FinTech Platforms and Mutual Fund Distribution

Claire Yurong Hong, Xiaomeng Lu, and Jun Pan*

August 4, 2020

Abstract

This paper studies the economic impact of the emergence of FinTech platforms on financial intermediation. In China, platform distributions of mutual funds emerged in 2012 and grew quickly into a formidable presence. Utilizing the staggered fund entrance onto platforms, we find markedly increased flow sensitivities to performance. Akin to the winner-take-all phenomenon in the platform economy, net flow captured by top 10% performing funds more than triples its pre-platform level. This pattern of platform-induced performance chasing is further confirmed using private data from Howbuy, a top platform in China. Consistent with this added incentive of becoming top performers in the era of large-scale platforms, fund managers increase risk taking to enhance the probability of becoming top performers. Meanwhile, organizational cohesiveness of fund families weakens as platforms level the playing field for all funds.

*Hong (yrhong@saif.sjtu.edu.cn) and Lu (xmlu@saif.sjtu.edu.cn) are from the Shanghai Advanced Institute of Finance at Shanghai Jiao Tong University. Pan (junpan@saif.sjtu.edu.cn) is from the Shanghai Advanced Institute of Finance at Shanghai Jiao Tong University, CAFR and NBER. This paper was previously entitled "The Economic Impact of Distributing Financial Products on Third-Party Online Platforms." We are grateful to Darrell Duffie, Hao Jiang, Andrew Karolyi, Jennifer Huang, Xing Huang, Yi Huang (discussant), Wenlan Qian, Clemens Sialm, Laura Stark, Baolian Wang, Joakim Westerholm (discussant), Shangjin Wei, Wei Xiong, Xiaoyun Yu, Lu Zheng, and Haoxiang Zhu for valuable discussions and comments. We thank seminar and conference participants at Tsinghua University PBC School of Finance, Chinese University of Hong Kong (Shenzhen), Lingnan University, Shanghai Advanced Institute of Finance, Hong Kong University of Science and Technology, National University of Singapore, the 2019 China FinTech Research Conference, the 2020 Finance Down Under Conference, the behavioral finance online seminar organized by Wei Xiong. We are grateful to the Howbuy platform for data provision. We thank Linchen Liu, Shiwen Tian, and Heming Zhang for research assistance.

1 Introduction

The rise of the platform economy over the past decade is transforming the way we live. Empowered by technological innovations, 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 their respective industries, and, for better or worse, our actions follow accordingly.

In this paper, we focus on the impact of the emergence of FinTech platforms on financial intermediation. Technological developments over the past quarter century have greatly facilitated online trading of financial products,[1] but the recent emergence of platform economy is an entirely new phenomenon. In particular, even with the widespread presence of online trading, the intermediation of financial products such as mutual funds remains segmented by the numerous distribution channels organized by fund families, banks, and brokers. The emergence of the FinTech platforms, created by tech-driven firms independent of the traditional distribution channels, threatens to break this institutional segmentation and reshape financial intermediation as Amazon did for books and retail goods. On the consumer side, FinTech integrates mutual fund investment into investors' everyday life. With increased technological efficiency, investors can access a vast number of mutual funds, which, via apps on mobile devices, are literally at their fingertips. On the product side, fund managers, no matter how small or invisible, have the potential to reach the entire user base of these platforms. By vastly improving the means of connectivity and offering technological efficiency, the platform model takes down barriers, allows information to flow more freely, and levels the playing field for all mutual funds. But as the distribution of funds is made more efficient via the platform model, what is the impact on investors' allocations of risk? Likewise, as the platforms improve the means of connectivity, what are the economic consequences, both intended and unintended, of this new and powerful distribution channel on fund investors, fund managers, and fund families?

Our paper provides direct empirical evidence to address these important questions. Platform intermediation of financial products has often been discussed in the literature because of its huge growth potential (e.g., Goldstein, Jiang, and Karolyi (2019), Philippon (2018), and Frost et al. (2019)). Nonetheless, there is limited empirical evidence with respect to what actually happens when platforms take hold of a sizable market share in the distribution of financial products. Taking advantage of a 2012 policy change in China, which allowed FinTech platforms to distribute mutual funds, our paper is the first to fill in the knowledge

[1]See, for example, Barber and Odean (2001, 2002) and Choi, Laibson, and Metrick (2002) on how internet affects investor behavior.

gap. Living in the era of digital payments via Alipay, and later fueled by the enthusiasm for Yu'ebao, the money market fund provided by Ant Financial in 2013, the Chinese customers are early adopters of FinTech platforms. By 2018, the platforms have already grown into a formidable presence in distributing mutual funds, with the top platforms covering almost all of the equity, bond, and mixed mutual funds in China.[2]

Focusing first on the impact of the 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 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 1.88% pre-platform (2008–2012) to 19.65% post-platform (2013–2017). This amplification of the performance chasing post-platform shows up not only in the equity funds but also in the mixed funds. Using the US equity funds as a benchmark, we do not find such a pattern and the average net flow to the top-decile funds in the US is around 6% in both time periods. 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 further test this pattern of amplified performance chasing at the fund level. By regressing quarterly fund net flows on fund rankings and controlling for fund-level characteristics and time and style fixed effects, we find that the post-platform performance sensitivity is around three times the pre-platform level for both equity and mixed funds.

The fact that our results can be detected in the publicly observed data is significant – it indicates that the platforms have grown important enough to influence the entire mutual fund industry. We further provide direct evidence by taking advantage of a proprietary dataset obtained from Howbuy, one of the top platforms in China. We find that performance chasing is indeed stronger on the platforms. For example, 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 goes to the top-decile equity funds.

Performance chasing has long been documented as a salient feature of investor behavior in the mutual fund industry.[3] What is new and important in our findings is the strong amplification effect associated with the emergence of platforms. Understanding the reason behind this amplified performance chasing is therefore important for the future of FinTech

[2]While the sales numbers have been closely guarded by the platforms, it was estimated that, by 2018, about one-third of the sales of equity, bond, and mixed mutual funds took place on the platforms and another one-third via banks, the largest distribution channel in the pre-platform era.

[3]See, for example, Gruber (1996), Brown, Harlow, and Starks (1996), and Chevalier and Ellison (1997).

platforms. First and foremost, we hypothesize that the unique features of FinTech platforms – their technological efficiency and centralized information structure – result in a pattern of synchronized performance chasing, which are the main driver of the amplified flow-performance sensitivity. Central to our argument is the observation that the flow of information is uniquely different on and off platforms. Off platform, the information flow is dispersed in nature, with different investors receiving different information from their respective distribution channels. On platform, the information flow is uniform in nature. Almost all the platforms adopt a simple performance rank list setting to display funds in their mobile apps.[4] With investors receiving almost identical signals focusing mostly on past performance, performance chasing at the individual investor's level gets synchronized and this synchronized performance chasing gives rise to the amplified performance chasing.

To formally test our hypothesis of synchronized performance chasing, we take advantage of the fact that the front page of each FinTech platform's mobile app has limited space. Depending on the size of their cell phones, investors normally see 6 to 10 funds per page on their mobile apps. 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 are more likely to show up on the front page of the mobile apps. This is exactly what we find. The platform-induced performance chasing is the strongest for the top 6 funds and decreases precipitously with the ranking of the funds as they become less likely to appear on the front page.

We further investigate other alternative channels through which amplified performance chasing can arise. For example, platforms might attract new and inexperienced investors who are more prone to performance chasing. Focusing on the time surrounding the introduction of FinTech platforms, we do not find significant changes in the number and fraction of retail investors, either at the individual fund level or the aggregate level. Another possibility is that the timing of funds' entrance onto platform might be endogenous. For example, it just happens that funds enter the platform exactly when, for various reasons, investors of such funds become more prone to performance chasing. Such stories, while possible, are hardly plausible, given the sudden amplification of performance chasing occurring immediately after funds' entrance onto platforms. Nevertheless, we go over each of such endogenous scenarios carefully in the paper to rule them out. A third possibility is that improving market condition might enhance investors' propensity for performance chasing. Building on our staggered

[4]Investors on the platforms share the same set of information displayed on their digital devices. Most platforms group mutual funds by style into tabs for equity, bond, mixed, and index funds. Within each tab, the default page displays the funds in the order of their past raw returns. More recently, the traditional channels such as banks and brokers are moving to the platform model by building their own digital apps, which very much resemble the apps provided by the platforms. There is, however, one important difference – the default page of the banks' apps usually displays their affiliated funds at the top.

entrance test, which utilizes the different timing of funds' entrance onto platforms, we further control for the time-varying flow-performance sensitivity for each year. We find that the platform effect still exists, suggesting that changing market conditions cannot explain our results.

To understand the broader impact of FinTech platforms, we further investigate the behaviors of fund managers and document the changing landscape for fund families. We find that, in the presence of amplified performance chasing, fund managers increase risk taking to enhance the probability of getting into the top rank. Specifically, we find that funds in the top decile exhibit a pattern of increased volatility for at least two quarters prior to getting into the top ranking. In contrast, funds outside the top decile do not exhibit such a pattern. Decomposing the fund volatility further into systematic and idiosyncratic components, we find that this added risk taking is present in both components, but the increased risk taking in the systematic component is more troubling. 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 relatively small, the emergence of such a practice points to the unintended consequences associated with the platform intermediation of financial products.

The emergence of these platforms also has a profound impact on large fund families. Before the rise of the platform economy, large fund families are like segmented mini-platforms whose resources are attractive to fund managers. This is similar to how, before Uber arrived, taxi drivers relied heavily on dispatch services. In the era of the platform economy, however, large fund families lose their cohesiveness as organizations. Empirically, after joining the top platforms, the importance of within-family-ranking weakens, whereas the importance of universal ranking gets amplified in attracting subsequent flows. In other words, after the introduction of platforms, fund managers are increasingly being compared to the entire universe of funds, resulting in the lowered importance of their relative standing within a family. At the same time, fund families' incentive to groom star managers also drops, as they no longer have a strong hold on their fund managers. Consistent with this hypothesis, we find that, pre platform, funds from the top ten largest families account for a significantly higher share in the top decile than in other deciles. Post platform, however, they no longer have a large presence in the top decile.

Our paper contributes to the new and exciting field of FinTech by offering the first comprehensive study on the large-scale disruption of FinTech platforms in the mutual fund industry. Relative to Goldstein, Jiang, and Karolyi (2019), Philippon (2018) and Frost et al. (2019), where FinTech opportunities and their potential impact on existing financial institutions are discussed and anticipated, our paper is the first to provide extensive empirical evidence on what actually happens when the tech-driven mobile-device-based platforms are allowed to enter the financial intermediation industry to distribute financial products. Given that this large-scale disruption in the mutual fund industry has not yet happened elsewhere, our paper offers a glimpse into the future, documenting the intended and unintended consequences of such a disruption. The scope of our results is much broader than what has been documented in the existing literature. While most of the existing empirical work in this area that relies on proprietary data from one particular platform to measure the impact of FinTech,[5] we provide evidence using both the publicly available data of the entire mutual fund industry and the data from a top platform in China. In other words, we are reporting the impact of FinTech on the entire industry, not just one platform or one company.

As such, our findings serve as important and essential building blocks to facilitate the much needed discussion on the welfare implications of the FinTech development. As expected, FinTech platforms can considerably lower the barrier to financial market participation and level the playing field for all mutual funds. But also shown in our paper is the fact that technological efficiency of the platforms does not necessarily imply economic efficiency, and there is indeed cause for concern. Among the most significant results of our paper is the power of information flow in the platform economy and its unintended consequences. In particular, the winner-take-all effect is overwhelmingly strong on these FinTech platforms. Whether or not the platforms should be more proactive in regulating the flow of information or in offering financial advices to alleviate the unintended consequences is a topic of great interest.[6]

Our paper is also related to the existing literature that studies the effectiveness of distribution channels of financial products. As documented by Bergstresser, Chalmers, and Tufano (2009), Chalmers and Reuter (2020), Christoffersen, Evans, and Musto (2013), Jenkinson, Jones, and Martinez (2016), and Cookson et al. (2020), there is ample evidence of the conflicts of interest among brokers, financial advisors, and web-based platforms. We complement their study by examining the impact of FinTech platforms. The conflict-of-interest issue is arguably less of a concern, as these FinTech platforms often display funds according to objective measures, like performance ranking. We show that, in the absence of guidance from banks and brokers, individual investors pay more attention to the prominent features

[5] See, for example, D'Acunto, Prabhala, and Rossi (2019) on the impact of robo-advising, Wei and Yang (2019) on online and offline mutual fund investing, Cookson et al. (2020) on the conflict-of-interest issue of online platforms, Vallee and Zeng (2019) on P2P lending, Hau et al. (2017) on the impact of FinTech credit on entrepreneur growth, and Buchak et al. (2018) and Fuster et al. (2019) on mortgage origination.

[6] Outside the financial intermediation industry, the fact that the platforms can influence investor behavior through personalized information flow has been recognized, and its validity debated. For example, Sun et al. (2019) document the large economic impact of the platforms' information flow on customer buying behavior through a large-scale field experiment with Alibaba's retail platform.

of platform apps, e.g., performance ranking lists.

Finally, our paper also adds to the extensive literature on the impact of mutual fund performance on investment flows. For example, Chevalier and Ellison (1997), Sirri and Tufano (1998), Goldstein, Jiang, and Ng (2017) among others document the flow-performance sensitivity for equity funds and bond funds. More relevantly, Kaniel and Parham (2017) investigate how visibility and prominence through media coverage affect investors' attention and flow to top performers. We find that the technological efficiency and information structure on large-scale FinTech platforms can exacerbate the flow-performance sensitivity in the market.

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 flow-performance sensitivity and presents direct evidence of amplified performance chasing using proprietary data from Howbuy. Section 4 investigates the channels and alternative explanations of the results. Section 5 explores the economic consequences of platforms on fund managers and fund families. Section 6 conducts robustness checks under alternative settings. Section 7 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 may distribute mutual funds. CSRC further issued guidelines in March 2013 for sales agencies distributing funds through e-commerce platforms.[7] Before the introduction of platforms, funds could only be distributed through banks, brokers, and fund families. The upper left panel of Figure 1 shows the number of major types of distribution channels over time. Since 2008, there has been a steady increase in the number of distribution channels via banks and brokers, with the banks growing faster than the brokers. Platforms entered the scene in 2012, quickly catching up with the banks and brokers and reaching a total number of 115 by 2018. As is typical in the platform economy, the top platforms grabbed most of the market shares while the smaller platforms struggled for survival. Thus, of the 115 platforms, only a handful are active.

As of 2018, the two largest platforms were Tiantian and Ant Financial in terms of market share. Tiantian is among the first four institutions to obtain the fund distribution license

[7] http://www.csrc.gov.cn/pub/csrc_en/laws/overRule/Announcement/201306/t20130603_228916.html

from China Securities Regulatory Commission (CSRC) in February 2012. Ant Financial missed the first batch of license issuance, but quickly entered the platform business in April 2014 by acquiring Hundsun, the parent firm of a platform called Shumi.[8] The introduction of Yu'ebao and the acquisition of Hundsun are highlighted in the graphs, marking two milestone events for Ant Financial and the entire mutual fund industry.

The upper right and bottom left panels of Figure 1 report the coverage of actively managed mutual funds in our sample by the top four platforms (Ant, Howbuy, Tiantian, and Tong Huashun) and an average bank and a broker. The coverage is reported both in percentage (bottom left panel) and in number (upper right panel). As we can see, the adoption of platforms by mutual funds has been swift. Over the span of just one year, from 2012Q2 to 2013Q2, the coverage increased from zero to over 60% for the top three platforms, indicating that over 60% of the actively managed mutual funds in our sample have signed up to be covered by the platforms. The coverage of mutual funds has become significantly large since the emergence of platforms as compared to that of an average broker or bank. For example, by 2018, each of the top four platforms covered over 2000 actively managed funds, while an average bank carried less than 300 funds and an average broker carried less than 1000 funds.

Overall, the entrance of the platforms has been swift, with mutual funds quickly signing up with the platforms. It should be emphasized, however, that coverage does not equate to actual transactions. While the actual sales numbers have been closely guarded by the platforms, we get a glimpse of these numbers using the annual reports from East Money, the parent company of Tiantian platform, one of the first and largest platforms in China. The 2018 sales of mutual funds on Tiantian totaled RMB 525 billion, including RMB 328.7 billion for money market funds. Excluding money market funds, the 2018 sales number of mutual funds was RMB 196.4 billion for Tiantian and RMB 2.3 trillion for the entire market. In other words, as one of the top platforms, Tiantian's market share was about 8.5% in 2018. This number is roughly consistent with the estimated magnitude reported in the press – the platforms in aggregate account for one-third of the market share.

2.2 The Features of FinTech Platforms

The features and designs of the FinTech platforms in China are highly homogeneous. In particular, all the platforms adopt a simple performance rank list setting to display funds in their mobile apps. Most of the FinTech platforms mainly operate through mobile apps instead of websites. Based on the survey evidence from Asset Management Association of China in 2018, around 71% of retail investors purchase mutual funds through apps on mobile

[8] Since customers from Alipay are the major source of investor flow for Ant Financial platform, we use the acquisition date as the starting date of the platform operated by Ant Financial in our later analysis.

phones, and only 17.4% stick to the Internet website purchases.[9] Panel A of Appendix Figure A1 exhibits cell phone screenshots of two platforms, Ant Financial and Howbuy, for illustration purposes. The first screenshot shows the front page of the Alipay app provided by Ant Financial. Alipay is a catch-all app developed by Alibaba, which integrates all kinds of services from calling a taxi to ordering takeout. Alipay has an embedded mutual funds section in its ecosystem, making mutual fund investment as easy as other aspects of everyday life. After entering this fund section, investors can choose funds from a performance rank list, as shown in the second screenshot. All funds in a specific style are ranked according to their past raw returns, and investors can choose a return horizon of 1, 3, 6, or 12 months to rank funds. By clicking on a fund, investors can view detailed information about it, as shown in the third screenshot. According to the current regulation, platforms cannot rank funds at their discretion on measures not directly obtained from the fund reports or prospectus. For example, platforms cannot rank funds based on the platforms' own version of risk-adjusted returns. The limited screen space on mobile apps, together with tech firms' emphasis on simple user interface, also constrain the platforms' ability to display additional information. As a result, all FinTech platforms in China rank funds based on past performance, which is one of the most important factors that investors care about in mutual fund investment. As shown in the last screenshot, the performance rank list from the Howbuy app (taken on the same day) is almost identical to the one from Alipay, with exactly the same list of funds on top. Since the performance rank list is based on funds' raw returns, there is little room for platforms to intervene based on their incentive. Therefore, the potential conflict-of-interest issue is arguably mitigated in this setting.

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 all the available funds. Finally, as a typical financial firm, they provide rich information and abundant criteria for investors to 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.

[9]http://www.amac.org.cn/researchstatistics/report/tzzbg/202001/P020200106520189708039.pdf

2.3 Data and Methodology

We obtain the data for mutual funds from CSMAR (China Stock Market & Accounting Research) and Wind. In China, there are four types of mutual funds: equity mutual funds, mixed mutual funds, bond mutual funds, and money market funds. We focus on the actively managed equity, mixed, and bond mutual funds and exclude index funds, passive funds, structured funds, and QDII funds from our analysis. For mutual funds with multiple share classes, we sum all the share classes to derive the total net assets (TNA) of the funds. We compute fund returns and fund fees as the TNA-weighted average across all the share classes.

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. 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. To alleviate any concern about outliers, flow is winsorized at 2% and 98% levels. We exclude fund-quarter observations when the absolute values of two adjacent quarter flows are both larger than 100% but in different signs, which may have been caused by errors in reporting TNA. We further require a minimum fund size of RMB 1 million and a minimum fund age of two years to be included in our sample. We end up with 26,412 fund-quarter observations from 2008 through 2017 for our sample.

To examine the impact of platforms, we focus our analyses on two time periods: before 2008–2012 and after 2013–2017. We define our post-platform period from 2013 because, although some platforms obtain their licenses from the CSRC in February 2012, it is not until the end of 2012 that the first batch of funds become available for sale on the platforms. Table 1 provides the summary statistics of the actively managed mutual funds in our sample, with Panel A reporting the aggregate fund information by year and Panel B reporting the key fund-level variables for the before and after periods.

