Smart(Phone) Investing?
An analysis of new technologies and trading behavior.*

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Using transaction-level data from two German banks, we study the effects of smartphones on investor behavior. Comparing trades by the same investor in the same month across different platforms, we find that smartphones increase the purchase of riskier, lottery-type, non-diversifying assets, and of past winners and losers. On average, investors do not offset these trades on other platforms. Our evidence suggests that, when trading on their smartphones, investors are more likely to choose specific assets and trading hours and to rely more on intuitive (system 1) thinking and to engage less deliberative (system 2) thinking. Smartphone effects are neither transitory nor innocuous: assets purchased via smartphones deliver lower returns and Sharpe ratios. More experienced traders and investors well in their 60s still exhibit strong smart phone effects. Our findings caution against the indiscriminate use of smartphones as the key technology to facilitate access to financial markets for younger and older generations alike.

Keywords: fintech, investment biases, system 1 vs. system 2 thinking, aging.

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1 Introduction

Technology has dramatically changed how retail investors trade, from placing orders using direct dial-up connections in the 1980s or Internet-based trading in the 1990s to the more recent rise of robo-advisers. With few exceptions, the introduction of these new technologies is generally associated with a decline in investor portfolio efficiency.[1] Whether good or bad for investors, it is accepted that new technologies influence investor behavior. The empirical evidence in these studies comes from some comparisons of investor behavior before and after the adoption of the new technology, potentially contrasted with the behavior over time of another group that did not adopt the technology. Under the assumption that, absent the innovation, investors would have behaved in the exact same way, a common interpretation of this evidence is that new technologies influence investors and change their behavior. An alternative explanation is that investors, instead, adopt the new technology because they are willing to change their trading behavior in the first place. Even if we could randomly assign the new technology to investors,[2] it would still not be straightforward to conclude that the new technology changes the overall investor portfolio. If investors manage investments across different accounts or platforms, they could decide to substitute across technologies. Therefore, observing trades on one platform might not be informative of the overall investor trading behavior.

While previous studies lack the data to distinguish between these alternative interpretations, their implications are, however, starkly different. If the new technology influences investor preferences and beliefs, absent the technology investors would have not changed their trading behavior. If, instead, it fulfills untapped investor demand, then the new tech-

1. For example, when moving to online trading, investors increased turnover and reduced performance (Barber and Odean, 2002). More recent studies document, instead, that robo-advisers could reduce investment mistakes (see D'Acunto et al., 2019; Loos et al., 2020).

2. D'Acunto et al. (2019) use the randomness in investors answering their phone to the marketing enrollment calls as a plausibly exogenous shock to the probability of joining the robo-advisor.

nology at best accelerates or makes less costly a change in investor behavior that would have happened anyway. Therefore, simple comparisons of investor behavior pre- and post-adoption or analyses of trades on one single platform could vastly overestimate the effects of the new technology. Furthermore, the policy implications could not be any more different. Is the technology helping investors to achieve their goals by facilitating their trades? Or is technology influencing adopters in profound ways that could stray investors away from their original goals? In an aging population, technology has the potential to simplify information processing and to promote better decision-making in the face of of cognitive decline. Conversely, technology could negative influence trading decisions in subtle and profound ways even for the more experienced investors.

In this paper, we use unique data on German investors to overcome these empirical challenges and to weigh in on the question if technology drives changes, just fulfills untapped investor demand, or channels substitution across platforms. We focus on smartphones—one of the most widely used and controversial technology nowadays—and provide novel micro-level evidence on the effects of its use on investor behavior. Our data comes from two large German retail banks that have introduced trading applications for mobile devices. For over 18,000 bank clients that have used these mobile apps in the years 2010-2017, we can observe all holdings and transactions, and, more importantly, the specific platform used for each trade (e.g., personal computer vs. smartphone). These unique features of the data prove fruitful for our analyses. They allow us to account for time-varying investor characteristics by comparing trades done by the same investor in the same month across different platforms. Moreover, we can directly test for substitution effects. Additionally, our data provides the ability to carefully investigate the mechanisms behind our findings.

In our baseline analyses, we examine if the use of smartphones induces differences in risk-taking, gambling tendencies, and investment biases, such as underdiversification and purchasing attention-grabbing assets like past winners and losers. We find that the proba-

bility of purchasing risky assets increases in smartphone trades compared to non-smartphone trades. Analogously, smartphone trades involve assets with higher volatility and more positive skewness. This evidence is best summarized by our analyses of lottery-type investments (i.e., assets with high volatility and high skewness). Smartphones increase the probability of buying lottery-type stocks by 67% of the unconditional mean for smartphone users.

Our results also document a significant impact of smartphones on investment biases. Smartphones increase the fraction of non-diversifying assets (e.g., non-mutual fund investments) purchased by 62.5% of the unconditional mean. Analogously, the probability of buying assets in the top decile of past 12 month performance increases by 8.7 percentage points (or 51.2% of the unconditional mean). Finally, smartphone trading increases the probability of purchasing assets in the bottom decile by 6.6 percentage points (or 68.8% of the unconditional mean).

These results may stem from investors selectively using smartphones to execute their risky, lottery-type, non-diversifying, and past-return based trades. In this scenario, investors could simply substitute their trades from one device to another without any real consequences for their overall portfolio. Using a difference-in-differences design that compares iOS and Android users, we test for such selection effects and find that, following the launch of smartphone apps, investors are—if anything—more likely to purchase risky, lottery-type, and non-diversifying assets as well as chase winners and losers on *non-smartphone* platforms.[3] While inconsistent with substitution effects, this evidence potentially suggests that investors are learning behaviors from smartphone trades and carrying them over to other platforms.

We next evaluate the mechanisms that may drive these smartphone effects. We begin by examining whether the ability to trade anytime and everywhere—an ability that smartphones

3. For this analysis we rely on the fact that one of the two banks in our sample had a staggered introduction of the smartphone app across iOS and Android operating systems.

provide—drives our results. To evaluate the importance of this channel, we repeat our baseline analyses, including year-by-time-of-the-day fixed effects. In this specification, our estimates become smaller but remain economically and statistically significant. Alternatively, investors may use smartphones to trade different investments and this selection of riskier asset classes may drive our results. We evaluate this and re-estimate our main analyses including year-by-asset-class fixed effects, and find again smaller but still strong smartphone effects. These analyses suggest that the choice of both time of the day and asset classes traded across different platforms contribute to but do not fully explain our findings.

Another possibility is that differences in information display across platforms might contribute to our results.[4] Smartphones, for instance, may more prominently feature assets that have experienced dramatic positive and negative performance in the recent past. If these assets are also riskier and have higher skewness, their more salient display could drive our results. To test for 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 only to mutual funds, whose performance is not prominently featured on the trading apps. In both analyses, we still find very strong smartphone effects, quantitatively comparable with our main estimates.

The differences in information display are likely to manifest owing to differences in screen size across platforms. Motivated by this plausibility, we further explore the information display mechanism, and separately investigate the effects of trading via devices with different screen sizes (i.e., iPhones vs. iPads). We do not find stronger results for trades via iPhones relative to iPads. Overall, our results are inconsistent with the differences in information display driving the main effects.

4. The apps associated with our sample are not just trading apps but also provide a host of other banking services allowing account holders to check balances on their savings and checking accounts, make transfers, check portfolio etc. Hence, some features that commonly appear with many trading apps do not apply in our setting. For instance, there are no explicit digital nudges related to assets, or gamification features that may encourage some trades over others.

Smartphones may also affect trading by allowing more timely access to information. If more volatile stocks or past winners and losers are more likely to have associated information events, the release and subsequent ubiquitous access to information relating to such events via smartphones can potentially contribute to smartphone effects. We test this hypothesis and examine heterogeneity in the effects based on days with and without unexpected announcements. Inconsistent with more timely access to information driving our results, we do not find stronger results for days with unexpected announcements.

Yet another possibility is that smartphones may allow for more intuitive and impulsive trading, similar to more system 1 based thinking in Kahneman (2011)'s framework, which could contribute to our results.[5] In models of system 1 vs 2 based economic decision making, the more logical and effort based system 2 type thinking contributes less to the process when cognitive effort is more costly or yields lower benefits (see for e.g., Ilut and Valchev (2021)). Kahneman (2011) argues that this can happen, for instance, during times of ego depletion or elevated moods. We test for the role of system-1 thinking in our setting and estimate the heterogeneity in our findings based on pre- vs post- lunch hour, after-hours vs market-hours, and days with different levels of sunshine. While ego is likely to be more depleted during pre-lunch hour and after-hours, owing to low glucose levels and fatigue respectively, mood is likely to be elevated during good weather days. Consistent with smartphone trades being more reliant on system 1, we find stronger smartphone effects during pre-lunch hour, after-hours and days with better weather.

Moreover, our results do not appear to be short-lived and driven by the initial enthusiasm or the learning curve of the new technology. Our estimates do not change significantly between the first quarter up to seven years after the initial use of the smartphone app.

Finally, we explore the implications of our findings for investor performance and for the

5. For example, consumers are more inclined to make impulsive purchases such as ordering more unhealthy food when using mobile devices. See Benartzi and Lehrer (2015) for a review of the effects of smartphones on consumer choices.

use of smartphones to facilitate retail investors' access to financial markets. Smartphones lead to the selection of assets that after the purchase have 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 relation between smartphone effects, investor experience, and age. Our results are stronger for investors with below median experience and for investors in their 30s and 40s.[6] Nonetheless, smartphone effects remain both economically and statistically significant for more experienced traders and for investors well in their 60s. Collectively, the evidence in our paper cautions against the indiscriminate and aggressive use of smartphones as the key technology to facilitate access to financial markets for younger or older generations alike.

Our findings contribute to the literature on the effects of technology on investor behavior. Barber and Odean (2002) document that investors who switched from phone-based to online trading start trading more frequently, but less profitably than before. Choi et al. (2002) document similar results in 401(k) plans. Our evidence complements these studies by documenting that smartphones induce increases in risk-taking, gambling behavior, and investment biases. More importantly, our data allows us to document different behaviors within the same investor *and* month, but across platforms. This identification strategy enables us to more convincingly address selection effects when examining how a new technology impacts investor behavior.

