FinTech Platforms and Mutual Fund Distribution

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Abstract

We document a novel platform effect caused by the emergence of FinTech platforms in the intermediation of financial products. In China, platform distributions of mutual funds emerged in 2012 and grew quickly into a formidable presence. Utilizing the staggered entrance of funds onto platforms, we find a marked increase of performance-chasing, driven by the centralized information flow unique to FinTech platforms. This pattern is further confirmed using proprietary data from a top platform. Examining the platform impact on fund managers, we find that, incentivized by the amplified performance-chasing, fund managers increase risk taking to enhance their probability of getting onto the top ranking.

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1 Introduction

Over the past couple of decades, the rise of the platform economy has transformed the way we live. Empowered by technological innovations and leveraging on giant user bases, platforms are like intermediaries on steroids, creating social and business connectivity on a previously unimaginable scale. Widely adopted platforms such as Google for information, Amazon for retail, Facebook for social networking, and Uber for taxi rides have profoundly reshaped how information is aggregated and disseminated in the society, altering individual behavior and disrupting the respective industries.

This paper focuses on the emergence of platforms in the asset-management industry, taking advantage a 2012 policy in China that allows tech-driven platforms to distribute mutual funds directly to individual investors, bypassing and replacing the traditional distribution channels organized by fund families, banks and brokers.[1] Akin to what Amazon did for books and retail goods, such platforms break down the market segmentation and connect investors directly to the financial products. Unlike the retail products sold on Amazon, the quality of the financial products (i.e., the mutual-fund performance) is inherently unpredictable at the time of transaction, making investors rely more heavily on the information fed to them via the platforms.[2] From this perspective, the FinTech platforms distribute to their giant user bases not only financial products, but also financial information.

Unique to our study is this synergy between the centralized information and product distribution inherent in the FinTech platforms. Our hypothesis is that the highly centralized platform structure in the distribution of both product and information, coupled with the enormous scale of the big-tech platforms, can lead to highly synchronized investor behavior. Moreover, on the production side, fund managers, no matter how small or invisible, have the potential to reach the entire user base of these platforms. As their reliance on platform distribution increases, the platform-induced investor behavior can in turn affect their incentives.

Focusing first on the impact of platforms on investor behavior, our empirical results document a strong platform-induced amplification of performance chasing. We find a striking increase in performance sensitivity, driven by flows chasing the top-ranked funds much more

[1]In February 2012, China Securities Regulatory Commission (CSRC) announced that tech firms, independent from fund families, banks, and brokers, are allowed to distribute mutual funds. Since then, FinTech platforms have grown into a formidable presence. By 2014, top platforms like Tiantian and Ant Financial have covered almost the entire universe of mutual funds in China. By end of 2018, about one-third of the non-family sales of funds took place on FinTech platforms.

[2]Prior to the emergence of the FinTech platforms, the pure informational effect has been documented by Del Guercio and Tkac (2008) and Kaniel and Parham (2017) on influences of the MorningStar ratings and the WSJ rankings, respectively. See also Barber et al. (2021) on Robinhood investors and Hu et al. (2021) on the Reddit users involved in the GameStop trading.

aggressively after the emergence of the platforms. Upon ranking actively managed equity funds by their past 12-month returns into deciles, the average net flow to the funds in the top decile increases from 3.03% pre-platform (2008–2012) to 20.84% post-platform (2013–2017).[3] We further take advantage of the fact that our data include the exact dates on which each mutual fund signs up for the platforms. Using this information on staggered entrance, we find that the increase in flow-performance sensitivity occurs exactly on and after a fund enters platforms. In particular, controlling for fund-level characteristics and time and fund fixed effects, the post-platform performance sensitivity is over three times the pre-platform level for both equity and mixed funds. Moreover, we do not observe such a marked increase in flow-performance sensitivity under placebo tests, estimated by randomly assigning funds to be on- or off-platforms. In particular, our actual estimates on platform-induced performance chasing exceed 94.9% and 99.8% of the placebo estimates for equity and mixed funds, respectively.[4]

To further provide evidence on the platform-induced performance chasing, we directly examine investors' behaviors on a FinTech platform – Howbuy, one of the top platforms in China. With the proprietary dataset obtained from Howbuy, we find that performance chasing is indeed stronger on the FinTech platforms. From 2015 through 2018, the top-decile equity funds account for an average of 49.37% of the quarterly purchases on Howbuy, significantly larger than the average of 37.61% for the entire market, which aggregates purchases over all distribution channels, both on- and off-platform. Pre-platform, only 23.79% of the quarterly purchases in the entire market goes to the top-decile equity funds.

Given the striking increase in flow-performance sensitivity, it is important to understand what specific features of platforms drive the amplification in performance chasing. As investors rely on the platform information to form expectations about fund future performance, we hypothesize that the highly centralized and uniform information display on these FinTech platform apps may generate a pattern of coordinated or synchronized performance chasing. Off-platform, information signal is dispersed with funds distributed via various segmented channels. On-platform, investors receive and trade on the same set of information. In particular, as platforms invariably list mutual funds by their past performance, the top-performing funds are displayed prominently at the front page of every investor's mobile device, causing an otherwise diverse set of investors to chase the same set of front-page funds. Consequently, performance chasing behavior at an individual level might be synchronized

[3] As a benchmark, the average net flow to the top-decile equity funds in the US is very stable, with a magnitude of around 6% in both time periods.

[4] With a battery of robustness checks, we show that this platform effect cannot be explained by the endogenous entrance of funds, time-varying market conditions, aggregate changes in the composition of funds and investors, and the availability of other distribution channels in the post-platform era.

and lead to amplified performance-chasing at the aggregate level.

To test such a hypothesis of centralized information display, we offer evidence from three perspectives. First, we examine the platform effect on a small set of funds displayed on the front page of the platform app. As a common default setting, FinTech platforms usually display mutual funds by past 12-months raw returns in a descending order via the performance rank list in mobile apps. Depending on the size of their cell-phone screen, investors normally see 8 to 12 funds on the front page of the performance rank list. The front-page funds attract lots of attention as investors would need to scroll down on the phone to see the funds with lower returns. If our hypothesis of synchronized performance chasing is correct, we expect to see platform-induced performance chasing to concentrate among those few top performing funds that show up on the front page. This is exactly what we find. The platform-induced performance chasing is the strongest for the top 12 funds and decreases almost precipitously with the ranking of the funds as they become less likely to appear on the front page.

Second, we take advantage of the unique features of the default ranking list to provide causal evidence on the centralized information display. In particular, although platforms allow investors to rank funds by past 3, 6, 12, and 36 months returns, sorting by past 12-month raw returns (instead of risk-adjusted returns) is often a default choice, widely adopted by Tiantian and Ant among others. If the amplification in performance chasing is indeed driven by investors actively responding to the front-page information, we expect the default setting of the performance rank list to have a higher explanatory power of platform-induced flows, compared to other alternative rank lists. Following this intuition, we conduct horse-race analyses between our baseline front-page effect and those estimated using performance measures with different look-back horizons and when ranked by fund alphas. We find that the ranking based on the default setting overwhelmingly beats the rankings based on these alternatives. Third, we use funds' intra-family ranking as a placebo test. Pre-platform introduction, funds' performance ranking within the family is an important determinant of flow. Post-platform introduction, as funds' intra-family ranking is not displayed on platforms, consistently, we do not find any platform effect associated with their intra-family ranking. Taken together, these results largely support the hypothesis that the amplified performance chasing we document is closely tied to the centralized information display unique to FinTech platforms, as opposed to a market-wide general tendency to chase performance in the post-platform era.

Besides the centralized information display, reduction in participation costs might be another potential mechanism through which platforms could amplify the performance chasing. In particular, platforms reduce the information costs and transaction costs of participation, allowing investors to easily access funds and meantime waiving 90% of the front-end loads.[5] To examine the role of reduction in participation cost on the amplified performance chasing, we compare subsamples of funds that experience varying levels of cost reduction after platform entrance. Using funds' family size, advertising expense, and front-end loads to capture cross-fund variations in participation cost reduction, we find that the magnitudes of platform effects are similar across different subsamples, suggesting that reduction in participation cost is unlikely to be the main driver of the amplified performance chasing.

Finally, to examine the broader impact of FinTech platforms on the production side of the market, we investigate the responses of fund managers to the advent of platform distribution, as well as the implications on fund performance. Specifically, we find that, in the presence of this amplified performance chasing, top-ranked funds exhibit a pattern of increased volatility to "gamble" the market and enhance their chance of making onto the top list. This added risk taking incentive for top ranked funds is consistent with the much more convex flow-performance relationship that they face after the introduction of platforms. Decomposing fund volatility further into systematic and idiosyncratic components, we find that this added risk taking is mainly present in the systematic component. Given the positive risk premium associated with systematic risk, boosting the systematic component in risk taking does provide higher expected returns, which indicates that the fund managers have already reached the limit of their own skills and are using leverage to get ahead. While the economic magnitude of the result is not big, the emergence of such a practice points to the unintended consequences associated with the platform intermediation of financial products.

Turning to the implications on fund performance, we find that top-performing funds fail to outperform both in the pre- and post-platform era. Moreover, associated with the platform effect, we observe an increase in volatility and a decrease in Sharpe ratio in the first year after the funds successfully make into the top. Due to a short sample period in our setting, these asset pricing results are relatively weak and inconclusive. Nonetheless, our evidence is consistent with existing literature, which provides extensive theories and empirical findings pointing to the potential negative impact of platforms on fund performance. In particular, with the decreasing returns of scale effect in Berk and Green (2004) and the return deterioration from managerial risk-shifting documented in Huang, Sialm, and Zhang (2011), our previous findings on post-platform amplified performance chasing and changing managerial risk taking point to the potential investor welfare loss in the long run, i.e.,

[5] Ex ante, it is unclear how such reduction in participation costs would affect the flow-performance sensitivity. Huang, Wei, and Yan (2007) argue that reduction in information acquisition cost will decrease the magnitude of performance chasing, as investors require a lower performance threshold to learn about a potential fund. On the other hand, with reduction in participation costs, platforms might attract new and immature investors who exhibit stronger performance sensitivity.

distributional efficiency does not necessarily lead to allocational efficiency.

Our paper contributes to three strands of literature. First, our paper speaks to the literature on the impact of information dissemination on investor behavior. In particular, investor behaviors are altered by the rapidly changing information environment associated with the emergence of digital platforms, for example, in the gamification of stock trading environment on Robinhood, and through social media like Reddit or StockTwit (e.g., Barber et al. (2021), Hu et al. (2021), Cookson, Engelberg, and Mullins (2022)). Focusing on the impact of information display on mutual fund investment,[6] Kaniel and Parham (2017), Del Guercio and Tkac (2008), Evans and Sun (2021), and Ben-David et al. (2022) document that flows are sensitive to fund rankings displayed on Wall Street Journal and Morningstar. Sharing the same mechanism, our paper is unique in that FinTech platforms distribute to their giant user base not only information, but also financial products. This combination of centralized fund ranking with fund distribution is of unique importance: As identical information is fed to a much broader user base simultaneously through technology-empowered platforms, investors' trading behavior is synchronized at a much larger scale and with more precision, resulting in an overwhelming increase in market-level flow-performance sensitivity.

Our paper also contributes to the growing literature on FinTech platforms. In particular, focusing on asset management platforms, Reher and Sokolinski (2021), D'Acunto, Prabhala, and Rossi (2019), and Loos et al. (2020) find that the introduction of automated management tools and robo-advisors encourage financial participation and improve diversification. Different from this existing literature, we focus on the centralized platform distribution and its market-wide impact. More broadly, we are also related to Hong, Lu, and Pan (2022), Buchak, Hu, and Wei (2022), and Ouyang (2021) who study the synergy of bundling financial services with digital payments via big-tech platforms. We offer evidence on the synergy between centralized fund ratings and fund distributions on FinTech platforms. Finally, Cong et al. (2021) study the uniqueness of financial platforms, emphasizing the cross-side network effect in the context of P2P market. Relatedly, we show that platform-induced investor behavior change can lead to managerial incentive change, and ultimately the riskiness of the underlying financial product as well.

Finally, our paper is also related to the classic literature on the performance-chasing by mutual fund investors and its impact on managerial incentives. As documented by Gruber (1996), Brown et al. (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998), mutual fund flows tend to chase past performance, resulting in a convex flow-performance

[6]Relatedly, Frydman and Wang (2020) and Liao et al. (2021) find that information display exacerbates individual heuristics in the form of disposition effect and fast thinking, and Fedyk (2022) finds that front-page positioning induces higher trading volumes and larger price changes.

relationship, which in turn alters fund managers' risk-taking incentives.[7] Huang, Sialm, and Zhang (2011) further show that such distortions lead to deterioration in fund future performance. Our paper contributes to this literature by showing that the existing flow-performance relation can be dramatically amplified in a platform economy where the distribution of information is highly centralized and investor actions are highly synchronized. Moreover, building on the economic mechanism suggested in this literature, we show that this platform effect impacts not only investor behavior but also managerial incentives.

The remainder of this paper is organized as follows: Section 2 describes the data used in our study and the institutional background. Section 3 presents the main results related to platform-induced performance chasing. Section 4 discusses the economics mechanism of the platform effect, focusing primarily on the centralized information distribution of platforms. Section 5 explores the economic consequences of platforms on fund managers' incentives and on fund performance. Section 6 concludes.

2 Data and Institutional Background

2.1 The Emergence of FinTech Platforms

In China, platforms are allowed to distribute mutual funds since 2012. China Securities Regulatory Commission (CSRC) announced in February 2012 that tech firms, independent of fund families, banks, and brokers, are allowed to distribute mutual funds via e-commerce platforms. Since then, platforms started to emerge and the total number of platforms reached 115 by year 2018.

The business model of FinTech platforms share similarities to other two-sided markets.[8] Platforms serve as intermediaries between funds and investors, allowing both parties to get on board a bigger playing ground. As more funds are available on a platform, investors enjoy the convenience of completing all transactions and managing their entire portfolio on a single app. As more investors join a platform, funds experience a substantial reduction in customer acquisition cost. As a result, the top platforms grab most of the market shares while the smaller ones struggle for survival. Of the 115 platforms, the two largest platforms, which are

[7]Other studies in this area include Berk and Green (2004), Lynch and Musto (2003), Huang, Wei, and Yan (2007), Ivković and Weisbenner (2009), Ferreira et al. (2012), Spiegel and Zhang (2013), Sialm, Starks, and Zhang (2015), Barber, Huang, and Odean (2016), Berk and Van Binsbergen (2016), Franzoni and Schmalz (2017), among many others.

[8]Unlike preferences for consumption goods, investors' preference for mutual funds is highly homogeneous ex ante, centering around the dimensions of risk and return. Therefore, the matching on platforms is mostly through one-sided search, i.e., investors actively choose which funds to invest in.

also the focus of our paper, are Tiantian and Ant Financial.[9] Anecdotal evidence suggests that Tiantian and Ant together account for 80% of the platform business. Therefore, in our main analyses, we define a fund's platform status by its availability on the Tiantian and the Ant Financial platforms.

To reach a larger investor base via platforms, mutual funds of various types joined platforms quickly. As shown in Figure 1, the coverage of actively managed mutual funds by the top four platforms, Ant, Howbuy, Tiantian, and Tong Huashun, increases swiftly from zero to 60% over the span of just one year from 2012Q2 to 2013Q2. The fraction of funds available for sale on each top platform further increases to around 80% of entire fund universe by year 2014, and has been stabilized afterwards. Compared with other distribution channels at the time, platforms stand out in terms of fund coverage, as the fraction of mutual funds available for sale via brokers and banks are only around 40% and 20%, respectively. Examining the determinants of funds' entrance, we find that non-bank-affiliated funds and funds with lower retail ratios, smaller sizes, and longer histories are more likely to enter platforms early (Appendix A1). Funds' past performance and performance volatility, however, have no impact on the timing of their entrance.

Platforms further attract more investors getting on board this powerful distribution channel, leading to a rapid rise in platforms' market share. While the sales numbers have been closely guarded by the platforms, based on the asset management industry report offered by China International Capital Corporation (CICC), FinTech platforms capture 20%, 22%, 35%, and 42% of the total mutual fund indirect sales (non-family channel) market share in year 2015, 2016, 2017, and 2018, respectively. Based on Ant Group (Ant Financial) IPO prospectus, the sales and net income from mutual fund distribution is RMB 2.23 trillion and RMB 10.5 billion, respectively, in 2017. For a large bank like China Merchants Bank, as reported in the annual report, the fund distribution sales and net income is only RMB 705.5 and 5.0 billion in 2017.

2.2 Centralized Information Distribution on FinTech Platforms

The designs of the FinTech platforms in China are highly homogeneous. In particular, platforms unanimously adopt a simple performance rank list to display the entire universe of mutual funds via mobile apps. For illustration, Panel A of Appendix Figure A1 exhibits the cell phone screenshots of two platforms, Ant Financial and Howbuy.

The first screenshot shows the front page of the Alipay app, a catch-all app developed by

[9] Tiantian is among the first four institutions to obtain the fund distribution license from CSRC in February 2012. Ant Financial missed the first batch of license issuance, but quickly entered the platform business in April 2014 by acquiring Shumi platform.

Ant Financial, which integrates all kinds of services from calling a taxi to ordering takeout. Service on mutual fund distribution is also embedded inside this ecosystem, making mutual fund investment as easy as other aspects of everyday life. Once a user logs into the platform app, it takes only one or two clicks to view the performance rank list on the second screenshot in Figure A1.[10] On this list, all funds are grouped by style into tabs for equity, bond, mixed, index funds, etc. Within each tab, the default page displays the funds in the descending order of their past n-months raw returns, with n=12 as a common default choice. Investors have the discretionary to change the specific return horizon out of the window of 1, 3, 6, 12, and 36 months to rank funds. By clicking on a fund, investors will enter the page in the third screenshot, where they can explore more detailed information and make the purchase.

Since all the FinTech platforms rank funds based on past raw returns, the information display of their performance rank list is almost identical. Specifically, on the same day, the performance rank list from the Howbuy app (the fourth screenshot) and the one from Alipay (the second screenshot) display exactly the same list of funds on the front page of the app. The simple and identical information display across different platforms indicates that investors, regardless of place and time, will receive common information signal when they purchase mutual funds through FinTech platforms.[11]

For comparison, Panel B of Appendix Figure A1 shows a screenshot from Charles Schwarb OneSource, a typical brokerage for mutual funds in the US. One can observe several key differences between OneSource and the FinTech platforms in China. First, OneSource operates mainly through Internet websites. They list their own affiliated funds on top, at a position more salient for investors. Second, below their affiliated funds, they display a subset of third-party funds according to their own selection criteria, as opposed to the entire universe of funds. Finally, as a typical financial firm, they provide rich information and abundant criteria for investors to filter and select funds. They offer individual investors more freedom to customize their own pool of funds but arguably make fund investment decisions more complicated. Other standard online brokerage firms and websites of fund families share similar features along these dimensions.

[10]In more recent years, Alipay has been enriching its mutual fund distribution platform by incorporating "hot pick funds" and "hot pick sectors", etc. However, staff members from Alipay indicate that such functions played a very limited role in attracting investors. Investors pay attention overwhelmingly to fund performance rank list. In this paper, we only intend to document the importance of the performance rank list. We leave it open in terms of the usefulness of other newly introduced platform functions.

[11]Platforms rank funds by their past raw returns partially because regulatory authority, in the concern of potential abuse of flexibility, do not allow platforms to rank funds on measures that are not directly obtained from the fund reports or prospectus.

2.3 Data and Methodology

Data on mutual funds, including fund total net assets, return, inception date, and historical style, etc., are obtained from Wind for the sample period from 2008 to 2020. We focus on the actively managed equity, mixed, and bond mutual funds by excluding index funds, passive funds, structured funds, and QDII funds from our sample. Funds with a size below RMB 1 million and an age less than two years old are excluded. We further exclude funds that are likely to be wealth management products by requiring the daily returns of the fund to be nonzero for at least half of its life. Since platforms treat different share classes of the same fund as different units, to mimic investors' choice set on platforms, we conduct our analyses using each fund share class.[12]

Following prior literature (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)), the flow to fund i in quarter t is computed using the following equation:

$$\text{Flow}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1}\,(1 + \text{Ret}_{i,t})}{\text{TNA}_{i,t-1}},$$

where $\text{Ret}_{i,t}$ is the quarter-t split and dividend adjusted return of fund i and $\text{TNA}_{i,t}$ refers to the total net assets under management of fund i at quarter t end. We assume that inflows and outflows occur at the end of each quarter, and that investors reinvest the dividend they receive in the same fund.