As shown in Panel A of Table 1, the total number of funds steadily increases from fewer than 200 in 2008 to close to 3000 by 2019. The number of bond funds is particularly small in the early years, with only 20 funds by 2009, which prompts us to start the before period for bond funds from 2010. The same pattern can be observed from the bottom right panel of 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. Another visible change in our sample is the dramatic decrease in the size of equity funds, along with the dramatic increase in the size of mixed funds in 2015. This is caused by a policy change in August 8, 2015, which increases the minimum stock holding requirement from 60% to 80% for equity mutual funds. As a result, a large number of equity funds switch to mixed funds around 2015Q3. The second half of 2015 is also unique because of the sudden collapse of the Chinese stock market in June 2015. To ensure that our main results are not driven by these major market events, we perform a few robustness tests with the following criteria: 1) shrink our before and after windows to 2011–2012 (before) and 2013–2014 (after) to avoid the inclusion of 2015; 2) exclude 2015 altogether; and 3) exclude the second and third quarters of 2015. Overall, our results remain robust and often become stronger both economically and statistically.

Panel B of Table 1 reports the summary statistics of our main variables for the before and after periods. There are a few important observations with respect to the differences between the characteristics of the before and after periods. The first is a significant decrease in fund size. Taking equity funds as an example, the average fund size decreases from RMB 3.05 billion to 0.62 billion over our sample period, driven by large initiations of new and smaller funds over our sample period. It should be mentioned, however, that this large-scale initiation of new funds occurs steadily over our sample period and is not uniquely associated with the introduction of platforms. Moreover, to show that our main results are not driven by this difference in sample characteristics, we perform a robustness test that require funds in the after period to exist in the before period; accordingly, our main results are robust.

We find the before and after samples to also have a difference in fund returns. The average monthly return for equity funds is 0.34% in the before sample and 1.43% in the after sample, although the difference is statistically insignificant. This difference, driven by the aggregate stock market returns, is unlikely to affect our main results on the cross-section of fund performance and flow. Therefore, in addition to controlling the time trend by including time fixed effects, we also perform a robustness test by adopting a narrower window of before (2010–2012) and after (2013–2014), which exclude the unusual years of the 2008 financial crisis and the 2015 China stock market crash.

In terms of quarterly flows, the before and after periods do not exhibit any statistically significant difference in the average level, but there is a rather strong difference in the cross-sectional standard deviation. Specifically, the standard deviation of flows increases substantially from 11.09% to 31.96% for equity funds and from 11.71% to 31.70% for mixed funds. This indicates that although the level of flow remains stable, the cross-sectional dispersion in flow increases significantly in the after period. As our main results will indicate later on, this is strongly related to the emergence of the platforms. For bond funds, the average flows are positive for both the periods. Compared to the standard deviation of 11.09% for the equity funds and 11.71% for the mixed funds in the before period, the flow standard deviation for the bond funds is quite large at 26.67%, mostly driven by the small sample size and large institutional ownership of bond funds. Overall, this limited pre-platform sample size of bond funds complicates our main analysis of the difference between the before and after samples, making the results on bond funds less stable.

The fees charged by funds, including management fee, redemption fee, and subscription fee, are the nominal fees quoted in percentage points. The usefulness of these fees in our analysis turns out to be rather limited, as the quoted fees may not reflect the actual fees charged to investors. The subscription fees are often waived by different channels, depending on their promotional policies. As of 2019, both Tiantian and Ant Financial waive 90% of the subscription fees for all funds offered on their platforms. For management fees, there is little cross-sectional variation. Most of the equity and mixed funds charge an annual management fee of 1.5% and bond funds lesser at 0.6%. Our talk with industry practitioners also suggests that funds follow industry routines when setting the quoted fees. We do observe significant changes in the fees for the before and after samples. However, they are often in mixed signs, and the economic magnitude is small.

3 Platform-Induced Performance Chasing

To examine how platform intermediation alters investor behavior, we begin with the flow-performance relationship, one of the most salient features of investor behavior documented in the mutual fund literature.

3.1 Evidence from Policy Change

Before and After the Introduction of Platforms

We first examine the flow-performance sensitivity for the period around the emergence of platforms. Using the start of 2013 as the cutoff point, we test the difference in the flow-performance sensitivity over two sample periods: before (2008–2012) and after (2013–2017). 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 raw returns over the past 12 months, following the methodology of platform apps. Figure 2 reports the flow-performance relation by plotting the average quarterly flows for the ten performance deciles.

Focusing first on equity funds, we see evidence of performance chasing in both the before and after periods, with the flow to the top-decile funds on average higher than the flows to the other deciles. But the magnitude of performance chasing increases strikingly post the emergence of platforms: the top-decile flow increases from 1.88% in the before period to 19.65% in the after period. This result of amplified performance chasing can be best summarized by the upper left panel of Figure 2, where the flow-performance curve steepens dramatically in the "after" sample. This amplified performance chasing is also observed in mixed funds, which are of lower expected returns and lower risk compared with the equity funds. There is very limited evidence of performance chasing prior to the emergence of platforms: the top-decile funds attract a statistically insignificant average flow of 1.21%. Post platforms, however, the top-decile flow increases to 9.51% with a t-stat of 4.19.

We further compare our results against the flow-performance relation in the US. For the same time periods, the upper right panel of Figure 2 plots the flow-performance relation for actively managed equity mutual funds in the US. Since there is no obvious shock to the US fund market around 2013, the flow-performance relation remains stable in the before and after periods. The average flow to the top-decile funds is around 6% per quarter, larger than the average flow of 1.88% per quarter in the pre-platform period and much smaller than the average flow of 19.65% per quarter in the post-platform period. Given that the distribution of US mutual funds is still under the traditional model, it makes sense that the flow-performance sensitivity in the US is much lower than in China's post-platform era.

For bond funds, the results are less conclusive. Though the top-decile flow is on average 10.21% per quarter (t-stat = 2.12) in the post-platform period, it is not significantly different from that of the pre-platform period. As discussed in Section 2.3, the bond sample is rather small and noisy. China's fixed-income market, particularly the credit market, starts to take off only after 2010 (Geng and Pan (2019)). Besides, we expect the effect of platforms to be smaller for bond funds, which are dominated by institutional investors. Institutional ownership is 58% for bond funds in the post-platform period, while their holding fractions are only 19% and 25% for equity and mixed funds, respectively.

In addition to the graphical representation in Figure 2, Table 2 further details the fund flow and return information for the ten performance deciles, for the samples before (2008–2012) and after (2013–2017) the emergence of platforms. Here, one potential concern is that the amplified performance chasing might have been caused by a drastically different post-platform sample, owing to, for example, more dispersed cross-fund returns post platforms. However, we address this potential concern by including the statistics for fund returns and return dispersions in Table 2. The cross-decile variation in returns, measured by the return difference between the top- and bottom-decile funds, remains stable at around 2-3% per month. Moreover, the magnitude of within-decile return dispersion also remains stable across the two time periods.

Time-Series Variation of Flow-Performance Sensitivity

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 can expect this amplification effect to take place only on and after 2013. For this, we focus on the quarterly excess flow to the top-decile funds, measured as the quarterly difference between the top-decile flow and the flow averaged across all deciles. The upper left panel of Figure 3 plots this excess flow (red line marked with "o") for equity funds, with the shaded area indicating the 95% confidence intervals. 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 when we restrict the sample to the narrow window of two years after the policy change (shaded red region). Extending the window to five years after the policy change (shaded blue region), we observe a much bigger increase in flows to the best performing funds, though the confidence interval becomes wider due to the unusual year of 2015. Following this time series over the long time span, it is interesting to observe that this amplified performance chasing varies over time, with some quarters exhibiting a higher level of performance chasing than others.

Comparing this time-series pattern against that in the US, we see a rather different trend. The overall flow-performance relationship in the US does not exhibit any significant shift from 2007 to 2017. As shown in upper right panel of Figure 3, the excess flow to the top-decile funds in the US also varies over time, peaking at 31% during the first quarter of 2000, after sustained positive flow at the aggregate level, as measured by the value-weighted average flow (the blue line marked with "x"). Around the same time, the dot-com bubble peaks in March 2000. One might argue that the boom and bust of the Chinese stock market in 2015 resembles that of the US market in 1999–2000. But taking out that time period, we still observe a rather substantial increase in performance chasing. In fact, our results are stronger after excluding 2015 (See row (1) of Panel A of Table 11). Repeating the same exercise for the mixed mutual funds, the bottom left panel of Figure 3 paints a similar picture of increasing performance chasing after 2013. The evidence for the bond funds, as shown in the bottom right panel, is mixed and inconclusive.

3.2 Evidence from Staggered Entrance of Funds

To build upon the previous analyses, we further take advantage of 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 effect of platforms on flow-performance sensitivity.

We measure the extent of fund i's coverage by the platforms using the dummy variable $\text{Platform}_{i,t}$, which equals one when fund i, at the beginning of quarter t, is available on the two major platforms, Tiantian and Ant Financial. We choose Tiantian and Ant Financial because these two are the biggest and dominant players in the market.[10] Using the fund-level variable $\text{Platform}_{i,t}$, we investigate the change in the flow-performance relationship in a panel regression setting as follows:

$$\text{Flow}_{i,t} = \alpha + \beta_1 \cdot \text{Decile } 10_{i,t-1} + \beta_2 \cdot \text{Platform}_{i,t} + \beta_3 \cdot \text{Decile } 10_{i,t-1} \times \text{Platform}_{i,t} + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t} \,. \quad (1)$$

The results are summarized in Table 3. We include time fixed effects to control for time-varying market conditions. As detailed in Table 3, we also include the natural logarithm of fund size, natural logarithm of fund age, fund's last quarter flow, and fees as controls. Columns (1) to (4) report the results estimated using the five years before (2008–2012) and five years after (2013–2017) the introduction of platforms, for equity, mixed, bond, and all funds, respectively. Focusing first on equity funds, the excess flow to the top-decile equity funds is on average 6.99% per quarter before joining the platforms. After signing up to the platforms, the same fund in the top decile would attract an additional quarterly inflow of 16.96% (t-stat = 3.75). Overall, the excess flow to the top-decile funds on platforms is 23.95%.

For mixed funds, we also see a substantial increase in performance chasing after a fund joins the top two platforms. The excess flow to the top-decile mixed funds on platforms is 17.53% per quarter, which is 2.86 times the off-platform level. For bond funds, the increase in excess flow to the top-decile funds after joining the platforms is not significant under this specification. Finally, by grouping all three styles together, we find that the excess flow to the top-decile funds on the platforms is on average 16.10% per quarter, which is 1.98 times the off-platform level of 8.13%.

To focus more precisely on the event time, we use data from 2011 through 2014 and split the sample around 2013 into two 2-year windows before and after 2013. As shown in the last four columns in Table 3, our main results are rather robust. The economic significance of our results actually increases during this narrow window. The on-platform excess flow to the top-decile funds is 3.39 times the off-platform level for equity funds and 4.43 for mixed

[10] Anecdotal evidence suggests that Ant Financial and Tiantian together account for bulk of the platform business. For example, see http://fund.jrj.com.cn/2018/08/27012825002151.shtml. The entrance of funds onto Tiantian and Ant are highly correlated with a correlation of 0.88. Our results remain similar if using either of the two platforms to create the platform entrance dummy.

funds. This specification has the advantage of the year 2015 being excluded from our tests, which would have introduced two issues into our sample. First, the Chinese stock market experiences a dramatic run up in the first half of 2015 and then a dramatic crash in the second half, which would have introduced noise and potentially unusual investor behavior into our sample. Second, 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. Moreover, the narrow window specification also excludes 2008, the year of the financial crisis, from the analysis. The fact that our main results become stronger by avoiding these unusual years indicates that these market-level events are not the main drivers of our results.

One potential concern here is that unknown changes in the market are driving the change in the flow-performance relationship. In one of the robustness checks in Section 6, we directly address this issue. In particular, we specify a dummy variable DYear($t = k$) for each year, and control for all the interactions between the Decile 10 dummy and the year dummies (Decile $10_{i,t-1}\times$ DYear($t = k$)) in this specification to control for time-varying flow-performance relationships. These interaction terms absorb any changes in the flow-performance relationship due to changes in the market conditions for each year. The significance of the interaction term Decile $10_{i,t-1}\times\text{Platform}_{i,t}$ remains, as reported in row (2) in Panel A of Table 11. This time-varying flow-performance channel is also discussed in detail in Section 4.4. In addition to the aforementioned analysis, we also investigate the staggered entrance of funds onto platforms using a constant sample of funds, adding fund fixed effect, controlling for bank and broker exposures, or using alternative performance measures. The results are qualitatively the same, as reported in Section 6.

3.3 Direct Evidence from Howbuy

In this section, we provide direct evidence for platform-induced performance chasing utilizing a proprietary dataset obtained from Howbuy, one of the top five platforms in China.

The dataset from Howbuy contains the share of purchase for funds in each performance decile, that occurred on their platform from 2015 through 2018.[11] To compare the economic magnitude of the performance-chasing behavior on Howbuy with that of the whole market, we also obtain the quarterly purchase data at the fund level from CSMAR. The market share in purchase for each performance decile is calculated as the amount of purchase of all funds within a particular performance decile, divided by the total amount of purchase of all funds in the ten deciles. Therefore, the market shares for all ten deciles add up to 100%. The market shares of purchase occurring on Howbuy and that of the whole market are calculated

[11]We thank Howbuy for providing this data.

in exactly the same way, using the same sample of funds and the corresponding 12-month return decile rank for each fund, allowing for direct comparison. Since the whole market data is the aggregation over all distribution channels, we expect to observe much stronger performance-chasing behavior with pure-platform trading data from Howbuy.

Table 4 presents the market share in purchases for funds in each performance decile. Focusing first on the actively managed equity mutual funds, we can observe a monotonically increasing market share in purchase from past loser (Decile 1) funds to past winner (Decile 10) funds for the whole market. In the pre-platform period (2008–2012), an average of 23.79% of the quarterly purchases goes to the top-decile funds, while only 5.14% of purchases goes to the bottom-decile funds. This purchase-performance chasing behavior becomes much stronger in the post-platform period (2008–2012). The purchase market share of Decile 10 funds increases from 23.79% to 36.50%. This dramatic increase of 12.71% (t-stat = 4.00) is consistent with our prior findings using fund net flow.

Next, we turn to Howbuy for direct evidence. From 2015 through 2018, an average of 49.37% of the quarterly purchases on Howbuy goes to the top-decile funds. In other words, on pure platform trading, the top 10% funds claim close to 50% of the market share. In comparison, when aggregated over all distribution channels, the market share of the top 10% funds during the same time period is on average 37.61%, much smaller than that of Howbuy. The fact that investors exhibit stronger performance-chasing purchasing behaviors on pure platform trading lends further support to our interpretation: The rise in flow-performance sensitivity in the mutual fund market is caused by the introduction of platforms.

The results for mixed funds are similar to those for equity funds. In particular, the average market share of purchase for the top-decile funds increases from 19.65% in the pre-platform period to 27.46% in the post-platform period for the whole market. The difference is 7.81%, with a t-stat of 2.60. The performance-chasing behavior for mixed funds again is much stronger for the data from Howbuy. The market share of purchases for top-decile mixed funds accounts for 39.50% of total purchases on Howbuy, 10.47% (t-stat = 2.35) larger than that of the whole market. For bond funds, the effect is less pronounced, partially due to the smaller number of bond funds and larger institutional ownership. The average market share of purchase for the top-decile bond funds increases only slightly from 13.46% in the pre-platform period to 15.48% in the post-platform period. This number is higher on Howbuy, with a magnitude of 24.76%, though the difference on this count between Howbuy and the whole market is statistically insignificant.

Comparing across the three categories of funds, we see a pattern that is consistent with our hypotheses: equity funds, with the largest performance variation among the three categories, start with the highest demand for top performing funds.[12] The increase in purchase fraction for the top-decile funds is also the largest after the introduction of platforms. Mixed funds exhibit a similar pattern and bond funds a much weaker pattern.

Figure 4 further plots the market shares of purchases for funds in the ten performance deciles. Across the three samples, the market share of purchase increases moderately as performance decile rises from 1 to 9, wheres the market share jumps up for the top decile, especially for the post-platform sample and the Howbuy sample. Top-decile funds enjoy the largest purchase market share on Howbuy, followed by the whole market in the after period, and then followed by the whole market in the before period.

The lower left panel shows the time-series variation of market share of purchases for the top-decile equity funds. We present the fraction for the whole market as well as that for the Howbuy platform. The horizontal blue lines denote the average purchase fractions in the pre- and post-platform periods, respectively. One can observe a sharp increase in the market share of purchases for the top-decile funds after the introduction of platforms. When comparing the market share on Howbuy with that for the whole market quarter by quarter, we find that the market share of purchases for the top-decile funds on the Howbuy platform comoves well with that of the whole market. Besides, for the majority of the quarters during this time, the share on the Howbuy is larger than that for the whole market. The upper right and lower right panels present the corresponding results for mixed funds. The results for mixed funds exhibit a similar pattern, though with slightly smaller magnitude when compared to equity funds. Overall, the data from Howbuy provide direct evidence that added flow-performance sensitivity on the platform drives the magnified performance-chasing effect in the mutual funds market.

4 Channels and Alternative Explanations

So far, using both the whole market data and the pure-platform trading data from Howbuy, we have documented a startling increase in flow-performance sensitivity associated with the emergence of platforms. In this section, we present the potential channels for our results.

4.1 Platform Information Structure and Technology Efficiency

The unique features of platforms, especially the information structure and the technological efficiency, might help explain the amplified flow-performance sensitivity. In particular, the unique information structure makes high past performance more salient to investors, which

[12]The return standard deviation of equity funds is the highest among the three styles, as reported in Panel B in Table 1.

can contribute to the amplification of flow-performance sensitivity. Platforms also grant investors access to almost the entire universe of funds, allowing them to search and transact with great ease. We provide suggestive evidence along this dimension.

Information Structure — Front-Page Funds

If the information structure, i.e., the performance rank list provided by FinTech platforms, is contributing to our results, then funds ranked at the very top on the front page of mobile apps would attract more attention and get extra flows. As shown in Appendix Figure A1, within a specific style, the front page of the performance rank list normally displays around 6 to 10 funds, depending on the screen and font size of the cell phone. Since there can be thousands of funds in each style and investors are unlikely to scroll down for hundreds of pages, visibility on the front page could be an important determinant of extra flow from platforms.

To test the information structure hypothesis, we examine whether the platform effect is the most pronounced for the top 10 funds and becomes less pronounced as the ranking goes down, as investors need to scroll down the page to see them. To capture this intuition, we conduct the same analyses using top X funds instead of top decile funds. In particular, for each fund style and in each quarter, we classify funds into five ranking groups: Top 10, Top 11 to 20, Top 21 to 50, Bottom 100, and others. We create dummies for each group. For example, "Top 10" is a dummy variable that equals one for the 10 funds ranked the highest on the performance list, and zero otherwise. Table 5 presents the corresponding panel regression results with the ranking dummies and their interactions with the $\text{Platform}_{i,t}$ dummy. "Bottom 100" is omitted in the regression, and the coefficients on the other ranking dummies can be interpreted as the additional flow for the group relative to the "Bottom 100" group.

The coefficients on the interactions between the ranking dummies and the $\text{Platform}_{i,t}$ dummy display a general decreasing pattern: In the regression with all styles, the increase in flow after joining platforms is 19.04%, 10.61%, and 8.02% for Top 10, Top 11 to 20, Top 21 to 50 funds, respectively. For individual styles, equity and mixed funds display a similar pattern, while there is no significant increase in flow for top bond funds. This decreasing pattern is in line with the information structure of platforms: after joining platforms, the extreme top performers displayed on the front page of the app can attract the most flows.[13]

[13] The average monthly returns in the past 12 months are 2.76%, 2.04%, and 1.54% for the top 10, top 11 to 20, and top 21 to 50 funds respectively. It is unlikely that such return difference explains the big flow difference. In addition, the on- and off-platform return differences for the Top 10, Top 11 to 20, and Top 21 to 50 funds, are all insignificant. Therefore, the additional flow to the top performers cannot be explained by a change in return after funds enter platforms.

