Smart(Phone) Investing?*

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Using transaction-level data from two German banks, we study the effects of smartphones on investor behavior. Employing two complementary identification strategies, we document that smartphones increase the purchase of riskier, lottery-type, non-diversifying assets and past winners and losers. Digital nudges or differences in smartphone information display do not explain our results. Our evidence suggests that smartphones promote more automatic and intuitive thinking. Assets purchased via smartphones yield lower returns and reduce portfolio Sharpe ratio. Our findings caution against the indiscriminate use of smartphones as the key technology to facilitate access to financial markets.

Keywords: fintech, investor behavior, financial risk-taking, lottery-type assets, investment biases.

JEL Classification: G11, D10, O33

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1 Introduction

Online trading platforms like Robinhood have popularized mobile apps offering convenient and ubiquitous financial market access. Today, even traditional financial institutions provide their clients with mobile trading options, with more than 20% of worldwide retail investors' trades now executed via smartphones.[1] Despite their convenience and widespread use, mobile trading apps have been criticized for "gamifying" trading, fostering gambling-like behaviors, and contributing to significant losses for retail investors. Regulators have sought to protect investors by targeting gamification elements within trading apps.[2]

Yet, to adequately address these concerns, it is crucial to understand the specific impacts of mobile trading apps on investor behavior and the mechanisms through which these effects manifest. However, evaluating the impact of mobile trading presents several challenges. First, these platforms may disproportionately attract more risk-seeking or less sophisticated investors. These investors might have made similarly poor financial decisions without the app. Second, investors may allocate only a small portion of their wealth to these apps, precisely the fraction they are willing to allocate to high-volatility or exotic assets. Third, aside from these potential selection and substitution effects, several elements make smartphone trading unique, from the app design and push notifications to the actual smartphone device, its screen size, and the ubiquitous access to data and trading. Teasing out the relative importance of these elements requires detailed micro-level data.

This paper analyzes how smartphone trading affects investors' portfolios using proprietary data from two large German banks. We rely on two complementary empirical approaches to evaluate the impact of smartphones on trading behavior, addressing both selection and substitution effects. At the transaction level, we use investor-by-time fixed effects to

1. Brière and Thomadakis (2024)

2. For example, in January 2024, Robinhood settled charges with the Massachusetts Securities Division, paying a $7.5 million fine and agreeing to revise its gamification strategies, which allegedly encouraged risky trading by inexperienced investors.

compare trades made by the same investor in the same month across different platforms (i.e., smartphones versus desktops). At the investor level, we employ a differences-in-differences approach, leveraging the staggered introduction of smartphone trading apps across the two banks. Both methods yield similar findings: when trading using smartphones, investors are more likely to buy volatile assets, are more susceptible to investment biases, and exhibit more gambling-like behaviors. As a result, smartphone trading generates lower returns and Sharpe ratios.

We explore several potential mechanisms behind these behavioral changes. While digital nudges, gamification features, and screen size may influence behavior in other settings, these factors do not explain our findings. Instead, we present evidence that smartphones encourage greater reliance on intuitive thinking and less deliberate decision-making.

Our data come from two large German commercial banks, which introduced mobile trading applications for their clients in 2010 and 2013, respectively. From 1999 to 2017, we observe all holdings and transactions, including the specific platform used for each trade. This dataset offers several advantages for analyzing the effects of smartphone trading. By studying only smartphone users' trading behaviors, we can mitigate concerns about selection and differences between users and non-users. Furthermore, the richness of the data allows us to apply investor-by-time fixed effects to control for unobserved, time-varying investor heterogeneity. Including these fixed effects is critical, as some investors may begin using a trading app specifically to alter their investment behavior. The staggered introduction of the apps across the two banks also enables us to implement a second empirical approach: a difference-in-differences strategy that controls for a rich set of demographic variables to account for differences in trading behaviors between the two banks. This latter strategy allows us to estimate smartphone effects at the investor portfolio level, accounting for potential substitution effects.

Studying German retail bank investors presents several distinct advantages. The trading apps used in our sample do not incorporate gamification elements, such as visual rewards (e.g., confetti upon stock purchases), nor do they include push notifications related to stock prices. In addition, investors in our sample tend to be more experienced and wealthier than typical users of platforms like Robinhood. These clients generally maintain long-term relationships with their banks, reducing concerns that they might have multiple investment accounts outside our dataset.[3]

We present four sets of results. First, we conduct transaction-level analyses using investor-by-month fixed effects. We find that investors are significantly more likely to purchase higher-volatility, positively skewed assets (i.e., lottery-type assets) when trading on smartphones compared to desktop computers. Additionally, smartphone trading amplifies behavioral biases, as investors are more inclined to buy individual stocks (instead of diversified mutual funds) and more salient assets, such as recent winners or losers. These effects are statistically and economically significant, with the probability of purchasing these assets increasing by at least 50% of smartphone users' unconditional mean. Smartphone effects are neither temporary nor driven by initial enthusiasm, as they persist for several quarters following the app's adoption. Notably, the selection of asset classes does not entirely account for these smartphone effects. After controlling for asset-class fixed effects, we still observe smaller, economically meaningful impacts. While within-investor-time analyses suggest a causal link between smartphone use and trading behavior, they do not entirely rule out the possibility that investors may first choose the type of trade (e.g., lottery stocks) and then select the device to execute it. In this case, smartphones may facilitate gambling-like behavior but may not necessarily cause it.

To address this concern, we complement the transaction-level analyses with investor-level analyses. Although our data lack random variation in smartphone access,[4] we leverage the

3. As a robustness check, we find similar smartphone effects for investors who hold their primary accounts in these banks.

4. There are no outages in the availability of the German banks' apps in our sample, preventing us from

staggered introduction of smartphone apps across the two banks to implement a difference-in-differences design.[5] By comparing smartphone users at the first adopting bank with (future) users at the second bank, we assume that these two groups would have traded similarly—on parallel trends—if the app had not been introduced. Our findings indicate that users at both banks had similar trading patterns before the smartphone app launch. However, after the launch, treated clients increase their trades in high-volatility and high-skewness assets, individual stocks, and recent winners and losers.

Overall, our investor-level analyses confirm that smartphones systematically influence trading behavior. This evidence from client portfolios also helps to rule out substitution effects across trading platforms.

We proceed by exploring the mechanisms driving the observed effects of smartphones. Specifically, we consider three potential explanations: smartphones provide constant access to trading, they enable digital nudges and tailored information displays, and they promote more intuitive, less deliberate decision-making. To explore whether the ability to trade at any time influences our results, we re-estimate our baseline models with year-by-time-of-day fixed effects. Although the magnitude of the estimates diminishes, they remain both economically and statistically significant. This evidence suggests that variations in trading times across platforms contribute to smartphone effects, but they do not fully account for our findings.

We then investigate if digital nudges or differences in information display across platforms contribute to our results. The apps in our setting do not send push notifications to clients or have any gamification features that might influence trading behaviors.[6] Nonetheless, smart-

replicating the identification strategy used by, for example, Barber et al. (2020).

5. We use the introduction of the smartphone application as our event date. Not all bank customers will download and start using the app as soon as it is available. This specification allows us to better account for endogenous timing of starting to use the app.

6. The apps in our sample are not just trading apps but also provide other banking services, allowing account holders to check balances on their savings and checking accounts, make transfers, and check their portfolios.

phone apps might display information differently. For instance, they may more prominently feature assets that have recently experienced dramatic positive and negative performance. If these assets are riskier and have higher skewness, their more salient display could drive our results. To test this hypothesis, we conduct two separate tests. First, we exclude from our analyses the purchases of daily winners and losers. Second, we limit our analyses to mutual funds, whose performance is not prominently featured on the trading apps. In both analyses, we still find strong smartphone effects that are quantitatively comparable with our main estimates. Differences in physical screen size across platforms can also lead to differences in information display. Motivated by this possibility, we separately investigate the effects of trading using devices with different screen sizes. We do not find stronger results for trades via iPhones relative to iPads. Our results are inconsistent with digital nudges or differences in information display driving smartphone effects.

Finally, we examine whether smartphones encourage more automatic and intuitive thinking.[7] Cognitive psychology posits that problem-solving involves an interplay between intuitive and analytical thinking, often described through the metaphor of two systems (e.g., Stanovich and West (2000); Kahneman (2003)). System 1 operates automatically and effortlessly and relies on associative processes, whereas System 2 is deliberative, effortful, and relies on analytical reasoning. While System 1 continuously works, the costly System 2 is only engaged when individuals are not confident enough in the System 1 solution. For example, Ilut and Valchev (2023) develop a bounded rationality model based on this dual-system framework, where individuals are less likely to activate System 2 in usual states of the world.

Similarly, System 2 engagement is reduced in contexts perceived as less risky because of mood (Bassi et al. (2013) or when individuals are cognitively depleted or fatigued (Kahneman (2011), Danziger et al. (2011)). Motivated by these insights, we conduct a series

7. For instance, smartphones have been linked to impulsive consumer behaviors, such as ordering more unhealthy food via mobile devices. See Benartzi and Lehrer (2015) for a review of the impact of smartphones on consumer decision-making.

of heterogeneity tests to explore whether smartphone effects are amplified when System 2 engagement is expected to be lower. Specifically, we find that smartphone effects are more pronounced in the following scenarios: (i) usual trading days without (unexpected) earnings announcements or high volatility, (ii) days with higher mood levels, as proxied by increased sunshine, (iii) pre-lunch hours when glucose levels are likely lower, and (iv) after-hours trading sessions when individuals are more prone to end-of-day fatigue. These findings suggest that smartphones promote greater reliance on intuitive, System 1 thinking at the expense of analytical, System 2 engagement. This shift toward more intuitive thinking may lead smartphone investors to assume higher financial risks, prefer gambling-like assets, and display heightened investment biases.

In our last set of analyses, we explore the implications of our findings. Smartphones lead to purchasing assets with worse returns per unit of risk, as measured by lower Sharpe ratios. Both higher volatility and worse market-adjusted returns of the assets purchased via smartphones drive the lower Sharpe ratios. We then investigate the relationship between smartphone effects and investor experience. While smartphone effects are stronger for investors with below-median experience, they remain economically and statistically significant even for more experienced investors.[8]

Our paper contributes to three key strands of literature. First, it relates to research on the impact of FinTech applications on household financial decision-making. FinTech apps have the potential to enhance the rationality of household financial choices (for a review, see D'Acunto and Rossi (2023)). For instance, such applications can improve consumption and saving decisions by offering households timely and convenient access to both their own (Levi and Benartzi (2024)) and their peers' consumption data (D'Acunto et al. (2020)). Similarly, robo-advisors have been shown to mitigate investment errors (D'Acunto et al.

8. This evidence suggests that our estimates using German investors might underestimate the effects of smartphones on younger, less experienced investors, such as Robinhood users.

(2019)) and increase stock market participation among middle-class investors (Reher and Sokolinski (2024)). Our study extends this work by examining the effects of smartphone-based trading apps. Specifically, our finding that investors make poorer financial decisions on smartphones contributes to a more nuanced understanding of the trade-offs associated with FinTech innovations. In particular, our evidence that smartphones foster more intuitive, System 1 thinking underscores the role of the device itself in shaping household financial behaviors and determining the effectiveness of FinTech applications.

Second, our findings contribute to the literature on how technology shapes investor behavior. For example, Barber and Odean (2002) show that investors transitioning from phone-based to online trading tend to trade more frequently but with lower profitability. Similarly, Choi et al. (2002) find comparable results in the context of 401(k) plans. Using data from one large German broker, Arnold et al. (2022) document that sending standardized push messages to retail investors' cell phones increases their risk-taking in derivative markets (i.e., contracts for difference or CFDs). We contribute to this literature in several ways. By studying smartphone trading using an application without push notifications or elements of gamification, we can isolate the effects of the device from those of digital nudges. By examining how investors trade across different platforms simultaneously, our study allows for an evaluation of the impact of technology while addressing selection biases and potential time-varying investor preferences. By observing the investor's primary accounts, we also capture substitution effects across platforms and provide a clearer picture of how technology influences clients' overall portfolios.

Third, recent research has explored the impact of smartphone trading apps on aggregate markets. For instance, using data from the US retail brokerage Robinhood, Welch (2020) finds that a portfolio replicating the aggregate holdings of Robinhood investors did not underperform standard academic benchmarks.[9] Using the same data, Barber et al. (2020)

9. Robinhood operates entirely online, with most trades executed through its smartphone app.

document that negative returns follow periods of intense buying activity by Robinhood users. Similarly, using data from a major investment advisor in China, Cen (2024) shows that introducing a mobile trading app led investor flows into mutual funds to become more volatile and responsive to short-term fund performance and market sentiment. Our results nicely dovetail with these findings while making three distinctive contributions. First, we focus specifically on the effects of smartphones on individual retail investors rather than aggregate market outcomes. Market-wide effects can obscure significant heterogeneity across investors, making it harder to evaluate the redistributive impact of this technology. Second, our access to granular, micro-level trading data allows us to sharpen the causal effects of smartphone use and explore the mechanisms behind these effects. Third, while Robinhood's user base primarily consists of younger, inexperienced investors, the German investors in our sample who adopt smartphone trading are, on average, 45 years old and have nine years of prior investing experience with their banks. Our findings, therefore, highlight that smartphones can substantially influence trading behavior even among more experienced investors.

2 Data and Empirical Strategy

This section describes the data used in the analyses, discusses our sample, and details our empirical strategy.