Table 1 provides the summary statistics of the actively managed mutual funds in our sample, with Panel A reporting the information on the aggregate mutual fund industry year by year and Panel B reporting the information at fund-quarter-level. As shown in Panel A, the total number of funds steadily increases from fewer than 200 in 2008 to over 4000 by 2020. The number of bond funds, however, is particularly small in the early years, with only around 25 funds by 2009. The same pattern can be observed from Figure 1. The aggregate industry size for equity and mixed funds remain relatively stable around 2012, whereas the industry size for bond funds increases substantially only after 2015. Considering the limited presence of bond funds in the pre-platform era, we rely more on equity and mixed funds to study the impact of platforms.

Another visible change in our sample is the sudden decrease in the number of equity funds, along with the sudden increase in the number of mixed funds in 2015. This is caused by a policy change in August 8, 2015, which increases the minimum stock holding requirement for equity mutual funds from 60% to 80%. As a result, a large number of equity funds switch to mixed funds around 2015Q3. Apart from the change in fund style classification, the Chinese

[12]Some funds have multiple share classes, in the form of A share and C share, that only differ in how they charge fees (e.g., front-end or back-end loads). All our results hold if conducted at the master fund level.

stock market experiences a dramatic run up in the first half of 2015 and then a dramatic crash in the second half. This would have introduced noise and potentially unusual investor behavior into our sample. To ensure that our results are not driven by these major events, we perform two tests in subsequent analyses: (1) shrink our analyses to a narrow window (2011–2014) to avoid the inclusion of 2015; (2) exclude 2015 altogether as a robustness test.

Comparing the risk-return profile across different fund styles, Panel A of Table 1 indicates that equity funds have the most volatile return distribution, followed by mixed funds and then bond funds. There exists substantial variation in equity funds' monthly return, ranging from the lowest value of -5.55% in 2008 to the highest value of 4.89% in 2009. Mixed funds, with the flexibility to invest in bonds, experience the lowest monthly return of -4.58% in 2008 and highest monthly return of 4.09% in 2009.

Panel B of Table 1 further reports the distribution of the main variables used in our analyses, summarized using fund-quarter observation for each style category, respectively. All continuous variables are winsorized within each style category at the 2% and 98% percentiles to alleviate the concern on outliers.[13] Taking equity fund as an example, an average equity fund in our sample has a size of RMB 1.19 billion, an age of around 5 years, an annual return of 11%, and a daily return standard deviation of 141 bps. The standard deviation of fund annual return is 28.8%, 29.6%, and 13.8% for equity, mixed, and bond funds, respectively, indicating large variations both across funds and over time. Turning to the main variable of interest – fund flow, the average quarterly flows for equity and mixed funds are close to zero, with a standard deviation of around 30%. Bond funds, however, exhibit very volatile flow with a standard deviation of 74.1%, possibly driven by their heavy institutional ownership.

3 Performance Chasing in the Post-Platform Era

The emergence of FinTech platforms could lead to substantial changes in the mutual fund industry. Focusing on investors' performance chasing behaviors, in this section, we first compare and contrast the sensitivity of flow to fund past performance for periods before and after platform introduction. Direct evidence on platform-induced performance chasing is further provided, based on a proprietary dataset from Howbuy – one of the largest FinTech platform in China. Finally, utilizing the staggered sign-up dates of funds onto platforms, we provide plausibly causal evidence on the effect of platforms on performance chasing.

[13] Our results hold with alternative winsorization cutoffs at 1% or 2.5%.

3.1 Pre- and Post-Platform: Market-Wide Impact

We start by documenting the sensitivity of flow to fund past performance for the five years before (2008 to 2012) and five years after (2013 to 2017) the introduction of platforms. We use 2013Q1 as the beginning of the post-platform period because, following the initial issuance of platform licenses in February 2012, the first batch of funds become available for sale on the platforms around the end of 2012. To study the change in market-wide flow-performance relationship, we form performance-based deciles by sorting, at the beginning of each quarter, all the actively managed funds within each style category into ten groups, according to their respective cumulative raw returns over the past 12 months. The 12-month return horizon is chosen because FinTech platforms usually display mutual funds by their past 12-month returns in a descending order as a default setting. We then examine the quarterly flows to the ten performance deciles, summarized separately for the periods before and after the introduction of platforms.

As demonstrated in Figure 2, the flow-performance curve steepens dramatically in the post-platform sample for both equity and mixed funds, which is driven mostly by the increase in flow to the top decile. Focusing first on equity funds, pre-platform, there is some evidence of performance chasing, with the flow to the top-decile funds on average slightly higher than the flows to the other deciles. After the emergence of platforms, the magnitude of performance chasing increases strikingly. According to Panel A of Table 2, the top-decile average flow increases from 3.03% in the pre-platform period to 20.84% in the post-platform period, the difference of which is 17.81% with a t-stat of 3.19.

To further connect the amplified performance chasing to the emergence of platforms, we examine how the flow-performance sensitivity varies over time. If the drastic increase in flow-performance relation is driven by the introduction of platforms, we expect this amplification effect to take place only on and after 2013. The upper left panel of Figure 3 plots the excess flow (red line marked with "o") for top-decile equity funds quarter by quarter, with the shaded area indicating the 95% confidence intervals.[14] Focusing on the time-series variation around 2013, one can observe a sudden increase in the excess flow into the top-decile funds shortly after the introduction of platforms. The change is visible even within the narrow window of two years after the policy change. In comparison, according to the upper right panels of Figure 2 and Figure 3, the flow-performance sensitivity in the US remains stable around 2013. Top decile flows are around 6% in both the pre- and post-platform periods. Given that the distribution of US mutual funds is still under the traditional model and is not affected by the platform shock, it makes sense that the flow-performance sensitivity in

[14]Here, excess flow is measured as the difference between the top-decile flow and the flow averaged across all deciles.

the US is much lower than that for China's post-platform era.

For mixed funds, we observe a similar pattern with comparable magnitudes. In particular, top-decile mixed funds attract an average quarterly flow of 13.21% in the post-platform era, 9.37% (t-stat = 2.69) higher than their pre-platform level of 3.84%. For bond funds, however, the results are less conclusive. As reported in Panel A of Table 2, though the top-decile bond fund flow is on average higher in the post-platform period, it is not significantly different from that of the pre-platform period. At least two reasons contribute to the nosier pattern in the performance chasing of bond funds: First, as discussed in Section 2.3, the bond fund sample is rather small in the pre-platform period. China's fixed-income market, particularly the credit market, starts to take off only after 2010 (Geng and Pan (2019)). Second, bond funds are dominated by institutional investors, who presumably rely less on FinTech platforms to execute trades. As shown in Appendix Figure A2, the average institutional ownership for bond, equity, and mixed funds are 64.9%, 19.5% and 16.1% in the post-platform period, respectively. As FinTech platforms should primarily affect retail investors' trading behavior, we expect the platform effect to be weaker for bond funds. Due to the above reasons, we mainly focus on equity and mixed funds to study the impact of platform emergence in our subsequent analyses.

3.2 Direct Evidence from a Top FinTech Platform

Up to now, we document a sharp rise in performance chasing at the market level in the post-platform era. If platforms indeed amplify investors' performance chasing tendency, we should observe a higher level of performance chasing on platforms than in traditional channels. In this section, we provide direct supporting evidence using a proprietary dataset obtained from Howbuy, one of the top five platforms in China.[15]

To measure performance-chasing behavior, we compute the market share of purchase for each performance decile on Howbuy as well as the whole market. Specifically, in each quarter, we calculate this measure as the amount of all fund purchase in one decile divided by the total amount of fund purchase summed across the ten deciles on Howbuy (or the whole market). Thus, the market shares of purchase for the ten deciles add up to 100%. To allow for direct comparison between Howbuy and the whole market, we use the same sample of funds and the same 12-month performance decile rank for each fund in the calculation. Since the whole market data is the aggregation over all distribution channels (both on- and off-platforms) and Howbuy data is a pure representation of the platform economy, a comparison of the two enables us to visualize the transition from traditional channel to the platform channel.

[15]The dataset from Howbuy contains the share of purchase for funds in each performance decile, that occurred on their platform from 2015 through 2018. We thank Howbuy for providing this data.

Panel B of Table 2 reports the average top-decile market share of purchase on Howbuy and in the whole market from 2015 through 2018. Focusing first on equity funds, we find that an average of 49.37% of the quarterly purchases goes to the top-decile equity funds on Howbuy. That is, on pure platform trading, the top 10% funds claim close to 50% of the market share, which is much larger than the corresponding fraction of 37.61% in the whole market. Despite a relatively short sample period, the difference between Howbuy and the whole market is still marginally significant with a t-stat of 1.69. Mixed funds exhibit a similar pattern: An average of 39.50% of the quarterly purchases goes to the top-decile mixed funds on Howbuy, which is 10.47% (t-stat = 2.35) larger than that of the whole market during the same time. For bond funds, the contrast between Howbuy and the whole market is less pronounced, echoing the findings in Section 3.1.

As a graphical illustration, the upper panels of Figure 4 provide an intuitive comparison of the market share of purchase across the three samples, i.e., the pre-platform market, the post-platform market, and the Howbuy sample. For both equity and mixed funds, the top-decile market share of purchase is the largest on Howbuy – a pure platform channel, followed by the post-platform market – a combination of traditional and platform channels, and then followed by the pre-platform market – pure traditional channels. The time-series variation of the top-decile market shares, reported in the lower panels of Figure 4, adds further evidence on the effect of platform on performance chasing. For both equity and mixed funds, the top-decile market share of purchase in the whole market (blue line) increases sharply and immediately after the introduction of platforms. Moreover, top-decile market share of purchase on Howbuy (red line) is larger than that in the whole market for almost every quarter from 2015 trough 2018. In other words, although the magnitude of performance chasing fluctuates over time, the performance chasing tendency on platforms is almost always higher than that in the whole market.

3.3 Evidence from Staggered Fund Entrance onto Platforms

Section 3.1 and Section 3.2 provide suggestive evidence on the market-wide increase in flow-performance sensitivity after 2012, possibly associated with platform emergence. To further establish the casual impact of FinTech platforms on flow-performance sensitivity, we utilize the information of the exact dates on which each mutual fund signs up for the platforms. As shown in Figure 1, funds gradually adopted platform distribution, mainly in the first two years after platform introduction. This staggered entrance of funds onto the platforms provides a unique setting for us to precisely identify the platform effect on flow-performance sensitivity.

We measure the extent of fund i's platforms coverage using dummy variable $\text{Platform}_{i,t}$, which equals one when fund i at the beginning of quarter t is available on Tiantian or Ant Financial, the two biggest and dominant players in the market.[16] Using this fund-quarter-level variable $\text{Platform}_{i,t}$, we investigate the change in the flow-performance relationship in a panel regression setting as follows:

$$\text{Flow}_{i,t} = \alpha + \beta_1 \cdot \text{Decile10}_{i,t-1} + \beta_2 \cdot \text{Platform}_{i,t} + \beta_3 \cdot \text{Decile10}_{i,t-1} \times \text{Platform}_{i,t} + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t}\,, \quad (1)$$

where $\text{Decile10}_{i;t-1}$ is a dummy variable that equals one if fund i belongs to the top decile based on past 12-month cumulative raw return from quarter $t-4$ to quarter $t-1$, and zero otherwise. The coefficients on the interaction terms (Decile10×Platform) capture the platform effect, where a positive value indicates an increase in the flow to top-decile funds after they enter either of the two platforms. We include the natural logarithm of fund size, natural logarithm of fund age and fund's last quarter flow as controls, and further include time fixed effects to control for the effect of time-varying market conditions on fund flow in all specifications. The analyses are conducted both with and without fund fixed effects, and the reported t-statistics correspond to standard errors that are double clustered by fund and time.

The results are summarized in Table 3. For each fund style, we present regression results obtained using both a narrow window and a long window of sample period. The narrow window (2011–2014) focuses more precisely around the time of the introduction of platforms, which helps to pin down an immediate platform effect. Moreover, some years with unusual market condition are naturally excluded in this setting, alleviating the concern that changing market condition may affect the results.[17] In comparison, the long window (2008–2017) setting has the advantage of estimating a permanent platform effect, which can partially reduce the estimation noise in the narrow window specification.

We find a strong platform effect across all specifications. Focusing first on equity funds in the narrow window in column (1), the extra flow to the top-decile equity funds, benchmarking to other deciles, is on average 6.73% per quarter before joining the platforms. After signing

[16]Funds' entrance onto Tiantian and Ant are highly correlated. Our results are robust when defining platform entrance using Tiantian and Ant separately, and when using the total number of platforms. The details are discussed and reported in Appendix A3.

[17]In particular, the narrow window has the following benefits: First, the noisy year of 2015 is automatically excluded. The Chinese stock market experienced a dramatic crash in the second half of 2015, which may potentially introduce unusual investor behaviors. Meanwhile, the policy change introduced in August 2015 increases the minimum requirement of stock holding from 60% to 80% for equity mutual funds, causing many equity funds to switch to mixed funds in 2015Q3. Second, the narrow window specification also excludes 2008, the year of the global financial crisis, from the analysis.

up to the platforms, the same fund in the top decile would attract an additional quarterly flow of 10.53% (t-stat = 2.46). Further including fund fixed effects in column (2) to control for any time-invariant (unobserved) fund characteristics, consistently, we find that joining platforms brings an additional flow of 16.32% (t-stat = 3.33) for top-decile funds, which is 2.40 times the off-platform level. In other words, the magnitude of post-platform performance chasing more than triples its pre-platform level. Note that the platform effect becomes even larger after we control for fund fixed effects. Therefore, the large increase in performance chasing is not caused by some funds with an unconditionally higher level of flow that self-select to enter platforms. Repeating the analyses using the long window, we find a similar economic and statistical significance on the Decile10 dummies and the interaction terms. In particular, the quarterly excess flow to top-decile equity funds, benchmarking to other deciles, increases by 14.20% from their pre-platform level of 6.62% after joining platforms.

For mixed funds, we observe a rather similar pattern. In the narrow window specification in column (5), top-decile mixed funds off platforms attract an excess flow of 4.60% per quarter, which is slightly smaller than the corresponding estimate for equity funds (6.73%). Post platforms, we observe a substantial increase in performance chasing. Benchmarking to their off-platform counterparts, top-decile mixed funds attract an additional flow of 11.79% per quarter on platforms, which is 2.56 times the off-platform level. The estimates are qualitatively the same when estimated with fund fixed effects and under the long window specifications. Overall, these results suggest that the estimates on the platform effect are robust across difference specifications.

Placebo Test on Platform Entrance

One might be concerned that the platform effect may be driven by some confounding factors unrelated to platform entrance. For example, the post-platform market may contain more extrapolative and speculative investors, whose responses to past performance are highly convex. To investigate the possibility that our results are driven by market-wide changes or factors unrelated to platform introduction, we conduct a placebo test. Specifically, we ask the following question: Suppose we randomly assign a fund to be an on-platform or off-platform fund, how likely can we obtain a platform effect that is equivalent to the magnitude in our previous tests?

To this end, we randomly reshuffle the value of the platform dummy across funds and meantime maintain its overall distribution within each quarter. That is, we require the fraction of funds on the top two platforms to equal to the true value in each quarter, but randomize on which funds in the sample are on platforms. Then, we re-estimate the baseline regression in Equation (1) based on those pseudo platform dummies and save the coefficient on Decile10×Platform. For brevity, we focus on the long window specifications with fund fixed effects in Table 3. We repeat this analysis for 1,000 times and report the distribution of the coefficient estimates in Figure 5.

As is obvious from the figure, the actual estimates in columns (4) and (8) of Table 3, denoted by the green dotted lines, lie well in the right tail of the entire distribution of the coefficient estimates from the placebo tests. Due to the swift adoption of platforms, the fraction of funds on platforms increases over time, and the platform dummies in the randomized samples tend to correlate with the actual value. Therefore, we naturally observe an average positive coefficient on Decile10×Platform across the simulated samples. However, the increase in the magnitude of flow-performance sensitivity in the actual sample is still significantly larger than that estimated using the simulated samples. In particular, out of the 1,000 simulations, the actual coefficient estimate of 14.20% for equity funds is larger than 94.9% of the placebo estimates in the simulated samples, i.e., our actual estimate is a 5.1% event in the simulated sample. For mixed funds, with a larger sample and larger cross-fund platform variation, the actual coefficient estimate of 17.04% happens with an extremely rare probability, as it exceeds 99.8% of the placebo estimates. The evidence suggests that the actual entrance dates of individual funds onto platforms contain important information in the identification of the platform effect.[18]

4 Understanding Post-Platform Performance Chasing

Investor behavior is influenced by the information fed to them – a fact made abundantly clear by the emergence of social-media platforms in disseminating information to the public. Likewise, FinTech platforms distribute to their giant user bases not only financial products, but also information, which in turn drives investor behavior. In this section, we study the extent to which the post-platform increase in performance chasing is the outcome of the uniquely centralized information distribution on FinTech platforms.

4.1 The Platform Effect: Centralized Information Distribution

Prior to the arrival of FinTech platforms, information and product distributions to mutual-fund investors are decentralized and multifaceted. Investors purchase from dispersed sources, either directly from the fund families or indirectly from the local branches of hundreds of banks and brokers, each offering their own collections of funds with fund advisers dispens-

[18]To further alleviate the concern that our results are driven by confounding events or time-varying market conditions unrelated with platform entrance, we conduct and discuss a battery of robustness tests in Appendix A3.

ing recommendations according to their own incentives. By contrast, information flow on FinTech platforms is highly centralized and uniform. Investors on FinTech platforms are essentially fed the same information – the front page of their mobile apps displays mutual funds by their past n-month returns in a descending order, with n=12 as a common default choice. Depending on the screen size of the mobile devices, the front page contains roughly 8 to 12 funds, making those front-page funds highly visible to all platform investors regardless of where such investors live or which platform they are using. Imagine massive number of investors reacting almost simultaneously to identical information via FinTech platforms, even a small amount of performance chasing by a small fraction of the population can be synchronized into the significant performance chasing observed in the post-platform era.

Front-Page Visibility in the Post-Platform Era

To test this channel of synchronized performance chasing, we focus our analysis on the front-page funds. As there can be thousands of funds in each style category and investors are unlikely to scroll down for hundreds of pages, the front-page visibility could be an important determinant of the platform-induced flow. In particular, our hypothesis is that the platform effect is the strongest for the few very top funds and then weakens for funds outside the front page. By contrast, this sharp prediction of front-page visibility does not apply to the pre-platform era, as, lacking the synchronization mechanism and the product distribution offered by the platforms, most investors chase top-ranked funds only within their own segmented universe of funds.

Indeed, as shown in the upper panel of Figure 6, pre-platform, the performance chasing is mostly flat among the top 30 funds – relative to the group of funds ranked below 30, the excess flow to the top 1–3 (front-page) funds is 8.19%, similar in magnitude to an average of 3.55% from top 19 to top 30 (off front-page) funds. Post-platform, the excess flow to the top 1–3 funds increases to 44.60%, 36.39% larger than its pre-platform level. While the excess flow to the top 19 to top 30 funds also increases, the average magnitude of 9.20% is significantly smaller than those for the front-page funds.[19] For brevity, we pool equity and mixed funds together in this analysis. The results are qualitatively the same for each style when we conduct the analysis separately. The lower panel of Figure 6 further plots the differences in the on- and off-platform performance chasing across the top 30 funds. We find that the post-platform increase in flow is the largest for funds ranked above top 12 and then drops gradually in magnitude and statistical significance outside of the top 12 ranking. In particular, the on and off-platform flow difference is on average 23.01% for the

[19]The flows to the Top-X funds are estimated in a regression setting similar to column (4) and column (8) in Table 4.

top 1–12 funds, whereas this difference is only 5.65% for the top 19–30 funds, suggesting a much weaker platform effect for the off-platform funds. In our setting, investors can scroll down to view lower ranked funds and there is not a clear cutoff point in ranking associated with the front-page visibility. Nevertheless, we still observe an economically and statistically significant platform effect for the top 12 funds on the front page.

