NBER WORKING PAPER SERIES

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Working Paper 26576
http://www.nber.org/papers/w26576

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2019

We thank Linchen Liu, Shiwen Tian, and Heming Zhang for research assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. G0,G10,G15,G2,G20,G23,G4,G40,G5

ABSTRACT

The emergence of third-party online platforms in intermediating financial products has been a new and exciting development in FinTech. In China, the platforms are allowed to distribute mutual funds since 2012, and have quickly grown into a formidable presence. Examining the economic impact of this new distributional channel, we use the staggered entrance of mutual funds onto the platforms to identify the casual effect of online platforms on the behaviors of fund investors and fund managers. We find that, post-platform, fund flows become markedly more sensitive to fund performance. The net flow to the top 10% performing funds more than triples their pre-platform level, and this pattern of increased performance sensitivity is further confirmed using private data from Howbuy, a top-five platform in China. Consistent with the added incentive of becoming a top ranking performer in the era of large-scale platforms, we find that fund managers increase their risk taking to enhance the probability of getting into the top rank. Meanwhile, the organization structure of large fund families weakens as the introduction of platforms levels the playing field for all funds.

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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 connectivities on a previously unimaginable scale. The widely adopted platforms, such as Google for information, Amazon for retails, Facebook for social networking, and Uber for taxi rides, have profoundly re-shaped how information is aggregated and disseminated in their respectively industries, and, for better or worse, our actions follow accordingly.

In this paper, we focus on the impact of the platform economy on financial intermediation. With the technological developments over the past quarter century, online trading of financial products has been widely adopted. But the intermediation of financial products, such as mutual funds, are still segmented by the numerous distribution channels organized by fund families, banks, and brokers. Under this traditional model, the flow of information is severely barricaded and segmented – different distribution channels often offer different collections of funds and, within the same distribution channel, the offering also varies across different branches and advisers. The flow of information can also be biased, as the distribution channels promote their own affiliated funds more aggressively, both online on their websites and offline at their local branches.

The emergence of the third-party online platforms (TPOP), created by tech-driven firms independent of the traditional distribution channels, threatens to break this institutional segmentation and reshape financial intermediation like what Amazon did for books and retail goods. On the consumer side, investors on the platforms 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 and invisible, have the potential to reach the entire user base on the platforms. By vastly improving the means of connectivity and offering technological efficiency, the platform model takes down the 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' allocation of risk? Likewise, as the platforms improve the means of connectivity, what is their impact on the means of production, particularly for the actively-managed funds? More generally, 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 evidences 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)). But there remains very 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 allows third-party online platforms to distribute mutual funds, our paper is the first to fill the blank. Living in the era of digital payments via Alipay, and later fueled by the enthusiasm for Ant Financial's money market fund, Yu'ebao, in 2013, the Chinese customers are fast adopters of the new 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. While the sales numbers have been closely guarded by the platforms, it has been estimated that, by 2018, about one-third of the sales of equity, bond, and mixed mutual funds takes place on the platforms, and another one-third via banks, the largest distribution channel in the pre-platform era.

Focusing first on the impact of the platforms on investor behavior, our empirical results document a strong platform-induced amplification in performance chasing. We find a striking increase in performance sensitivity, driven by flows chasing after the top ranked funds much more aggressively after the emergence of the platforms. Ranking actively-managed equity funds by their past 12-month returns into deciles,[1] the average net flow to the funds in the top decile increases from 2.55% pre-platform (2008-2012) to 19.18% post-platform (2013-2017). Using the US equity funds as a benchmark, the average net flow to the top-decile funds is around 6% in both time periods. This amplification of the performance-chasing post-platform shows up not only in the equity funds, but also in the mixed funds. Moreover, our data has information on when each mutual fund signs up to which platform. Taking advantage of this information on staggered entrance, we further test this pattern of amplified performance-chasing at the fund level. 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 over 3.5 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 be felt by 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. Focusing first on the actively-managed equity mutual funds, we find that, 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. By

[1] Our results are robust to alternative constructions of past winners. For example, we use the absolute performance ranking of mutual funds, assuming that investors are more likely to pay attention to the top 10, 20, or 50 funds. We also use past one, three, and six-month returns to rank the funds, since performance ranks based on these return frequencies are commonly provided on the platforms as alternatives.

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%, smaller than that observed on Howbuy, but larger than the pre-platform number of 23.79%.

Performance-chasing has long been documented as a salient feature of investor behavior in the mutual fund industry (Gruber (1996), Brown, Harlow, and Starks (1996), and Chevalier and Ellison (1997)). What is new and potentially alarming of our findings is the strong amplification effect associated with the emergence of platforms. With respect to changes in investor behavior, this amplification can be caused by the vastly improved technological efficiency that allows investors easy access to trading, or entrances of new and less sophisticated platform investors who are more prone to performance-chasing.[2] Absent of any changes in investor behavior, this amplification can still arise out of the unique information structure associated with the platform technology. Off platform, the information flow is dispersed in nature, with different investors receiving different information from their respective distribution channels, attenuating the aggregated effect of performance-chasing. On platform, the information flow is uniform in nature, with investors receiving almost identical signals focusing mostly on past performances, further synchronizing the individual-level performance-chasing.[3] As a result, the amplified performance-chasing can be observed at the aggregate level, even if the propensity of individual performance-chasing remains the same both on and off the platforms.

Focusing next on the impact of platforms on fund managers, we find that, in the presence of amplified performance-chasing, fund managers increase their 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. By contrast, funds outside of the top decile do not exhibit such a pattern. Moreover, this pattern of increased volatility only emerges after 2013, after the introduction of the platforms. This increased risk taking behavior is most significant for actively-managed equity fund managers, but is also present for the mixed funds. Repeating the same exercise for the US equity mutual funds, we find no evidence of increased risk taking by the top decile

[2]While the emergence of platforms did help attract new mutual fund investors in China, it happens mostly to the money market mutual funds (e.g., Yu'ebao) and less to the actively-managed equity, bond, and mixed mutual funds. The large magnitude of our results cannot be fully explained by the entrance of such investors.

[3]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 performance. 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 display their affiliated funds at the top. Overall, this reaction of the traditional channels to the platform phenomenon can also contribute to amplified performance-chasing.

funds.

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. Prior to 2013, funds in the top ranking decile are associated with higher idiosyncratic risk, both before and after getting into the top decile, relative to the funds outside of the top decile. But there is no evidence of such top fund managers taking higher systematic exposure. This result indicates that prior to 2013, fund managers rely on their own abilities in stock and bond selections to get into the top decile. Post 2013, however, the risk taking behavior increases not only in the idiosyncratic component, but also in the systematic component. Given the positive risk premium associated with the systematic risk, dialing up the systematic component in risk taking does provide higher expected returns. It indicates that the fund manager has already maxed out his own skills and is 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.

Finally, the emergence of 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. Just like prior to Uber, taxi drivers rely heavily on the dispatch services. In the era of the platform economy, however, large fund families as organizations lose their cohesiveness. Empirically, we find that after joining the top two platforms, the importance of within-family-ranking weakens, whereas the importance of universal-ranking is amplified in attracting subsequent flow. In other words, after the introduction of platforms, fund managers are increasingly being compared against the entire universe of funds, and their relative standing within a family becomes less important. Moreover, the within family co-movement of fund flows also weakens after the introduction of platforms. 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 accounts 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 is related to the new and exciting field of FinTech. Among others, Goldstein, Jiang, and Karolyi (2019), Philippon (2018) and Frost et al. (2019) discuss the FinTech opportunities and how their entrance might affect the incumbent financial institutions.[4] Using

[4] Also related are papers by Barber and Odean (2001, 2002) on how internet affects investor behavior, D'Acunto, Prabhala, and Rossi (2019) on the impact of robo-advising, Wei and Yang (2019) on online and offline mutual fund investing, Tang (2019) and Vallee and Zeng (2019) on P2P lending, and Buchak et al. (2018) and Fuster et al. (2019) on mortgage origination.

proprietary data from Ant Financial, Hau et al. (2017) provide empirical evidence on how FinTech credit might help mitigate credit supply frictions for small businesses on Alibaba's retail platform. Our paper contributes to this young and active research area by proving extensive empirical evidence on what happens when the technology driven platforms are allowed to enter the industry of financial intermediation to distribute financial products. Given that this large-scale disruption to 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. It is also worthwhile to point out that, while most of the empirical work in this area relies on proprietary data from one particular platform to measure the impact of FinTech, the main results of our paper build on the publicly available data of the entire mutual fund industry in China. In other words, we are reporting the impact of FinTech on the entire industry, not just one platform or one company. In that respect, the scope of our results is much broader than what has been documented in the existing literature.

The empirical results documented in our paper can also help shed light on how the varied distribution channels of financial products can better serve their customers, and the appropriate regulatory policies, if any, to help achieve this goal. There are ample evidences on the distortions in the traditional system, with issues of conflicts of interest at the center stage.[5] Relative to this literature, we fill in the gap by providing, for the first time, empirical evidences on the benefits and costs of large-scale platforms. On the one hand, the third-party platforms largely alleviate the conflict of interest caused by affiliated relations, is free of the cognitive biases of human advisors, and level the playing field for all mutual funds. On the other hand, the technological efficiency of the platforms does not equate economic efficiency and there are indeed causes for concerns. In particular, the platform induced amplification in performance-chasing points to the possibility that behavior at an individual level can be further amplified on the platforms. Whether or not the platforms should be more proactive in regulating the flow of information or offering financial advices to alleviate the unintended consequences is a topic of great interest going forward.[6]

Our paper also adds to the large literature on the impact of mutual fund performance on investment flows. Within this literature, our paper is closest to the work of Kaniel and

[5]See, for example, Bergstresser, Chalmers, and Tufano (2009), Chalmers and Reuter (2012), Christoffersen, Evans, and Musto (2013), and Jenkinson, Jones, and Martinez (2016) on the issues of conflicts of interest on mutual fund advising, and Linnainmaa, Melzer, and Previtero (2018) for the cognitive biases of fund advisers.

[6]Outside the industry of financial intermediation, 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 platform's information flow on customer buying behavior through a large-scale field experiment with Alibaba's retail platform.

Parham (2017), who investigate how visibility and prominence affect the flow to top performers and document that media attention does increase fund flow. Our paper documents this effect over a much larger scale and finds that the presence of large-scale platforms amplifies the flow-performance sensitivity in the Chinese mutual fund industry. Moreover, we find that this influence on investor behavior has implications on the risk-taking behavior of fund managers and the competitions within fund families.

The remainder of this paper is organized as follows. Section 2 describes the data used in our study. Section 3 presents the main results related to flow-performance sensitivity and presents direct evidence of amplified performance-chasing using proprietary data from Howbuy. Sections 4 explores the consequences of platforms on fund managers and fund families. Section 5 conducts robustness checks and Section 6 concludes.

2 Data

2.1 The Emergence of Third-Party Online Platforms

Information on the mapping between mutual funds and their distribution channels is collected from Wind, a prominent financial data provider in China. The data contains the start and end dates of the distribution relation between mutual funds and their respective distribution channels. There are three major types of distribution channels in China: banks, brokers, and third-party online platforms (TPOPs), which are summarized by the upper left panel of Figure 1. Since 2008, there has been a steady increase in the number distribution channels via banks and brokers, with the banks growing faster than the brokers. TPOPs burst onto the scene in 2012, catching up quickly with the banks and brokers and reaching a total number of 115 by 2018. As it is typical in the platform economy, the top platforms grab most of the market shares while the smaller platforms struggle for survival. In this sense, out of the 115 platforms, only a handful of them are really active.

As of 2018, the two largest TPOPs are Tiantian and Ant Financial in terms of market share. Tiantian is among the first four institutions that obtained the fund distribution license from China Securities Regulatory Commission (CSRC) in February 2012. Ant Financial missed the first batch of license issuance, but quickly entered the TPOP business in April 2014 by acquiring Hundsun, the parent firm of a TPOP called Shumi.[7] The introduction of Yu'ebao and the acquisition of Hundsun are highlighted in the graphs, which marked two milestone events for Ant Financial and the entire mutual fund industry.

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

The connections between mutual funds and their respective distribution channels are summarized by the bottom two panels of Figure 1, which report the coverage of actively-managed mutual funds in our sample by the top-four TPOPs (Ant, Howbuy, Tiantian, and Tong Huashun) and an average bank and broker. The coverage is reported both in percentage (bottom left panel) and in number (bottom right panel). As we can see, the adoption of TPOPs by mutual funds has been swift. Over the span of just one year, from 2012Q2 to 2013Q2, the coverage increases from zero to over 60% for the top-three TPOPs, indicating that over 60% of the actively-managed mutual funds in our sample sign up to be covered by the TPOPs. Compared with that of an average broker or bank, the coverage of the TPOP's has become significantly larger after the emergence of the platforms. For example, by 2018, each of the top-four TPOPs covers over 2000 actively-managed funds, while an average bank carries less than 1000 funds and an average broker carries less than 300 funds.

Along with their broad fund coverage, the TPOPs also overlap significantly in their coverage. As shown in the top right panel of Figure 1, by 2018, over 90% of the equity mutual funds are simultaneously covered by all of the top four TPOPs. For mixed and bond mutual funds, the common coverage of TPOPs are around 80% and 70%, respectively. This high degree of overlap effectively levels the distribution landscape, maximizing the connections between TPOPs and mutual funds. By contrast, in the traditional distribution model, the established connection between funds and banks or brokers might be driven by their affiliated relationship.

Overall, the entrance of the platforms has been swift, with mutual funds signing up quickly to the platforms. Compared with the traditional channels, each TPOP covers a larger number of funds, with a significantly high degree of overlap with the other TPOPs. It should be emphasized, however, coverage does not equate 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, one of the first and the largest TPOPs in China. The 2018 sales of mutual funds on Tiantian total RMB 525 billion, including 328.7 billion for money market funds. Excluding money market funds, the 2018 sales number of mutual funds is 196.4 billion for Tiantian and 2.3 trillion for the entire market. In other words, as one of the top platforms, Tiantian's market share is about 8.5% in 2018. This number is roughly consistent with the estimated magnitudes reported in the press – the platforms in aggregate account for one-third of the market share.

2.2 Mutual Fund Characteristics and Performance

We obtain the data for mutual funds from CSMAR, China Stock Market & Accounting Research. 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, the total net assets (TNA) is summed across all share classes to derive the TNA of the fund. We compute fund returns and fund fees as the TNA-weighted average across all 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 as:

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

where $\mathrm{Ret}_{i,t}$ is the quarter-t return of fund i. We assume that inflows and outflows occur at the end of each quarter, and that investors reinvest their dividend distributions in the same fund. To alleviate the concern of outliers, flow is winsorized at 1%. We further exclude fund-quarter observations when the absolute value of two adjacent quarter flows are both larger than 100% but in different signs, which may be caused by errors in reporting TNA. We further require a minimum fund size of 1 million RMB and a minimum fund age of two years to be included in our sample. We end up with 24,569 fund-quarter observations for our sample from 2008-2017.

