informs
https://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Vol. 70, No. 10, October 2024, pp. 6897–6916
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Smartphone Trading Technology, Investor Behavior, and Mutual Fund Performance

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Received: June 26, 2021
Revised: June 21, 2022; March 28, 2023
Accepted: May 29, 2023
Published Online in Articles in Advance: November 28, 2023

https://doi.org/10.1287/mnsc.2021.02099

Abstract. Using proprietary individual-level trading data around a natural experiment—the release of a smartphone trading app by a large investment advisor—this study investigates how smartphone trading technology affects retail investor behavior and mutual fund performance. App adoption by retail investors leads to an increase in investor attention and trading volume. App adopters' flows become more sensitive to short-term fund returns and market sentiment, resulting in higher aggregate flow volume among adopters. The funds more exposed to the shock experience a greater decline in abnormal returns, likely attributable to higher fund flow volume and liquidity costs. As a result, both adopters and nonadopters experience a decline in their mutual fund investment returns.

History: Accepted by Lin William Cong, finance.
Funding: The W. Edwards Deming Center and the Eugene Lang Entrepreneurship Center at Columbia University provided funding to support this research.
Supplemental Material: The online appendices and data files are available at https://doi.org/10.1287/mnsc.2021.02099.

Keywords: smartphone technology • investment • mutual fund • fintech • investor behavior

1. Introduction

The rise of financial technology in recent decades has transformed the way people access financial services, but our understanding of how technology influences the decisions of financial market participants and security prices remains limited. This study addresses these questions by examining the impact of an important technological innovation: smartphone trading. The number of smartphone users is projected to reach 4.5 billion worldwide by 2022 (Lee et al. 2022). The surge in smartphone use has led to a boom in mobile trading applications, which have enabled investors to access market information and trade financial securities more conveniently. Smartphone trading has become a substantial force in financial markets,[1] which has the potential to affect not only the trades of individual stocks but also those of diversified investment products such as mutual funds. Although recent studies primarily focus on the impact of smartphone technology on the trading of individual stocks (Barber et al. 2022, Welch 2022), its effect on funds remains relatively unexplored. Using proprietary individual-level transaction records from a large investment advisor (hereafter, the Advisor), this paper investigates how the adoption of smartphone trading technology by mutual fund investors influences retail investor behavior and mutual fund performance.[2]

How "going mobile" affects investor trading decisions and mutual fund performance is an open question. On the one hand, traditional personal computer (PC) trading already provides high-speed execution with low transaction costs. The incremental cost reduction associated with going mobile may not significantly affect investor trading decisions if the trading apps provide the same information content as PC platforms.[3] On the other hand, the convenient access and intuitive interface of the smartphone apps may lead to increased usage of a trading platform and heightened investor attention. This greater exposure to market information may amplify trading patterns of mutual fund investors (e.g., flow-performance sensitivity), which could result in higher flow volume and liquidity costs at the mutual fund level (Edelen 1999, Coval and Stafford 2007).

To investigate the effect of smartphone trading on investor behavior and fund performance, I explore the release of a smartphone trading app by one of China's largest investment advisors as a shock to investors' adoption of smartphone trading technology. The app provides investors with a more flexible way to access market information and execute trades compared with the existing online trading platform for PCs. I start by using a difference-in-differences (DID) framework to compare the behavior changes of app adopters (investors who switched from PC trading to the app) and matched nonadopters (investors who continued to use only the traditional online platform) following the release of the app. This approach enables me to isolate the incremental effect of going mobile while controlling for investor heterogeneity and some key trading platform features (e.g., transaction fees and execution speeds).

My analysis indicates that following the release of the app, adopters demonstrate a significant increase in attention, as measured by the number of logins to the trading platform, as well as in trading volume, relative to nonadopters with similar predetermined characteristics. Interestingly, going mobile also affects adopters' responses to short-term market signals. For example, relative to nonadopters after the shock, the adopters' flow displays significantly higher sensitivity to fund returns in the previous week, which has not been previously documented. Additionally, adopters' flow sensitivity to market sentiment increases compared with that of nonadopters. Further analyses based on the cross-individual variation in incremental attention suggest that increased investor attention likely contributes to the observed changes in trading behavior.

The previous analysis has one caveat—investors may self-select into adopting the app, leading to endogeneity concerns. To address this issue, I use the variation in treatment intensity around the border between two provinces differentially exposed to the technology shock. The variation in exposure arises from the heterogeneity in mobile network quality and smartphone penetration rates across provinces.[4] Specifically, I compare investors living in pairs of neighboring prefectures[5] that share a border but belong to different provinces with varying smartphone penetration rates. Prior to the shock, these investors had similar observable characteristics, except for the exposure to the technology shock. After the shock, these investors' trading behavior diverges, lending support to the causal interpretation of the app's impact on investor attention, trading volumes, and (weekly) flow sensitivity to fund performance and market sentiment.

One natural question is whether the changes in investor behavior can have a significant impact on the mutual funds as a whole. One possibility is that the increased trading comovement among individual investors leads to a higher volume of fund flows, which in turn could result in greater liquidity costs for mutual funds. To investigate the technology's impact on fund flows, I first compare adopters with nonadopters in terms of the aggregate flows around the time of the app's release. I find that the absolute value of aggregate flows from adopters more than doubles, and adopters' incremental flows are significantly higher than those of nonadopters. Second, I explore the differences in technology exposure across mutual funds. I create three proxies for such exposure based on investors' app adoption rates, predetermined investor-type composition, and predetermined geographic distribution of investors. My analysis reveals a significant increase in the absolute value of fund flows after the app's release, and this increase is more pronounced in the mutual funds with high technology exposure. These findings suggest that the app's release has an amplifying effect on the volume of flow at the fund level.

To understand whether the increase in fund flow volume results in lower fund performance, I compare funds with different technology exposure levels in terms of the change in abnormal returns around the shock. The analysis reveals that the funds available on the app experience a significant decline in abnormal returns after the shock. Regardless of the technology exposure measures, the reduction in abnormal returns is particularly pronounced among the high-exposure funds, consistent with a causal interpretation of the fund performance effect.

The concurrent increase in fund flow volume and decrease in returns suggests that the heightened liquidity costs arising from increased app flows likely contribute to the decline in fund performance. To further support the liquidity cost mechanism, I document a negative association between the absolute value of fund flows and the fund returns during the subsequent week in the postshock period. In addition, the treatment effects of the technology on fund returns become weaker after controlling for the absolute value of aggregate fund flows in the previous week, suggesting that the heightened volume of fund flow partly explains the deterioration in fund performance. Overall, these results are consistent with the liquidity cost mechanism.[6]

This paper makes several contributions to the literature. First, it is the first study, to my knowledge, that examines the impact of smartphone trading technology on mutual funds. Evidence on how smartphone trading affects security prices or fund performance remains scarce, likely due to data constraints. This study uses proprietary data that provides individual-level login and trading records, enabling me to identify the trades of app users and investigate the aggregate effects of smartphone trading technology on the pricing of mutual fund shares. Also, the DID design employed in this study allows me to connect increased investor attention and changes in trading behavior to the fund performance effect.

Second, this study contributes to the literature on how technology affects investors' trading behavior. Prior studies have documented that investors trade more frequently after transitioning from telephone trading to an Internet platform (Barber and Odean 2002, Choi et al. 2002). However, what we learned about the shift from telephone to online trading does not necessarily carry over to smartphone trading. Given that the Internet already provides high-speed execution with low trading costs, it is unclear whether the migration from PCs to smartphones has marginal effects (Liao et al. 2021). The results of this study suggest that the migration to smartphone trading significantly affects investors' trading behavior and amplifies investors' response to short-term market trends and fund returns.

Several recent studies also address the broad theme of smartphone trading and FinTech. Welch (2022) focuses on the collective stock investment of Robinhood users and finds these users' portfolios tilt toward high-volume stocks and large firms. Using similar data, Barber et al. (2022) document how app notifications, such as displaying "top movers," affect investor trading decisions. Additionally, Ozik et al. (2021) document an increase in retail trading during the COVID-19 pandemic lockdown. Using transaction-level data, Kalda et al. (2021) show that investors purchase more lottery-like assets on smartphones than on nonsmartphone platforms. In a contemporaneous study, Hong et al. (2021) focus on digital payment technology's spillover effect on risky investment participation. D'Acunto et al. (2021) study the effect of adopting a FinTech app that provides households with peers' spending information. In comparison, this study departs from the literature by examining how smartphone trading technology affects mutual fund investors' response to market information and how the investor behavior changes affect mutual fund performance. Also, the granular data and empirical setting used in this study enable me to conduct a geographic variation analysis to shed light on causal inferences.

The remainder of this paper is organized as follows: Section 2 discusses the institutional background; Section 3 details the research design and the empirical results on how smartphone trading technology affects investor behavior; Section 4 analyzes the technology's effect on fund flow and performance and its implications on individual wealth; and Section 5 concludes.

2. Institutional Background and Data

2.1. Empirical Setting

This study focuses on the mutual fund industry and explores the release of a smartphone trading app by one of the largest mutual fund management companies in China. The mutual fund industry in China operates similarly to that in the United States, with open-ended investment funds that are professionally managed and pool funds from numerous investors. The focal company, the Advisor, managed more than 300 billion RMB (approximately $43 billion USD) in assets by the end of 2017 through 65 different mutual funds, including equity, bond, hybrid, and money market funds. About 73% of the holdings in these funds were purchased through the Advisor's direct sales platform, which allows investors to trade the company's mutual funds directly without involving an external distributor.[7]

The smartphone trading app is an integral part of the Advisor's direct sales platform, and it enables investors to trade all mutual funds provided by the Advisor, but no other assets, through the app.[8] This app is different from more generic trading apps provided by brokerage firms like Robinhood because it exclusively serves the mutual fund investors of the Advisor, and it does not provide access to mutual funds in other fund families or nonmutual fund assets.