Closeness to the Front Page

In addition to focusing on just a few front-page funds, we further extend the idea of front-page visibility to include the broad set of funds in our analysis. For each fund, we measure its closeness to the front page by sorting it into one of the four ranking groups – "Top 10" for the top-10 ranked funds, "Top 11–30" for top 11 to 30, "Top 31–50" for top 31 to 50, and the rest ranked below 50 in the whole fund universe. We then examine the front-page effect in the following regression specification:

$$\begin{aligned}\text{Flow}_{i,t} = \alpha + \beta_1 \cdot \text{Top10}_{i,t-1} + \beta_2 \cdot \text{Top11–30}_{i,t-1} + \beta_3 \cdot \text{Top31–50}_{i,t-1} + \beta_4 \cdot \text{Platform}_{i,t} \\ + \beta_5 \cdot \text{Top10}_{i,t-1} \times \text{Platform}_{i,t} + \beta_6 \cdot \text{Top11–30}_{i,t-1} \times \text{Platform}_{i,t} + \beta_7 \cdot \text{Top31–50}_{i,t-1} \times \text{Platform}_{i,t} \\ + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t}\,, \quad (2)\end{aligned}$$

where Top10, Top11–30, and Top31–50 are the front-page dummies defined using past 12-month raw returns. The coefficient on the interaction terms, Top-$\text{X}_{i,t-1} \times \text{Platform}_{i,t}$, capture the additional flow after a Top-X fund is available for purchase on platforms, i.e., the joint effect of centralized information and fund distribution via FinTech platforms. We also control for all the performance rank dummies, fund $\text{Log(Size)}_{i,t-1}$, $\text{Log(Age)}_{i,t-1}$, and Flow_{t-1}. Fund fixed effects and time fixed effects are included in all the specifications.

The corresponding results are reported in Table 4. Funds that are closer to the front page of a FinTech app experience a larger increase in fund flow in the post-platform period: Taking equity funds as an example, in the long window estimation with fund fixed effects, the increase in flow in the post-platform period is 30.00%, 12.24%, and 9.18% for Top 10, Top 11 to 30, and Top 31 to 50 funds, respectively. Across all regression specifications, the magnitude of the platform effect drops uniformly with the drops in performance ranking. This pattern is exactly what we expect: As investors scroll down the performance rank list, they may view and invest in the funds that are closer to the front page with a higher chance. Therefore, the increase in flow is positively related to funds' closeness to the front page. Moreover, comparing the economic importance of front-page visibility with that of the performance Decile ranking, we find that the platform-induced performance chasing is overwhelmingly stronger for front-page funds. In particular, for a well-performed top decile equity fund, the increase in flow in the post-platform period is 14.2%, less than half of the magnitude for top-10 ranked funds. The contrast between Decile ranking and front-page ranking, in the post-platform era, also points to the important role of front-page visibility in explaining platform-induced synchronized performance chasing.

4.2 Default Ranking Choice

FinTech platforms offer investors the discretionary to sort funds, within each style category, by their past cumulative raw returns in the horizon of 3, 6, 12, and 36 months. Though the front-page interface could differ across different platforms, many use 12-month raw return as the default setting. If the centralized information distribution does contribute to the amplification in performance chasing, we expect the performance measure that is most often being used as the default choice to have the strongest explanatory power of platform-induced flow. In particular, we compare and contrast our baseline front-page effect with those estimated using performance measures with different look-back horizons and when ranked by fund alphas.

To offer preliminary evidence, we begin by estimating the front-page effect under alternative performance measures following the same regression specification as in columns (4) and (8) of Table 4. Figure 7 plots the coefficient estimates on the interaction term, Top10$\times$Platform. Focusing on equity funds in the upper graph, we find that the default ranking of 12-month raw return generates the highest coefficient estimate among all the look-back windows. For a top 10 fund defined based on the past 12-month cumulative raw return, the on-platform flow is 30% higher than the off-platform flow; while the platform-induced flow is only around 20% when performance ranking is defined based on the nearby horizons of 9 months and 15 months. Since the nearby horizons differ from the default horizon by only three months, the abnormal flow to the 12 months rank points to the importance of default ranking in the platform era. Coefficient estimates for mixed funds yield a similar pattern: 12-month raw return generates the highest on- and off-platform flow difference of 32%, followed by the 6-month and 9-month specification of 30%, and the rest of around 20%.

Apart from the horizon of returns, another important feature of the default choice is that platforms rank funds based on their raw returns, instead of risk-adjusted returns, which may prohibit investors from learning about funds' true skills or alphas. To test such a hypothesis, we compare the power of raw return defined ranks with the alpha defined ranks in driving the platform flows. As shown by Barber, Huang, and Odean (2016), investors attend most to market risk (beta) when evaluating funds in the US. Therefore, we compute fund alpha using a two-factor model that includes a bond market factor and a stock market factor. We use the value-weighted equity and bond fund returns for market portfolio, and the one-year deposit rate as the risk free rate. Fund alphas are estimated using daily observations in the corresponding look-back window. As is obvious from Figure 7, the coefficient estimates on Top10×Platform are uniformly lower when estimated using alphas (grey bars), compared to that estimated using raw returns (blue bars). In the case of 12-month horizon, the best alpha funds attract an extra platform flow of 18.5%, which is only around half the magnitude of 32% estimated for the best raw return funds.

Figure 7 provides suggestive evidence that the 12-month-raw return matters more in driving the platform-induced flow, compared with other performance measures. To offer further evidence, Table 5 conducts a horse-race test between our baseline performance measure and each of the alternative performance measures. In particular, we simultaneously estimate the front-page effect using performance ranks defined based on 12-month raw returns and the performance ranks defined under measure X in the following regression specification:

$$\begin{aligned}\text{Flow}_{i,t} &= \alpha + \beta_1 \cdot \text{Top10}_{i,t-1} \times \text{Platform}_{i,t} + \gamma_1 \cdot \text{Top10}^X_{i,t-1} \times \text{Platform}_{i,t} \\ &+ \beta_2 \cdot \text{Top11–30}_{i,t-1} \times \text{Platform}_{i,t} + \gamma_2 \cdot \text{Top11–30}^X_{i,t-1} \times \text{Platform}_{i,t} + \beta_3 \cdot \text{Top31–50}_{i,t-1} \times \text{Platform}_{i,t} \\ &+ \gamma_3 \cdot \text{Top31–50}_{i,t-1} \times \text{Platform}_{i,t} + \beta_4 \cdot \text{Platform}_{i,t} + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t}, \quad (3)\end{aligned}$$

where Top10, Top11–30, and Top31–50 are the front-page dummies defined using past 12-month raw returns, and Top10^X, Top11–30^X, and Top31–50^X are the performance dummies defined under alternative measures of X. We control for all the performance rank dummies, fund Log(Size)$_{i,t-1}$, Log(Age)$_{i,t-1}$, and Flow$_{t-1}$. Fund fixed effects and time fixed effects are included in all the specifications.

Table 5 reports the coefficient estimates of β_1 and γ_1 estimated for different performance measures of X. The coefficient estimates for Top10×Platform are significant across all the 26 horse-race specifications, with a magnitude ranging between 19.50 to 34.97. It suggests that controlling for the effect of alternative performance ranks, the explanatory power of 12-month raw return remains strong both economically and statistically. Moreover, the coefficient estimates for Top10×Platform are bigger than that of Top10^X×Platform for 25 out of the total 26 horse-race tests (a winning rate of 96%). The only exception occurs in the horse-race test with the performance measured by past 6-month raw return, where the coefficient estimates for Top10×Platform and Top10^X×Platform are very close at 19.98 and 20.98, respectively. The difference of the two is also insignificant with a F-stat of 0.02.[20]

Overall, our evidence suggests that centralized information distribution, and in particular, the specific performance measure (e.g., 12-month raw return) in which platforms rank funds,

[20]It is not surprising to observe a big coefficient estimates for the horizons of 3M and 6M, as they are provided as alternative ranking choices on many platforms.

plays an important role in driving the front-page effect, which lends further support to the causal impact of platforms on the amplified performance chasing that we observe.

4.3 Intra-Family Ranking as a Placebo

To shed further light on the importance of centralized information distribution in explaining the amplified performance chasing, we compare and contrast the sensitivity of investor flow to fund's intra-family ranking pre- and post-platform. As a major distribution channel in the pre-platform era, fund families offer funds under their brand umbrella. With individual funds competing for limited capital attracted through their family brand, fund's performance ranking within the family can be an important determinant of flow (Kempf and Ruenzi (2007)). Moving from the family edge to the platform edge, the centralized platform distribution disrupts the information structure of the entire mutual fund industry. In particular, platforms rank funds within each style by their past performance, irrespective of which family they are from. As intra-family ranking is not displayed on platforms, we expect the sensitivity of flow to funds' intra-family ranking to stay the same pre- and post-platform.

To test this hypothesis, we examine the response of flow to the intra-family performance ranking in the pre- and post-platform period. We require a family to have at least five funds under its brand to be included, which reduces our fund-quarter observations slightly. Since the average number of funds in a family is 8.74 for the pre-platform sample, we focus on the performance quintile ranks as opposed to the decile ranks within each family. Following the long window specification with fund fixed effect in Table 3, we create the family top quintile dummy (FMQuintile5) and its interaction with the Platform dummy. FMQuintile5 equals one if a fund's return in the past twelve months belongs to the top quintile within its own fund family, and zero otherwise.

As shown in Table 6, though flow positively responds to funds' intra-family ranking in the pre-platform era, there is not any significant increase in the post-platform era. Taking equity funds as an example, before a fund joins platforms, being in the top quintile group of its own family helps obtain an additional flow of 2.96%. Post platform, the sensitivity of flow to funds' intra-family ranking remains at a similar magnitude , as reflected in a small and insignificant coefficient on FMQuintile5×Platform. In contrast, the position of a fund in the whole universe becomes more important. A top-decile fund in the whole fund universe enjoys an extra flow of 15.35% after it joins the platforms, controlling for the effect of intra-family ranking.[21] For mixed funds, we observe a similar pattern. Before a fund joins platforms, being in the top family quintile and top platform decile attracts an additional flow of 3.12%

[21] Since intra-family ranking and universal ranking tend to correlate with each other, we rely on column (3) and (6) to disentangle the relative importance of the two.

and 1.16%, respectively. Post platform, the same fund attracts an extra insignificant flow of 1.43% for being in the top family quintile, and an extra significant flow of 15.63% for being in the top platform decile.

In summary, by studying the time-varying importance of funds' performance ranking within its family and in the whole fund universe, we offer evidence on the uniqueness of platform ranking in explaining the amplified performance chasing. The absence of platform effect within fund families suggests that the amplified performance chasing is closely tied to the information display of platforms, and it cannot be explained by a market-wide general tendency to chase performance.

4.4 Centralized Distribution in Synchronizing Retail Behavior

Since FinTech platforms are introduced to facilitate retail investors in the investment of mutual funds, institutional investors, equipped with in-depth research and sophisticated financial expertise, are less reliant on the centralized platform distribution. Comparing the behaviors of retail and institutional investors, in response to the introduction of platforms, offers another way to identify the platform effect. With individual investors' tendency to chase past winner funds synchronized and amplified via the platform information display, we expect the increase in post-platform performance chasing to be mostly driven by retail flows, instead of institutional flows.

Utilizing the additional information on fund investor composition, we decompose fund flow into two components – retail and non-retail flows – and examine the platform effect on each components. In particular, retail flow is computed using the following formula:

$$\text{Retail Flow}_{i,t} = \frac{\text{TNA}_{i,t} \cdot \text{Retail Ratio}_{i,t} - \text{TNA}_{i,t-1} \cdot \text{Retail Ratio}_{i,t-1}(1 + \text{Ret}_{i,t})}{\text{TNA}_{i,t-1}}, \quad (4)$$

where $\text{Retail Ratio}_{i,t}$ is fund i's retail ratio at the end of quarter t.[22] Institutional flow is computed accordingly. Table 7 reports the pre- and post-platform flow-performance sensitivity using retail and institutional flows as the dependent variables. Consistent with our hypothesis, we observe a much larger platform effect for the retail flow than the institutional flow. Taking equity funds as an example, retail flow increases by 20.75% for the top-10 ranked platform funds, benchmarking to the same top 10 funds off-platform. By contrast, the corresponding increase in institutional flow is only 6.50%. Moreover, the increase in retail flow is positively related to funds' closeness to the front page, whereas the increase in

[22] Retail ratios are available at the semi-annual frequency. To match with the flow frequency in our baseline results, we interpolate the variables linearly to obtain quarterly values. Our results are qualitatively the same if we conduct the analyses at semi-annual frequency without interpolation.

institutional flow is relatively flat across the top 50 funds. Specifically, for top 10, 11–30, and 31–50 funds, the post-platform increase in retail flows are 20.75%, 8.94%, and 5.25%, respectively, dropping precipitously with the performance ranking of funds. For the increase in institutional flow, the contrast is less obvious: 6.50%, 2.16%, and 3.00% for top 10, 11–30, and 31–50 funds. Repeating the same exercise for mixed funds, we find a qualitatively similar pattern. Taken together, we find that institutional investors exhibit a weak pattern of performance chasing, and the platform effect is mainly driven by retail investors.

4.5 Reduction in Participation Costs

Apart from the centralized distribution, FinTech platforms also substantially reduce the information costs and the transaction costs of participation. In terms of search costs, investors can access detailed documents of fund prospectus and managerial background information via a few clicks on the platform apps. As both Tiantian and Ant waive 90% of the front-end loads for all funds offered on the platforms, investors also face a much lowered transaction costs when investing with platforms.

Ex ante, it is unclear how reduction in participation costs would affect the flow-performance sensitivity. In the framework of Huang, Wei, and Yan (2007), investors consider both the fund past performance and his participation costs in each fund when deciding which funds to learn about. The performance chasing effect is then more pronounced for funds with higher participation costs, as investors will only investigate and eventually invest in a few funds with superior performance. A reduction in participation costs then implies a lower cost of learning and lower performance threshold for the candidate pool of funds, which should lead to a weakened pattern of performance chasing. On the other hand, if platform attracts new investors who are originally being excluded from the mutual fund investment, and for whatever reasons, are more reliant on funds' past performance in their decision making, reduction in participation cost could lead to a more pronounced performance chasing in the aggregate.

To better understand whether participation costs play a role in explaining the amplified performance chasing, we examine the pre- and post-platform flow-performance sensitivity for subsamples of funds conditional on their reductions in participation costs. Following Huang, Wei, and Yan (2007), we proxy for the information costs of funds using various fund characteristics that capture the visibility and information barriers of funds. In particular, funds with higher marketing expenses and funds from large families, are endowed with higher visibility before the platform introduction, and hence less reduction in information cost afterwards. To capture reduction in transaction costs, we use the front-end loads of funds. Platforms waive the front-end loads when investors initially purchase the fund, while the back-end loads charged when they sell the fund are not waived. Hence, transaction costs are substantially reduced for funds that charge a high front-end loads, while less so for back-end-load funds.

Appendix Table A2 reports the subsample results conditional on various proxies of participation costs, following the baseline specification as in Table 3 and Table 4. For funds with low participation costs in the pre-platform era, i.e., funds from big families, with high marketing expenses, and funds that charge low front-end loads, we find a similar pattern of platform effect both economically and statistically, benchmarking to their high participation costs counterparts. For example, as reported in Panel B of Appendix Table A2, a top-10 fund with above-median front-end loads attract an extra flow of 30.5% after platform entrance, which is similar in magnitude to the value of 26.7% estimated for funds with below-median front-end loads. Overall, the subsample analyses suggest that participation costs is not a key driver for the documented amplified performance chasing.

5 Managerial Incentives and Fund Performance

In analogy to other two-sided market (e.g., P2P, e-commerce), the systematic behavior change from the investor side affects the managerial incentives on the other side of the market. Fund managers, with an objective to maximize the total assets under management, might change their risk taking strategically in response to the shape change in the flow-performance relation, as demonstrated by the seminal work of Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997). With the flow-performance relation becoming much more convex in the winner end of the curve, we study in this section whether or not the amplified performance chasing induced by platform investors would lead to amplified distortion in managerial incentives. To further establish the real impact and study the welfare implications of platform introduction, we also explore how the platform-induced performance chasing affects fund performance.

5.1 Increased Risk-Taking by Fund Managers

We start by examining how the synchronized tendency to chase past winner funds affects managerial risk taking. At the beginning of each quarter, we estimate the closeness of each fund to the top-performer list using its relative performance over the past nine months and gauge its subsequent risk taking over the next three months. In structuring this test, our hypothesis is that, attempting to get into the 12-month top-performer list, funds that are closer to the top by the 9-month mark have stronger incentives to "gamble" over the next three months. This approach follows the original test of Chevalier and Ellison (1997), who, assuming that investors react to year-end fund performances, use the January-September returns as main information variable to differentiate funds that are more likely to gamble and then test the hypothesis by focusing on their subsequent fourth-quarter risk taking. We perform our analysis at the quarter end, as in the post-platform era, fund rankings are updated continuously and there is no need to fix the test at the year end. We adopt the same 12-month horizon, as discussed in Section 4.2, one of the default settings prevalent on FinTech platforms is to display mutual funds within each category according to their past 12-month returns.

To formally test our hypothesis of platform-induced risk taking, we apply quarterly panel regressions of the following form:

$$\text{Vol}_{i,t} = a + b\,\text{Platform}_{i,t} + c\,\text{Decile10}_{i,t-1} + d\,\text{Decile10}_{i,t-1} \times \text{Platform}_{i,t} + \varepsilon_{i,t}\,, \tag{5}$$

where, for each fund i, $\text{Vol}_{i,t}$ measures its risk taking in quarter t, $\text{Platform}_{i,t}$ captures its entrance onto the platform by quarter t, and $\text{Decile10}_{i,t-1}$ is a dummy that equals one if fund i ranks among the top decile within its style category, based on past 9-month return up to the end of quarter $t-1$. As in any difference-in-difference approach, the coefficient of the most interest is associated with the interaction term, which captures the post- and pre-platform difference in risk taking between a top-decile fund and a non-top-decile fund. We further include time and fund fixed effects as well as fund-level variables measured up to quarter-end $t-1$ to take out the influences on fund volatility unrelated to managerial incentives or platform entrances.

The fund's risk taking, $\text{Vol}_{i,t}$, is measured in three dimensions. Using the daily fund returns in quarter t, we first calculate the fund's total volatility, and then use a two-factor model that includes aggregate stock and bond portfolios to decompose the total volatility into systematic and idiosyncratic volatilities. We use the value-weighted equity fund returns for the stock market portfolio, and the value-weighted bond fund returns for the bond market portfolio. The one-year deposit rate is used as the risk free rate. The factor loadings are estimated using the daily returns within each quarter.

Panel A of Table 8 reports the results. Consistent with our hypothesis, with amplified performance chasing, arises amplified distortion in risk taking. Focusing first on the results for total volatility, pre-platform, we do not find a significant relation between the likelihood to gamble and subsequent managerial risk taking. The pre-platform difference in total volatility between top-decile funds and other funds is -0.56 bps per day and statistically insignificant. Post-platform, the top-decile funds increase their risk taking more relative to the funds in other deciles – the difference in total volatility between the top-decile funds and the other funds increase by 8.84 bps per day for equity funds and 11.01 bps per day for mixed funds, equivalent to an annualized volatility of 1.40% and 1.74%, respectively, which are significant both economically and statistically.[23]

Turning next to the results on systematic and idiosyncratic risk taking, we see that, pre-platform, fund managers of a top-decile fund "gamble" by taking more idiosyncratic risk (i.e., security selection) over the subsequent quarter. The pre-platform extra idiosyncratic volatility is 3.46 and 3.50 bps per day for equity and mixed funds, respectively. Post-platform, the differences in idiosyncratic volatility remain almost unchanged as the coefficients on the interaction term are small and insignificant. In other words, even though the managerial incentives for extra risk taking is high in the post-platform era, such fund managers do not significantly take more risk in the form of idiosyncratic volatility. One direct interpretation of this result is that, pre-platform, fund managers have already exerted their skills in security selection, and, in spite of the amplified incentives in the post-platform era, there is little room for further improvement.