To examine the impact of TPOPs, we focus our analyses on two time periods: before (2008-2012) and after (2013-2017). We begin 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 increases steadily from fewer than 100 in 2008 to over 2000 by 2018. The number of bond funds is particularly small in the early years, with fewer than 20 funds by 2009, which prompts us to start the before period for bond funds from 2010. Another visible change in our sample is the dramatic decrease in the size of equity funds in 2015, along with the dramatic increase in the size of mixed funds. This is caused by a policy change in August 8, 2015, which increases the minimum requirement of stock holding 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 including 1) shrink our before and after windows to 2011-2012 (before) and

2013-2014 (after) to avoid the inclusion of 2015; 2) exclude the year of 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 difference in characteristics between the before and after periods. First, there is a significance decrease in fund size. Taking equity funds as an example, the average fund size decreases from RMB 3.05 billion to 0.60 billion, driven by large initiations of new and smaller funds over our sample period. It should be mentioned, however, this large initiation of new funds actually occurs steadily over our sample period and is not uniquely associated with the introduction of TPOPs. Moreover, to show that our main results are not driven by this difference in sample characteristics, we perform robustness test by requiring that funds in the after period to exist in the before period, and our main results are robust to this sample requirement.

The before and after samples also have significantly different fund returns. The average monthly return is -0.61% in the before sample and 1.24% in the after sample, partially because of the 2008 financial crisis. This difference, driven by the aggregate stock market returns, is unlikely to affect our main results. In addition to controlling the time trend by including time fixed effects, we also perform robustness test by adopting a narrower window of before (2010-2012) and after (2013-2014), which exclude the unusual years of 2008 and 2015.

In terms of quarterly flows, the before and after periods do not exhibit 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 9.93% to 34.38% for equity funds, and from 11.73% to 38.54% 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. After we will see later in our main results, this is very much related to the emergence of the platforms. For bond funds, the average flows are positive in both periods. Compared with the standard deviation of 9.93% for the equity funds and 11.73% for the mixed funds during the before period, the flow standard deviation for the bond funds is quite large, at 24.89%, which is driven mostly by the small sample size of bond funds in the before period. Overall, this limited pre-platform sample size of bond funds complicates our main analysis on 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 annual 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. For example, the fees might be waived by different channels, conditioning on various promotional policies. TPOPs often waive the subscription fees by 40% to 90% if investors purchase the funds on their platforms. The change in fees are generally statistically significant due to the highly persistent nature of the quoted fees. Besides, the cross sectional standard deviation and range of fees are very small indicating that funds often follow industry routines when setting the quoted fees.

3 Empirical Results: Flow-Performance Relation

3.1 Main Results

To examine the extent to which platform intermediation alters investor behavior, we focus on the flow-performance sensitivity, the most salient feature of investor behavior in the mutual fund industry. We document our main results by measuring the emergence of TPOPs at two levels. At the aggregate level, we use the beginning of 2013 as the break point, and test the difference in flow-performance sensitivity over two sample periods: before (2008-2012) and after (2013-2017). Taking advantage of the staggered entrance of funds onto the platforms, we further improve the information at the aggregate level by including information at the individual fund level to examine the impact of TPOPs on flow-performance sensitivity.

Flow-Performance: Before and After 2013

We form performance-based deciles by sorting, at the beginning of each quarter, all actively-managed funds within each style category into ten groups, according to their respective returns over the past 12 months. 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 TPOPs: the top-decile flow increases from 2.55% in the before period to 19.18% 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 post TPOPs. This amplified performance-chasing is also observed in mixed funds, which are of lower expected returns and lower risk compared with the equity funds. Prior to TPOPs, there is very limited evidence of performance chasing: the top-decile funds attract a statistically insignificant average flow of 1.17%. Post TPOPs, however, the top-decile flow increases to 11.59% with a t-stat of 4.75.

For bond funds, the results are mixed. In the before period, the bond sample is rather small, as China's fixed-income market, particularly the credit market, starts to take off only after 2010. For this reason, the deciles flows measured for the before period are not very reliable. Post TPOPs, we observe evidence of performance-chasing in bond funds: the top-decile flow is on average 13.07% per quarter with a t-stat of 2.37, while the flows to the lower-ranking deciles are generally smaller in magnitude (with the exception of Decile 9) and statistically insignificant. In terms of magnitude, this top-decile flow of 13.07% is close to the 11.59% for the mixed funds and 19.18% for the equity funds. The volatile nature of the bond-fund flows, however, makes the results for bond funds less conclusive.[8]

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 2.55% per quarter in the pre-platform period and much smaller than the average flow of 19.18% per quarter in the post-platform period. Given that the distribution of US mutual funds is still under the tradition model, it makes sense that the flow-performance sensitivity in the US is much smaller than the post-platform era in China.

In addition to the graphical presentation in Figure 2, Table 2 further details the fund flow and return information for the ten performance deciles, both before and after 2013. One potential concern is that the amplified performance-chasing might be caused by a drastically different post-platform sample, owning to, for example, a more dispersed cross-fund returns post TPOPs. Comparing the return distribution reported in Table 2 for two sample periods, we do not find any support for this concern. In particular, the cross-decile variation in returns, measured by the return difference between the top- and bottom-decile funds, remains stable at 4.29% per month during the pre-platform period, and 4.22% during the post-platform period. Moreover, the magnitude of within-decile dispersion also remains stable across the two time periods.

Time-Series Variation of Flow-Performance

To further connect the amplified performance-chasing to the emergence of TPOPs, we examine how the flow-performance sensitivity varies over time. 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

[8]Although the bond funds are the least volatile among the three fund categories, their quarterly flows are the most volatile, making our results on flow-performance rather noisy. Moreover, while the equity and mixed funds are dominated by retail investors, the bond funds actually have a large institutional presence, especially in the after period when the retail ratio is only 42% on average.

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 TPOPs. 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 light 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. 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. While the driver for this time-series variation of performance-chasing is an interesting topic on its own right, the strong performance-chasing during the dot-com bubble does indicate a connection between investor enthusiasm and performance-chasing. Similarly, the recent trend of reduced performance-chasing in the US market coincides with the decreasing appeal of the actively-managed equity mutual funds in the US. Since 2007, there has been substantial fund flows out of the actively-managed funds and into the passively-managed funds.

Applying this observation to the Chinese market, the increasing trend of performance-chasing after 2013 is rather puzzling as there has not been any sudden change, neither increase nor decrease, in investor enthusiasm for equity mutual funds in China. One might argue that the boom and burst 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. 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 of the bond funds, as shown in the bottom right panel, is mixed and inconclusive.

Panel Regression using the After-2013 Dummy

To formally test the difference in performance-chasing and control for fund characteristics and the changing market conditions, we investigate the fund flow-performance relationship in a panel regression setting as follows:

$$\text{Flow}_{i,t} = \alpha + \beta_1 \cdot \text{Decile } 10_{i,t-1} + \beta_2 \cdot \text{Decile } 10_{i,t-1} \times \text{After}_t + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t}\,, \tag{1}$$

where Decile $10_{i,t-1}$ equals one if fund i belongs to the top decile in quarter $t-1$ and zero otherwise, and where After$_t$ equals one if quarter t is after 2013 and zero otherwise.[9] While the coefficient associated with Decile $10_{i,t-1}$ captures the average level of flow-performance sensitivity, the coefficient associated with the interaction term captures the increase in flow-performance sensitivity after 2013. As detailed in Table 3, the control variables include log of fund size, log of fund age, and fund fees. Given the persistence in fund flow, we also include the previous quarter's flow as a control variable. We include time fixed effects in all of the specifications.

The first three columns of Table 3 report our main results for equity, mixed and bond funds. Using data from 2008 through 2017, we split the sample around 2013 into two five-year windows before and after 2013. Focusing first on the coefficient associated with Decile $10_{i,t-1}$, we see the presence of performance-chasing before 2013, which amounts to average excess flow of 4.9% per quarter to the top-decile equity funds. The coefficient associated with the interaction term is 14.2% for equity funds and is statistically significant, providing strong evidence of amplified performance-chasing after 2013. Overall, the excess flow to the top-decile funds is 19.13% per quarter post 2013, which is 3.89 times the pre-2013 level of 4.9%. For the mixed funds, we also see a substantial increase in performance chasing after 2013. For the bond funds, we do not see evidence of increased performance chasing using this specification. We further group all three styles together and include style fixed effects in the panel regression. Using the estimates from the "All" column, we find that the excess flow to the top-decile funds is on average 13.9% per quarter post 2013, which is 2.89 times the pre-2013 level of 4.8%.

To focus more precisely around the event time, we use data from 2011 through 2014 and split the sample around 2013 into two two-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. Post TPOPs, the excess flow to the top-decile funds is 4.4 times the pre-2013 level for equity funds and 3.6 for all funds. This specification has the advantage of excluding from our tests the year of 2015, which introduces two issues into our sample. First, the Chinese stock market experiences a dramatic run up in first half of 2015 and then a dramatic crash in the second half, introducing noises and potential unusual investor behavior to our sample. Second, the policy change introduced in August 2015 increases the minimum requirement of stock holding from 60% to

[9] We exclude After$_t$ from the regressions as we include time fixed effects.

80% for equity mutual funds, causing many stock funds to switch to mixed funds in 2015Q3. The fact that our main results become stronger by avoiding this unusual year indicates that these market-level events are not the main driver of our results.

Panel Regression using Staggered Entrance of Funds onto Platforms

Building upon the previous section, we further improve the information on the emergence of TPOPs by taking advantage of the fact that we have the exact start and end dates of the sales relationship between a fund and a platform. Specifically, 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] 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.

Using the fund-level variable $\text{Platform}_{i,t}$, our panel regression is a modification of the one specified in Equation (1):

$$\text{Flow}_{i,t} = \alpha + \beta_1 \cdot \text{Decile } 10_{i,t-1} + \beta_2 \cdot \text{Platform}_{i,t} + \beta_3 \cdot \text{Decile } 10_{i,t-1} \times \text{Platform}_{i,t} + \sum_j \gamma_j \cdot \text{Control}^j_{i,t-1} + \varepsilon_{i,t} \,. \quad (2)$$

The results are summarized in Panel B of Table 3, where the first four columns report our main results 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 7.18% 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 18.60% (t-stat=3.81). Overall, the excess flow to the top-decile funds on platform is 25.78%, much larger than the 19.13% excess flow estimated using dummy variable After_t in Panel A. This suggests that despite the swift adoption of platform, the exact sign-up time of a fund onto the platform contains additional information than the time After_t. In the robustness test of Section 5, we further include both $\text{Platform}_{i,t}$ and After_t and their interactions with $\text{Decile } 10_{i,t-1}$ in the panel regression estimation. The significance of the interaction term $\text{Decile } 10_{i,t-1} \times \text{Platform}_{i,t}$ remains, indicating that funds' staggered entrance onto platform indeed captures their differing exposure to TPOPs.

For mixed funds, we also see a substantial increase in performance chasing after a fund

[10] Anecdotal evidence suggests that Ant Financial and Tiantian together account for majority of the TPOPs business. For example, see http://fund.jrj.com.cn/2018/08/27012825002151.shtml. Our results are robust if we use alternative ways to define $\text{Platform}_{i,t}$, as shown in Section 5.

joins the top two platforms. The excess flow to the top-decile mixed funds on platform is 18.12% per quarter, which is 3.59 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, when we group all three styles together, we find the excess flow to the top-decile funds on the platforms is on average 15.86% per quarter, which is 2.40 times the off-platform level of 6.62%.

The last four columns of Panel B of Table 3 report the results when we focus on the two-year windows before and after 2013. The results are similar to those in the previous specification. On platform, the excess flow to the top-decile funds is 4.39 times the off-platform level for equity funds and 4.67 for mixed funds. Interestingly, the increase in performance chasing for bond funds is also significant under this specification, partially because the two-year narrow window avoids the nosier sample in the early 2010. 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. We provide further discussions on robustness checks in Section 5.

3.2 Direct Evidence from Howbuy

In this section, we provide direct evidence on 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 and redemption for funds in each performance deciles, occurred on their platform from 2015 to 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 and redemption data at the fund level from CSMAR. The market share in purchase (redemption) for each performance decile is calculated as the amount of purchase (redemption) of all funds within a particular performance decile, divided by the total amount of purchase (redemption) of all funds in the ten deciles. Therefore, the market shares for all ten deciles sum up to 100%.[12] The market shares of purchase (redemption) occurring on Howbuy and that of the whole market are calculated in exactly the same way, using the same sample of funds and the corresponding performance 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 a much stronger performance-chasing behavior on pure-platform trading data from Howbuy.

[11]We thank Howbuy for providing this data.

[12]As the fraction of purchase and fraction of redemption use different denominator, the two values are not directly comparable to each other.

Panel A of Table 4 presents the market share in purchases for funds in each performance deciles. Focusing first on the actively-managed equity mutual funds, we observe a monotonically increasing market share in purchase from past loser (Decile 1) funds to past winner (Decile 10) funds. 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 drastic increase of 12.71% (t-stat = 4.00) in purchase of top-decile funds is consistent with our prior findings documented 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. By 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 what is observed on 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 the ones 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 27.36% 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 when documented using 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 in the pre-platform period. 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 between Howbuy and that of 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.[13] The increase in purchase fraction for the top-decile funds is also the largest after the introduction of platforms. Mixed

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

funds exhibit a similar pattern and bond funds a much weaker pattern.

Figure 4 shows the market shares of purchases for funds in the ten performance deciles. The upper left panel exhibits the average purchase fraction by performance deciles for equity funds. The green line marked with "o" plots the average market share of purchases in the pre-platform period (2008–2012); the red line marked with "x" plots the fractions in the post-platform period (2013–2017); the purple line marked with diamonds plots the fractions for the Howbuy platform. 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 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 period, respectively. One can observe a sharp increase in the market share of purchases for the top-decile funds after the introduction of TPOPs. When comparing the market share on Howbuy with that of the whole market quarter by quarter, we find the market share of purchases for the top-decile funds on Howbuy platform comoves well with that of the whole market. Besides, for the majority of the quarters during this time, the share on 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 is driving the magnified performance-chasing effect in the mutual fund market.

Panel B of Table 4 presents the corresponding results on the redemption side. Top performance decile funds also constitute a large fraction of total fund redemption. For example, the average market share of redemption for top-decile funds is 18% for equity funds and 15% for mixed funds in the pre-platform period. This is consistent with the disposition effect: Investors are more likely to sell winner funds than loser funds.[14] Interestingly, this performance-chasing redemption behavior is also amplified on the platforms. For equity funds, the fractions of redemption for top deciles are 45.00% on Howbuy and 26.93% for the whole market. For mixed funds, the fractions of redemption for top deciles are 35.64% on Howbuy and 16.67% for the whole market. The "Howbuy-All" differences are both significant

[14]Previous studies find a mixed pattern of selling past winner funds in U.S. (e.g., Barber, Odean, and Zheng (2000), Ivković and Weisbenner (2009), Chang, Solomon, and Westerfield (2016)). The disposition effect of selling past winner funds in China, however, is very robust (e.g., Li et al. (2019).

for these two styles. As platforms provide a more convenient method of trading, it can also exacerbate the behavioral biases of investors, similar to the findings in Barber and Odean (2001). As a result, there is a significant increase in redemption fraction for the top decile in the whole market.

3.3 Change in Investor Compositions

So far, using both the whole market data and the pure-platform trading data from Howbuy, we document a startling increase in flow-performance sensitivity associated with the emergence of platforms. There are at least two potential explanations for this amplified performance-chasing behavior on platforms. One explanation is that the introduction of TPOPs brings naive platform investors into the mutual fund industry. With vastly improved technological efficiency, those less sophisticated retail investors have easier access to trading and are more prone to performance-chasing. The second potential explanation is that the unique information structure associated with platform technology contributes to this amplification even in the absence of investor composition change. Off-platforms, the information flow is dispersed in nature, with different investors receiving different information from their respective distribution channels, attenuating the aggregated effect of performance-chasing. On platform, the information flow is uniform in nature, with investors receiving almost identical signals focusing mostly on fund past performance ranking. As a result, the aggregate flow-performance relation is amplified by the synchronized individual-level performance-chasing.