Given the large diffusion of robo-advisers in the past decade, D'Acunto et al. (2019) and Loos et al. (2020) have investigated the effects of this innovation on investor behavior. Both studies highlight that robo-advice has the potential to reduce investment biases and improve portfolio performance. Our evidence provides a more nuanced picture of the effects of new technologies on investor behavior. Smartphones appear to foster increases in gambling

6. This evidence suggests that our estimates using more experienced German investors are likely to be a lower-bound for the effects of smartphones in younger, less experienced investors, such as Robinhood users.

behavior and investment biases. Our paper also contributes to the recent literature on the effect of mobile apps on financial behaviors. Levi and Benartzi (2020) and D'Acunto et al. (2020) study the effects of mobile applications on spending behaviors. We contribute to these studies by investigating investment decisions. Our setting provides a nice laboratory to understand the consequences of providing constant feedback and ease of execution of trades to retail investors.

More recently, a series of studies have investigated the effects of trading smartphone apps on aggregate markets. Using data from the US retail brokerage company Robinhood, Welch (2020) finds that a portfolio mimicking the aggregate holdings of Robinhood investors did not underperform standard academic benchmarks.[7] Using the same data, Barber et al. (2020) document that episodes of intense buying activity by Robinhood users are followed by negative returns. Using data from a leading investment adviser in China, Cen (2019) shows that, after the mobile app introduction, investor flows into mutual funds become more volatile and more sensitive to short-term fund returns and market sentiment. Our results nicely dovetail with the findings in these studies and make three distinctive contributions. First, we focus on the consequences of smartphones on retail investors, and not aggregate markets. Aggregate effects might mask substantial investor heterogeneity, making it difficult to understand potential redistributive effects of this technology. Second, our investor trading data allow us to sharpen the causal interpretation of smartphone effects and to investigate the mechanisms driving them. Third, while Robinhood investors are Millennials with little or no trading experience, the German investors who adopt smartphone trading in our sample are, on average, 45 years old with nine years of experience investing with the banks. Therefore, our findings document how smartphones can substantially influence the trading behavior of more experienced traders or of an aging population.

7. Robinhood operates entirely online with the vast majority of its trades made via smartphone apps.

2 Hypotheses Development

New technologies can change the way households make economic decisions, including labor supply, borrowing, and investor behavior.[8] Broadly speaking, we investigate if smartphones influence risk-taking, preferences for gambling, and investment biases. The effects of smartphones on these outcomes are 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 that we have two modes of thinking: system 1, which is fast, instinctive, and emotional; and system 2, which is slower, more deliberative, and logical (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 option traders take less risk when randomly assigned to the treatment of receiving more frequent feedback.

Smartphones can also affect 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

8. 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 effect of Fintech lending on borrowing decisions; and D'Acunto et al. (2019) document the effect of robo-advising on investment decisions.

for lottery stocks are amplified by attention and social interaction, both of which may be affected by smartphone use. Collectively, 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 are more likely to invest in more salient assets such as stocks with exceptional (good or bad) performance. By allowing frequent access to information and the ability to impulsively execute trades, smartphones could promote more concentrated trades and more interest in salient past winners and losers. 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 have also 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 along with a high speed of execution, 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 that their effects are plausibly ambiguous, 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.

3 Data and Empirical Strategy

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

3.1 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), 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 during the years 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.[9]

In our analyses, we use transaction data after imposing three sample filters. First, we limit our sample between 2010 and 2016 for one bank and from 2013 to 2017 for the other bank. We choose these years to reflect the earliest smartphone apps' introduction for each bank. Second, we drop trades associated with savings plans and wealth management services because these are either automated or do not involve an active choice from investors. Third, we drop trades without information on the asset traded (e.g., asset class). Applying these filters results in a sample of about ten million transactions by roughly one hundred fifty thousand investors. Over eighteen thousand of these investors use smartphone trading apps at least once.

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

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

reports summary statistics for variables used in our analyses within our 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, 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 also 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 probability of buying salient assets, such past winners and losers. We measure underdiversification as the value-weighted fraction of purchases of individual security over all the purchases in the same month.[10] In our sample, 51% of all the purchases involve individual assets as opposed to 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

10. 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.

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 purchasing 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 purchasing a warrant is 29% (3% for a certificate).

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 in 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 have a significant impact on 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. For non-users, we compute summary statistics over all the years in our sample. For smartphone users, instead, we use only information 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. 5 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%).[11] 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 assets experience lower market-adjusted returns and Sharpe ratios in the following twelve months as compared to purchases of non-smartphone users (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 one year shorter tenure at the bank, are about 8 years younger, and 13% more likely to be males compared to non-users.

3.2 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 buy individual securities (as opposed to mutual funds), and more likely to buy past winners and losers. These differences highlight the importance of conducting within-investor analyses to address this type of selection. 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 the trading platform. Therefore, the

11. 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)

selection effects could operate at the investor-time level.

Thanks to the richness of our data, we are able to go one step further in addressing this potential concern. We exploit within individual-by-time variation by including individual-by-month (or by-year) fixed effects in our estimations. By comparing trades across different platforms made by the same investor within the same month (or year), we can account for time-varying investor characteristics and selection at the investor-time level. Specifically, we estimate the following model:

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

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 (year) fixed effects that account for time-varying unobserved differences at the investor level. Robust standard errors are double-clustered at the investor and year-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.

There is a potential trade-off when using investor-by-time fixed effects. We gain benefits in terms of better identification but potentially at the expense of generalizability since we exploit variation only from those investors who trade using both platforms within the same year or month. These investors might not be representative of all the smartphone traders. To be transparent about this trade-off, we run all our major analyses using different specifications. First, we report results without any fixed effect. Then, we include investor and time fixed effects. Last, we introduce results with investor-by-year and investors-by-month fixed effects. As we introduce more and more restrictive specifications, we move towards better

identification but possibly away from greater generalizability and external validity.

Another concern when estimating the effects of new technologies is that investors could use the new platform to execute specific types of trades (e.g., buying riskier investments), substituting them away from other platforms. In the presence of such substitution effects across devices, we might mistakenly attribute variation in trading strategies to the use of smartphones, when indeed investors are just reallocating their trades across platforms. To test for this possibility, we conduct a difference-in-differences analysis, exploiting the staggered introduction of mobile apps across different operating systems (i.e., iOS vs. Android). By comparing *non-smartphone* trades for smartphone users before and after the launch of different trading apps, we can establish the prevalence of substitution effects across devices. In subsection 4.4, we discuss this analysis and its results in detail.

4 Main Results

We examine the effects of smartphones on financial risk-taking, preferences for gambling, and investment biases. As discussed in Section 2, the effects of smartphones on these behaviors are not obvious ex-ante.

4.1 Risk-taking

We first analyze the effects of smartphones on financial risk-taking. In Table 3, we report results for this analysis, estimating different versions of Equation 1. In Panel A, our outcome is an indicator variable that captures the probability of purchasing risky assets. We define risky assets as direct and indirect stock investments—that is, individual stocks and equity mutual funds. In Column (1) we do not include fixed effects. In this specification we find that the probability of purchasing risky assets is 22.2 percentage points higher for trades done using smartphones relative to other trades. This effect corresponds to an increase

of 32.6% of the unconditional sample mean for smartphone users (0.68). While we find a significant effect of smartphones, unobservable (to us) heterogeneity between smartphone users and non-users can drive this result. In Column (2), we control for time-invariant investor heterogeneity by including investor fixed effects. We also account for nation-wide time trends by including year fixed effects. Consistent with these factors playing a role, our estimates are smaller—11.3% of the sample mean—but still statistically significant at the 1% level.

Our estimates in Column (2) could also be biased because of omitted time-varying investor characteristics. For example, investor risk preferences could vary over time and this variation could be correlated with the decision to adopt smartphone trading. We control for this possibility in Column (3) by including investor-by-year fixed effects in our estimation. This specification compares trades done by the same investor within the same year using smartphones versus other platforms. Using this specification, we find that investors are 11.5 percentage points more likely to purchase a risky asset when trading using smartphones. Finally, in Column (4) we use our most stringent specification by including investor-by-month fixed effects and comparing trades done by the same investor within the same year-month. Following the discussion in subsection 3.2, we recall that while this more stringent specification allows for better identification, these results are based solely on those investors who execute multiple trades across different platforms during the same month. Using this specification, we find that the probability of purchasing a risky asset increases by 15.9 percentage points—23.4% of the sample mean—when using the smartphone versus other platforms.

Since smartphones could also promote trading in risky non-equity assets such as certificates and warrants, the previously estimated effects might not fully capture the increased risk-taking induced by smartphone use. Therefore, we investigate the volatility of all the assets purchased as a second complementary measure of risk-taking. We measure this volatility as the annualized standard deviation of returns over the past twelve months. We report the

volatility results in Panel B of Table 3. Using a specification without any fixed effects (Column 1), we find that the volatility of assets purchased using smartphones is 10.6 percentage points higher compared to the volatility of other assets. This magnitude is economically large as it corresponds to 48.2% of the sample mean (22.0%). However, both across- and within- investor heterogeneity might drive this estimate. When we control for both investor and year fixed effects in Column (2), we estimate a smaller effect for smartphones, equal to 3.2 percentage points. In our most stringent specification in Column (4), we find that volatility of assets purchased using smartphones is 7.4 percentage points higher than the volatility of other assets purchased by the same investor within the same year-month. This magnitude is economically large as it corresponds to 33.4% of the unconditional mean.

In the online Appendix Table A1, we replicate a similar analysis using the banks' internal risk-categories. The two banks classify the riskiness of all the asset purchases (not just equities) using five categories from one (lowest riskiness) to five (highest). We confirm our results that smartphones lead to riskier purchases by also using these classifications. To further strengthen our evidence on financial risk-taking, we also investigate the probability of purchasing non-equity instruments, such as warrants and certificates, which are often deemed riskier. In Appendix Table A2, we document that—after controlling for investor-by-month fixed effects—smartphones increase the probability of purchasing warrants by 29.5% of the unconditional mean for smartphone users (17.5% for certificates).