While taking uninformed idiosyncratic risk does not get rewarded, fund managers know very well that leveraging on systematic risk do earn extra risk premium. Moreover, since investors exhibit the strongest sensitivity to fund past raw returns, instead of risk-adjusted excess returns (Section 4.2), managers are not penalized by leveraging on the systematic factor. Indeed, our results show that, post-platform, fund managers gamble by taking on more systematic risk and earning the extra market risk premium. The pre-platform differences in systematic volatility between a top-decile fund and a non-top-decile fund are in general small and statistically insignificant, indicating that, pre-platform, fund managers do not take additional systematic risk to get into the top-performer list. Post-platform, top-decile funds dial up their exposures in systematic risk relative to the other funds – the difference in systematic volatility increases by 8.04 and 10.87 bps per day for equity and mixed funds, respectively. Compared with the daily volatility of 100 bps of a typical mixed fund, such increases in risk taking are significant economically.

In an alternative setting, we further capture funds' incentive to gamble by their closeness to the front page of a FinTech app. We sort funds, within each category, by their past 9-month returns into four ranking groups – "Top 10" for the top-10 ranked funds, "Top 11–30" for top 11 to 30, "Top 31–50" for top 31 to 50, and the rest ranked below 50. We follow the same specification as in Equation (5), with the Decile ranking replaced by "Top-X" dummies (Top 10, Top 11–30, and Top 31–50). All three "Top-X" (Top 10, Top 11–30, and Top 31–50) groups are included, and the respective regression coefficient picks up the cross-fund difference in risk taking relative to the group of funds ranked below 50. Panel B of Table 8 reports the corresponding results, and the evidence is consistent with those reported

[23]Interestingly, the result is slightly stronger for mixed funds, which are less volatile than equity funds but can dynamically adjust portfolio across bond and equity, indicating time-varying exposures to systematic risk as a channel of increased risk-taking.

in Panel A. For example, post-platform, the difference in systematic volatility between funds in the Top 10, Top 11-30, and Top 31–50 groups and those in the below-50 group increases by 22.3, 7.5, and 5.1 bps per day for mixed funds, respectively. The increase in risk taking is especially strong for the Top 10 group and is mostly driven by their systematic risk taking. For idiosyncratic risk taking, post-platform, we observe a risk taking increase of 4.75 bps and 7.8 bps for the Top 10 equity and mixed funds, benchmarking to the below-50 ones. However, the economic magnitude is small, considering that the corresponding increases in systematic risk taking are 15.4 bps and 22.3 bps, respectively, for equity and mixed funds.

Overall, relative to the literature on how certain investor behavior can engender managerial incentives, our findings are unique and important in that the advent of FinTech platform offers a brand new and plausibly exogenous shock in investor behavior – akin to the winner-take-all phenomenon in the platform economy, the top-ranked funds attract disproportionately high flows from investors in the post-platform era. Accordingly, such shift in investor behavior affects managerial incentives in a rather significant way – in their attempt to get into the top-performer list and capture the amplified flow, fund managers dial up their risk taking. Having already exhausted their skills in security selection (i.e., idiosyncratic risk), fund managers gamble by taking on more systematic risk and earning the extra market risk premium. As FinTech platforms further disrupt the existing distribution channels of mutual funds and seize market shares globally, this finding of increased systematic risk exposure could have important ramifications in market stability.

5.2 Fund Performance

Our results have shown that the entrance of FinTech platforms alters investor behavior, which in turn distorts managerial incentives. But to what extent does the presence of FinTech platforms affect fund performance? Given the prevalence of amplified performance chasing on FinTech platforms, we then focus our analysis on whether or not top-performing funds continue to outperform. Following Carhart (1997), the answer is in general a resounding negative – mutual funds do not exhibit performance persistence, and the performance chasing by mutual-fund investors does not pay.

Consistent with this general observation, Table 9 shows that, top-performing funds fail to outperform both in the pre- and post-platform era. In particular, we measure funds' post-ranking performance by the 12-month return that starts shortly after the performance ranking (i.e., month 4 to 15).[24] We find that, pre-platform, the return difference between

[24] We estimate funds' future performance as a function of its past performance rank, in a panel regression setting, controlling for time fixed effects as well as fund-level variables measured up to the end of the performance ranking quarter t. The first three months immediately after the performance ranking is skipped

top-decile and non-top-decile equity funds is only 0.065% and statistically insignificant. Post-platform, this return difference largely remains the same for equity funds, as indicated by a small and insignificant coefficient estimate on Decile10×Platform. A similar pattern is observed for mixed funds. Overall, these results suggest that the performance chasing by mutual-fund investors is not value-enhancing.

In addition to fund return, investor welfare is also affected by the risk of fund and the corresponding risk-return tradeoff. In particular, Section 5.1 shows that top-ranked fund managers dial up their systematic risk taking, in the attempt to capture the amplified performance chasing. Managers' post-platform extra risk taking may undermine investors' risk and return tradeoff. Table 9 proceeds to examine the cross-fund difference in the standard deviation and Sharpe ratio of fund returns for the 12-month period after the performance ranking. Specifically, fund standard deviation is calculated based on the 12 monthly return observations in the post-ranking period. Annualized Sharpe ratio is measured as the monthly excess returns multiplied by the square root of twelve, divided by their standard deviation. Consistent with the increased risk taking documented for the pre-ranking period in Section 5.1, we observe an increase in the standard deviation of fund returns in the post-ranking period as well. For top decile equity and mixed funds, benchmarking to the other funds, the monthly standard deviations in the post-ranking 12-month period increase by 0.34% and 0.70%, respectively, after platform entrance. Associated with this increase in standard deviation is a slight decrease in annualized Sharpe ratio of -0.24 for equity funds.

Generally speaking, it is challenging to identify a causal effect of platform entrance on fund performance under an event study approach. On one hand, the power of asset pricing tests typically relies on data from a long time period. On the other hand, if extending our sample period to include return data long after the staggered entrance of funds, we are less confident to attribute any change in fund performance to funds' platform entrance. Caught in this dilemma, the current empirical findings on fund future performance are naturally inconclusive.

Nonetheless, the existing literature provides extensive theories and empirical findings on the potential negative impact on fund performance in our setting. In particular, the decreasing returns of scale effect in Berk and Green (2004) might be exacerbated by the platform-induced excessive flows. The deterioration in return from managerial risk-shifting might intensify as top ranked fund managers attempt to capture the amplified performance chasing (Huang, Sialm, and Zhang (2011)). Coupled with these arguments, our previous findings on post-platform amplified performance chasing and changing managerial risk taking suggest that fund performance could suffer in the long run. As FinTech platforms are adopted

to avoid mechanical increase in return driven by investors' capital flow.

more broadly across the globe, our findings call for the attention from FinTech regulators to safeguard the welfare of mutual-fund investors.

6 Conclusions

The success of the platform economy has transformed the way we live, and the emergence of FinTech platform intermediation for financial products may lead to one of the next disruptions of the platform economy. Just as other products and services such as retail goods or taxi rides are important to our daily lives, financial products are of unique importance because of their impact on the allocation of financial capital in the economy. Financial products are also unique in their ex-ante opaque quality, acute sensitivity to information, and their inherent liquidity, making their intermediation difficult to control, especially during adverse market conditions. These considerations, along with the rapid expansion of technology in financial intermediation over the recent years, make it all the more important for practitioners and policy makers to understand the economic impact of bringing financial products to large-scale, tech-driven platforms.

Our paper contributes to this fast-growing area by providing, for the first time in the existing literature, empirical evidences on the profound impact of platform distribution on the asset management industry. FinTech platforms integrate mutual fund investment into our everyday life. Through a few clicks on mobile phones, investors can access the entire universe of funds. This substantially lowers the barriers for individual investors to invest in complicated financial products. However, distributional efficiency does not necessarily translate into allocational efficiency. The amplified performance chasing documented in our paper is one very important example of the unintended consequences of the platform economy entering the industry of financial intermediation. Given that there is no evidence of performance persistence in mutual funds, either in the US or in China, performance-chasing investors on the platforms are not using the technological efficiency to help themselves build more efficient investment portfolios.

Moreover, improvements in means of connectivity do not necessarily equate to improvement in means of production. With amplified performance chasing, arises amplified distortion in managerial incentives. In the presence of large-scale platforms, fund managers dial up their risk taking to enhance the probability of getting onto the top rank. As FinTech platforms are adopted more broadly both within China and across the globe, this finding of increased systematic risk exposure could have important ramifications in market stability.

Effective financial practices and regulations build on clear understanding and reliable data. Relative to the traditional distribution channels, platform companies, equipped with superior customer data and advanced analytical technology, do have comparative advantages in offering financial services to their customers in the new era. The empirical evidences documented in this paper serves to better inform researchers, practitioners, and policy makers. In particular, our findings lead us to believe that platform companies need to move beyond technology and incorporate insights from finance and economics in the design of their systems — to achieve not only technological efficiency but also financial efficiency and to improve not only means of connectivity but also means of productivity. Consequently, how to design policies to alleviate the unintended consequences documented in our paper while maintaining the technological advantages of FinTech platforms presents a challenge as well as an opportunity for platform companies.

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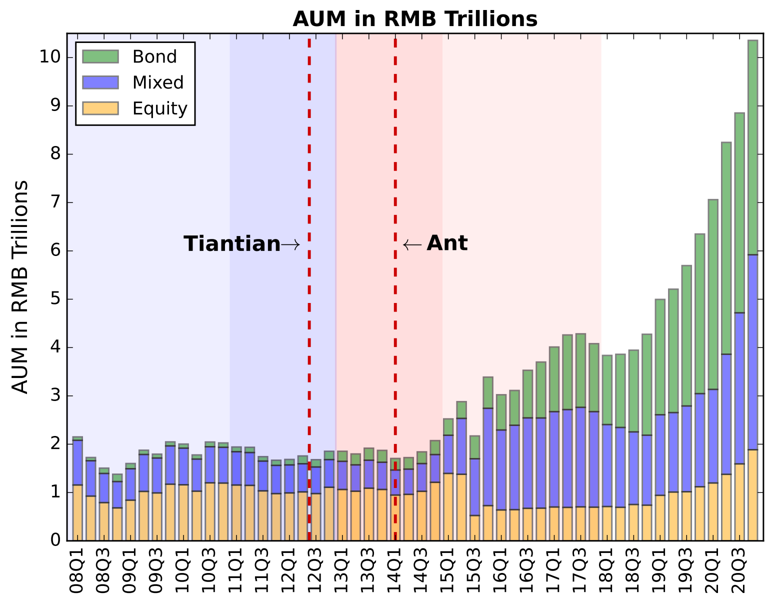
Figure 1. Introduction of Platforms

The upper graph reports the aggregate industry size for equity, mixed, and bond mutual funds from year 2008 to 2020. The lower graph shows the coverage of mutual funds on major platforms as a fraction of the whole universe of funds. The two vertical lines denote the entrance of Tiantian and Ant Financial into the platform business. Dark (light) shaded areas exhibit two (five) years around the introduction of platforms.



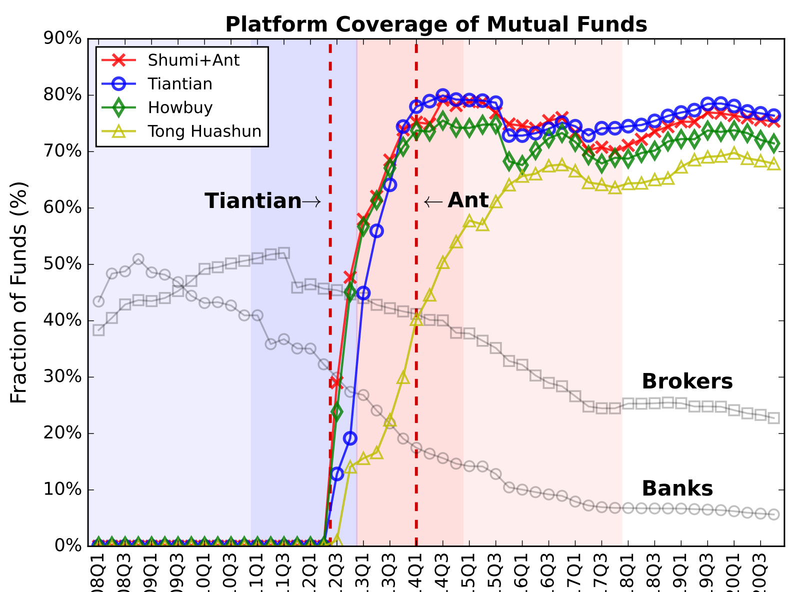


Figure 2. Flow-Performance Sensitivity, Before and After the Introduction of Platforms

This figure shows the net capital flow into the funds in each performance decile, for the period before (2008–2012) and after (2013–2017) the introduction of platforms. At the beginning of each quarter t, we sort all funds into deciles based on their past 12-month cumulative raw returns. Quarter t flow for each decile is the equal-weighted average flow of all funds in that decile. Plotted on the graph is the decile flows averaged over time for the before and after periods, respectively. The shaded area indicates the 95% confidence intervals. The four graphs show the average fund flow for actively managed China equity funds, U.S. equity funds, China mixed funds, and China bond funds, respectively.

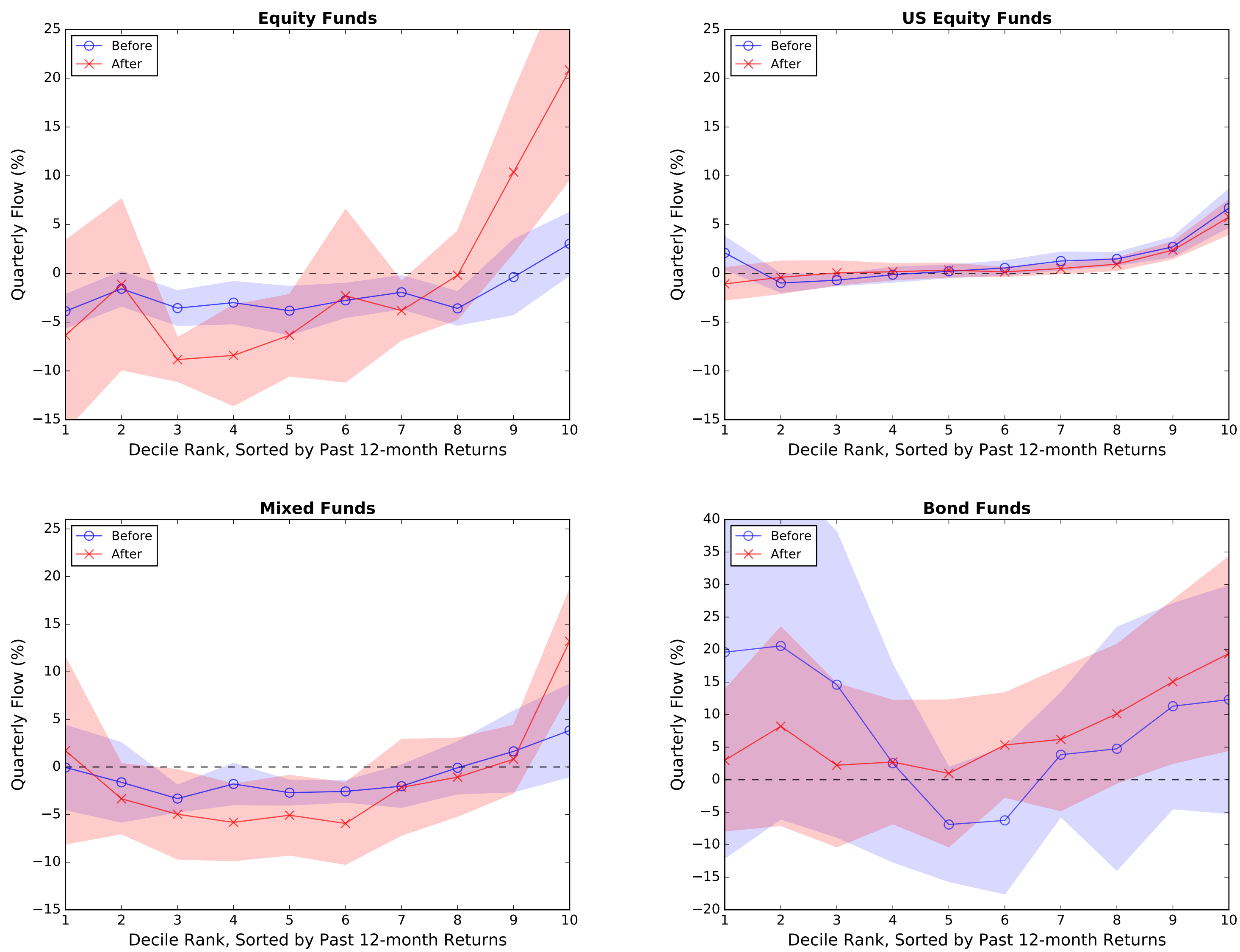


Figure 3. Time-Series Variation of Flow-Performance Sensitivity

The blue lines marked with "x" plots the value-weighted average flow of all deciles; The red lines marked with "o" plots the difference between top-decile flow and the average flow. The top decile contains the top 10% of funds with the highest past 12-month returns. The shaded area indicates the 95% confidence intervals. The panels correspond to actively managed China equity, U.S. equity, China mixed, and China bond funds, respectively.

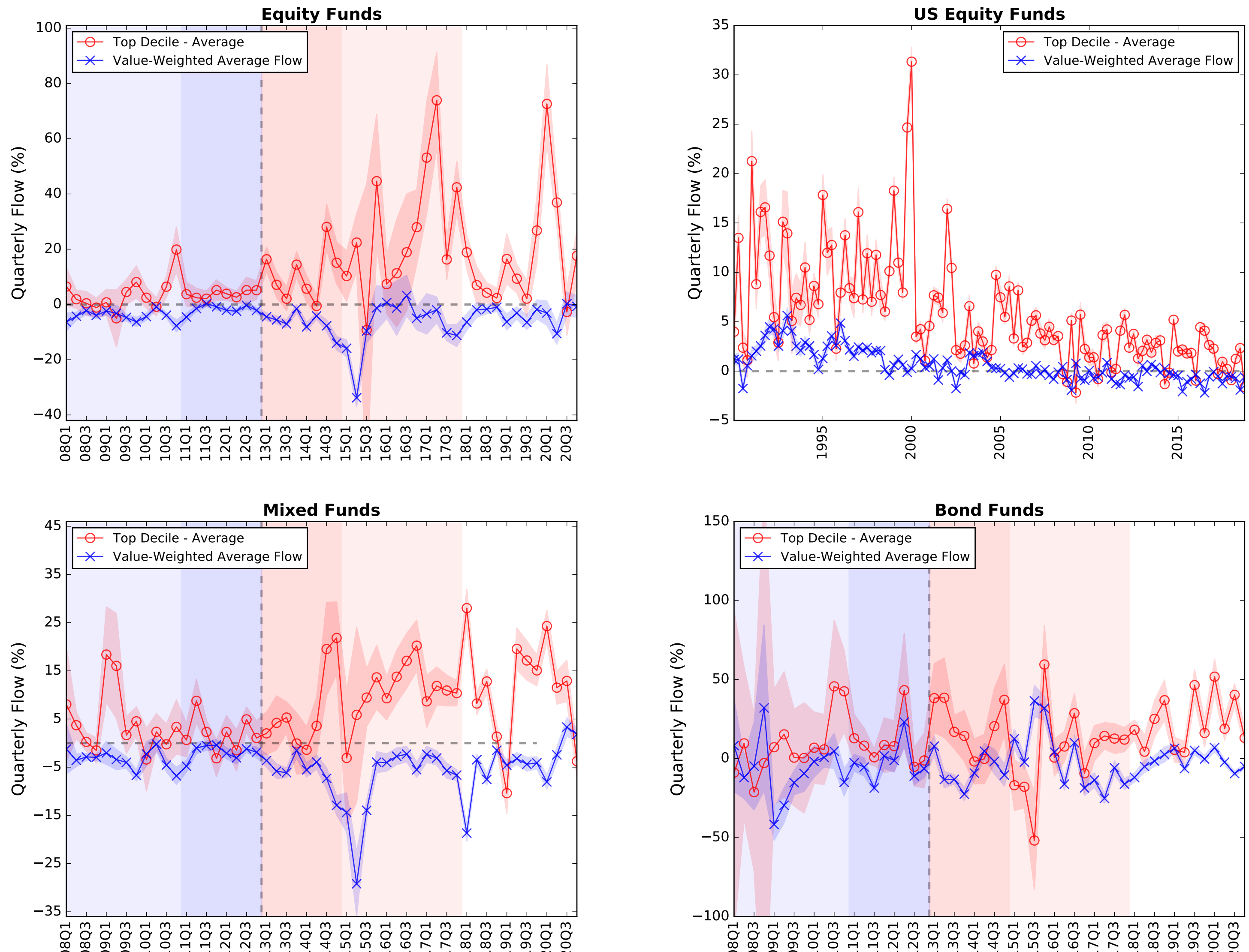


Figure 4. Purchase Fraction: The Whole Market versus Howbuy Platform

This figure shows the market share of purchase for each performance decile. At the beginning of each quarter t, we sort funds into deciles based on past 12-month cumulative return. In each quarter, market share of purchase for each decile is calculated as the total purchase amount for funds in that decile divided by the aggregate purchase amount across all deciles. The upper two graphs present the market share of purchase for each decile, averaged quarter by quarter for the period before (2008–2012) and after (2013–2017) the introduction of platforms. The dotted lines represent the results using data from Howbuy, which is only available from 2015 to 2018. The shaded areas indicate the 95% confidence intervals. The lower two graphs exhibit the time-series purchase fraction of decile-10 funds on the Howbuy platform and in the whole market from 2008 to 2018.