These two explanations are not mutually exclusive and our main results likely capture the combined effect of the two. To provide additional perspective, we examine the change in investor composition after a fund joins TPOPs. Given those two channels, we expect an increase in the number of retail investors after a top-decile fund is available for sale through platforms. For institutional investors, since they are less likely to purchase through platforms, we anticipate there is no such amplified performance-chasing behavior for institutional investors.

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 of a fund; (3) retail ratio, which is the asset fraction of a fund held by individual investors. Since funds are only required to report their investor composition on a semi-annual basis, we do not further decompose semi-annual flow into retail and institutional flows. The estimation of flow relies on the assumption that all transactions occur at period end, which makes the flow measure nosier when the estimation horizon is longer. Besides, the mutual fund industry in China is dominated by retail investors. Equity, mixed, and bond funds on average have a retail ratio of 78%, 85%, and 59% in our before sample. Despite the overall mild increasing trend in the ownership of institutional investors, the retail ratio for all three style categories remain high at 81%, 75%, and 42% respectively in our after sample.[15]

Table 5 shows the results for investor composition change. We regress semi-annual investor composition proxies on $\text{Platform}_{i,t}$ dummy, Decile $10_{i,t-1}$ dummy, and the interactions 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 investor composition.

In columns (1), (3), and (5), we include only the $\text{Platform}_{i,t}$ dummy to examine the change in investor composition when a fund enters the top two platforms. The coefficient on $\text{Platform}_{i,t}$ dummy is insignificant, indicating that an average fund's investor base on platform is not substantially different from its off-platform investor base. In columns (2), (4), and (6), we further add Decile $10_{i,t-1}$ dummy and its interaction with $\text{Platform}_{i,t}$ dummy. We find an increase in the number of fund holders, a drop in the average holding value, and an increase in retail ratio for a top-decile fund after joining the platform. Conditioning on joining the platform and successfully getting into the top rank, the number of holders for a top-decile fund increases by 32.4%, the average dollar value held by each investor drops by 14.7%, and the retail ratio increases by 2.57%. This increase in retail ratio matches well with our estimate using net flow in Table 3. For example, consider a fund with an asset under management of 100 million, of which 80% 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 9.24%. 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 3.12% ($= (80 + 9.24 \times 2)/(100 + 9.24 \times 2) - 80\%$). Overall, our result is more in support of the second explanation that the unique information sharing structure on platforms contributes to the amplified performance chasing. The performance ranking that displayed on every individual's mobile device functions as a coordination device, resulting in synchronized trading and amplified performance-chasing at the aggregate level.

4 Empirical Results: Fund Managers and Families

In this section, we examine the economic consequences of introducing TPOPs on fund managers and fund families.

[15] We find institutions purchase a large bulk of mixed and bond funds in the crash period of 2015, which contributes to the decrease in retail ratio for mixed and bond funds. The transactions made by institutional investors are often large in size, making the estimation of institutional flow difficult. We thus focus on the publicly reported retail ratio to infer retail and institutional investors' change in holdings.

4.1 Risk Taking by Fund Managers

The flow-performance relation can be thought of as an implicit incentive contract for mutual fund managers. A fund manager, in its desire to maximize his compensation, has an incentive to take actions that 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 is a substantial change in managerial incentive in this performance region. Specifically, consider a fund that is close to 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 to capture 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 caused by the platforms. To the contrary, the convexity at the bottom and medium performance deciles do not change much. Therefore, there is less change in risk taking behavior for the losing and mediocre funds.

Impact on Fund Portfolio Volatility

To examine managers' change in 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 5 shows the difference in risk taking for winner (Decile 10) and loser (Decile 1) funds around the performance ranking date for the period before and after the policy change, respectively. At the beginning of each quarter t, we sort all funds into deciles based on the past twelve months return. 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 times series average and confidence interval of this difference around $t=0$.

The upper left graph of Figure 5 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 in the before sample, the incentive to boost performance is similar for funds in the high performance range and funds in the low performance range.

The upper right graph of Figure 5 presents the corresponding results for equity funds in the U.S. 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 5 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: Introduction of TPOPs 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.[16]

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 (past winners) 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:

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

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 the change in risk taking is driven by any aggregate market trend or unobserved time-invariant fund characteristics.

Panel A of Table 6 reports the coefficients on Decile $10_{i,t-1} \times \text{After}_t$ and Decile $10_{i,t-1}$. We can see that dop-decile funds increase their daily return volatility by an extra 0.114% (t-stat =3.55) in quarter $t = -1$ after the introduction of platforms, which is equivalent

[16] We also report the summary statistics of daily returns in the before and after period in Table A1. 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.

to an annualized volatility increase of 1.80%. Consistent with the figure, the increased risk taking starts at least two quarters before the ranking date ($k = -3$ and $k = -2$) and disappears shortly after quarter $k = 0$.[17] One caveat is that this increase in risk taking is not economically huge if taking into consideration that the average standard deviation of fund daily return is around 1.5% as shown in Table A1. An extra 11.4 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).[18]

We replace the total volatility in equation (4) with systematic/idiosyncratic volatility, and report the regression results in Panel B and C of Table 6, respectively. We find an increase in both dimensions of volatilities in the two quarters before the ranking date for funds in Decile 10. 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 $k = -2$ to $k = -1$, which indicates that, due to the added incentive in the post-platform period, fund managers in Decile 10 exert even more effort in boosting their idiosyncratic volatility to enhance the 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

[17] 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. We also examine the effect of flow in predicting future fund return and risk taking. As shown in Table A2, current flow is not indicative of future fund return and volatility.

[18] 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.

suggests that, in the pre-platform period, there is no evidence of fund managers in decile 10 to take more systematic risk relative to other funds before the ranking date. To 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.

4.2 Disruptions to Fund Families

In this section, we investigate the impact of platforms on the organization structure of fund families. Platforms could affect fund families through multiple dimensions. First, platforms provide a common playing field and this may expand the degree of competition from within families to outside families. Related with this shift in industry organization structure, we might observe changes in within-family flow co-movement and the incentives for families to create star funds. Second, platforms bring new opportunity to the fund industry. Families that quickly seize the platform opportunity will enjoy increase in market share, while those that are slow in adopting the new technology might lose.

Within-Family Flow Competition

Before the introductions of TPOPs, 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 capitals attracted through 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, we expect flow to become less sensitive to fund's within family performance ranking after a fund joins platforms.

To test this hypothesis, in Table 7, we examine the response of flow to the performance ranking within each family. We require a family to have at least three funds and exist for at least three years before the introduction of platforms to allow for meaningful comparison. This reduces our sample slightly from 26,265 fund-quaretr observations to 22,221. Since the average number of funds in a family is 8.15 for the pre-platform sample, we focus on performance quintile rank within each family. Column (1) of Table 7 shows the response of fund flow to the within-family quintile rank ($\text{FamilyRank}_{i,t}$) and the cross term between $\text{FamilyRank}_{i,t}$ and the $\text{Platform}_{i,t}$ dummy. We use the same set of control variables in Panel B of Table 3 and further include family fixed effect in this specification. Column (2) presents the results of fund flow on the Decile $10_{i,t-1}$ dummy and the cross term between Decile $10_{i,t-1}$ and the $\text{Platform}_{i,t}$ dummy used in our main analysis as a benchmark. Consistent with our main results, we also find an increase in excess flow to top-decile funds in the post-platform period under this specification.

Performance rankings within the family and in the whole fund universe tend to correlate with each other. To disentangle the two effects, we include both performance indicators and the cross terms between these two variables and 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 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 0.91% (t-stat =3.76) if its within-family quintile ranking increases by one. However, the coefficient on the cross term between within-family quintile rank and the Platform_t dummy is negatively significant at -0.81 (t-stat = -2.01). In other words, after a fund joins platforms, the same change in the quintile rank will only bring 0.09% (=0.91%-0.81%) (t-stat =3.76) of extra flow. The incremental effect of within-family ranking almost disappears after a fund joins platforms. To the contrary, the position of the fund in the whole universe of funds becomes more important. A top-decile fund in the whole fund universe will enjoy an extra flow of 13.26% after it joins the platforms, which is 2.77 times its off-platform level.

Within-Family Flow Correlation

Related with this change in market structure from within-families to outside families, the co-movement of fund flows within a family might also change. Before the introductions of TPOPs, since funds are tightly connected through families, sharing similar source of capital and resources, the flow to a fund is closely related to other fund in the same family. We argue that the introduction of TPOPs will weaken the role of families, and this effect tend to become less pronounced for funds on the top platforms.

To test this hypothesis, we use two model specifications. First, we regress the flow for a particular fund in quarter t on the highest fund flow ($\text{MaxFlow}_{i,t}$) within a fund family during that quarter. We exclude the funds with the highest flow within a family in quarter t from our analysis to avoid mechanical relationship. Column (1) in Table 8 reports the results of this regression after controlling for the control variables in our main specifications. We observe that the coefficient on $\text{MaxFlow}_{i,t}$ is positive and significant at 0.065 (t-stat = 5.77). This suggests that flow to the fund with highest flow in the family has a spillover effect to the fund we examine. This spillover effect weakens when the fund is available on platforms. The coefficient on the cross term between $\text{MaxFlow}_{i,t}$ and the $\text{Platform}_{i,t}$ dummy is -0.016 (t-stat

= -1.80). Column (2) further include the Decile $10_{i,t-1}$ dummy, the Platform$_{i,t}$ dummy, as well as the cross term between the two. The weakening of the spillover effect remains the same in this setting. In the second specification, we compute the aggregate flow of all other funds within a family, Flow^{-i}, and use this measure to capture the within-family spillover effect. Column (3) and (4) report the corresponding results. In both columns, we find a decrease in the response of fund i's flow to Flow^{-i}. As reported in column (4), for a fund that is not available on the top platforms, the fund flow is positively related to Flow^{-i}. The coefficient is 0.244 (t-stat = 2.54). For a fund on the top two platforms, this effect is reduced to 0.089. Overall, the results are consistent with our expectation that the within family flow spillover weakens for funds on top platforms.

Star Funds from Top Families

In the pre-platform period, funds are closely linked to the families, and families will allocate resources across different funds to maximize the benefit of the entire family. One conventional strategy applied by families is to create "star" funds. "Star" funds attract flows and bring positive spillover effect to funds in the same family (Nanda, Wang, and Zheng (2004)). After the introduction of platforms, the linkage between family and individual funds becomes looser. As discussed in the previous results, the spillover effect within family diminishes and fund flows are highly sensitive to funds' own performance ranking in the whole fund universe. Given this weakening of connection between funds and families, we expect families to have lesser control on funds. As a result, large families 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 top families indeed decreased in the post-platform period. Panel A of Table 9 presents the proportion of funds from large families in each performance decile rank for the sample before and after the introduction of TPOPs. Each quarter end for each style category, we sort all funds into deciles based on the past twelve months return. We then calculate the fraction of funds that belongs to the top ten largest families (or top five families or top one family) for the decile. In the pre-platform period, the fraction of funds in the top performance decile that belongs to the large families is significantly larger than that in the bottom performance decile. We take the largest ten families as an example. Large family funds account for 38.04% of the best-performing funds and only 28.46% of the worst-performing funds. While this pattern reversed in the post-platform period that large family funds only account for 19.64% of the best-performing funds, and 24.48% of the worst-performing funds. This pattern is consistent with the interpretation that large families attracting flows through "star" funds in the pre-platform period, but fails to or are less inclined to apply this strategy in the post-platform era.

Family Entrance onto Platforms

Finally, the rise of platforms could also affect the distribution of family market shares. TPOPs have become one of the leading players in the marketplace for mutual funds. They help divert flow to better-performing funds in the platform, no matter it big or small, well-known or invisible. Fund families that embrace the new channel and perform well will capture more 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 change the market, we first examine the change in market shares for top families. Panel B of Table 9 exhibits the top ten fund families by market share before and after the introduction of TPOPs. The top families' market shares shrink over time. The largest ten families on average account for 50.42% of the industry for the pre-platform period, while it shrinks to 41.42% in the post-platform period.

Next, we investigate the relation between change in family market share and its entrance time to platforms. Figure 6 plots families' entering time onto Tiantian and its change in market share from three years before (2010–2012) to three years (2013–2015) after the introduction of TPOPs.[19] We label the largest 15 families and use different colors for bank- (blue) and broker-affiliated families (red). 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 big customer base, may overlook the importance of platform. Bank-affiliated families often have their own distribution channel and sticky capitals, hence lack the incentive to join platform early as well.[20]

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 the December of 2013 and experienced a decline in its market share during this period. While for early entrants like Fullgoal and China Universal, they had a positive increase in market share.

The overall evidence is consistent with our interpretation: Families that were rich in resources in the before period tend to overlook the potential of platforms. They tend to join platforms late and the reluctance of these families to join platform contributes to the decline in their market shares in the after period.

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[19]We choose 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.

[20]We conduct analysis on the determinants of funds' and families' entry onto TPOPs in Appendix Table A3. The results are consistent with this interpretation.

5 Robustness and Further Exploration

5.1 Absolute Performance Ranking

In this subsection, we conduct the same analyses using absolute performance ranking instead of relative performance ranking. In particular, for each fund style and in each quarter, we sort funds into five ranking groups: Top 10, Top 11 to 20, Top 21 to 50, Bottom 100, and others. We create dummy variable for each of the groups. Table 10 presents the corresponding panel regression results with the ranking dummies and cross terms between the ranking dummies and the $\text{Platform}_{i,t}$ dummy. "Bottom 100" is omitted in the regression. The coefficients on the other ranking dummies can be interpreted as the additional flow for the group relative to "Bottom 100" category.

For equity funds, the Top 10 funds attract an extra flow of 11.01% for a fund offline, whereas this number rises to 34.29% for a fund on the top platforms. For Top 11 to 20 equity funds, the additional flows are 7.07% off-platform and 31.28% on-platform. We find similar pattern for mixed funds, and the change for bond funds is less pronounced. Overall, the results are consistent with our baseline results. These results highlight the impact of platforms on promoting the top performers, especially the most prominent ones on the billboard.

5.2 Short-Term Fund Performance

We also examine the robustness of the results under a variety of settings. To this point in the analysis, we have been using past twelve months return as a proxy for past performance. We investigate the robustness of this result by changing the horizon of the past performance measure. In addition to the Decile $10_{i,t-1}$ dummy based on the past twelve months, we also conduct the same analysis for the Decile $10_{i,t-1}$ dummy using past one, three, and six months. These specifications are consistent with return horizons used in the ranking list provide by the platforms. Panel A of Table 11 reports the panel regression results following the model specification of Panel B 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.

5.3 Other Alternative Specifications

To further test the robustness of our results, we also conduct analyses under a variety of settings with certain deviation from the baseline specification in Panel B of Table 3. We only report the coefficients on the two main variables, the Decile $10_{i,t-1}$ dummy and the interaction between Decile $10_{i,t-1}$ and the $\text{Platform}_{i,t}$ dummy.

(1) Excluding 2015: Before August 8th, 2015, equity mutual funds are required to hold at least 60% of total assets in stocks. After the implementation of a new policy in 2015Q3, equity funds are required to hold at least 80% of total assets in stocks. As a result, a large number of equity funds switched to mixed funds. Most of the switching were clustered around 2015Q3, accompanied with the sudden collapse of the Chinese stock market in the second half of 2015. The roller-coaster 2015 experienced huge ups and downs in the stock market, and meantime witnessed over 300 equity funds switching to mixed funds. In Row (1) in Panel B of Table 11, we repeat our analysis by excluding the whole year of 2015 and find our results remain both economically and statistically.