2.1 Data and Summary Statistics

We use proprietary investor transaction-level data from two large German retail banks. For a large random sample of clients at the banks, we observe all their trades, including information on the securities traded, the type of trade (buy or sell), the day and time of the trade execution, price and units of each transaction, and, importantly for our analysis, the platform used for each trade. This data covers about sixty-five million transactions from

1999 to 2017 by more than two hundred and twenty-five thousand investors. At the investor level, we observe monthly snapshots of portfolio holdings and demographic characteristics such as gender, age, wealth, and income.[10]

We apply two sample filters to our data. First, we exclude trades associated with savings plans and wealth management services, as these are either automated or do not involve active decision-making by investors. Second, we remove trades lacking information on the traded asset (e.g., asset class). Our analysis uses two distinct samples: one at the transaction level and another at the investor level. The transaction-level sample includes trades from 2010 to 2016 for one bank and from 2013 to 2017 for the other, corresponding to each bank's earliest introduction of smartphone apps. After applying these filters, the resulting dataset consists of approximately ten million transactions made by roughly 150,000 investors, with over 18,000 of these investors using smartphone trading apps at least once. The investor-level analysis aggregates transaction data to the investor-month level and includes data from 2005 to 2017 to provide sufficient observations both before and after the first app's launch in 2010.[11]

We complement the proprietary data from the two banks with publicly available data on prices, returns, and other characteristics for all securities traded in Germany. Table 1 reports summary statistics for variables used in our analyses within our transaction sample. Smartphone is a dummy variable that takes a value of one for trades executed using smartphones. On average, 2% of trades in our sample are placed using smartphones (standard deviation of 0.13). However, conditional on ever using them, investors execute over 15% of their trades via smartphones. We first measure risk-taking as the probability of purchasing risky assets (i.e., direct and indirect equity investments). For the purpose of this analysis, we classify all other assets, including treasuries, bonds, non-equity mutual funds, warrants,

10. Wealth and income are only recorded at the account opening.

11. We also confine the investor-level sample to those investors who have had at least one smartphone trade during the sample period.

and certificates, as non-risky assets. In our sample, investors, on average, buy equities in 60% of their trades. Given that smartphones could significantly affect the trading of non-equity assets such as derivatives, we complement this measure by investigating the volatility of all the assets purchased, measured as the annualized standard deviation over a trailing twelve-month rolling window. The mean volatility in our sample is 20.65% with a standard deviation of 16.54%.

Our measures for gambling preferences include investment skewness, calculated on a twelve-month rolling window, and the probability of purchasing lottery-type assets. Following the approach in Kumar (2009), we define lottery-type assets as those with below median price and above median volatility and skewness. The mean probability of purchasing a lottery-type asset within our sample is 10%. To investigate the effects of smartphones on investment biases, we examine underdiversification and the likelihood of buying salient assets, such as past winners and losers. We measure underdiversification as the value-weighted fraction of individual security purchases over all the same month's purchases.[12] In our sample, 51% of purchases involve individual assets instead of diversifying assets such as mutual funds. We measure winner and loser assets as assets in the top and bottom deciles of the past twelve-month return distribution. Sixteen percent of all the purchases in our sample are in the top decile of past performance, while eight percent are in the bottom decile.

We complement our main measures with additional measures of investor behavior such as the bank-reported risk categories of the assets purchased and the probability of buying warrants or certificates. The banks assign a riskiness score from one to five to all the assets traded, with higher values representing greater risks. The average risk category for the assets purchased in our sample is 4.28. The mean probability of buying a warrant is 29% (3% for a certificate).

12. Given that all our analyses are at the transaction level, we compute the underdiversification as the euro value of the purchases of individual securities over the average value of all the purchases in the current month. By definition, this variable takes a value of zero for mutual fund purchases.

Finally, in order to examine the impact of the use of smartphones on performance, we use market-adjusted return and Sharpe ratio as our main measures. On average, the trades in our sample earn a market-adjusted return of -3% and a Sharpe ratio of 0.52, assuming a twelve-month holding period.

In Figure 1, we explore the evolution of smartphone penetration over our sample period. Panel A plots the percentage of users that adopt smartphone trading over different calendar years. The two banks in our sample launched their smartphone trading apps in 2010 and 2013. By the end of our sample in 2017, over 24% of users had made at least one trade using smartphones. The percentage of adopters drops slightly in 2013 because we add to the sample investors from the second bank that launched the app that year. Panel B plots the percentage of trades via smartphones for adopters. Among these investors, over 20% of trades are executed via smartphone by 2017. Thus, if smartphone trades differ from other trades, they might significantly impact the overall portfolio efficiency.

Since investors endogenously choose to use smartphones, adopters might be inherently different from non-adopters. In Table 2, we compare trading behavior (Panel A) and investor characteristics (Panel B) across smartphone users and non-users. We compute summary statistics for non-users over all the years in our sample. Instead, we use only information for smartphone users until their first smartphone trade. Therefore, trading statistics for adopters do not reflect the effects of smartphones. Compared to non-users, adopters trade more frequently (10 vs. five trades per month) and place larger trades (4,477 euros vs. 3,813 euros in average trades). Smartphone users are also more likely to buy riskier assets (68% vs. 58%) and purchase more volatile assets (22% vs. 16.52%).[13] Finally, adopters display a higher probability of buying lottery-type assets and investments in the top and bottom deciles of the past return distribution. In terms of performance, smartphone users' purchased

13. Smartphone users also purchase less negatively skewed assets before the technology adoption (-5.61 vs. -9.02). After they start using smartphones, the average skewness of the assets purchased becomes positive (equal to 5.62)

assets experience lower market-adjusted returns and Sharpe ratios in the following twelve months compared to non-smartphone users' purchases (respectively, -4% vs. -3%, 0.39 vs. 0.54).

Panel B reports investor-level characteristics for smartphone users and non-users. While there are no substantial differences in terms of income, adopters are five percentage points (12% vs. 17%) more likely to be in the highest wealth bin (i.e., above 100K euros). Smartphone users also tend to be younger males with a shorter tenure at the bank. Specifically, smartphone users have a one-year shorter tenure at the bank, are about eight years younger, and are 13%

2.2 Empirical Challenges and Methodology

Investigating the effects of new technologies on trading activity poses significant empirical challenges due to selection and substitution effects. Individuals who use smartphones to trade could be different from investors who use other platforms. In our sample, smartphone users are more active, more likely to buy higher volatility and lottery-type assets, more likely to purchase individual securities (as opposed to mutual funds), and more likely to buy past winners and losers. Moreover, investor characteristics could also change over time. For instance, individuals can become more sophisticated or start trading more actively over time. These changes might drive their choice of trading platform. Therefore, the selection effects could operate at the investor-time level.

There is also a potential for significant substitution effects where investors can choose to make specific trades on smartphones versus other devices. Investors could use the new platform to execute particular trades (e.g., buying riskier investments), substituting them away from different platforms. In the presence of such substitution effects across devices, one might mistakenly attribute variation in trading strategies to the use of smartphones when, indeed, investors are just reallocating their trades across platforms.

Leveraging the richness of our data, we address these challenges by employing two distinct specifications, each with its own strengths. The first operates at the transaction level, comparing trades made by the same investor within the same month across different platforms. This approach allows us to observe several characteristics of the trade, such as time of day and asset type, providing unique opportunities to explore various mechanisms. However, it does not account for potential substitution effects. The second specification focuses on the investor level, utilizing variation in the availability of the smartphone app to compare changes in outcomes for those with and without app access. While this approach is more limited in investigating specific mechanisms, it estimates the effect of the smartphone app net of any plausible substitution effects by evaluating changes in portfolio-level outcomes.

The transaction-level analysis exploits within investor-by-time variation by including investor-by-month fixed effects in our estimations. By comparing trades across different platforms made by the same investor within the same month, we can account for time-varying investor characteristics and selection at the investor-time level. Specifically, we estimate the following model:

$$y_{i,j,t} = \beta \times Smartphone_{i,j,t} + \delta_{i,t} + \epsilon_{i,j,t} \tag{1}$$

where y measures behaviors (such as risk-taking, preference for lottery assets, and past winners or losers) by investor i using platform j during year-month t. $Smartphone_{i,j,t}$ is an indicator variable equal to one for investor i for smartphone trades in month t. $\delta_{i,t}$ are investor-by-month fixed effects that account for time-varying unobserved differences at the investor level. Robust standard errors are double-clustered at the investor and month level. This estimation strategy controls for both across- and within-investor heterogeneity while allowing trades within the same investor and the same month to be correlated.

The investor-level analysis leverages the variation in the timing of the smartphone app introductions by the two banks providing our data. While one bank launched its app in May 2010, the other introduced it in Jan 2013. We exploit this distinct launch timing using a difference-in-differences (DiD) framework to estimate the effect of smartphone access on investor behavior. Crucially, we do not rely on endogenous individual smartphone adoption decisions. Instead, our analysis compares outcomes for investors from the bank that launched its app earlier to those from the bank that introduced it later. The dataset spans monthly observations at the investor level, capturing investor activity both before and after the app launch.

Specifically, we estimate the following model:

$$y_{i,t} = \beta \times SmartphoneLaunch_{i,t} + \delta_i + \gamma_i + \epsilon_{i,t} \tag{2}$$

where y measures behaviors similar to those before but at the investor-month level for investor i during month t. $SmartphoneLaunch_{i,t}$ is an indicator variable equal to one for investor i during month t if their bank has already launched the app. δ_i are investor fixed effects that account for time-invariant differences at the investor level. γ_t are time-fixed effects that account for economy-wide time trends. Robust standard errors are double-clustered at the investor and month levels.

The key underlying assumption for β to identify the causal effect of access to smartphones on investor outcomes is that of parallel trends. This assumption posits that, in the absence of the smartphone launch at the first bank, trends in the outcome variables for investors at both banks would have followed a parallel trajectory.

3 Main Results

We examine the effects of smartphones on financial risk-taking, preferences for gambling, and investment biases. As discussed in Section A1, the impact of smartphones on these behaviors are not obvious ex-ante.

3.1 Transaction-level analysis

We begin by analyzing the effects of smartphone usage with transaction-level analysis. In Table 3, we report the results of this analysis, estimating Equation 1 for our primary outcome variables, starting with risk-taking. Our measure of risk-taking is the volatility of the assets purchased, calculated as the annualized standard deviation of returns over the past twelve months. Column (1) presents the estimates, showing that the volatility of assets purchased via smartphones is 7.4 percentage points higher than the volatility of other assets purchased by the same investor within the same year-month but through a different platform. This magnitude is economically significant, representing 33.4% of the unconditional mean.

To ensure the robustness of our results, we employ two additional measures of risk-taking. First, we use the banks' internal risk categories. Both banks classify the riskiness of asset purchases (including non-equities) into five categories, ranging from one (lowest risk) to five (highest risk). Second, we analyze the probability of purchasing non-equity instruments, such as warrants and certificates, which are typically considered riskier. In the online Appendix, Table A1 provides estimates for this analysis, where we find similar results across both measures, consistent with our baseline. These effects remain economically substantial; for example, smartphone use increases the probability of purchasing warrants by 29.5% of the unconditional mean (17.5% for certificates).

Our second set of outcomes examines investor preferences for skewness and lottery-type assets. The first variable captures the skewness in returns over the past twelve months. Column (2) of Table 3 reports the estimates, showing that, after controlling for investor-by-month fixed effects, smartphone use increases the skewness of purchased assets by 10.6 percentage points or 18.3% of the standard deviation of skewness for smartphone users. To measure preferences for lottery-type assets, we follow the approach of Kumar (2009), defining lottery-type assets as those with below-median prices, above-median volatility, and above-median skewness. As shown in Column (3), smartphone trades increase the probability of purchasing lottery-type assets by 5.6 percentage points or 46.7% of the unconditional mean.

If smartphones facilitate riskier and more gambling-like behaviors, they may also lead investors toward more concentrated portfolios. We investigate this possibility by examining the probability of purchasing non-diversifying assets (i.e., non-mutual fund investments), such as individual stocks and securities. Column (4) reports these estimates, where, after controlling for investor-by-month fixed effects, we find that smartphones increase the fraction of non-diversifying assets by 40.6 percentage points or 62.5% of the unconditional mean for smartphone users.

Smartphones could provide more frequent access to information and enable impulsive trading, potentially making investors more susceptible to attention-grabbing stocks (Barber and Odean (2008)). To explore this, we examine whether smartphones increase the tendency to buy assets with extreme (either good or bad) past performance. Consistent with this hypothesis, smartphone users' unconditional probability of purchasing assets in the top decile of the past twelve-month return distribution increases from 17% to 22% after adopting the technology. Similarly, the purchase probability increases from 9% to 12% for assets in the bottom decile. We formally test this and report the results in Columns (5) and (6), finding that smartphone trades increase the likelihood of purchasing past winners (losers) by 8.7 (6.6) percentage points, representing 51.2% (68.8%) of the unconditional mean.[14]

We investigate the dynamics of smartphone effects to determine whether they are temporary or persistent. If investors initially rely heavily on smartphones but then reduce their usage, our findings might overstate the relevance of smartphones. Additionally, investors may learn to offset these effects over time by adjusting their behavior or avoiding smartphone

14. Our results are robust to even more granular variation. After controlling for investor-by-day fixed effects, we estimate the effects and find that the smartphone effects persist, as reported in Table A2.

trading altogether (Seru et al., 2009).

Figure 2 presents the results of this analysis, showing the interaction of the indicator for smartphone trades in Equation 1 with indicators for the quarters after the adoption of smartphone trading. We include investor-by-month fixed effects in all specifications. Panel A shows that the impact on asset volatility remains stable from the first quarter of usage through nine or more quarters. We observe similar patterns for all other outcome variables in Panels C through F. These findings suggest that smartphone effects are persistent, not driven by short-term excitement or experimentation, and learning effects do not diminish their impact on trading behaviors.

A potential concern with our analysis is that we compute our outcome variables using transaction-level data without accounting for the value of trades. For example, we assign one to those purchases that involve lottery-type assets and zero otherwise. Given this variable construction, our procedure is akin to computing equally weighted averages of all the purchases. This approach can overestimate the effects of smartphones if investors are more likely to make smaller and more frequent purchases using smartphones than other platforms. In our sample, the average purchase made using smartphones is only about 5% smaller in size compared to purchases on different platforms (4,004.65 vs. 4,223.18 euros).