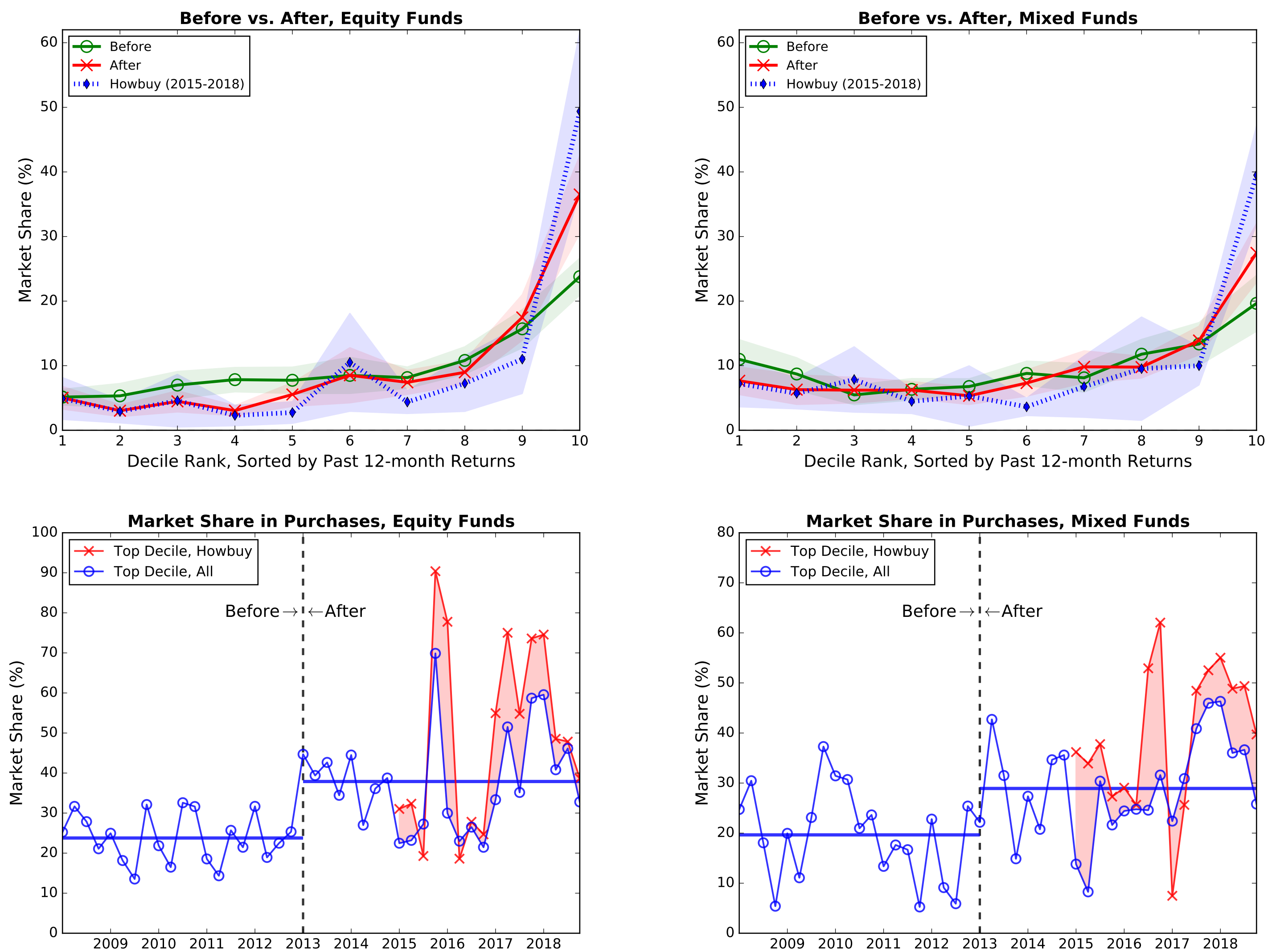
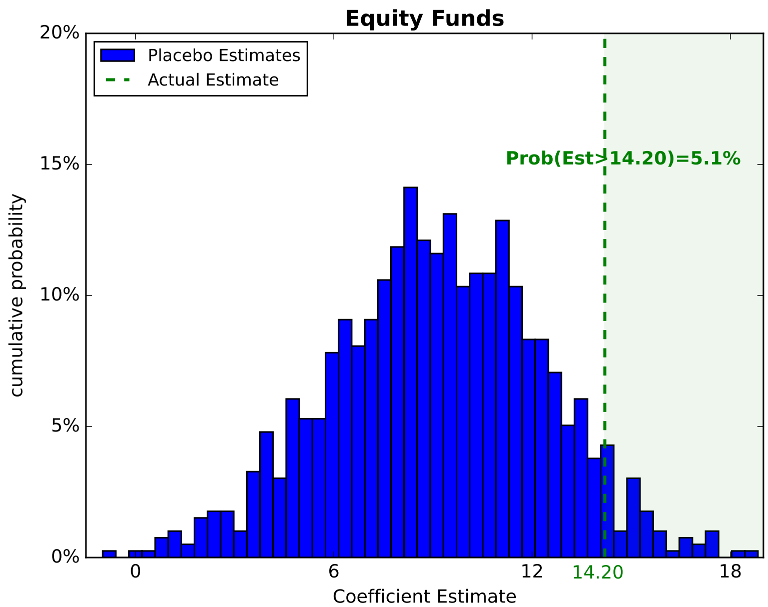


Figure 5. Placebo Tests on Platform Entrance

This figure reports the distribution of the coefficient estimates from the placebo tests. For each quarter, we randomly reshuffle the value of the platform dummy across funds and meantime maintain its overall distribution. We then estimate the regression specification in column (4) and column (8) of Table 3 and save the coefficient estimates on the interaction term, Decile10×Platform. We conduct the placebo analysis for 1,000 times. The upper and lower graphs show the distribution of the coefficient estimates for equity and mixed funds, respectively. The green dotted lines denote the actual estimates.



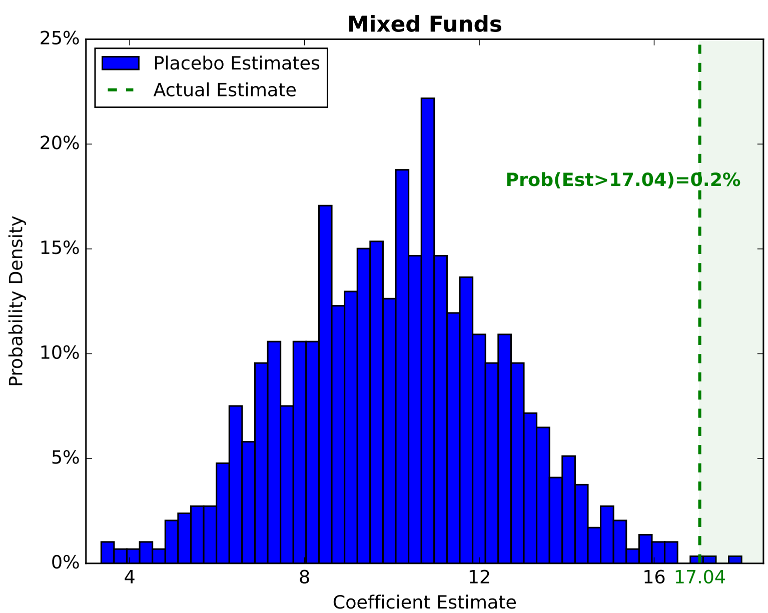
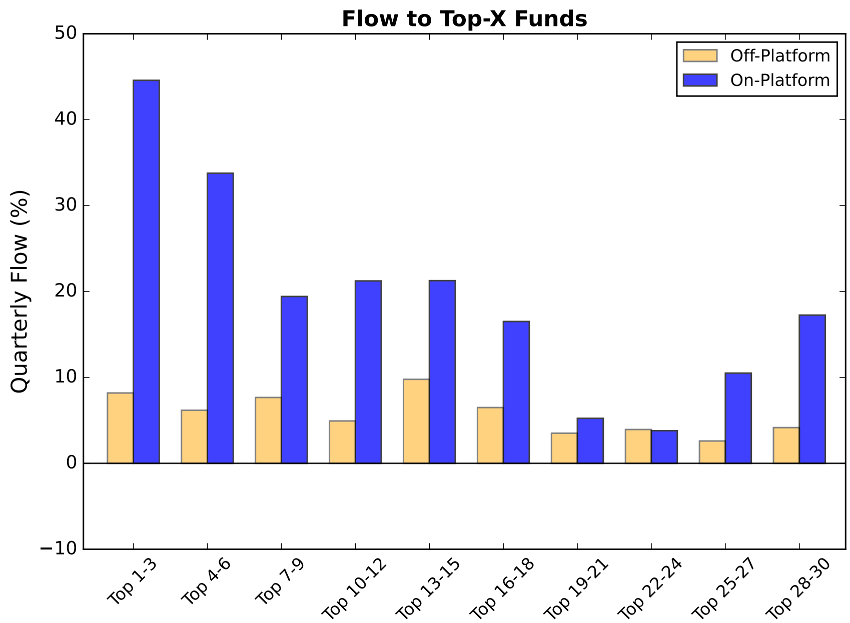


Figure 6. Front-Page Visibility and Flow-Performance Sensitivity

This figure shows the flows to the Top-X funds before and after a fund enters platforms. The flows to the Top-X funds are estimated in a regression setting similar to column (4) and column (8) in Table 4. The only difference is that we further divide the top 30 funds into 10 equal groups (Top 1–3, 4–6, etc.). Since the "Others" group is omitted in the regression estimation, the flows shall be interpreted as the additional flow benchmarking to the "Others" group. The upper panel reports the flows to the Top-X funds when they are off- and on-platforms, respectively. The lower panel reports the on- and off-platform difference for each Top-X funds group, and the corresponding 95% confidence intervals.



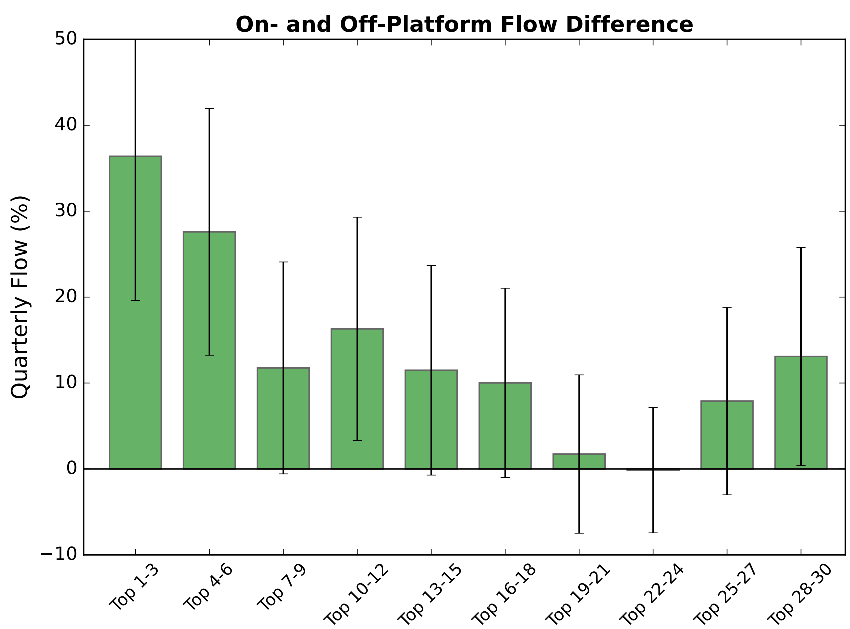


Figure 7. Front-Page Visibility under Alternative Performance Measures

This figure shows the extra flows to the Top-10 funds, constructed under alternative performance measures. At the beginning of each quarter, we rank funds into Top 10, Top 11–30, and Top 31–50 categories based on funds' past X-month raw returns and alphas, respectively, with X referring to the look-back horizons of 3, 6, 9, 12, 15, 18, and 21 months. Platform-induced flows to the Top-10 funds are estimated for each performance specification, following the regression model in columns (4) and (8) of Table 4. The graphs plot the coefficient estimates for the interaction term Top10×Platform for equity (upper graph) and mixed funds (lower graph), respectively.

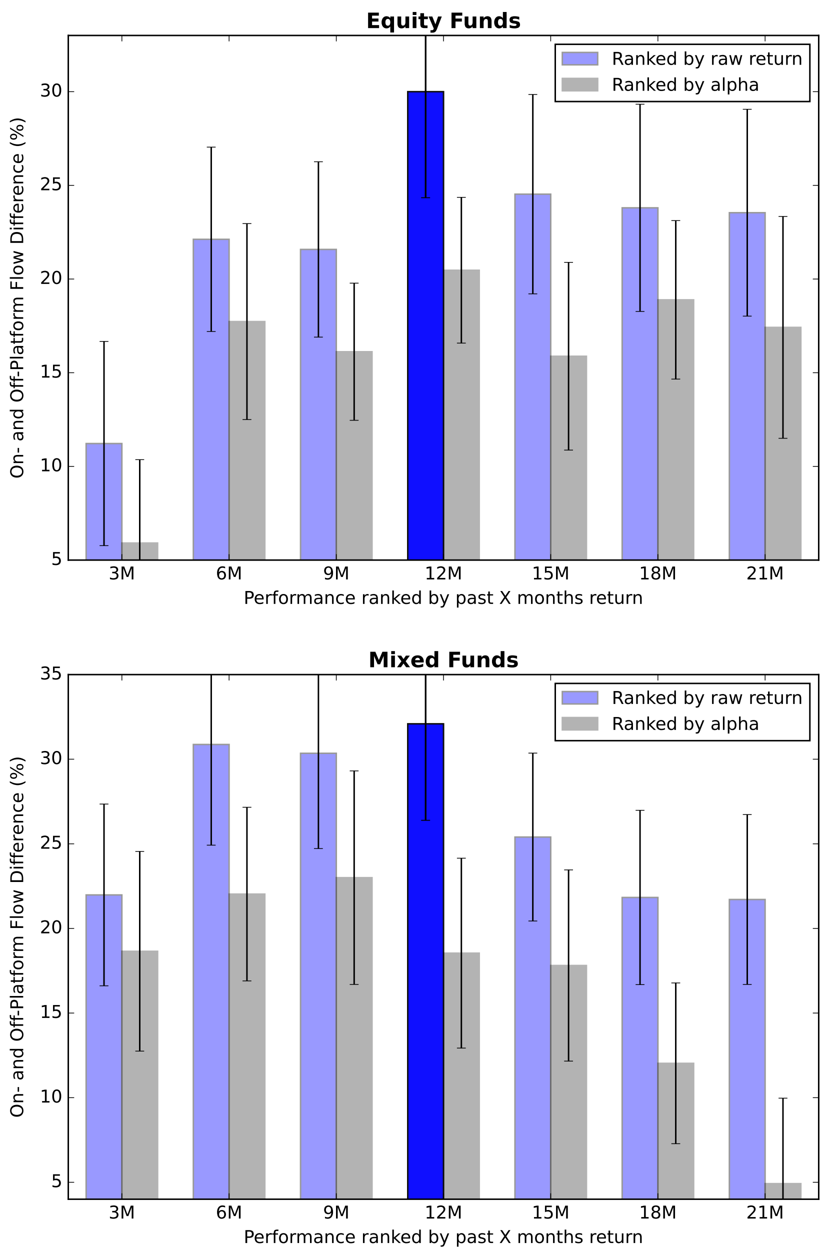


Table 1. Summary Statistics

Panel A shows the summary statistics of actively managed mutual funds year by year. For each fund style and year, we report the average number of unique funds (#Funds), aggregate assets under managements (AUM) in billion-yuan, equal-weighted fund monthly returns (Ret), and standard deviation of fund monthly returns (STD), estimated using 12-month observations in the year. Panel B reports the summary statistics for the key variables in our sample. Log(Size) is the natural logarithm of fund's total net assets (TNA) at each quarter end. Age is the number of months since a fund's inception. Ret12m is the cumulative fund return in the past twelve months. Flow is fund's quarterly flow, calculated as $\frac{TNA_t - TNA_{t-1}(1+Ret_t)}{TNA_{t-1}}$. Subscript t indexes the quarter. Std Return is the standard deviation of fund returns in bps, estimated using daily observations within each quarter. The sample period is from 2008 through 2017.

Panel A. Size of Mutual Fund Industry, by Year

	Equity				Mixed				Bond			
Year	#Funds	AUM	Ret	STD	#Funds	AUM	Ret	STD	#Funds	AUM	Ret	STD
2008	52	270	-5.55%	8.75%	103	425	-4.58%	7.16%	25	70	0.47%	0.92%
2009	96	800	4.89%	8.60%	122	762	4.09%	7.41%	29	28	0.37%	1.33%
2010	131	770	0.23%	5.60%	136	698	0.43%	4.69%	68	63	0.55%	0.89%
2011	171	589	-2.24%	4.67%	158	528	-1.88%	4.03%	120	64	-0.25%	1.33%
2012	223	630	0.62%	5.89%	166	525	0.44%	4.93%	135	86	0.60%	0.85%
2013	285	669	1.31%	5.21%	187	519	1.08%	4.38%	192	78	0.03%	1.42%
2014	344	634	1.92%	3.47%	214	481	1.67%	2.80%	281	123	1.82%	1.52%
2015	362	640	3.54%	13.12%	612	964	3.06%	10.26%	413	371	0.91%	2.09%
2016	54	46	-0.50%	9.29%	734	873	-0.80%	7.71%	498	423	-0.10%	1.35%
2017	146	183	1.28%	2.72%	1,163	1,436	0.98%	2.13%	458	233	0.10%	0.79%
2018	195	150	-2.43%	3.84%	1,686	1,051	-1.58%	2.64%	764	648	0.15%	0.58%
2019	264	230	3.53%	4.93%	2,148	1,440	2.54%	3.54%	1,036	1,380	0.60%	0.67%
2020	338	463	4.27%	6.22%	2,594	2,715	3.11%	4.55%	1,434	2,226	0.42%	0.79%

Panel B. Summary Statistics

	Variable	N	Mean	Median	Q1	Q3	STD
Equity	Log(Size)	6,083	20.9	21.2	19.9	22.2	1.6
	Age	6,083	54.6	49.0	34.0	70.0	24.6
	Ret12m	6,083	11.0%	7.2%	-6.2%	22.1%	28.8%
	Flow	6,083	-2.9%	-4.1%	-11.5%	-0.8%	27.6%
	Std Return	6,083	140.6	128.6	105.3	156.9	53.6
	Variable	N	Mean	Median	Q1	Q3	STD
Mixed	Log(Size)	12,246	20.5	20.8	19.4	21.8	1.6
	Age	12,246	75.7	70.0	43.0	104.0	38.2
	Ret12m	12,246	11.1%	5.8%	-5.4%	19.5%	29.6%
	Flow	12,246	-0.7%	-3.6%	-9.3%	-0.6%	36.6%
	Std Return	12,246	118.4	100.4	72.4	144.0	73.9
	Variable	N	Mean	Median	Q1	Q3	STD
Bond	Log(Size)	7,149	19.3	19.4	18.1	20.5	1.6
	Age	7,149	58.2	51.0	36.0	74.0	28.2
	Ret12m	7,149	7.1%	5.0%	0.8%	9.9%	13.8%
	Flow	7,149	8.3%	-6.9%	-21.5%	6.2%	74.1%
	Std Return	7,149	28.2	18.1	10.7	33.9	27.5

Table 2. Pre- and Post-Platform Flow-Performance Sensitivity

Panel A reports the average flow into each performance decile of funds, before and after the introduction of platforms. At each quarter end and for each style category, we sort all funds into deciles based on their past 12-month cumulative raw return. We then compute the average next-quarter flow for each decile group, and average the flow quarter by quarter for the five-year sample before (2008–2012) and after (2013–2017) the introduction of platforms. "After-Before" denotes the post- and pre-platform flow differences, with the corresponding t-statistics reported in parentheses. Panel B reports the purchase fractions for each performance decile on a top FinTech platform – Howbuy, during the sample period from 2015 through 2018. For each quarter, the fraction of purchase for each decile group is computed as the amount of purchase of all funds in that decile divided by the total amount of purchase. The same-period purchase fraction for the whole market ("Market-Wide") is computed following the same methodology. "Difference" reports the average purchase fraction differences between Howbuy and the whole market, with t-statistics reported in parentheses.