Before the launch of the smartphone app, investors had two methods to access the direct sales platform. The primary method involves visiting the official website through an Internet browser, mostly through PCs. Similar to the smartphone app, the official website provides access exclusively to the mutual funds managed by the Advisor and no other assets. A visit to the website allows investors to trade mutual fund shares and access information such as market updates, fund profiles, and fund performance. The second method is through a web-based client terminal designed for feature phones, which investors rarely use due to its slow and unstable connection. Even before the release of the app, investors widely adopted the direct sales platform. By trading fund shares through direct sales, investors incur lower transaction fees than when using external distribution channels such as banks and securities companies. This makes the direct sales channel particularly attractive to investors who are sensitive to transaction costs.[9]

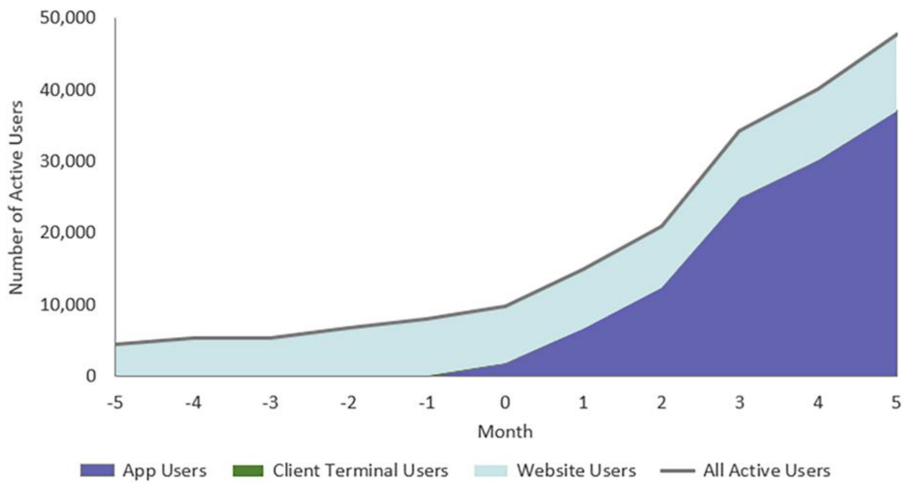
In September 2013, the Advisor made a major upgrade to the direct sales platform with the launch of a smartphone app. However, trading through the official website remained unchanged. The app offers comprehensive services and is a significant improvement over the web-based client terminal in several ways. First, the app is faster and more reliable than the client terminal as it works in tandem with local devices rather than relying on a remote server. Second, the app has a more intuitive and user-friendly interface, allowing users to conveniently monitor portfolios, place orders, and obtain information. Finally, the app streamlines wire transfers between trading and bank accounts, improving efficiency for investors.

The desirable features of the app quickly enticed many investors to adopt it. As shown in Figure 1, the growth in the number of active users[10] on the platform significantly accelerated following the launch of the smartphone app. Within three months of its debut, the number of active users more than tripled, primarily due to the expansion of app users after the technology shock.[11]

The app and the website have many similarities. For example, both allow investors to trade only mutual funds managed by the Advisor and transfer money in and out of the investment accounts. Both also provide information such as asset balances, portfolio performance, transaction history, fund profiles, and market performance.

However, there are two key differences between the app and the website. First, the app provides more convenient access to the direct sales platform, allowing users to access information and trade mutual fund shares from

Figure 1. (Color online) Number of Active Users on the Direct Sales Platform



Notes. The figure displays monthly active users of the direct sales platform before and after the release of the smartphone trading app. The horizontal axis represents the month relative to the app's release. The vertical axis represents the number of investors who logged into the platform (through the official website, the client terminal, or the smartphone trading app) at least once during a given month and the number of users who primarily log in through the app, website, and client terminal, respectively.

any location covered by a mobile network. The convenience may affect investors' trading behavior by increasing investors' attention to fund investment. Second, the app presents information in a different format than the website due to the smaller screens of smartphones. Prior studies find the information presentation format may affect investors' behavior. For instance, D'Acunto and Rossi (2021) show differences in the graphical features of information can change people's interpretation of the information and may be interpreted as robo-advising. D'Acunto et al. (2021) find graphics that show peers' and users' spending can affect users' spending decisions.

Online Appendix A presents a detailed comparison of the information content and display of the app and the website. Overall, the information content available on the app is comparable to that on the website. Because of the smaller screen size of smartphones, the app typically provides less-detailed information on each screen and instead uses buttons that direct users to additional screens with more information. The app may also use notification functions to deliver information.[12] These disparities, combined with the convenience of accessing information and trading, could contribute to behavior changes of app adopters.

The introduction of the smartphone app offers a natural empirical setting to study the impact of smartphone trading technology on both investor behavior and mutual fund performance. By using proprietary transaction records at the individual level, I am able to track investors' trading behavior over time and investigate how the technology affects investors' behaviors. Additionally, the varying levels of exposure to the app across different mutual funds allow me to examine how the technology affects mutual fund performance.

2.2. Data and Overview

My analysis builds on a proprietary administrative database that contains all transactions made by retail investors with the Advisor from 2012 through 2014. In the raw data, each transaction record includes the trade date, internal customer ID, mutual fund ticker, number of shares bought or sold, and transaction prices.[13] The Advisor also provides login records for a randomized 20% sample of direct sales platform users, with complete login records available daily. The data track investors' logins on the direct sales platform through both the website and the app, which is an important data input for measuring investor attention and app usage. The data are anonymized and does not contain any identifying information about individual investors. I aggregate the transaction and login records to investor-week-level panel data to analyze the evolution of investor attention and trading behavior around the app's release. Additionally, the data are aggregated to the investor-fund-week level to examine how the shock affects investor flow sensitivity to mutual fund performance and market sentiment. The analysis is supplemented by the mutual funds' weekly return data from the Wind database.

The data set used in this study also includes individual characteristics such as age, gender, education, occupation, and county/prefecture of residence, which were collected when investors opened investment accounts. The residence location information is particularly useful for conducting a geographic variation analysis to draw causal inferences.

This study focuses on mutual funds that primarily invest in equity markets. This filter yields a sample of 27 equity and hybrid mutual funds managed by the Advisor. The analysis focuses on retail investors who conducted at least one transaction for the mutual funds in the sample during the preshock period (January 2012 to August 2013) and used the direct sales platform in the same period. This process results in a sample of 51,771 investors, of which 22,550 adopted the smartphone trading app after the shock during the sample period.

Panel A of Table 1 provides the summary statistics for the mutual funds and investors in the main sample. An average mutual fund in the sample managed 3.2 billion RMB at the end of 2012, with 85% of the fund invested in equities. The management fee for a typical fund in the sample is 1.5% of assets under management (AUM), and the custodian service fee is 0.25%, which are consistent with prevailing fees in the same asset classes. At the end of 2012, retail and institutional investors held 81% and 19% of the fund shares, respectively. During the sample period, an average mutual fund delivered an annual gross return of 9% (0.75% × 12) and earned an abnormal return of 0.5% based on the Carhart four-factor model (Carhart 1997). All unbound variables are winsorized at the percentiles of 0.5 and 99.5.

A typical retail investor in the sample is middle-aged, with an average age of 42 when the smartphone app was released. About half of the investors are female. An average investor who self-reports the education level claims to hold an associate's degree at the time of account opening. About 40% of a fund's existing investors adopted the app by the end of 2014. Before the app's release, an

Table 1. Summary Statistics

Panel A: Summary statistics	Mean (1)	Standard deviation (2)	Minimum (3)	25th percentile (4)	Median (5)	75th percentile (6)	Maximum (7)
AUM (billion RMB)	3.19	3.87	0.13	0.45	2.60	3.81	13.67
FundAge	4.32	2.07	1.53	2.73	3.98	5.86	8.07
% Equity	85.35%	7.41%	69.25%	80.41%	85.51%	91.29%	94.95%
Management Fee	1.28%	0.38%	0.50%	0.90%	1.50%	1.50%	1.50%
Custodian Fee	0.22%	0.06%	0.10%	0.25%	0.25%	0.25%	0.25%
% Retail Investors	81.34%	25.08%	25.21%	62.03%	80.39%	91.09%	99.49%
% App Adopters	39.42%	30.07%	12.85%	23.36%	40.99%	52.18%	72.15%
MonthlyGrossReturn	0.75%	4.76%	−15.32%	−2.18%	1.13%	3.46%	15.07%
Ret^{sec} (weekly)	0.04%	1.56%	−14.04%	−0.49%	0.00%	0.56%	10.35%
Ret^{pri} (weekly)	0.06%	1.92%	−16.00%	−0.56%	0.01%	0.64%	12.83%
Ret^{style} (weekly)	0.07%	1.78%	−8.72%	−0.73%	0.02%	0.81%	10.09%
AbnRet_Fund (three factors, weekly)	0.07%	1.89%	−17.13%	−0.76%	0.07%	0.86%	18.88%
AbnRet_Fund (four factors, weekly)	0.01%	1.51%	−10.24%	−0.69%	0.02%	0.71%	13.25%
Sentiment	0.35	0.03	0.31	0.32	0.34	0.37	0.45
Investor characteristic							
Age	41.82	11.55	22.00	33.00	40.00	49.00	78.00
Male	0.52	0.50	0.00	0.00	1.00	1.00	1.00
Education	2.67	0.74	1.00	2.00	3.00	3.00	5.00
D^{adopt}	0.40	0.49	0.00	0.00	0.00	1.00	1.00
Account Size (in thousand shares)	37.58	144.64	0.16	3.90	10.71	29.66	744.95
Login (weekly, preshock)	0.84	4.76	0.00	0.00	0.00	0.00	81.00
Volume (weekly, preshock)	300.09	3061.09	0.00	0.00	0.00	0.00	26,110.25
NetFlow_Indiv (weekly)	−0.05%	15.75%	−100.00%	0.00%	0.00%	0.00%	98.49%
Prate	0.17	0.11	0.05	0.07	0.12	0.25	0.37

Panel B: Matched-sample balance on predetermined characteristics	Adopter (1)	Nonadopter (2)	Difference (3)	*p* value (4)
Age	36.00	37.51	−1.51	0.13
Male	0.61	0.61	0.00	0.86
Education	2.74	2.65	0.09	0.14
LoginPre (monthly)	7.60	6.78	0.82	0.39
VolumePre (monthly)	2,051.26	2,003.82	47.44	0.94
Account Size (in thousand shares)	40.93	37.85	3.08	0.66
No. of individuals	13,354	11,482		

Notes. Panel A reports the summary statistics of the mutual funds and the retail investors in the full sample. Panel B compares the adopters with nonadopters in the matched sample on predetermined individual characteristics. Columns (1) and (2) report the mean of the matched adopters and nonadopters, respectively. Columns (3) and (4) present the estimated difference between the two groups and the corresponding *p* value. Table IA1 in the online appendix defines all variables.