To further pin down this amplification effect after platform entrance, we divide the Top 20 funds into ten equal groups, and conduct similar regression analyses using the Top 1–2, Top 3–4, ..., and Top 19–20 dummies, and their interactions with the platform dummy. The results are exhibited in upper panel of Figure 5. The orange bars exhibit flows to the Top X funds before they enter platforms. The blue bars exhibit flows to the Top X group funds after they enter platforms. Since "Bottom 100" is omitted in the regression estimation, the flows shall be interpreted benchmarking to "Bottom 100" group. Before the funds join platforms, although all of the ten groups of top performers attract more flow than the medium performers (the "others" group), the magnitude of the flow is rather flat: Top 1–2 funds obtain a flow of 8.93%, whereas the Top 19–20 funds obtain a flow of 6.83%. In contrast, after platform entrance, the flow to the Top 1–2 funds increases to 41.96%, 4.7 times its off-platform level, while the flow to the Top 19–20 funds only increases to 14.93%. As shown in lower panel of Figure 5, the on- and off-platform difference decreases and becomes less significant as the ranking goes down, consistent with our prior finding that the extreme top performers on the front page of our mobile phone are more visible. They obtain the highest benefit from their exposure on performance rank list.[14]

Technology Efficiency — Fund Turnover

Another direct implication of this unique feature channel is on fund turnover. In particular, the technological efficiency and information structure of platforms reduce investors' trading cost and search cost, and make it easier for investors to find funds with high past performance and trade on them. This increase in trading tendency can also contribute to the flow-performance sensitivity after a fund joins platforms, and will also be reflected in the fund turnover. Columns (1) and (2) of Table 6 exhibit the impact on fund turnover. Fund turnover is measured as the sum of purchase and redemption amount in quarter t divided by the average fund TNA in quarter t and $t-1$.

We regress quarterly turnover on $\text{Platform}_{i,t}$ dummy, Decile $10_{i,t-1}$ dummy, and the interaction of the two. Following the specification in Table 3, we include controls of fund size, age, past flow, and fees. Fund and time fixed effects are included in the estimation so that the coefficient estimates can be interpreted as change in fund turnover. We find that after joining platforms, a fund in the top decile experiences a significant increase in fund turnover. This is consistent with the interpretation that the unique features of platforms contribute to additional trading in the top decile funds after they enter platforms.

[14] The estimation of coefficients in this setting can be quite noisy given that there are only two funds in each group. Despite this issue, we still obtain significant results for the Top 1–2, Top 3–4, Top 5–6 groups. For the funds ranked slightly lower, the results are also significant when we group more funds together, as shown in Table 5.

Overall, our results are in support of the "unique features" channel. The broad coverage of funds on platforms breaks down the segmentation in the mutual fund industry; the performance ranking displayed on every individual's mobile device functions as a signaling device; the technological efficiency of platforms reduces both the explicit and implicit trading cost. These unique features of platforms contribute to the amplified flow-performance sensitivity in the market after the introduction of platforms.

4.2 Endogeneity Issues Related to Investors' Entrance

Apart from the unique features of platforms, one alternative channel is that a certain type of investors endogenously choose to enter platforms. Those self-selected investors are more sensitive to fund performance, which results in the amplification of flow-performance relation that we observe. There are potentially two types of self-selected investors: (1) Existing investors who used to buy funds through banks or brokers and now switch to FinTech platforms; (2) New investors, attracted by FinTech platforms, who choose to enter the mutual fund industry. The first type of investors cannot explain our results, as it only represents a reallocation of investors from traditional channels to FinTech platforms. In the absence of any impact from platforms, the aggregate investors composition stays the same and investors' tendency to chase performance shall stay the same.

Besides, we find little support in the data whereby the entrance of new investors might explain our results, either. At the aggregate level, we do not observe any obvious inflow of new money or new investors into the actively managed mutual fund industry around the introduction of platforms.[15] Specifically, as shown in the bottom right graph of Figure 1, the size of the equity and mixed fund sectors do not experience any substantial change around 2012. Moreover, as shown in Figure 3, the average flows to equity and mixed funds are both negative and close to zero around 2012. Therefore, the actively managed equity and mixed funds do not experience a large inflow of new money. In addition, the upper panel of Appendix Figure A2 exhibits the average retail ratio of funds in the market. There is no systematic change of investor composition in the market around the introduction of platforms. Therefore, the amplified performance chasing in our analysis is unlikely to be caused by a systematic entrance of new retail investors.

To further rule out this channel, we examine the change in investor composition after a fund joins platforms. If the amplified performance chasing is caused mainly by the entry of new platform investors into the market, we would expect a spike in retail investors holding

[15] While the emergence of platforms did help attract new fund investors in China, it has happened mostly to the money market funds and less to the actively managed equity, mixed, and bond funds. For details of the recent development of the Chinese mutual fund market, please refer to Jiang (2019).

the fund after its entrance onto platforms. In particular, we use three measures as proxies for investor composition of a fund: (1) number of investors that hold the fund; (2) average dollar value held by an investor in a fund; (3) retail ratio, which is the asset fraction of a fund held by individual investors.

Table 6 shows the results for investor composition change. We regress semi-annual investor composition proxies on Platform$_{i,t}$ dummy, Decile 10$_{i,t-1}$ dummy, and the interaction of the two. We follow similar specifications as in Table 3. Fund and time fixed effects are included in the estimation so that the coefficient estimates can be interpreted as change in investor composition. In columns (3), (5), and (7), we include only the Platform$_{i,t}$ dummy to examine the change in investor composition when a fund enters the top two platforms. The coefficient on Platform$_{i,t}$ dummy is insignificant, indicating that joining platforms, by itself, does not bring new retail investors to the fund. Therefore, the new investors introduced to the market by platforms are unlikely to fully explain our main results. In columns (2), (4), and (6), we further add Decile 10$_{i,t-1}$ dummy and its interaction with the Platform$_{i,t}$ dummy. We find that conditioning on joining the platform and successfully getting into the top rank, the number of holders for a top-decile fund increases by 37.1%, the average dollar value held by each investor drops by 25.9%, and the retail ratio increases by 3.62%.[16] This is actually in support of the "unique features" channel in Section 4.1, that the information structure on platforms might contribute to the startling increase in flow-performance sensitivity.

4.3 Endogeneity Issues Related to Funds' Entrance

Another potential concern is that funds self-select to enter platforms, and those that endogenously choose to enter happen to have higher flow-performance sensitivity. We conduct several tests to address this endogeneity issue.

First, we directly examine the determinants of funds' entrance decisions. As shown in Appendix Table A1, we find that non-bank-affiliated funds and funds with low retail ratios, smaller sizes, and longer histories are more likely to enter platforms early. These static (or highly persistent) fund characteristics, however, are unlikely to drive the results in the staggered entrance test, as we are measuring the difference in flow-performance sensitivity for the same funds on- and off-platforms. To further control for fund unobservable static characteristics, we add fund fixed effect to our baseline specification and cluster standard errors at both the fund and time levels. The results are reported in row (3) of Panel A

[16] This increase in retail ratio matches well with our estimate using net flow in Table 3. For example, consider a fund with assets under management of 100 million, of which 75% is held by retail investors; when the fund gets into the top rank and is available for sale on platforms, Table 3 suggests that it will attract an extra quarterly inflow of 7.97%. Assuming all the extra capital inflow is driven by retail investors and lasts for two quarters, this will lead to an extra increase in retail ratio of 3.44% (= $(75+7.97\times2)/(100+7.97\times2)-75\%$).

of Table 11. With fund fixed effect, we are utilizing the time-series variation of a fund's platform exposure to explore the change in flow-performance relationship. The results are essentially the same as our baseline specification both qualitatively and quantitatively.

The previous test rules out the possibility that any fund *static* characteristics can drive our results. Hence, for the self-selection channel to explain our results, there have to be some *time-varying* factors that satisfy the following two criteria simultaneously: (1) it correlates with investors' flow-performance sensitivity; (2) the change of the factor coincides with the platform entrance window. Although it is very difficult to completely rule out such alternatives, we provide analyses on several main concerns below.

We first examine the exact timing of the change in flow-performance sensitivity. If some confounding factors affect flow-performance sensitivity around funds' platform entrance time but do not exactly coincide with fund entrance, one can expect the timing of the change in flow-performance sensitivity not to be perfectly aligned with the platform entrance time. On the other hand, if the increase in flow-performance sensitivity is driven by the platform inclusion event, one can expect the increase in performance chasing to take place right after the fund is added to the platforms. Accordingly, we investigate the dynamic effect using the following model specification:

$$\begin{aligned}\text{Flow}_{i,t} &= \alpha + \beta_1 \cdot \text{Decile10}_{i,t-1} + \beta_2 \cdot \text{Platform}(q=-1)_{i,t} + \beta_3 \cdot \text{Platform}(q=0)_{i,t} + \\ &\beta_4 \cdot \text{Platform}(q=1)_{i,t} + \beta_5 \cdot \text{Platform}(q \geq 2)_{i,t} + \beta_6 \cdot \text{Decile10}_{i,t-1} \times \text{Platform}(q=-1)_{i,t} \\ &+ \beta_7 \cdot \text{Decile10}_{i,t-1} \times \text{Platform}(q=0)_{i,t} + \beta_8 \cdot \text{Decile10}_{i,t-1} \times \text{Platform}(q=1)_{i,t} + \\ &\beta_9 \cdot \text{Decile10}_{i,t-1} \times \text{Platform}(q \geq 2)_{i,t} + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t}\,, \end{aligned} \tag{2}$$

where $\text{Platform}(q=-1)_{i,t}$ is a dummy that equals one for the first quarter before fund i enters platform. $\text{Platform}(q=0)_{i,t}$ and $\text{Platform}(q=1)_{i,t}$ are similarly defined. $\text{Platform}(q \geq 2)$ equals one for the second quarter after inclusion and for the subsequent quarters. The omitted group is $q \leq -2$. The interactions of $\text{Platform}(q=k)_{i,t}$ with Decile $10_{i,t-1}$ capture the dynamic impact around the time when a fund enters platforms.

Table 7 shows that increase in flow-performance sensitivity, captured by the interaction of Platform dummies with Decile $10_{i,t-1}$, happens exactly after a fund is included by platforms ($q=0$ or $q=1$). Taking equity funds as an example, the entrance onto platforms allows top-decile funds to attract additional 21.69% flow for the first quarter after the fund being included. The magnitude remains large at 20.83% for subsequent quarters. The coefficient on the interaction term is small and insignificant for quarter $q=-1$, indicating that on-platform and off-platform funds are not significantly different in flow-performance relationship before the platform entrance event. Hence, the results suggest that entrance onto platforms induces a drastic increase in flow-performance sensitivity and the effect is likely causal.

In addition, we examine some specific factors that may coincide with funds' entrance decision. One potential candidate is whether funds strategically time their entrance onto platforms based on past performance. Funds may choose to enter the platform exactly at the time when their recent return is good. In addition, knowing that investors prefer funds with high past returns, platforms may choose to cover top performing funds early on to promote their business. However, we do not find evidence for this conjecture. As given in Appendix Table A1, funds with higher recent returns are not more likely to be covered by platforms early on. Moreover, our regressions estimate the *change* in flow-performance sensitivity, which captures *investors'* differential response to performance. Consider a fund that expects its performance to be good in the future and chooses to join platforms now; if platform investors and traditional-channel investors react similarly to a top-performing fund, there will be no change in flow-performance sensitivity in the whole market.

Fund marketing effort is another potential candidate (Jain and Wu (2000), Gallaher, Kaniel, and Starks (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. Though it is difficult to completely rule out such alternatives, in the lower panel of Appendix Figure A2, we plot funds' advertising fees over time. The advertising expenses for bond and mixed funds are very smooth over time. Unrelated to the platform entrance, there is a temporary increase in advertising expense for equity funds around the 2015 market crash. Overall, there is little evidence that change in marketing expense is contributing to our results.

4.4 Time-Varying Market Conditions

Finally, one potential explanation is that the sudden increase in flow-performance sensitivity is related to the variation in market conditions unrelated to the introduction of platforms.

To directly address this concern, we conduct a strong robustness test, controlling for the effect of any unknown changes in market conditions on flow-performance sensitivity. In particular, we include year dummies and their interactions with Decile $10_{i,t-1}$ in the panel regression so that any changes in the flow-performance relations between the different years will be absorbed by the interaction terms between year dummies and Decile $10_{i,t-1}$. Even with such strong controls, we still observe a significant platform effect, captured by the cross term between Decile $10_{i,t-1}$ and the Platform dummy. This result comes purely from the staggered entrance of funds onto platforms, as reported in row (2) of Panel A Table 11. This result suggests that the change in market conditions cannot fully explain our main result.[17]

Second, time-varying market conditions cannot explain the difference in performance chasing between Howbuy and the whole market. The bottom two graphs in Figure 4 display the fraction of purchase that goes to the top decile equity and mixed funds on Howbuy and in the whole market. Although both fractions are time varying, they move in similar directions most of the time. Moreover, for almost every quarter, the top decile fraction on Howbuy is larger than that for the whole market, suggesting a larger magnitude of performance chasing on platforms throughout the sample period.

Finally, we also conduct tests to address specific concerns related to the abnormal market conditions. As discussed in Section 2.3, our sample period includes the 2008 global financial crisis, the 2015 China stock market crash, and a policy change causing a large number of equity funds switch to mixed funds around 2015Q3. Excluding these periods of unusual market conditions does not affect our results: First, in our baseline tests in Table 3, we report the results for the short window that focuses on the two years before (2011–2012) and two years after (2013–2014) the introduction of platforms. Second, we also exclude the year 2015 for the robustness test reported in row (1) of Panel A of Table 11. Our results remain similar in these settings.

5 Economic Impact on Fund Managers and Families

Section 3 and Section 4 show that FinTech platforms bring drastic changes to fund investors through their technological efficiency and information structure. Those performance-chasing investors on platforms are not using the technological efficiency to help themselves build more efficient investment portfolios.[18] Instead, they pay more attention to the prominent features, i.e., the performance rank list, in the platform apps. In this section, we further examine the impact of platform introduction on the production side of the industry. More generally, what are the economic consequences, both intended and unintended, of this new and powerful distribution channel on fund managers and fund families?

[17]Note that part of the change in flow-performance sensitivity over the years can be caused by the platform effect. Therefore, the coefficient in this setting should be a lower limit for the actual platform effect.

[18]Performance chasing is not benefiting investors as past return fail to predict future fund return, both in China and in the US. Jiang (2019) find that fund performance is not persistent in China. We further confirm this result in our sample in Appendix Table A2.

5.1 Risk Taking by Fund Managers

The flow-performance relation can be thought of as an implicit incentive contract for mutual fund managers. Fund managers, in their desire to maximize their compensation, have incentives to take actions to increase fund capital inflows. Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997) argue that mutual funds respond to these implicit incentives, the convex flow-performance relation, by altering the riskiness of their funds so as to secure a favorable ranking. In the post-platform era, flow into the top performance decile increases dramatically. As a result, there may be a substantial change in managerial incentive in this performance region. Specifically, consider a fund that is close to the top performer list; the manager has two choices, one is to play it safe and lock in a mediocre inflow, and the other is to gamble with a probability of capturing a large inflow as a top performer. We posit that, in the after period, funds that are close to the top performer list have higher incentive to gamble in order to capture the extremely high inflow induced by the platforms. On the contrary, the convexity at the bottom and medium performance deciles does not change much. Therefore, there is less change in risk-taking behavior for the losing and mediocre funds.

Impact on Fund Portfolio Total Volatility

To examine change in the managers' risk taking behaviors, we adopt a difference-in-difference methodology, exploiting the differential treatment effects of funds belonging to different decile groups. Decile 10 funds are the treated funds as they are most affected by the platform-induced performance-chasing behavior.

Figure 6 shows the difference in risk taking for winner (Decile 10) and loser (Decile 1) funds around the performance ranking date for the period before (2008–2012) and after (2013–2017) the policy change, respectively. At the beginning of each quarter t, we sort all the funds into deciles based on the past 12-month returns. Then, we follow the standard event time method and examine the daily return standard deviation for funds in each performance decile from quarter $t-4$ to $t+4$. Quarter $t=0$ is the quarter immediately after the performance sorting. We compute the difference in average daily return standard deviation between Decile 10 and Decile 1, and plot the time-series average and confidence interval of this difference around $t=0$.

The upper left graph of Figure 6 shows the change in risk taking for equity funds. In the post-platform period, funds in the top performance decile, relative to the funds in the bottom performance decile, exhibit increased daily return volatility from quarter $t-3$ to quarter $t-1$. This difference gradually declines to zero in the two quarters after the ranking date of quarter $t-1$. The graph suggests that fund managers of top-decile funds increase their portfolio risks more than the fund managers of bottom-decile funds at least two quarters before they successfully get into the top decile. A potential alternative explanation is that funds with higher volatility before the ranking date might be more likely to enter the top rank by accident. However, in the before sample, the difference in volatility is close to 0 from $t-4$ to $t+4$. This is consistent with the previous results on the change in flow-performance sensitivity. As the flow-performance relation is relatively flat for the before sample, the incentive to boost performance is similar for funds in the high-performance and low-performance ranges.

The upper right graph of Figure 6 presents the corresponding results for equity funds in the US as a placebo test. There is no obvious difference between the before and after curves. Both curves are relatively flat and close to zero around the ranking date. The bottom two graphs of Figure 6 show the results for China mixed funds and China bond funds, respectively. The overall pattern for mixed and bond funds is similar to that for equity funds in China. Overall, the evidence is consistent with our hypothesis: The introduction of platforms largely increases the flow to top performing funds, and creates additional incentive for fund managers to take extra risk in order to get into the top decile.[19]

We further confirm our results using panel regressions with controls. Since the strengthened convex flow-performance relation is mostly driven by performance Decile 10, we create a dummy variable Decile $10_{i,t-1}$ that equals one if a fund i enters the top performance decile category at the end of quarter $t-1$. We regress quarter $t+k$ volatilities on dummy variable Decile $10_{i,t-1}$ and the interaction of Decile $10_{i,t-1}$ with dummy variable After_t, which equals one for the sample on and after 2013. The model specification is as follows:

$$\text{Std}_{i,t+k} = \alpha^k + \beta_1^k \cdot \text{Decile } 10_{i,t-1} \times \text{After}_t + \beta_2^k \cdot \text{Decile } 10_{i,t-1} + \sum_j \gamma_j^k \text{Control}_{i,t-1}^j + \varepsilon_{i,t+k}\,, \quad (3)$$

where $\text{Std}_{i,t+k}$ is the daily fund return standard deviation for fund i at quarter $t+k$. Coefficients on Decile $10_{i,t-1}$ captures the risk taking behavior of funds in Decile 10, compared to the risk taking behavior of funds in the other deciles. The coefficient on Decile $10_{i,t-1} \times \text{After}_t$ captures the extra risk taking due to the policy change in 2012. We include controls of fund size, age, and fees at the end of quarter $t-1$. Time fixed effects and fund fixed effects are included for all the specifications, which alleviates the concern that changes in risk taking may be driven by any aggregate market trend or unobserved time-invariant fund characteristic.

Panel A of Table 8 reports the coefficients on Decile $10_{i,t-1} \times \text{After}_t$ and Decile $10_{i,t-1}$. We can see that top-decile funds increase their daily return volatility by an extra 0.109% (t-stat =3.26) in quarter $t=-1$ after the introduction of platforms, which is equivalent to an

[19] We also report the summary statistics of daily returns in the before and after period in Table A3. We observe a significant increase in return volatility in the post-platform era, whereas the mean, skewness, and kurtosis of daily returns do not experience any obvious change.

annualized volatility increase of 1.72%. Consistent with the figure, the increased risk taking begins at least two quarters before the ranking date ($k = -3$ and $k = -2$) and disappears shortly after quarter $k = 0$.[20] This increase in risk taking is not economically huge when taking into consideration that the average standard deviation of fund daily return is around 1.5% as shown in Table A3. An extra 10.9 basis points increase in volatility for top-decile funds relative to the other funds is a reasonable magnitude in terms of change in managerial risk taking.