Panel A. Market-Wide Impact, Fund Quarterly Flow (in %)

		Decile 1 (Bottom)	2	3	4	5	6	7	8	9	Decile 10 (Top)
Equity	Before	-3.89	-1.58	-3.57	-3.01	-3.83	-2.77	-1.94	-3.60	-0.39	3.03
	After	-6.37	-1.13	-8.84	-8.41	-6.35	-2.31	-3.82	-0.20	10.38	20.84
	After-Before	-2.48	0.45	-5.27	-5.40	-2.52	0.46	-1.88	3.40	10.77	17.81
		(-0.53)	(0.11)	(-3.86)	(-2.02)	(-1.09)	(0.11)	(-1.14)	(1.47)	(2.48)	(3.19)
Mixed	Before	-0.05	-1.61	-3.32	-1.78	-2.7	-2.56	-2.02	-0.08	1.64	3.84
	After	1.72	-3.34	-4.97	-5.81	-5.06	-5.93	-2.14	-1.07	0.82	13.21
	After-Before	1.77	-1.73	-1.65	-4.03	-2.36	-3.37	-0.12	-0.99	-0.82	9.37
		(0.34)	(-0.65)	(-0.7)	(-1.84)	(-1.13)	(-1.59)	(-0.05)	(-0.42)	(-0.31)	(2.69)
Bond	Before	19.6	20.56	14.61	2.53	-6.89	-6.26	3.84	4.75	11.3	12.31
	After	2.99	8.21	2.22	2.71	0.97	5.33	6.20	10.13	15.06	19.39
	After-Before	-16.61	-12.35	-12.39	0.18	7.86	11.59	2.36	5.38	3.76	7.08
		(-1.04)	(-0.84)	(-0.97)	(0.02)	(1.15)	(1.75)	(0.34)	(0.52)	(0.39)	(0.65)

Panel B. Direct Evidence from Howbuy, Purchase Fraction (in %)

		Decile 1 (Bottom)	2	3	4	5	6	7	8	9	Decile 10 (Top)
Equity	Market-Wide	4.60	3.56	5.08	2.79	4.89	9.01	7.65	8.61	16.19	37.61
	Howbuy	4.92	2.91	4.58	2.29	2.75	10.52	4.37	7.26	11.02	49.37
	Difference	0.32	-0.65	-0.50	-0.50	-2.14	1.51	-3.27	-1.35	-5.17	11.76
		(0.19)	(-0.63)	(-0.23)	(-0.58)	(-1.73)	(0.35)	(-2.52)	(-0.59)	(-1.60)	(1.69)
Mixed	Market-Wide	8.59	7.39	7.00	6.05	5.82	6.14	7.32	9.86	12.80	29.02
	Howbuy	7.22	5.72	7.87	4.47	5.30	3.64	6.76	9.54	10.00	39.50
	Difference	-1.38	-1.68	0.87	-1.58	-0.52	-2.51	-0.56	-0.32	-2.80	10.47
		(-0.66)	(-1.11)	(0.33)	(-1.40)	(-0.23)	(-2.21)	(-0.24)	(-0.08)	(-1.42)	(2.35)
Bond	Market-Wide	6.07	8.35	7.56	9.43	9.00	7.86	10.32	12.41	11.28	17.72
	Howbuy	2.82	8.00	8.19	7.64	9.71	2.87	10.16	17.03	8.82	24.76
	Difference	-3.25	-0.35	0.62	-1.78	0.71	-4.99	-0.16	4.62	-2.45	7.04
		(-2.39)	(-0.12)	(0.19)	(-0.62)	(0.21)	(-5.83)	(-0.04)	(0.91)	(-0.97)	(1.21)

Table 3. Staggered Entrance onto Platform and Flow-Performance Sensitivity

This table examines the flow-performance sensitivity utilizing the staggered entrance of funds onto platforms. The model specification is as follows:

$$\text{Flow}_{i,t} = \alpha + \beta_1 \cdot \text{Decile10}_{i,t-1} + \beta_2 \cdot \text{Platform}_{i,t} + \beta_3 \cdot \text{Decile10}_{i,t-1} \times \text{Platform}_{i,t} + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t}\,,$$

where $\text{Flow}_{i,t}$ is fund i's flow in quarter t. $\text{Decile10}_{i,t-1}$ is a dummy that equals one if fund i belongs to the top performance decile based on the 12-month cumulative return up to the end of quarter $t-1$, and zero otherwise. $\text{Platform}_{i,t}$ is a dummy that equals one if fund i is available for sale as of the beginning of quarter t through the two major platforms: Ant Financial and Tiantian. We control for $\text{Log(Size)}_{i,t-1}$, the natural logarithm of funds' TNA at the end of quarter $t-1$, $\text{Log(Age)}_{i,t-1}$, the natural logarithm of the number of months since fund inception at quarter $t-1$, and Flow_{t-1}, the fund flow in the previous quarter. We conduct the analyses separately for equity and mixed funds. "[-2,2]" denotes the results estimated using a narrow window in the two years before (2011–2012) and two years after (2013–2014) platform introduction. "[-5,5]" denotes the long-window results estimated using the five years before (2008–2012) and five years after (2013–2017) platform introduction. Time fixed effects and fund fixed effects are included as indicated. Standard errors are double-clustered at the time level and fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Dep.Var.: Fund Quarterly Flow (in %)							
	Equity				Mixed			
	[-2,2]		[-5,5]		[-2,2]		[-5,5]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Decile10	6.733***	6.806***	6.408***	6.620***	4.601**	3.823	6.010***	2.217
	(4.23)	(3.72)	(3.87)	(3.50)	(2.21)	(1.34)	(3.15)	(1.07)
Platform	-1.658	-0.157	-1.298	-1.549	-0.218	-1.398	-0.181	-3.078*
	(-1.23)	(-0.13)	(-0.84)	(-1.19)	(-0.19)	(-0.87)	(-0.10)	(-1.83)
Decile10×Platform	10.531**	16.324***	12.159***	14.203***	11.794**	13.947**	14.432***	17.043***
	(2.46)	(3.33)	(3.07)	(3.40)	(2.40)	(2.39)	(5.33)	(5.72)
Log(Size)	-2.411**	-16.979***	-3.065***	-16.087***	-2.615***	-8.210***	-4.282***	-19.508***
	(-2.46)	(-5.63)	(-4.51)	(-6.72)	(-4.36)	(-4.03)	(-8.25)	(-9.23)
Log(Age)	3.999***	-0.825	0.451	6.538	3.060***	12.361	2.531*	-2.657
	(4.22)	(-0.15)	(0.24)	(1.04)	(3.77)	(1.38)	(1.95)	(-0.47)
Flow_{t-1}	0.166***	0.111*	0.135***	0.078	0.035	-0.024	0.014	0.006
	(3.63)	(2.10)	(3.65)	(1.54)	(1.15)	(-1.25)	(0.43)	(0.21)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	N	Y	N	Y	N	Y	N	Y
Observations	3,758	3,758	6,083	6,083	2,752	2,752	12,246	12,246
R-squared	0.094	0.287	0.097	0.258	0.060	0.193	0.060	0.207

Table 4. Post-Platform Performance Chasing and Closeness to the Front Page

This table estimates the sensitivity of flow to fund's past performance ranking, conditional on fund's closeness to the front page. In particular, we replace the Decile10 dummy in Table 3 with "Top-X" dummies (Top 10, Top 11–30, and Top 31–50), and estimate the following regression specification:

$$\begin{aligned}\text{Flow}_{i,t} = \alpha + \beta_1 \cdot \text{Top10}_{i,t-1} + \beta_2 \cdot \text{Top11–30}_{i,t-1} + \beta_3 \cdot \text{Top31–50}_{i,t-1} + \beta_4 \cdot \text{Platform}_{i,t} \\ + \beta_5 \cdot \text{Top10}_{i,t-1} \times \text{Platform}_{i,t} + \beta_6 \cdot \text{Top11–30}_{i,t-1} \times \text{Platform}_{i,t} + \beta_7 \cdot \text{Top31–50}_{i,t-1} \times \text{Platform}_{i,t} \\ + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t}\,,\end{aligned}$$

where "Top 10" is a dummy variable that equals one for the top-10 ranked funds within each style category, and "Top 11–30" for top 11 to 30 funds, "Top 31–50" for top 31 to 50 funds, and the rest ranked below 50. The dummy variable for funds ranked below 50 is omitted in the regression because of multicollinearity. The $\text{Platform}_{i,t}$ dummy, and the interaction terms between "Top-X" dummies and the Platform dummy are also included. We control for last quarter-end fund Log(Size), Log(Age), and Flow in all the specifications. Time fixed effects and fund fixed effects are included as indicated. The sample period is from 2008 through 2017. Standard errors are double-clustered at the time level and fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Dep.Var.: Fund Quarterly Flow (in %)							
	Equity				Mixed			
	[-2,2]		[-5,5]		[-2,2]		[-5,5]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top10	7.624**	8.624**	6.297***	6.835***	1.539	1.705	5.272**	1.481
	(2.60)	(2.95)	(3.13)	(3.00)	(0.60)	(0.48)	(2.25)	(0.53)
Top11–30	3.550**	4.569**	4.136**	4.672**	6.461***	6.109***	4.379***	2.876**
	(2.18)	(2.32)	(2.21)	(2.28)	(3.57)	(3.25)	(4.07)	(2.28)
Top31–50	2.355	2.104**	1.112	1.298	0.414	0.647	1.304	0.238
	(1.37)	(2.18)	(1.04)	(1.30)	(0.33)	(0.43)	(1.21)	(0.23)
Platform	-2.929*	-1.992	-3.333**	-3.162**	-0.565	-2.288	-0.963	-5.146***
	(-1.86)	(-1.42)	(-2.04)	(-2.20)	(-0.51)	(-1.44)	(-0.48)	(-2.76)
Top10×Platform	17.970**	28.190***	25.684***	30.004***	21.587***	24.503***	27.366***	32.091***
	(2.75)	(3.02)	(4.53)	(5.30)	(3.06)	(2.98)	(4.71)	(5.63)
Top11–30×Platform	10.251**	15.811***	9.046**	12.241***	0.315	2.599	12.620***	12.349***
	(2.35)	(3.97)	(2.68)	(3.61)	(0.08)	(0.60)	(2.93)	(3.25)
Top31–50×Platform	9.214**	12.975***	8.170***	9.178***	2.669	3.203	8.020**	8.072**
	(2.66)	(3.47)	(2.96)	(3.27)	(1.17)	(1.06)	(2.55)	(2.60)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	N	Y	N	Y	N	Y	N	Y
Observations	3,758	3,758	6,083	6,083	2,752	2,752	12,246	12,246
R-squared	0.104	0.303	0.110	0.271	0.069	0.201	0.057	0.206

Table 5. Horse-Race Tests: Default Performance Measure v.s. Alternative Performance Measures

This table reports the horse-race tests between the default performance ranking measure of 12-month raw return and performance measures under alternative specifications. We estimate the specifications in columns (4) and (8) of Table 4, by simultaneously including the performance ranks defined using 12-month raw returns and the performance ranks defined under measure X. In particular, we estimate the following regression specification:

$$\begin{aligned}\text{Flow}_{i,t} = \alpha + \beta_1 \cdot \text{Top10}_{i,t-1} \times \text{Platform}_{i,t} + \gamma_1 \cdot \text{Top10}^X_{i,t-1} \times \text{Platform}_{i,t} + \beta_2 \cdot \text{Top11–30}_{i,t-1} \times \text{Platform}_{i,t} + \gamma_2 \cdot \text{Top11–30}^X_{i,t-1} \times \text{Platform}_{i,t} \\ + \beta_3 \cdot \text{Top31–50}_{i,t-1} \times \text{Platform}_{i,t} + \gamma_3 \cdot \text{Top31–50}_{i,t-1} \times \text{Platform}_{i,t} + \beta_4 \cdot \text{Platform}_{i,t} + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t}\,,\end{aligned}$$

where Top10, Top11–30, and Top31–50 are the front-page dummies defined using past 12-month raw returns, and Top10^X, Top11–30^X, and Top31–50^X are the performance dummies defined under alternative performance measures of X. The controls include all the performance rank dummies, fund Log(Size)$_{i,t-1}$, Log(Age)$_{i,t-1}$, and Flow$_{t-1}$. Fund fixed effects and time fixed effects are included in all the specifications. The coefficient estimates of β_1 and γ_1 are reported. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A. Equity funds

X=	Raw,3M	Raw,6M	Raw,9M	Raw,15M	Raw,18M	Raw,21M	Alpha,3M	Alpha,6M	Alpha,9M	Alpha,12M	Alpha,15M	Alpha,18M	Alpha,21M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Top10×Platform (a)	28.525***	23.668***	27.909***	25.054***	27.830***	26.299***	30.398***	27.326***	27.806***	27.108***	29.661***	28.013***	28.313***
	(4.94)	(4.04)	(4.16)	(3.02)	(4.73)	(4.53)	(5.59)	(5.12)	(4.69)	(3.61)	(4.73)	(4.17)	(4.03)
Top10^X×Platform (b)	1.173	8.791	2.803	5.507	3.748	6.394	-2.426	7.605*	3.047	4.165	-0.605	3.549	3.939
	(0.22)	(1.66)	(0.53)	(0.70)	(0.58)	(1.15)	(-0.71)	(1.77)	(0.77)	(0.74)	(-0.11)	(0.66)	(0.49)
(a)-(b)	27.352***	14.877	25.106**	19.547	24.082**	19.905**	32.824***	19.721***	24.759***	22.943*	30.266***	24.464**	24.374*
F-stat	9.76	2.58	5.78	1.71	5.37	4.71	29.18	8.19	9.03	3.51	9.34	5.14	3.26

Panel B. Mixed Funds

X=	Raw,3M	Raw,6M	Raw,9M	Raw,15M	Raw,18M	Raw,21M	Alpha,3M	Alpha,6M	Alpha,9M	Alpha,12M	Alpha,15M	Alpha,18M	Alpha,21M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Top10×Platform (a)	27.215***	19.983***	19.497**	27.503***	30.564***	29.290***	29.766***	27.844***	27.149***	33.311***	33.181***	34.192***	34.970***
	(5.14)	(3.73)	(2.48)	(4.21)	(5.17)	(4.87)	(5.57)	(5.19)	(4.97)	(4.46)	(4.93)	(5.46)	(6.01)
Top10^X×Platform (b)	13.314**	20.982***	17.997**	6.333	2.609	6.187	11.803**	12.596**	11.201*	-1.348	0.662	-3.465	-8.545
	(2.59)	(3.92)	(2.45)	(1.12)	(0.46)	(1.17)	(2.13)	(2.66)	(1.87)	(-0.18)	(0.10)	(-0.63)	(-1.59)
(a)-(b)	13.901*	-0.999	1.50	21.170*	27.955***	23.103**	17.963***	15.248**	15.948*	34.659**	32.519***	37.657***	43.515***
F-stat	3.76	0.02	0.01	3.90	8.27	6.75	7.98	5.38	3.48	6.41	8.46	14.19	22.61

Table 6. Intra-Family Ranking as a Placebo

This table reports the sensitivity of flow to funds' intra-family performance ranking and platform performance ranking. In particular, columns (3) and (6) report the sensitivity of flow to funds' intra-family ranking after controlling for the impact of platform ranking. We follow similar model specifications as in Table 3. Platform ranking is captured by Decile$10_{i,t-1}$, which is defined using funds' past 12-month returns up to the end of quarter $t-1$. Intra-family ranking is captured by FMQuintile5, a dummy variable that equals one if the fund's past 12-month return ranks among the highest quintile group across that of all funds within its family, and zero otherwise. We include as controls fund Log(Size), Log(Age), and Flow measured at the end of quarter $t-1$. Time fixed effects and fund fixed effects are included in all the specifications. The sample period is from 2008 through 2017. Standard errors are double-clustered at the time and fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Equity			**Mixed**		
	(1)	(2)	(3)	(4)	(5)	(6)
FMQuintile5	4.314**		2.962*	3.649**		3.124*
	(2.58)		(1.87)	(2.38)		(1.87)
FMQuintile5×Platform	2.388		-1.668	6.352**		1.428
	(0.62)		(-0.43)	(2.63)		(0.60)
Decile10		6.457***	5.394***		2.353	1.158
		(3.45)	(2.94)		(1.03)	(0.48)
Decile10×Platform		14.761***	15.350***		16.779***	15.632***
		(3.51)	(3.77)		(5.30)	(4.85)
Platform	-0.128	-1.51	-1.21	-2.467	-3.631*	-3.587*
	(-0.09)	(-1.07)	(-0.87)	(-1.28)	(-1.91)	(-1.87)
Log(Age)	9.016	8.528	8.456	-4.053	-3.851	-3.804
	(1.31)	(1.22)	(1.21)	(-0.69)	(-0.67)	(-0.66)
Log(Size)	-14.324***	-15.904***	-15.968***	-18.877***	-19.466***	-19.577***
	(-5.85)	(-6.67)	(-6.64)	(-8.31)	(-8.52)	(-8.53)
Past Flow	0.093*	0.066	0.066	0.015	0.011	0.011
	(1.89)	(1.36)	(1.34)	(0.51)	(0.35)	(0.34)
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Observations	5,542	5,542	5,542	11,195	11,195	11,195
R-squared	0.246	0.263	0.264	0.200	0.208	0.209

Table 7. Retail v.s. Institutional Flow

This table examines the sensitivity of retail and institutional flows to fund's past performance. We calculate a fund's quarterly retail flow using the formula $\frac{\text{TNA}_t*\text{Retail Ratio}_t-\text{TNA}_{t-1}*\text{Retail Ratio}_{t-1}(1+\text{Ret}_t)}{\text{TNA}_{t-1}}$. Institutional flows are defined similarly. The independent variables are the same as those in Table 4, where the "Top-X" dummies (Top 10, Top 11–30, and Top 31–50) capture funds' closeness to the front page. Platform$_{i,t}$ is a dummy that equals one if fund i is available for sale on the two major platforms as of the beginning of quarter t. We further control for fund's Log(Size), Log(Age), Flow in quarter $t-1$, and fund and time fixed effects. The sample period is from 2008 through 2017. Standard errors are double-clustered at the fund and time levels. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Equity		**Mixed**	
	Retail Flow	Institutional Flow	Retail Flow	Institutional Flow
	(1)	(2)	(3)	(4)
Top10	3.305**	3.303***	1.716	0.498
	(2.15)	(3.29)	(0.92)	(0.53)
Top11–30	0.695	3.277***	0.406	2.156***
	(0.55)	(4.65)	(0.68)	(3.10)
Top31–50	0.389	0.801	-0.498	0.667
	(0.61)	(1.64)	(-0.90)	(1.48)
Platform	-2.320**	-0.267	-3.892***	-0.259
	(-2.03)	(-0.50)	(-5.09)	(-0.30)
Top10×Platform	20.753***	6.497***	17.180***	8.439***
	(4.96)	(3.02)	(5.55)	(2.83)
Top11–30×Platform	8.937***	2.162	5.868***	3.648**
	(3.76)	(1.51)	(3.72)	(2.26)
Top31–50×Platform	5.250***	3.003**	3.767***	4.062***
	(3.03)	(2.34)	(2.88)	(2.77)
Time FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
Observations	6,057	6,057	12,150	12,150
R-squared	0.278	0.226	0.242	0.203