Nonetheless, we repeat all our main analyses to test for this possibility by computing a value-weighted version of our outcome variables. Following our approach to measuring underdiversification, we compute, for example, the purchase of lottery-type assets as the fraction of the value of each lottery asset bought over the average value of all the purchases in that month. We report these analyses in Table A3. Comparing these results to the results in Table 3, we note that the effects of smartphones remain economically and statistically significant even after using value-weighted measures of investor behaviors. Economic magnitudes of our value-weighted estimates range from 46% to 112% of the equally-weighted ones.

We observe only trades in the investment accounts with the two banks in our sample. Therefore, a potential concern could be that investors might substitute trades across investment accounts at different financial institutions. While we do not observe all the investors' investment accounts, as a robustness check, we analyze smartphones' effects on investors with their primary accounts with our two banks.[15] In Table A4, we document that, similar to our baseline effects, these investors buy assets that are more volatile, have a higher skewness, and become more likely to purchase lottery-type and non-diversifying assets, as well as past winners and losers. Our results are inconsistent, with substitution effects playing a role.

3.2 Investor-level analysis

While our within-investor-time analyses make progress in addressing potential selection biases, investors still endogenously choose which trading platform to use for each of their trades. They may execute their riskier, gambling-type trades primarily on smartphones. In such cases, smartphone trades might simply substitute trades that would have otherwise occurred on different platforms. If substitution effects are present, any changes in outcome variables for smartphone trades could be offset by opposite changes in non-smartphone trades. We conduct investor-level analyses that account for this and examine the characteristics of overall portfolios, allowing us to estimate the effects of smartphones net of any potential substitution effects.

We evaluate our main outcome variables with the difference-in-differences specification from Equation 2 and report the results in Table 4. This specification captures the differential response in the dependent variables for investors at the first bank, which launched its app in May 2010, compared to those at the second bank. As in previous analyses, we begin by

15. In Germany, retail investors have tax allowances on their capital gains. Therefore, they communicate to our two banks the amount of tax allowance to be applied to their account. We conservatively define primary accounts as those allocated the maximum tax allowance.

evaluating risk-taking, now measured as the mean trailing 12-month volatility of all assets purchased by an investor within a month. Column (1) presents the estimates, indicating that the volatility of assets purchased by investors at the first bank increases by 3.1 percentage points relative to those at the second bank following the smartphone app launch. This effect is economically significant, representing 10.7% of the unconditional mean.

Our second set of outcomes examines investor preferences for skewness and lottery-type assets, with results reported in Columns (2) and (3). Similar to the volatility calculation, we compute skewness as the mean 12-month trailing skewness of all assets the investor purchases within a month. We measure lottery-type assets by the average likelihood of purchasing such assets by the same investor in the same month. We find that skewness for investors at the first bank increases by 14.6 percentage points more than for those at the second bank. The economic significance of this effect is notable, corresponding to 30.4% of the standard deviation of skewness for smartphone users. Similarly, the relative increase in the likelihood of purchasing lottery-type assets is 7.9 percentage points or 56.8% of the sample mean.

The second half of the analysis evaluates whether smartphone access leads investors to shift toward more concentrated portfolios and whether it increases the likelihood of purchasing attention-grabbing assets. We measure these effects using the probability of purchasing non-diversifying assets and assets with extreme past performance (either positive or negative) as outcome variables. Column (4) presents the estimates for non-diversifying assets, showing a relative increase of 18.6 percentage points in the probability of purchasing such assets for investors at the first bank compared to those at the second bank. Likewise, the likelihood of purchasing assets in the top (bottom) deciles based on past performance increases by 3.9 (4.9) percentage points, corresponding to 19.5% (37.6%) of the unconditional mean.

The identifying assumption for this analysis is that of parallel trends following the application launch. While we cannot directly test for this assumption, we can test for parallel trends before the smartphone app launch. Based on event-time, we estimate a dynamic specification that splits the $SmartphoneLaunch_{i,t}$ variable from Equation 2. This analysis also allows us to evaluate how long the smartphone effects persist over time. Formally, we estimate the following regression:

$$y_{i,t} = \sum_{\tau=-4}^{8} \beta_\tau \times SmartphoneLaunch_{i,\tau} + \delta_i + \gamma_i + \epsilon_{i,t} \tag{3}$$

so that we can plot the estimated coefficients β_τ with the corresponding confidence intervals. $SmartphoneLaunch_{i,\tau}$ is an indicator variable that takes a value of one τ quarters relative to the launch of app by investor i's bank. Each of these coefficients captures the effect of the smartphone app launch by event-quarter. Our sample includes more than eight quarters post-launch, and the dummy variable at the end captures all subsequent quarters. Specifically, $\tau = 8$ represents all quarters after seven quarters from treatment.

The six panels of Figure 3 plot these coefficients. We also report them in Table A5. Across all outcomes, we find no differential trends in the quarters prior to the app launch, supporting the assumption of parallel trends. However, investor behavior changes significantly after the app launch for those with access, relative to those whose bank has not yet launched the app. While we observe an immediate shift in the outcome variables following the launch, the effect strengthens over time, likely due to increasing adoption. These effects also persist over the long term.

We also examine differences in the levels of investor characteristics across the two banks prior to the smartphone launch. Using an OLS regression framework, we compare these differences while controlling for characteristics included in our baseline analysis, such as age-by-time and gender-by-time fixed effects. Although we observe unconditional differences between the two groups of investors, the key question in our empirical setting is whether we can adequately account for these differences through our controls.[16] Table A6 presents the

16. Wealth at account opening is a categorical variable that splits the population into six wealth categories

results of these cross-sectional comparisons, showing no significant differences in our main outcomes across investors from the two banks prior to the smartphone launch.

Overall, consistent with the transaction-level analysis, we find that smartphone access alters investor behavior by increasing the riskiness of assets purchased, heightening preferences for skewness and lottery-type assets, reducing portfolio diversification, and increasing the likelihood of buying assets with extreme performances. These results are robust across different specifications and persist over time.

4 Mechanism

This section investigates what drives the differential trading behavior associated with smartphones. First, we test whether trading on smartphones at different times of the day can explain our results. Next, we examine whether digital nudges and tailored information displays on smartphones contribute to our findings. Finally, we examine if smartphones promote more System 1, intuitive thinking. The transaction-level analysis provides detailed data, including the time stamps for trades and the locations of traders. We leverage this information to test various potential mechanisms.

4.1 Constant Access to Trading

Smartphones potentially provide immediate access to trading across an extended period of time. To assess whether this extended access drives our results, we use data from one of the banks that includes information on trading hours. We begin by examining trading dynamics at different times of the day. In Panel A of Figure 4, we plot the density of trades per hour for all users, including both smartphone and non-smartphone users. Trading activity shows two peaks, coinciding with the opening (9:00 to 10:00 a.m.) and closing

and is collinear with investor fixed effects in our baseline.

(4:00 to 5:00 p.m.) of financial markets in Germany. In Panel B of Figure 4, we plot the same density separately for smartphone and non-smartphone users. The two density plots largely overlap, with smartphone users slightly more likely to trade around closing hours. Finally, in Panel C of Figure 4, we limit the analysis to smartphone users and compare their trades made on smartphones versus other platforms. Again, the density plots show no significant differences, indicating that traders use smartphones and other platforms with similar frequency throughout the day.

In Table 5, we formally examine the effects of trading hours on our results by incorporating both investor-by-month and trading hour-by-year fixed effects into our transaction-level analyses. This specification enables us to compare trades made during the same hour of the day (e.g., 9:00 a.m.) within the same year. All our previous results remain robust to this additional specification. Smartphone users are more likely to purchase volatile, high-skewness, lottery-type, non-diversifying assets and past winners and losers. Compared to our baseline results in Table 3, the economic magnitudes are attenuated. For example, the effect size for purchasing past winners is reduced to 27.6% of the previous estimate (2.4 percentage points vs. 8.7 percentage points), while the skewness of purchased assets is attenuated to 44.8% of the baseline (4.7 vs. 10.5). Despite this attenuation, all results remain economically significant. For instance, the probability of purchasing lottery-type assets via smartphones increases by 2.1 percentage points, or 17.5% of the unconditional mean (12%).[17]

Overall, the evidence suggests that the choice of trading hours contributes to but does not fully explain our findings.

17. When we run specifications with both hour-of-the-day and asset-class fixed effects, we find smaller but still economically and statistically significant smartphone effects. We report these results in the Appendix Table A7.

4.2 Do Information Display and Digital Nudges Drive Our Results?

Choice of architecture and nudges can significantly affect economic decisions, from personal investments to saving for retirement or from credit cards to mortgages (for a review see Thaler and Sunstein, 2008). Smartphone apps are very effective in nudging consumers and changing their consumption and spending behaviors (Levi and Benartzi, 2024; D'Acunto et al., 2020). Analogously, investing apps can influence behaviors by using push notifications or by giving more salience to specific information. For example, the Robinhood trading app prominently features the winning and losing stocks of the previous day.[18] Welch (2020) and Barber et al. (2020) document that Robinhood investors are more likely to buy top winners and top losers. Thus, prominently displaying "top mover" stocks in the app could contribute to generating these trading patterns. Similarly, in our setting, information displayed in the smartphone app could mechanically generate trades that favor riskier, lottery-type, non-diversifying assets, or past winners and losers.[19]

To directly test if digital nudges drive our results, we would need to observe how information is displayed on the mobile apps as opposed to other platforms. This information is only partially available to us.[20] We overcome this data limitation by running other tests that indirectly capture the effect of nudges and information display.

First, we exclude daily winners and losers from our analysis. Following the approach in Kumar et al. (2020), we define the top 100 stocks with the highest daily returns as daily winners. Analogously, we define daily losers as the 100 stocks with the worst daily returns.

18. Under the recent news, Robinhood displays the "*Top Movers*" list, presenting the four stocks with the highest absolute return since the market closing the previous day. By clicking on the "*Show More*" option, the investors could see an expanded list of the 20 stocks with the largest price movements.

19. Note that, as discussed earlier, the apps associated with our sample do not have features like explicit push notifications related to assets that may encourage some trades over others.

20. While we can observe the current app for one of the two banks, we do not know what information was displayed when the app was first introduced nor if any meaningful change has occurred.

In Panel A of Table 6, we present results from running our main analyses after excluding purchases of daily winners and losers both on the same day and the day prior to the purchase (i.e., we exclude purchases of daily winners and losers associated with both days). Not only are all our results statistically and economically significant, but our point estimates are also very similar to the baseline estimates in Table 3.

Second, given that smartphone apps feature only past winners and losers among individual stocks, we run another robustness test by limiting our analyses to mutual funds. If digital nudges mechanically drive our results, we would not expect to find smartphone effects in trades that involve mutual funds. We report the results of these analyses in Panel B of Table 6, where we find that smartphone effects are also strong when investors buy mutual funds using smartphones. These results are consistent with investors moving away from passive mutual funds (that are, in general, less volatile and less likely to earn extreme returns) towards actively managed funds when using smartphones. To account for the fact that banks could potentially nudge investors towards more expensive, actively managed funds using smartphones, we repeat this analysis by limiting our sample to purchases of active mutual funds. In Panel C of Table 6, we document that even among actively managed funds, investors are more likely to buy funds that have higher volatility, higher skewness, more lottery-type characteristics as well as past winners or past losers.

Differences in physical screen size across platforms can also lead to differences in information display. Smartphones have a smaller screen, where information can be more challenging to navigate and more prominent features can capture much of the investor's attention. This physical attribute of smartphones can exacerbate existing trading biases or create new ones (for a review, see Benartzi and Lehrer, 2015). Therefore, we test if a smartphone's smaller screen size contributes to our results.

Looking at one bank from 2010 to 2015, we can observe if trades occur through a smartphone (iPhone), iPad, or desktop, thus providing variation in the device's screen size. In this analysis, we estimate the effect of smartphones and iPads separately by comparing them to other platforms.[21] We report our results in Table A8. In Panel A, we include individual and year-fixed effects. We do not have enough power to include investor-by-month fixed effects as in our previous analyses because such estimates would be based only on those investors who trade in the same month using at least three platforms: a smartphone, iPad, and desktop (or other platform). The estimates in Panel A are less restrictive because they only use variation from those investors who make at least one trade across the three different platforms during our sample period. Using this specification, we find that iPhones and iPads increase the likelihood of buying more volatile, higher skewness, less-diversifying assets, and past winners. The magnitudes are very similar for the volatility of assets purchased and, possibly, stronger in iPad trades for skewness, underdiversification, and past winners.

The estimates in Panel A of Table A8 are identified by comparing trades of the same investors across devices with different screen sizes. Nonetheless, investors that use three different platforms could be a non-representative sample of the other traders at the two banks. To address this selection, we include only year-fixed effects in Panel B of Table A8 and exploit both within- and across-individual variation. Consistent with our results in panel A, we also find in this specification that the effects of iPhones and iPads are very similar across all our outcome variables. Collectively, this evidence suggests that the smaller screen size of smartphones does not drive our main results. Our findings are consistent with the evidence in Liao et al. (2020) that differences in the devices' physical attributes per se do not drive investor behavior in a peer-to-peer lending platform.

These findings suggest that digital nudges and information display likely do not drive the smartphone effects we document. One could argue that even if these were to drive our results mechanically, they are features of the smartphone app and, ultimately, just the channel through which smartphones influence trading behavior. While documenting these channels

21. In our main analyses, the smartphone platform included both smartphones and tablets such as iPads.

would still be interesting, showing that smartphones have effects above and beyond automatic nudges or information display has more profound implications. First, given that each smartphone app has specific features and potentially employs different nudges or information display, our results—not being driven by any particular nudge or display—are more likely to generalize to smartphone trading apps in general. Second, the policy implications are starkly different. If digital nudges or display drive trading behavior, regulating them could limit the effects of smartphones. Alternatively, if these are not the sole drivers of trading behaviors, any policy intervention regulating the choice architecture in these apps might not be as effective as hoped.