*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

average investor logged into the direct sales platform (mostly through PCs) 0.84 times per week and held 38,000 fund shares in the account. Typically, an investor rebalanced every three months and traded 300 shares per week before the shock. During the sample period, an average investor sold 0.05% of the investment in a week.

3. Smartphone Trading and Investor Behavior

A natural starting point for understanding how smartphone trading technology affects financial markets is to investigate its effect on the trading behavior of investors who adopt the technology. This section presents the empirical strategy and the baseline results before delving into a geographic variation analysis to shed light on the causal effect of going mobile on investor behavior.

3.1. Effect of Smartphones on Attention and Trading Intensity

The impact of smartphone trading technology on investor behavior is not yet clear. On the one hand, traditional online trading via PCs already involves low transaction costs and high execution speeds, so the further reduction in costs (mostly nonpecuniary) brought about by smartphone trading technology may have little incremental effect on investor behavior. On the other hand, the convenient access to the user-friendly trading app may change investor behavior, for example, by triggering addictive use of the app. The resulting increase in attention to market signals may create an illusion of knowledge, which may in turn induce investors to trade excessively (Barber and Odean 2000, 2001b).

To begin, I analyze the impact of smartphone trading technology on two aspects of investor behavior: investor attention and trading intensity. Using a DID framework, I compare the existing investors who switched from the official website to the smartphone trading app (adopters) with investors who continued to use only the official website (nonadopters), before and after the smartphone app's release.[14]

A potential concern is that the app adopters may differ fundamentally from nonadopters.[15] To mitigate this issue, I match the adopters with nonadopters based on a set of predetermined characteristics, including age, education, gender, county of residence, trading account value at the time of the app's release, and the average monthly trading volume before the shock. I use a one-to-one nearest-neighbor matching with replacement, requiring the county of residence and gender to be matched exactly. This matching procedure implicitly requires that all individuals in the matched sample have nonmissing values for the above characteristics, resulting in a sample of 13,354 adopters and 11,482 nonadopters.[16]

Panel B of Table 1 shows the balance of the two groups. Columns (1) and (2) display the mean value of predetermined characteristics for adopters and nonadopters, respectively. Columns (3) and (4) show the differences between the two groups and the corresponding p-value. The two groups do not exhibit significant differences in any of the characteristics.

To examine how the two groups diverge in behavior around the shock, I estimate a DID model:

$$Outcome_{i,t} = \alpha_i + \alpha_t + \beta_1 D_t^{post} \times D_i^{adopt} + \varepsilon_{i,t}, \qquad (1)$$

where i and t represent an individual and a week, respectively. The variable D_i^{adopt} is a dummy variable equal to one if investor i adopts the app after its release (i.e., an adopter), and zero if the investor continues to use only the official website (i.e., a nonadopter). D_t^{post} is a dummy variable equal to one after the shock and zero otherwise. To control for investor heterogeneity, I include individual fixed effects (α_i) in the regression. I also incorporate year-week fixed effects (α_t) to control for the macroeconomic trend.

Two outcomes of interest emerge. The first is $Login_{i,t}$, which is the number of logins made by investor i (either through the website or an app) to the direct sales platform during week t. Following Karlsson et al. (2009) and Sicherman et al. (2015), I use logins to the direct sales platform as a proxy for investor attention.[17] To account for the count nature of *login*, I use a Poisson model to estimate the investor attention effect, where the dependent variable $Login_{i,t}$ is assumed to be Poisson distributed with a mean equal to $e^{\alpha_i+\alpha_t+\beta_1 D_t^{post} \times D_i^{adopt}}$. The second outcome of interest is $Volume_{i,t}$, which is the number of fund shares investor i trades during week t. Because *Volume* is skewed, I use the logarithm of $Volume_{i,t}$ after adding one as the outcome variable in Equation (1). β_1 captures the change in the logarithm of *Login* (*Volume*) for adopters around the shock, relative to the prepost change for nonadopters. Panel A of Table 2 reports the results.[18]

In column (1), the estimated effect on the total number of logins for investors is reported using a Poisson model with the matched sample. The coefficient on $D^{post} \times D^{adopt}$ is significantly positive at the 1% level, indicating that the app adopters pay more attention to fund investment after the shock compared with nonadopters who are similar to them ex ante. Specifically, the login frequency for adopters increases by 163% ($e^{0.966} - 1$) from the preshock level relative to the matched nonadopters. In column (2), I examine the impact of the technology on investors' weekly logins through the app (or the client terminal). The outcome variable captures the number of logins through the client terminal for the preshock period, whereas it captures the number of logins through the smartphone app and the client terminal for the postshock period. Column (3) focuses on logins through the official website. The significantly positive coefficient on $D^{post} \times D^{adopt}$ in column (2) and the insignificant corresponding coefficient in column (3) suggest that the effect is mainly explained by the increased logins via the smartphone app rather than the official website.

Table 2. Impact of Smartphone Trading Technology on Investor Behavior

Panel A: Investor attention and trading intensity

	Login	*Login*		*log*(*Volume* + 1)	
		Mobile app	Website		
	Poisson model	Poisson model		Linear model	
	(1)	(2)	(3)	(4)	(5)
$D^{post} \times D^{adopt}$	0.966***	2.882***	0.035	0.703***	0.692***
	[0.061]	[0.308]	[0.042]	[0.076]	[0.076]
$D^{post} \times D^{adopt} \times Quintile(\Delta Login)$					0.353***
					[0.028]
$D^{post} \times LoginPre$	−0.020***	−0.020***	−0.021***	−0.019***	−0.019***
	[0.005]	[0.003]	[0.003]	[0.004]	[0.004]
$D^{post} \times Age$	0.020***	0.024***	0.019***	0.018***	0.018***
	[0.002]	[0.003]	[0.002]	[0.004]	[0.004]
$D^{post} \times Male$	−0.184***	−0.179***	−0.188***	−0.161**	−0.161**
	[0.039]	[0.044]	[0.042]	[0.067]	[0.067]
$D^{post} \times Education$	0.046***	0.042***	0.049***	0.034	0.034
	[0.014]	[0.016]	[0.017]	[0.024]	[0.024]
No. of observations	3,179,008	3,179,008	3,179,008	3,179,008	3,179,008
No. of investors	24,836	24,836	24,836	24,836	24,836
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year-week fixed effects	Yes	Yes	Yes	Yes	Yes
Observation level	Individual-year-week				

Panel B: Investor flow-performance sensitivity

	NetFlow_Indiv					
	Secondary	Primary	Style	Secondary		
	Weekly			Biweekly	Monthly	Weekly
	(1)	(2)	(3)	(4)	(5)	(6)
$D^{adopt} \times D^{post} \times Ret_{t-1}$	0.629***	0.516**	0.452*	0.431*	0.259	0.611***
	[0.237]	[0.217]	[0.263]	[0.247]	[0.409]	[0.237]
$D^{adopt} \times D^{post} \times Ret_{t-1} \times Quintile(\Delta Login)$						0.259***
						[0.038]
$D^{post} \times Ret_{t-1}$	−0.139	−0.081	−0.041	−0.273	−0.448	−0.139
	[0.199]	[0.182]	[0.251]	[0.203]	[0.314]	[0.199]
$D^{adopt} \times Ret_{t-1}$	−0.294	−0.232	−0.106	−0.188	−0.131	−0.294
	[0.224]	[0.204]	[0.268]	[0.226]	[0.349]	[0.224]
$D^{adopt} \times D^{post}$	−0.001	−0.001	−0.001	0.000	0.001	−0.001
	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]
Ret_{t-1}	0.371	0.299	0.255	0.409*	0.689***	0.371
	[0.241]	[0.212]	[0.242]	[0.215]	[0.264]	[0.240]
No. of observations	16,011,160	16,011,160	16,011,160	8,005,562	3,735,924	16,011,160
No. of investors	24,836	24,836	24,836	24,836	24,836	24,836
Individual-fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 2. (Continued)

Panel B: Investor flow-performance sensitivity

	NetFlow_Indiv					
	Secondary	Primary	Style	Secondary		
	Weekly			Biweekly	Monthly	Weekly
	(1)	(2)	(3)	(4)	(5)	(6)
Year-week fixed effects	Yes	Yes	Yes	No	No	Yes
Year-fortnight fixed effects	No	No	No	Yes	No	No
Year-month fixed effects	No	No	No	No	Yes	No
Observation level	Individual-fund-year-week			Individual-fund-year-fortnight	Individual-fund-year-month	Individual-fund-year-week

Panel C: Investor flow sensitivity to market sentiment

	Net flows at the individual level		
	(1)	(2)	(3)
$D^{adopt} \times D^{post} \times Sentiment_{t-1}$	0.099**	0.099**	0.098**
	[0.049]	[0.048]	[0.048]
$D^{adopt} \times D^{post} \times Sentiment_{t-1} \times Quintile(\Delta Login)$			0.037***
			[0.012]
$D^{post} \times Sentiment_{t-1}$	−0.030		−0.030
	[0.054]		[0.054]
$D^{adopt} \times Sentiment_{t-1}$	−0.064	−0.064	−0.064
	[0.055]	[0.055]	[0.055]
$D^{adopt} \times D^{post}$	−0.032	−0.032	−0.032
	[0.021]	[0.021]	[0.021]
$Sentiment_{t-1}$	0.027		0.027
	[0.052]		[0.052]
D^{post}	0.008		0.008
	[0.019]		[0.019]
No. of observations	16,011,160	16,011,160	16,011,160
No. of investors	24,836	24,836	24,836
Individual-fund fixed effects	Yes	Yes	Yes
Year-week fixed effects	No	Yes	No
Observation level	Individual-fund-year-week		