Table 8. The Impact on Managerial Risk Taking

This table shows the impact of platforms on managerial risk taking. At the beginning of each quarter t, we use funds' past 9-month performance ranking to examine their risk taking in quarter t. In panel A, the regression specification is as below:

$$\text{Vol}_{i,t} = a + b\,\text{Platform}_{i,t} + c\,\text{Decile10}_{i,t-1} + d\,\text{Decile10}_{i,t-1} \times \text{Platform}_{i,t} + \varepsilon_{i,t}\ ,$$

$\text{Decile10}_{i,t-1}$ is a dummy that equals one if fund i ranks among the top decile within its style category, based on past 9-month return up to the end of quarter $t-1$. In panel B, we replace the Decile10 dummy with the "Top-X" dummies (Top 10, Top 11–30, and Top 31–50). For example, "Top 10" stands for the top-10 ranked funds based on past 9-month return. $\text{Platform}_{i,t}$ is a dummy variable that equals one if fund i is available for sale on platforms in quarter t. We report results for three volatility measures ($\text{Vol}_{i,t}$): TotalVol, SysVol, and IdioVol. TotalVol is the standard deviation of fund i's daily returns in quarter t in basis points. Fund systematic and idiosyncratic volatilities are estimated based on a two-factor model, including a stock fund factor and a bond fund factor, using fund daily returns in quarter t. We control for fund's Log(Size), Log(Age), and Flow at the end of quarter $t-1$. Time fixed effects and fund fixed effects are included in all specifications. The sample period is from 2008 through 2017. Standard errors are double clustered at fund and time levels. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A. Conditional on Past 9-Month Decile Rank

	Equity			Mixed		
	TotalVol	SysVol	IdioVol	TotalVol	SysVol	IdioVol
	(1)	(2)	(3)	(4)	(5)	(6)
Decile10	-0.557	-1.636	3.464***	-3.54	-4.768	3.504***
	(-0.26)	(-0.74)	(3.19)	(-1.03)	(-1.38)	(3.40)
Platform	2.291	2.668	-0.295	2.756	3.468	0.904
	(1.17)	(1.51)	(-0.25)	(1.19)	(1.42)	(0.84)
Decile10×Platform	8.840***	8.036**	2.714	11.009**	10.870**	1.448
	(2.95)	(2.62)	(1.57)	(2.53)	(2.55)	(1.02)
Log(Size)	-0.721	0.627	-2.669***	-8.377***	-7.341***	-4.335***
	(-0.53)	(0.48)	(-3.82)	(-3.29)	(-2.77)	(-5.99)
Log(Age)	-10.357	-11.211*	1.154	15.530**	13.687*	5.278**
	(-1.58)	(-1.90)	(0.29)	(2.16)	(1.84)	(2.32)
Flow_{t-1}	-1.556	-1.585	-0.339	-3.983	-4.314	-0.066
	(-0.69)	(-0.71)	(-0.36)	(-1.26)	(-1.33)	(-0.11)
Fund FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	6,083	6,083	6,083	12,246	12,246	12,246
R-squared	0.896	0.902	0.712	0.879	0.882	0.731

Panel B. Conditional on Past 9-Month Front-Page Closeness						
	Equity			Mixed		
	TotalVol	SysVol	IdioVol	TotalVol	SysVol	IdioVol
Top10	-1.935	-3.124	3.821***	-6.200	-7.679	3.735***
	(-0.73)	(-1.13)	(3.02)	(-1.25)	(-1.54)	(3.21)
Top11–30	-1.614	-1.901	0.449	-1.206	-1.378	0.636
	(-0.78)	(-0.88)	(0.55)	(-0.56)	(-0.63)	(1.00)
Top31–50	1.975	1.777	-0.376	0.651	0.601	0.522
	(1.26)	(1.28)	(-0.44)	(0.33)	(0.29)	(1.01)
Platform	1.901	2.325	-0.705	1.324	2.301	0.074
	(0.93)	(1.18)	(-0.61)	(0.54)	(0.90)	(0.07)
Top10×Platform	16.429***	15.432***	4.750*	24.403***	22.288***	7.789***
	(3.84)	(3.79)	(1.85)	(4.12)	(3.71)	(3.74)
Top11–30×Platform	7.430*	6.853	3.442**	8.749**	7.456**	4.196***
	(1.80)	(1.55)	(2.31)	(2.49)	(2.19)	(3.01)
Top31–50×Platform	0.086	-0.597	3.205**	5.764*	5.104	2.351**
	(0.02)	(-0.17)	(2.12)	(1.86)	(1.63)	(2.16)
Controls	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	6,083	6,083	6,083	12,246	12,246	12,246
R-squared	0.896	0.903	0.712	0.880	0.882	0.732

Table 9. Implications on Fund Performance

This table reports the impact of platforms on funds' future performance. At the end of each quarter $t-1$, we rank all funds based on their past 12-month cumulative return, and then examine their performance in the subsequent 12 months. The regression specification is as below:

$$\text{Performance}_{i,[t+1,t+4]} = a + b\,\text{Platform}_{i,t} + c\,\text{Decile10}_{i,t-1} + d\,\text{Decile10}_{i,t-1} \times \text{Platform}_{i,t} + \sum_j \gamma_j \text{Control}^j_{i,t} + \varepsilon_{i,t}\,,$$

where the dependent variables, $\text{Performance}_{i,[t+1,t+4]}$, are average monthly return, standard deviation of monthly returns, and Sharpe ratio in the twelve months from quarter $t+1$ to quarter $t+4$. We skip quarter t in the performance calculation to avoid its time overlap with fund flow. $\text{Decile10}_{i,t-1}$ is a dummy that equals one if fund i belongs to the top performance decile based on the twelve-month cumulative return up to the end of quarter $t-1$, and zero otherwise. $\text{Platform}_{i,t}$ is a dummy that equals one if fund i is available for sale as of the beginning of quarter t through the two major platforms. The control variables include Log(Size), Log(Age), Flow at the end of quarter $t-1$, and time fixed effects. Standard errors are double-clustered at the fund and time levels. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Monthly Return		**STD**		**Sharpe Ratio**	
	Equity	Mixed	Equity	Mixed	Equity	Mixed
	(1)	(2)	(3)	(4)	(5)	(6)
Decile10	0.065	-0.012	0.144	-0.109	0.100*	0.011
	(0.73)	(-0.09)	(0.52)	(-0.31)	(1.88)	(0.19)
Platform	-0.039	-0.086	-0.35	0.106	-0.101	-0.089
	(-0.33)	(-0.73)	(-0.93)	(0.51)	(-1.01)	(-0.79)
Decile10×Platform	-0.019	0.103	0.342	0.701*	-0.235**	0.065
	(-0.11)	(0.78)	(0.79)	(1.78)	(-2.54)	(0.80)
Log(Size)	-0.037	-0.034**	-0.079	0.012	-0.043**	-0.02
	(-1.34)	(-2.54)	(-1.47)	(0.29)	(-2.48)	(-1.61)
Log(Age)	-0.131*	-0.101	-0.436***	0.374**	0.005	-0.116**
	(-1.71)	(-1.41)	(-3.25)	(2.69)	(0.11)	(-2.46)
Past Flow	0.00	-0.000**	0.003	-0.001	0.001**	0.000
	(-0.51)	(-2.16)	(1.35)	(-1.04)	(2.46)	(-0.30)
Time FE	Y	Y	Y	Y	Y	Y
Observations	6,066	12,179	6,066	12,179	6,066	12,179
R-squared	0.818	0.679	0.784	0.613	0.763	0.586

Appendix

A1 Determinants of Fund Entrance

After the introduction of platforms, we observe a staggered entrance of funds onto platforms. What affects funds' decide on whether and when to enter a platform? In this section, we investigate the factors that are associated with funds' entrance decision.

We use two variables to capture the early or late entrance of a fund (or family) onto platforms: (1) D(Enter$\leq$2013Q1) is a dummy variable that equals one if the fund (or family) enters onto the Tiantian platform on or before March 31, 2013; (2) Log(Enter months) is the natural logarithm of the number of months from March 2012 to the time when the fund (or family) enters Tiantian. We use the entrance onto Tiantian to define funds' earliest platform status because Tiantian is among the first batch to get platform license in 2012. Ant Financial entered the platform business a bit late in April 2014 via the acquisition of Shumi. Nevertheless, fund's decisions to enter Tiantian and Ant are highly correlated with a correlation of 0.88. To examine the determinants of entrance, we conduct logistic and OLS regressions with the two entrance variables as dependent variables. The explanatory variables are a variety of fund characteristics, including fund size, age, past flow, past return, past return volatility, broker or bank affiliation, and retail ratio. The results are shown in Appendix Table A1.

At the fund level, as shown in column (1), we find that non-bank-affiliated funds and funds with lower retail ratios, larger past flows, smaller sizes, and longer histories are more likely to enter platforms early. Intuitively, bank-affiliated funds, with a strong distribution network in the pre-platform era, have less incentives to enter platforms early. Funds with a smaller retail base and smaller size may want to seize the opportunity from platform to expand their customer base. More importantly, we find that the coefficients on funds' past returns and past return volatility are insignificant, suggesting that past performance is not correlated with their platform entrance decisions. The results are qualitatively the same when we use Log(Enter months) as a proxy for late entrance in column (2). At the fund family level, we also observe consistent patterns. Among the 60 fund families, we find that non-bank-affiliated families and families with lower retail ratios tend to join platforms early.

Endogenous Entrance in Explaining Performance Chasing

While certain types of funds choose to enter platforms early, our main concern is whether the endogenous entrance of funds onto platforms can explain the amplified performance chasing documented in the paper. In particular, if some funds, embedded with a higher flow-performance sensitivity, choose to enter platforms early on, then platform funds in general will exhibit a higher flow-performance sensitivity than the off-platform funds, even if platforms do not affect investors' tendency to chase performance. However, we believe such type of hypothesis unlikely explains our findings and we illustrate as below.

If the endogenous entrance of funds is driven by some *static* characteristic, e.g., size and retail ratio, such time invariant or highly persistent fund characteristics cannot explain a time-varying flow-performance pattern around platform entrance. In particular, our staggered entrance test in Section 3.3 captures the difference in flow-performance sensitivity for the same funds on- and off-platforms. For any fund characteristic (factor) to explain our results, it has to satisfy the following three criteria simultaneously: (1) it correlates with investors' flow-performance sensitivity; (2) the change of the factor coincides with the fund's platform entrance date; (3) the change of the factor is not directly related with the platform.

Though difficult to come up with such a factor, fund's past performance might be one candidate. Funds may strategically choose to enter platforms exactly when they have a good tracking record. Knowing that investors prefer funds with high past returns, platforms may choose to cover top performing funds early on to promote their business. However, this conjecture is not supported in the data. As given in Appendix Table A1, funds with higher recent returns are not more likely to be covered by platforms early on. More importantly, fund past performance fails to satisfy the criteria (1) listed above, i.e. in the absence of a platform effect, good past performance cannot generate a *change* in flow-performance sensitivity. Consider a fund that expects its performance to be good in the future and chooses to join the platforms; if platform investors and traditional-channel investors react similarly to a top-performing fund, there will be not any change in flow-performance sensitivity. In other words, high return is correlated with high flows, but not high flow-performance sensitivity.

Fund's marketing effort could be another potential candidate to explain the flow-performance sensitivity (Jain and Wu (2000), Gallaher et al. (2015)). It is possible that a fund increases its spending on marketing when it gets into the top rank, and this happens to be the time that the fund enters platforms. Even if platforms have nothing to do with the increased flow, we might still observe a positive correlation between platform entry and increase in flow-performance sensitivity. Again, we find limited evidence of such hypothesis in the data. If the amplified performance chasing in the market is driven by a market-wide change in funds' marketing expenditure, we shall observe a rise in funds' advertising fees around the introduction of platforms. However, when we plot funds' advertising fees over time in the upper left panel of Appendix Figure A2, we find that these expenses appear to be smooth around 2013. There is even a drop in advertising expense for bond funds after 2013. The evidence suggests that increases in advertising expense cannot explain our results.

A2 Changing Market Conditions

One may wonder if the amplified performance chasing is caused by a drastically different post-platform sample, unnecessarily related to the presence of FinTech platforms. The Chinese stock market climbs up rapidly in the first half of 2015, followed by a sudden collapse in the second half of 2015. Would the documented pattern in performance chasing possibly be explained by a much more volatile market condition in the post-platform era? Apart from aggregate market conditions, how would the change in the structure of the mutual fund industry, e.g., the composition of funds and the availability of other distribution channels, affect the overall flow-performance sensitivity? To address these concerns, we conduct the following analyses.

Excluding 2015: To ensure that our long-window results are not driven by the extreme market movements in 2015, we exclude the year 2015 from our sample. Row (1) of Table A3 suggests that top decile funds, compared with their peers, attract an extra quarterly flow of 18.1% after joining platforms. The magnitude is even slightly larger than the 16.85% quarterly flow estimated under the baseline specification, suggesting that the post-platform increase in performance chasing is not driven by the market crash in 2015.

Time-Varying Performance Chasing: To ensure that our results are not driven by confronting factors that affect market-wide performance chasing via channels unrelated to platforms, we further allow for time-varying performance chasing by adding After$\times$Decile10 in our baseline specification, where After is a dummy variable that equals one for periods on and after platform introduction. As platform is important enough to disrupt the entire mutual fund industry, naturally, we shall expect some of the platform effect to be absorbed by After$\times$Decile10. Still, row (2) of Table A3 suggests that our findings cannot be fully explained by time-varying market-wide performance chasing. Focusing solely on the cross-fund variations in flow-performance sensitivity, by controlling for the level of performance chasing at the market level, we find that top decile funds attract an extra inflow of 10.32% in the post-platform era.

Change in Morningstar Rating: To alleviate the concerns that post-platform performance chasing is caused by platform funds receiving better Morningstar ratings, in row (3) of Table A3, we control for Morningstar ratings by including dummy variables Ms5star and Ms4star, and their interactions with the Platform dummy. Ms5star (Ms4star) equals one if the fund's Morningstar rating is five (four) star, and zero otherwise. The results remain the same qualitatively. Though not reported in the table, the interactions between platform and Morningstar ratings are not significant, indicating that the performance ranking rather than the Morningstar rating is playing a major role.

Control for Linkages to Banks/Brokerages: How does the presence of alternative distribution channels, e.g., distribution of funds via banks and brokers, coincide with the platform emergence and affect the performance chasing? As can be seen in Figure 1, the coverage of funds via banks and brokers exhibit a decreasing trend during our sample, suggesting a less important role played by traditional channels in the post-platform era. Meanwhile, controlling for the number of sales relationships between mutual funds and banks/brokers and their interactions with $\text{Decile10}_{i,t-1}$ in our baseline specification, row (4) suggests that the effect of platform-induced performance chasing remain qualitatively and quantitatively similar.

Constant Fund Sample: During our sample period from 2008 to 2017, the mutual fund industry experiences a steady growth, reflected in both the size of assets under management and the number of funds available for sale (Figure 1 and Table 1). To show that our results are not driven by an increased pool of funds that creates more dispersed performance rank, row (5) of Table A3 reports the magnitude of performance chasing, estimated using a sample of funds that exist before 2012. The coefficient on the interaction term is 15.54%, similar to that of the baseline specification.

Value-Weighted: To further rule out the concern that our results are driven by the entrance of small funds with more volatile flows, we conduct weighted least squares regressions for our main analysis using the $\text{TNA}_{i,t-1}$ of each fund as the weight for each observation. The results, as reported in row (6) of Table A3, are similar to our baseline results.

A3 Alternative Specifications

In this section, we further conduct robustness tests using alternative measures to capture funds' platform entrance and performance ranking.

Replace Platform with Log(#Platforms): In row (7) of Table A3, we replace the $\text{Platform}_{i,t}$ dummy with the natural logarithm of the total number of platforms on which a fund is available for sale, $\text{Log}(\#\text{Platforms})_{i,t}$. The coefficient on the cross term between $\text{Decile10}_{i,t-1}$ dummy and $\text{Log}(\#\text{Platforms})_{i,t}$ is 7.3 with a t-stat of 9.12. It suggests that a one standard deviation increase in fund's platform exposure leads to an extra quarterly flow of 7.8% for a top-decile fund.[25]

Replace Platform with Tiantian and Ant: In our main analysis, we define a fund's platform status by its availability on the Tiantian platform or Ant financial platform, as these two capture around 80% of the platform business. In row (8) and row (9), we separately examine the platform effect for Tiantian and Ant. By replacing the Platform dummy with a Tiantian dummy in row (8), which equals one if the fund is available for sale via Tiantian, and zero otherwise, we find a quantitatively similar coefficient estimate of 16.47

[25] $\text{Log}(\#\text{Platforms})_{i,t}$ has a mean of 2.2 and standard deviation of 1.07 in our sample.

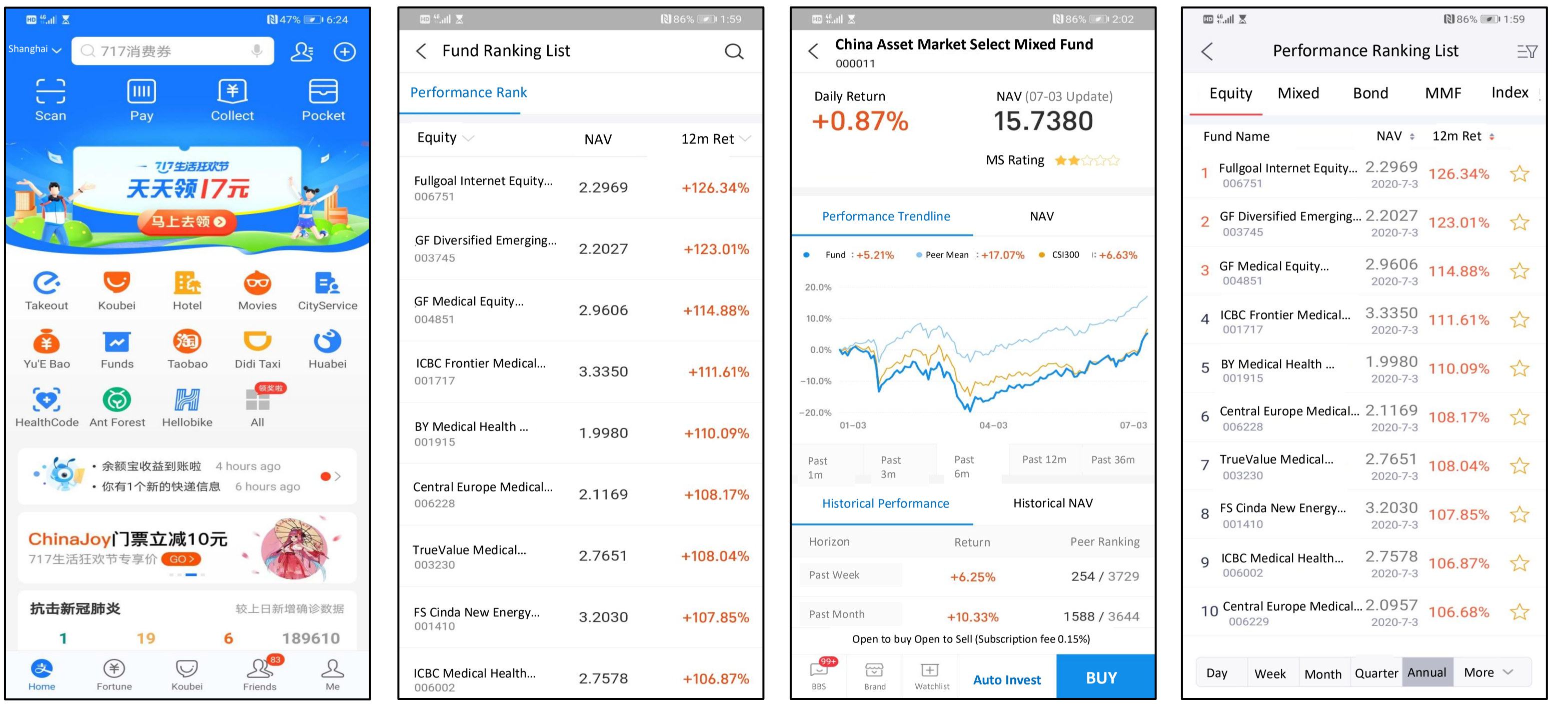
(t-stat=7.82) for the interaction term. Conducting the same exercise for Ant platform in row (9), the corresponding coefficient estimate is 14.08 (t-stat=6.73), also similar in magnitude to the baseline estimate of 16.85 (t-stat=8.03). The evidence suggests that both of the two platforms are capable in generating the amplified flow-performance sensitivity that we observe in aggregate.