4.3 Does Greater Reliance on Intuitive, System 1 Thinking Drive Our Results?

Smartphones may facilitate more intuitive and impulsive trading, which could help explain our results. In System 1 versus System 2 (dual) economic decision-making models, individuals engage less in analytical System 2 thinking when this cognitive effort is more costly or yields lower benefits. For example, Ilut and Valchev (2023) develop a bounded rationality model based on the System 1 versus System 2 duality, where rely less on System 2 in typical, usual conditions. Similarly, Kahneman (2011) suggests that System 2 engagement decreases when individuals are tired or cognitively depleted or in a better mood and perceive situations as less risky.

Motivated by these insights, we test for the role of System 1 thinking in our context by examining heterogeneity in our findings across different conditions: days with usual vs unusual states, after-hours versus exchange hours, pre- versus post-lunch hours, and days with varying levels of sunshine. Individuals might be less likely to engage System 2 during dates with usual states, when their ego is more depleted during after-hours trading (due to fatigue) or in pre-lunch hours (due to low glucose levels), and when their mood is better because of sunshine.

We begin our analysis by examining heterogeneity in the effects on days with and without unexpected announcements. This test is instrumental because it allows us to disentangle if more intuitive thinking or timely access to information drives smartphone effects. If smartphones promote more System 1-based thinking, we would expect stronger effects on days without unexpected information, as such days are closer to the usual states of the world (Ilut and Valchev (2023)). Alternatively, smartphones might influence trading by providing more timely access to information. More volatile assets, lottery stocks or past winners/losers can grab investor attention on days when new information is released. In this case, timely access to this information via smartphones might explain our findings. Therefore, we would expect stronger effects on days with unexpected announcements.

Table 7 presents the results of this analysis. Panels A and B display the findings for days with and without unscheduled announcements, respectively. We observe significantly stronger effects on days without unscheduled announcements, suggesting that System 1-based decision-making likely contributes to our findings. These results imply that information-based trading and more timely access to information via smartphones are unlikely to drive our results. A potential concern to this interpretation is that we may lack power for the sub-sample of unscheduled announcement days. Though possible, the coefficients' magnitudes across the two groups are different, suggesting that this may not affect our inference.

Alternatively, we can use the overall market volatility to capture days with typical market conditions or lower perceived risk. We repeat our analysis to evaluate heterogeneity in our findings based on days with different levels of volatility, using the VDAX index. This index measures the implied volatility of the German stock market, specifically for the DAX 30, Germany's primary stock index, which comprises 30 major blue-chip companies listed on the Frankfurt Stock Exchange. The VDAX is analogous to the VIX index, which measures implied volatility for the S&P 500 in the United States.

Table 8 presents the results of this analysis, with Panels A and B showing the findings for days with above- and below-median levels of implied volatility, respectively. Consistent with the hypothesis of more System 1-based trading on smartphones, we find stronger effects on days with low volatility.

Our subsequent analyses examine heterogeneity based on hours of the day. Table 9 reports these results where we re-estimate our main specifications separately for trades during market hours (9 a.m. to 5 p.m.) vs. trades during after-hours (5 p.m. to 10 p.m.).[22] The effects of smartphones vs. other trading platforms are significantly stronger during after-hours (Panel B) as compared to market hours (Panel A). Excluding purchasing past winners, our estimates are, on average, roughly 2.5 times higher during after-hours, ranging from a 46% increase in the probability of buying risky stocks to a three-fold increase in the skewness of the assets purchased.

A potential concern with this analysis is that institutional features could be systematically different when trading during market hours instead of after-hours when markets are closed. These different institutional features—and not a higher reliance on system 1—could drive our results. To help address this concern, we run a falsification test by estimating smartphone effects in the morning, between 8 a.m. and 9 a.m. During this morning hour, national stock exchanges are still closed in Germany. In contrast, investors are less likely to suffer from decision fatigue earlier in the morning. If institutional features drive our results, we would expect to find similar results during after-hours and this particular morning hour. Alternatively, if fatigue-induced higher reliance on system 1 drives our results, we would expect stronger smartphone effects during after-hours. Consistent with this latter interpretation, we document in Panel C that smartphone effects are weaker in the morning hour

22. Local German market makers allow investors to trade between 5pm and 10pm, even if national stock exchanges are closed.

compared to trades during after-hours.

We next examine the heterogeneity in our effects based on whether the trade occurred during the hours just before or post lunch. Glucose levels are low before lunch. During these times, decision-making is likely less reliant on logical but effort-based System 2 thinking. Consistent with this argument, Danziger et al. (2011) show that experienced judges are much more likely to give favorable rulings on parole cases immediately after food breaks than prior to breaks. Since we do not directly observe the lunch time for investors in our sample, we assume a lunch hour from noon to 1:00 pm and examine heterogeneity in smartphone effects for trades that occur during the hour prior to lunch hour (i.e., 11:00 am-12:00 pm) versus those that occur after lunch hour (i.e., 1:00-2:00 pm).

Table 10 presents results for this estimation. While Panel A includes results for the sub-sample of trades that occur prior to lunch, Panel B includes results for trades during the post-lunch hour. Consistent with greater reliance on system 1 thinking during the hour prior to lunch, we find stronger smartphone effects between 11am-12pm relative to trades between 1-2pm. On average, across all outcomes, the coefficients during pre-lunch are 1.87 times the estimates during the post-lunch hour.

Our final test pertaining to the role of system 1 thinking involves investigating the heterogeneity based on trades executed during days with different types of weather. Literature has shown that weather affects different household economic decisions, including car purchases (Busse et al. (2015)) and risk-taking (Bassi et al. (2013)). When individuals are in a good mood, the reliance on system 2 in the decision-making process could decline. Hence, good weather may lead to more system-1 based trades and exacerbate smartphone effects. Table 11 reports results for this analysis where we re-estimate our baseline effects for trades that occur during days with above and below median levels of sunshine. We find stronger results during days with above-median levels of sunshine. Across all outcomes, the estimates are about 10% higher for days with higher levels of sunshine.

Overall, the results in this section suggest that a greater reliance on intuitive, System 1 thinking during smartphone trades contributes to our findings.

5 Implications

In previous sections, we investigate the effects of smartphones on investor behavior and the mechanisms behind these effects. In this section, we explore the implications of our findings for investor performance and the external validity of our results. These analyses also help shed light on the relation between smartphone effects, experience, and age.

5.1 Investor Performance

Do investors harm their performance when trading via smartphones? The literature has linked the behaviors associated with smartphone trading to lower investor performance.[23] We test whether smartphone use, which promotes risky, gambling-type trades and investment biases, is associated with negative performance using both transaction- and investor-level analyses. The transaction-level analysis allows us to examine whether purchases made via smartphones underperform, while the investor-level analysis sheds light on the broader effects of smartphone access on overall portfolio performance.

In Table 12 we report results from transaction-level regressions of smartphone usage on Sharpe ratios of the assets purchased. We report the Sharpe ratios of all the assets purchased, assuming four hypothetical holding periods: one month, three months, six months, and up to twelve months.[24] We choose these four horizons based on the average annual buy turnover for similar German investors, estimated to be between 80 to 90 percent (see, for example, Loos

23. Kumar (2009) documents that investors who disproportionately buy lottery-type stocks experience more significant underperformance. Calvet et al. (2007) and Goetzmann and Kumar (2008) find that underdiversification can lead to substantial welfare losses for some investors. Kumar et al. (2020) show that stocks classified as past winners and losers underperform other stocks in the month following the ranking.

24. While we could potentially compute the actual holding period for each purchase, this approach would become challenging to implement when investors buy and sell assets using different platforms.

et al., 2020). In Columns 1-4, we report that using smartphones reduces the Sharpe ratios of the assets purchased across all hypothesized holding periods. These effects are statistically and economically significant. For example, smartphones reduce the Sharpe ratio by 0.14 or 35.9% of the unconditional mean for smartphone users (equal to 0.39) over a twelve-month horizon.

In Figure 5, we analyze the distribution of the Sharpe ratios of assets purchased, separately for smartphone vs. non-smartphone trades. To avoid selection effects, we limit this analysis only to smartphone users. This figure plots evidence consistent with the results in Table 12. Smartphone purchases have systematically lower Sharpe ratios across the entire distribution.

As previously documented, investors are more likely to buy more volatile assets using smartphones. Therefore, this increase in volatility could determine lower Sharpe ratios. Alternatively, lower Sharpe ratios could also result from assets purchased via smartphones having lower returns. To better understand the drivers of lower performance, we analyze market-adjusted returns in Table A9 of the Appendix. Regardless of the holding period (from one to twelve months), we find that assets purchased using smartphones have lower market-adjusted returns. For example, smartphone trades earn 60 basis points lower returns or 15% of the unconditional mean for smartphone users (-4%) over a twelve-month horizon.

While the transaction-level analysis shows that purchases made using smartphones by the same investor underperform, this approach has two limitations. First, it requires assumptions about holding periods, although the results appear robust across different holding periods. Second, it does not reveal whether smartphone trading negatively impacts overall portfolios. If smartphone trades represent only a small fraction of total trades, their underperformance might not significantly affect portfolio outcomes.

To address these limitations, we complement the transaction-level analysis with investor-level tests to examine the broader impact of smartphone trading on investor performance.

Using our difference-in-differences approach and the variation in smartphone app launch dates across the two banks, we estimate Equation 3 with investor performance as the outcome variable. We employ two performance measures: value-weighted excess portfolio returns and the Sharpe ratio. Figure 6 plots the estimated coefficients. Across both measures, we find no differential trends in the quarters prior to the app launch. However, investor performance declines significantly after the app launch for clients with access, relative to those whose bank has not yet launched the app. These effects persist over time.

Collectively, the evidence shows that trades executed on smartphones underperform compared to non-smartphone trades, and smartphone usage negatively impacts the overall portfolio performance of investors.

5.2 Heterogeneity by Investor Experience and Age

The investors in our sample tend to be older and more experienced than the Robinhood crowd investigated in other recent studies (e.g., Welch, 2020 and Barber et al., 2020). In Panel B of Table 2, we report that our German smartphone users are 45 years old with 8.7 years of experience on average. Having a more experienced and age-balanced sample of investors allows us to investigate smartphone effects in both younger and older generations.

First, we formally investigate how smartphone effects vary by investor experience. We hypothesize that the impact of smartphones might decrease with investment experience. If this is the case, then our results might underestimate the effects of smartphones on younger and less experienced investors. In Table 13, we report our main results across two equal sub-samples: "new" investors with below-median investment experience and "old" investors with above-median experience. We report results from estimates using investor-by-month fixed effects. To account for the likelihood that the investment experience with the banks may mechanically increase with age, we add to our estimation age-by-year fixed effects to flexibly control for time-varying effects of age.

We find evidence of strong smartphone effects across all investment behaviors in both sub-samples. Consistent with our hypothesis, we find stronger effects for less experienced investors. The effects of smartphones are, on average, 23% stronger for inexperienced investors. Nonetheless, smartphone effects remain about three-quarters as strong for investors with more than nine years of trading experience with the bank.

We present results for different age groups in Table A10. For most investment behaviors, smartphone effects are the strongest among investors 40 years old or younger. Except for two out of six behaviors, we also find economically and statistically significant smartphone effects for investors 60 years or older. Smartphone effects range from 30% to 50% of the average magnitude estimated for all the other age groups.

Overall, this evidence suggests that smartphone effects remain strong for more and less experienced investors and for younger and older generations.

6 Conclusion

Smartphones represent one of the most widely used technologies, with over 250 million devices in the US alone. Large online brokers report that over 20% of all retail investor annual trades have been executed using mobile devices and estimate that this percentage will double in the next few years. As smartphone trading has become increasingly popular, so have concerns about its potential negative effects for young and inexperienced investors.[25]

Using a novel dataset from two large German retail banks, we investigate whether and how smartphones influence investor behavior. Employing two distinct empirical strategies, we find that smartphones encourage purchases of assets with higher volatility and skewness, reduce diversification, and promote chasing past winners and losers. Notably, substituting

25. In a 2020 article titled "*Robinhood Has Lured Young Traders, Sometimes With Devastating Results*", the New York Times features a series of stories of investors that have lost a substantial amount of money trading on their mobile phones.

trades across platforms by the same investor does not drive these effects.

We conduct several analyses to understand the mechanism behind these results better. The selection of specific times of the day when using smartphones contributes to — but does not fully explain—our results. We do not find evidence that information display, digital nudges, or screen size drives our results. Conversely, our findings are consistent with smartphones facilitating or fostering a higher reliance on more intuitive, system 1 thinking.

These trading behaviors have significant implications for retail investors. Smartphones encourage the purchase of assets with lower Sharpe ratios and worsen overall portfolio performance. Furthermore, experience lowers but does not eliminate the adverse effects of smartphone trading. As a result, our estimates, based on a sample of more experienced German investors, likely represent a lower bound for the potential adverse effects on younger and less experienced retail investors, such as Robinhood users.

Overall, our findings caution against relying on smartphones as the primary technology for facilitating retail investors' access to financial markets. They also suggest that policies targeting specific app features like gamification might be limited in successfully addressing the broader adverse effects of the device itself. Although this paper focuses on the impact of smartphones on individual investors, our findings could have wider implications for stock market returns. As smartphone trading becomes increasingly pervasive, investor demand for high-volatility, high-skewness, lottery-type stocks, and past winners and losers could rise significantly. This excess demand may, in turn, systematically influence the pricing of these assets in financial markets.