Notes. Panel A reports how the app affects investor attention and trading volume at the individual-year-week level, corresponding to Equation (1). Columns (1)–(3) report estimation results based on Poisson models. The outcome variable in column (1), *Login*, is the total number of logins to the direct sales platform for an investor in a given week. The outcome variable in column (2) is the number of logins via the app (or the client terminal) for an investor in a given week. Column (3) focuses on the logins via the official website of an investor in a given week. Columns (4) and (5) report estimation results based on linear models, where the outcome variable, *log(Volume+1)*, is the logarithm of the number of fund shares an investor trades in a given week after adding 1. Panels B and C report the app's effect on investors' flow-performance sensitivity and flow-sentiment sensitivity, respectively. Columns (1)–(3) of Panel B estimate Equation (2) at the individual-fund-year-week level, where the outcome variable, *NetFlow_Indiv*, is an investor's net flow into a fund in a given week. Ret_{t-1} measures a fund's gross return relative to other funds with the same objective in week $t-1$. In columns (1), (2), and (3), Ret_{t-1} is equal to Ret^{sec}_{t-1}, Ret^{pri}_{t-1}, and Ret^{style}_{t-1}, as defined in Table IA1. Column (4) ((5)) reports an analysis similar to column (1) of Panel B using biweekly (monthly) return and investor flow data. Columns (1) and (2) of Panel C estimate variants of Equation (3) at the individual-fund-year-week level. In the last column of each panel, *Quintile*(Δ*Login*) is the *demeaned* quintile of an investor (i.e., ranging from −2 to 2) when sorted by an investor's change in the number of logins around the app's release. The outcome variable is all columns of Panel C is *NetFlow_Indiv*. Table IA1 in the online appendix defines all other variables. Standard errors are two-way clustered by individual and fortnight (month) for column (4) ((5)) of Panel B and are clustered by individual and week for all other specifications.

*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

Column (4) in Panel A of Table 2 displays the effect of the technology on investors' trading volume. The coefficient on $D^{post} \times D^{adopt}$ is significantly positive at the 1% level, indicating that investors who adopted the app trade more intensively than nonadopters after the app's release. Specifically, the coefficient suggests that there is an 102% ($e^{0.703} - 1$) increase in trading volume for app adopters around the shock relative to nonadopters. Taken together, the results imply that app adoption increases investor attention to portfolios and leads to more-intensive trading.[19]

The increased investor attention as a result of app adoption may contribute to the heightened trading volume. The incremental attention could expose investors to more market information and lead to greater trading activity in response to "signals." Also, the increased attention may create an illusion of knowledge and lead to excessive trades due to overconfidence.[20]

To investigate whether investor attention partly explains the trading volume effect, I use the variation in the extent to which investors increase attention after the shock. I conduct a triple-differences analysis, which tests whether the app adopters who increase attention to a greater extent have higher trading volumes than other adopters. The result is reported in column (5) of Table 2, Panel A. $Quintile(\Delta Login)$ is the demeaned quintile, ranging from -2 to 2, of an investor when sorted by the incremental logins around the shock. The coefficient on the triple interaction term is significantly positive, indicating that the effect is more pronounced among investors who exhibit a large increase in attention. This finding suggests that the increased attention resulting from app adoption contributes to the heightened trading volume.

3.2. Effect of Smartphones on Investors' Response to Signals

Thus far, my analysis suggests the adoption of the smartphone app by investors results in increased investor attention and trading volume. Furthermore, app adopters who increase attention to a greater extent demonstrate a more significant increase in trading volume. Given that app adopters tend to log in to the platform more frequently after the app' release, these investors are presumably exposed to more information about stock market performance and mutual fund returns. A natural question that arises is whether the adoption of the app (and the resulting increase in attention) can alter the way investors respond to information provided in the app.

In this subsection, I examine investors' flow response to two types of signals: recent fund performance and overall market sentiment. Mutual fund investors tend to invest in funds that were top performers and withdraw from funds that underperformed in the previous period (Sirri and Tufano 1998). The convenience of accessing fund performance information through the app may make such information more salient to investors and induce a greater response in trades. Furthermore, the real-time nature of the information suggests that investors are likely to increase exposure to short-term signals more than other signals. In other words, app adoption may disproportionately amplify investors' response to short-term fund performance.

To test this possibility, I examine how the smartphone trading app affects investor flow sensitivity to fund performance in the previous week. Specifically, I use a shorter horizon than what prior studies have employed, focusing on a one-week period. Following the literature (Ivković and Weisbenner 2009), I use a fund's gross return relative to other funds with the same objective as the return measure in the flow-performance-sensitivity tests.

Specifically, I estimate a triple-differences specification of the following form:

$$\begin{aligned} NetFlow\_Indiv_{i,j,t} = {} & \alpha_{i,j} + \alpha_t + \beta_1 D_i^{adopt} \times D_t^{post} \times Ret_{j,t-1} \\ & + \beta_2 D_t^{post} \times Ret_{j,t-1} + \beta_3 D_i^{adopt} \\ & \times Ret_{j,t-1} + \beta_4 D_i^{adopt} \times D_t^{post} \\ & + \beta_5 Ret_{j,t-1} + \varepsilon_{i,j,t}, \end{aligned} \tag{2}$$

where i, j, and t represent an investor, a fund, and a week, respectively. $NetFlow\_Indiv_{i,j,t}$ is defined as investor i's net flow into fund j during week t. The net investor flow is the number of shares purchased minus the number of shares redeemed during a week, divided by the number of shares an investor holds at the beginning of the week. $Ret_{j,t-1}$ measures fund j's relative return for week $t-1$. For the baseline analysis, I use $Ret^{sec}_{j,t-1}$ as the relative return measure, which is defined as fund j's gross returns in excess of the average gross returns of all funds under the same secondary category in a week. To test the robustness of the findings, I also use two alternative measures: $Ret^{pri}_{j,t-1}$, which represents fund j's gross returns in excess of the gross returns of all funds in the same primary category, and $Ret^{style}_{j,t-1}$, which represents fund j's gross returns in excess of the gross returns of all funds with the same investment style.

The key coefficient, β_1, measures the extent to which adopters increase weekly flow-performance sensitivity compared with matched nonadopters after the shock. A significantly positive β_1 would indicate that going mobile amplifies investors' flow-performance sensitivity. Panel B of Table 2 presents the result.

Columns (1)–(3) reveal a significantly positive coefficients on $D^{adopt} \times D^{post} \times Ret_{t-1}$, indicating that after the shock, adopters experience a more substantial increase in weekly flow-performance sensitivity relative to nonadopters. The insignificant coefficients on $D^{post} \times Ret_{t-1}$ imply that nonadopters' flow-performance sensitivity does not significantly change around the shock, and the divergence between the two groups is driven by adopters. The insignificant coefficients on Ret_{t-1} and $D^{adopt} \times Ret_{t-1}$ suggest neither adopters nor nonadopters respond to the previous week's fund returns before the shock, and this pattern only becomes detectable after the shock. Taken together, these findings suggest that going mobile amplifies investors' flow sensitivity to fund performance in the previous week, which has not been documented in prior research.

To examine whether the technology disproportionately affects investors' responses to short-term fund performance, I conduct a horserace analysis across return (and flow) measures with different horizons. I repeat the analysis presented in column (1) of Panel B using biweekly and monthly data, and the results are reported in columns (4) and (5), respectively. Column (4) focuses on how investor flows in a two-week period respond to the previous two weeks' fund returns, and column (5) focuses on investors' monthly flow-performance sensitivity. According to columns (1), (4), and (5), the significance level and magnitude of the coefficient on $D^{adopt} \times D^{post} \times Ret_{t-1}$ decrease monotonically with the return horizon, suggesting the technology shock has the strongest effect on investors' flow sensitivity to short-term fund performance. As the app likely increases investors' attention to recent signals more than others, this finding is consistent with the notion that increased attention contributes to the change in investors' trading pattern.

In column (6), the significantly positive coefficient on the quadruple interaction term indicates that the technology shock has a more substantial impact on the weekly flow-performance sensitivity for app adopters who experience a greater increase in attention around the shock. This finding provides further evidence that investor attention is likely a driving force behind the technology's effect on investors' flow-performance sensitivity.

To further investigate how app adoption affects investors' trading patterns, I analyze a second pattern—investors' flow sensitivity to market sentiment. Previous research indicates that noise traders tend to excessively sell (buy) assets when market sentiment decreases (increases) (De Long et al. 1990, Tetlock 2007). As mutual fund retail investors are broadly regarded as uninformed, these investors are likely to follow the market sentiment in trading behavior (Ben-Rephael et al. 2012). The app's release could amplify this pattern by increasing investors' exposure to market signals. To explore the technology's effect on investors' flow sensitivity to market sentiment, I estimate the following regression:

$$\begin{aligned} NetFlow\_Indiv_{i,j,t} = {} & \alpha_{i,j} + \beta_1 D_i^{adopt} \times D_t^{post} \times Sentiment_{t-1} \\ & + \beta_2 D_t^{post} \times Sentiment_{t-1} \\ & + \beta_3 D_i^{adopt} \times Sentiment_{t-1} + \beta_4 D_i^{adopt} \\ & \times D_t^{post} + \beta_5 Sentiment_{t-1} + \beta_6 D_t^{post} + \varepsilon_{i,j,t}. \end{aligned} \quad (3)$$

The variable $Sentiment_{t-1}$ is a measure that gauges investor sentiment in China's stock market during week $t-1$. I create the measure using the definition established in Yi and Mao (2009), which is akin to the measure used by Baker and Wurgler (2006) for the U.S. market. The coefficient β_1 captures the prepost change in investors' flow sensitivity to market sentiment for app adopters, relative to nonadopters.

Panel C of Table 2 presents the results. The coefficients on the triple interaction term in columns (1) and (2) are significantly positive, indicating that app adopters become more sensitive to market sentiment after the app's release, compared with nonadopters. The significantly positive coefficient on the quadruple interaction term in column (3) suggests that the increased investor attention likely contributes to the technology's impact on investor flow sensitivity to market sentiment.