Collectively, these results suggest that smartphones promote higher financial risk-taking.

4.2 Preferences for Skewness and Lottery-type Assets

We begin the investigation of preferences for gambling in financial markets by studying the skewness of the assets purchased. We present these results in Table 4. In Column (1), we find that smartphone use increases the skewness of investments by 15.1 or 26.3% of the standard deviation of the skewness for phone users (57.6). As in previous tables, this first

column does not include any fixed effects. When we add fixed effects, we estimate smaller, but still economically and statistically significant results consistent with previous results. For example, in Column (4) we find that, after controlling for investor-by-month fixed effects, smartphone use increases skewness of assets purchased by 10.6 percentage points, or 18.3% of the standard deviation of the skewness for phone users.

In Panel B of Table 4, we measure preferences for lottery-type assets more directly. Following the approach in Kumar (2009), we define as lottery-type those assets that have below median prices, above median volatility, and above median skewness. In Column (1), we find that—without including any fixed effects—smartphone trades increase the probability of purchasing lottery-type assets by 7.8 percentage points, or 65.0% of the unconditional mean for smartphone users. We still find the results to be statistically and economically significant, even after the inclusion of the same fixed effects previously used. Under the most restrictive specification with investor-by-month fixed effects, we find that smartphone trades increase the probability of purchasing lottery-type assets by 5.6 percentage points, or 46.7% of the unconditional mean.

4.3 Underdiversification, Buying Past Winner and Past Losers

If smartphones facilitate riskier and gambling behaviors, they can also lead investors towards more concentrated portfolios. We investigate this possibility in Panel A of Table 5. We document that smartphones increase the purchases of non-diversifying assets (i.e., non-mutual fund investments) such as individual stocks and securities. In Column 1, without fixed effects we estimate that smartphones substantially increase the fraction of non-diversifying purchases by 48.4 percentage points. We find similar effects after controlling for individual-by-month fixed effects: 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 allow more frequent access to information and the ability to impul-

sively execute trades, making investors more susceptible to attention-grabbing stocks (Barber and Odean (2008). Therefore, we investigate if smartphones increase the tendency to buy assets with exceptional (good or bad) performance. Consistent with this possibility, the unconditional probability of purchasing assets in the top decile of the past twelve month return distribution increases for smartphone users from 17% to 22% following the technology adoption. Analogously, purchase probability increases from 9% to 12% for assets in the bottom decile.

In Panel B of Table 5, we formally test for this possibility. We document that smartphone trades increase the probability of buying past winners. Without fixed effects, in Column (1), we find that the probability of buying past winners goes up by 13.6 percentage points. After controlling for individual-by-month fixed effects, we still find an economically and statistically significant result. Smart phone trades increase the likelihood of purchasing past winners by 8.7 percentage points or 51.2% of the unconditional mean. In Panel C, we report similar results for the propensity to buy assets in the bottom decile of the past return distribution. For example, in the most stringent specification with individual-by-month fixed effects, using smartphones increases the likelihood of buying past losers by 6.6 percentage points or 68.8% of the unconditional mean.

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 other platforms (4,004.65 vs. 4,223.18 euros). Nonetheless, to test for this possibility we repeat all our main analyses by computing a value-weighted

version of our outcome variables. Following our approach to measure 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 Tables 3, 4, and 5, 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.

Overall, our results suggest that smartphones affect investor trades. Even comparing trades within the same investor-month, we still find that investors buy assets that are riskier, more volatile, and have higher skewness assets when using smartphones. These tendencies result in a significant increase in the probability of purchasing lottery-type assets. Moreover, investors become significantly more prone to investment biases, such as underdiversification or buying stocks at the top and bottom of the past return distribution.

4.4 Do Investors Substitute Their Trades Using Smartphones?

While our within investor-time analyses make progress in addressing potential selection problems, investors still endogenously decide which trading platform to use for each of their trades. They can execute their riskier and gambling-type trades predominantly on their smartphones. In this case, smartphone trades are just substituting trades that would have occurred anyway on different platforms. In the presence of substitution effects, we should expect non-smartphone trades to display lower volatility, lower skewness, and to be less likely to involve lottery-type assets, non-diversifying assets, or past winners and past losers. Our data with information on both smartphone and non-smartphone trades allow us to directly test this prediction from substitution effects.

To examine these substitution effects, we use a difference-in-differences approach that exploits the staggered adoption of the smartphone app by different clients of the two banks.

This empirical approach allows us to compare different users before and after they start using the trading app. In practice, in this empirical design we limit our analysis only to smartphone users and compare early versus late smartphone adopters. Specifically, we estimate the following equation:

$$y_{i,t} = \beta \times SmartphoneUse_{i,t} + \delta_i + \gamma_t + \epsilon_{i,j,t} \tag{2}$$

where y measures risk-taking, volatility, skewness, preferences for lottery-type assets, non-diversifying assets, and past winners and losers for trades in *non-smartphone platforms* by investor i during year-month t. $SmartphoneUse_{i,t}$ is an indicator variable equal to one for investor i in the months following the first trade using the smartphone app. δ_i represents investor fixed effects that control for non time-varying unobserved differences at the investor level. γ_t represents year-month fixed effects.

We present these estimates in Panel A of Table 6. Under the null hypothesis of substitution effects across trading platforms, we would expect to estimate statistically significant negative coefficients in all the trading behaviors previously analyzed. The coefficient of interest, β, is, instead, positive for all outcomes and statistically significant for five out of the six outcome variables (with the exception being the probability of buying past losers). Although much smaller in economic magnitude than our main effects, we find positive spillover effects on non-smartphone trades. After using the smartphone app, investors begin buying assets with higher volatility and more positive skewness on non-smartphone platforms, and become more likely to purchase lottery-type assets, non-diversifying assets, and past winners. This evidence goes against substitution effects and the hypothesis that investors largely select smartphones to execute their riskier and gambling-type trades. These results are instead more consistent with investors learning from smartphone trading and carrying over their behavior to other platforms.

A potential concern with this design is that investors endogenously choose when to adopt the smartphone trading app. In other words, this analysis suffers from the potential selection effects between early and late users. To overcome this limitation, we run an additional difference-in-differences analysis that exploits the staggered launch of trading apps for different smartphone operating systems (iOS vs. Android).[12] This empirical approach allows us to compare different users before and after the launch of the trading app that is compatible with their smartphone's operating system. In practice, we estimate the following equation:

$$y_{i,t} = \beta' \times SmartphoneLaunch_{i,t} + \delta'_i + \gamma'_t + \epsilon'_{i,j,t} \tag{3}$$

where y measures our outcome of interest for trades in *non-smartphone platforms* by investor i during year-month t. $SmartphoneLaunch_{i,t}$ is an indicator variable equal to one for investor i in the months following the launch of the trading app for their smartphone operating system. δ'_i represents investor fixed effects and γ'_t represents year-month fixed effects.

We present these estimates in Panel B of Table 6. Consistent with the results in Panel A, we do not find evidence of substitution effects for any of the outcome variables. With the exception of skewness, for which we still estimate a positive statistically significant coefficient, all the other estimates are very small and not statistically different from zero.

The identification assumption for this analysis is that of parallel trends. In the absence of the app launch, the trading behavior of investors who own different types of smartphones—iOS or Android devices—would have evolved in a parallel way. Although this assumption cannot be fully tested, we examine its validity in the pre-period by estimating the dynamics of smartphone effects over time. Figure 2 plots the coefficients of specifications in which the smartphone type is interacted with event-time in quarters. We plot estimates for the

12. This data is only available for one of the two banks in our sample. Hence, we limit this analysis to this one bank.

volatility of asset purchased (Panel A), for their skewness (Panel B), the probability of buying lottery-type assets (Panel C), non-diversifying assets (Panel D), past winners (Panel E), and past losers (Panel F). Across all outcomes, we find no statistically significant differences for investors owning different smartphones in the two-year period before the app launch. After the launch, we do not detect negative effects, a finding that is inconsistent with substitution effect. If anything, we generally observe small delayed positive spillover effects on non-smartphone trades (statistically significant for four out of six variables). In this specification, the effects on non-smartphone trades are further delayed by the fact that not all the investors begin using the app immediately after its launch. Moreover, if investors learn from smartphone trades, spillover effects could take time to manifest. Overall, this evidence is potentially consistent with investors adopting similar behaviors also when trading using *other* devices.

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 not just across platforms within the same bank, but also across investment accounts at different financial institutions. While we do not observe all the investment accounts of the investors, as a robustness check we analyze smartphones' effects on those investors who have their primary account with our two banks.[13] In Table A4, we document that, similar to our baseline effects, these investors buy assets that are more volatile, have a higher skewness, are become more likely to purchase lottery-type and non-diversifying assets, as well as past winners and losers.

Overall, our results are inconsistent with substitution effects playing a role. If anything, our evidence suggests that there are small positive spillover effects and that investors learn from their smartphone trading and carry over their behavior to other platforms.

13. 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 as primary accounts those accounts that are allocated the maximum tax allowance.

5 Mechanism

In this section we investigate what drives the differential trading behavior associated with smartphones. First, we test if using smartphones to trade at specific times of the day or to trade specific assets can explain our results. Then, we study if information display or more timely access to information generates our results. Third, we examine the role of more intuitive trading on smartphones in driving our estimates. Last, we investigate if smartphone effects are short-lived or more permanent.

5.1 Choice of Asset Classes and Trading Hour

Investors could use smartphones to trade specific asset classes. This selection effect could drive our results. We test for this possibility by including in our main specifications asset-class-by-year fixed effects. For this analysis, we classify assets into six categories: individual stocks, bonds, mutual funds, warrants, certificates, and options. We report these analyses in Panel A of Table 7. We exclude from this table our measure of underdiversification because diversifying trades belong to only one specific asset class (i.e., mutual funds). Smartphone effects are also economically and statistically significant in trades within the same asset class, in the same year. For example, the volatility of the assets purchased increases by 2.2 percentage points or 10.0% of the unconditional mean for smartphone users (22%). Analogously, the probability of buying lottery-type assets increases by 2.4 percentage points or 20.0% of the unconditional mean. Although important, asset-class effects cannot fully account for our results. Even within the same asset class, investors are more likely to purchase assets that are more volatile, with higher skewness, with lottery-type characteristics, and those that have recently experienced unusual performance when using smartphones.