Systematic and Idiosyncratic Volatility

There are two ways for fund managers to increase their risk taking. One is to rely on their own abilities in stock and bond selections and increase their idiosyncratic volatility to get into the top decile. The other is to load more on systematic risk factors and obtain higher systematic volatility. To disentangle the two channels, we further decompose daily volatility into systematic volatility and idiosyncratic volatility based on a two-factor model (with an aggregate stock market factor and an aggregate bond factor).[21]

We replace the total volatility in equation (4) with systematic/idiosyncratic volatility to obtain the regression results reported in Panel B and Panel C of Table 8, respectively. An increase in both the dimensions of volatility in the two quarters before the ranking date for funds in Decile 10 can be observed. The results suggest that both systematic and idiosyncratic volatilities contribute to the overall increase in managers' risk taking.

In particular, as shown in Panel C, the coefficients on Decile $10_{i,t-1}$ are positive from $k = -3$ to $k = -1$. This suggests that, in the pre-platform period, fund managers in Decile 10 already rely on their own abilities in stock and bond picking to get into the top decile. The coefficients on Decile $10_{i,t-1} \times \text{After}_t$ are also positive from $k = -3$ to $k = -1$, indicating that, due to the added incentive in the post-platform period, fund managers in Decile 10 exert even more effort to boost their idiosyncratic volatility and enhance their probability of getting into the top decile.

The results on systematic volatility in Panel B show a different pattern. The coefficients on Decile $10_{i,t-1}$ are negative and mostly insignificant from quarter $k = -3$ to $k = -1$. This suggests that there is no evidence of fund managers in decile 10 taking more systematic

[20]One potential reason for the rise in volatility after the ranking date is because managers invest in assets with higher volatility, and these assets will remain in the portfolio for a while after the portfolio ranking.

[21]For each fund-quarter, we regress daily fund return on contemporaneous daily market factor and daily bond factor. The systematic volatility is the standard deviation of the fitted return and the idiosyncratic volatility is the standard deviation of the residual terms. To construct factors, we use value-weighted A share stock return for market return, ChinaBond composite index return for bond return, and one-year deposit rate for risk free rate.

risks relative to the other funds before the ranking date in the pre-platform period. On the contrary, in the post-platform period, fund managers in Decile 10 increase their systematic volatility relative to the other funds. This is a sign that the fund managers have already maxed out their own skills and are using leverage to get ahead.

5.2 Disruptions to Fund Families

In this section, we present our investigation of the impact of platforms on the organizational structure of fund families. Platforms can affect fund families along multiple dimensions. First, platforms provide a common playing field, and this may expand the degree of competition from within families to outside families. Related to this shift in industry organization structure, changes in within-family flow co-movement and the incentives for families to create star funds may be observed. Second, platforms bring new opportunities to the fund industry. Families that quickly seize the platform opportunity will grab the market share from those that are slow in adopting platforms.

Within-Family Flow Competition

Before the introduction of platforms, family affiliation segments the market through its brand image and free-switching options for funds in the family (Massa (2003), Nanda, Wang, and Zheng (2004), Gaspar, Massa, and Matos (2006), etc.). Sheltered under the family umbrella, individual funds rely largely on the capital attracted through the family brand. As a result, fund's performance ranking within the family can be an important determinant of flow (Kempf and Ruenzi (2007)). In the post-platform era, however, platforms act as one big family, bring down the barriers, and level the playing field for all funds. Performance rank in the whole fund universe now plays a more important role in attracting flows, which weakens the role played by families. Therefore, one would expect flow to become less sensitive to a fund's within-family performance ranking after the fund joins platforms.

To test this hypothesis, as shown in Table 9, we examine the response of flow to the performance ranking within each family. We require a family to have at least five funds and to have existed for at least three years before the introduction of platforms to allow for meaningful comparison. This reduces our sample slightly from 26,412 fund-quarter observations to 22,268. Since the average number of funds in a family is 7.70 for the pre-platform sample, we focus on the performance quintile ranks within each family. We use the same set of control variables given in Table 3 and further include the family fixed effect in this specification.

Column (1) of Table 9 shows the response of fund flow to the within-family quintile rank, $\text{FamilyRank}_{i,t}$. Column (2) presents the results of fund flow on the Decile $10_{i,t-1}$ dummy used in our main analysis as a benchmark. Performance rankings within a family and in the whole fund universe tend to correlate with each other. To disentangle the two effects, we include both performance indicators and their interactions with the $\text{Platform}_{i,t}$ dummy in column (3). We find a significant erosion of the effect of within-family quintile rank after a fund joins platforms. Before a fund joins platforms, both the within-family performance quintile rank and the universal $\text{Decile } 10_{i,t-1}$ dummy play important roles in bringing flow. Controlling for the universal top decile indicator, a fund will still enjoy an extra flow of 1.12% (t-stat = 4.60) if its within-family quintile ranking increases by one unit. However, the coefficient on the cross term between within-family quintile rank and the Platform_t dummy is negatively significant at -1.03 (t-stat = -2.54). In other words, after a fund joins platforms, the same change in the quintile rank will only bring 0.09% (= 1.12% - 1.03%) of extra flow. The incremental effect of within-family ranking almost disappears after a fund joins platforms. On the contrary, the position of a fund in the whole universe becomes more important. A top-decile fund in the whole fund universe will enjoy an extra flow of 15.85% after it joins the platforms, which is 2.64 times its off-platform level.

Star Funds from Top Families

So far, we have shown that investors now rely less on family-specific information to evaluate an individual fund; instead, they evaluate each fund in isolation after the emergence of platforms. The positive spillover effect within family diminishes and flow is highly sensitive to the fund's own performance ranking in the whole fund universe. Given this weakening of connection between funds and families, we can expect families to have lesser control on funds. As a result, large families would have lower incentive and ability to create "star" funds by diverting resources to these specific funds in the post-platform period.

We find that the presence of "star" funds in large families has indeed decreased in the post-platform period. Panel A of Table 10 presents the proportion of funds from large families in each performance decile rank for the sample before and after the introduction of platforms. For each quarter end and each style category, we sort all the funds into deciles based on the past 12-month returns. We then calculate the fraction of funds that belongs to the top ten largest families (or top five families or top one family) in each decile. In the pre-platform period, the fraction of large-family funds in the top performance decile is significantly larger than that in the bottom performance decile. Taking the largest ten families as an example, large-family funds account for 36.22% of the best-performing funds and only 21.38% of the worst-performing funds. However, this pattern is reversed in the post-platform period. Large-family funds only account for 18.98% of the best-performing funds, and 23.04% of the worst-performing funds. These findings are consistent with the interpretation that large families attract flows through "star" funds in the pre-platform period, but fail to or are less inclined to apply this strategy in the post-platform era.

Family Entrance onto Platforms

Finally, platforms may also affect the distribution of family market shares. Platforms have become one of the leading players in the marketplace for mutual funds. They help divert flow to better-performing funds on the platform, no matter how big or small, well-known or invisible. Fund families that embrace the new channel and perform well will capture a sizable market share, while families that join the platform late or fail to enter the top performer list will lag behind.

To get a gut feeling of the market landscape, we first examine the changes in the market shares of the top families. Panel B of Table 10 exhibits the top ten fund families by market share before and after the introduction of platforms. The top families' market shares shrink over time. The largest ten families on average account for 45.63% of the industry for the pre-platform period, while they only account for 39.65% in the post-platform period.

Next, we investigate the relation between change in family market share and their entrance time onto platforms. Figure 7 plots families' entering time onto Tiantian and their change in market share from three years before (2010–2012) to three years (2013–2015) after the introduction of platforms.[22] We label the largest 15 families and use different colors for bank- (blue) and broker-affiliated (red) families. At first glance, it seems that big families and bank-affiliated families enter the platform late. This is consistent with the intuition that big families, sitting on a large customer base, may overlook the importance of platforms. Bank-affiliated families often have their own distribution channels and sticky capitals, thereby lacking the incentive to join platforms early.[23] Moreover, we also observe a negative relation between the time a fund enters onto the platform and its change in market share. The fitted line has a slope of -0.129 with a t-stat of -2.81. The largest fund family in our sample is China Asset Management. It joined Tiantian platform late in December of 2013 and experienced a decline in its market share during this period, whereas for early entrants like Fullgoal and China Universal had a positive increase in market share.

The overall evidence is consistent with our interpretation: Families that were rich in resources tend to overlook the potential of platforms. The slow response of these families to join platforms contributes to the decline in their market shares in the post-platform period.

[22] We choose a three-year window because all the families enter the platform in the three years after the policy change. The results are qualitatively the same when using two-year or five-year window.

[23] We conduct analysis on the determinants of funds' and families' entry onto platforms in Appendix Table A1. The results are consistent with this interpretation.

6 Robustness Check under Alternative Settings

In this section, we discuss alternative channels that are potentially related to our main results, and conduct further tests to examine the robustness of our findings.

Excluding 2015: We exclude the year 2015 from our sample, as it involves an unusual market crash, and our results remain both economically and statistically significant, as reported in row (1) of Panel A of Table 11.

Time-Varying Market Conditions: To control for the impact of time-varying flow-performance sensitivity due to changes in market conditions, we include year dummies and all the interactions between the year dummies and Decile 10 dummy in the regression in row (2) of Panel A Table 11. Our results cannot be explained by changes in market conditions that may affect flow-performance sensitivity.

Fund Fixed Effect and Double-Clustered Standard Errors: In our baseline regression, we follow the standard setting in the literature to estimate flow-performance sensitivity. Our results are essentially the same when we include fund fixed effect and double-clustered standard errors at both fund and time level, as shown in row (3) of Panel A Table 11.

Change in Morningstar Rating: If a fund enters platforms when it receives a better Morningstar rating, we might mistakenly attribute the flow attracted through Morningstar rating to platform entrance (Del Guercio and Tkac (2008), Ben-David et al. (2019)). Thus, as given in row (4) of Panel A Table 11, we also control for Morningstar ratings. We include dummy variables Ms5star and Ms4star, and their interactions with the Platform dummy. Ms5star (Ms4star) equals one if the fund Morningstar rating is five (four) star, and zero otherwise. The results remain the same qualitatively. [24]

Constant Fund Sample: The number of funds grow gradually during our sample period (Panel A of Table 1). To show that our results are robust with a constant sample of funds, we require a fund to exist before 2012 to be included in our analysis in this alternative setting. The result is close to the baseline result, as reported in row (5) of Panel A Table 11.

Control for Linkages to Banks/Brokerages: As can be seen in Figure 1, the number of banks and brokers with a funds distribution license also increased during our sample period. Moreover, the sales relationship between mutual funds and banks/brokers also increased. To distinguish between the effects of these traditional channels, we further control for the number of sales relationships between mutual funds and banks/brokers and their interactions with Decile $10_{i,t-1}$ in our analysis. The effect from the platforms remains after these controls, as shown in row (6) of Panel A Table 11.

[24]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.

Value-Weighted: Another potential concern may be that our results are mainly driven by small funds. 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 (7) of Panel A, are similar to our baseline results.

Using Performance Rank: We replace the top decile dummy with the performance decile rank, ranging from one to ten, based on the past twelve months' performance. In row (8) of Panel A Table 11, the coefficient on the cross term between the performance rank and the Platform dummy remains significant.

Using the Number of Platforms: In row (9) of Panel A Table 11, we replace the $\text{Platform}_{i,t}$ dummy with the natural logarithm of the total number of platforms a fund enters, $\text{Log}(\#\text{Platforms})_{i,t}$. The coefficient on the cross term between Decile $10_{i,t-1}$ dummy and $\text{Log}(\#\text{Platforms})_{i,t}$ is also significant.

Alternative Performance Horizons: In addition to the Decile $10_{i,t-1}$ dummy based on the past 12 months, we also conduct the same analysis with the Decile $10_{i,t-1}$ dummy for the past 1, 3, 6, 24, and 36 months. These specifications are consistent with return horizons used in the ranking list provided by the platforms. Panel B of Table 11 reports the panel regression results following the model specification of Table 3. The results are qualitatively the same for all return horizons, although the change in flow-performance sensitivity seems to be more pronounced for the model with past six months than for other return horizons.

7 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 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.

Second, we also examine the consequences of platform-induced performance chasing on fund managers and fund families. We find that improvements in means of connectivity do not necessarily equate to improvement in means of production. The amplified performance chasing incentivizes fund managers to increase risk taking to enhance the probability of getting into the top rank. By documenting the weakening fund-family ties, we also shed light on how the traditional organizational structures in financial intermediation can be disrupted by the emergence of the platform economy.

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.

References

Barber, B. M., and T. Odean. 2001. The internet and the investor. *Journal of Economic Perspectives* 15:41–54.

———. 2002. Online investors: Do the slow die first? *The Review of Financial Studies* 15:455–88.

Ben-David, I., J. Li, A. Rossi, and Y. Song. 2019. What do mutual fund investors really care about? Working paper.

Bergstresser, D., J. M. Chalmers, and P. Tufano. 2009. Assessing the costs and benefits of brokers in the mutual fund industry. *The Review of Financial Studies* 22:4129–56.

Brown, K. C., W. V. Harlow, and L. T. Starks. 1996. Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. *The Journal of Finance* 51:85–110.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru. 2018. FinTech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics* 130:453–83.

Chalmers, J., and J. Reuter. 2020. Is conflicted investment advice better than no advice? *Journal of Financial Economics.* Forthcoming.

Chevalier, J., and G. Ellison. 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* 105:1167–200.

Choi, J. J., D. Laibson, and A. Metrick. 2002. How does the internet affect trading? Evidence from investor behavior in 401 (k) plans. *Journal of Financial Economics* 64:397–421.

Christoffersen, S. E., R. Evans, and D. K. Musto. 2013. What do consumers' fund flows maximize? Evidence from their brokers' incentives. *The Journal of Finance* 68:201–35.

Cookson, G., T. Jenkinson, H. Jones, and J. V. Martinez. 2020. Best buys and own brands: Investment platforms' recommendations of mutual funds. *Review of Financial Studies.* Forthcoming.

D'Acunto, F., N. Prabhala, and A. G. Rossi. 2019. The promises and pitfalls of robo-advising. *The Review of Financial Studies* 32:1983–2020.

Del Guercio, D., and P. A. Tkac. 2008. Star power: The effect of morningstar ratings on mutual fund flow. *Journal of Financial and Quantitative Analysis* 43:907–36.

Frost, J., L. Gambacorta, Y. Huang, H. S. Shin, and P. Zbinden. 2019. BigTech and the changing structure of financial intermediation. BIS Working paper.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery. 2019. The role of technology in mortgage lending. *The Review of Financial Studies* 32:1854–99.

Gallaher, S. T., R. Kaniel, and L. T. Starks. 2015. Advertising and mutual funds: From families to individual funds. Working paper.

Gaspar, J.-M., M. Massa, and P. Matos. 2006. Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization. *The Journal of Finance* 61:73–104.

Geng, Z., and J. Pan. 2019. Price discovery and market segmentation in china's credit market. Working paper.

Goldstein, I., H. Jiang, and D. T. Ng. 2017. Investor flows and fragility in corporate bond funds. *Journal of Financial Economics* 126:592–613.

Goldstein, I., W. Jiang, and G. A. Karolyi. 2019. To FinTech and beyond. *The Review of Financial Studies* 32:1647–61.

Gruber, M. J. 1996. Another puzzle: The growth in actively managed mutual funds. *The Journal of Finance* 51:783–810.

Hau, H., Y. Huang, H. Shan, and Z. Sheng. 2017. FinTech credit, financial inclusion and entrepreneurial growth. Working Paper.

Jain, P. C., and J. S. Wu. 2000. Truth in mutual fund advertising: Evidence on future performance and fund flows. *The Journal of Finance* 55:937–58.

Jenkinson, T., H. Jones, and J. V. Martinez. 2016. Picking winners? Investment consultants' recommendations of fund managers. *The Journal of Finance* 71:2333–70.

Jiang, W. 2019. Investment funds in china. *The Handbook of China's Financial System (Chapter 15)* .

Kaniel, R., and R. Parham. 2017. WSJ category kings–The impact of media attention on consumer and mutual fund investment decisions. *Journal of Financial Economics* 123:337–56.

Kempf, A., and S. Ruenzi. 2007. Tournaments in mutual-fund families. *The Review of Financial Studies* 21:1013–36.

Massa, M. 2003. How do family strategies affect fund performance? When performance-maximization is not the only game in town. *Journal of Financial Economics* 67:249–304.

Nanda, V., Z. J. Wang, and L. Zheng. 2004. Family values and the star phenomenon: Strategies of mutual fund families. *The Review of Financial Studies* 17:667–98.

Philippon, T. 2018. The FinTech opportunity. Working Paper.

Sirri, E. R., and P. Tufano. 1998. Costly search and mutual fund flows. *The Journal of Finance* 53:1589–622.

Sun, T., Z. Yuan, C. Li, and K. Zhang. 2019. The value of personal data in the internet commerce: A high-stake field experiment on data regulation policy. Working paper.

Vallee, B., and Y. Zeng. 2019. Marketplace lending: A new banking paradigm? *The Review of Financial Studies* 32:1939–82.

Wei, S., and C. Yang. 2019. Do internet finance platforms mitigate conflicts of interest? The case of mutual fund investment. Working Paper.

Figure 1. Introduction of Platforms

The upper left graph reports the number of entities in each type of distribution channel: banks, brokers, and FinTech platforms from 2008 through 2019. The upper right graph reports the number of actively managed mutual funds on major platforms. The lower left graph shows the coverage of actively managed mutual funds on platforms as a fraction of the whole universe of funds. The lower right graph reports the aggregate industry size for actively managed equity, mixed, and bond funds. The two vertical lines denote the introduction of Yu'ebao and the entrance of Ant Financial into the platform business. Dark (light) shaded areas exhibit two (five) years around the introduction of platforms.

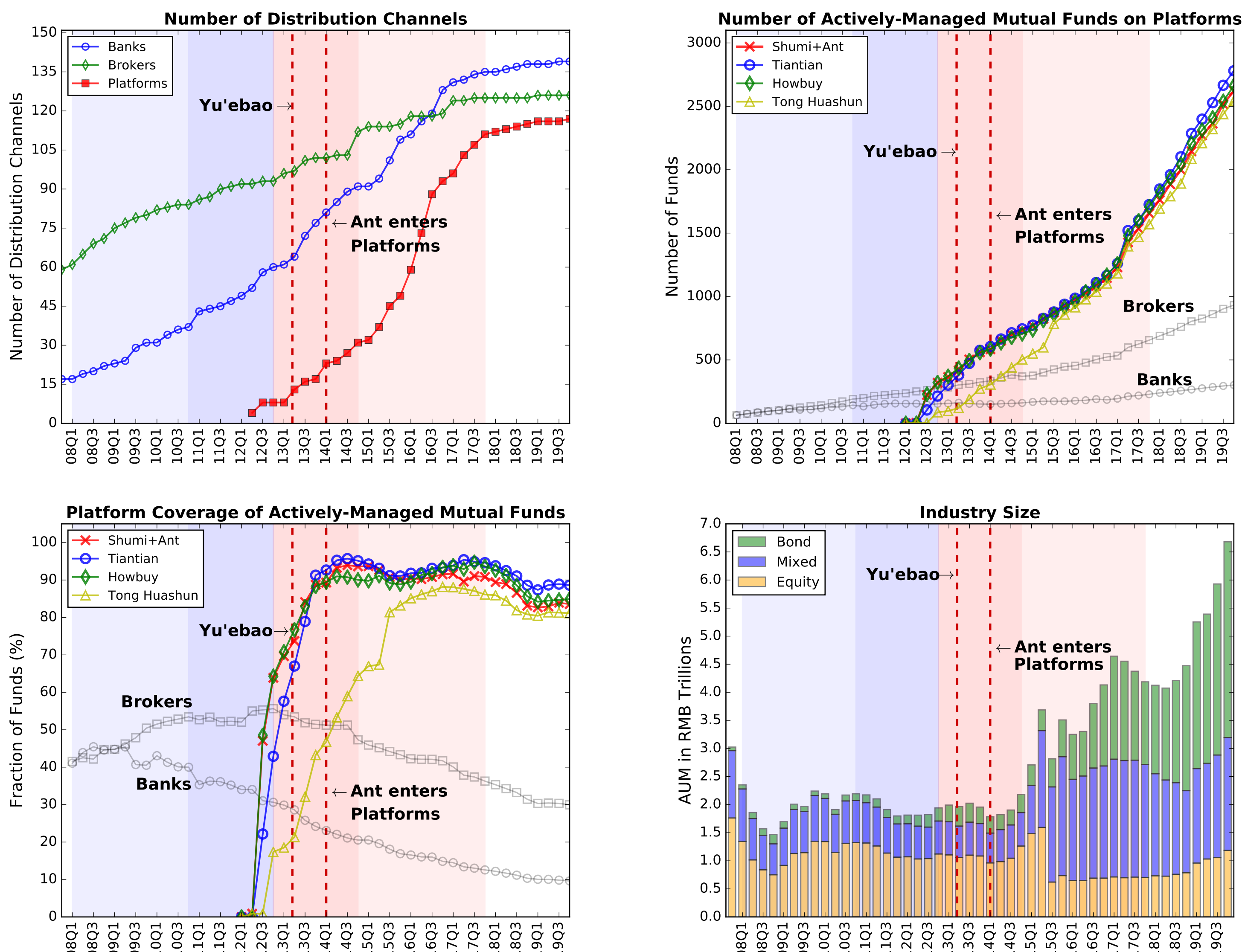


Figure 2. Flow-Performance Sensitivity, Before and After the Introduction of Platforms

This figure shows the flow of funds for each performance decile, for the sample 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 raw returns. Quarter t flow for each decile is the average flow of all funds in that decile. Then, we average the decile flow over time for the before and after period, 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.