(2) Constant Fund Sample: As shown in Panel A of Table 1, the number of funds also grow gradually during our sample period. To control for the change in 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 (2).

(3) Control for Before and After 2013: Another potential issue is that some other change in the market around the year 2013 is driving the change in the flow-performance relation. To alleviate this concern, we include an extra control variable Decile $10_{i,t-1} \times \text{After}_t$ in this regression. The coefficient on Decile $10_{i,t-1} \times \text{Platform}_{i,t}$ remains significant with similar magnitude. This suggests that the entry to platforms by each mutual fund is the main driver of the change in flow-performance relation.

(4) Control for Linkages to Banks/Brokerages: According to Figure 1, the number of banks and brokers with funds distribution license also increased during our sample period. Moreover, the sales relationship between mutual funds and banks/brokers also increased. To distinguish the effect of these traditional channels, we further control the number of sales relationship between mutual funds and banks/brokers in our analysis. The effect from the platforms still exists after these controls.

(5) Control for Fund Fixed Effect: In our baseline analysis, we follow the literature on flow-performance relation to determine our control variables. In row (5), we further control for fund fixed effect.[21] Adding fund fixed effect, we are utilizing the staggered incorporation of funds onto platforms to explore both the cross sectional and time series variation of change in exposure to TPOPs. The results remain similar to our baseline results.

(6) Value Weighted: Another potential concern is that our results are mainly driven by small funds. We conduct weighted least squared regressions for our main analysis using the $\text{TNA}_{i,t-1}$ of each fund as the weight for each observation. The results remain similar to

[21]The sample shrinks slightly, as 153 fund-quarter observations were dropped because these funds only have one observation in our sample.

our baseline results.

(7) 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. The coefficients remain significant, and the magnitudes of these coefficients estimates are similar to our main specification. For example, when the performance decile rank of a fund increases by 9 from Decile 1 to Decile 10, its excess flow increases by 5.92% per quarter. When the same fund is available through platforms, the excess flow increases to 12.70% per quarter, which is 2.14 times its off-platform level.

(8) Using the Number of Platforms: Finally, we replace the platform$_{i,t}$ dummy with the natural logarithm of the total number of TPOPs a fund enters, Log(#Platforms)$_{i,t}$. The coefficient on the cross term between Decile $10_{i,t-1}$ dummy and Log(#Platforms)$_{i,t}$ is also significant.

6 Conclusions

The success of the platform economy has transformed the way we live, and the emergence of platform intermediation of financial products could lead to one of the next disruptions of the platform economy. Relative to other products and services such as retail goods or taxi rides, 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 the intermediation of financial products difficult to control, especially during adverse market conditions. These considerations, along with the rapid expansion of technology into financial intermediation in recent years, make it all the more important for practitioners and policy makers to understand the economic impact of bringing financial products to the 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 economic impact of platform distribution of financial products. First, we find that distributional efficiency does not necessarily translate to allocational efficiency. The vast scale and informational efficiency associated with the platforms have the tendency to synchronize and amplify individual investor behavior. 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, neither in the US nor in China, the performance-chasing investors on the platforms are not using the technological efficiency to help themselves build more efficient investment portfolios. Second, we also show that improvement in means of connectivity does not equate improvement in means of production. Indeed, the amplified performance-chasing incentivizes fund managers to increase risk taking to enhance the probability of getting into the top rank. Third, by documenting the weakening fund-family ties, we also shed light on how the traditional organization 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. The empirical evidences documented in this paper serve to better inform the 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 designs 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. For example, whether or not the platforms should be more proactive in offering financial advices to alleviate the unintended consequences documented in our paper is a topic of great interest going forward. 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. How to design policies to promote efficient usage of the technological advantages and avoid unintended consequences presents a challenge as well as an opportunity for the platform companies.

Finally, although our paper focuses only on the intermediation of mutual funds, we believe that our findings could provide broader insights on platform distributions of other financial products. Indeed, although each type of financial products has its unique design, they share many common features and concerns, with the risk and return tradeoff functioning as a common thread. From money market funds to P2P loans, the return and risk characteristics of financial products expand over a wide spectrum, and the role of platforms can also vary substantially across these different products. Even in our study of mutual funds, we find that the platform impact differs between the high return and high risk equity funds and the low return and low risk bond funds. As the platform economy expands further into the industry of financial intermediation, we expect our findings to be relevant and instructive to platform intermediation of the broader collection of financial products.

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Figure 1. Introduction of Third-Party Online Platforms

The upper left graph reports the number of entities in each type of distribution channel: banks, brokers, and TPOPs (third-party online platforms) from 2008 through 2018. 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 TPOPs as a fraction of the whole universe of funds. The lower right graph reports the common coverage of the four major platforms.

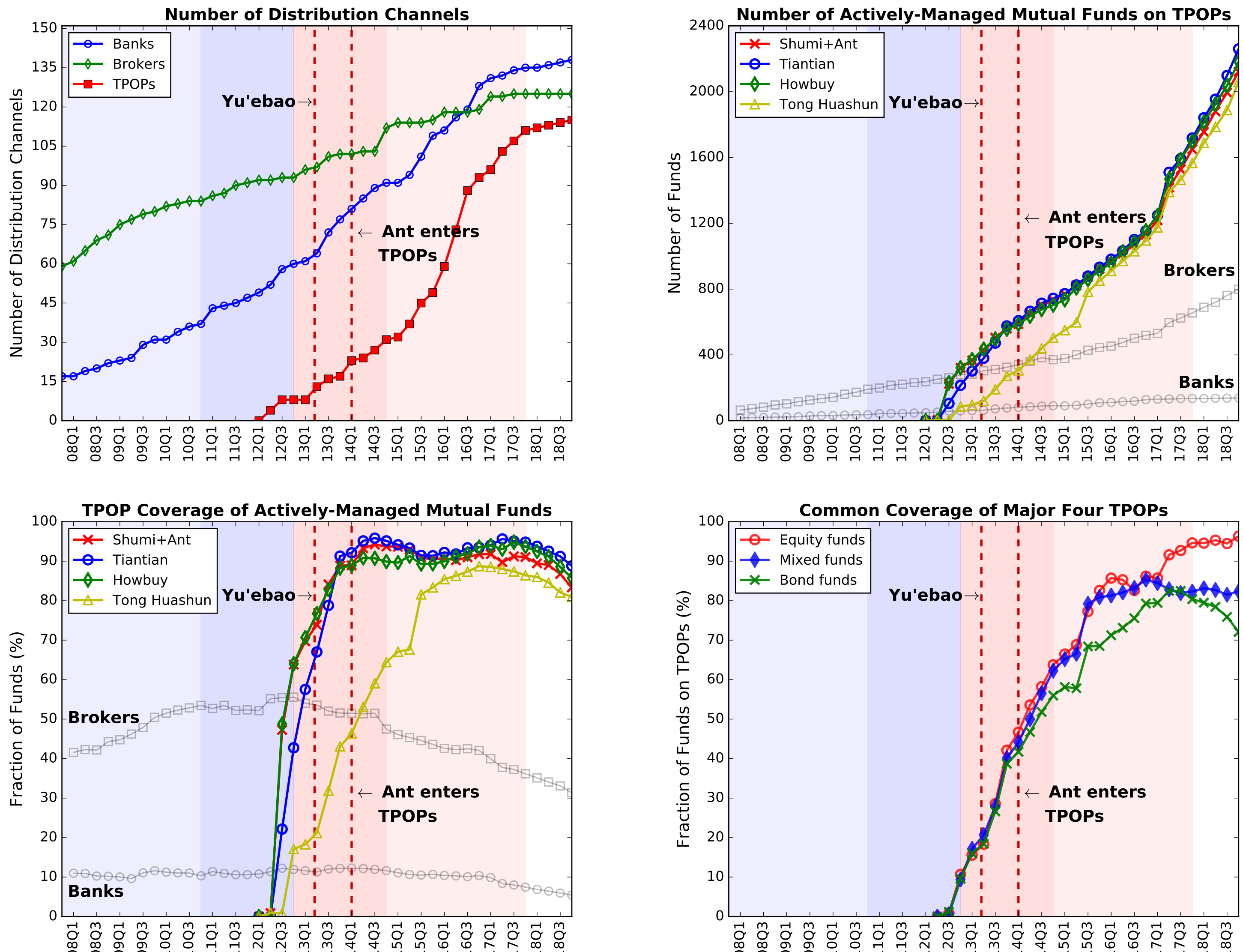

Figure 2. Flow-Performance Sensitivity, Before and After the Introduction of Third-Party Online Platforms

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 TPOPs. At the beginning of each quarter t, we sort all funds into deciles based on their past 12 months 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 four graphs show the average fund flow for China equity funds, U.S. equity funds, China mixed funds, and China bond funds, respectively.

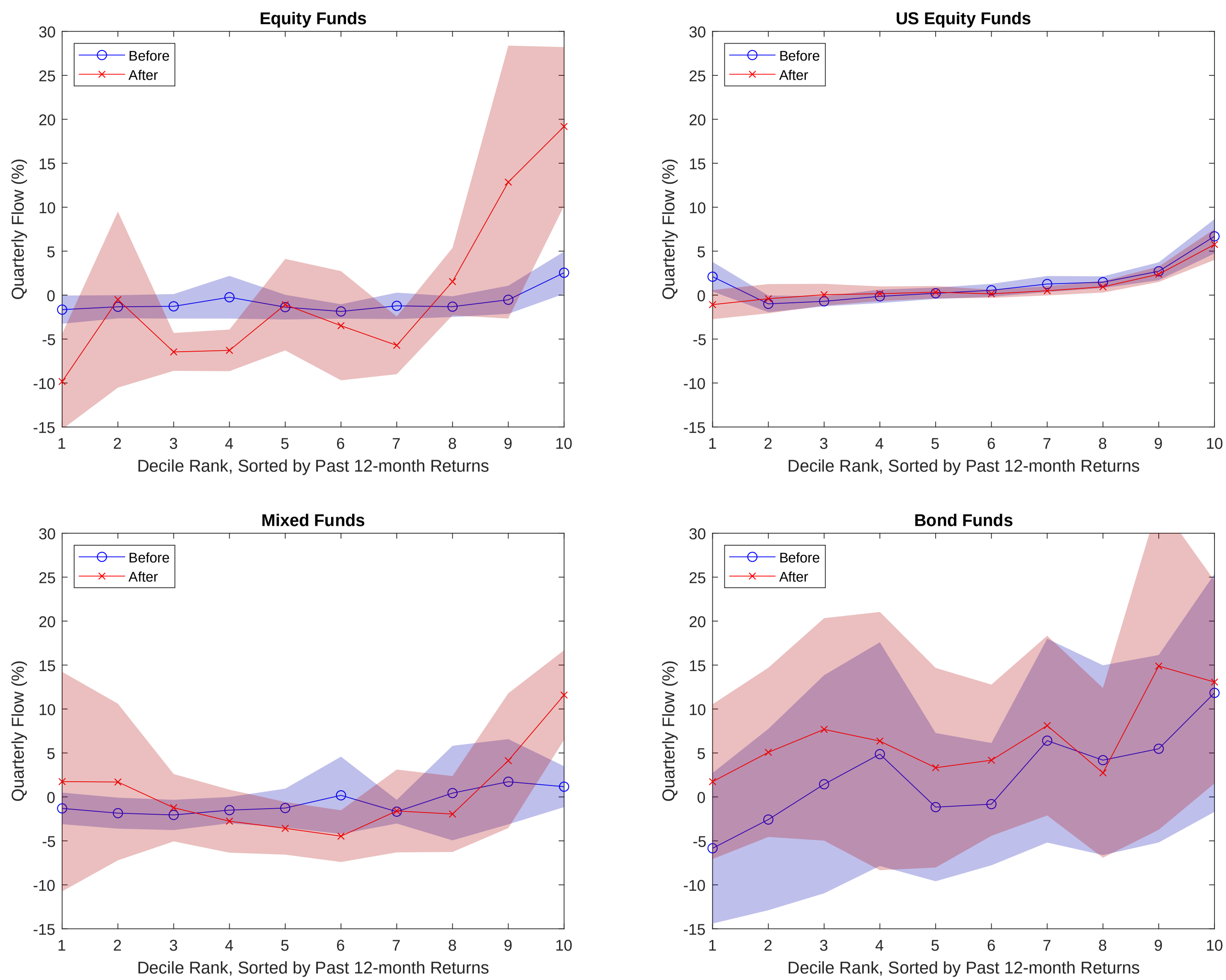

Figure 3. Time-Series Variation of Performance Chasing

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 mutual funds, respectively.

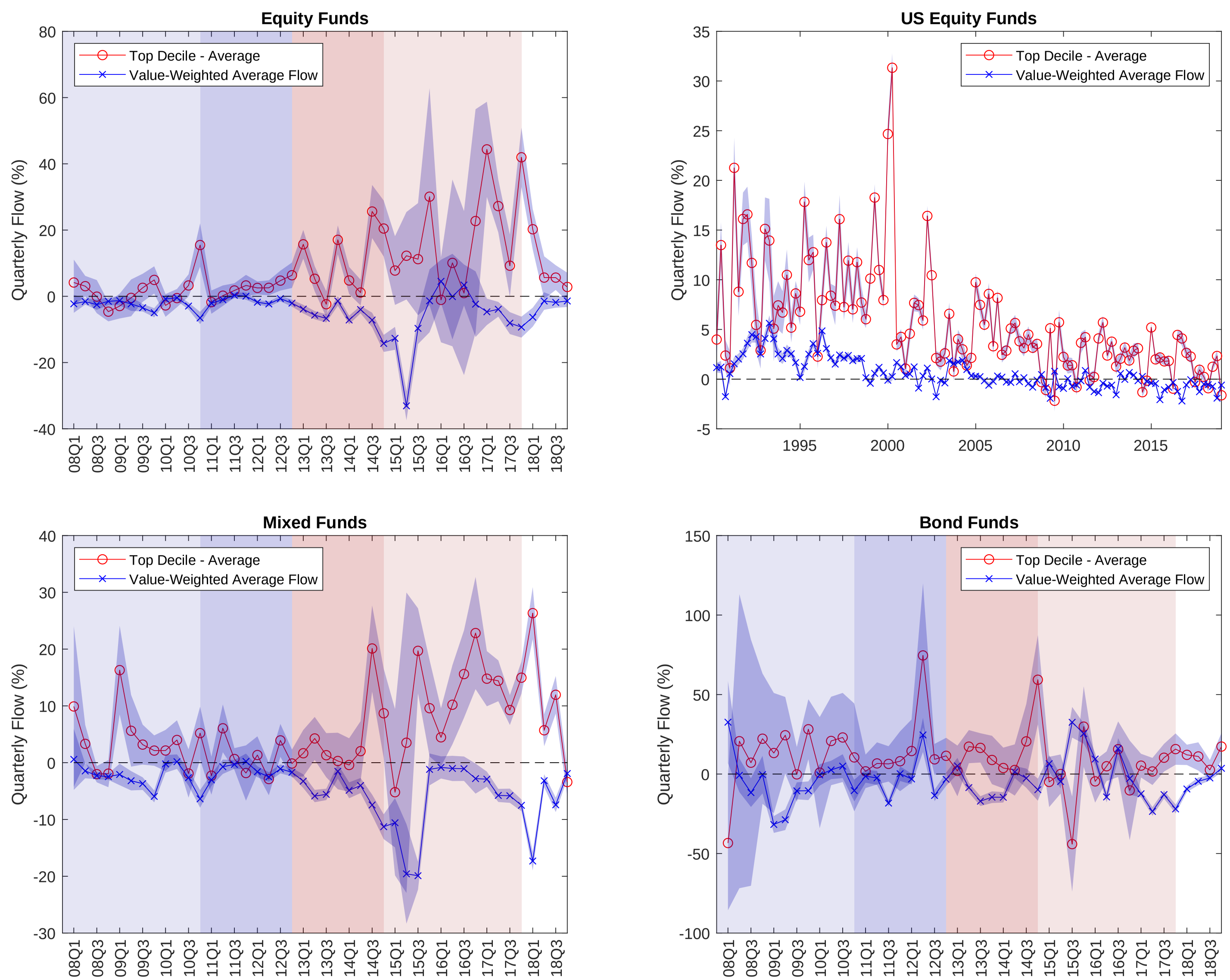

Figure 4. Purchase Fraction: The Whole Market versus Howbuy Platform

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 months 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 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.