Smartphones potentially allow an immediate access to trading over an extended period of time. To evaluate if this extended access to trading drives our results, we use data from

one of the banks for which we observe information on trading hours. We begin by investigate trading dynamics over different hours of the day. In Panel A of Figure 3, we plot the density of trades per hour of the day for all users, including both smartphone and non-smartphone users. There are two peaks in trading activity. They coincide with the opening (9:00 to 10:00am) and the closing of the financial markets in Germany (4:00 to 5:00pm). In Panel B of Figure 3, we plot the same density separately for smartphone and non-smartphone users. The two density plots largely overlap, with smartphone users marginally more likely to trade around closing hours. In Panel C of Figure 3, we limit our analysis to smartphone users and plot separately their smartphone versus non-smartphone trades. Again, there is no apparent difference in the two density plots. Traders use smartphones and other trading platforms with similar frequency during the day.

In Panel B of Table 7, we investigate more formally the effects of trading hours on our results by including in our analyses both investor-by-month and trading hour-by-year fixed effects. This specification allows us to also compare trades made during the same hour of the day (e.g., 9:00 a.m.) in the same year. All our previous results are robust to this additional specification. Investors on smartphones are more likely to buy more volatile, higher skewness, lottery-type, non-diversifying assets, and past winners and losers. Compared to our previous results in Tables 3 to 5, the economic magnitudes are attenuated. They range from 27.6% of the previous estimate for the probability of purchasing past winners (2.4 percentage points vs. 8.7 percentage points) to 44.8% for the skewness of the assets purchased (4.7 vs. 10.5). All the results remain economically significant. For example, the probability of buying lottery-type assets via smartphone increase by 2.1 percentage points, or 17.5% of the unconditional mean for smartphone users (12%).[14]

Overall, the evidence in this sections suggests that the choice of asset classes and trading

14. 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 A6.

hours contributes to but does not fully explain our findings.

5.2 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, 2020; 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.[15] 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.[16]

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.[17] We overcome this data limitation by running two robustness tests.

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

15. Under the recent news, Robinhood displays the "*Top Movers*" list, presenting the four stocks with 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.

16. 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.

17. While we are able to 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.

winners. Analogously, we define daily losers as the 100 stocks with the worst daily returns. In Panel A of Table 8, 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 estimates in Tables 3 to 5.

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 8. After controlling for investor-by-time fixed effects, 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 8, 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.

Collectively, these findings suggest that digital nudges do not drive the smartphone effects that we document. One could argue that even if these nudges were to mechanically drive our results, they are features of the smartphone app and, ultimately, just the channel through which smartphones influence trading behavior. While documenting this channel would still be interesting, showing that smartphones have effects above and beyond automatic nudges has more profound implications. First, given that each smartphone app has specific fea-

tures and potentially employs different nudges, our results—not being driven by any specific nudge—are more likely to generalize to smartphone trading apps in general. Second, the policy implications are starkly different. If digital nudges drive trading behavior, regulating them could limit the effects of smartphones. Alternatively, if these nudges are not the sole driver of trading behaviors, any policy intervention regulating the choice architecture in these apps might not be as effective as hoped.

5.3 Does Device Screen Size Drive Our Results?

Smartphones have a smaller screen, where information can be more difficult 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.[18] We report our results in Table A7. In Panel A, we include individual and year fixed effects. We do not have enough power to include individual-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 anytime during our sample period. Using this specification, we find that both iPhones and iPads increase the likelihood of buying more volatile, higher skewness, less-diversifying assets, and past winners. The magnitudes are very similar for volatility of assets purchased

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

and, possibly, stronger in iPad trades for skewness, underdiversification, and past winners.

The estimates in Panel A of Table A7 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. As already pointed out in Section 3.2, gains in terms of identification could come at the expense of external validity of these results. To address this trade-off, in Panel B of Table A7 we include only year fixed effects and we 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 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.

5.4 Does more Timely Access to Information Drive our Results?

Smartphones may affect trading by allowing more timely access to information. If more volatile stocks or past winners and losers are more likely to have associated information events, the release and subsequent ubiquitous access to information relating to such events via smartphones can potentially encourage purchasing of such assets and contribute to smartphone effects.

We test for this hypothesis in our setting by examining heterogeneity in the effects based on days with and without unexpected announcements. If our results are driven by smartphones inducing more information based days by providing more timely access to information, one would expect to find stronger smartphone effects during days with unscheduled announcements when the likelihood of making such trades is higher. To estimate this heterogeneity, we hand-collect information on the universe of unscheduled announcements related

to German firms during our sample period, and split our sample based on days with and without such announcements.

Table 9 presents results for this analysis. Panels A and B show results for days with and without unscheduled announcements respectively. We do not find stronger results during days with unscheduled announcements, suggesting that information based trading and more timely access to information through smartphones does not drive our results. A potential concern to this interpretation is that we may lack power for the sub-sample of unscheduled announcement days. Though a possibility, the magnitudes of the coefficients across the two groups are different suggesting that this may not affect our inference.

5.5 Does Greater Reliance on System 1 Drive Our Results?

Smartphones may allow for more intuitive and impulsive trading, similar to more system 1 based thinking in Kahneman (2011)'s framework, which could contribute to our results. In models of system 1 vs 2 based economic decision making, the more logical and effort based system 2 type thinking contributes less to the process when cognitive effort is more costly or yields lower benefits (see for e.g., Ilut and Valchev (2021)). Kahneman (2011) argues that this can happen, for instance, during times of ego depletion or elevated moods. We test for the role of system-1 thinking in our setting and estimate the heterogeneity in our findings based on pre- vs post- lunch hour, after-hours vs exchange hours, and days with different levels of sunshine. While ego is likely to be more depleted during pre-lunch hour and after-hours, owing to low glucose levels and fatigue respectively, mood is likely to be elevated during good weather days.

Table 10 reports the results for heterogeneity tests 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.). We define the after-hour window based on the fact that local German market makers allow investors to trade between 5pm and 10pm, even if na-

tional stock exchanges are closed. The effects of smartphones vs. other trading platforms are significantly stronger during after-hours (Panel B) as compared to market-hours (Panel A). Averaging across all outcomes (excluding purchasing past winners), our estimates are roughly 2.5 times higher during after-hours, ranging from a 46% increase for 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 as opposed to 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, earlier in the morning investors are less likely to be in more relaxed environments and should not suffer from decision fatigue. If institutional features drive our results, we would expect to find similar results during after-hours and this particular morning hour. Alternatively, if 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 compared to trades during after-hours.

We next examine the heterogeneity in our effects based on whether the trade occurred during the hours just prior to or post lunch. During times of low levels of glucose, decision making is likely to be 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 1pm, and examine heterogeneity in smartphone effects for trades that occur during the hour prior to lunch hour (i.e., 11am-12pm) versus those that occur after lunch hour (i.e., 1-2pm).

Table 11 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 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 types of household economic decisions including car purchases (Busse et al. (2015)), and risk taking (Bassi et al. (2013)). When individuals are elated, the reliance on system 2 in the decision making progress declines (Ilut and Valchev (2021)). Hence, to the extent weather affects investor mood, it may lead to more system 1 based trades and exacerbate its role in smartphone effects. Table 12 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 are consistent with heavier reliance on system 1 thinking while executing smartphone trades contributing to our findings.

5.6 Are Smartphone Effects Transitory?

Last, we investigate the dynamics of smartphone effects. Do investors get excited about this new technology and temporarily change their behavior? Or are smartphone effects persistent over time? If investors heavily rely on this new technology just in the few months after the adoption and then stop using it, our findings might overstate the relevance of smartphone effects. By relying on investor-by-time fixed effects, our results in fact reflect

only trading behavior in those potentially few initial months when investors actively use smartphones to trade. Additionally, investors can learn to offset the effects of smartphones by either changing their behavior or by avoiding using smartphones to trade altogether (Seru et al., 2009). Our estimates so far might not capture this learning.

We examine the dynamics of smartphone effects and provide a graphical representation of the results of this analysis in Figure 4. We plot 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 our specifications. In Panel A, we report results for the volatility of assets purchased. The effects of smartphones are stable from the first quarter of usage up to nine or more quarters afterwards. Smartphone effects are also stable over time for skewness of purchases (Panel B), lottery-type assets (Panel C), non-diversifying assets (Panel D), and past winners (Panel E) and past losers (Panel F).

Overall, this evidence suggests that smartphone effects are not short-lived or transitory. Therefore, investors' initial excitement or their willingness to experiment with riskier and more gambling-type trades do not drive our results. Analogously, learning effects do not lead us to overstate the impact of smartphones on trading behaviors.

6 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 will also help shed light on the relation between smartphone effects, experience, and age.

6.1 Investor Performance

Do investors harm their performance when they trade using smartphones? The behaviors promoted by smartphones have generally been associated with lower investor performance.[19] We test whether smartphone trades, which are more likely to be risky, gambling-type trades or more prone to biases, are associated with negative performance.

In Table 13 we report results from 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.[20] 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 et al., 2020). All the estimates include investor-by-month fixed effects, the most stringent specification in our analyses. 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 13. Smartphone purchases have systematically lower Sharpe ratios across the entire distribution.

As previously documented, investors are more likely to buy more volatile assets using

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

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

smartphones. Therefore, this increase in volatility could determine lower Sharpe ratios. Alternatively, lower Sharpe ratios could also be the results of assets purchased via smartphones having lower returns. To better understand the drivers of lower performance, we analyze market-adjusted returns in Table A8 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.

6.2 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 on average 49 years old with 8.7 years of experience. 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 our smartphone effects vary by investor experience. We hypothesize that the effects of smartphones might decrease with investment experience. If this is the case, then our results might underestimate the effects of smartphones for younger and less experienced investors. In Table 14, 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.