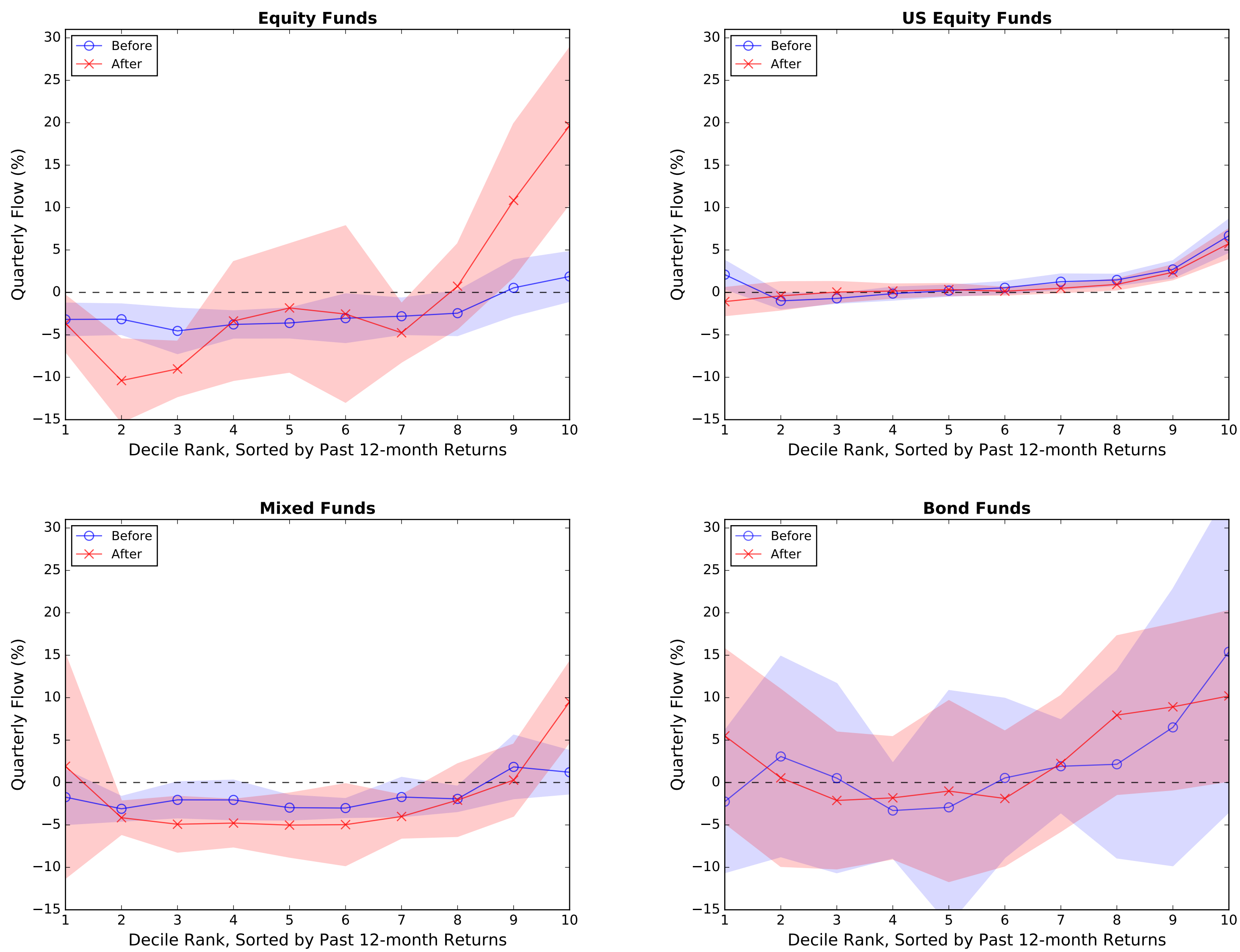


Figure 3. Time-Series Variation of Flow-Performance Sensitivity

The red line marked with "o" plots the difference between top-decile flow and the average flow; the blue line marked with "x" plots the value-weighted average flow of all deciles. The top decile contains funds with top 10% 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.

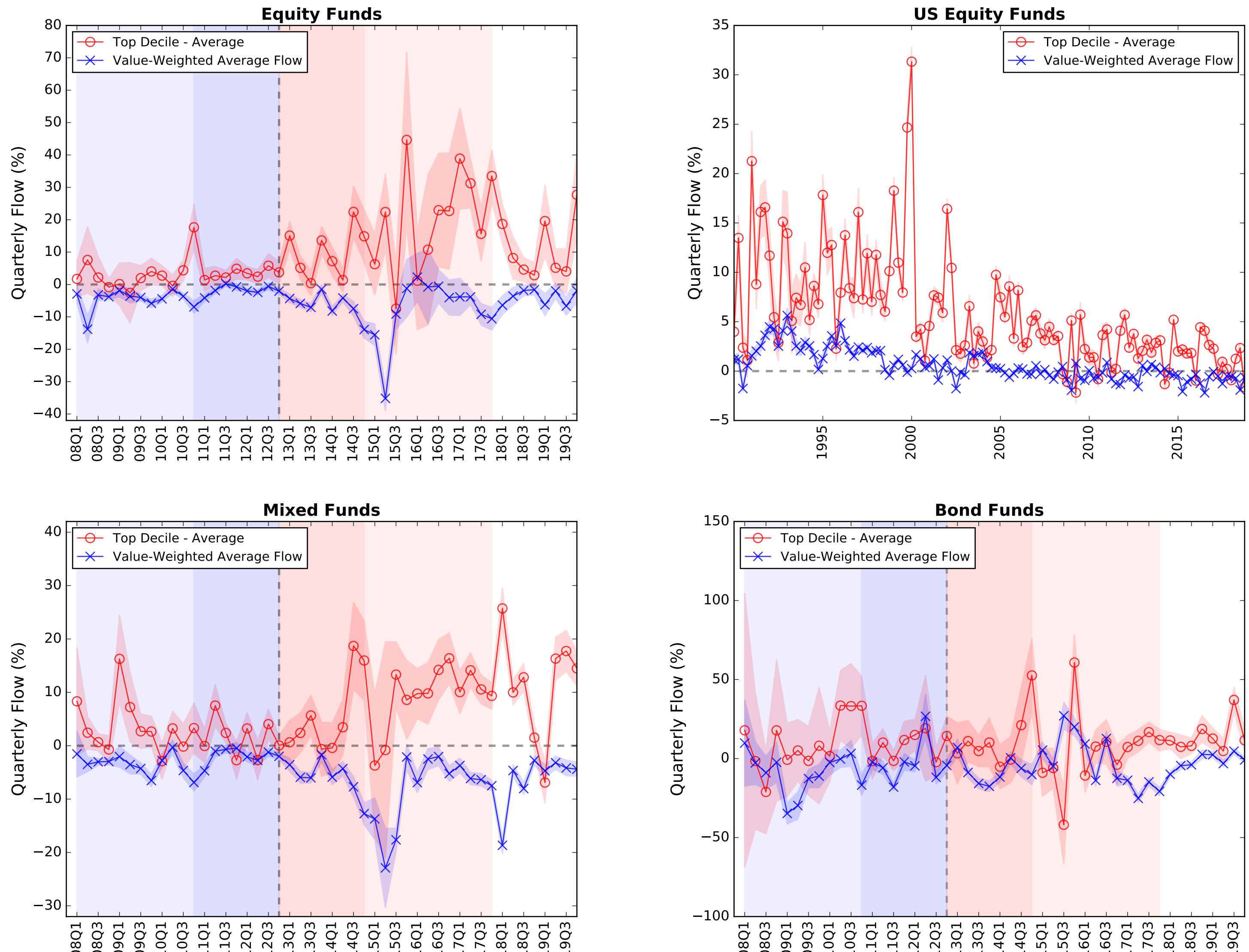


Figure 4. Purchase Fraction: The Whole Market versus Howbuy Platform

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 return. Market share of purchase for each decile in quarter t 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 average market share of purchase for each decile in the before (2008–2012) and after (2013–2017) period for equity and mixed funds respectively. The solid lines represent the average fractions using the whole market; the dotted lines represent the results using data from Howbuy. The shaded area in the upper two graphs indicates the 95% confidence intervals. The lower two graphs exhibit the time series of the market share of purchase for decile 10 funds. The blue line marked with "o" represents the whole market and the red line marked with "x" represents the Howbuy platform.

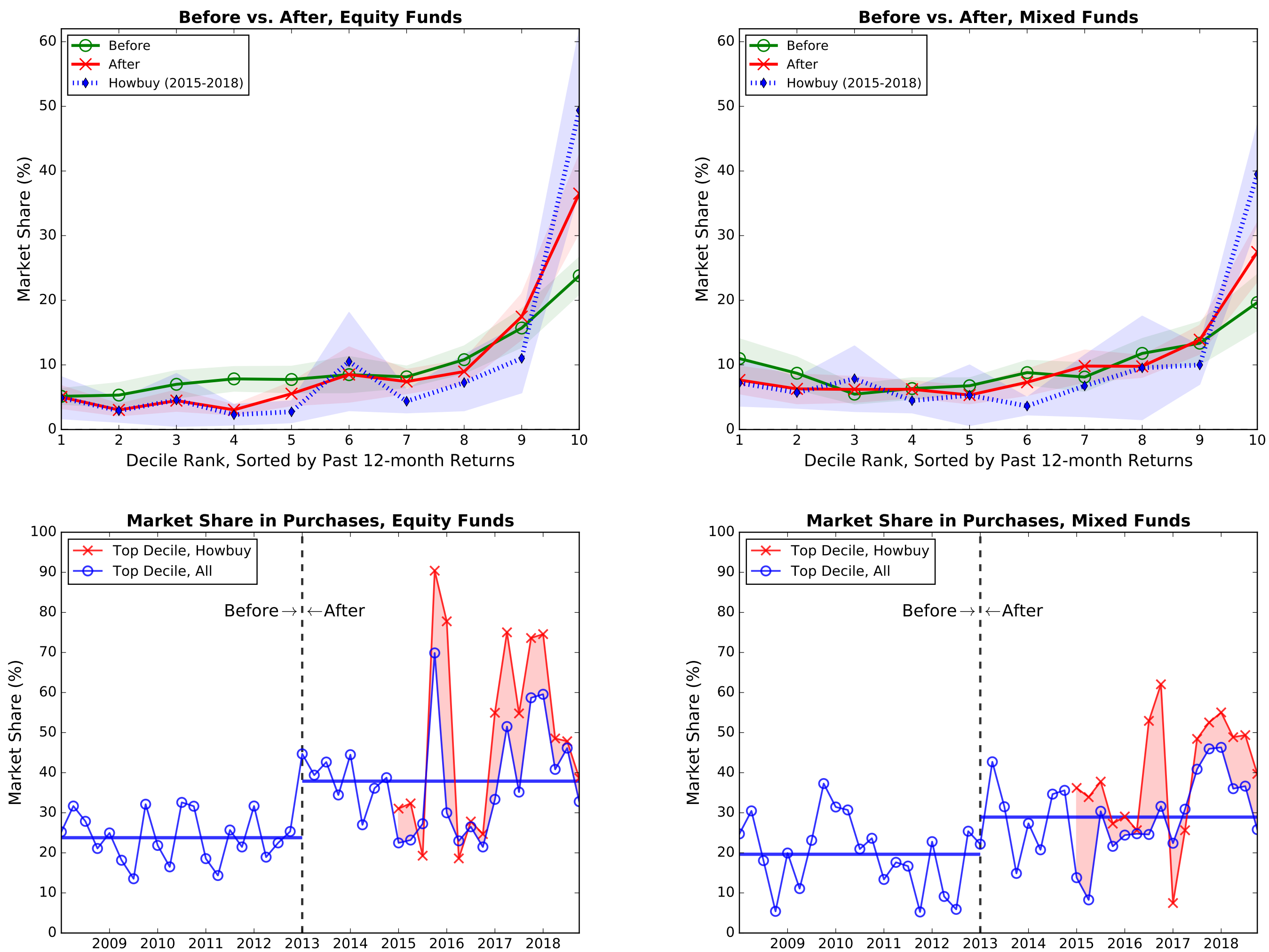


Figure 5. Amplified Flow-Performance Sensitivity for Front-Page Funds

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 the one in Table 5. The only difference is that we further divide the top 20 funds into 10 equal groups (Top 1–2, 3–4, etc.). The "Others" and the "Bottom 100" groups are defined in the same way as in Table 5. Since the "Bottom 100" is omitted in the regression estimation, the flows shall be interpreted benchmarking to "Bottom 100" group. The upper panel reports the flows to the Top X funds. The orange and blue bars denote the flows 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.

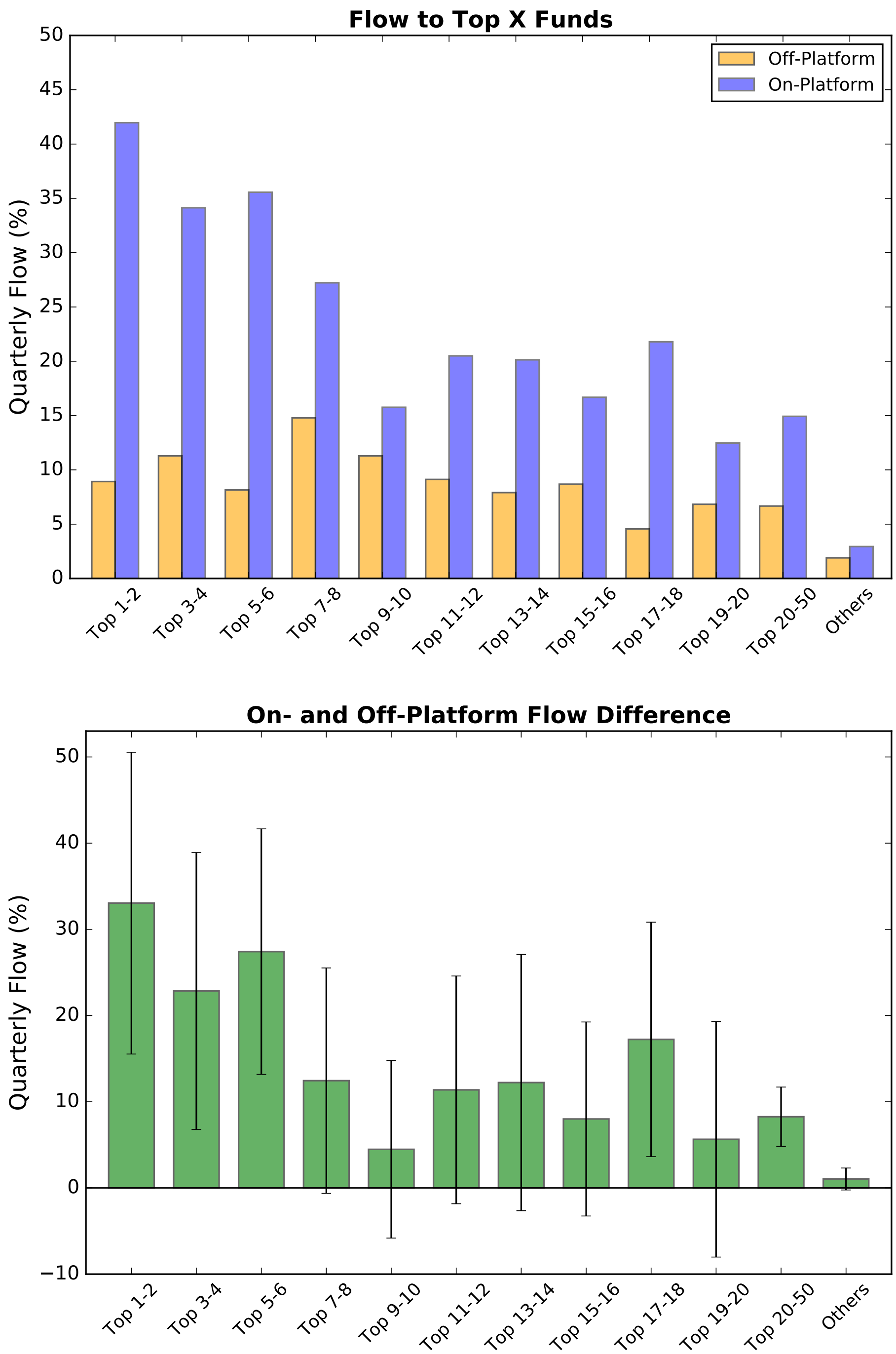


Figure 6. The Impact on Standard Deviation, Before and After the Introduction of Platforms

This figure shows fund daily return standard deviation by performance decile rank, for the sample 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 the past 12-month return from quarter $t-4$ to quarter $t-1$. Fund performance deciles are obtained at the end of quarter $t-1$, indicated by a dotted vertical line. We then examine the difference in daily return standard deviation between Decile 10 and Decile 1 funds from $t-4$ to $t+4$. The shaded areas denote the 95% confidence intervals. The panels correspond to actively managed China equity, U.S. equity, China mixed, and China bond mutual funds, respectively.