Overall, the previous findings suggest that the adoption of smartphone trading technology leads to an amplification of shared trading patterns among retail investors, possibly due to increased investor attention. Going mobile not only increases trading volume but also alters the way investors respond to market and fund signals. The result of the horserace analysis across flow-performance sensitivities with different horizons supports the idea that app adoption increases investors' attention to short-term information more than other type of information.

3.3. Identification Concerns

The previous analyses are based on the assumption that adopters and nonadopters would have experienced similar trends in the absence of the app's release. Although the assumption is inherently nontestable without observing the counterfactual state, I examine preexisting trends to shed light on the assumption.

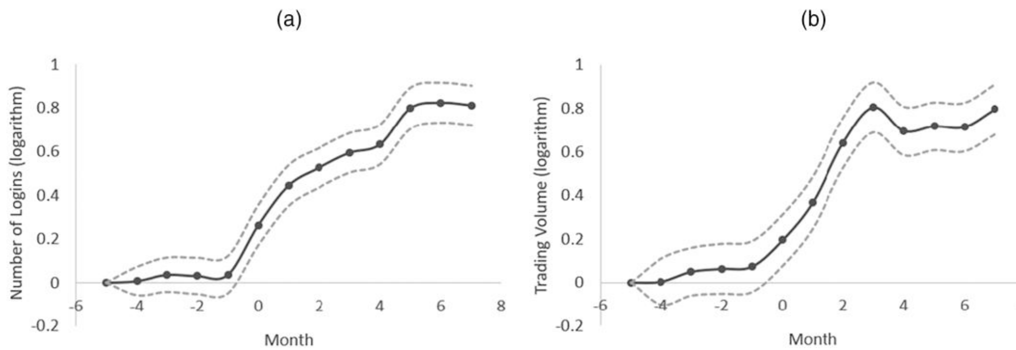
3.3.1. Parallel Trends Test. To investigate how investor behavior evolves over time around the release of the app, I estimate the dynamic effect using the following equation:

$$Outcome_{i,t} = \alpha_i + \alpha_t + \sum_{\tau=-5}^{7} \beta_\tau D_t^\tau \times D_i^{adopt} + \varepsilon_{i,t}. \quad (4)$$

The variable D_t^τ is a dummy variable that takes the value of one if month t is the τth ($-\tau$th) month after (before) the shock and zero otherwise. The coefficient β_τ represents the difference between the behavior of app adopters and nonadopters during the τth ($-\tau$th) month after (before) the shock. These estimated coefficients are then plotted in Figure 2.

Panels (a) and (b) of Figure 2 focus on investor attention and trading volume, respectively. For Panel (a), I use a Poisson model with $Login_{i,t}$ as the outcome variable, whereas the analysis in Panel (b) uses a linear model with $log(Volume_{i,t}+1)$ as the outcome variable. The horizontal axis is the month relative to the app's

Figure 2. Parallel Trends Test



Notes. This figure reports the result of the parallel trends analysis corresponding to Equation (4). The outcome variables of (a) and (b) are (the logarithms of) an investor's number of logins and trading volume in a given month, respectively. The horizontal axis represents the month relative to the app's release. The solid dots represent the difference between the adopters and nonadopters in terms of the corresponding outcome variable. The dotted lines represent the 95% confidence intervals of the estimates. (a) Investor login frequency around the shock. (b) Trading volume around the shock.

release, and the vertical axis shows the estimated β_τ for that month. The results show no significant differences between adopters and nonadopters during all months before the shock, which is consistent with the parallel trends assumption.

3.3.2. Geographic Variation Analysis. Although the parallel trends analysis is helpful for causal inference, the endogeneity of the app adoption decision can pose a challenge. Differences between adopters and nonadopters that are not observable may lead to a divergence in trading behavior after the shock. To refine the identification strategy, I explore the treatment-intensity variation around the border between two neighboring provinces that were differently exposed to the technology shock. This identification strategy relies on cross-province variation in the quality and coverage of mobile networks, which are largely determined by local carriers and the province-specific policies related to the telecommunication infrastructure.

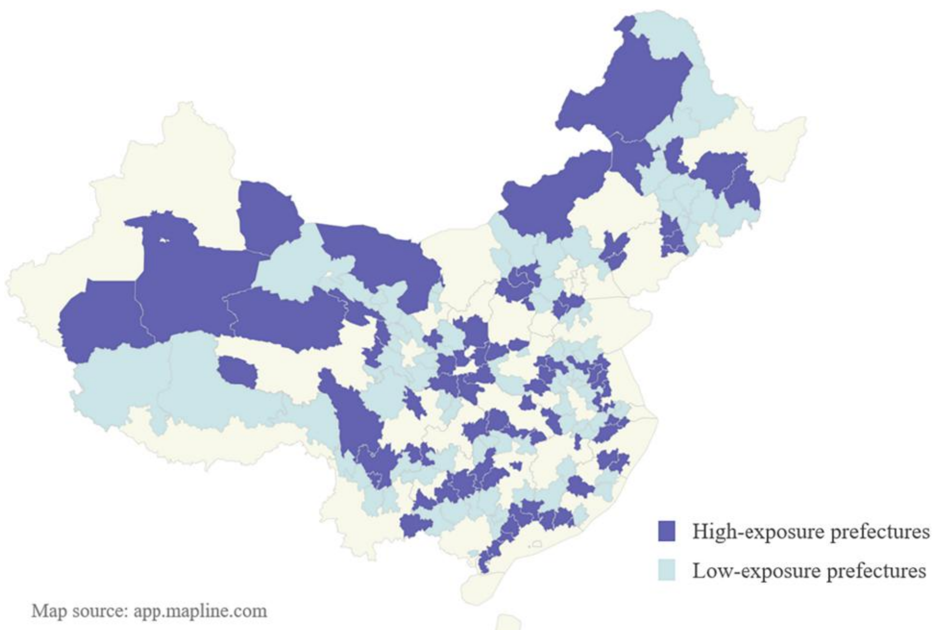
Access to high-quality mobile networks is an important factor in determining smartphone adoption rates and, subsequently, the likelihood of using a native trading app designed for smart devices. To capture this variation in technology exposure, I use the predetermined smartphone penetration rate as a proxy for the province-specific policies regarding mobile networks. As reported in Table 1, the mean smartphone penetration rate for a province was 16.6% by the end of 2011, with a standard deviation of 10.9%, providing a decent amount of variation for the analysis.[21] To refine the identification strategy, I compare mutual fund investors residing in neighboring prefectures on both sides of a border between provinces with different predetermined smartphone penetration rates. This approach is similar in spirit to a spatial regression discontinuity design (Brown and Matsa 2020). The smartphone penetration rate can also be considered as an instrumental variable for individuals' app adoption.

The analysis first identifies pairs of neighboring prefectures that share a border and belong to different provinces using data from the China Geo-Explorer platform, resulting in 262 pairs of prefectures that meet the criteria. From this set, the focus is narrowed to the 240 pairs that contain at least one retail investor in the main sample. The prefecture with the higher predetermined smartphone penetration rate is classified as "high exposure," whereas the other is classified as "low exposure" within each pair. Because a prefecture could be paired to multiple neighboring prefectures, some prefectures may be classified as high exposure in one pair and low exposure in another pair. To minimize noise, pairs containing a "mixed" prefecture or a direct-administered municipality are excluded.[22] The resulting sample consists of 146 pairs of prefectures and 10,402 investors, with 5,305 investors residing in high-exposure prefectures and 5,097 investors residing in low-exposure prefectures. A map indicating the high- and low-exposure prefectures is presented in Figure 3.

In the geographic variation analysis, it is assumed that investors in neighboring prefectures around province borders are comparable except for the exposure to the technology shock. Although testing the balance of unobservable covariates is technically infeasible, I attempt to shed light on this assumption by comparing each pair of neighboring prefectures on predetermined demographic characteristics and the trading behavior of mutual fund investors residing in them. The results are presented in Panel A of Table 3, where all the prefecture characteristics are sourced from the 2010 Population Census of China, and all predetermined retail investor characteristics are aggregated to the prefecture level.

Columns (1) and (2) show the mean value of each variable for high-exposure and low-exposure prefectures,

Figure 3. (Color online) Prefectures with High and Low Exposures to the Technology Shock



Notes. This figure illustrates the high- and low-exposure prefectures used in the geographic variation analysis.

respectively. Columns (3) and (4) present the estimated differences between the two groups and the corresponding standard deviations. The results indicate that the two groups do not exhibit significant differences in any of the prefecture characteristics or investor attributes, which is consistent with the covariate-balance assumption.

An additional identification assumption is that retail investors cannot perfectly manipulate the province of residence in anticipation of the technology shock. This assumption is likely to hold due to the significant costs involved in reallocating across provinces in China, including those associated with the household registration system ("Hukou"). For example, moving out of a registered province may result in parents losing access to public education for children, and obtaining residency in a different province may take many years, depending on provincial policies (Zhou and Cheung 2017). These factors make it unlikely that investors could perfectly manipulate the province of residence in this setting.

Having verified the identification assumptions, I conduct an analysis to investigate the impact of a province's smartphone penetration rate on investors' adoption of the trading app. Column (1) of Panel B in Table 3 reports the result. In this analysis, I use *PRate*, the smartphone penetration rate in 2011 for the province where an investor resides at the account opening, as the main explanatory variable. The analysis also incorporates predetermined control variables, including *LoginPre*, *Age*, *Male*, *Education*, and *Account Size*, as defined in Table IA1 in the online appendix. The significantly positive coefficient on *PRate* indicates that high-exposure investors are more likely to adopt the app than low-exposure counterparts. This finding suggests that the smartphone penetration rate is a valid proxy for an investor's exposure to smartphone trading technology.

Based on this premise, I compare the behavior of investors in each pair of prefectures around the technology shock. Panel B of Table 3 presents the results. Column (2) reports the effect on investors' logins based on a Poisson model, whereas column (3) examines the effect on the logarithm of trading volume. The significantly positive coefficients on $D^{post} \times PRate$ in both columns indicate that high-exposure investors increase attention and trade intensity after the shock compared with low-exposure investors in the neighboring prefectures. Because the high- and low-exposure investors are ex ante indistinguishable except for the exposure to the technology shock, these findings are consistent with a causal effect of smartphone trading technology on investors' attention and trading volume.