In both sub-samples, we find evidence of strong smartphone effects across all investment behaviors. 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 that have more than nine years of trading experience with the bank.

In Table 15, we present results for different age groups in our sample. For most investment behaviors, smartphone effects are the strongest among investors 40 years old or younger. With the exception of two out of six behaviors, we also find economically and statistically significant smartphone effects also 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 suggest that smartphone effects remain strong for more and less experienced investors, and for younger and older generations.

7 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.[21] As smartphone trading has become increasingly popular, so have concerns about its potential negative effects for young and inexperienced investors.[22]

Using a novel data set from two large German retail banks, we investigate if and how smartphones influence investors. Comparing trades made by the same investor in the same month across different platforms, we document that traders on smartphones buy assets with higher volatility and higher skewness, diversify less, and chase past winners and losers. Moreover, investors do not offset these trades with those on other platforms. If anything, investors display similar behaviors across devices after they begin using smartphones.

21. Sources: https://www.statista.com/topics/2711/us-smartphone-market/; https://www.cnbc.com/2018/11/29/td-ameritrade-sees-more-people-trading-on-their-phones.html

22. 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.

We conduct several analyses to better understand the mechanism behind these results. The selection of specific times of the day or specific asset classes when using smartphones contribute to—but do not fully explain—our results. We do not find evidence that information display, digital nudges, or screen size drive our results.

System 1 (or intuitive) thinking has been associated with the behaviors that we document, namely higher risk-tolerance, preference for gambling, and investment biases. Collectively, our evidence suggests that smartphones facilitate or foster a higher reliance on system 1 thinking and impact investment behaviors where high monetary stakes are involved.

These trading behaviors are not innocuous for retail investors. Smartphones lead to the purchase of assets with worse performance per unit of risk, as measured by lower Sharpe ratios. Furthermore, the effects of smartphones remain economically and statistically significant for investors that are more experienced or well in their 60s. Overall, our findings caution against relying on smartphones as the leading technology to facilitate retail investors' access to financial market, for younger or older generations alike.

References

Bali, T., D. A. Hirshleifer, L. Peng, and Y. Tang (2019). Attention, social interaction, and investor attraction to lottery stocks. *Working Paper*.

Barber, B. M., X. Huang, T. Odean, and C. Schwarz (2020). Attention induced trading and returns: Evidence from robinhood users. *Working Paper*.

Barber, B. M. and T. Odean (2002). Online investors: Do the slow die first? *Review of Financial Studies 15*(2), 455–487.

Barber, B. M. and T. Odean (2008). All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *Review of Financial Studies 21*(2), 785–818.

Bassi, A., R. Colacito, and P. Fulghieri (2013). 'o sole mio: An experimental analysis of weather and risk attitudes in financial decisions. *Review of Financial Studies*.

Benartzi, S. and J. Lehrer (2015). *The Smarter Screen: Surprising Ways to Influence and Improve Online Behavior*. Penguin Books, New York.

Benartzi, S. and R. H. Thaler (1995). Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics 110*(1), 73–92.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics 130*(3), 453–483.

Busse, M. R., D. G. Pope, J. C. Pope, and J. Silva-Risso (2015). The psychological effect of weather on car purchases. *Quarterly Journal of Economics 130*(1), 371—-414.

Butler, J., L. Guiso, and T. Jappelli (2013). Manipulating reliance on intuition reduces risk and ambiguity aversion. *Working Paper*.

Butler, J. V., L. Guiso, and T. Jappelli (2011). The Role of Intuition and Reasoning in Driving Aversion to Risk and Ambiguity. *CEPR Discussion Paper No. DP8334*.

Calvet, L. E., J. Y. Campbell, and P. Sodini (2007). Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy 115*(5), 707–747.

Cen, X. (2019). Going mobile, investor behavior, and financial fragility. *Working Paper*.

Choi, J. J., D. Laibson, and A. Metrick (2002). How does the internet affect trading? evidence from investor behavior in 401(k) plans. *Journal of Financial Economics 64*(3), 397–421.

D'Acunto, F., N. Prabhala, and A. Rossi (2019). The promises and pitfalls of robo-advising. *The Review of Financial Studies 32*(5), 1983–2020.

D'Acunto, F., A. G. Rossi, and M. Weber (2020). Crowdsourcing peer information to change spending behavior. *Chicago Booth Research Paper No. 19-09, Fama-Miller Working Paper*.

Danziger, S., J. Levav, and L. Avnaim-Pesso (2011). Extraneous factors in judicial decisions. *Proceedings of the National Academy of Sciences*.

Di Maggio, M. and V. Yao (2019). Fintech borrowers: Lax-screening or cream-skimming? *Working Paper*.

Fos, V., N. Hamdi, A. Kalda, and J. Nickerson (2019). Gig-labor: Trading safety nets for steering wheels. *Working Paper*.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery (2019). The role of technology in mortgage lending. *The Review of Financial Studies 32*(5), 1854–1899.

Gargano, A. and A. Rossi (2018). Does it pay to pay attention? *Review of Financial Studies 31*(12), 4595–4649.

Goetzmann, W. N. and A. Kumar (2008). Equity portfolio diversification. *Review of Finance 12*(3), 433–463.

Haigh, M. S. and J. A. List (2005). Do professional traders exhibit myopic loss aversion? an experimental analysis. *Journal of Finance 60*(1), 523–534.

Ilut, C. and R. Valchev (2021). Economic agents as imperfect problem solvers. *working paper*.

Jackson, E. (2019). Availability of the gig economy and long run labor supply effects for the unemployed. *Working Paper*.

Jensen, R. (2007). The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *The Quarterly Journal of Economics 122*(3), 879–924.

Kahneman, D. (2003). A perspective on judgement and choice. *American Psychologist 58*(9), 697–720.

Kahneman, D. (2011). *Thinking, Fast and Slow*. New York: Farrar, Straus and Giroux.

Koustas, D. (2018). Consumption insurance and multiple jobs: Evidence from rideshare drivers. *Working Paper*.

Kumar, A. (2009). Who gambles in the stock market? *Journal of Finance 64*(4), 1889–1933.

Kumar, A., S. Ruenzi, and M. Ungeheuer (2020). Daily winners and losers. *Working Paper*.

Levi, Y. and S. Benartzi (2020). Mind the app: Mobile access to financial information and consumer behavior. *Working Paper*.

Liao, L., Z. Wang, J. Xiang, H. Yan, and J. Yang (2020). User interface and firsthand experience in retail investing. *The Review of Financial Studies*.

Linnainmaa, J., B. Melzer, and A. Previtero (2020). The misguided beliefs of financial advisors. *Journal of Finance*.

Loos, B., A. Previtero, S. Scheurle, and A. Hackethal (2020). Robo-advisers and investor behavior. *Working Paper*.

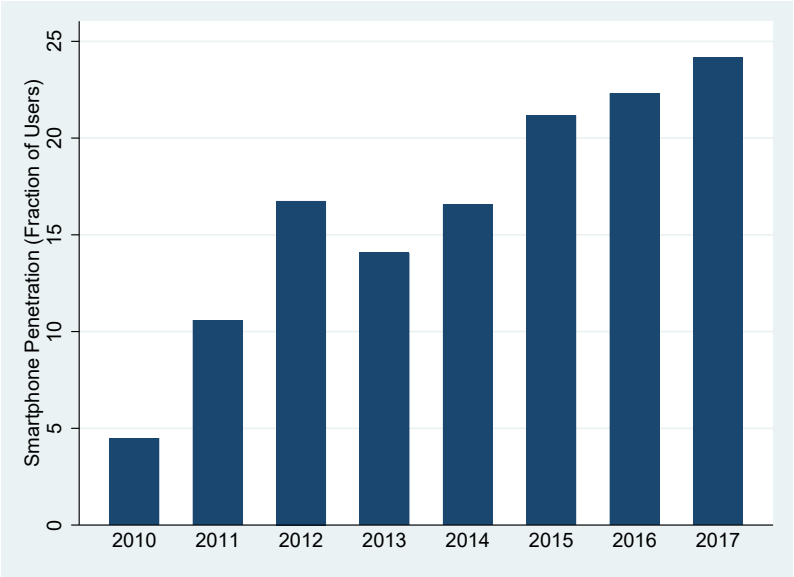
Seru, A., T. Shumway, and N. Stoffman (2009, 09). Learning by Trading. *The Review of Financial Studies 23*(2), 705–739.

Stanovich, K. E. and R. F. West (2000). Individual difference in reasoning: Implications for the rationality debate? *Behavioral and Brain Sciences 23*(5), 645–726.

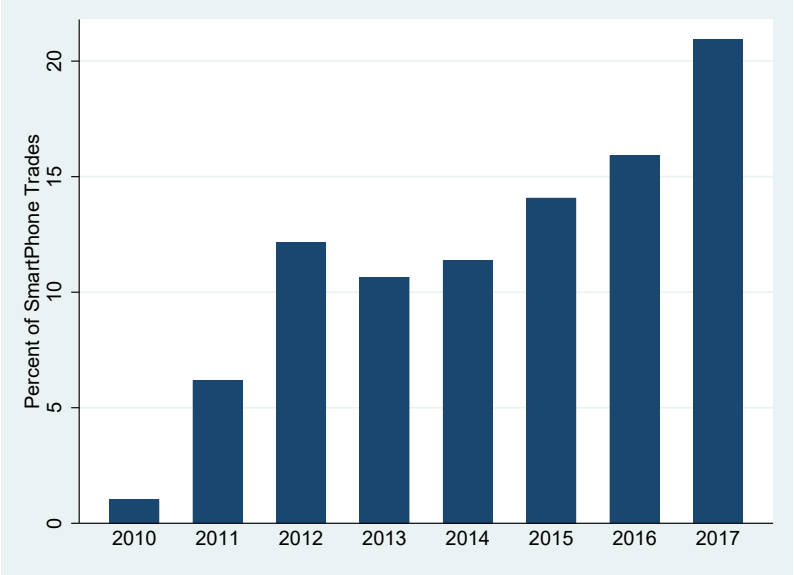
Thaler, R. H. and C. R. Sunstein (2008). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.