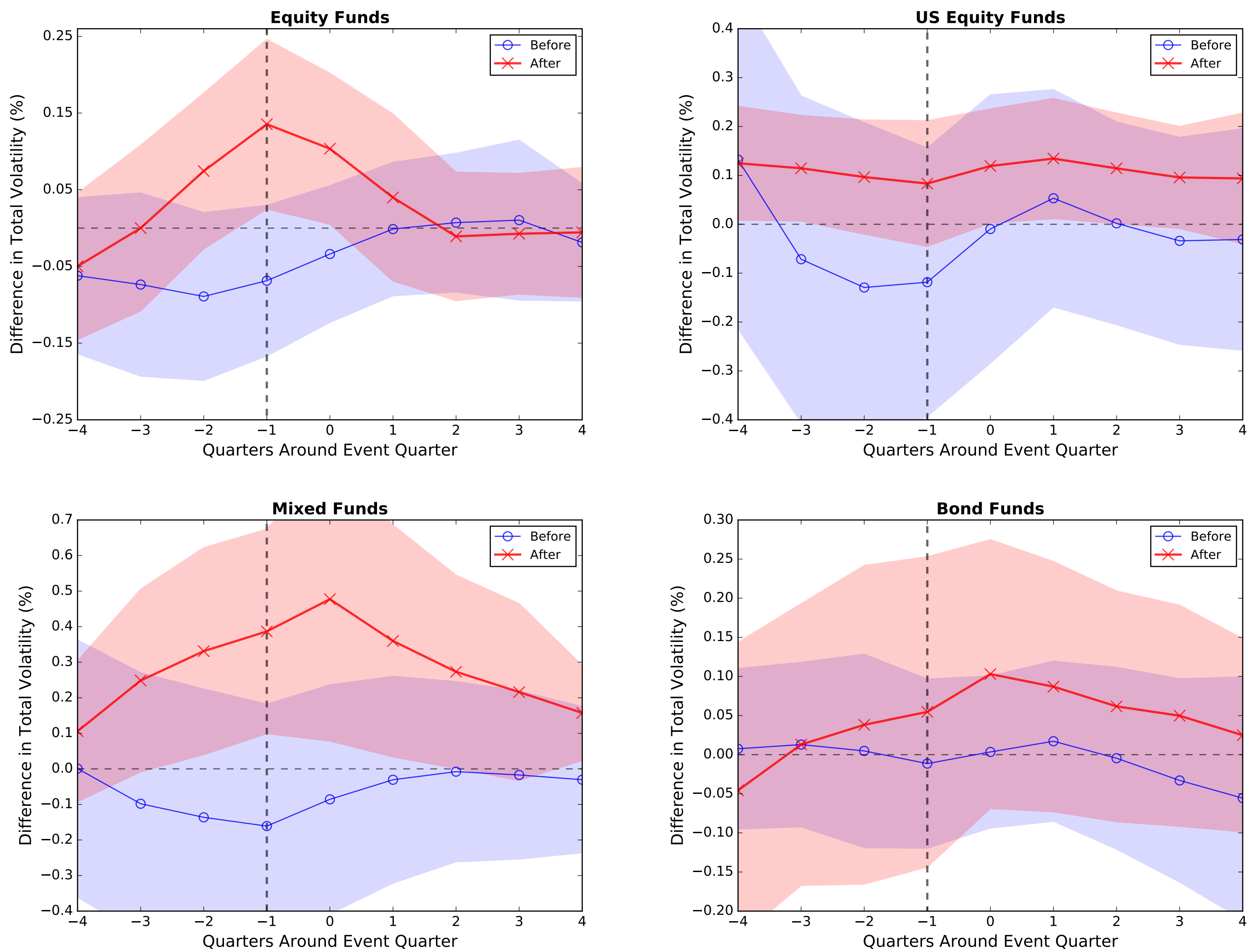


Figure 7. Entering Time and Changes in Market Share for Fund Families

This graph shows the entering time of families onto Tiantian platform and the changes in their market shares. Change in family market share is calculated as the average family market share in the three years after (2013–2015) the introduction of platforms minus the average market share in the three years before (2010–2012). The graph includes the largest 50 fund families in our before sample, and we further label the names of the largest 15 families in the graph.

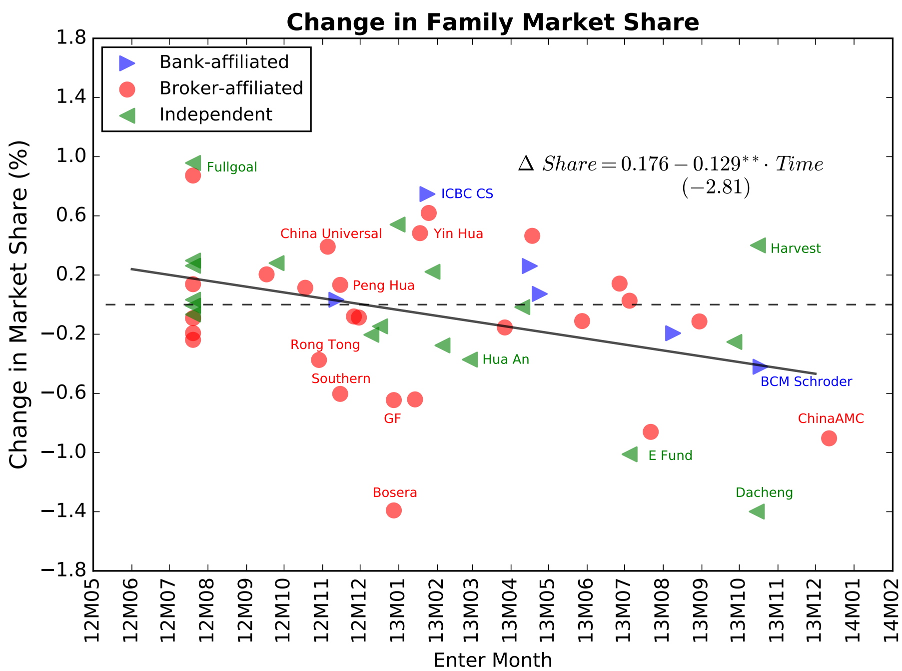


Table 1. Summary Statistics

Panel A shows the size of the actively managed mutual fund industry year by year. We report the average number of unique funds (#Funds), aggregate assets under managements (AUM) in billion-yuan, fund quarterly returns (Ret%) in percent, cross-sectional standard deviation of fund quarterly returns (StdRet%) by averaging across four quarters each year for equity, mixed, and bond funds, respectively. Panel B reports the summary statistics for the 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. $\text{MRet}_{(t-1,t-4)}$ is the average monthly 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. We winsorize flow at the 2% and 98% levels. Annual management fee, subscription fee, and redemption fee are calculated by aggregating different fund share classes and are reported in percentage points. We compute the mean, first quartile (Q1), median, third quartile (Q3), and standard deviation for each variable quarter by quarter, and report the time-series averages of the quarterly statistics for the five years before (2008–2012) and five years after (2013–2017) the introduction of the platforms. The last two columns report the differences in the mean statistics for the before and after sample and the corresponding t-statistics. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A. Size of Mutual Fund Industry, by Year

	Equity				Mixed				Bond			
Year	#Funds	AUM	Ret%	StdRet%	#Funds	AUM	Ret%	StdRet%	#Funds	AUM	Ret%	StdRet%
2007	55	323.3	22.7	6.2	80	468.1	20.4	8.0	10	23.1	4.5	3.2
2008	72	376.3	-15.6	3.9	97	488.0	-13.6	5.1	16	50.7	1.9	1.4
2009	111	723.3	14.3	4.4	121	692.7	12.3	5.2	20	32.1	1.0	1.4
2010	143	810.4	1.3	3.8	134	690.8	1.5	4.3	40	59.0	1.6	1.5
2011	185	730.0	-6.7	3.1	156	601.4	-5.7	3.2	72	68.4	-0.7	1.7
2012	220	636.9	1.5	3.3	167	529.6	1.0	2.7	85	90.4	1.8	1.3
2013	270	669.3	3.8	5.5	187	531.4	3.1	4.7	124	130.2	0.1	2.0
2014	326	617.1	6.1	6.6	210	477.1	5.2	5.7	185	131.4	5.0	5.2
2015	186	358.9	12.7	8.8	432	760.2	9.8	10.7	308	321.6	2.7	3.8
2016	42	38.0	-2.2	4.0	712	905.7	-3.0	4.8	409	650.7	-0.0	2.0
2017	123	166.0	3.6	5.3	1,020	1,292.2	2.8	4.7	468	529.1	0.4	1.2
2018	178	175.7	-7.0	4.9	1,418	1,229.9	-4.6	5.0	649	721.4	0.9	2.0
2019	225	210.5	11.1	5.5	1,763	1,373.2	8.0	6.5	946	1,703.9	1.5	1.9

Panel B. Summary Statistics

		Before					After					Difference	
		Mean	Q1	Median	Q3	Std.	Mean	Q1	Median	Q3	Std.	Mean	t-stat
Equity	*Log(Size)*	21.84	21.35	21.93	22.62	1.07	20.25	19.17	20.36	21.36	1.46	-1.59***	(-10.64)
	Age	57.51	34.08	47.33	71.70	31.45	55.56	35.55	49.13	70.03	26.38	-1.96	(-0.87)
	$MRet_{(t-1,t-4)}$	0.34	-0.10	0.35	0.77	0.67	1.43	0.81	1.43	2.06	1.08	1.09	(1.43)
	Flow	-2.41	-6.48	-2.59	0.02	11.09	-0.45	-13.41	-7.22	0.14	31.96	1.97	(1.23)
	Management fee	1.49	1.50	1.50	1.50	0.06	1.46	1.50	1.50	1.50	0.15	-0.03***	(-3.49)
	Subscription fee	1.10	1.05	1.10	1.16	0.12	1.09	1.01	1.10	1.17	0.14	-0.01***	(-3.93)
	Redemption fee	0.16	0.12	0.13	0.13	0.20	0.30	0.18	0.29	0.35	0.22	0.14***	(3.54)
Mixed	*Log(Size)*	21.65	21.05	21.94	22.61	1.30	20.58	19.61	20.80	21.67	1.42	-1.07***	(-9.83)
	Age	63.26	45.38	65.00	79.35	21.22	81.49	47.38	78.68	114.38	38.69	18.23***	(6.99)
	$MRet_{(t-1,t-4)}$	0.33	-0.18	0.31	0.82	0.82	1.23	0.65	1.23	1.85	0.98	0.90	(1.30)
	Flow	-1.54	-5.00	-2.69	-0.69	11.71	-1.84	-12.48	-6.63	-2.42	31.70	-0.30	(0.24)
	Management fee	1.47	1.50	1.50	1.50	0.13	1.43	1.49	1.50	1.50	0.18	-0.03***	(-3.66)
	Subscription fee	1.13	1.00	1.12	1.31	0.25	1.07	0.98	1.11	1.19	0.24	-0.05***	(-6.12)
	Redemption fee	0.23	0.13	0.13	0.27	0.23	0.30	0.13	0.14	0.37	0.35	0.07***	(6.36)
Bond	*Log(Size)*	20.25	19.32	20.25	21.20	1.20	20.01	19.06	20.06	21.02	1.33	-0.24**	(-2.23)
	Age	49.19	33.13	40.54	59.67	23.18	55.65	34.80	47.88	68.23	28.04	6.46***	(4.33)
	$MRet_{(t-1,t-4)}$	0.30	0.12	0.30	0.48	0.26	0.58	0.35	0.54	0.78	0.50	0.28	(1.67)
	Flow	2.03	-16.03	-5.42	13.42	26.67	2.84	-20.82	-5.86	11.57	45.07	0.81	(0.15)
	Management fee	0.64	0.60	0.62	0.70	0.06	0.66	0.60	0.70	0.70	0.11	0.01***	(3.36)
	Subscription fee	0.24	0.00	0.23	0.39	0.23	0.34	0.17	0.36	0.51	0.21	0.11***	(9.08)
	Redemption fee	0.05	0.00	0.01	0.05	0.12	0.11	0.00	0.02	0.05	0.26	0.06***	(10.34)

Table 2. Fund Flows and Returns in Each Performance Decile

This table reports the average fund flow and return for each performance decile, before and after the introduction of platforms. At each quarter end for each style category, we sort all funds into deciles based on the past 12-month return ($\text{MRet}_{(t-1,t-4)}$). We then compute the quarterly average flow (*Flow*), average past 12-month return ($\text{MRet}_{(t-1,t-4)}$), cross-sectional standard deviation of flows (*StdFlow*) and cross-sectional standard deviation of returns (*StdMRet*) for each performance decile. We compute the statistics quarter by quarter and report the time-series averages for the five-year sample before (2008–2012) and after (2013–2017) the introduction of platforms. t-statistics are reported in parentheses.

			Decile 1 (Loser)	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10 (Winner)
Equity	*Flow*	Before	-3.18	-3.16	-4.54	-3.78	-3.60	-3.04	-2.81	-2.45	0.54	1.88
			(-3.47)	(-3.67)	(-3.55)	(-4.93)	(-4.28)	(-2.22)	(-2.74)	(-1.94)	(0.34)	(1.34)
		After	-3.64	-10.39	-9.02	-3.37	-1.83	-2.55	-4.76	0.73	10.84	19.65
			(-2.30)	(-4.43)	(-5.78)	(-1.01)	(-0.51)	(-0.51)	(-2.88)	(0.30)	(2.51)	(4.47)
	StdFlow	Before	7.00	8.41	8.15	7.25	7.44	9.88	8.03	12.23	14.02	13.52
		After	18.71	15.30	14.61	23.38	27.54	24.06	17.94	24.53	36.67	39.18
	$MRet_{(t-1,t-4)}$	Before	-0.86	-0.36	-0.11	0.09	0.26	0.43	0.60	0.78	1.01	1.49
		After	-0.58	0.41	0.79	1.04	1.31	1.53	1.78	2.07	2.53	3.31
	StdMret	Before	0.32	0.09	0.07	0.06	0.05	0.05	0.05	0.06	0.09	0.30
		After	0.69	0.17	0.09	0.07	0.07	0.07	0.08	0.09	0.15	0.48
Mixed	*Flow*	Before	-1.73	-3.10	-2.04	-2.05	-2.96	-3.01	-1.71	-1.93	1.84	1.21
			(-1.12)	(-4.45)	(-2.02)	(-1.84)	(-4.23)	(-5.66)	(-1.55)	(-2.71)	(1.03)	(0.99)
		After	1.92	-4.15	-4.92	-4.78	-5.02	-4.97	-4.01	-2.07	0.28	9.51
			(0.30)	(-4.42)	(-3.13)	(-3.56)	(-2.78)	(-2.15)	(-3.29)	(-1.01)	(0.14)	(4.19)
	StdFlow	Before	11.53	5.79	7.71	7.90	6.96	6.56	8.96	9.45	15.40	14.08
		After	34.47	25.64	24.46	24.43	24.25	25.36	26.70	29.40	31.46	39.24
	$MRet_{(t-1,t-4)}$	Before	-1.10	-0.46	-0.18	0.03	0.21	0.40	0.60	0.82	1.16	1.84
		After	-0.53	0.27	0.64	0.90	1.12	1.34	1.57	1.85	2.19	2.96
	StdMret	Before	0.45	0.11	0.07	0.06	0.06	0.06	0.06	0.08	0.14	0.41
		After	0.52	0.14	0.08	0.07	0.07	0.06	0.07	0.08	0.13	0.51
Bond	*Flow*	Before	-2.25	3.07	0.51	-3.30	-2.93	0.54	1.92	2.15	6.50	15.41
			(-0.59)	(0.57)	(0.10)	(-1.30)	(-0.47)	(0.13)	(0.77)	(0.43)	(0.88)	(1.80)
		After	5.50	0.55	-2.11	-1.81	-1.01	-1.88	2.25	7.94	8.92	10.21
			(1.12)	(0.11)	(-0.55)	(-0.52)	(-0.20)	(-0.50)	(0.59)	(1.78)	(1.91)	(2.12)
	StdFlow	Before	24.05	31.19	23.66	22.93	20.11	23.76	22.77	23.86	25.22	29.25
		After	48.10	43.63	43.05	37.82	41.94	40.60	39.80	45.94	43.08	46.65
	$MRet_{(t-1,t-4)}$	Before	-0.15	0.02	0.11	0.19	0.26	0.34	0.41	0.48	0.58	0.77
		After	-0.23	0.22	0.35	0.43	0.50	0.58	0.66	0.78	0.96	1.52
	StdMret	Before	0.09	0.04	0.03	0.02	0.02	0.02	0.03	0.03	0.05	0.08
		After	0.38	0.05	0.03	0.02	0.02	0.02	0.03	0.04	0.07	0.39

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:

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

where $\text{Flow}_{i,t}$ is fund i's flow for quarter t. Decile $10_{i,t-1}$ 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 $t-1$ in its style group, 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 $t-1$, Flow_{t-1}, the fund flow in the previous quarter, and fund management fees, subscription fees, and redemption fees in all specifications. We report the estimations using the long window and short window. The long window includes the sample in the five years before (2008–2012) and five years after (2013–2017) the introduction of platforms. The short window includes the sample in the two years before (2011–2012) and two years after (2013–2014). In the "All" column, we pool funds from all styles together in the regression, while the decile 10 dummies are still obtained within each style. We include time fixed effects for all the specifications, and further include style fixed effects as indicated. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Staggered Entrance onto Platforms							
	[-5,5]				[-2,2]			
	Equity	Mixed	Bond	All	Equity	Mixed	Bond	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Decile10	6.985***	6.127***	14.383***	8.132***	7.606***	4.555***	8.422***	6.742***
	(6.03)	(4.71)	(4.79)	(8.32)	(5.67)	(3.16)	(2.92)	(6.57)
Decile10×Platform	16.964***	11.399***	-5.101	7.966***	18.158***	15.625***	22.710**	18.850***
	(3.75)	(5.34)	(-1.26)	(4.72)	(2.61)	(2.74)	(1.98)	(4.16)
Platform	-3.097	1.759	1.432	-0.702	-4.915	0.98	10.187**	0.895
	(-1.07)	(1.29)	(0.67)	(-0.63)	(-1.18)	(0.24)	(2.08)	(0.34)
Log(Size)	-2.987***	-3.949***	-6.073***	-4.260***	-2.046***	-1.536***	-4.663***	-2.488***
	(-9.17)	(-14.21)	(-11.96)	(-21.06)	(-5.13)	(-5.35)	(-6.48)	(-9.64)
Log(Age)	-0.513	1.715***	0.867	1.019**	2.343**	3.089***	3.124*	3.712***
	(-0.72)	(2.62)	(0.63)	(2.10)	(2.53)	(3.78)	(1.71)	(5.82)
Flow_{t-1}	0.065***	0.014	0.030***	0.031***	0.104***	0.067**	0.085***	0.086***
	(3.23)	(1.35)	(2.87)	(4.51)	(3.52)	(2.46)	(4.29)	(5.89)
Management Fee	-5.901	3.837**	-16.326***	1.16	-2.339	3.617	1.349	3.061
	(-0.74)	(2.26)	(-2.87)	(0.68)	(-0.33)	(1.59)	(0.14)	(0.95)
Subscription Fee	-2.957	-0.927	-6.918**	-1.991*	-4.063	-0.14	-3.583	-1.371
	(-0.89)	(-0.67)	(-2.58)	(-1.72)	(-1.14)	(-0.09)	(-1.07)	(-0.98)
Redemption Fee	1.704	3.193***	-2.023	2.259***	-0.202	-1.11	-2.534	-1.054
	(1.05)	(2.88)	(-0.97)	(2.65)	(-0.13)	(-0.91)	(-0.62)	(-1.02)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Style FE	N	N	N	Y	N	N	N	Y
Observations	6,705	12,941	6,766	26,412	4,000	2,876	1,863	8,739
R^2	0.079	0.065	0.123	0.066	0.084	0.086	0.144	0.071

Table 4. Purchase Fraction: The Whole Market versus Howbuy

This table reports the purchase fractions for each performance decile rank for the whole market ("All") and for Howbuy, respectively. We compute the fractions within each fund style as follows: For each quarter, the fraction of purchase for each decile is computed as the amount of purchase of all funds in that decile divided by the total amount of purchase of all funds in that quarter. The time-series average of purchase fractions for the whole market in the pre- and post-platform periods are reported. "After-Before" denotes the difference between the two sample periods, and t-stats are reported in parentheses. The data for purchase on Howbuy is available from 2015 through 2018. The fraction of purchase on Howbuy is computed in the same way as the fractions for our whole sample. "Howbuy-All" reports the differences between the average purchase fractions on Howbuy and the average purchase fractions for the whole market during the same sample period.