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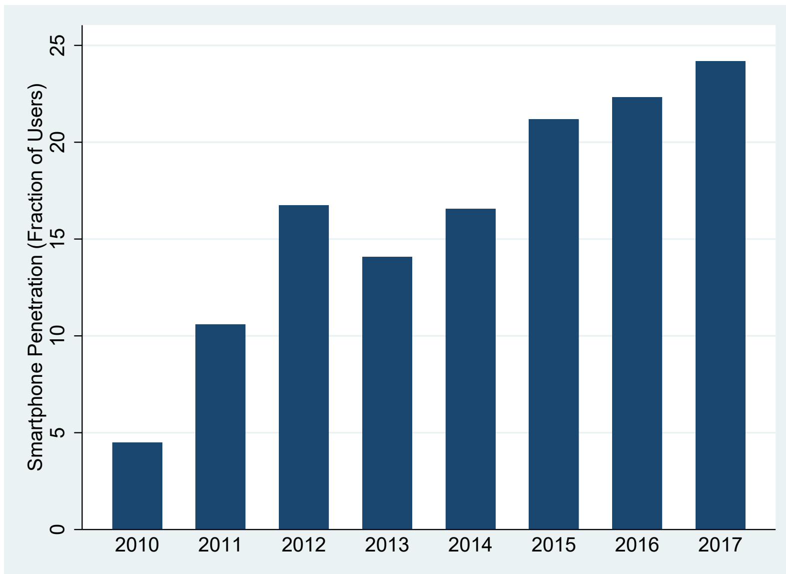
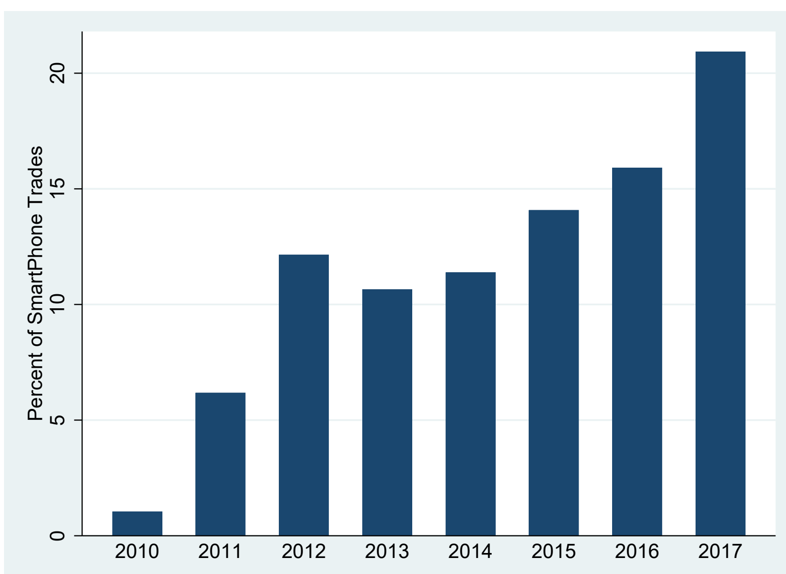
Figure 1:
Smartphone Penetration
This figure plots the smartphone penetration both over users and trades through time. Panel A plots the fraction of users who adopt the technology in different years. Panel B plots the number of trades executed over smartphones by investors who use the smartphone at least once.



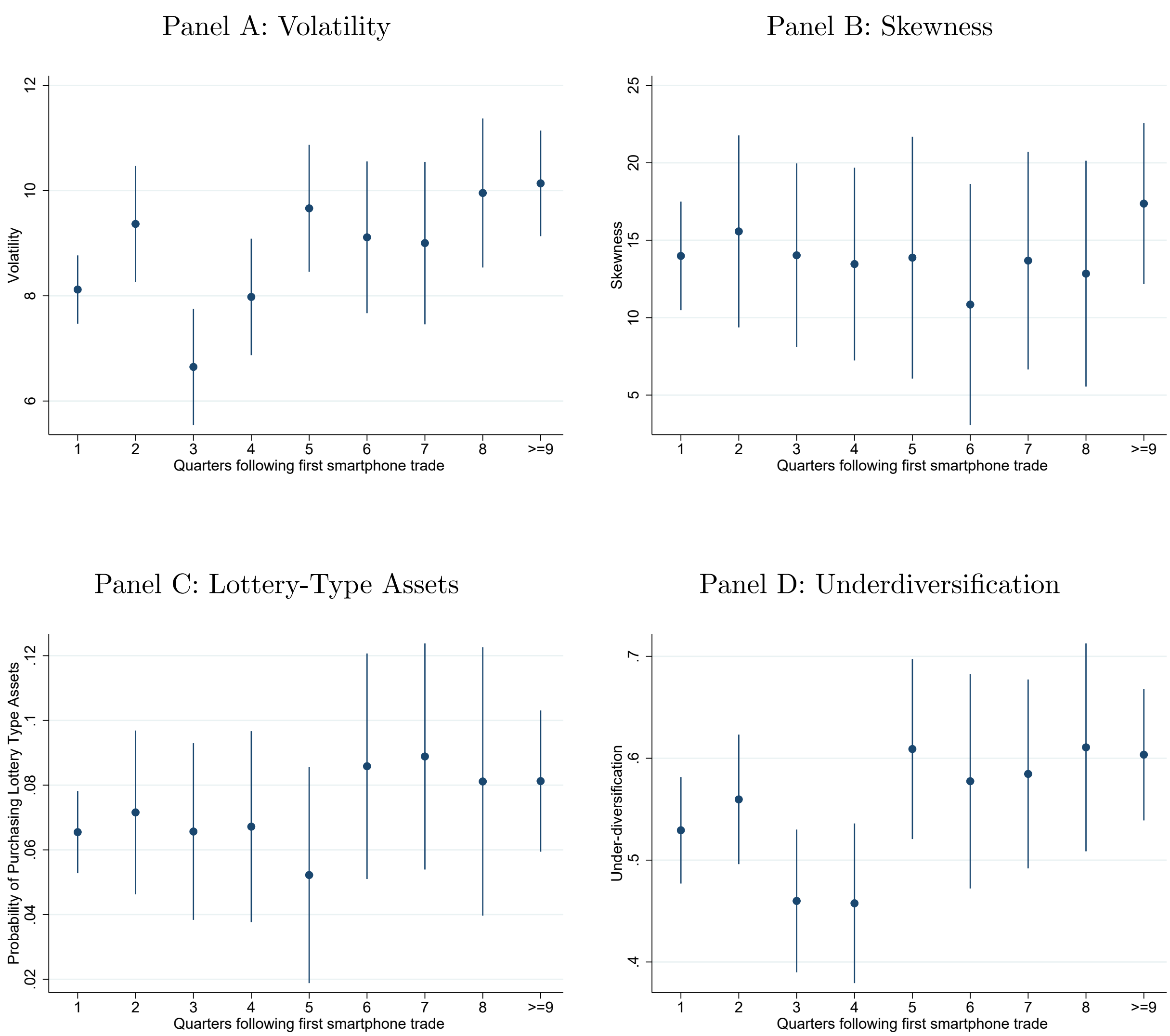
Panel A: Fraction of users

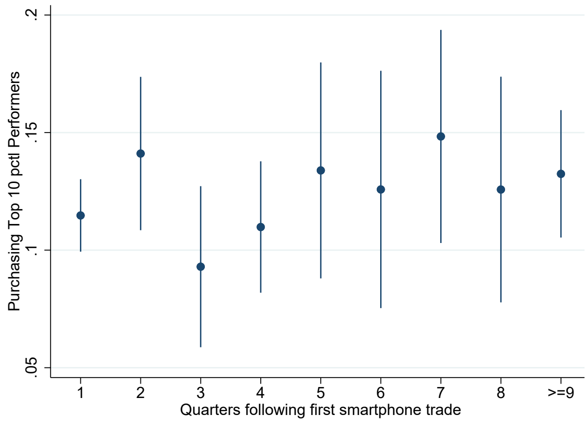


Panel B: Fraction of trades for adopters

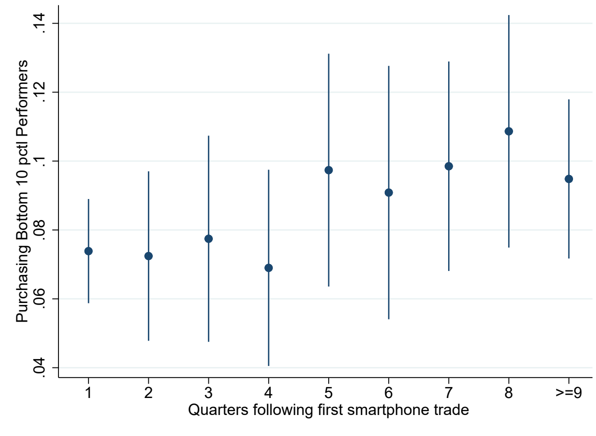
Figure 2:
Dynamics of Smartphone Effects: Transaction Level

This figure plots the dynamics of the baseline effects estimated using transaction-level analysis relative to the first use of a smartphone. Each coefficient represents the impact of smartphone use on outcomes for different event quarters. The outcome variables include the volatility of assets purchased (Panel A), the skewness of assets purchased (Panel B), the probability of purchasing lottery-type assets (Panel C), underdiversification (Panel D), and the probability of purchasing past winners (Panel E) and past losers (Panel F). Confidence intervals are displayed at the 5% level.





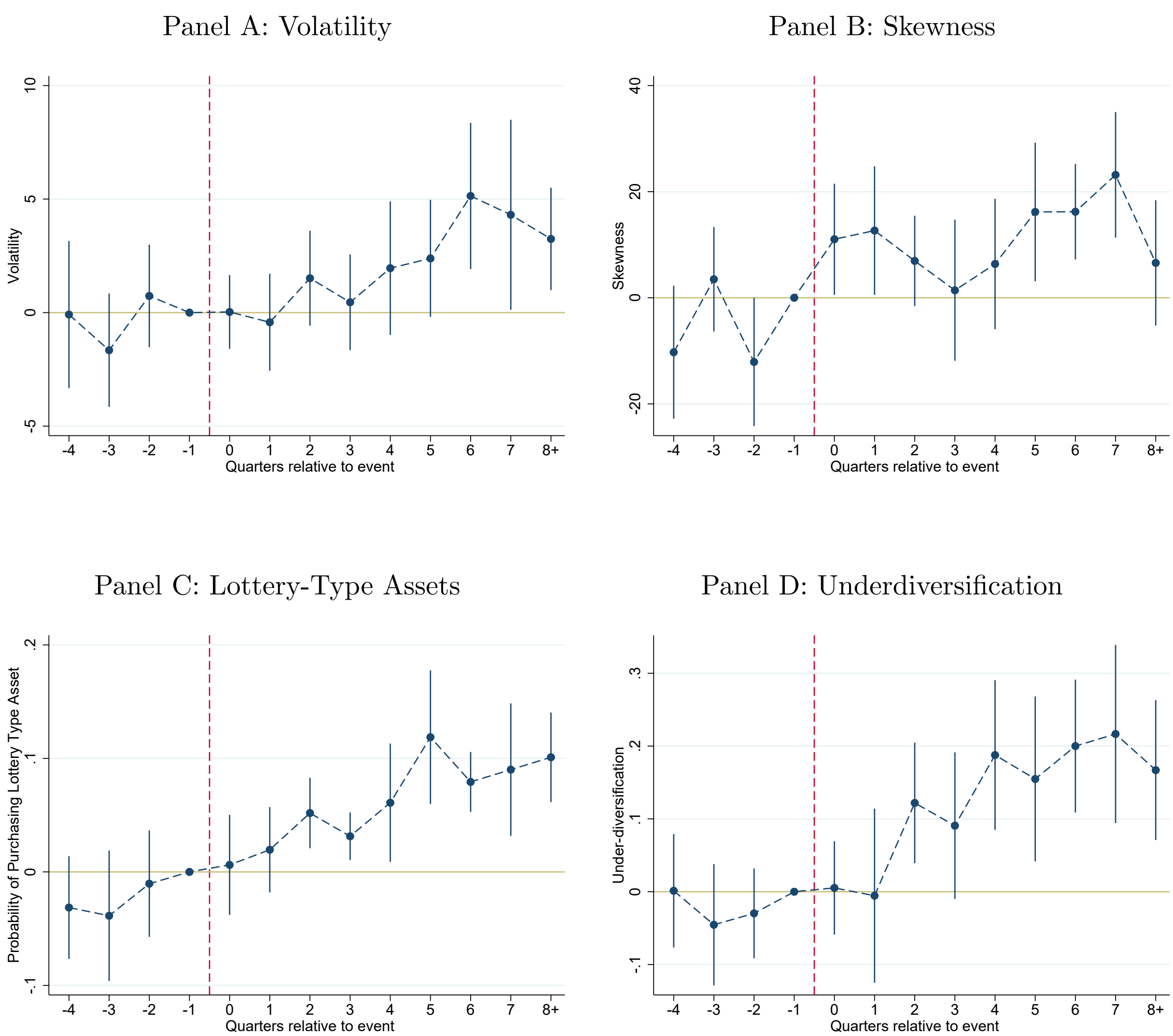
Panel E: Past Winners

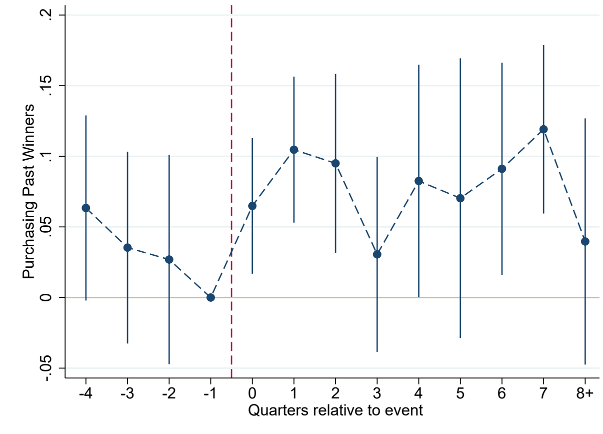


Panel F: Past Losers

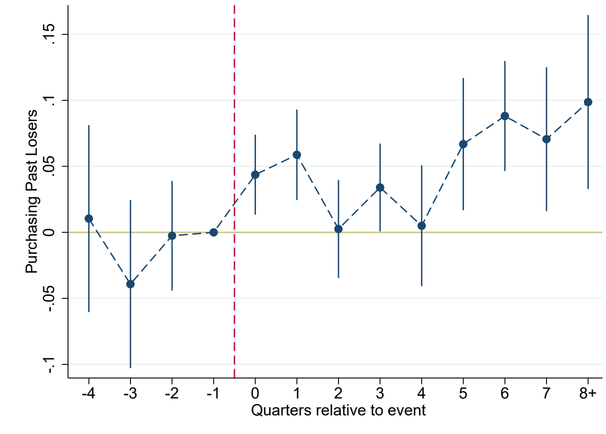
Figure 3:
Dynamics of Smartphone Effects: Investor Level

This figure plots the dynamics of the baseline effects estimated using investor-level analysis relative to smartphone launch at one of the banks. Each coefficient represents the impact of smartphone access on outcomes for different event quarters. The outcome variables include the volatility of assets purchased (Panel A), the skewness of assets purchased (Panel B), the probability of purchasing lottery-type assets (Panel C), underdiversification (Panel D), and the probability of purchasing past winners (Panel E) and past losers (Panel F). Confidence intervals are displayed at the 5% level.