Welch, I. (2020). Retail raw: Wisdom of the robinhood crowd and the covid crisis. *Working Paper*.

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 by different years. Panel B plots the number of trades executed over smartphones by investors who use the smartphone at least once.

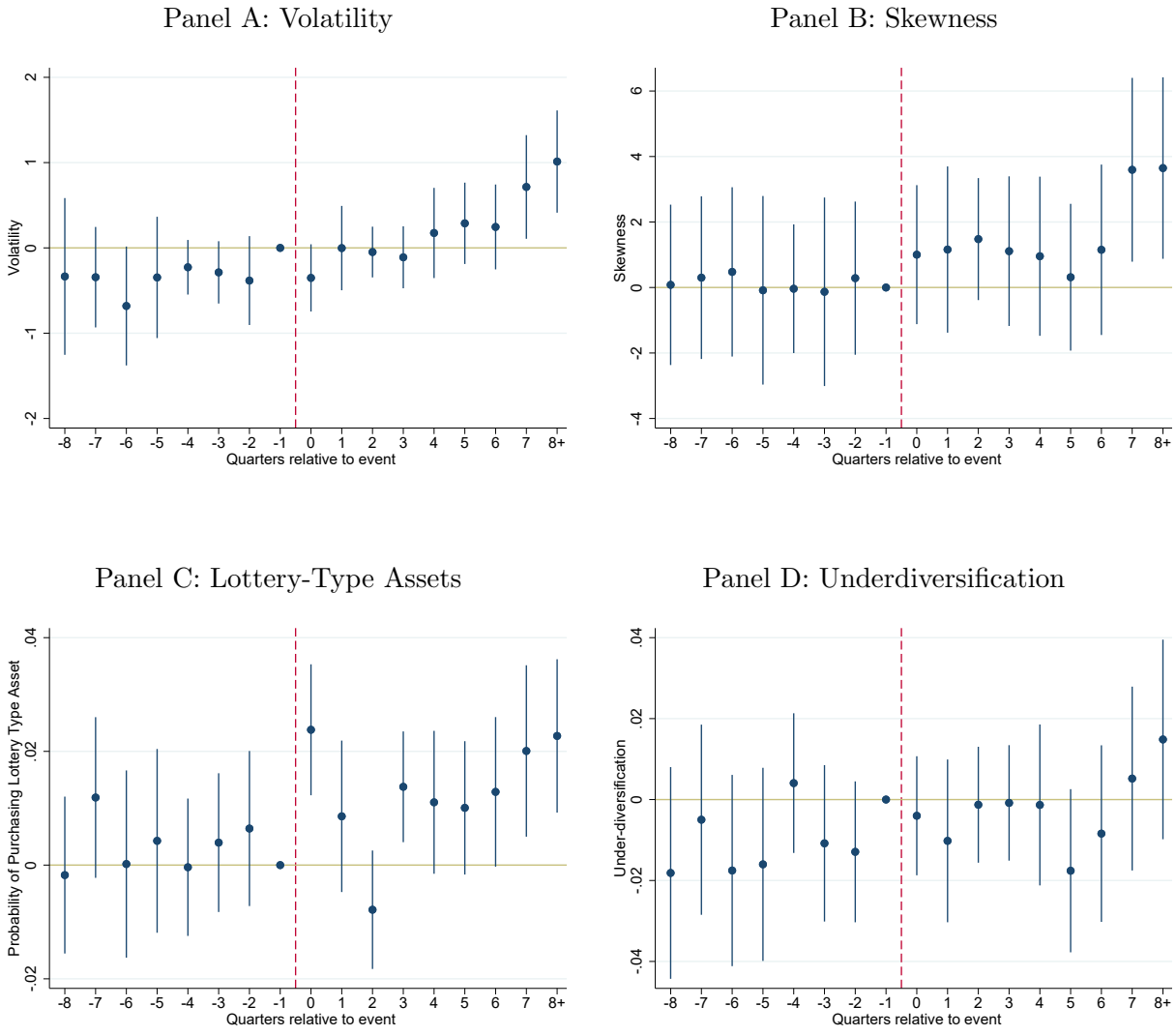


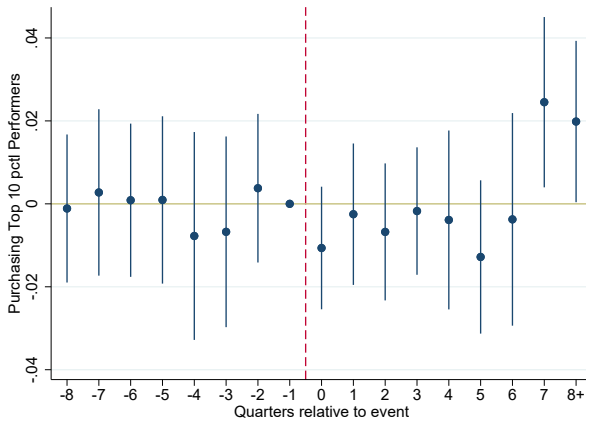
Panel A: Fraction of users



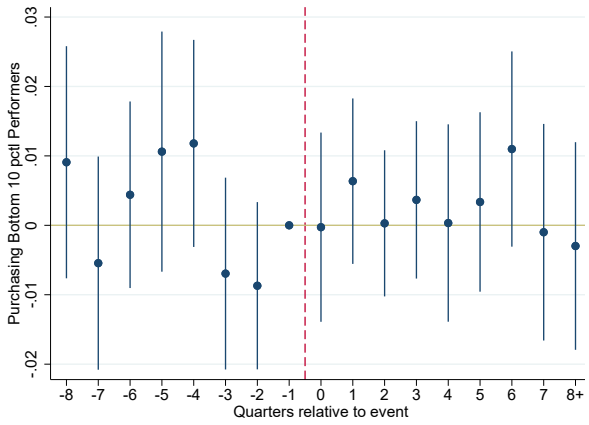
Panel B: Fraction of trades for adopters

Figure 2:
Substitution Effects: Dynamics
This figure plots the dynamics of the substitution effects of smartphone use on trades executed using other, non-smartphone platforms. We estimate substitution effects using difference-in-differences regressions. The first difference comes from before and after the launch date of a smartphone app. The second difference comes from the type of smartphone an investor owns (e.g., iPhone vs. Android). Each coefficient represents the effect of the use of smartphone on outcomes for the same investor on other platforms for different event quarters. The outcome variables include volatility of assets purchased (Panel A), skewness of assets purchased (Panel B), probability of purchasing lottery-type assets (Panel C), underdiversification (Panel D), and the probability of purchasing past winners (Panel E) and losers (Panel F). The confidence intervals are plotted at 5% levels.



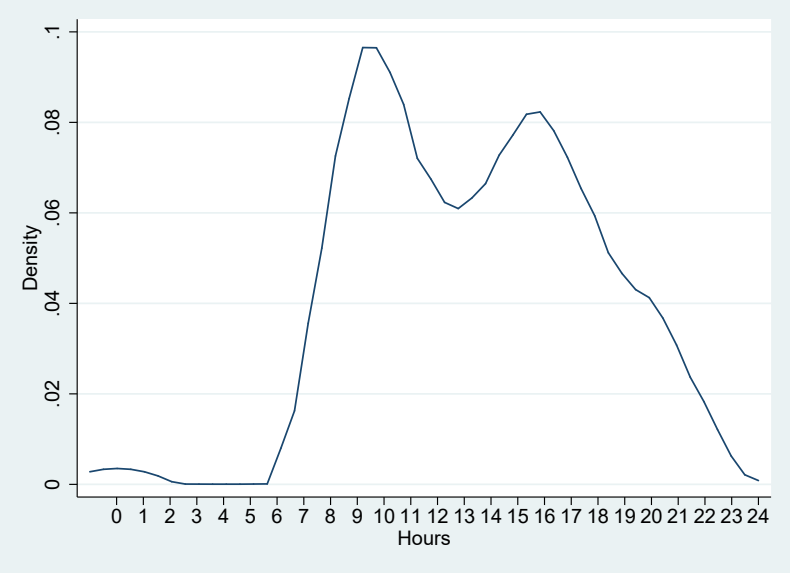


Panel E: Past Winners

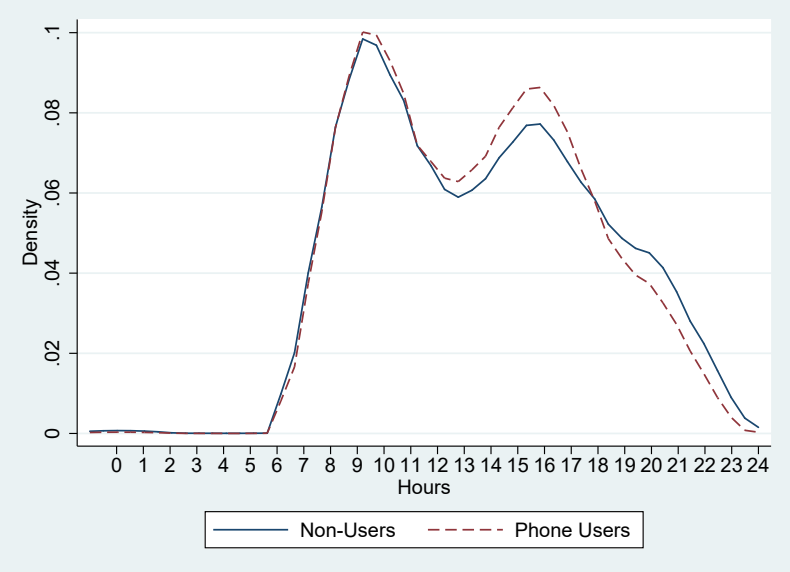


Panel F: Past Losers

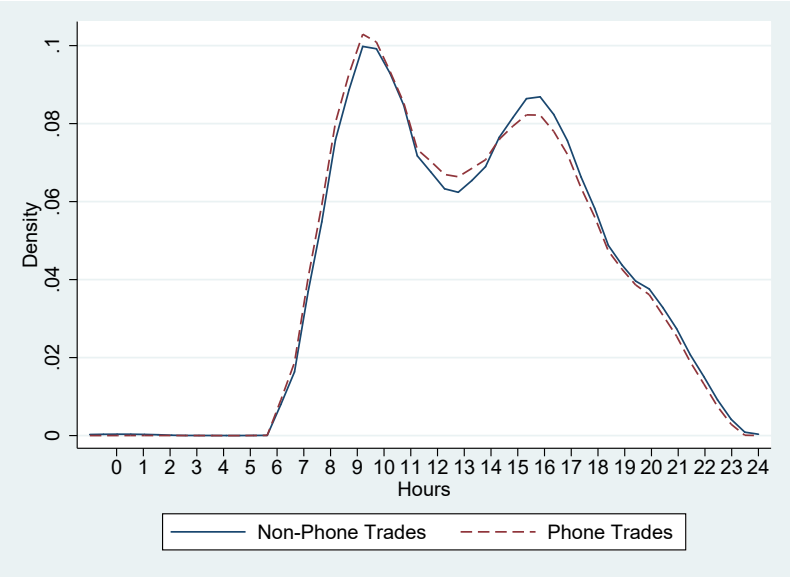
Figure 3:
Trading Hour Density
This figure plots the density for hour of the day when a trade occurs. Panel A plots this density for the entire sample. Panel B compares this density for smartphone users (dashed) versus non-users (solid). Panel C plots this density only for smartphone users and compares smartphone (dashed) and non-smartphone trades (solid).