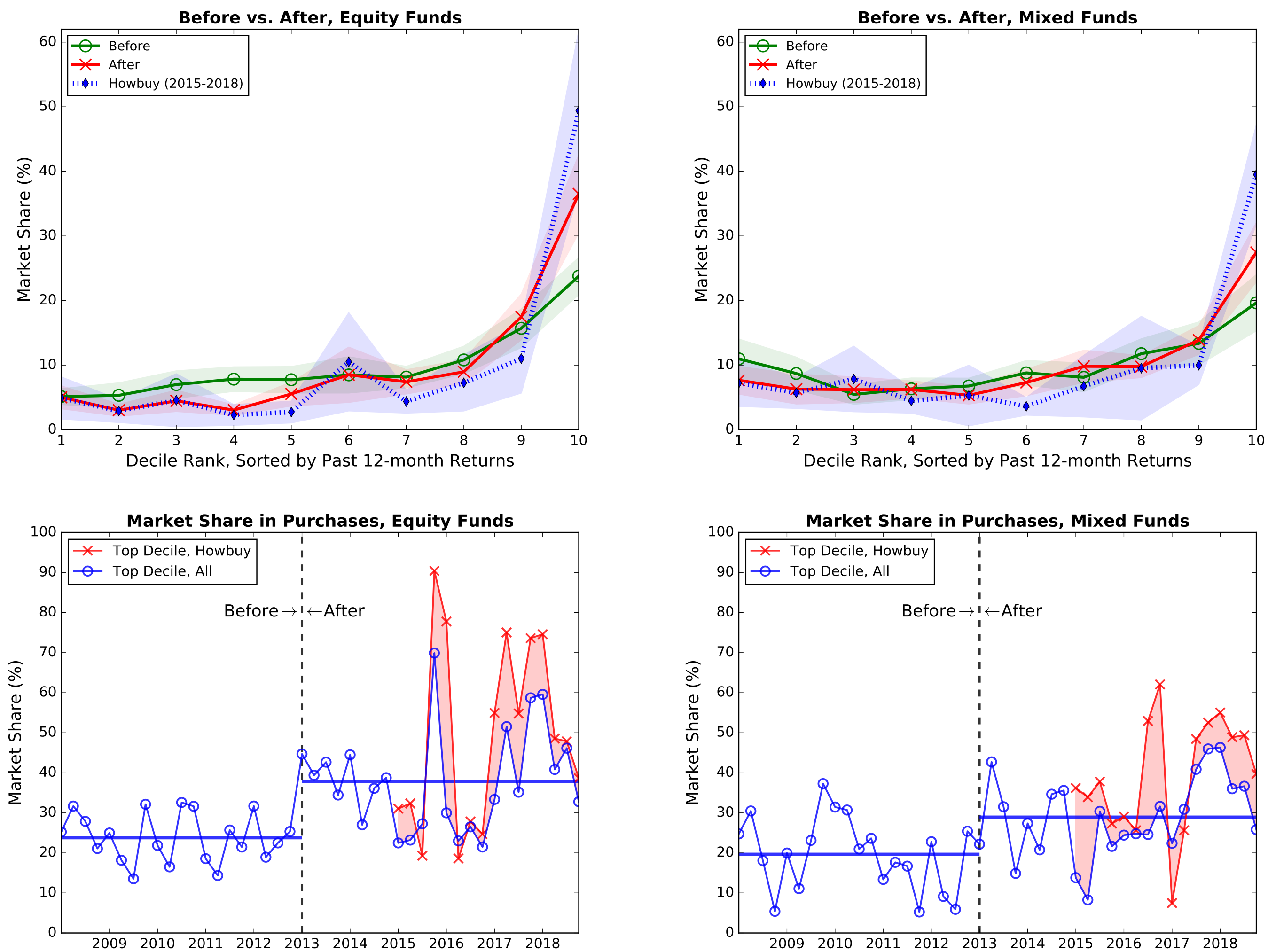

Figure 5. The Impact on Standard Deviation, Before and After the Introduction of Third-Party Online Platforms

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 TPOPs. At the beginning of each quarter t, we sort all funds into deciles based on the past 12 months return from quarter $t-4$ to quarter $t-1$. We then examine the daily return standard deviation for funds in each performance decile rank from $t-4$ to $t+4$. Quarter $t=0$ is the quarter immediately after the performance sorting. Graph A, B, C, and D show the fund daily return deviation around the event quarter for China equity funds, U.S. equity funds, China mixed funds, and China bond funds respectively. The shaded areas denote the 95% confidence intervals.

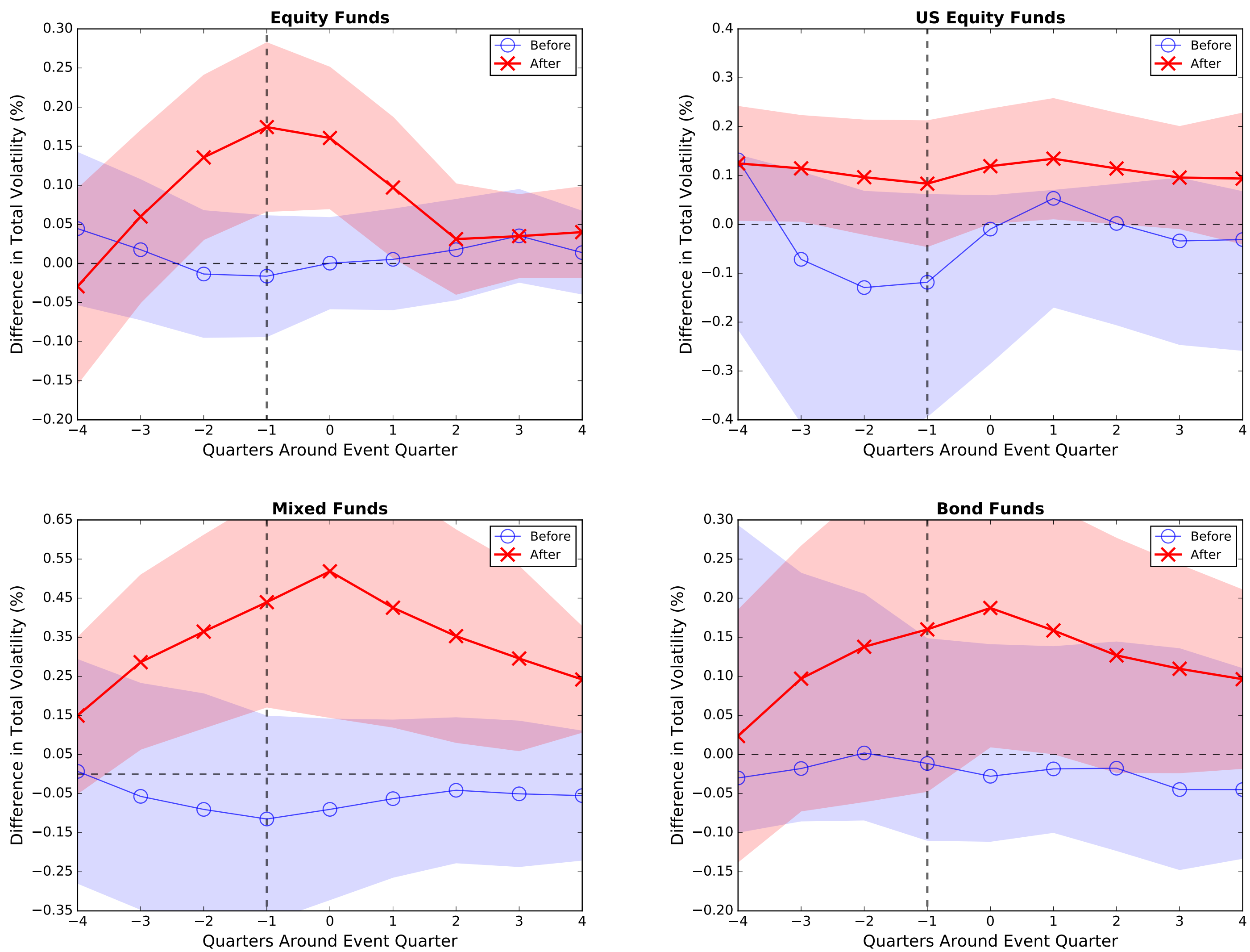

Figure 6. Entering Time and Changes in Market Share for Fund Families

This graph shows the entering time of the fund families into Tiantian 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 introdution of TPOPs 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.

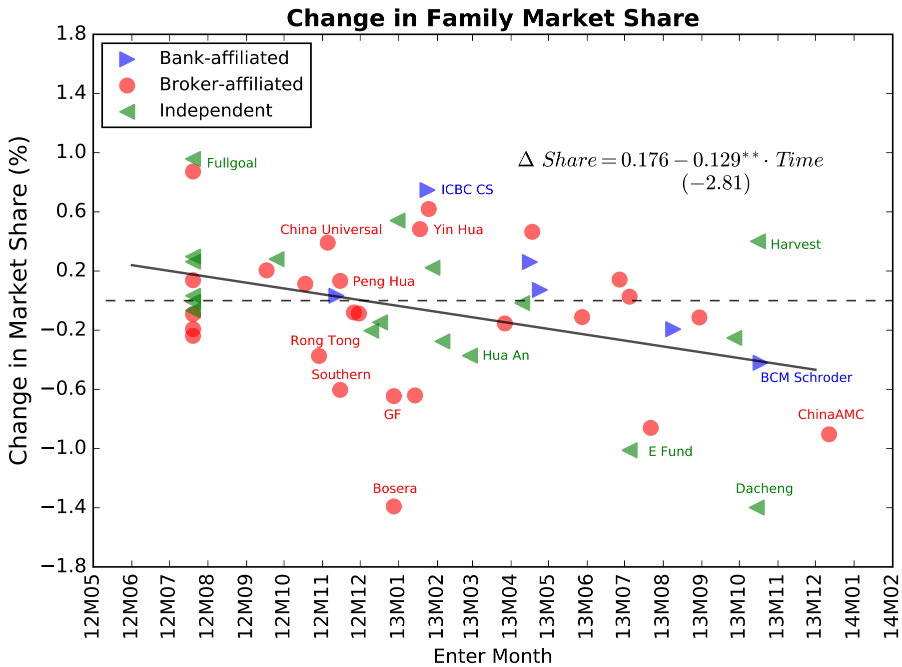

Table 1. Summary Statistics

Panel A shows the size of actively managed mutual funds year by year. We report the average number of unique funds (#Funds), total net assets (TNA) in billion-yuan, fund quarterly returns (Ret), cross-sectional standard deviation of fund quarterly returns (StdRet) by averaging across four quarters each year, for bond, equity, and mixed funds respectively. Panel B reports the summary statistics for the variables in our sample. Log(Size) is the natural logarithm of funds TNA at each quarter end. Age is the number of months since a fund's inception. $\mathrm{MRet}_{(t-1,t-4)}$ is the average monthly return in the past twelve months. Flow is funds' quarterly flow, calculated as $\frac{TNA_t - TNA_{t-1}(1+Ret_t)}{TNA_{t-1}}$. Subscript t indexes the quarter. Annual management fee, subscription fee, and redemption fee are calculated by aggregating different fund share classes and are reported in percentage. We compute the means, lower quintile (Q1), upper quintiles (Q3), medians, and standard deviations, quarter by quarter and report the time-series averages of the quarterly statistics for the five years before and five years after the introduction of third party online platforms (TPOPs). The before sample is from 2008 to 2012. The after sample is from 2013 to 2017. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A. Size of Mutual Funds, by Year

	Equity				Mixed				Bond			
Year	#Funds	TNA(B)	Ret(%)	StdRet(%)	#Funds	TNA(B)	Ret(%)	StdRet(%)	#Funds	TNA(B)	Ret(%)	StdRet(%)
2007	55	323.9	12.60	18.01	80	468.1	4.95	25.08	10	23.1	1.83	3.98
2008	72	376.5	-20.86	10.38	97	488.0	-15.88	8.29	16	50.7	0.44	2.45
2009	111	723.3	13.29	6.52	121	692.7	11.72	6.15	20	32.1	-0.06	2.12
2010	143	810.4	-0.23	5.63	134	690.8	0.07	6.37	40	59.0	-0.08	2.55
2011	184	729.1	-7.64	4.39	156	601.4	-6.53	4.51	72	68.4	-1.49	2.42
2012	220	636.3	1.26	3.90	167	529.6	0.78	3.44	85	91.0	1.19	1.82
2013	270	668.6	3.57	5.98	187	531.4	2.77	5.01	125	132.5	-0.59	2.40
2014	326	616.6	5.62	7.05	210	477.0	4.38	6.37	187	135.3	4.37	5.71
2015	186	357.2	12.40	11.32	431	760.2	8.42	11.39	304	320.6	1.29	5.02
2016	42	35.8	-3.06	6.19	712	905.7	-4.78	8.07	397	632.4	-1.20	3.92
2017	123	159.5	3.21	5.94	1,020	1,300.8	2.24	5.50	456	518.2	-0.11	2.54
2018	177	171.9	-7.24	5.09	1,414	1,237.6	-4.93	5.33	639	715.1	0.28	2.70

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	1.08	20.22	19.12	20.33	21.31	1.43	-1.63***	(-10.46)
	Age	57.60	34.25	47.40	71.85	31.46	55.22	35.48	48.93	69.43	26.20	-2.37	(-1.03)
	$\text{MRet}_{(t-1,t-4)}$	-0.61	-1.40	-0.47	0.27	1.26	1.24	0.55	1.27	1.99	1.18	1.85**	(2.51)
	Flow	-0.83	-4.31	-1.86	0.18	9.93	0.11	-13.31	-7.05	0.63	34.38	0.94	(0.71)
	Management Fee	1.25	1.20	1.50	1.50	0.50	1.45	1.50	1.50	1.50	0.17	0.20***	(5.15)
	Subscription Fee	0.82	0.42	1.03	1.16	0.49	1.00	0.97	1.08	1.18	0.32	0.19***	(8.11)
	Redemption Fee	0.15	0.06	0.12	0.13	0.21	0.29	0.18	0.28	0.35	0.22	0.14***	(3.87)
Mixed	Log(Size)	21.67	21.05	21.94	22.61	1.29	20.58	19.61	20.81	21.67	1.40	-1.09***	(-9.76)
	Age	63.26	45.38	65.00	79.35	21.22	81.52	47.43	78.70	114.40	38.68	18.25***	(7.00)
	$\text{MRet}_{(t-1,t-4)}$	-0.51	-1.22	-0.49	0.35	1.29	0.96	0.33	1.03	1.68	1.12	1.47**	(2.32)
	Flow	-0.61	-4.52	-2.48	0.19	11.73	0.32	-11.85	-6.35	-1.56	38.54	0.93	(0.51)
	Management Fee	1.46	1.50	1.50	1.50	0.18	1.43	1.48	1.50	1.50	0.17	-0.02**	(-2.55)
	Subscription Fee	1.00	0.90	1.08	1.30	0.44	0.98	0.91	1.05	1.19	0.38	-0.02***	(-3.04)
	Redemption Fee	0.23	0.13	0.13	0.28	0.23	0.30	0.13	0.14	0.38	0.35	0.07***	(7.08)
Bond	Log(Size)	20.26	19.32	20.25	21.20	1.17	20.01	19.06	20.07	21.03	1.31	-0.25***	(-2.36)
	Age	49.16	33.08	40.54	59.67	23.18	55.86	34.83	47.73	68.48	28.08	6.70***	(4.52)
	$\text{MRet}_{(t-1,t-4)}$	-0.02	-0.21	-0.02	0.17	0.30	0.29	-0.02	0.29	0.61	0.65	0.31*	(1.74)
	Flow	2.38	-15.75	-4.43	14.35	24.89	6.63	-19.98	-5.24	12.62	55.09	4.25	(0.63)
	Management Fee	0.64	0.60	0.62	0.70	0.06	0.66	0.60	0.70	0.70	0.12	0.02***	(3.59)
	Subscription Fee	0.24	0.00	0.23	0.41	0.23	0.33	0.12	0.36	0.52	0.23	0.09***	(8.32)
	Redemption Fee	0.05	0.00	0.01	0.05	0.12	0.10	0.00	0.02	0.05	0.25	0.05***	(7.95)

Table 2. Summary of Fund Flows and Returns in Each Performance Decile Rank

This table reports the summary of flow and return for each performance decile, before and after the introduction of platforms. Each quarter end for each style category, we sort all funds into deciles based on the past 12 months return ($\text{MRet}_{(t-1,t-4)}$), we then compute the quarterly average flow, average past 12 months return ($\text{MRet}_{(t-1,t-4)}$), cross sectional standard deviation of flows and returns for each performance deciles. We compute the statistics quarter by quarter and report the time-series averages for the five years before and five years after the introduction of TPOPs.

			Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Equity	Flow	Before	-1.65	-1.33	-1.28	-0.24	-1.37	-1.86	-1.22	-1.31	-0.53	2.55
			(-2.15)	(-2.11)	(-1.92)	(-0.21)	(-2.04)	(-4.74)	(-1.7)	(-2.33)	(-0.7)	(2.22)
		After	-9.83	-0.51	-6.46	-6.29	-1.08	-3.48	-5.72	1.54	12.86	19.18
			(-3.78)	(-0.11)	(-6.28)	(-5.55)	(-0.44)	(-1.17)	(-3.65)	(0.84)	(1.73)	(4.44)
	Std Flow	Before	7.47	7.72	8.69	9.40	7.20	6.96	8.79	7.67	9.65	12.73
		After	23.02	24.45	14.98	17.32	28.23	23.66	17.70	26.07	41.48	39.48
	MRet	Before	-3.01	-1.97	-1.41	-0.99	-0.62	-0.33	-0.02	0.27	0.64	1.28
		After	-0.98	0.06	0.50	0.87	1.12	1.41	1.69	1.99	2.42	3.23
	Std MRet	Before	0.68	0.19	0.15	0.13	0.10	0.10	0.08	0.10	0.13	0.32
		After	0.64	0.14	0.13	0.10	0.07	0.08	0.09	0.10	0.14	0.51
Mixed	Flow	Before	-1.31	-1.85	-2.05	-1.50	-1.27	0.18	-1.68	0.44	1.73	1.17
			(-1.52)	(-2.19)	(-2.49)	(-2.1)	(-1.2)	(0.09)	(-2.61)	(0.17)	(0.75)	(1.05)
		After	1.74	1.70	-1.23	-2.76	-3.57	-4.47	-1.60	-1.95	4.12	11.59
			(0.29)	(0.40)	(-0.67)	(-1.61)	(-2.5)	(-3.18)	(-0.71)	(-0.94)	(1.13)	(4.75)
	Std Flow	Before	9.62	8.29	8.15	6.40	8.37	9.95	7.63	11.50	13.57	13.97
		After	39.16	40.70	34.23	29.93	29.96	26.44	31.48	32.61	39.68	45.77
	MRet	Before	-2.98	-1.75	-1.24	-0.92	-0.65	-0.34	0.01	0.35	0.81	1.60
		After	-1.18	-0.15	0.32	0.64	0.91	1.15	1.39	1.68	2.04	2.82
	Std MRet	Before	0.68	0.19	0.12	0.08	0.08	0.10	0.10	0.12	0.16	0.45
		After	0.62	0.18	0.11	0.08	0.07	0.07	0.08	0.09	0.13	0.52
Bond	Flow	Before	-5.84	-2.57	1.44	4.87	-1.16	-0.82	6.40	4.18	5.48	11.84
			(-1.5)	(-0.55)	(0.26)	(0.84)	(-0.3)	(-0.26)	(1.22)	(0.85)	(1.13)	(1.92)
		After	1.74	5.07	7.68	6.35	3.32	4.18	8.11	2.74	14.88	13.07
			(0.41)	(1.1)	(1.27)	(0.91)	(0.61)	(1.02)	(1.66)	(0.59)	(1.67)	(2.37)
	Std Flow	Before	15.57	23.10	22.07	26.20	18.48	22.00	25.37	24.12	25.87	29.08
		After	51.44	51.00	54.67	51.88	48.99	48.93	57.74	46.93	63.27	52.33
	MRet	Before	-0.56	-0.35	-0.22	-0.12	-0.06	0.01	0.09	0.18	0.30	0.50
		After	-0.81	-0.21	-0.02	0.11	0.23	0.35	0.47	0.62	0.81	1.39
	Std MRet	Before	0.14	0.05	0.04	0.03	0.02	0.02	0.03	0.03	0.05	0.10
		After	0.45	0.08	0.04	0.03	0.03	0.04	0.04	0.05	0.08	0.49

Table 3. The Impact on Flow-Performance Sensitivity

This table examines the flow-performance sensitivity in a panel regression setting. Panel A examine the flow-performance sensitivity difference for the sample "before" and "after" the introduction of TPOPs. The model specification is:

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

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 twelve-month cumulative return up to the end of quarter $t-1$. The performance deciles are formed within each fund style. After_t is a dummy that equals one if quarter t is after the introduction of TPOPs, and zero otherwise. We include interaction term between Decile $10_{i,t-1}$ and After_t. The After_t dummy is absorbed in the regression as we included time fixed effects. $\text{Log(Size)}_{i,t-1}$ is the natural logarithm of funds TNA at the end of quarter $t-1$. $\text{Log(Age)}_{i,t-1}$ is the natural logarithm of the number of months since fund inception at quarter $t-1$. Fees include annual management fees, subscription fees, and redemption fees in percentage. We include time fixed effects in all the specifications, and further include style fixed effects when we pool all fund styles together in column (4) and (8). Standard errors are clustered at the fund level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

A. Before vs. After								
	[-5,5]				[-2,2]			
	Equity	Mixed	Bond	All	Equity	Mixed	Bond	All
Decile10	4.917***	2.269*	11.028**	4.827***	3.840***	2.208	9.916**	4.507***
	(4.58)	(1.82)	(2.55)	(5.00)	(2.93)	(1.37)	(2.17)	(3.58)
Decile10×After	14.226***	13.901***	-4.438	9.118***	13.058***	7.599**	11.315	11.870***
	(4.52)	(5.97)	(-0.85)	(5.26)	(3.67)	(2.51)	(1.56)	(4.71)
Log(Size)	-3.032***	-4.852***	-8.319***	-5.012***	-2.237***	-1.540***	-4.527***	-2.432***
	(-8.36)	(-11.92)	(-10.67)	(-17.56)	(-5.21)	(-5.51)	(-6.15)	(-9.23)
Log(Age)	-1.216	2.078**	0.517	0.780	2.477**	3.145***	4.265**	3.682***
	(-0.97)	(2.46)	(0.26)	(1.19)	(2.14)	(3.93)	(2.19)	(5.07)
Flow_{t-1}	0.026*	-0.001	0.019***	0.007	0.171***	0.111***	0.085***	0.111***
	(1.67)	(-0.09)	(2.67)	(1.33)	(4.75)	(3.36)	(3.40)	(6.26)
Management Fee	-1.890	3.134	-17.359**	0.154	1.202	3.555**	-15.345	1.289
	(-0.97)	(1.64)	(-2.21)	(0.14)	(0.81)	(2.31)	(-1.28)	(1.10)
Subscription Fee	-0.587	-1.054	-7.235**	-1.453*	-1.024	-0.987	-4.465	-1.261*
	(-0.49)	(-1.13)	(-2.07)	(-1.84)	(-0.91)	(-1.43)	(-1.37)	(-1.87)
Redemption Fee	1.172	4.457***	-0.534	3.344***	-0.954	-1.326	-2.586	-1.519
	(0.56)	(2.83)	(-0.15)	(2.65)	(-0.58)	(-1.17)	(-0.55)	(-1.59)
Constant	68.219***	85.681***	185.219***	100.624***	32.990***	12.247**	83.793***	32.278***
	(7.24)	(9.19)	(9.79)	(16.06)	(3.83)	(2.02)	(4.36)	(5.90)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6,700	12,935	6,630	26,265	3,996	2,873	1,861	8,730
R^2	0.053	0.053	0.099	0.056	0.092	0.078	0.128	0.067

In Panel B, we replace the After_t dummy with the $\text{Platform}_{i,t}$ dummy to exploit 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 twelve-month cumulative return up to the end of quarter $t-1$. The performance deciles are formed within each fund style. $\text{Platform}_{i,t}$ is a dummy that equals one if fund i is available for sale as of the beginning of quarter t through the two major TPOPs: Ant Financial and Tiantian. $\text{Log(Size)}_{i,t-1}$ is the natural logarithm of funds TNA at the end of quarter $t-1$. $\text{Log(Age)}_{i,t-1}$ is the natural logarithm of the number of months since fund inception at quarter $t-1$. Fees include annual management fees, subscription fees, and redemption fees in percentage. We include time fixed effects in all the specifications, and further include style fixed effects when we pool all fund styles together in column (4) and (8). Standard errors are clustered at the fund level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

B. Staggered Entrance onto Platforms								
	[-5,5]				[-2,2]			
	Equity	Mixed	Bond	All	Equity	Mixed	Bond	All
Decile10	7.181***	5.040***	8.590***	6.622***	6.647***	3.541***	10.086***	6.636***
	(6.86)	(3.79)	(2.64)	(6.84)	(5.43)	(2.81)	(3.75)	(7.04)
Decile10×Platform	18.602***	13.080***	-2.229	9.240***	22.514***	12.981**	26.975**	21.297***
	(3.81)	(4.94)	(-0.46)	(4.54)	(2.98)	(2.54)	(2.10)	(4.33)
Platform	-4.714	1.643	-0.376	-1.766	-6.723	1.208	8.398	-1.064
	(-1.41)	(0.87)	(-0.11)	(-1.10)	(-1.62)	(0.32)	(1.54)	(-0.38)
Log(Size)	-3.011***	-4.811***	-8.323***	-5.024***	-2.158***	-1.526***	-4.293***	-2.376***
	(-8.30)	(-11.88)	(-10.64)	(-17.54)	(-5.18)	(-5.49)	(-5.78)	(-9.16)
Log(Age)	-1.043	1.450*	0.659	0.966	2.528**	3.020***	2.238	3.502***
	(-0.84)	(1.65)	(0.32)	(1.39)	(2.34)	(3.73)	(1.20)	(5.17)
Flow_{t-1}	0.024	-0.001	0.019***	0.007	0.163***	0.108***	0.083***	0.108***
	(1.60)	(-0.13)	(2.67)	(1.33)	(4.47)	(3.27)	(3.36)	(6.09)
Management Fee	-1.806	2.589	-17.151**	0.311	1.239	3.425**	-17.69	1.261
	(-0.92)	(1.32)	(-2.18)	(0.27)	(0.88)	(2.16)	(-1.45)	(1.10)
Subscription Fee	-0.674	-0.927	-7.291**	-1.439*	-1.116	-1.005	-4.937	-1.355**
	(-0.56)	(-1.00)	(-2.08)	(-1.82)	(-1.02)	(-1.43)	(-1.51)	(-2.02)
Redemption Fee	0.884	4.370***	-0.516	3.297***	-0.946	-1.502	-3.666	-1.739*
	(0.43)	(2.79)	(-0.14)	(2.62)	(-0.61)	(-1.31)	(-0.81)	(-1.82)
Constant	68.561***	87.130***	184.852***	100.882***	32.623***	12.511**	86.665***	32.223***
	(7.33)	(9.35)	(9.82)	(16.17)	(3.86)	(2.03)	(4.40)	(5.90)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6,700	12,935	6,630	26,265	3,996	2,873	1,861	8,730
R^2	0.056	0.054	0.099	0.056	0.101	0.083	0.138	0.073

Table 4. Purchase and Redemption: The Whole Market versus Howbuy

This table reports the purchase and redemption fractions for each performance decile rank for the whole market ("All") and for Howbuy, respectively. Panel A and B report the results for purchase and redemption, respectively. For each quarter, the fraction of purchase (redemption) is computed as the amount of purchase (redemption) of all funds in a particular decile divided by the total amount of purchase (redemption) of all funds in our sample in that quarter. The time-series average of purchase (redemption) 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 and redemption on Howbuy is available from 2015 to 2018. The fraction of purchase (redemption) 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. t-stats are reported in parentheses.

