure robustness, we drop fund-month observations where fewer than 10 weekly return observations are available in the rolling window, and winsorize estimated returns at the 99.9th percentiles.

Appendix C Consumption Risk

We assume that individuals correctly anticipate the expected growth of their log consumption conditional on their age, gender, location, and their past financial status. We begin by computing, for each individual, the change in log consumption on non-durable goods. The definition of non-durable consumption contains expenditures on basic living goods and services, personal and family care, mobility and communication, healthcare, and leisure. Specifically, we estimate:

$$c_{it} - c_{it-1} = f(a_{i,t}, g_i, l_{i,t}, c_{i,t-1}, w_{i,t-1}) + \hat{\varepsilon}_{it}, \tag{22}$$

where $f(.)$ is the linear combination of gender, age dummies, location city dummies, and the investor's lagged log consumption and log wealth, and is estimated for all individuals to capture the deterministic component of consumption growth. The residuals from this regression $\hat{\varepsilon}_{it}$ capture the unexpected change in consumption.

We then group individuals by age and gender, under the assumption that individuals within the same group face similar consumption risk. Individuals of the same gender and at similar stages of the life cycle are likely to face comparable levels of expenditure uncertainty. Ideally, additional individual characteristics—such as marital status and parental status—would further refine the grouping, as they play an important role in shaping consumption volatility. However, the dataset does not include labels related to household structure. For each group and month, we compute the cross-sectional standard deviation of residual consumption shocks as the month t consumption risk measure for all individuals in this group. Overall, our methodology largely follows Blundell et al. (2008) and Catherine et al. (2024).