Panel A: All Investors



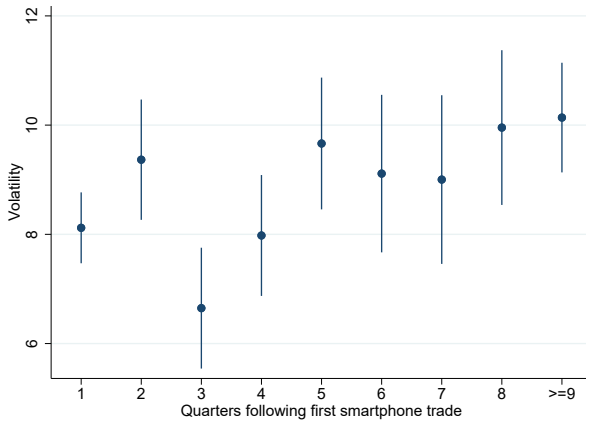
Panel B: Smartphone vs. Non-smartphone Users



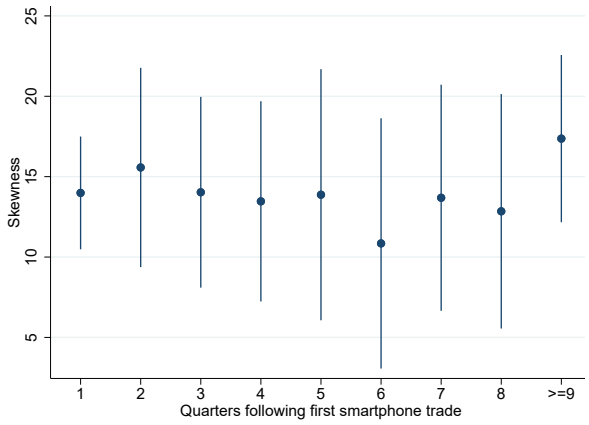
Panel C: Smartphone vs. Non-smartphone Trades (for adopters)

Figure 4:
Dynamics of Smartphone Effects
This figure plots the dynamics of our effects relative to the first use of a smartphone. Each coefficient represents the effect of the use of a smartphone on investor outcomes for different event quarters. The outcome variables include volatility of assets purchased (Panel A), skewness of assets purchased (Panel B), probability of purchasing lottery-type assets (Panel C), underdiversification (Panel D), and the probability of purchasing past winners (Panel E) and losers (Panel F). The confidence intervals are plotted at 5% levels.

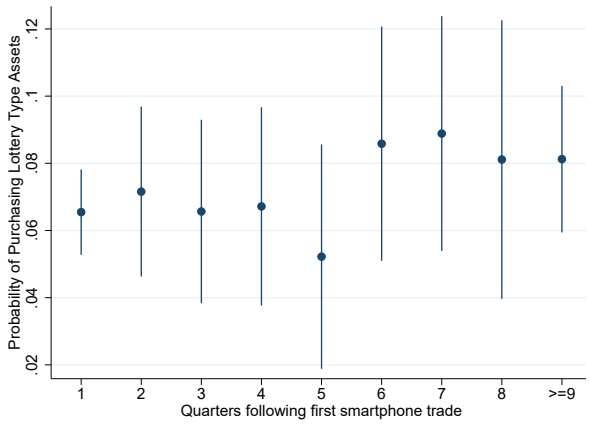
Panel A: Volatility



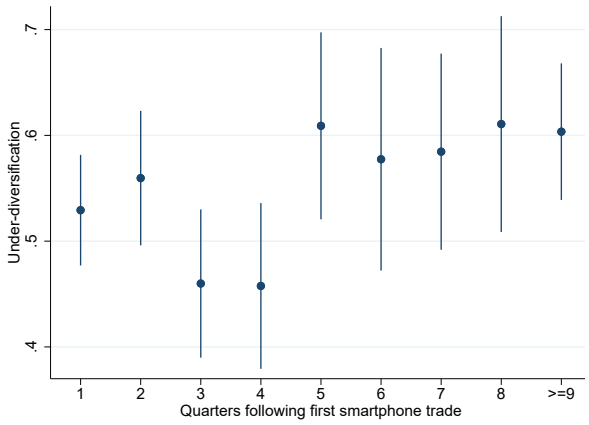
Panel B: Skewness

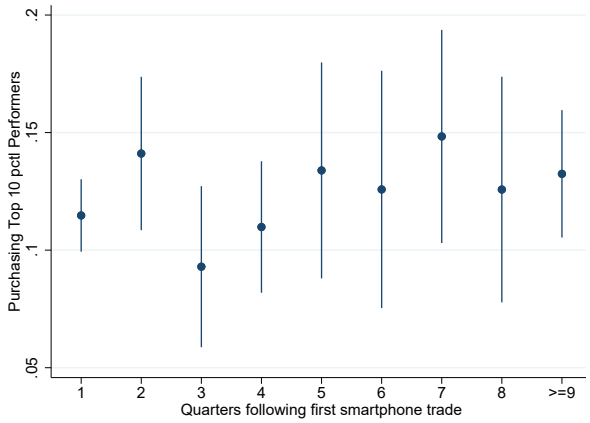


Panel C: Lottery-Type Assets

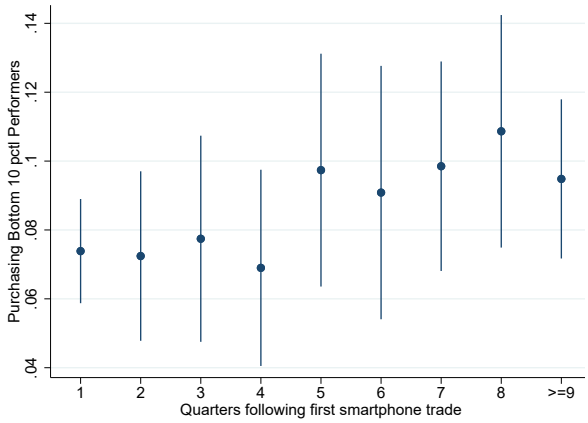


Panel D: Underdiversification





Panel E: Past Winners



Panel F: Past Losers

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

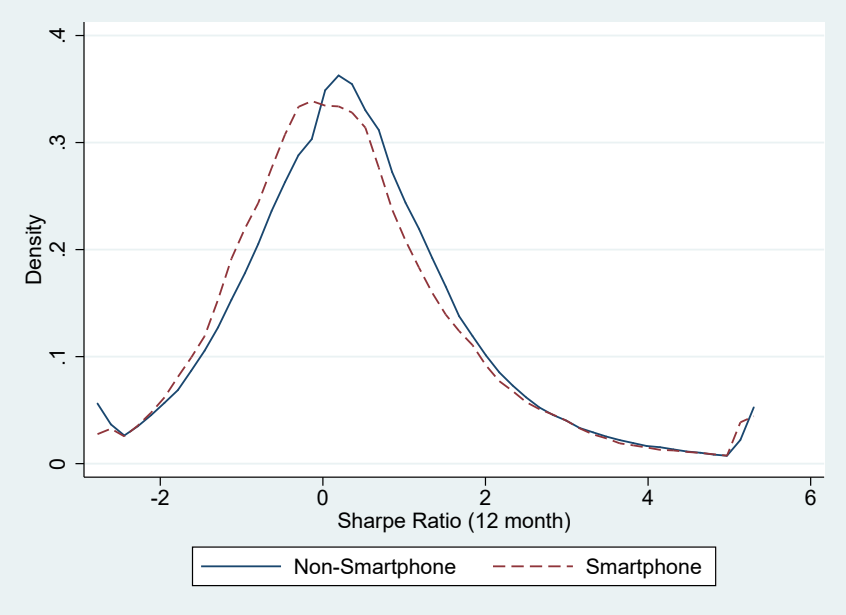


Table 1:
Summary Statistics
This table reports the summary statistics of the variables used in our analyses for all the investors in our sample for the years 2010 to 2017. Volatility of the asset purchased is reported in percentage points. Sharpe ratios and market adjusted returns are computed assuming 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 demographics variables. 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:
Risk-taking
This table reports estimates from regressing risk-taking on the use of smartphones. We measure risk-taking by the probability of purchasing risky assets (Panel A) and the volatility of assets purchased (Panel B). Each observation corresponds to a purchase trade, and different columns include different fixed effects 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

	Probability of Purchasing Risky Assets			
	(1)	(2)	(3)	(4)
Smartphone	0.222***	0.077***	0.115***	0.159***
	(19.82)	(13.96)	(17.30)	(18.79)
Individual FE	No	Yes	No	No
Year FE	No	Yes	No	No
Individual x Year FE	No	No	Yes	No
Individual x Month FE	No	No	No	Yes
Observations	9,068,770	9,058,288	9,036,099	8,707,146
R^2	0.003	0.520	0.499	0.565