		A. Purchase (%)									
		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)

		B. Redemption (%)									
		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)	6.11	6.66	8.35	8.50	8.53	9.68	9.93	10.67	13.57	18.00
	All After (2013-2017)	8.60	6.06	7.74	5.97	7.71	10.19	8.81	9.17	12.73	23.02
	After-Before	2.49	-0.61	-0.60	-2.53	-0.82	0.51	-1.12	-1.50	-0.84	5.02
		(1.93)	(-0.61)	(-0.49)	(-3.33)	(-0.84)	(0.27)	(-1.13)	(-1.48)	(-0.78)	(1.93)
	All (2015-2018)	7.70	5.95	7.95	5.13	7.21	9.88	8.44	9.12	11.69	26.93
	Howbuy (2015-2018)	6.57	3.89	6.15	2.93	3.72	11.06	4.46	7.45	8.77	45.00
	Howbuy-All	-1.13	-2.06	-1.80	-2.20	-3.49	1.18	-3.98	-1.67	-2.92	18.07
		(-0.50)	(-1.66)	(-0.66)	(-2.63)	(-2.81)	(0.25)	(-3.28)	(-0.76)	(-1.49)	(2.71)
Mixed	All Before (2008-2012)	9.25	9.15	7.34	7.52	8.46	9.77	9.21	11.62	11.93	15.75
	All After (2013-2017)	11.61	8.29	7.44	8.40	7.72	9.37	9.05	10.14	11.36	16.64
	After-Before	2.36	-0.86	0.10	0.87	-0.74	-0.41	-0.16	-1.49	-0.56	0.89
		(1.38)	(-0.69)	(0.14)	(1.55)	(-1.01)	(-0.46)	(-0.17)	(-1.64)	(-0.50)	(0.52)
	All (2015-2018)	11.74	8.69	7.76	7.88	7.73	8.27	8.31	10.09	10.56	18.98
	Howbuy (2015-2018)	10.77	6.87	6.75	5.59	5.28	4.60	6.27	8.67	9.55	35.64
	Howbuy-All	-0.96	-1.82	-1.01	-2.29	-2.44	-3.67	-2.04	-1.42	-1.00	16.67
		(-0.33)	(-1.34)	(-0.57)	(-1.95)	(-1.20)	(-4.14)	(-1.39)	(-0.52)	(-0.68)	(4.95)
Bond	All Before (2010-2012)	11.37	7.69	15.24	7.96	7.09	10.71	8.76	10.39	8.14	12.64
	All After (2013-2017)	7.98	11.27	9.30	9.97	9.64	8.76	9.29	9.98	10.92	12.90
	After-Before	-3.38	3.58	-5.95	2.01	2.55	-1.95	0.53	-0.42	2.78	0.26
		(-2.21)	(1.82)	(-1.90)	(1.54)	(2.69)	(-1.10)	(0.39)	(-0.21)	(2.08)	(0.08)
	All (2015-2018)	7.68	9.66	8.49	12.16	9.14	8.31	10.00	10.18	11.17	13.22
	Howbuy (2015-2018)	5.05	11.66	8.58	11.52	7.68	3.53	8.78	14.56	7.56	21.07
	Howbuy-All	-2.63	2.00	0.09	-0.63	-1.46	-4.78	-1.21	4.38	-3.60	7.84
		(-1.76)	(0.59)	(0.03)	(-0.18)	(-0.82)	(-5.05)	(-0.43)	(0.96)	(-2.37)	(1.29)

Table 5. The Impact on Investor Composition Change

This table reports the panel regression estimates of investor composition change after a fund being incorporated onto platforms. 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. Retail Ratio (%) is the fraction of a fund (in percentage) held by individual investors. We merge the semi-annual investor composition data in each June and December with the closest last quarter control variables: $\text{Platform}_{i,t}$ is a dummy that equals one if a fund is available for sale at Ant Financial and Tiantian in quarter $t-1$ (March when the investor composition data is in June). 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 $t-1$. We further control for fund size, age, flow, and fees in quarter $t-1$. Time fixed effects and fund fixed effects are included. Standard errors are clustered at the fund level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Log(#Holders)		Log(HolderDollarValue)		Retail Ratio (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Platform	0.003	-0.018	0.031	0.042	0.081	-0.086
	(0.09)	(-0.59)	(0.81)	(1.08)	(0.08)	(-0.09)
Decile10		-0.071**		0.149***		-3.115***
		(-2.40)		(5.64)		(-3.35)
Decile10×Platform		0.281***		-0.159***		2.565**
		(7.04)		(-3.94)		(1.97)
Log(Size)	0.421***	0.415***	0.413***	0.413***	-10.466***	-10.441***
	(19.13)	(19.02)	(17.89)	(17.81)	(-19.73)	(-19.66)
Log(Age)	0.607***	0.592***	-0.547***	-0.538***	-1.717	-1.885
	(10.05)	(9.85)	(-8.95)	(-8.83)	(-0.81)	(-0.88)
Flow_{t-1}	-0.020***	-0.020***	0.048***	0.048***	-0.518***	-0.513***
	(-4.03)	(-4.00)	(4.88)	(4.89)	(-2.96)	(-2.95)
Management Fee	0.610***	0.605***	-0.305	-0.305	4.408	4.427
	(4.03)	(4.05)	(-1.54)	(-1.55)	(0.88)	(0.89)
Subscription Fee	-0.558*	-0.558*	0.423	0.426	-28.588***	-28.658***
	(-1.91)	(-1.92)	(1.02)	(1.02)	(-4.98)	(-4.98)
Redemption Fee	0.324*	0.332**	-0.523**	-0.522**	17.691***	17.638***
	(1.93)	(2.03)	(-2.16)	(-2.17)	(3.55)	(3.54)
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Observations	13,215	13,215	13,215	13,215	13,215	13,215
R-squared	0.955	0.955	0.845	0.845	0.785	0.785

Table 6. The Impact on Risk Taking Behavior by Fund Managers

This table shows the managerial risk taking behavior when a fund gets into 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 the daily fund return standard deviation for fund i at 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 twelve-month cumulative return up to the end of quarter $t-1$. The performance deciles are formed within each fund style. After_t is a dummy variable that equals one for the sample in and after 2013. The table reports the panel regression estimates by regressing quarter $t+k$ volatilities on the dummy variable Decile $10_{i,t-1}$ and the interaction of Decile $10_{i,t-1}$ with dummy variable After. In Panel B and C, we further decompose daily volatility into systematic volatility and idiosyncratic volatility, based on a two-factor model (an aggregate stock market factor and an aggregate bond factor). We include controls of quarter $t-1$ end fund size, age, flow, and fees. Time fixed effects and fund fixed effects are included for all the specifications. Standard errors are double clustered at fund and time levels. Only the coefficient estimates for Decile $10_{i,t-1}$ and its interaction with After_t are reported. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

A. Total Volatility							
	$k=-3$	$k=-2$	$k=-1$	$k=0$	$k=1$	$k=2$	$k=3$
Decile 10×After	0.081**	0.100***	0.114***	0.083***	0.017	-0.006	-0.015
	(2.22)	(3.04)	(3.55)	(3.06)	(0.90)	(-0.27)	(-0.68)
Decile 10	-0.021	-0.019	-0.017	0.000	0.012	0.020	0.014
	(-0.82)	(-0.77)	(-0.82)	(0.02)	(1.08)	(1.39)	(0.86)
B. Systematic Volatility							
	$k=-3$	$k=-2$	$k=-1$	$k=0$	$k=1$	$k=2$	$k=3$
Decile 10×After	0.050	0.067**	0.082**	0.068**	0.014	-0.001	-0.013
	(1.43)	(2.04)	(2.60)	(2.26)	(0.77)	(-0.03)	(-0.67)
Decile 10	-0.035	-0.043	-0.041*	-0.017	-0.002	0.007	0.004
	(-1.30)	(-1.66)	(-1.88)	(-0.97)	(-0.15)	(0.48)	(0.27)
C. Idiosyncratic Volatility							
	$k=-3$	$k=-2$	$k=-1$	$k=0$	$k=1$	$k=2$	$k=3$
Decile 10×After	0.042*	0.048**	0.049**	0.033*	0.003	-0.015	-0.004
	(1.92)	(2.29)	(2.31)	(1.81)	(0.27)	(-0.78)	(-0.22)
Decile 10	0.033**	0.052***	0.049***	0.037***	0.031***	0.030*	0.017
	(2.28)	(3.95)	(4.02)	(3.16)	(3.46)	(2.01)	(1.03)

Table 7. Within-Family Ranking

This table shows the panel regression for the sensitivity of funds' flow to past performance, both within fund families and across fund families. We include funds in families with at least three funds and require the families to exist at least three years before the introduction of platforms. We follow similar model specification as in Panel B of Table 3. Decile $10_{i,t-1}$ is the performance ranking in the whole universe, defined as 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 $t-1$. FamilyRank is the past twelve months return quintile rank among the funds in the same fund family. $\text{Platform}_{i,t}$ is a dummy that equals one if a fund is available for sale through the major two TPOPs: Ant Financial and Tiantian. We include controls of quarter $t-1$ end fund size, age, flow, and fees. Time fixed effects, family fixed effects, and style fixed effects are included for all the specifications. Standard errors are clustered at fund level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Dep. Var.: Next Quarter Flow			
	(1)	(2)	(3)
FamilyRank	1.278***		0.907***
	(5.71)		(3.76)
Decile10		6.212***	4.788***
		(6.25)	(4.49)
FamilyRank×Platform	-0.125		-0.814**
	(-0.32)		(-2.01)
Decile10×Platform		7.202***	8.468***
		(4.01)	(4.46)
Platform	-1.215	-2.198	-0.715
	(-0.75)	(-1.63)	(-0.44)
Log(Size)	-4.977***	-5.007***	-5.016***
	(-19.77)	(-19.96)	(-19.98)
Log(Age)	2.844***	2.899***	2.995***
	(5.17)	(5.35)	(5.49)
Flow_{t-1}	0.052***	0.047***	0.047***
	(6.03)	(5.52)	(5.54)
Management Fee	2.520***	2.324***	2.201**
	(2.89)	(2.68)	(2.53)
Subscription Fee	-1.285**	-1.262**	-1.250**
	(-2.07)	(-2.05)	(-2.02)
Redemption Fee	2.488**	2.601***	2.625***
	(2.57)	(2.72)	(2.73)
Time FE, Style FE, Family FE	Y	Y	Y
Observations	22,221	22,221	22,221
R^2	0.071	0.076	0.077

Table 8. Within-Family Flow Correlation

This table shows the contemporaneous relation of fund flow and family flow. We include funds in families with at least three funds and require the families to exist at least three years before the introduction of platforms. We use two proxies for fund i's family flow. Columns (1) and (2) show the results using MaxFlow, defined as the maximum fund flow within fund i's family. We exclude the max flow fund itself in the regression estimates to avoid mechanical relationship. Columns (3) and (4) show the results using Flow^{-i}, defined as the value weighted flow in fund i' family, excluding fund i itself. We follow similar model specification as in Panel B of Table 3. Decile10$_{i,t-1}$ is the performance ranking in the whole universe, defined as 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. Platform$_{i,t}$ is a dummy that equals one if a fund is available for sale through the major two TPOPs: Ant Financial and Tiantian. We include controls of quarter $t-1$ end fund size, age, flow, and fees. Time fixed effects, family fixed effects, and style fixed effects are included for all the specifications. Standard errors are clustered at fund level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Dep. Var.: Current Quarter Flow				
	(1)	(2)	(3)	(4)
MaxFlow	0.065***	0.064***		
	(5.77)	(5.71)		
MaxFlow×Platform	-0.016*	-0.016*		
	(-1.80)	(-1.83)		
Flow^{-i}			0.253**	0.244**
			(2.68)	(2.54)
Flow^{-i}×Platform			-0.154*	-0.155*
			(-1.69)	(-1.69)
Decile10		2.904***		6.068***
		(3.92)		(4.52)
Decile10×Platform		6.649***		7.277**
		(3.32)		(2.08)
Platform	1.530	0.868	-2.165	-3.042**
	(1.49)	(0.83)	(-1.62)	(-2.13)
Log(Size)	-1.900***	-1.943***	-4.944***	-4.991***
	(-4.09)	(-4.19)	(-6.40)	(-6.46)
Log(Age)	3.110***	3.376***	2.460**	2.844***
	(3.60)	(3.93)	(2.48)	(2.89)
Flow$_{t-1}$	1.783	1.507	5.141**	4.711**
	(1.23)	(1.03)	(2.45)	(2.29)
Management Fee	3.380**	3.073*	2.698	2.215
	(2.09)	(1.96)	(1.41)	(1.20)
Subscription Fee	-1.240***	-1.165***	-1.337**	-1.248**
	(-3.02)	(-2.86)	(-2.36)	(-2.21)
Redemption Fee	0.058	0.31	2.278*	2.626**
	(0.07)	(0.39)	(1.90)	(2.19)
Time FE, Style FE, Family FE	Y	Y	Y	Y
Observations	20,317	20,317	22,221	22,221
R^2	0.089	0.097	0.071	0.077

Table 9. Star Funds and Top Families

Panel A reports the fraction of funds in the largest ten fund families for each performance decile rank. Each quarter end for each style category, we sort all funds into deciles based on the past 12 months return ($\text{MRet}_{t-1,t-4}$), we then calculate the fraction of funds in the decile category that belongs to the ten largest families (or top five families or China Asset Management Co. or China Universal Asset Management Co.) in that quarter. The difference between the "Before" and "After" sample is reported. Panel B reports the largest top ten fund families for the sample before and after the introduction of TPOPs. We report the average fund family total net assets for actively managed funds, 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.

Panel A. Fraction of Large Family Funds in Each Performance Decile												
	Top Ten Largest Families				Top Five Largest Families				China Asset Management			
Decile Rank	Before	After	Difference	t-stat	Before	After	Difference	t-stat	Before	After	Difference	t-stat
Decile 1	28.46	24.48	-3.98	(-1.55)	13.76	13.23	-0.53	(-0.29)	4.27	2.25	-2.02**	(-2.06)
Decile 2	32.20	25.84	-6.36**	(-2.66)	18.02	13.74	-4.28**	(-2.06)	2.01	2.22	0.21	(0.34)
Decile 3	32.04	27.71	-4.33*	(-1.76)	17.07	13.57	-3.50	(-1.67)	3.22	2.24	-0.98	(-1.16)
Decile 4	32.77	28.54	-4.23*	(-1.92)	18.52	15.48	-3.04	(-1.68)	3.53	3.28	-0.25	(-0.30)
Decile 5	30.90	25.26	-5.64**	(-2.56)	16.94	12.32	-4.62**	(-2.56)	3.58	2.50	-1.08	(-1.48)
Decile 6	34.68	23.64	-11.04***	(-4.73)	16.94	12.09	-4.85***	(-2.72)	3.35	1.96	-1.39*	(-1.81)
Decile 7	33.28	23.84	-9.44***	(-4.80)	17.67	12.95	-4.72***	(-3.09)	4.60	3.05	-1.55**	(-2.15)
Decile 8	34.81	26.46	-8.35**	(-2.42)	16.37	14.22	-2.15	(-0.81)	4.35	3.50	-0.85	(-1.02)
Decile 9	32.08	21.93	-10.15***	(-3.91)	16.28	11.96	-4.32**	(-2.45)	5.18	1.24	-3.94***	(-3.12)
Decile 10	38.04	19.64	-18.40***	(-6.73)	26.57	9.76	-16.81***	(-6.64)	10.30	0.80	-9.50***	(-6.37)
Decile 10-1	9.58***	-4.84*	-14.42***		12.82***	-3.47	-16.28***		6.03**	-1.46**	-7.49***	
	(3.07)	(-1.99)	(-3.65)		(4.73)	(-1.71)	(-4.81)		(2.81)	(-2.57)	(-3.37)	

Panel 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	109.19	14.0	8.97%	China Asset Management	92.82	21.4	6.37%
2	Bosera Asset Management	77.67	11.2	6.54%	E Fund Management	83.50	26.3	5.36%
3	Gf Fund Management	69.17	7.3	5.76%	Harvest Fund Management	71.14	27.7	4.70%
4	Harvest Fund Management	62.47	12.1	5.23%	China Southern Asset Management	60.61	25.8	3.99%
5	China Southern Asset Management	58.60	12.0	4.74%	Gf Fund Management	57.39	23.0	3.92%
6	E Fund Management	57.39	11.0	4.65%	Bosera Asset Management	57.85	28.2	3.88%
7	Dacheng Fund Management	54.20	10.0	4.41%	ICBC Credit Suisse Asset Management	55.12	25.8	3.58%
8	Fullgoal Fund Management	41.27	10.1	3.44%	China Universal Asset Management	53.86	20.9	3.52%
9	Invesco Great Wall Fund Management	40.44	8.3	3.40%	Fullgoal Fund Management	50.80	25.9	3.39%
10	Hua An Fund Management	40.83	7.9	3.28%	Bank Of China Investment Management	42.10	21.2	2.71%
	The Largest Ten Fund Families	61.12	10.4	50.42%	The Largest Ten Fund Families	62.52	24.6	41.42%
	The Rest Fund Families (N=51)	15.33	5.5	49.58%	The Rest Fund Families (N=78)	12.34	10.7	58.58%