		Purchase Fraction (in %)									
		Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Equity	All Before (2008-2012)	5.14	5.33	7.00	7.84	7.74	8.49	8.15	10.81	15.71	23.79
	All After (2013-2017)	5.03	3.03	4.48	3.05	5.54	8.51	7.42	8.97	17.47	36.50
	After-Before	-0.11	-2.30	-2.52	-4.79	-2.20	0.02	-0.73	-1.84	1.76	12.71
		(-0.11)	(-2.26)	(-1.97)	(-4.91)	(-1.67)	(0.01)	(-0.61)	(-1.37)	(0.80)	(4.00)
	All (2015-2018)	4.60	3.56	5.08	2.79	4.89	9.01	7.65	8.61	16.19	37.61
	Howbuy (2015-2018)	4.92	2.91	4.58	2.29	2.75	10.52	4.37	7.26	11.02	49.37
	Howbuy-All	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	All Before (2008-2012)	10.98	8.71	5.47	6.34	6.78	8.81	8.12	11.78	13.36	19.65
	All After (2013-2017)	7.66	6.29	6.21	6.23	5.34	7.31	9.82	9.78	13.90	27.46
	After-Before	-3.32	-2.42	0.73	-0.11	-1.44	-1.50	1.70	-2.00	0.54	7.81
		(-1.87)	(-1.49)	(0.61)	(-0.11)	(-1.67)	(-1.13)	(1.07)	(-1.47)	(0.28)	(2.60)
	All (2015-2018)	8.59	7.39	7.00	6.05	5.82	6.14	7.32	9.86	12.80	29.02
	Howbuy (2015-2018)	7.22	5.72	7.87	4.47	5.30	3.64	6.76	9.54	10.00	39.50
	Howbuy-All	-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	All Before (2010-2012)	8.57	5.87	14.85	8.40	6.23	11.44	10.21	10.70	10.27	13.46
	All After (2013-2017)	6.08	9.46	8.06	9.47	9.66	8.92	10.76	10.76	11.35	15.48
	After-Before	-2.49	3.59	-6.79	1.07	3.44	-2.53	0.55	0.07	1.08	2.02
		(-1.82)	(2.63)	(-2.50)	(0.59)	(3.16)	(-1.27)	(0.29)	(0.03)	(0.53)	(0.69)
	All (2015-2018)	6.07	8.35	7.56	9.43	9.00	7.86	10.32	12.41	11.28	17.72
	Howbuy (2015-2018)	2.82	8.00	8.19	7.64	9.71	2.87	10.16	17.03	8.82	24.76
	Howbuy-All	-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 5. Staggered Entrance and Front-Page Funds

This table shows the panel regression results using the Top X fund dummies instead of the top decile dummy in Table 3. To mimic investors' choice on the performance rank list, we estimate the regressions using all fund units, without aggregating different share classes to the fund level. We divide all fund units in the same style into five ranking groups: Top 10, Top 11-20, Top 21-50, Bottom 100, and others. We then create dummy variables that equal to one if a fund's past 12-month return falls into the ranking category, and zero otherwise. The regression setting is similar to the one in Table 3. We regress quarterly flow on last quarter end Top X fund dummies, the platform dummy, and the interactions between the two. Group "Bottom 100" is omitted because of multicollinearity. We include as controls last quarter end fund Log(Size), Log(Age), Flow, and Fees. In the "All" column, we pool funds from all styles together in the regression, while the rank dummies are still obtained within each style. The sample is from 2008 through 2017. Standard errors are clustered at the fund level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Dep. Var.: Next Quarter Flow			
	Equity	Mixed	Bond	All
Top 10×Platform	19.319***	30.088***	10.006	19.037***
	(3.26)	(3.98)	(0.96)	(4.34)
Top 11-20×Platform	21.403***	10.703*	0.965	10.613***
	(3.51)	(1.87)	(0.12)	(2.78)
Top 21-50×Platform	14.707***	8.429**	3.416	8.021***
	(4.25)	(2.37)	(0.73)	(3.61)
Others×Platform	-0.401	1.504	0.143	0.699
	(-0.18)	(0.65)	(0.06)	(0.57)
Top 10	15.257***	4.555***	14.210***	10.912***
	(6.25)	(2.66)	(5.28)	(7.92)
Top 11-20	7.231***	2.755*	14.956***	7.533***
	(4.49)	(1.70)	(4.35)	(5.73)
Top 21-50	5.385***	3.487***	13.504***	6.749***
	(5.67)	(3.43)	(7.03)	(8.75)
Others	0.637	-3.385**	8.088***	2.078***
	(0.92)	(-2.11)	(4.91)	(2.91)
Controls, Time FE	Y	Y	Y	Y
Observations	8,892	18,855	15,210	42,957
R^2	0.064	0.062	0.098	0.053

Table 6. The Impact on Fund Turnover and Investor Composition

This table reports the change in fund turnover and investor composition after a fund enters onto platforms. Fund turnover is measured as the sum of purchase and redemption amount in quarter t divided by the average fund TNA in quarter t and $t-1$. Log(#Holders) is the natural logarithm of the number of investors that hold the fund. Log(HolderDollarValue) is the natural logarithm of the average dollar value held by an investor of a fund. RetailRatio (%) is the fraction of a fund held by individual investors. In columns (1) and (2), the dependent variable is fund turnover. Decile $10_{i,t-1}$ is a dummy that equals one if fund i belongs to the top performance decile based on the 12-month return up to the end of quarter $t-1$. $\text{Platform}_{i,t}$ 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 further control for fund's Log(Size), Log(Age), Flow, and Fees in quarter $t-1$. In columns (3) to (8), we merge the semi-annual investor composition data in each June and December with the control variables in the closest previous quarter: $\text{Platform}_{i,t}$ is a dummy that equals one if a fund is available on platforms in quarter $t-1$ (e.g., March when the investor composition data is in June). Time fixed effects and fund fixed effects are included in all specifications. The sample is from 2008 through 2017. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Fund Turnover		Log(#Holders)		Log(HolderDollarValue)		Retaio Ratio (%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Platform	-0.019	-0.027	-0.008	-0.036	0.042	0.065*	-0.006	-0.373
	(-0.75)	(-1.04)	(-0.25)	(-1.24)	(1.16)	(1.78)	(-0.01)	(-0.39)
Decile10		0.176***		-0.079***		0.147***		-3.824***
		(6.51)		(-2.88)		(6.27)		(-4.10)
Decile10*Platform		0.113**		0.371***		-0.259***		3.626***
		(2.59)		(8.76)		(-6.17)		(2.80)
Log(Size)	-0.085***	-0.097***	0.408***	0.396***	0.387***	0.392***	-9.722***	-9.723***
	(-5.82)	(-6.37)	(19.54)	(19.24)	(17.87)	(18.00)	(-18.75)	(-18.56)
Log(Age)	0.054	0.053	0.585***	0.574***	-0.513***	-0.506***	-1.632	-1.711
	(0.79)	(0.80)	(9.82)	(9.76)	(-9.04)	(-8.98)	(-0.78)	(-0.83)
Flow_{t-1}	0.187***	0.163***	-0.050***	-0.057***	0.172***	0.172***	-3.014***	-2.925***
	(6.33)	(5.94)	(-4.08)	(-4.79)	(10.84)	(10.93)	(-7.49)	(-7.30)
Management Fee	-0.051	-0.077	0.734***	0.707***	-0.465**	-0.460**	7.891	8.069
	(-0.47)	(-0.72)	(3.98)	(3.89)	(-2.28)	(-2.27)	(1.45)	(1.49)
Subscription Fee	-0.346**	-0.337**	-0.444*	-0.435*	0.349	0.345	-24.830***	-24.792***
	(-2.65)	(-2.66)	(-1.94)	(-1.93)	(1.17)	(1.16)	(-4.49)	(-4.48)
Redemption Fee	-0.101	-0.086	0.516***	0.534***	-0.707***	-0.713***	16.689***	16.661***
	(-1.54)	(-1.38)	(2.79)	(2.99)	(-2.69)	(-2.75)	(2.98)	(2.99)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	24,110	24,110	13,427	13,427	13,427	13,427	13,427	13,427
R-squared	0.432	0.441	0.955	0.956	0.853	0.853	0.786	0.786

Table 7. Dynamic Effect of Platform Entrance

In the table, we examine the dynamic effect of entering platforms on the flow-performance relationship around the quarter when a fund is added to the two major platforms. The model specification is:

$$\begin{aligned}\text{Flow}_{i,t} &= \alpha + \beta_1 \cdot \text{Decile10}_{i,t-1} + \beta_2 \cdot \text{Platform}(q=-1)_{i,t} + \beta_3 \cdot \text{Platform}(q=0)_{i,t} + \beta_4 \cdot \text{Platform}(q=1)_{i,t} \\ &+ \beta_5 \cdot \text{Platform}(q \geq 2)_{i,t} + \beta_6 \cdot \text{Decile10}_{i,t-1} \times \text{Platform}(q=-1)_{i,t} + \beta_7 \cdot \text{Decile10}_{i,t-1} \times \text{Platform}(q=0)_{i,t} \\ &+ \beta_8 \cdot \text{Decile10}_{i,t-1} \times \text{Platform}(q=1)_{i,t} + \beta_9 \cdot \text{Decile10}_{i,t-1} \times \text{Platform}(q \geq 2)_{i,t} + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t} \,,\end{aligned}$$

where $\text{Platform}(q=0)_{i,t}$ is a dummy that equals one for the quarter when fund i is first available for sale through the two platforms. $\text{Platform}(q=-1)_{i,t}$ is a dummy variable that equals one for the first quarter before fund i enters platforms. $\text{Platform}(q=1)_{i,t}$ is defined similarly. $\text{Platform}(q \geq 2)$ equals one for the second quarter after inclusion and for the subsequent quarters. The omitted group is $q \leq -2$. We include $\text{Platform}(q=-1)_{i,t}$, $\text{Platform}(q=1)_{i,t}$, $\text{Platform}(q \geq 2)$, and their interactions with Decile $10_{i,t-1}$ to examine the dynamic impact. The control variables are the same as those in Table 3. In the "All" column, we pool funds from all styles together in the regression, while the decile 10 dummies are still obtained within each style. The sample is from 2008 through 2017. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Dep. Var.: Next Quarter Flow			
	Equity	Mixed	Bond	All
Decile10	6.697***	5.184***	16.816***	8.178***
	(5.66)	(4.50)	(5.25)	(8.30)
Platform(q=-1)×Decile10	4.168	6.587	-13.883	0.092
	(0.78)	(1.20)	(-1.62)	(0.02)
Platform(q=0)×Decile10	4.413	17.526***	-15.121*	5.132
	(0.66)	(2.76)	(-1.79)	(1.26)
Platform(q=1)×Decile10	21.691**	13.389*	-0.467	13.027**
	(2.22)	(1.77)	(-0.04)	(2.43)
Platform(q≥2)×Decile10	20.832***	11.792***	-7.138	7.933***
	(3.36)	(5.45)	(-1.55)	(4.24)
Platform(q=-1)	0.08	-0.492	3.132	2.368
	(0.02)	(-0.19)	(0.72)	(1.19)
Platform(q=0)	1.07	0.473	3.879	2.502
	(0.27)	(0.21)	(1.01)	(1.39)
Platform(q=1)	-0.128	3.425	5.169	3.774**
	(-0.03)	(1.46)	(1.44)	(2.04)
Platform(q≥2)	-6.43	1.649	1.129	-1.455
	(-1.50)	(1.03)	(0.47)	(-1.12)
Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Style FE	N	N	N	Y
Observations	6,705	12,941	6,766	26,412
R^2	0.083	0.065	0.124	0.067

Table 8. The Impact on Managerial Risk Taking

This table shows the managerial risk taking behavior when a fund gets into the top performance decile. The model specification is as follows:

$$\text{Std}_{i,t+k} = \alpha^k + \beta_1^k \cdot \text{Decile10}_{i,t-1} \times \text{After}_t + \beta_2^k \cdot \text{Decile10}_{i,t-1} + \sum_j \gamma_j^k \text{Control}_{i,t-1}^j + \varepsilon_{i,t+k}\,,$$

where $\text{Std}_{i,t+k}$ is fund i's daily return standard deviation in quarter $t+k$. Decile $10_{i,t-1}$ is a dummy that equals one if fund i belongs to the top performance decile based on the 12-month return up to the end of quarter $t-1$. After_t is a dummy variable that equals one for the sample in and after 2013. Panel A reports the panel regression estimates with fund total volatility as the dependent variable. We further decompose total volatility into systematic volatility and idiosyncratic volatility based on a two-factor model (an aggregate stock market factor and an aggregate bond factor). We replace the total volatility in the regression with systematic/idiosyncratic volatility, and report the results in Panel B and C, respectively. We include controls of quarter $t-1$ end fund's Log(Size), Log(Age), Flow, and Fees. Time fixed effects and fund fixed effects are included for all the specifications. Only the coefficient estimates for Decile $10_{i,t-1}$ and its interaction with After_t are reported. 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.

	$k=-3$	$k=-2$	$k=-1$	$k=0$	$k=1$	$k=2$	$k=3$
A. Total Volatility							
Decile 10×After	0.082**	0.105***	0.109***	0.070**	0.017	-0.009	-0.017
	(2.39)	(3.32)	(3.26)	(2.44)	(0.93)	(-0.40)	(-0.78)
Decile 10	-0.008	-0.022	-0.018	0.013	0.022*	0.027	0.026
	(-0.32)	(-0.86)	(-0.74)	(0.61)	(1.70)	(1.49)	(1.41)
B. Systematic Volatility							
Decile 10×After	0.049	0.067**	0.077**	0.057*	0.01	-0.006	-0.014
	(1.43)	(2.12)	(2.30)	(1.82)	(0.59)	(-0.24)	(-0.70)
Decile 10	-0.023	-0.044	-0.043*	-0.007	0.004	0.01	0.012
	(-0.88)	(-1.61)	(-1.71)	(-0.33)	(0.38)	(0.57)	(0.72)
C. Idiosyncratic Volatility							
Decile 10×After	0.037**	0.046**	0.036*	0.019	0.001	-0.015	-0.006
	(2.18)	(2.51)	(1.84)	(1.00)	(0.09)	(-0.79)	(-0.34)
Decile 10	0.040***	0.051***	0.058***	0.050***	0.040***	0.037**	0.025
	(3.45)	(4.26)	(4.95)	(4.37)	(4.56)	(2.48)	(1.52)

Table 9. Within-Family Ranking

This table reports the panel regression estimates for the sensitivity of fund flow to past performance ranking, both within fund families and across fund families. We include funds in families with at least five funds and require the families to exist at least three years before the introduction of platforms. We follow similar model specification as in Table 3. Decile$10_{i,t-1}$ 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 $t-1$. The performance deciles are formed within each fund style. FamilyRank is the past 12-month-return quintile rank among the funds in the same fund family. Platform$_{i,t}$ is a dummy that equals one if a fund is available for sale through the major two platforms: Ant Financial and Tiantian. We include controls of quarter $t-1$ end fund's Log(Size), Log(Age), Flow, and Fees. Time fixed effects, family fixed effects, and style fixed effects are included for all the specifications. The sample is from 2008 through 2017. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Dep. Var.: Next Quarter Flow			
	(1)	(2)	(3)
FamilyRank	1.583***		1.122***
	(6.86)		(4.60)
Decile10		7.784***	5.992***
		(7.01)	(5.10)
FamilyRank×Platform	-0.277		-1.033**
	(-0.70)		(-2.54)
Decile10×Platform		8.213***	9.853***
		(4.30)	(4.93)
Platform	-0.697	-1.905	-0.086
	(-0.44)	(-1.46)	(-0.05)
Log(Size)	-5.238***	-5.378***	-5.370***
	(-21.62)	(-22.09)	(-22.12)
Log(Age)	1.942***	2.231***	2.247***
	(3.59)	(4.23)	(4.23)
Flow$_{t-1}$	0.041***	0.035***	0.035***
	(5.41)	(4.64)	(4.61)
Management Fee	3.430**	2.054	2.133
	(1.97)	(1.16)	(1.21)
Subscription Fee	-2.087*	-2.217*	-2.046*
	(-1.70)	(-1.83)	(-1.68)
Redemption Fee	2.547**	2.623***	2.707***
	(2.57)	(2.71)	(2.76)
Time FE, Style FE, Family FE	Y	Y	Y
Observations	22,268	22,268	22,268
R^2	0.067	0.074	0.074

Table 10. Star Funds and Top Families

Panel A reports the fraction of funds in the Top fund families for each performance decile. Each quarter end for each style category, we sort all funds into deciles based on the past 12-month return ($\text{MRet}_{t-1,t-4}$). We then calculate the fraction of funds in the decile that belongs to the top ten families (or top five families or top one family) in that quarter. The differences between the before (2008–2012) and after (2013–2017) sample are reported. The bottom two rows report the differences between Decile 10 and Decile 1, and the corresponding t-statistics. Panel B reports the ten largest fund families for the sample before and after the introduction of platforms. We report the average total net assets (in billion-yuan) of actively managed funds for each family, number of actively managed funds in the family, and the average market share. The average statistics for the rest of fund families are also reported.

A. Fraction of Large Family Funds in Each Performance Decile

	Top Ten Largest Families				Top Five Largest Families				China Asset Management (Top One)			
Decile Rank	Before	After	Difference	t-stat	Before	After	Difference	t-stat	Before	After	Difference	t-stat
Decile 1	21.38	23.04	1.65	(0.58)	8.73	11.17	2.44	(1.62)	0.75	1.21	0.46	(1.17)
Decile 2	29.10	22.25	-6.86***	(-2.95)	13.15	10.53	-2.62*	(-1.70)	3.32	2.32	-1.01	(-1.20)
Decile 3	30.32	22.65	-7.68***	(-2.85)	13.19	11.17	-2.02	(-0.98)	3.00	2.91	-0.10	(-0.13)
Decile 4	23.94	23.91	-0.03	(-0.02)	9.68	11.24	1.56	(1.17)	2.80	3.28	0.48	(0.60)
Decile 5	28.14	22.33	-5.81**	(-2.47)	11.50	10.44	-1.05	(-0.62)	3.70	2.60	-1.10	(-1.14)
Decile 6	33.46	20.89	-12.56***	(-6.93)	15.78	10.21	-5.57***	(-3.55)	3.43	2.82	-0.62	(-0.69)
Decile 7	32.65	22.33	-10.32***	(-5.24)	14.04	10.23	-3.81***	(-2.69)	4.26	3.07	-1.19	(-1.34)
Decile 8	27.40	24.60	-2.79	(-1.00)	11.33	10.39	-0.94	(-0.50)	3.96	2.17	-1.79	(-1.59)
Decile 9	33.10	20.73	-12.37***	(-5.35)	16.88	9.54	-7.34**	(-4.47)	6.08	1.82	-4.25***	(-3.36)
Decile 10	36.22	18.98	-17.24***	(-6.96)	25.77	8.41	-17.36***	(-6.13)	11.10	0.78	-10.32***	(-5.64)
Decile 10-1	14.84***	-4.06	-18.89***		17.04***	-2.76*	-19.80***		10.35***	-0.43	-10.78***	
	(3.98)	(-1.54)	(-4.14)		(5.42)	(-1.80)	(-5.66)		(5.31)	(-1.16)	(-5.44)	

B. Largest Ten Fund Families

	Before (2008–2012)				After (2013–2017)			
Largest 10	Fund name	TNA ($B)	#Funds	Share	Fund name	TNA ($B)	#Funds	Share
1	China Asset Management	105.32	13.25	8.01%	China Asset Management	92.92	21.45	5.92%
2	Bosera Asset Management	76.54	10.8	5.82%	E Fund Management	84.35	26.70	5.37%
3	Gf Fund Management	69.17	7.3	5.26%	Harvest Fund Management	69.45	27.50	4.42%
4	Harvest Fund Management	59.07	11.35	4.49%	China Southern Asset Management	60.61	25.75	3.86%
5	China Southern Asset Management	58.51	11.85	4.45%	Bosera Asset Management	57.89	28.15	3.69%
6	E Fund Management	56.75	10.55	4.32%	Gf Fund Management	57.34	22.95	3.65%
7	Dacheng Fund Management	53.33	9.6	4.06%	ICBC Credit Suisse Asset Management	55.12	25.80	3.51%
8	Hua An Fund Management	40.83	7.85	3.11%	China Universal Asset Management	53.86	20.85	3.43%
9	Invesco Great Wall Fund Management	40.44	8.25	3.08%	Fullgoal Fund Management	48.86	25.45	3.11%
10	Fullgoal Fund Management	39.95	9.6	3.04%	Bank Of China Investment Management	42.10	21.20	2.68%
	The Largest Ten Fund Families	59.99	10.0	45.63%	The Largest Ten Fund Families	62.25	24.6	39.65%
	The Rest Fund Families (N=50)	14.29	4.6	54.37%	The Rest Fund Families (N=92)	10.30	8.84	60.35%