In addition, I investigate the impact of app adoption on investor response to signals and present the results in Panel C of Table 3. The significantly positive coefficients on the triple interaction terms suggest that high-exposure investors exhibit a significant increase in flow sensitivity to fund performance and market sentiment compared with low-exposure counterparts in neighboring prefectures. This finding provides further evidence to support the idea that the technology has a causal effect

Table 3. Impact on Investor Behavior: Geographic Variation Analysis

Panel A: Covariate balance

	High exposure (1)	Low exposure (2)	Difference (3)	Standard deviation (4)
Predetermined prefecture characteristics				
GDP per Cap (RMB)	36,153.20	34,145.59	2,007.61	2,110.32
Male (% of prefecture population)	51.3%	51.2%	0.1%	0.1%
Mortality Rate	0.6%	0.6%	0.0%	0.0%
Age [15, 65]	73.1%	72.8%	0.3%	0.4%
Age Above 65	8.7%	8.7%	−0.1%	0.2%
Age Below 15	18.3%	18.5%	−0.2%	0.4%
Years of Education	8.58	8.45	0.13	0.10
College Graduate	3.2%	2.8%	0.4%	0.3%
Housing Area per Cap (m^2)	30.16	29.92	0.23	0.60
Predetermined investor characteristics				
VolumePre (monthly)	854.72	793.54	61.18	46.85
LoginPre (monthly)	2.89	2.88	0.01	0.18
Account Size (in thousand shares)	19.59	19.92	−0.33	1.15
Male	51.6%	53.3%	−1.6%	1.3%
Age	41.37	41.25	0.11	0.29
Education	2.70	2.68	0.02	0.03
No. of individuals	5,305	5,097		

Panel B: App adoption, investor attention, and trading intensity

	D^{adopt} Linear model (1)	*Login* Poisson model (2)	$log(Volume + 1)$ Linear model (3)
PRate	0.342***		
	[0.039]		
$D^{post} \times PRate$		0.454**	0.365**
		[0.197]	[0.165]
No. of observations	10,402	1,331,456	1,331,456
No. of investors	10,402	10,402	10,402
Control variables	Yes	Yes	Yes
Individual fixed effects	No	Yes	Yes
Prefecture pair fixed effects	Yes	No	No
Year-week-prefecture pair fixed effects	No	Yes	Yes
Observation level	Individual	Individual-year-week	

Panel C: Investor flow sensitivity to fund performance and market sentiment

	Net flows at the individual level			
	Secondary (1)	Primary (2)	Style (3)	(4)
$PRate \times D^{post} \times Ret_{t-1}$	0.529**	0.495**	0.577**	
	[0.220]	[0.206]	[0.243]	
$PRate \times D^{post} \times Sentiment_{t-1}$				0.211**
				[0.089]
$D^{post} \times Ret_{t-1}$	−0.013	−0.017	−0.024	
	[0.047]	[0.044]	[0.052]	
$PRate \times Ret_{t-1}$	−0.053	−0.071	−0.106	
	[0.206]	[0.197]	[0.226]	
$PRate \times Sentiment_{t-1}$				−0.074
				[0.084]
$PRate \times D^{post}$	0.000	0.000	−0.001	−0.078
	[0.003]	[0.003]	[0.003]	[0.062]
Ret_{t-1}	0.115	0.096	0.116	
	[0.094]	[0.092]	[0.099]	

Table 3. (Continued)

Panel C: Investor flow sensitivity to fund performance and market sentiment				
	Net flows at the individual level			
	Secondary (1)	Primary (2)	Style (3)	(4)
No. of observations	6,396,744	6,396,744	6,396,744	6,396,744
No. of investors	10,402	10,402	10,402	10,402
Individual-fund fixed effects	Yes	Yes	Yes	Yes
Year-week-prefecture pair fixed effects	Yes	Yes	Yes	Yes
Observation level	Individual-fund-year-week			

Notes. Panel A reports the covariate balance between the high-exposure and low-exposure prefectures used in the geographic variation analysis. All prefecture characteristics are obtained from the 2010 Population Census of China and are aggregated at the prefecture level. Columns (1) and (2) show the mean of the prefecture/investor characteristics for the high-exposure and low-exposure groups, respectively. Columns (3) and (4) report the estimated differences between the two groups and the corresponding standard deviations. Panel B reports the results on how app adoption affects investor attention and trading volume. Column (1) reports the app adoption analysis at the individual level, and columns (2) and (3) show the results of the login and trading volume analyses at the individual-year-week level, based on a Poisson model and a linear model, respectively. *PRate* is the smartphone penetration rate in 2011 for the province where an investor resides at the initiation of the investor's trading account. Panel C shows how app adoption affects investors' flow-performance and flow-sentiment sensitivity at the individual-year-week level. The outcome variable in all columns of Panel C is *NetFlow_Indiv*. Table IA1 in the online appendix defines all variables. Standard errors are two-way clustered by individual and week in columns (2) and (3) of Panel B and all columns of Panel C.

*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

on shared trading patterns, such as the flow-performance and flow-sentiment sensitivity.

4. Impact of Smartphone Trading on Mutual Funds

Thus far, the analyses suggest smartphone trading technology not only increases investor attention and trading volume but also alters investors' trading patterns in response to market and fund signals. A critical question that arises is whether the heightened trading comovement at the individual level translates into amplified investor flows at the fund level. If such a relationship exists, the technology change may have an aggregate impact on mutual fund performance.

4.1. Impact of Smartphones on Fund Flows

To investigate the impact of app adoption on investor flows, I conduct a comparison of adopters and nonadopters in aggregate flows around the app's release. Table 4 reports the result in Panels A and B.

Panel A presents the summary statistics for the absolute value of the aggregate flow generated by adopters and nonadopters in the matched sample, before and after the shock. The unit of observation is the fund-investor-group-week, where an investor group is defined as the set of either adopters or nonadopters of a fund. Columns (1) and (2) report the average absolute value of weekly net flows for adopters and nonadopters, respectively. The weekly net flow is defined as the net shares of a mutual fund an investor group purchases during a week, divided by the investment balance in the fund at the end of the previous week. The results show that adopters experience a much greater increase in the absolute value of net flow (125.70%) compared with nonadopters (3.43%). This observation is consistent with an amplification effect of app adoption on investor flows. Columns (3) and (4) use gross flows as an alternative measure for the aggregate flows of an investor group. Following Edelen (1999), gross flow is defined as the sum of inflows and outflows for an investor group of a fund in a given week. Again, adopters exhibit a greater increase in gross flows than nonadopters.

To examine whether the divergence in the absolute value of flows between the two investor groups is statistically significant, I perform a DID analysis and report the results in Table 5, Panel B. The analysis is conducted at the fund-investor-group-week level, where two observations are generated for each fund-year-week: one for app adopters and one for nonadopters. $D^{adopter}$ is a dummy variable equal to one for adopters and zero for nonadopters. The results show that the increase in aggregate flow volume for adopters is significantly greater than that for nonadopters.

To examine the impact of the technology on fund flows directly, I analyze the change in the absolute value of fund flows around the shock for the focal mutual funds at the fund-week level. The results are reported in Table 5, Panel C. As shown in columns (1) and (2), these funds experience a significant increase in the absolute value of fund flows after the shock. The weekly absolute value of fund flows increases by 1.28%–2.17% depending on the flow measures or by 59.6%–61.9% relative to the preshock level.

To refine the identification of the technology's impact on fund flows, I explore a range of cross-sectional variations on the extent to which a fund is exposed to the technology shock. The first variation I use is the percentage of app adopters in a fund's investor pool. If the observed increase in flows is due to a confounding factor unrelated

Table 4. Impact on the Absolute Value of Fund Flows

Panel A: Summary statistics of fund flows

	Abs(NetFlow_Fund) (%)		*Abs(GrossFlow_Fund)* (%)	
	Adopter (1)	Nonadopter (2)	Adopter (3)	Nonadopter (4)
Preshock period	2.14	2.33	3.50	3.30
Postshock period	4.83	2.41	7.53	3.84
Pre–post difference	125.70	3.43	115.14	16.36

Panel B: Change in the absolute value of fund flows: Adopters vs. nonadopters

	Abs(NetFlow_Fund) (%) (1)	*Abs(GrossFlow_Fund)* (%) (2)
$D^{post} \times D^{adopter}$	2.617***	3.597***
	[0.556]	[0.697]
No. of observations	6,544	6,544
No. of funds	27	27
Year-week fixed effects	Yes	Yes
Fund × investor group fixed effects	Yes	Yes
Observation level	Year-week-fund-investor group	

Panel C: Technology's impact on the absolute value of aggregate fund flows

	Absolute value of fund flows (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D^{post} \times AdoptersQuintile$			0.622**	1.158***				
			[0.256]	[0.264]				
$D^{post} \times RetailQuintile$					0.492*	0.882***		
					[0.274]	[0.230]		
$D^{post} \times PRateQuintile$							0.475*	0.908*
							[0.281]	[0.499]
D^{post}	1.275**	2.168***						
	[0.573]	[0.608]						
No. of observations	3,272	3,272	3,272	3,272	3,272	3,272	3,272	3,272
No. of funds	27	27	27	27	27	27	27	27
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-week fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observation level	Fund-year-week							

Notes. Panel A presents summary statistics for the absolute value of the aggregate flows created by adopters and nonadopters around the app's release, based on the matched sample. The unit of observation is a week-fund-investor-group, where an investor group is either app adopters or nonadopters. Columns (1) and (2) focus on the absolute value of the net weekly flow for a fund-investor-group pair, and columns (3) and (4) examine the absolute value of the gross weekly flow for a fund-investor-group pair. Panel B reports how the absolute values of the aggregate flows created by adopters and nonadopters diverge around the shock, based on a DID specification at the week-fund-investor-group level. $D^{adopter}$ is a dummy variable equal to one (zero) if an investor group of a fund contains adopters (nonadopters). Panel C examines the technology's impact on aggregate fund flows, where columns (1), (3), (5), and (7) (columns (2), (4), (6), and (8)) focus on *Abs(NetFlow_Fund)* (*Abs(GrossFlow_Fund)*). Table IA1 in the online appendix defines all variables. Standard errors are two-way clustered at the fund and week level.
*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

to app adoption, I anticipate observing similar patterns in fund flows across the affected funds with varying adoption rates.