Replace Decile10 with Performance Rank: In our baseline specification, we use Decile10 to capture funds' past performance because the relationship between flow and fund performance is convex, as shown in Figure 2 and also reported by prior literature (Chevalier and Ellison (1997)). To examine the robustness of our results, we further replace Decile10 dummy with funds' performance decile rank, which has a value ranging from one to ten, constructed based on funds' past 12-month return. In row (10) of Table A3, the coefficient on the cross term between the performance rank and the Platform dummy remains significant. In particular, when the performance decile rank of a platform fund increases by 9 from Decile 1 to Decile 10, it attracts an extra quarterly flow of 11.9%.

Figure A1. Information Display: FinTech Platforms vs. Online Broker

This figure shows the display of information on the FinTech platforms in China and a typical online brokerage firm in the US. The left three figures in Panel A are screenshots from the Ant Financial Platform. Specifically, the figures show the front page of Alipay, the performance rank list, and the detailed information for a specific fund on Alipay. The last figure in Panel A shows a performance rank list on the Howbuy platform, with the screenshot taken on the same day. Panel B shows a screenshot from Charles Schwarb OneSource, an online brokerage firm in the US, in comparison.

Panel A:



Panel B:

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Growth of 10,000 Hypothetical Investment | 3 Month Performance

Large Blend | Add Symbol | Add Symbol | Add Symbol | Add Symbol

Enter Mutual Fund Symbol | **Add**

Click the icon next to a symbol in the list below to add it to the chart, or enter any mutual fund symbol in the text box above.

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- Invest primarily in stocks that fall in the top 70% of the U.S. market capitalization range.
- Includes Large-Cap Growth, Value and Blend funds.
- No load and no transaction fee.
- Pre-screened by Schwab Experts.

Large-Cap U.S. Stock Funds

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17 Third-Party funds
1 Market-Cap Weighted Index Funds
(1) Schwab-Affiliate (0) Third-Party
1 Fundamental Index Funds
(1) Schwab-Affiliate (0) Third-Party
0 Balanced Funds
(0) Schwab-Affiliate (0) Third-Party
0 Target Funds
(0) Schwab-Affiliate (0) Third-Party
0 Alternative Funds
(0) Schwab-Affiliate (0) Third-Party

Click on the fund symbol for quarterly standardized returns and detailed fund expenses. Performance quoted is past performance and is no guarantee of future results. Current performance may be lower or higher. Investment value will fluctuate, and shares, when redeemed, may be worth more or less than original cost.

Q2 2020 OneSource Select List® Performance Data as of 05/31/2020 — How Funds Are Selected

Select Funds to Compare (max 5)	Symbol/Name	Morningstar Category	Return 3 Month	1 Year	3 Year	5 Year	10 Year	Inception	Upside Capture Ratio	Downside Capture Ratio	Net Expense Ratio (%)	Gross Expense Ratio (%)	Socially Responsible
			Average Annual Returns										
	Benchmark: S&P 500 TR		+3.59	+12.84	+10.23	+9.86	+13.15	--	NA	NA	NA	NA	NA
Leading Schwab Affiliate Funds (3 Funds)													Click icon to view on chart
	Laudus U.S. Large Cap Growth Fund LGILX	Large Growth	+11.28	+24.45	+19.14	+14.62	+16.40	+8.54 (10/14/1997)	115.86	80.57	0.75	0.75	No
— Fundamental Index Funds (1 Fund)													Click icon to view on chart
	Schwab Fundamental US Large Company Index Fund SFLNX	Large Value	-1.72	+3.47	+5.32	+6.09	+10.82	+7.13 (04/02/2007)	96.97	120.53	0.25	0.25	No
— Market-Cap Weighted Index Funds (1 Fund)													Click icon to view on chart
	Schwab® S&P 500 Index Fund SWPPX	Large Blend	+3.58	+12.79	+10.20	+9.80	+13.07	+7.71 (05/19/1997)	99.94	100.06	0.02	0.02	No
Leading 3rd Party Funds (17 Funds)													Click icon to view on chart
	Hartford Core Equity Fund Class A HAIAX	Large Blend	+2.08	+11.58	+10.90	+9.84	+13.77	+6.85 (04/30/1998)	96.78	91.85	0.74	0.74	No
	MFS Low Volatility Equity Fund Class A MLVAX	Large Blend	-0.50	+4.95	+7.91	+8.82	--	+9.50 (12/05/2013)	73.30	71.69	0.89	1.04	No
	Parnassus Core Equity Fund - Investor Shares PRBLX	Large Blend	+3.62	+11.19	+11.11	+9.78	+12.67	+10.64 (08/31/1992)	89.97	80.61	0.86	0.86	Yes
	T. Rowe Price Dividend Growth Fund PRDGX	Large Blend	+1.78	+8.62	+10.05	+9.87	+12.83	+9.69 (12/30/1992)	87.09	81.61	0.62	0.62	No
	TIAA-CREF Social Choice Equity Fund Retail Class TICRX	Large Blend	+3.15	+12.49	+9.42	+8.89	+11.77	+7.79 (03/31/2006)	98.81	102.30	0.45	0.45	Yes
	Wells Fargo Low Volatility U.S. Equity Fund Class A WLVLX	Large Blend	-0.71	+4.08	+5.23	--	--	+7.94 (10/31/2016)	65.22	73.46	0.73	1.50	No
	American Century Investments Focused Dynamic Growth Fund Investor Class ACFOX	Large Growth	+16.54	+42.43	+24.95	+17.15	+16.60	+11.15 (05/31/2006)	132.57	78.92	0.85	1.02	No

Figure A2. Retail Ratio and Fund Expense Ratios around Platform Entrance

The upper left graph reports the value-weighted retail ratio for each style of funds over time. The upper right graph plots the annual management fee for each style over time. In the lower two graphs, we plot the annualized total operating expense and advertising expense ratios. Advertising expense ratio is calculated as total operating expense subtracting management expense, custodian expense, transaction expense, and interest expense. Funds report operating expenses via income statement on a semi-annual basis. The annualized expense ratio is calculated as the corresponding expense scaled by average TNA, e.g., $\text{AdvertiseEXP\%} = \text{AdvertiseEXP} * 2/((\text{TNA}_t + \text{TNA}_{t-1})/2)$. The shaded areas indicate the 95% confidence intervals.

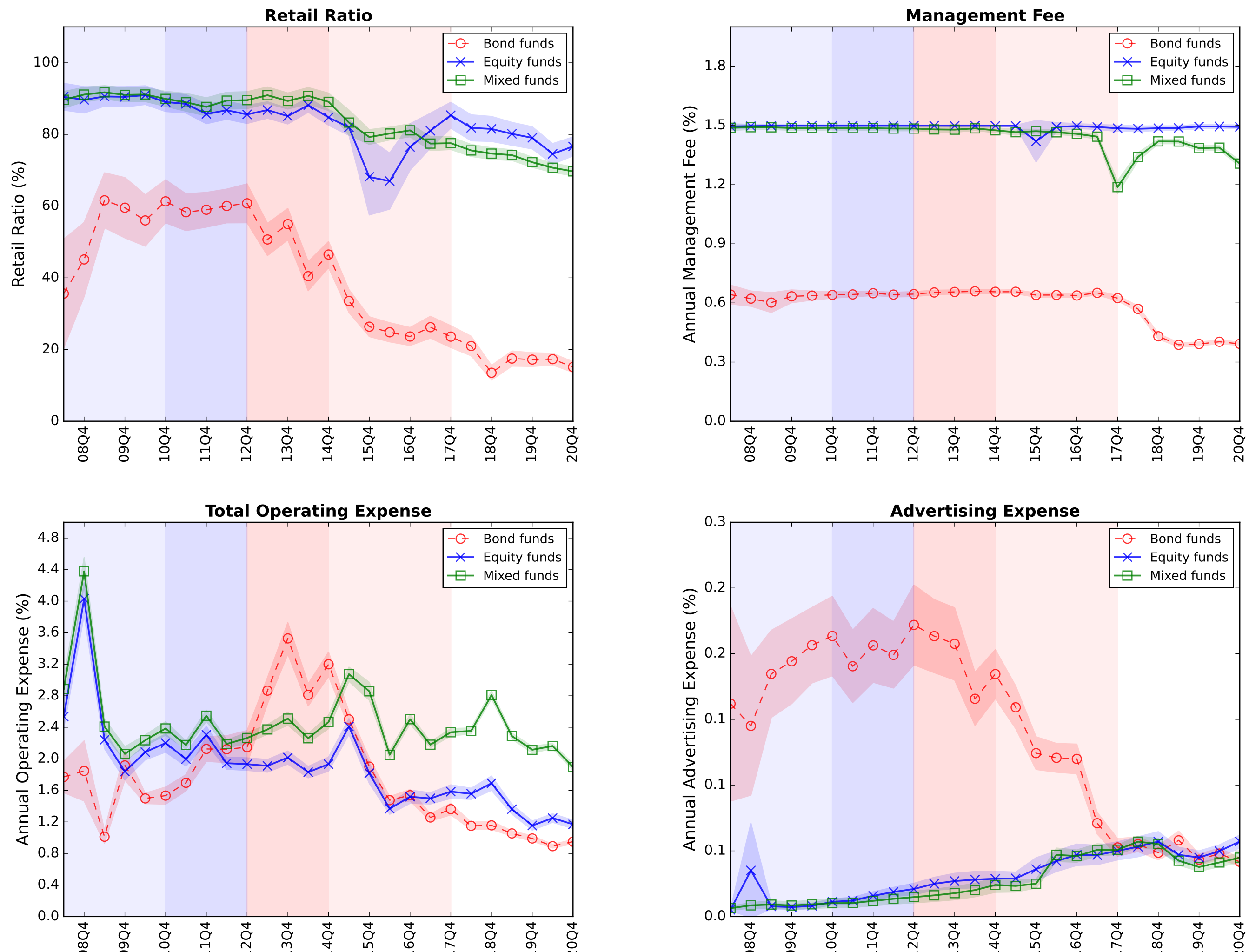

Table A1. Determinants of Entrance onto Platforms

This table examines the cross-sectional determinants for funds' and families' entrance onto platforms. Column (1) and (2) includes all the funds with inception dates before the end of 2012. Column (3) and (4) includes all the families with inception dates before the end of 2012. D(Enter≤2013Q1) is a dummy variable that equals one if the fund (or family) enters onto the Tiantian platform on or before March 31, 2013. Log(Enter months) is the natural logarithm of the number of months from March 2012 to the time when the fund (or family) enters Tiantian. Bank-affiliated is a dummy variable that equals one if the controlling shareholder (>30% ownership) is a bank, and Broker-affiliated is defined similarly. We also include control variables of Retail Ratio, which is the fraction of a fund held by individual investors at the end of June 2012, past 12-month return and the standard deviation of return by the end of June 2012 ($MRet_{t-1,t-4}$ and $MRetStd_{t-1,t-4}$), Log(Size), Log(Age), and Flow at the end of June 2012. Control variables for families are constructed as the value-weighted average of all funds within the family. We include style fixed effect for fund specifications. t-statistics are adjusted using heteroscedasticity-robust standard errors and are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Fund		**Family**	
	D(Enter≤2013Q1)	Log(Enter months)	D(Enter≤2013Q1)	Log(Enter months)
	Logit	OLS	Logit	OLS
	(1)	(2)	(3)	(4)
Log(Size)	-0.250***	0.113***	-0.855*	0.19
	(-2.92)	(2.98)	(-1.78)	(1.30)
Log(Age)	0.669**	-0.131	4.141*	-0.277
	(2.24)	(-1.16)	(1.68)	(-0.46)
Flow	0.587**	-0.200***	1.967	-0.711
	(2.43)	(-4.27)	(0.59)	(-1.01)
$MRet_{t-1,t-4}$	0.145	0.06	1.716	-0.015
	(0.69)	(0.70)	(1.41)	(-0.06)
$MRetStd_{t-1,t-4}$	-0.081	0.097	0.39	0.08
	(-0.65)	(1.11)	(0.45)	(0.38)
Bank-Affiliated	-1.681***	0.662***	-2.593*	0.973**
	(-4.83)	(6.50)	(-1.95)	(2.37)
Broker-Affiliated	-0.073	0.198**	0.389	0.134
	(-0.34)	(2.28)	(0.44)	(0.55)
Retail Ratio	-2.008***	0.575***	-10.140***	1.693*
	(-3.90)	(3.44)	(-3.09)	(1.69)
Style FE	Y	Y	Y	Y
Observations	481	481	60	60
R-squared	0.106	0.137	0.3252	0.266

Table A2. Flow-Performance Sensitivity Conditional on Participation Costs

This table reports the sensitivity of flow to fund past performance for subsamples of funds conditional on proxies of participation costs. The sample period is from 2008 through 2017. Panel A reports the subsample estimations following the specification in Table 3 and panel B reports the results following the specification in Table 4. We use parent family size, measured by either the number of funds offered or the total value of assets under management, to capture the variation in search costs across funds. Funds with above-median marketing expense, captured by total operating expense ratio and advertising expense ratio, also have lower search costs. To capture variations in transaction costs, we use the front-end loads of funds. Time fixed effects and fund fixed effects are included in all the specifications. Standard errors are double-clustered at the time level and fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A. Conditional on Performance Decile Rank

	Family #Funds		Family Size		Operating expense		Advertising expense		Front-end fee	
	Large	Small	Large	Small	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Decile10	3.530**	7.352***	4.252***	5.828***	5.223**	4.685***	6.008***	-8.153	5.758**	4.340**
	(2.58)	(3.45)	(2.96)	(2.74)	(2.14)	(2.92)	(4.51)	(-1.32)	(2.38)	(2.16)
Platform	-3.611***	-0.705	-3.160***	-1.492	0.64	-4.456**	-1.692	-3.829	-2.500**	-2.087
	(-2.87)	(-0.38)	(-3.10)	(-0.82)	(0.45)	(-2.69)	(-1.65)	(-0.50)	(-2.06)	(-1.29)
Decile10×Platform	15.255***	16.798***	12.303***	19.570***	20.912***	14.107***	14.739***	26.697***	15.546***	18.183***
	(4.52)	(4.95)	(4.51)	(5.75)	(5.06)	(5.84)	(4.47)	(3.91)	(4.38)	(5.70)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	9,132	9,003	9,058	9,057	9,084	9,026	10,023	8,088	9,354	8,865
R-squared	0.234	0.185	0.214	0.187	0.224	0.279	0.263	0.245	0.184	0.204

Panel B. Conditional on Front-Page Closeness

	Family #Funds		Family Size		Operating expense		Advertising expense		Front-end fee	
	Large	Small	Large	Small	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Top10	3.207**	5.611*	4.632**	3.483	4.713*	4.243***	6.139***	-11.857	5.919*	3.578
	(2.09)	(1.91)	(2.62)	(1.19)	(1.90)	(3.00)	(3.68)	(-1.75)	(1.99)	(1.60)
Top11–30	2.944**	5.298***	3.235***	3.800**	4.605**	2.313***	4.621***	-5.141	4.400***	2.6
	(2.03)	(3.86)	(2.74)	(2.08)	(2.18)	(3.46)	(3.82)	(-1.41)	(3.49)	(1.57)
Top31–50	0.63	1.137	0.137	1.495	1.445	0.307	1.206	-0.314	0.715	0.828
	(0.60)	(1.17)	(0.20)	(1.22)	(1.10)	(0.53)	(1.56)	(-0.09)	(0.95)	(0.68)
Platform	-5.074***	-2.191	-4.033***	-3.863**	-3.076	-2.183**	-3.436***	-2.894	-4.360***	-3.439*
	(-3.42)	(-1.13)	(-3.43)	(-2.08)	(-1.61)	(-2.47)	(-3.01)	(-0.38)	(-3.09)	(-1.98)
Top10×Platform	24.448***	31.921***	16.945***	39.061***	42.599***	13.994***	26.256***	48.407***	30.530***	26.678***
	(5.26)	(5.59)	(3.44)	(6.18)	(7.34)	(3.59)	(5.96)	(4.78)	(5.04)	(5.86)
Top11–30×Platform	9.481***	13.431***	7.393**	15.779***	14.797***	6.923***	9.015***	22.765***	9.989***	14.655***
	(2.79)	(3.37)	(2.58)	(4.21)	(3.74)	(3.74)	(3.24)	(4.13)	(3.79)	(3.83)
Top31–50×Platform	11.610***	6.886***	8.724***	9.333**	10.879***	5.174***	8.689***	8.605	9.946***	9.254***
	(3.09)	(3.11)	(3.48)	(2.62)	(3.41)	(3.53)	(3.64)	(1.66)	(3.24)	(3.65)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	9,132	9,003	9,058	9,057	9,045	9,052	10,023	8,088	9,354	8,865
R-squared	0.232	0.186	0.210	0.191	0.193	0.329	0.270	0.244	0.186	0.201

Table A3. Alternative Specifications

This table reports the regression estimations under alternative specifications, following a similar specification in Table 3. The sample period is from 2008 through 2017. The first row reports the baseline specification, estimated for mixed and equity mutual funds. In model (1), we report the regression estimates, excluding the whole year of 2015. Model (2) allows for time-varying performance chasing by controlling for After×Decile. In model (3), we control for dummy variable Ms5star (Ms4star), which equals one if the fund Morningstar rating is five (four) star, and zero otherwise, and their interactions with the Platform dummy. In model (4), we control for Log(#Bank)$_{i,t-1}$ and Log(#Brokers)$_{i,t-1}$, and their interactions with Decile10$_{i,t-1}$ dummy. Log(#Bank)$_{i,t-1}$ (Log(#Brokers)$_{i,t-1}$) is the natural logarithm of the number of banks (brokers) in which a fund is available for sale at quarter $t-1$. Model (5) restricts the sample to the funds with inception year on and before 2012. In model (6), we estimate weighted least squared regressions, using the TNA$_{i,t-1}$ of each fund as the weight for each observation. In model (7), we replace the Platform dummy with the natural logarithm of the number of platforms that a fund is available for purchase. In models (8) and (9), we replace the Platform dummy with the Tiantian and Ant dummy, which equal to one if a fund is available for sale via Tiantian and Ant platforms respectively, and zero otherwise. In model (10), we replace the Decile10$_{i,t-1}$ dummy with the performance decile rank variable that ranges from one to ten. Coefficients on the interaction term "Decile10×Platform" are reported. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Estimates under Alternative Specifications				
	Decile10×Platform	Decile10	N	R^2
Baseline	16.845***	4.944***	18,329	0.184
	(8.03)	(3.77)		
(1). Exclude 2015	18.070***	5.035***	15,930	0.213
	(8.07)	(4.03)		
(2). Control After×Decile10	10.318**	3.652**	18,329	0.184
	(2.48)	(2.60)		
(3). Control for MorningStar 5 & 4 ratings	15.013***	4.849***	18,329	0.187
	(6.92)	(3.76)		
(4). Control Bank & Broker	16.473***	2.89722	18,329	0.186
	(8.21)	(0.34)		
(5). Inception <2012	15.542***	4.708***	15,512	0.138
	(6.60)	(3.80)		
(6). Value-Weighted	16.400***	4.759***	18,329	0.181
	(8.54)	(3.77)		
(7). Replace Platform with Log(#Platforms)	7.300***	4.378***	18,329	0.184
	(9.12)	(3.50)		
(8). Replace Platform with Tiantian	16.467***	5.303***	18,329	0.184
	(7.82)	(3.88)		
(9). Replace Platform with Ant	14.078***	8.411***	18,329	0.183
	(6.73)	(6.20)		
(10). Replace Decile10 with Rank12m	1.321***	0.548***	18,329	0.176
	(5.13)	(3.64)		