Table 11. Alternative Specifications

This table shows various robustness tests. We follow specifications similar to the ones in Table 3. The sample period is from 2008 through 2017. Panel A shows the panel regression estimations under alternative specifications. In model (1), we report the regression estimates by excluding the whole year of 2015. In model (2), we create a dummy variable for each year, DYear($t = k$), that equals one for year k and zero otherwise. We control for DYear($t = k$) and Decile $10_{i,t-1}$×DYear($t = k$). In model (3), we include fund fixed effects, and double cluster the standard errors at fund and time level. In model (4), we control for morningstar ratings. We include dummy variable Ms5star and Ms4star, and their interactions with the Platform dummy. Ms5star (Ms4star) equals one if the fund morningstar rating is five (four) star, and zero otherwise. In model (5), we restrict the sample to funds with inception year before 2012. In model (6), we control for Log(#Bank)$_{i,t-1}$ and Log(#Brokers)$_{i,t-1}$, and the interactions between them and the Decile $10_{i,t-1}$ dummy. Log(#Bank)$_{i,t-1}$ is the natural logarithm of the number of banks in which a fund is available for sale at quarter $t-1$, and Log(#Brokers)$_{i,t-1}$ is defined similarly. In model (7), we estimate weighted least squared regressions, using the TNA$_{i,t-1}$ of each fund as the weight for each observation. In model (8), we replace the Decile $10_{i,t-1}$ dummy with the performance decile rank variable that ranges from one to ten. In model (9), we replace the Platform$_{i,t}$ dummy with the natural logarithm of the number of platforms that a fund is available for purchase in quarter $t-1$. Panel B shows the sensitivity of flow to past returns at different horizons. We replace past 12-month return Decile $10_{i,t-1}$ dummy with Decile $10_{i,t-1}$ dummies based on past 1, 3, 6, 24, and 36 months returns, respectively. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

A. Alternative Specifications

	Decile10×Platform	Decile10	N	R^2
(1). Exclude 2015	8.377***	10.610***	22,708	0.069
	(8.87)	(6.08)		
(2). Control Dummies of Year×Decile 10	6.598**	12.905***	26,412	0.067
	(2.13)	(4.32)		
(3). Fund Fixed Effects+Double Clustered S.E.	10.742***	8.231***	26,412	0.176
	(6.29)	(6.01)		
(4). Control for MorningStar 5 & 4 ratings	7.889***	7.525***	26,412	0.067
	(4.70)	(7.58)		
(5). Inception < 2012	8.493***	6.485***	18,925	0.058
	(4.42)	(7.64)		
(6). Control Bank & Broker	7.841***	5.210*	26,412	0.067
	(3.45)	(2.01)		
(7). Value-Weighted	8.584***	3.512***	26,412	0.222
	(5.47)	(3.59)		
(8). Replace Decile 10 with Rank$_{12m}$	0.579***	0.881***	26,412	0.064
	(3.43)	(9.25)		
(9). Replace Platform with Log(#Platforms)	4.444***	4.876***	26,412	0.177
	(7.76)	(3.11)		

B. Different Past Return Horizons

	Past 1 Month	Past 3 Months	Past 6 Months	Past 12 Months	Past 24 Months	Past 36 Months
	(1)	(2)	(3)	(4)	(5)	(6)
Decile10	5.507***	6.441***	8.058***	8.132***	4.466***	4.747***
	(5.06)	(6.38)	(7.88)	(8.32)	(5.34)	(5.03)
Decile10×Platform	4.233**	6.751***	12.171***	7.966***	4.409***	4.310**
	(2.40)	(3.93)	(6.79)	(4.72)	(2.75)	(2.57)
Controls, Time FE	Y	Y	Y	Y	Y	Y
Obs.	26,412	26,412	26,412	26,412	26,412	26,412
R^2	0.060	0.063	0.071	0.066	0.059	0.059

Appendix A

Table A1. Determinants of Entrance onto Platforms

This table reports the cross-sectional determinants regression 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 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 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 RetailRatio (%), which is the fraction of a fund held by individual investors at the end of June 2012, past 12-month return by the end of June 2012 ($MRet_{t-1,t-4}$), Log(Size), Log(Age), Flow, and Fees 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.

	Funds		Family	
	D(Enter≤2013Q1)	Log(Enter months)	D(Enter≤2013Q1)	Log(Enter months)
	Logit	OLS	Logit	OLS
	(1)	(2)	(3)	(4)
Bank-affiliated	-1.773***	0.574***	-2.073	0.586*
	(-4.78)	(6.48)	(-1.51)	(1.72)
Broker-affiliated	-0.028	0.089	0.867	-0.04
	(-0.13)	(1.51)	(0.92)	(-0.24)
RetailRatio	-0.021***	0.005***	-0.127***	0.019**
	(-3.80)	(3.44)	(-3.06)	(2.52)
Log(Size)	-0.261***	0.107***	-1.381**	0.200*
	(-2.87)	(4.55)	(-2.49)	(1.88)
Log(Age)	0.745**	-0.210***	5.369*	-0.334
	(2.57)	(-2.76)	(1.95)	(-0.81)
$Flow_{t-1}$	0.788*	-0.187***	0.414	-0.4
	(1.91)	(-3.07)	(0.17)	(-0.94)
$MRet_{t-1,t-4}$	0.187	-0.044	3.05*	-0.25
	(0.85)	(-0.70)	(1.94)	(-1.31)
$Std_{Mret,t-1,t-8}$	-10.981	-1.279	94.222	-15.971
	(-0.73)	(-0.31)	(0.92)	(-0.80)
Management Fee	-1.024	0.091	9.616*	-1.174
	(-0.62)	(0.24)	(1.80)	(-1.05)
Subscription Fee	-0.388	0.03	-3.281	0.503
	(-0.70)	(0.21)	(-0.78)	(0.67)
Redemption Fee	0.453	-0.172	4.302	-1.193**
	(0.92)	(-1.35)	(1.23)	(-2.06)
Style FE	Y	Y	N	N
Observations	457	457	60	60
R^2	0.115	0.18	0.396	0.358

Table A2. Predicting Future Fund Return with Flow and Current Return

This table shows the panel regression estimates of how past flow (or past return) predicts funds' future performance. The model specification is:

$$\text{Ret}_{i,t+k} = \alpha + \beta_1 \cdot \text{Platform}_{i,t} + \beta_2 \cdot \text{Flow}_{i,t}(\text{or Ret12m}_{i,t}) \times \text{Platform}_{i,t} + \sum_k \gamma_k \cdot \text{Control}_k + \varepsilon_{i,t},$$

where $\text{Ret}_{i,t+k}$ refers to fund i's quarterly return (%) in quarter $t+k$ ($k = 1, 2, 3$). In columns (1) to (3), we regress future fund returns in quarter $t+1$, $t+2$, $t+3$ on the $\text{Platform}_{i,t}$ dummy, and the interaction between the platform dummy and quarter t fund flow. In columns (4) to (6), we regress future fund returns on the $\text{Platform}_{i,t}$ dummy, and the interaction between the platform dummy and fund's past-12-month return up to quarter t end. We include controls of fund's Flow, Ret12m, Log(Size), Log(Age), and Fees at the end of quarter t. Time fixed effects and style fixed effects are included for all specifications. The standard errors are double-clustered at the fund level and the time level. The sample period is 2008 through 2017. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Dep. Var.: Future Quarterly Return					
	1st Qtr.	2nd Qtr.	3rd qtr.	1st Qtr.	2nd Qtr.	3rd qtr.
	(1)	(2)	(3)	(4)	(5)	(6)
Flow*Platform	-0.252	0.327	-0.127			
	(-0.48)	(0.63)	(-0.23)			
Ret12m*Platform				0.535	-0.23	0.012
				(0.73)	(-0.42)	(0.03)
Platform	0.006	-0.048	-0.001	-0.456	0.155	-0.013
	(0.03)	(-0.27)	(-0.00)	(-0.85)	(0.35)	(-0.04)
Ret12m	0.297	-0.102	-0.144	-0.072	0.056	-0.152
	(0.32)	(-0.15)	(-0.41)	(-0.14)	(0.14)	(-0.49)
Flow	0.052	-0.103	-0.128	-0.106	0.131	-0.224
	(0.06)	(-0.17)	(-0.33)	(-0.14)	(0.25)	(-0.67)
Log(Size)	-0.090	-0.082	-0.088	-0.094	-0.080	-0.088
	(-0.69)	(-0.88)	(-1.25)	(-0.71)	(-0.84)	(-1.23)
Log(Age)	-0.167	-0.003	-0.106	-0.158	-0.009	-0.105
	(-0.53)	(-0.01)	(-0.44)	(-0.49)	(-0.03)	(-0.43)
Management Fee	0.384	-0.767	-1.641	0.420	-0.785	-1.639
	(0.49)	(-0.80)	(-1.39)	(0.52)	(-0.82)	(-1.39)
Subscription Fee	0.120	0.239	0.170	0.095	0.249	0.170
	(0.51)	(0.88)	(0.51)	(0.40)	(0.92)	(0.51)
Redemption Fee	-0.496	-0.442	-0.599	-0.482	-0.448	-0.600
	(-0.92)	(-0.85)	(-1.09)	(-0.91)	(-0.87)	(-1.09)
Time FE, Style FE	Y	Y	Y	Y	Y	Y
Observations	26,356	26,277	26,190	26,356	26,277	26,190
R-squared	0.596	0.604	0.609	0.597	0.604	0.609

Table A3. Distribution of Fund Daily Return

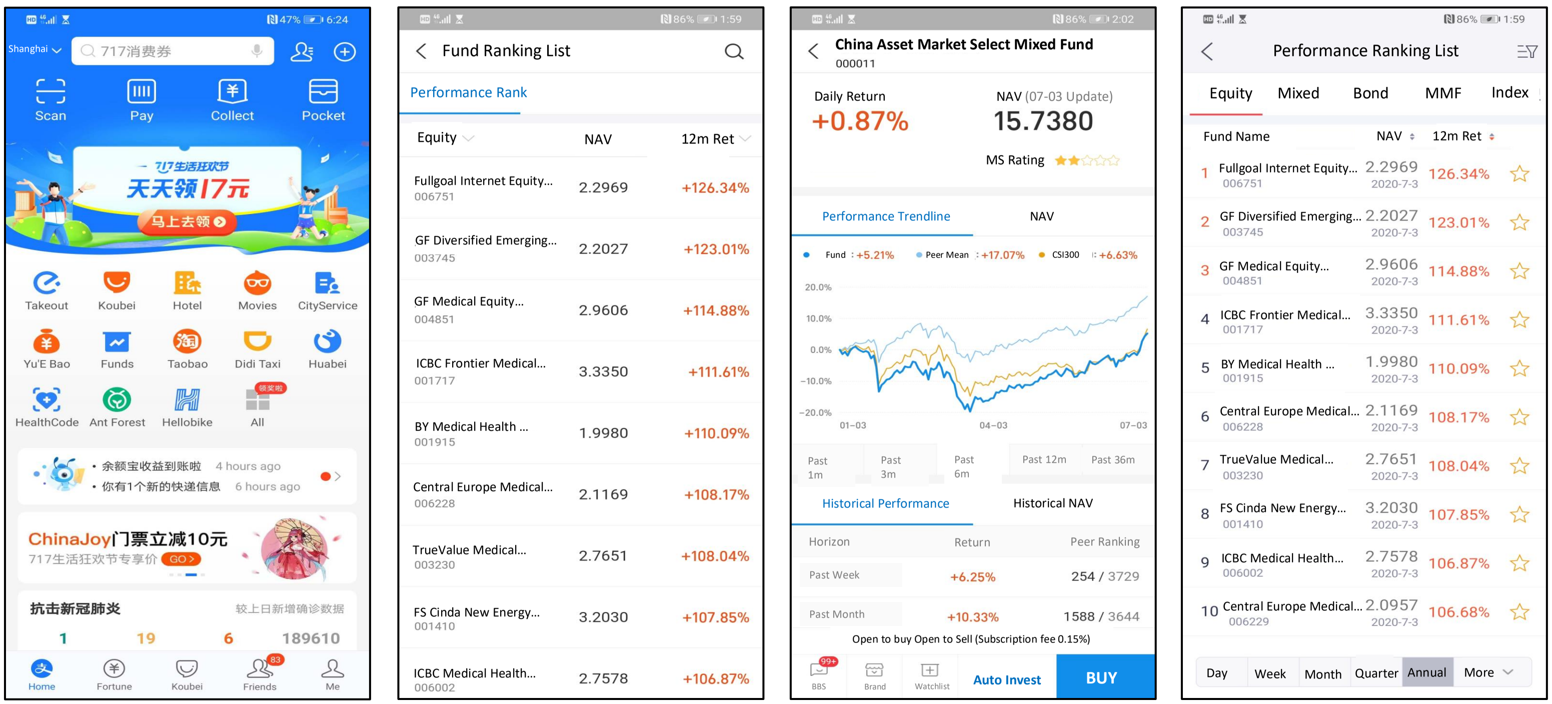
This table shows the distribution of fund daily returns conditional on the performance decile rank. Each quarter $t-1$ end for each style category, we sort all funds into deciles based on the past 12-month return ($\text{MRet}_{t-1,t-4}$). We then compute the daily average returns (Dret), daily return autocorrelation (AR1), standard deviation (Std), skewness (Skew), and kurtosis (Kurt) of daily fund returns in quarter t. We compute the statistics for each quarter and each decile, and then average the estimates over time for the before (2008–2012) and after (2013–2017) sample separately. "Decile 10-1" report the difference between Decile 10 and 1. The differences of "Decile 10-1" between after and before are reported in the last two columns, with t-statistics reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

			Daily return distribution by performance decile rank												
			Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10	Decile 10-1	t-stat	After-Before	
Equity	Dret	Before	-0.029	-0.020	-0.020	-0.018	-0.023	-0.022	-0.017	-0.022	-0.020	-0.014	0.016	(1.26)	0.010	(0.34)
		After	0.068	0.063	0.076	0.072	0.075	0.059	0.070	0.084	0.087	0.093	0.025	(0.98)		
	AR1	Before	0.028	0.026	0.027	0.021	0.021	0.025	0.023	0.026	0.017	0.038	0.011	(1.66)	0.006	(0.42)
		After	0.023	0.000	0.010	0.013	0.020	0.011	0.023	0.029	0.018	0.040	0.017	(1.26)		
	Std	Before	1.551	1.552	1.524	1.543	1.547	1.494	1.488	1.503	1.506	1.517	-0.034	(-0.79)	0.137**	(2.17)
		After	1.448	1.444	1.451	1.432	1.475	1.485	1.475	1.485	1.525	1.551	0.104	(2.2)		
	Skew	Before	-0.075	-0.076	-0.073	-0.064	-0.062	-0.084	-0.068	-0.059	-0.061	-0.073	0.002	(0.09)	-0.058	(-0.52)
		After	-0.419	-0.409	-0.439	-0.464	-0.466	-0.648	-0.460	-0.457	-0.477	-0.474	-0.055	(-0.52)		
	Kurt	Before	0.598	0.522	0.522	0.524	0.563	0.508	0.556	0.479	0.499	0.607	0.009	(0.07)	-0.026	(-0.06)
		After	1.429	1.539	1.335	1.566	1.482	2.649	1.186	1.233	1.316	1.412	-0.017	(-0.04)		
Mixed	Dret	Before	-0.008	-0.012	-0.016	-0.018	-0.016	-0.015	-0.018	-0.014	-0.015	-0.016	-0.008	(-0.36)	0.014	(0.41)
		After	0.059	0.054	0.041	0.049	0.052	0.055	0.064	0.066	0.072	0.065	0.006	(0.23)		
	AR1	Before	0.027	0.028	0.030	0.031	0.030	0.029	0.039	0.033	0.030	0.045	0.017	(2.25)	0.008	(0.69)
		After	0.013	0.024	0.035	0.019	0.028	0.028	0.026	0.026	0.028	0.039	0.026	(2.97)		
	Std	Before	1.225	1.247	1.331	1.296	1.292	1.281	1.313	1.331	1.269	1.140	-0.086	(-0.56)	0.563**	(2.30)
		After	0.975	1.047	1.135	1.185	1.192	1.246	1.290	1.316	1.357	1.452	0.477	(2.5)		
	Skew	Before	-0.118	-0.091	-0.087	-0.105	-0.085	-0.110	-0.078	-0.091	-0.063	-0.097	0.020	(0.49)	-0.142*	(-1.89)
		After	-0.384	-0.419	-0.441	-0.424	-0.429	-0.452	-0.460	-0.450	-0.401	-0.506	-0.121	(-1.94)		
	Kurt	Before	0.735	0.563	0.542	0.547	0.664	0.742	0.543	0.547	0.567	0.884	0.149	(0.6)	-0.718	(-1.52)
		After	2.090	1.687	1.853	1.630	1.747	1.536	1.493	1.469	1.240	1.521	-0.569	(-1.41)		
Bond	Dret	Before	0.014	0.011	0.016	0.014	0.019	0.017	0.014	0.014	0.010	0.016	0.002	(0.26)	0.004	(0.26)
		After	0.021	0.023	0.021	0.027	0.025	0.025	0.028	0.028	0.032	0.027	0.006	(0.49)		
	AR1	Before	0.039	0.077	0.051	0.061	0.081	0.076	0.064	0.090	0.066	0.093	0.054	(1.65)	-0.074**	(-2.29)
		After	0.095	0.099	0.112	0.095	0.125	0.120	0.108	0.097	0.092	0.075	-0.020	(-1.27)		
	Std	Before	0.222	0.223	0.208	0.219	0.212	0.206	0.204	0.229	0.224	0.225	0.003	(0.08)	0.100	(0.89)
		After	0.329	0.195	0.176	0.182	0.182	0.200	0.209	0.265	0.305	0.432	0.103	(1.25)		
	Skew	Before	0.167	-0.228	0.173	0.000	0.219	0.121	0.100	0.064	0.137	0.121	-0.046	(-0.17)	0.136	(0.55)
		After	-0.279	-0.172	-0.274	-0.249	-0.281	-0.298	-0.281	-0.360	-0.273	-0.189	0.090	(0.9)		
	Kurt	Before	2.536	2.872	2.232	1.557	2.139	1.398	2.207	1.827	2.954	1.414	-1.122	(-1.48)	0.090	(0.12)
		After	3.490	3.476	3.703	3.014	3.227	3.281	3.381	3.259	2.751	2.458	-1.032	(-2.72)		

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 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:

charles SCHWAB

Find a Branch | Contact Us | Search | Log In

What We Offer | What We Charge | Why Schwab | Insights | Open an Account

Select Lists | Funds Managed by Schwab | Laudus Funds | Find Funds | Compare Funds

OneSource Select List

OneSource Select List®

Log in to print Mutual Fund OneSource Select List

With thousands of mutual funds available, making confident investment decisions can seem difficult. Consisting only of Schwab OneSource® funds, available without a load or transaction fee, the Mutual Fund OneSource Select List® offers a cost effective and convenient way to invest in mutual funds. Charles Schwab Investment Advisory, Inc. (CSIA) conducts extensive research on the full range of actively-managed funds available through Schwab's Mutual Fund OneSource® service.

The Select List is built by identifying funds that offer you the best combination of factors such as performance, risk and expense. Learn more about how funds make the Select List and about how Schwab makes it easier for you to find the right fund.

Select List: **Large-Cap U.S. Stock**

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.

Large-Cap U.S. Stock Fund Characteristics

- 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

21 Total Funds
3 Schwab Affiliate Funds
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	Average Annual Returns: 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
	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 Advertising Expenses around the Entrance

The upper panel of this figure shows funds' retail ratio over time. Funds report retail ratio on a semi-annual basis. We report the cross-sectional average retail ratio for each style of funds. The lower panel of this figure shows funds' time-series advertising expenses. Funds report operating expense on a semi-annual basis. We calculate advertising expense as total operating expense subtracting management expense, custodian expense, transaction expense, and interest expense. The annualized advertising expense ratio is calculated as advertising expense scaled by average TNA, $\text{AdvertiseEXP\%} = \text{AdvertiseEXP} * 2/((\text{TNA}_t + \text{TNA}_{t-1})/2)$. We calculate the cross-sectional average expense ratio for each style of funds.The shaded area indicates the 95% confidence intervals.