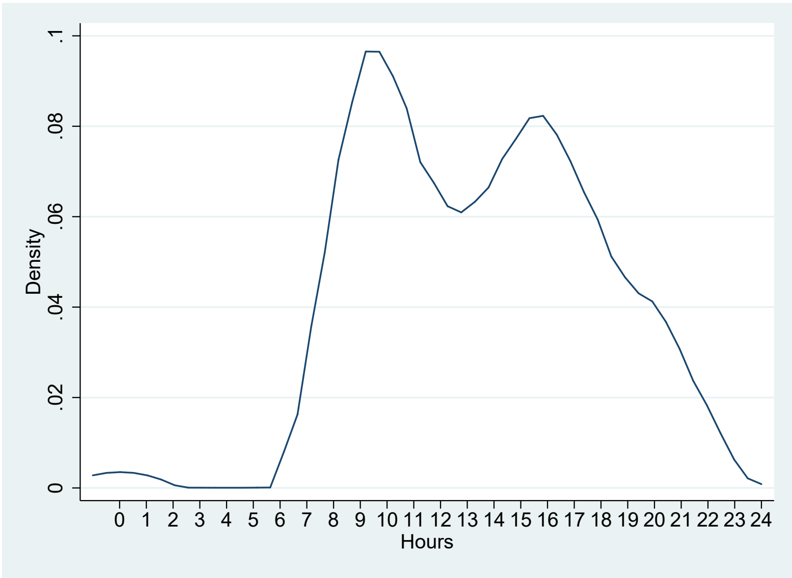


Panel E: Past Winners

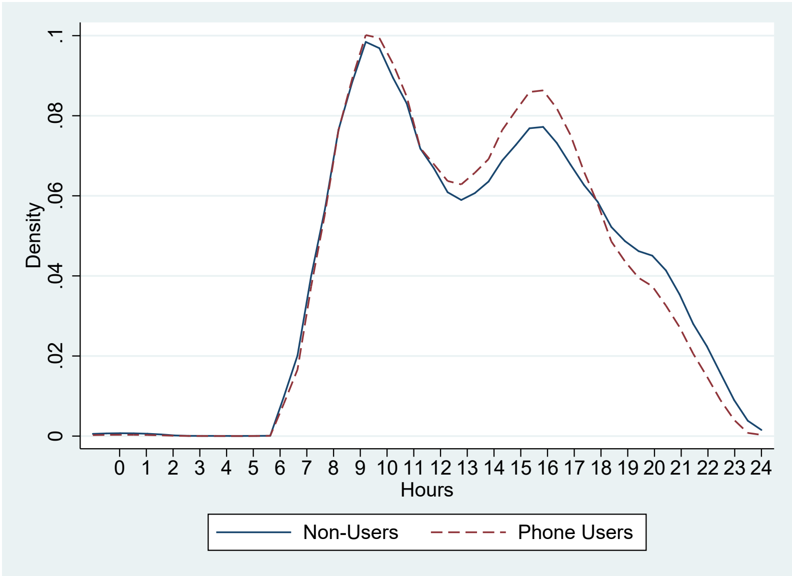


Panel F: Past Losers

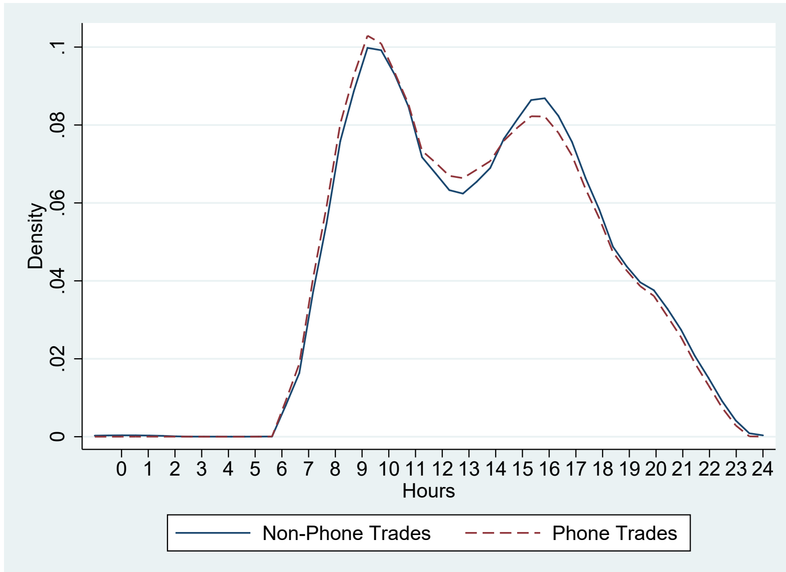
Figure 4:
Trading Hour Density
This figure plots the density for each hour of the day when a trade occurs. Panel A plots this density for the entire sample. Panel B compares this density for smartphone users (dashed) versus non-users (solid). Panel C plots this density only for smartphone users and compares smartphone (dashed) and non-smartphone trades (solid).



Panel A: All Investors



Panel B: Smartphone vs. Non-smartphone Users



Panel C: Smartphone vs. Non-smartphone Trades (for adopters)

Figure 5:
Performance: Distribution of Sharpe Ratios (Transaction Level)
This figure plots the density for the Sharpe ratio of assets purchased by device type. We assume a twelve-month holding period. The dashed (solid) line represents purchases made using smartphones (non-smartphone platforms).

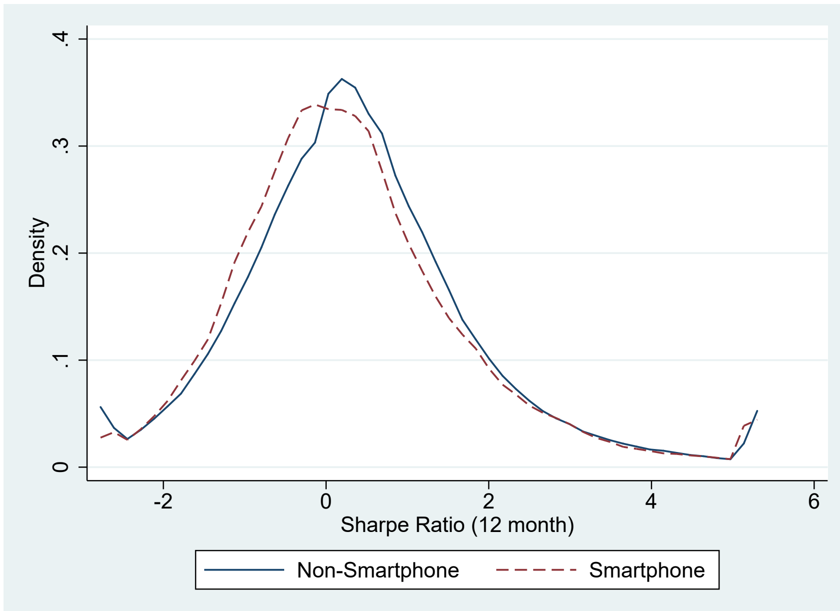
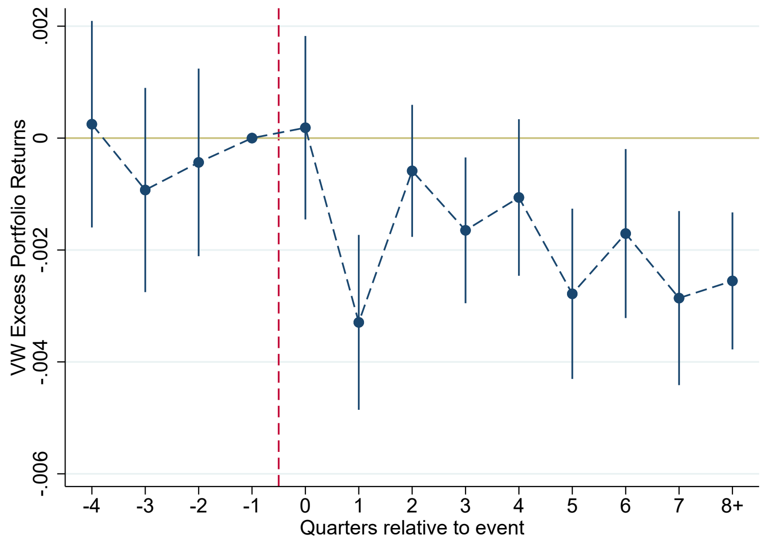
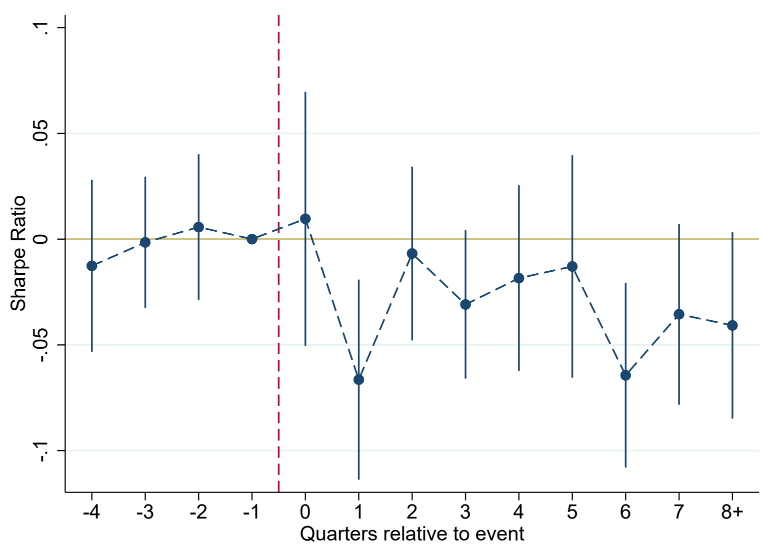


Figure 6:
Performance: Investor Level
This figure plots the dynamics of the smartphone effects on portfolio-level performance estimated using investor-level analysis relative to smartphone launch at one of the banks. Each coefficient represents the impact of smartphone access on value-weighted excess returns (Panel A) and Sharpe ratio (Panel B) for different event quarters. Confidence intervals are displayed at the 5% level.



Panel A: VW Returns



Panel B: Sharpe Ratio

Table 1:
Summary Statistics

This table reports the summary statistics of the variables used in our analyses for all the investors in our sample for the years 2010 to 2017. Volatility of the asset purchased is reported in percentage points. Sharpe ratios and market-adjusted returns are computed assuming a twelve-month holding period.

	Mean	Std.Dev.	p25	Median	p75
Smartphone Use	0.02	0.13	0.00	0.00	0.00
Prob of Purchasing Risky Assets	0.60	0.45	0.00	1.00	1.00
Volatility of Assets Purchased (%)	20.65	16.54	9.49	15.68	26.29
Skewness of Assets Purchased	-3.40	65.95	-40.99	-3.38	35.51
Prob of Purchasing Lottery-type Assets	0.10	0.31	0.00	0.00	0.00
Underdiversification	0.51	0.65	0.00	0.00	1.00
Prob of Purchasing Past Winners	0.16	0.37	0.00	0.00	0.00
Prob of Purchasing Past Losers	0.08	0.27	0.00	0.00	0.00
Risk Categories of Assets Purchased	4.28	0.86	4.00	5.00	5.00
Prob of Purchasing a Warrant	0.29	0.45	0.00	0.00	1.00
Prob of Purchasing a Certificate	0.03	0.18	0.00	0.00	0.00
Sharpe Ratio	0.52	1.42	-0.37	0.41	1.26
Market Adjusted Returns	-0.03	0.28	-0.15	-0.025	0.076

Table 2:
Who Uses Smartphones?
This table compares smartphone users to investors who never use smartphones to trade. In Panel A, we report descriptive statistics for variables associated with trading activity. These statistics are computed for smartphone users before the adoption. In Panel B, we report statistics for demographic variables. The volatility of the asset purchased is reported in percentage points. Sharpe ratios and market-adjusted returns are computed assuming a twelve-month holding period.