More specifically, I conduct a triple-differences analysis to examine how the prepost change in the absolute value of aggregate fund flows varies with the app adoption rate. The results are presented in columns (3) and (4) of Panel C in Table 5. Column (3) focuses on *Abs*(*NetFlow_Fund*), and column (4) focuses on *Abs*(*GrossFlow_Fund*). *AdoptersQuintile* is a categorical variable on one to five scale, which denotes the quintile to which a fund's app adoption rate belongs within the affected funds. The significantly positive coefficient on $D^{post} \times D^{treat} \times AdoptersQuintile$ indicates that funds with high app adoption rates experience a disproportionate increase in the absolute value of fund flows after the shock. This finding suggests that the smartphone app likely contributes to the heightened flow volume.

Although the analysis presented above is informative, it is worth noting that the decision to adopt the app is made after the shock, which may cloud the causal interpretation of the finding. To refine the analysis and tighten the identification, I explore two predetermined cross-fund variations in investor composition. The first variation is the percentage of retail investors for a fund

Table 5. Impact on Fund Returns

Panel A: Technology's impact on fund returns								
	Fund-level abnormal returns (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D^{post} \times AdoptersQuintile$			−0.017**	−0.016**				
			[0.007]	[0.007]				
$D^{post} \times PRateQuintile$					−0.027**	−0.027**		
					[0.013]	[0.013]		
$D^{post} \times RetailQuintile$							−0.020**	−0.019**
							[0.009]	[0.009]
D^{post}	−0.047***	−0.047***						
	[0.017]	[0.016]						
No. of observations	3,272	3,272	3,272	3,272	3,272	3,272	3,272	3,272
No. of funds	27	27	27	27	27	27	27	27
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-week fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observation level	Fund-year-week							

Panel B: Association between fund flows and returns								
	Fund-level abnormal returns (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Abs(NetFlow\_Fund)_{t-1}$	−0.838**	−0.828**						
	[0.370]	[0.364]						
$Abs(GrossFlow\_Fund)_{t-1}$			−0.798***	−0.786***				
			[0.278]	[0.274]				
$Inflow\_Fund_{t-1}$					−0.641**	−0.628**		
					[0.301]	[0.295]		
$Outflow\_Fund_{t-1}$							−1.281**	−1.258**
							[0.554]	[0.543]
No. of observations	1,636	1,636	1,636	1,636	1,636	1,636	1,636	1,636
No. of funds	27	27	27	27	27	27	27	27
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation level	Fund-year-week							

Notes. Panel A reports how the smartphone trading technology affects fund returns at the fund-year-week level. In columns (1), (3), (5), and (7) (columns (2), (4), (6), and (8)), the outcome variable is the abnormal return of a fund in a given week based on the Fama–French three-factor (Carhart four-factor) model. Panel B reports the association between fund returns and the absolute value of fund flows in the previous week during the postshock period, where the outcome variable in columns (1), (3), (5), and (7) (columns (2), (4), (6), and (8)) is a fund's weekly abnormal returns based on the Fama–French three-factor (Carhart four-factor) model. Table IA1 defines all variables. Standard errors are two-way clustered by fund and week.

*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

before the shock. As the app was designed to serve retail investors, retail-oriented funds are expected to be more exposed to the technology shock than institution-oriented funds. The second variation is the average smartphone penetration rate, measured as of 2011, for the residence location of a fund's investors before the shock. As shown in Section 3.3, the smartphone penetration rate of an investor's residence location is predictive of app adoption and is likely to be exogenous to the app's release.

The heterogeneous effects across funds are reported in columns (5)–(8) of Panel C, Table 4. Columns (5) and (7) focus on *Abs*(*NetFlow_Fund*), and columns (6) and (8) focus on *Abs*(*GrossFlow_Fund*). In columns (5) and (6), *RetailQuintile* is a time-invariant variable equal to the quintile of a fund when sorted by the percentage of retail investors in 2012, the year before the shock. In columns (7) and (8), *PRateQuintile* is a time-invariant variable equal to the quintile of a fund when sorted by the average predetermined smartphone penetration rate of its existing investors' residence locations before the shock. The significantly positive coefficients on the triple interaction terms indicate that funds with high predetermined retail investor ownership and smartphone penetration rates experience a particularly pronounced increase in the absolute value of fund flows. Because such funds are ex ante more exposed to the technology shock than others, these findings are consistent with an amplification effect of smartphone trading technology on fund flow volume. I acknowledge the caveat that the results are based on the sample period around the shock and cannot be directly extrapolated to a longer horizon.

4.2. Impact of Smartphones on Fund Performance

The analyses conducted thus far suggest the release of the app leads to a significant increase in aggregate flow volume at the fund level. However, it remains to be seen whether the amplified volume of fund flows have any impact on fund performance.

Additional costs can be incurred by a mutual fund due to the incremental liquidity demand from its investors. This is in part because the trades executed by a fund manager to meet the liquidity demand of investors may have a price impact (Coval and Stafford 2007, Lou 2012). Massive flows from app users may cause a fund manager to resort to fire sales at unfavorable prices or overpay when purchasing new assets, which can ultimately harm the fund's performance (Edelen 1999, Chen et al. 2010).[23] Furthermore, because uninformed traders tend to lose money to informed traders, the portfolio adjustments made by fund managers in response to uninformed investor flows may diminish fund returns even if no price impact occurs (Grossman and Stiglitz 1980). For example, the amplified flow sensitivity to market sentiment implies that funds may be compelled to sell (buy) when assets are undervalued (overvalued).

In this section, I investigate whether the introduction of smartphone trading technology has a significant impact on fund performance, which remains an empirical question despite the predictions. I examine the pre–post change in the performance of affected funds and explore cross-sectional variations in funds' exposure to the technology shock. To ensure the results are not driven by common risk factors, I use abnormal returns from the Fama–French three-factor model and the Carhart four-factor model as measures of fund performance. The results are presented in Panel A of Table 5.

Columns (1), (3), (5), and (7) focus on the abnormal return of a fund in a week, using the alpha in the Fama–French three-factor model. Columns (2), (4), (6), and (8) concentrate on a fund's abnormal return based on the Carhart four-factor model.[24] The regression results in columns (1) and (2) reveal a significantly negative coefficient on D^{post}, indicating a decline in funds' abnormal returns after the shock. Based on column (1), the affected funds experience a 2.3% decrease in annualized returns.[25] This magnitude of the coefficient aligns with the estimation of the liquidity cost for an average mutual fund in Edelen (1999). Although the return deterioration may not be entirely attributed to the app, these findings are overall consistent with a dampening effect of going mobile on fund returns.[26]

Next, I use the variation across funds in exposure to the technology shock. Building on Section 4.1, I use three measures to gauge a fund's treatment intensity: the percentage of app adopters, the percentage of retail investors, and the average smartphone penetration rate of a fund's investors' residence locations before the shock. The results presented in columns (3)–(8) of Table 5, Panel A, demonstrate that after the shock, funds with high levels of exposure to the app experience a more pronounced decline in abnormal returns than those with low levels of exposure. This finding remains consistent across different measures of return and technology exposure.

Taken together, the results suggest that the technology shock is likely to have a negative impact on fund performance and that this impact is disproportionately felt by funds with high exposure to the shock. It is worth noting that these high-exposure funds also experience a particularly pronounced increase in the absolute value of fund flows after the release of the app. The concurrent increase in flows and decrease in returns for these funds suggests that the heightened liquidity costs associated with the increased app flows likely contribute to the decline in fund performance.

4.3. Further Discussion About the Liquidity Cost Mechanism

To better comprehend whether the increased liquidity costs are responsible for the fund performance deterioration, I examine the influence of a fund's aggregate flows on its future performance. This test focuses on the post-shock period, which is particularly relevant to understanding the nature of the app's impact. Table 5, Panel B, presents the results. If the liquidity costs are a key contributor to the performance decline, we would anticipate observing a negative association between the absolute value of fund flows and fund returns in the subsequent period (Edelen 1999).

In Table 5, Panel B, columns (1)–(4), I examine the effect of the absolute value of a fund's aggregate flows in week $t-1$ on the abnormal fund returns in week t. Columns (1) and (2) focus on a fund's aggregate net flows, whereas columns (3) and (4) focus on a fund's aggregate gross flow. The significant negative coefficients on $Abs(NetFlow\_Fund)_{t-1}$ and $Abs(GrossFlow\_Fund)_{t-1}$ indicate that after the shock, an increase in fund flows is predictive of a decrease in the same-fund return in the following week. Additionally, in columns (5)–(8), the effects of aggregate fund inflows and outflows on funds' returns in the next week are examined. Similarly, aggregate fund inflows and outflows are both found to negatively predict fund returns in the next week. These findings suggest that fund performance is negatively impacted by fund flow volume in the previous week, consistent with the liquidity cost mechanism.

To further test the liquidity cost mechanism, I include the absolute value of fund flows in the previous week as a control variable when analyzing fund return changes around the shock. Table IA8 in the online appendix presents the results. If an increase in fund flow volume was a driving factor behind the reduced fund returns, the coefficients on D^{post} and the interaction terms would be partially subsumed by $Abs(NetFlow\_Fund)_{t-1}$. The results indicate that the coefficients on D^{post} and the interaction terms are weakened by the inclusion of the additional control variable. Specifically, compared with the same coefficient in Table 5, Panel A, the unsigned coefficient on D^{post} drops from 0.047 to 0.026 in column (1), and the significance level drops from 1% to 10%. Columns (2)–(8) show similar patterns, where controlling for fund flows weakens the treatment effect based on different specifications and technology exposure measures. These findings provide further support for the liquidity cost channel.