Table 10. Absolute Performance Ranking

This table shows the panel regressions of quarterly percentage flow on past twelve-month absolute performance ranking (similar to the Table 3). To mimic investors' choice set, we estimate the regressions using all fund units, without aggregating different share classes at 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 twelve-months performance falls into the ranking category, and zero otherwise. We regress quarterly flow on last quarter end fund absolute performance rank dummies, platform$_t$ dummy, and the interactions between the two. Group "Bottom 100" is omitted because of multicollinearity. We include as controls last quarter end fund size, age, and fees. Standard errors are clustered at the fund level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Dep. Var.: Next Quarter Flow			
	Equity	Mixed	Bond	All
Top 10×Platform	23.281***	23.539***	16.366*	20.453***
	(3.73)	(3.51)	(1.72)	(4.80)
Top 11-20×Platform	24.213***	17.181***	10.733	16.708***
	(3.96)	(2.95)	(1.26)	(4.37)
Top 21-50×Platform	10.814***	10.627***	6.799	9.485***
	(3.11)	(3.26)	(1.56)	(4.42)
Others×Platform	2.826	9.419***	3.618	4.744***
	(1.30)	(3.74)	(1.49)	(3.90)
Top 10	11.006***	3.867**	8.439***	7.526***
	(5.53)	(2.17)	(2.90)	(5.74)
Top 11-20	7.067***	4.768***	13.781***	7.810***
	(3.78)	(2.65)	(4.53)	(6.10)
Top 21-50	4.047***	1.850*	9.011***	4.171***
	(4.21)	(1.84)	(4.45)	(5.35)
Others	-0.400	-7.443***	2.783*	-0.934
	(-0.57)	(-3.92)	(1.77)	(-1.32)
Controls, Time FE	Y	Y	Y	Y
Observations	8,370	16,868	13,386	38,624
R^2	0.067	0.06	0.102	0.056

Table 11. Alternative Specifications

This table shows various robustness tests. We follow the same specification as in Panel B of Table 3. Panel A shows the sensitivity of flow to past returns at different horizons. We replace past twelve-months return Decile $10_{i,t-1}$ dummy with the performance Decile 10 dummy of past one month, past three months, and past six months. Decile $10_{i,t-1}$ is the performance decile rank based on past X-months returns. Panel B 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 restrict the sample to funds with inception year before 2012. In model (3), we further control for Decile $10_{i,t-1}\times\text{After}_t$, where After_t is a dummy variable that equals one for observations on or after 2013. In model (4), we control for $\text{Log(\#Bank)}_{i,t-1}$ and $\text{Log(\#Brokers)}_{i,t-1}$, and the interactions between them and the Decile $10_{i,t-1}$ dummy. $\text{Log(\#Bank)}_{i,t-1}$ is the natural logarithm of the number of banks a fund is available for sale at quarter $t-1$, and $\text{Log(\#Brokers)}_{i,t-1}$ is defined similarly. In model (5), we include fund fixed effects, and double cluster the standard errors at fund and time level. In model (6), we estimate weighted least squared regressions, using the $\text{TNA}_{i,t-1}$ of each fund as the weight for each observation. In model (7), we replace the Decile $10_{i,t-1}$ dummy with the performance decile rank variable that ranges from one to ten. In model (8), we replace the $\text{Platform}_{i,t}$ dummy with the natural logarithm of the number of TPOPs that a fund is available for purchase in quarter $t-1$. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

A. Different Past Return Horizons

	1 Month	3 Months	6 Months	12 Months
Decile10	5.546***	5.705***	7.839***	6.622***
	(4.04)	(5.52)	(6.62)	(6.84)
Decile10×Platform	5.469**	8.531***	14.737***	9.240***
	(2.26)	(3.89)	(5.94)	(4.54)
Controls, Time FE	Y	Y	Y	Y
Obs.	26,265	26,265	26,265	26,265
R^2	0.053	0.055	0.061	0.056

B. Alternative Specifications

	Decile10×Platform	Decile10	N	R^2
(1). Exclude 2015	13.051***	6.726***	22,588	0.057
	(5.71)	(7.55)		
(2). Inception < 2012	11.794***	6.149***	18,909	0.047
	(4.80)	(7.72)		
(3). Control for After×Decile 10	7.122***	4.843***	26,265	0.056
	(2.85)	(5.01)		
(4). Control for Bank&Broker	9.476***	6.610***	26,265	0.057
	(2.88)	(4.98)		
(5). Fund fixed effects	11.690***	8.414***	26,112	0.156
	(4.96)	(7.64)		
(6). Value weighted	8.198***	3.777***	26,265	0.066
	(5.77)	(6.38)		
(7). Replace Decile 10 with Rank_{12m}	0.753***	0.658***	26,265	0.055
	(3.36)	(5.25)		
(8). Replace Platform with Log(#Platforms)	3.163***	5.018***	26,265	0.056
	(4.37)	(4.05)		

Appendix A

This appendix provides additional results. In particular,

- Table A1 provides the daily return distribution for funds in the ten decile ranks before and after the introduction of TPOPs;
- Table A2 exhibits the results on the predictive power of flow on future fund return and risk taking behavior;
- Table A3 exhibits the determinants of funds'/fund families' entrance onto TPOPs.

Table A1. Distributon 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 months 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 rank, and then average the estimates over time for the "Before" and "After" sample separately. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

			Daily return distributions 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	-0.022	-0.025	-0.020	-0.016	-0.025	-0.016	-0.008	0.000	-0.001	-0.012	0.010	(1.03)	0.020	(0.82)
		After	0.066	0.068	0.079	0.071	0.067	0.084	0.064	0.081	0.090	0.096	0.030	(1.33)		
	AR1	Before	0.030	0.028	0.037	0.025	0.023	0.020	0.020	0.020	0.022	0.028	-0.002	(-0.18)	0.026 **	(2.11)
		After	0.011	0.021	0.006	0.016	0.016	0.022	0.025	0.029	0.022	0.035	0.024	(2.81)		
	Std	Before	1.512	1.507	1.562	1.523	1.536	1.510	1.495	1.484	1.455	1.513	0.000	(0.01)	0.160 ***	(3.12)
		After	1.431	1.402	1.467	1.443	1.474	1.515	1.498	1.490	1.523	1.591	0.161	(3.72)		
	Skew	Before	-0.080	-0.080	-0.061	-0.075	-0.069	-0.055	-0.099	-0.077	-0.074	-0.052	0.028	(2.08)	-0.080	(-0.74)
		After	-0.412	-0.474	-0.454	-0.423	-0.451	-0.458	-0.482	-0.485	-0.486	-0.464	-0.052	(0.49)		
	Kurt	Before	0.494	0.539	0.606	0.533	0.586	0.508	0.479	0.502	0.526	0.576	0.082	(0.62)	-0.151	(-0.39)
		After	1.410	1.504	1.384	1.418	1.286	1.384	1.213	1.270	1.345	1.340	-0.070	(0.19)		
Mixed	Dret	Before	-0.016	-0.019	-0.018	-0.018	-0.010	-0.012	-0.012	-0.010	-0.015	-0.016	0.000	(0.01)	0.019	(0.63)
		After	0.051	0.057	0.054	0.052	0.054	0.051	0.059	0.068	0.065	0.070	0.019	(0.73)		
	AR1	Before	0.030	0.031	0.032	0.022	0.032	0.032	0.034	0.035	0.032	0.040	0.01**	(2.08)	-0.029	(1.05)
		After	0.018	0.020	0.025	0.031	0.029	0.022	0.025	0.023	0.033	0.039	0.021	(2.22)		
	Std	Before	1.262	1.269	1.287	1.312	1.301	1.300	1.273	1.292	1.261	1.172	-0.090	(-0.82)	0.609 ***	(2.90)
		After	0.941	1.026	1.158	1.176	1.221	1.227	1.296	1.325	1.371	1.460	0.519	(2.91)		
	Skew	Before	-0.100	-0.087	-0.085	-0.096	-0.112	-0.066	-0.095	-0.073	-0.082	-0.104	-0.005	(-0.19)	-0.037	(-0.67)
		After	-0.438	-0.380	-0.435	-0.396	-0.426	-0.427	-0.436	-0.441	-0.429	-0.480	-0.042	(0.85)		
	Kurt	Before	0.608	0.515	0.602	0.569	0.533	0.610	0.663	0.559	0.573	0.553	-0.055	(-0.71)	-0.427 *	(-1.77)
		After	1.860	1.697	1.475	1.399	1.499	1.461	1.376	1.437	1.302	1.378	-0.482	(2.11)		
Bond	Dret	Before	0.016	0.015	0.012	0.021	0.012	0.010	0.016	0.019	0.013	0.010	-0.006	(0.77)	0.013	(0.66)
		After	0.024	0.024	0.024	0.023	0.023	0.026	0.028	0.026	0.031	0.031	0.007	(0.50)		
	AR1	Before	0.083	0.055	0.063	0.076	0.051	0.088	0.058	0.075	0.089	0.070	-0.013	(0.73)	-0.025	(-1.01)
		After	0.104	0.122	0.123	0.113	0.109	0.110	0.087	0.100	0.086	0.066	-0.038	(2.33)		
	Std	Before	0.253	0.239	0.209	0.185	0.204	0.222	0.202	0.217	0.222	0.225	-0.028	(0.74)	0.215	(1.89)
		After	0.254	0.206	0.176	0.181	0.201	0.220	0.241	0.258	0.317	0.441	0.187	(2.21)		
	Skew	Before	-0.135	0.144	0.000	0.125	0.271	-0.053	0.037	0.141	0.145	0.110	0.245	(1.91)	-0.297 *	(-2.04)
		After	-0.192	-0.279	-0.359	-0.219	-0.282	-0.297	-0.202	-0.337	-0.342	-0.244	-0.052	(0.63)		
	Kurt	Before	1.353	2.242	1.777	2.609	2.661	2.206	1.871	2.281	2.398	1.443	0.090	(0.16)	-0.856	(-1.41)
		After	3.208	3.171	3.277	2.838	3.183	3.335	3.094	3.206	3.447	2.442	-0.766	(2.32)		

Table A2. Predicting Future Fund Return and Risk Taking with Flow

This table shows the panel regressions of how past flow predicts funds' future performance and risk taking measured by daily return standard deviations. The model specification is:

$$\text{Ret (Std)}_{i,t+k} = \alpha + \beta_1 \cdot \text{Platform}_{i,t-1} + \beta_2 \cdot \text{Flow}_{i,t-1} + \beta_3 \cdot \text{Platform}_{i,t-1} \times \text{Flow}_{i,t-1} + \sum_k \gamma_k \cdot \text{Control}_k + \varepsilon_{i,t},$$

where $\text{Ret}_{i,t+k}$ refers to fund i's quarterly return (%) in quarter $t+k$. $\text{Std}_{i,t+k}$ refers to fund i's daily return standard deviation (%) in quarter $t+k$. We annualize the daily return standard deviation by multiplying with $\sqrt{250}$. We regress future fund returns and standard deviations on quarter t fund flow, $\text{Platform}_{i,t-1}$ dummy, and the interactions of the two. We include controls of fund size, age, flow, and fees at the end of quarter t. Time fixed effects and style fixed effects are included for all specifications. The standard errors are clustered at the fund level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Future Quarterly Return			Annualized daily return Std.		
	1st Qtr.	2nd Qtr.	3rd qtr.	1st Qtr.	2nd Qtr.	3rd qtr.
Platform×Flow	-0.004	0.001	-0.002	-0.002	-0.005	-0.004
	(-1.00)	(0.22)	(-0.58)	(-0.77)	(-1.28)	(-1.33)
Platform	0.131	0.037	0.171	0.737**	0.715	0.566
	(0.37)	(0.15)	(0.50)	(2.11)	(1.65)	(1.60)
Flow	0.003	-0.001	0.000	-0.008	-0.003	-0.001
	(0.55)	(-0.61)	(-0.18)	(-1.36)	(-0.84)	(-0.45)
Log(Size)	-0.093	-0.093	-0.089	-0.075	-0.006	0.042
	(-1.23)	(-1.21)	(-1.05)	(-0.76)	(-0.06)	(0.52)
Log(Age)	-0.593*	-0.474	-0.384	0.200	0.026	-0.018
	(-1.71)	(-1.42)	(-1.34)	(0.52)	(0.08)	(-0.06)
Management Fee	-0.128	-0.114	-0.027	-0.459	-0.434	-0.414
	(-0.98)	(-1.04)	(-0.24)	(-1.39)	(-1.36)	(-1.31)
Subscription Fee	-0.549	-0.546	-0.437	-4.925***	-4.663***	-4.257***
	(-0.72)	(-1.05)	(-0.90)	(-5.05)	(-4.89)	(-5.25)
Redemption Fee	1.354	-0.404	-0.909	12.484***	12.395***	12.496***
	(1.35)	(-0.45)	(-0.88)	(9.68)	(11.62)	(13.05)
Time FE, Style FE	Y	Y	Y	Y	Y	Y
Observations	26249	26089	25983	25458	25406	25360
R^2	0.537	0.544	0.556	0.714	0.721	0.737

Table A3. Determinants of Entrance onto Third-Party Online Platforms

This table reports the cross-sectional determinants regression for funds and families' entrance onto third-party online platform. Column (1) and (2) includes all the funds with existence before the end of 2012. Column (3) and (4) includes all the families with existence before the end of 2012 and have at least three funds in our sample. D(Enter≤2013Q1) is a dummy variable that equals one if the fund or family enters onto Tiantian on or before March 31, 2013. Log(Enter months) is the natural logarithm of the number of months from March 2012 to the time the fund first being covered by Tiantian. Bank-affiliated is a dummy variable that equals one if the controlling shareholder (>30% ownership) is a bank, and similarly for Broker-affiliated. We also include control variables of RetailRatio, which is the fraction of funds (in percentage) held by individual investors at the end of June 2012, past twelve month return by the end of June 2012 ($MRet_{t-1,t-4}$), natural logarithm of fund size, fund 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 for heteroscedasticity-robust standard errors. *, **, 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	-2.028***	0.385***	-2.591**	0.202
	(-4.66)	(5.74)	(-2.24)	(0.60)
Broker-affiliated	0.062	0.046	1.295	-0.273
	(0.29)	(1.18)	(1.25)	(-1.25)
RetailRatio	-0.012**	0.003***	-0.139***	0.003
	(-2.46)	(3.49)	(-3.02)	(0.60)
Log(Size)	-0.273***	0.058***	-0.543	0.146
	(-3.28)	(3.82)	(-1.14)	(1.29)
Log(Age)	0.495	-0.135**	1.67	-0.143
	(1.64)	(-2.54)	(0.87)	(-0.46)
$Flow_{t-1}$	0.007***	-0.001***	0.079	0.004
	(3.06)	(-3.39)	(1.07)	(0.62)
$MRet_{t-1,t-4}$	0.343*	-0.019	2.316	-0.004
	(1.75)	(-0.52)	(1.29)	(-0.02)
$Std_{Mret,t-1,t-8}$	-0.091	0.01	0.606	0.113
	(-0.70)	(0.43)	(0.50)	(0.80)
Management Fee	-0.667	0.109	2.047	-0.702
	(-0.59)	(0.47)	(0.50)	(-0.90)
Subscription Fee	-0.558*	0.016	0.46	0.027
	(-1.91)	(0.32)	(0.23)	(0.06)
Redemption Fee	0.06	-0.068	6.172	-0.377
	(0.11)	(-0.84)	(1.31)	(-0.40)
Style FE	Y	Y	Y	Y
Observations	456	454	60	60
R^2	0.110	0.170	0.339	0.151