Panel A: Trading Activity

	Phone Users		*Non Users*		*Mean diff*
	Mean	Median	Mean	Median	*p-value*
Avg No of Trades per Month	10.01	3.00	5.32	2.00	0.00
Avg Value of Trades	4,477.11	1,895.00	3,812.90	1,000.00	0.00
Prob of Purchasing Risky Assets	0.68	1.00	0.58	1.00	0.00
Volatility of Assets Purchased (%)	22.01	17.78	16.52	13.13	0.00
Skewness of Assets Purchased	-5.61	-5.09	-9.02	-8.48	0.00
Prob of Purchasing Lottery type Assets	0.12	0.00	0.07	0.00	0.00
Underdiversification	0.65	0.59	0.47	0.00	0.00
Prob of Purchasing Past Winners	0.17	0.00	0.10	0.00	0.00
Prob of Purchasing Past Losers	0.09	0.00	0.06	0.00	0.00
Risk Categories of Assets Purchased	4.12	4.00	3.97	4.00	0.00
Prob of Purchasing a Warrant	0.43	0.19	0.24	0.00	0.00
Prob of Purchasing a Certificate	0.04	0.00	0.03	0.00	0.00
Sharpe Ratio	0.39	0.28	0.54	0.44	0.00
Market Adjusted Returns	-0.04	-0.03	-0.03	-0.024	0.00

Panel B: Socio-demographic Characteristics

	Phone Users		*Non Users*		*Mean diff*
	Mean	Median	Mean	Median	*p-value*
Income Bin [20k,60k)	0.60	1.00	0.60	1.00	0.88
Income Bin [60k,100k)	0.32	0.00	0.32	0.00	0.67
Income Bin [>=100k]	0.09	0.00	0.08	0.00	0.34
Wealth Bin [20k,60k)	0.75	1.00	0.80	1.00	0.00
Wealth Bin [60k,100k)	0.09	0.00	0.08	0.00	0.13
Wealth Bin [>=100k]	0.17	0.00	0.12	0.00	0.00
Years since Member	8.71	9.32	9.82	9.32	0.00
Age	44.85	45.00	52.61	52.00	0.00
Female	0.05	0.00	0.18	0.00	0.00

Table 3:
Smartphone Effects: Transaction Level

This table reports the baseline results estimated using transaction-level analysis. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	7.352***	10.548***	0.056***	0.406***	0.087***	0.066***
	(22.55)	(10.08)	(12.34)	(18.45)	(14.19)	(14.58)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,529,126	8,527,701	8,527,701	8,452,120	8,418,764	8,418,764
R^2	0.565	0.347	0.381	0.408	0.393	0.411

Table 4:
Smartphone Effects: Investor Level
This table reports the baseline results estimated using investor-level analysis. Each observation corresponds to an investor-by-month, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone Launch	3.119***	14.600***	0.079***	0.186***	0.039**	0.049**
	(3.09)	(2.65)	(3.12)	(4.25)	(2.29)	(2.60)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Age x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Gender x YM FE	Yes	Yes	Yes	Yes	Yes	No
Observations	307,411	307,363	344,981	343,575	284,622	284,622
R^2	0.555	0.289	0.271	0.534	0.313	0.285

Table 5:
Choice of Trading Hour

This table reports estimates from transaction-level analysis after separately controlling for trading hour-by-year fixed effects. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Volatility (1)	Skewness (2)	Lottery-Type Assets (3)	Under-Divers. (4)	Past Winners (5)	Past Losers (6)
Smartphone	2.516***	4.717***	0.021***	0.113***	0.024***	0.020***
	(10.10)	(5.91)	(3.62)	(7.05)	(4.05)	(3.90)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Trade Hour x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,335,955	4,335,054	4,335,054	4,261,470	4,264,904	4,264,904
R^2	0.691	0.453	0.474	0.476	0.484	0.515

Table 6:
Digital Nudges

This table reports estimates from transaction-level analysis conducted using different samples of trades that are less likely to be influenced by digital nudges. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Panel A excludes purchases of stocks that rank among the top 100 daily winners or bottom 100 daily losers. Panel B restricts the sample to mutual funds, while Panel C focuses on active mutual funds. The measure of underdiversification is excluded from Panels B and C because, by definition, all mutual fund purchases are diversifying trades. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Excluding Daily Winners and Losers

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	7.242***	10.341***	0.054***	0.409***	0.088***	0.064***
	(22.58)	(9.99)	(12.41)	(18.50)	(14.16)	(14.33)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,457,406	8,456,049	8,456,049	8,380,484	8,349,669	8,349,669
R^2	0.560	0.346	0.377	0.411	0.393	0.407

Panel B: Mutual Funds

	Volatility	Skewness	Lottery-Type Assets	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)
Smartphone	3.910***	9.658***	0.081***	0.053***	0.048***
	(10.48)	(4.80)	(7.91)	(6.76)	(4.75)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes
Observations	3,995,909	3,995,439	3,995,439	3,967,692	3,967,692
R^2	0.463	0.403	0.316	0.323	0.357

Panel C: Active Funds

	Volatility	Skewness	Lottery-Type Assets	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)
Smartphone	1.335**	4.880**	0.036***	0.078***	0.006*
	(2.21)	(2.02)	(2.92)	(5.91)	(1.83)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes
Observations	1,934,239	1,934,157	1,934,157	1,930,734	1,930,734
R^2	0.499	0.463	0.303	0.372	0.314

Table 7:
Heterogeneity by Announcement and Non-announcement days
This table reports estimates from transaction-level analysis conducted separately for days with and without unscheduled announcements. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: (Unscheduled) Announcement Days

	Volatility	Skewness	Lottery Type Asset	Underdiversification	Top 10 Pctl Performers	Bottom 10 Pctl Performers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	0.470	9.270**	0.023	0.072	-0.009	-0.002
	(0.46)	(2.26)	(0.80)	(1.64)	(-0.34)	(-0.06)
Investor x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65076	65076	65076	65022	64524	64524
R^2	0.563	0.445	0.510	0.235	0.492	0.528

Panel B: Non-announcement Days

	Volatility	Skewness	Lottery Type Asset	Underdiversification	Top 10 Pctl Performers	Bottom 10 Pctl Performers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	5.277***	8.008***	0.035***	0.292***	0.071***	0.042***
	(21.03)	(8.98)	(9.50)	(16.93)	(13.43)	(9.77)
Investor x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8769503	8768135	8768135	8694960	8663392	8663392
R^2	0.519	0.216	0.262	0.410	0.279	0.279

Table 8:
Heterogeneity by Market Volatility
This table reports estimates from transaction-level analysis conducted separately for days with above and below median levels of implied market volatility measured using VDAX index. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Days with Above-Median Volatility

	Volatility	Skewness	Lottery Type Asset	Underdiver sification	Top 10 Pctl Performers	Bottom 10 Pctl Performers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	5.291***	7.534***	0.038***	0.328***	0.056***	0.047***
	(16.51)	(6.65)	(5.87)	(13.02)	(10.62)	(8.56)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3885907	3885360	3885360	3832274	3834354	3834354
R^2	0.638	0.396	0.429	0.478	0.429	0.474

Panel B: Days with Below-Median Volatility

	Volatility	Skewness	Lottery Type Asset	Underdiver sification	Top 10 Pctl Performers	Bottom 10 Pctl Performers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	6.930***	10.254***	0.058***	0.396***	0.094***	0.058***
	(16.45)	(6.51)	(10.25)	(10.26)	(9.95)	(9.48)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4190771	4189931	4189931	4168213	4135863	4135863
R^2	0.631	0.396	0.431	0.467	0.455	0.451

Table 9:
Trading During Market Hours versus After-hours
This table reports estimates from transaction-level analysis conducted separately for different trading hours. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. The panels correspond to different times of the day: market hours (9 a.m. to 5 p.m.), after-hours (5 p.m. to 10 p.m.), and morning hour (8 a.m. to 9 a.m.). Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Market Hours

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	1.107***	1.946**	0.011**	0.093***	0.000	0.009**
	(5.95)	(2.47)	(2.47)	3.44	(0.08)	(2.53)
Investor x YM FE FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,402,424	2,401,766	2,401,766	2,401,766	2,356,801	2,356,801
R^2	0.656	0.466	0.484	0.346	0.498	0.524

Panel B: After-hours

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	2.691***	6.074**	0.028*	0.241***	0.090*	0.027
	(4.58)	(2.60)	(1.71)	(4.28)	(1.91)	(1.52)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	950,468	950,290	950,290	950,290	936,250	936,250
R^2	0.802	0.553	0.603	0.770	0.597	0.635

Panel C: Morning Hour

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	1.634***	4.016***	0.01	0.16***	0.042***	0.002
	(6.73)	(4.01)	(0.58)	4.14	(4.00)	(0.09)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	392,454	392,420	392,420	392,420	385,923	385,923
R^2	0.723	0.492	0.467	0.601	0.515	0.531

Table 10:
Trading During Pre- vs Post- Lunch Hour

This table reports estimates from transaction-level analysis conducted separately for trading hours before and after lunch. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. The panels represent different times around the lunch hour: 11 a.m.–12 p.m. (Panel A) and 1–2 p.m. (Panel B). Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Pre-Lunch

	Volatility	Skewness	Lottery Type Asset	Underdiver sification	Top 10 Pctl Performers	Bottom 10 Pctl Performers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	1.458***	4.299**	0.015	0.070***	0.007	-0.001
	(4.21)	(2.19)	(1.35)	(4.45)	(0.60)	(-0.07)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	353837	353762	353762	353760	348083	348083
R^2	0.488	0.220	0.291	0.435	0.299	0.298

Panel B: Post-Lunch

	Volatility	Skewness	Lottery Type Asset	Underdiver sification	Top 10 Pctl Performers	Bottom 10 Pctl Performers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	0.649	3.622*	0.012	0.032**	0.005	-0.003
	(1.35)	(1.95)	(1.08)	(2.12)	(0.52)	(-0.27)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	207450	207383	207383	207383	203185	203185
R^2	0.442	0.217	0.282	0.220	0.306	0.302

Table 11:
Heterogeneity by Weather

This table reports estimates from transaction-level analysis conducted separately for days with different levels of sunshine. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Panel A presents results for days with above-median sunshine, while Panel B reports results for days with below-median sunshine. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Days with More Sunshine

	Volatility	Skewness	Lottery Type Asset	Underdiversification	Top 10 Pctl Performers	Bottom 10 Pctl Performers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	6.618***	9.171***	0.049***	0.367***	0.079***	0.059***
	(20.12)	(8.45)	(10.67)	(16.53)	(12.70)	(11.26)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3901509	3900777	3900777	3863512	3848095	3848095
R^2	0.636	0.409	0.444	0.487	0.455	0.477

Panel B: Days with Less Sunshine

	Volatility	Skewness	Lottery Type Asset	Underdiversification	Top 10 Pctl Performers	Bottom 10 Pctl Performers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	6.139***	7.853***	0.040***	0.359***	0.071***	0.054***
	(15.37)	(8.62)	(7.32)	(14.63)	(8.88)	(7.61)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3102702	3102194	3102194	3072436	3061733	3061733
R^2	0.653	0.418	0.463	0.508	0.473	0.492

Table 12:
Performance: Sharpe Ratios

This table reports estimates from transaction-level analysis using the Sharpe ratio of the assets purchased as the outcome variable. Each observation corresponds to a single purchase trade, with each column reflecting a different assumed holding period, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Sharpe Ratio			
Holding Period:	*1 month*	*3 months*	*6 months*	*12 months*
	(1)	(2)	(3)	(4)
Smartphone	-0.026***	-0.067***	-0.098***	-0.142***
	(-4.30)	(-5.56)	(-5.96)	(-5.82)
Investor x YM FE	Yes	Yes	Yes	Yes
Observations	8,554,182	8,524,675	8,486,768	8,290,569
R^2	0.452	0.453	0.442	0.412

Table 13:
Heterogeneity by Investor Experience
This table reports estimates from transaction-level analysis conducted separately for investors with different tenures at the banks in our sample. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Panel A presents results for "New Investors" defined as those with below-median tenure at the banks, while Panel B reports results for "Old Investors" or those with above-median tenure. All specifications include age-by-year fixed effects to account for age-related effects that may vary over time. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: New Investors

	Volatility	Skewness	Lottery Assets	Under-Divers.	Past Winners	Past Losers	Sharpe Ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Smartphone	4.203***	6.710***	0.033***	0.320***	0.050***	0.038***	-0.067***
	(7.90)	(5.39)	(4.62)	(8.94)	(6.27)	(6.07)	(-2.53)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,934,702	3,934,235	3,934,235	3,934,235	3,898,641	3,898,641	3,853,966
R^2	0.686	0.411	0.441	0.510	0.465	0.471	0.504

Panel B: Old Investors

	Volatility	Skewness	Lottery Assets	Under-Divers.	Past Winners	Past Losers	Sharpe Ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Smartphone	3.413***	5.234***	0.027***	0.269***	0.041***	0.033***	-0.056***
	(14.33)	(6.21)	(5.73)	(9.58)	(7.18)	(6.76)	(-3.54)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,193,525	4,192,631	4,192,631	4,192,631	4,123,537	4,123,537	4,047,198
R^2	0.703	0.429	0.460	0.532	0.479	0.499	0.523

Smart(Phone) Investing?

Appendix for Online Publication

A1. Hypotheses Development

New technologies can change how households make economic decisions, including labor supply, borrowing, and investor behavior. For example, Jensen (2007) studies the impact of mobile phones on the fishing industry in Kerala, a state in India. More recently, Fos et al. (2019), Jackson (2019), and Koustas (2018) document the effect of ride-sharing apps on labor market decisions; Di Maggio and Yao (2019), Buchak et al. (2018), and Fuster et al. (2019) document the impact of Fintech lending on borrowing decisions; and D'Acunto et al. (2019) document the effect of robo-advising on investment decisions. We investigate if smartphones influence risk-taking, preferences for gambling, and investment biases. The impact of smartphones on these outcomes is not obvious ex-ante.