Overall, the previous observations suggest that large fund flows likely contribute to the lower fund performance in the postshock period. The collective evidence, including the observation that the high-exposure funds experience a particularly pronounced increase in fund flow volume, suggests that the heightened liquidity cost is a likely mechanism by which the technology shock impacts fund performance. Based on previous literature, the incremental volume of fund flows after the app's release is likely significant enough to influence fund performance. Table 4, Panel C, column (2), and Table 5, Panel A, column (2), suggest that an average affected fund experiences a 9.4-percentage-point increase in monthly gross flow ($2.2 \times 30/7$) and a 2.3-percentage-point decrease in annual returns (0.047×50). These estimates imply a return-to-gross-flow sensitivity of 0.24 (2.3%/9.4%), which is comparable to the estimated return-to-gross-flow sensitivity (0.19) provided by Edelen (1999).

In theory, the decline in fund performance can also be attributed to a liquidity/trading volume effect (Lou and Shu 2017). If the affected mutual funds increase holdings in stocks with high trading volume, this change in the portfolio may lead to lower abnormal returns after the shock. To investigate the trading volume mechanism, I repeat the fund return analysis presented in Table 5 while controlling for the total trading volume of stocks in a fund's portfolio in the previous week. Table IA9 presents the results. In all columns of Panel A and Panel B, the key coefficients have similar magnitudes and significance to the same coefficients in Table 5. This finding suggests that the decline in fund performance is not solely explained by the changes in liquidity of the stocks in a fund's portfolio.

Another possible explanation for the decline in fund performance is the fund size effect (Berk and Green 2004). If mutual funds have a decreasing return to scale, an increase in fund size may result in lower fund returns, even without heightened fund flows. To examine whether the lower fund returns are driven by changes in fund size, I replicate the analyses presented in Table 5, Panel A, while controlling for fund AUM at the beginning of a week. The results are displayed in Table IA10 in the online appendix. In all specifications, the key coefficients after controlling for fund size have similar magnitudes and significance to the corresponding coefficients in Table 5, Panel A. These results suggest that a change in fund size may not be a first-order explanation for the decline in fund performance.

4.4. Smartphones and Individuals' Investment Performance

The previous analyses have provided evidence that the release of the smartphone app has a negative effect on fund performance. This finding suggests that the technology may also affect the wealth of individual investors.[27]

Accordingly, I examine how the abnormal returns of individual investors' fund portfolios change around the shock and report the results in Table IA11 in the online appendix. In columns (1) and (2), I focus on app adopters who invested in the 27 focal funds, whereas in columns (3) and (4), I focus on nonadopters who invested in the same group of funds. The significantly negative coefficients on D^{post} in all columns indicate that both groups experience a decline in fund investment returns after the shock. This observation is consistent with the notion that the smartphone trading technology may have an impact on investors' wealth.[28]

5. Conclusion

This paper investigates the impact of a smartphone trading app released by a leading investment advisor in China on retail investor behavior and mutual fund performance. The results suggest that the adoption of the technology leads to increased investor attention and trading activity. App adopters show a heightened sensitivity to short-term signals, as evidenced by these investors' flows becoming more responsive to the previous week's fund returns and market sentiment. A geographic variation analysis lends support to the causal interpretation of the above findings. The intensified trading comovement across individuals leads to higher flow volume and lower returns at the fund level, suggesting increased liquidity costs incurred by open-ended mutual funds due to the introduction of smartphone trading technology. Furthermore, investment returns decrease for both app adopters and nonadopters after the shock.

Acknowledgments

The author thanks the editor Lin William Cong, an anonymous associate editor, and two anonymous referees for support and comments; Wei Jiang for encouragement; Simona Abis, Tania Babina, Geert Bekaert, Daniel Bergstresser, Olivier Darmouni, Kent Daniel, Robert Dekle, Richard Evans, Xavier Giroud, Shane Johnson, Nan Li, Xiaoding Liu, Terrance Odean, Michaela Pagel, Tomasz Piskorski, Hongxun Ruan, Suresh Sundaresan, Paul Tetlock, Sumudu W. Watugala, Kairong Xiao, Haoxiang Zhu, and conference participants at the SFS Cavalcade Conference, the Northeastern University

Finance Conference, the University of Connecticut Financial Risk Conference, the Chapman University Money and Finance Conference, and the NFA Conference, and attendants of various seminars at Columbia University for comments; and an anonymous asset management company for the data.

Endnotes

[1] An example is the Robinhood–GameStop controversy in 2021.

[2] In China, the companies responsible for managing mutual funds are referred to as "mutual fund management companies," which is similar to the term "investment advisors" used in the United States.

[3] Liao et al. (2021) show that in peer-to-peer lending, the differences in the content of the mobile interface and PC platform, rather than the devices per se, explain the disparity in lending decisions.

[4] According to Dodini et al. (2016), smartphone adoption is a major determinant for investors' use of mobile financial services and applications.

[5] Prefectures are administrative subdivisions of provinces in China.

[6] Although the results are broadly consistent with the liquidity cost mechanism, these results do not necessarily imply that liquidity cost is the only explanation for the fund performance changes.

[7] In China, mutual fund companies can sell shares directly to investors through direct sales or through third-party channels such as securities companies or commercial banks. The Asset Management Association of China reported that in 2015, direct sales accounted for 67.1% of the purchase volume in China's mutual fund industry, with the remaining volume evenly split between commercial banks and securities companies (Asset Management Association of China 2016).

[8] Similarly, the Advisor offers all the funds it manages on its direct sales platform and does not list any funds managed by other investment advisors on the same platform.

[9] The majority of transaction fees are in the form of front-end loads, with an average of 10–15 basis points for trades made through the direct sales platform. In contrast, fees charged through third-party distributors are higher, averaging 100–150 basis points.

[10] An active user is defined as an investor who logged into the platform through the official website, the client terminal, or the smartphone app at least once during a given month.

[11] The plot builds on a randomized sample of 20% of the users on the direct sales platform that I have access to. As a result, the numbers presented in the plot represent approximately 20% of the total number of active users on the platform.

[12] Previous studies show that app notifications, such as displaying top movers, can affect investor trading decisions (Barber et al. 2022). To the best of my knowledge, in the sample period, the smartphone app does not actively send notifications for top movers or large price changes.

[13] The transaction data do not have an indicator for whether a transaction request is placed through the smartphone app or other platforms. For that reason, I define app adopters based on login information.

[14] Because of the expansion in the use of the direct sales platform, the population characteristics of platform users may change over time. For this reason, comparing the full sample of platform users across time may lead to a biased estimation of the app's impact on investor trading behaviors. My analyses focus on the existing platform users at the time of the app's release and track the same-investor changes in trading behavior over time. This design helps control for investor attributes in my sample.

[15] As reported in Online Appendix B, I find young and male investors are particularly prone to app adoption, consistent with the finding in D'Acunto et al. (2019).

[16] The sample size difference between the matched sample and the full sample reflects the investors not matched based on the procedure and those with missing values for the matched variables. Because the matching is with replacement, the number of nonadopters is smaller than the number of adopters in the matched sample.

[17] Some studies measure investor attention using more direct user activities such as page visits and clicks (Gargano and Rossi 2018). These data can directly capture the length of time an investor spends on the app and the amount of information the investor browses. The data provided by the Advisor do not include such detailed information.

[18] I also conduct a set of robustness tests based on the full sample and based on specifications incorporating county-year-week fixed effects. I report the results in Table IA3 in the online appendix.

[19] I can observe an investor's holding and trading of the mutual funds managed by the Advisor, but I cannot observe an investor's holding and trading of assets not managed by the Advisor. For this reason, I cannot test whether the Advisor's smartphone trading app has a spillover effect on assets not managed by the Advisor.

[20] Based on the results presented in Table IA5 in the online appendix, the impact of the app on investor behavior is stronger for male investors than for female investors, which is consistent with the overconfidence channel (Barber and Odean 2001a). In addition, self-control problems may also contribute to the app's effect on investor behavior, as shown in Table IA4 in the online appendix. Specifically, young investors, who are more prone to self-control problems (Ameriks et al. 2007), exhibit a greater increase in attention and trading volume than the older group.

[21] The smartphone penetration data are provided by Flurry Analytics.

[22] Direct-administered municipalities are often not economically comparable to neighboring prefectures.

[23] Additionally, large flows may negatively impact fund performance by increasing other trading costs, such as commission costs. (Edelen et al. 2007).

[24] Following the literature convention, I estimate the abnormal return by regressing the weekly excess fund returns (before fees) on the weekly Fama–French and momentum factors from the CSMAR database. The measure is constructed based on a rolling window of 12 weeks.

[25] Although it is possible that other distribution channels may have contributed to the decline in fund returns by launching a trading app around the same time as the focal technology shock, my search shows that only three of the top 50 securities companies (banks) released a trading app during the twelve months surrounding the shock. As the direct sales platform accounts for the majority of fund share transactions and only a small percentage of alternative distribution channels launched a new app around the focal app's release, it is unlikely that the fund performance deterioration can be fully explained by apps from other distribution channels.

[26] In a robustness test, I compare the funds managed by the Advisor (the treated group) with the peer funds provided by other investment advisors and under the same primary category (the control group), in terms of how these funds' performance changes around the app's release. To ensure the control funds are not exposed to a similar technology change around the time of the shock, I further require that a control fund not be managed by an investment advisor that launched a mobile trading app during the 12 months around the focal app's release. The results are reported in Table IA7 in the online appendix and suggest a negative effect of the technology on fund performance.

[27] Nonadopters' investment performance may be negatively affected due to the heightened liquidity costs. For example, a large outflow created by adopters may suppress the prices of a fund's assets and lower returns for other investors in the same fund (Chen et al. 2010). The effect on app adopters' investment performance is ex ante

unclear. On the one hand, increased liquidity costs may impair performance, and increased trading activity could incur additional costs for less-sophisticated investors. On the other hand, if the mutual funds experiencing large inflows enjoy persistent outperformance, the increased attention of app adopters may help improve investment performance (Gargano and Rossi 2018).

[28] Considering that the app may contribute to its users' utility through other channels, the lowered investment returns for app adopters does not necessarily indicate an overall welfare loss for app adopters.

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