Smartphones could promote financial risk-taking in two ways. First, smartphones can reduce participation costs in the stock market by facilitating searching and monitoring efforts. Second, smartphones may allow for more intuitive thinking and impulsive trading, providing the ability to virtually execute trades anytime and anywhere. Psychologists hypothesize a dual decision-making system: system 1, which is fast, intuitive, and emotional; and system 2, which is slower, more deliberative, and analytical (Stanovich and West, 2000; Kahneman, 2003). Butler et al. (2011) and Butler et al. (2013) provide survey and experimental evidence that a higher reliance on intuitive (or system 1) thinking increases risk tolerance.

Smartphones could also discourage risk-taking. If investors are sensitive to short-term losses, the more frequent feedback via smartphones could reduce risk-taking as predicted in the framework of myopic loss aversion by Benartzi and Thaler (1995). Consistent with myopic loss aversion, Haigh and List (2005) document that even professional options traders take less risk when randomly assigned to the treatment of receiving more frequent feedback.

Smartphones can also affect the preference for gambling activities. System 1 reasoning has been associated with a preference for lotteries (see Kahneman, 2011). Preferences for lotteries are, in turn, highly correlated with demand for lottery-type stocks—assets with positively skewed payoffs (Kumar, 2009). Furthermore, Bali et al. (2019) find that investor preferences for lottery stocks are amplified by attention and social interaction, which may be affected by smartphone use. This evidence suggests that smartphones might lead to strong preferences for lottery-type assets with positive skewness.

We investigate the effects of smartphones on two behavioral biases: underdiversification and buying attention-grabbing stocks, such as past winners or losers. Among others, Calvet et al. (2007) and Goetzmann and Kumar (2008) document how retail investors have the (costly) tendency to underdiversify their portfolios. Barber and Odean (2008) find evidence that retail investors buy more salient assets, such as stocks with exceptional (good or bad) performance. Smartphones could promote less diversifying trades and interest in salient past winners and losers by allowing frequent access to information and the ability to execute trades impulsively. This prediction would also be consistent with the notion that system 1 thinking, which operates more automatically and quickly, could be more prone to behavioral biases (Kahneman, 2011).

Alternatively, new technologies also have the potential to reduce gambling tendencies and investment biases. For instance, while human advisors might make the same investment mistakes as their clients (Linnainmaa et al., 2020), robo-advisers are a cost-effective solution that could increase portfolio efficiency (e.g., D'Acunto et al., 2019; Loos et al., 2020). Similarly, smartphones could grant ubiquitous access to information and a high execution speed, leading to better, more informed trades and fewer investment mistakes. Consistent with this argument, Gargano and Rossi (2018) document that more attention to investments leads to higher profits.

Given their plausibly ambiguous effects, we test whether smartphones influence financial risk-taking, preferences for lottery assets, diversification, and the willingness to buy more salient investments, such as past winners and losers.

Figure A1:
Trading Hour Density
This figure plots density for the hour of the day when a trade occurs by different asset classes.

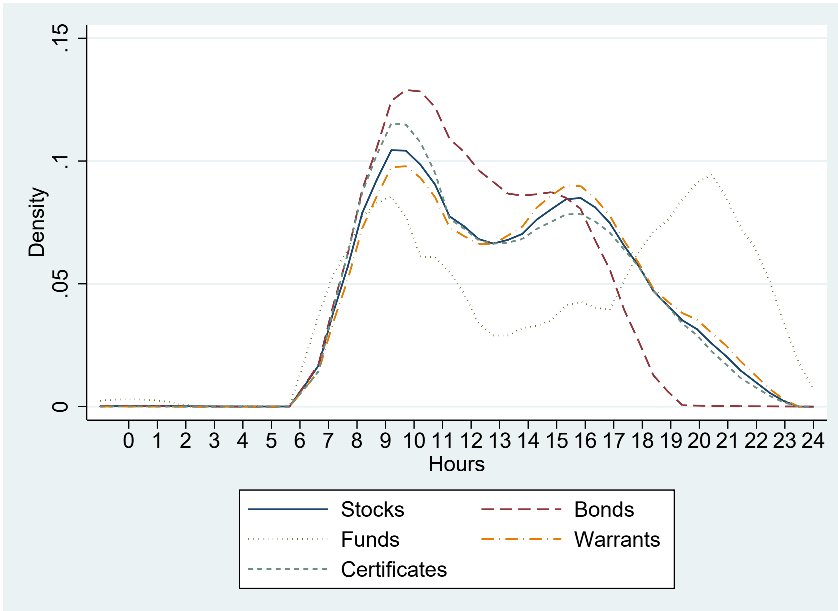


Table A1:
Alternative Measures of Risky Assets

This table reports estimates from transaction-level analysis estimated using alternative measures of risky assets as outcomes. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Risk Categories (1)	Warrants (2)	Certificates (3)
Smartphone	0.085***	0.056***	0.007***
	(11.41)	(7.33)	(3.48)
Investor x YM FE	Yes	Yes	Yes
Observations	9,229,168	8,798,775	8,798,775
R^2	0.449	0.724	0.431

Table A2:
Investor-by-Day Fixed Effects
This table reports estimates from transaction-level analysis estimated with investor-by-day fixed effects. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Volatility (1)	Skewness (2)	Lottery Type Asset (3)	Underdiversification (4)	Top 10 Pctl Performers (5)	Bottom 10 Pctl Performers (6)
Smartphone	2.272***	1.788*	0.016**	0.151***	0.014*	0.013**
	(8.56)	(1.69)	(2.43)	(6.54)	(1.84)	(2.01)
Investor x Calendar date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5674116	5673142	5673142	5603308	5600728	5600728
R^2	0.830	0.556	0.642	0.709	0.641	0.687

Table A3:
Value-weighted Outcome Measures

This table reports estimates from transaction-level analysis estimated using value-weighted outcomes. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. We exclude from this analysis our measure of underdiversification because it already accounts for the value of the trades. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Volatility	Skewness	Lottery-Type Assets	Past Winners	Past Losers	Sharpe Ratio
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	9.413***	8.315***	0.054***	0.088***	0.060***	-0.042**
	(14.40)	(10.97)	(11.24)	(10.28)	(12.97)	(-2.12)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,231,957	7,230,535	7,230,535	7,127,421	7,127,421	7,011,936
R^2	0.324	0.305	0.324	0.330	0.354	0.359

Table A4:
Sub-sample of Investors Trading Using Their Main Accounts
This table reports estimates from transaction-level analysis estimated using the sub-sample of investors with their primary accounts with the two banks in our sample. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Volatility	Skewness	Lottery-Type Asset	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	4.486***	3.882*	0.029***	0.481***	0.077***	0.036***
	(7.49)	(1.74)	(3.68)	(9.40)	(4.70)	(3.73)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	698,176	698,094	698,094	697,982	690,115	690,115
R^2	0.649	0.399	0.414	0.507	0.472	0.465

Table A5:
Smartphone Effects Dynamics: Investor Level

This table reports the dynamics of the baseline results estimated using investor-level analysis. Each observation corresponds to an investor-by-month, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Volatility (1)	Skewness (2)	Lottery-Type Assets (3)	Under-Divers. (4)	Past Winners (5)	Past Losers (6)
Smartphone Launch [-4]	-0.084	-10.279	-0.031	0.001	0.063	0.010
	(-0.04)	(-1.36)	(-1.15)	(0.03)	(1.60)	(0.24)
Smartphone Launch [-3]	-1.657	3.488	-0.039	-0.045	0.035	-0.039
	(-1.10)	(0.59)	(-1.11)	(-0.90)	(0.86)	(-1.02)
Smartphone Launch [-2]	0.735	-12.103*	-0.010	-0.030	0.027	-0.003
	(0.54)	(-1.66)	(-0.37)	(-0.80)	(0.60)	(-0.10)
Smartphone Launch [0]	0.028	11.029*	0.006	0.005	0.065**	0.044**
	(0.03)	(1.74)	(0.23)	(0.14)	(2.24)	(2.39)
Smartphone Launch [1]	-0.426	12.673*	0.020	-0.005	0.105***	0.059***
	(-0.33)	(1.73)	(0.86)	(-0.08)	(3.35)	(2.84)
Smartphone Launch [2]	1.514	6.952	0.052***	0.122**	0.095**	0.003
	(1.20)	(1.35)	(2.76)	(2.44)	(2.48)	(0.11)
Smartphone Launch [3]	0.455	1.408	0.031**	0.091	0.031	0.034*
	(0.36)	(0.18)	(2.48)	(1.49)	(0.73)	(1.69)
Smartphone Launch [4]	1.958	6.370	0.061*	0.188***	0.083*	0.005
	(1.10)	(0.86)	(1.94)	(3.02)	(1.66)	(0.18)
Smartphone Launch [5]	2.388	16.183**	0.119***	0.155**	0.070	0.067**
	(1.53)	(2.05)	(3.34)	(2.26)	(1.18)	(2.21)
Smartphone Launch [6]	5.139***	16.218***	0.079***	0.200***	0.091**	0.088***
	(2.64)	(2.98)	(4.97)	(3.63)	(2.01)	(3.50)
Smartphone Launch [7]	4.310*	23.168***	0.090**	0.217***	0.119***	0.071**
	(1.70)	(3.24)	(2.55)	(2.93)	(3.31)	(2.14)
Smartphone Launch [8+]	3.246**	6.578	0.101***	0.167***	0.040	0.099**
	(2.38)	(0.92)	(4.24)	(2.88)	(0.75)	(2.48)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Age x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Gender x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	307411	307363	344981	343575	284622	284622
R^2	0.555	0.289	0.271	0.534	0.313	0.286

Table A6:
Comparing Investors across Banks: Prior to Smartphone Launch

This table compares outcomes for investors across two banks for one year before smartphone launch. Each observation corresponds to an investor-by-month, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Bank I	1.766	6.780	-0.010	0.089	0.037	0.024
	(0.68)	(0.79)	(-0.24)	(1.14)	(1.29)	(0.92)
Wealth [at account opening]	Yes	Yes	Yes	Yes	Yes	Yes
Age x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Gender x YM FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56121	56105	74507	74395	43564	43564
R^2	0.276	0.245	0.127	0.278	0.196	0.158

Table A7:
Choice of Trading Hours and Asset Classes
This table reports estimates from transaction-level analysis estimated after controlling for time-varying effects of trading hours and asset classes. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Volatility	Skewness	Lottery-Type Assets	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)
Smartphone	1.139***	1.624***	0.015***	-0.001	0.011**
	(7.03)	(2.74)	(2.89)	(-0.19)	(2.26)
Investor x YM FE	Yes	Yes	Yes	Yes	Yes
Trade Hour x Year FE	Yes	Yes	Yes	Yes	Yes
Asset Class x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	4,335,025	4,334,124	4,334,124	4,264,004	4,264,004
R^2	0.709	0.462	0.477	0.495	0.518

Table A8:
Device Screen Size

This table reports results from transaction-level analysis that regresses investor behaviors on the use of smartphones and iPads. Each observation corresponds to a single purchase trade, and each column represents a different outcome, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Within-Individual Variation

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	1.927***	5.444***	0.008	0.075***	0.024**	0.003
	(5.06)	(3.74)	(0.85)	(8.11)	(2.38)	(0.39)
iPad	1.867***	12.867***	0.008	0.127***	0.043***	-0.000
	(3.56)	(4.61)	(1.00)	(8.47)	(3.41)	(-0.03)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,188,550	3,187,732	3,187,732	3,167,174	3,136,375	3,136,375
R^2	0.504	0.190	0.224	0.353	0.226	0.236

Panel B: Within- & Across- Individual Variation

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone	6.998***	14.950***	0.066***	0.256***	0.069***	0.043***
	(6.09)	(4.86)	(3.99)	(8.86)	(2.99)	(3.11)
iPad	4.696***	21.264***	0.032**	0.293***	0.101***	0.016
	(4.19)	(5.77)	(2.38)	(8.20)	(5.40)	(1.03)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,194,470	3,193,647	3,193,647	3,173,106	3,142,332	3,142,332
R^2	0.101	0.025	0.012	0.062	0.004	0.027

Table A9:
Performance: Market Adjusted Returns

This table reports estimates from transaction-level analysis estimated using market-adjusted returns of the assets purchased as the outcome. Each observation corresponds to a single purchase trade, and each column assumes different holding periods of the assets purchased, as indicated. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Market Adjusted Return			
Holding Period:	*1 month*	*3 months*	*6 months*	*12 months*
	(1)	(2)	(3)	(4)
Smartphone	-0.004***	-0.005***	-0.006**	-0.006**
	(-3.34)	(-2.68)	(-2.38)	(-2.19)
Investor x YM FE	Yes	Yes	Yes	Yes
Observations	8,563,063	8,528,909	8,490,943	8,294,634
R^2	0.411	0.396	0.374	0.360

Table A10:
Heterogeneity by Investor Age
This table reports estimates from transaction-level analysis conducted separately for investors in different age groups. Each observation corresponds to a single purchase trade, and each column represents a different age group, as indicated. All specifications include investor-by-month fixed effects. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Age Group:				
	30 or below	30-40	40-50	50-60	60 or above
Trading Behavior:					
Volatility	5.171***	5.656***	4.921***	4.400***	2.484***
	(7.74)	(9.05)	(9.28)	(10.68)	(5.71)
Skewness	2.67	7.078***	7.647***	8.463***	3.214**
	(1.08)	(4.95)	(5.11)	(7.24)	(2.13)
Lottery Assets	0.021**	0.038***	0.039***	0.037***	0.012
	(2.60)	(4.87)	(4.22)	(5.41)	(1.62)
Under-Diversification	0.527***	0.419***	0.312***	0.288***	0.127***
	(6.15)	(10.25)	(7.14)	(9.44)	(5.36)
Past Winners	0.089***	0.078***	0.049***	0.060***	0.030***
	(5.74)	(8.54)	(4.43)	(7.10)	(3.09)
Past Losers	0.049***	0.050***	0.042***	0.032***	0.011
	(3.53)	(6.80)	(4.58)	(5.14)	(1.66)