Panel B

	Volatility of Assets Purchased			
	(1)	(2)	(3)	(4)
Smartphone	10.601***	3.166***	5.249***	7.352***
	(18.51)	(12.60)	(20.80)	(22.55)
Individual FE	No	Yes	No	No
Year FE	No	Yes	No	No
Individual x Year FE	No	No	Yes	No
Individual x Month FE	No	No	No	Yes
Observations	8,895,433	8,884,934	8,862,466	8,529,126
R^2	0.005	0.542	0.518	0.565

Table 4:
Skewness and Lottery-type Assets
This table reports estimates from regressing preferences for skewness on the use of smartphones. We measure preferences for skewness as skewness of assets purchased (Panel A) and the likelihood of purchasing lottery-type assets (Panel B). Each observation corresponds to a purchase trade, and different columns include different fixed effects 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

	Skewness of Assets Purchased			
	(1)	(2)	(3)	(4)
Smartphone	15.122***	3.721***	7.949***	10.548***
	(7.98)	(3.95)	(8.96)	(10.08)
Individual FE	No	Yes	No	No
Year FE	No	Yes	No	No
Individual x Year FE	No	No	Yes	No
Individual x Month FE	No	No	No	Yes
Observations	8,894,062	8,883,571	8,861,098	8,527,701
R^2	0.001	0.158	0.214	0.347

Panel B

	Prob of Purchasing Lottery-Type Assets			
	(1)	(2)	(3)	(4)
Smartphone	0.078***	0.014***	0.034***	0.056***
	(10.18)	(3.29)	(9.45)	(12.34)
Individual FE	No	Yes	No	No
Year FE	No	Yes	No	No
Individual x Year FE	No	No	Yes	No
Individual x Month FE	No	No	No	Yes
Observations	8,894,062	8,883,571	8,861,098	8,527,701
R^2	0.001	0.229	0.261	0.381

Table 5:
Underdiversification, Buying Past Winners and Losers
This table reports estimates from regressing investor behaviors on the use of smartphones. The outcome variables include the value weighted fraction of undiversified trades (Panel A) and the probability of purchasing past winners (Panel B) and losers (Panel C). Each observation corresponds to a purchase trade, and different columns include different fixed effects 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

	Underdiversification			
	(1)	(2)	(3)	(4)
Smartphone	0.484***	0.207***	0.291***	0.406***
	(24.78)	(13.94)	(16.87)	(18.45)
Individual FE	No	Yes	No	No
Year FE	No	Yes	No	No
Individual x Year FE	No	No	Yes	No
Individual x Month FE	No	No	No	Yes
Observations	8,820,801	8,810,295	8,787,725	8,452,120
R^2	0.007	0.451	0.408	0.408

Panel B

	Prob of Purchasing Past Winners			
	(1)	(2)	(3)	(4)
Smartphone	0.136***	0.042***	0.070***	0.087***
	(11.24)	(7.91)	(13.21)	(14.19)
Individual FE	No	Yes	No	No
Year FE	No	Yes	No	No
Individual x Year FE	No	No	Yes	No
Individual x Month FE	No	No	No	Yes
Observations	8,788,937	8,778,428	8,755,715	8,418,764
R^2	0.002	0.241	0.278	0.393

Panel C

	Prob of Purchasing Past Losers			
	(1)	(2)	(3)	(4)
Smartphone	0.088***	0.027***	0.042***	0.066***
	(11.10)	(5.92)	(9.65)	(14.58)
Individual FE	No	Yes	No	No
Year FE	No	Yes	No	No
Individual x Year FE	No	No	Yes	No
Individual x Month FE	No	No	No	Yes
Observations	8,788,937	8,778,428	8,755,715	8,418,764
R^2	0.001	0.232	0.278	0.411

Table 6:
Substitution Effects Across Platforms
This table reports estimates of difference-in-differences regressions of investor behaviors on the use of smartphones. In this analysis, we only include purchases made by smartphone users on non-smartphone platforms. The outcome variables include the volatility of assets purchased, the skewness of assets purchased, the probability of purchasing lottery-type assets, the value weighted fraction of undiversified trades, and the probability of purchasing past winners and losers. Each observation is at the individual-by-month level and corresponds to the average outcome across all devices other than smartphones. Panel A considers the first time an investor uses a smartphone app as the event date. Panel B considers the launch date of the trading app for different smartphone operating systems as the event date. 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: Early versus Late Adopters

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone Use	0.529***	4.787***	0.005***	0.015***	0.005*	0.001
	(5.75)	(9.44)	(2.64)	4.21	(1.78)	(0.72)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427,665	428,285	287,169	287,169	279,971	279971
R^2	0.540	0.093	0.306	0.561	0.331	0.302

Panel B: iOS versus Android Users

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Smartphone Launch	0.094	3.978***	-0.003	0.003	-0.002	0.003
	(0.47)	(5.01)	(-0.63)	(0.36)	(-0.32)	(0.53)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	248,031	248,324	154,865	154,865	149,743	149743
R^2	0.496	0.090	0.287	0.506	0.314	0.294

Table 7:
Choice of Asset Classes and Trading Hour
This table reports estimates from regressing investor behaviors on the use of smartphones after separately controlling for asset class-by-year in Panel A and trading hour-by-year fixed effects in Panel B. The outcome variables include the volatility of assets purchased, the skewness of assets purchased, the probability of purchasing lottery-type assets, the value weighted fraction of undiversified trades, the probability of purchasing past winners, and the probability of purchasing past losers. Each observation corresponds to a purchase trade. 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: Asset Classes

	Volatility	Skewness	Lottery-Type Assets	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)
Smartphone	2.176***	2.449***	0.024***	0.011***	0.022***
	(13.30)	(5.65)	(7.12)	(3.08)	(7.26)
Ind x Month FE	Yes	Yes	Yes	Yes	Yes
Asset Class x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	8,500,780	8,499,363	8,499,363	8,400,232	8,400,232
R^2	0.672	0.379	0.401	0.432	0.434

Panel B: Trading Hour

	Volatility	Skewness	Lottery-Type Assets	Under-Divers.	Past Winners	Past Losers
	(1)	(2)	(3)	(4)	(5)	(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)
Ind x Month 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 8:
Digital Nudges

This table reports estimates from regressing investor behaviors on the use of smartphones for different samples of trades that are less likely to be driven by digital nudges. Panel A removes purchases of stocks that are in the top one hundred daily winners or the bottom one hundred daily losers. Panel B restricts the sample to mutual funds. Panel C shows results for active mutual funds. The outcome variables include the volatility of assets purchased, the skewness of assets purchased, the probability of purchasing lottery-type assets, the probability of purchasing past winners, and the probability of purchasing past losers. We exclude from Panel B and C our measure of underdiversification because all mutual funds purchases are diversifying trades according to our definition. Each observation corresponds to a purchase trade. 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)
Ind x Month 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)
Ind x Month 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)
Ind x Month 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 9:
Heterogeneity by Announcement and Non-announcement days
This table reports estimates from regressing investor behaviors on the use of smartphones for days with and without unscheduled announcement. The outcome variables include the volatility of assets purchased, the skewness of assets purchased, the probability of purchasing lottery-type assets, the probability of purchasing past winners, and the probability of purchasing past losers. Each observation corresponds to a purchase trade. 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)
Individual 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)
Individual 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 10:
Trading During Market Hours versus After-hours
This table reports estimates from regressing investor behaviors on the use of smartphones for different trading hours. The outcome variables include the volatility of assets purchased, the skewness of assets purchased, the probability of purchasing lottery-type assets, the value weighted fraction of undiversified trades, the probability of purchasing past winners, and the probability of purchasing past losers. Each observation corresponds to a purchase trade. Different panels represent different times of the day. Market hours is the window between 9 a.m. and 5 p.m.; after-hours is between 5 p.m. and 10 p.m.; morning hour is between 8 a.m. and 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)
Ind x Month 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)
Ind x Month 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)
Ind x Month 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 11:
Trading During Pre- vs Post- Lunch Hour

This table reports estimates from regressing investor behaviors on the use of smartphones for trading hours before and after lunch. The outcome variables include the volatility of assets purchased, the skewness of assets purchased, the probability of purchasing lottery-type assets, the value weighted fraction of undiversified trades, the probability of purchasing past winners, and the probability of purchasing past losers. Each observation corresponds to a purchase trade. Both panels represent different times around lunch hour – 11am-12pm (panel A) and 1-2pm (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	Underdiversification	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)
Individual 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	Underdiversification	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)
Individual 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 12:
Heterogeneity by Weather

This table reports estimates from regressing investor behaviors on the use of smartphones for days with different levels of sunshine. The outcome variables include the volatility of assets purchased, the skewness of assets purchased, the probability of purchasing lottery-type assets, the value weighted fraction of undiversified trades, the probability of purchasing past winners, and the probability of purchasing past losers. Each observation corresponds to a purchase trade. While Panel A reports results for a sub-sample with higher than median level of sunshine, 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)
Ind x Month 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)
Ind x Month 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 13:
Performance: Sharpe Ratios

This table reports estimates from regressing the Sharpe ratio of the assets purchased on the use of smartphones. The Sharpe ratios in different columns are computed assuming different holding periods of the assets purchased. Each observation corresponds to a purchase trade. 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)
Ind x Month 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 14:
Heterogeneity by Investor Experience
This table reports estimates from regressing investor behaviors on smartphone use for investors with different tenure with the banks in our sample. Panel A shows results for "New Investors" or investors with below median tenure at the banks. Panel B reports results for "Old Investors" or investors with above-median tenure at the banks. The outcome variables include the volatility of assets purchased, the skewness of assets purchased, the probability of purchasing lottery-type assets, the probability of purchasing under-diversifying assets, the probability of purchasing past winners, the probability of purchasing past losers, and Sharpe ratio of assets purchased assuming a twelve month holding period. All specifications include age-by-year fixed effects to control for age 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)
Ind x Month 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)
Ind x Month 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

Table 15:
Heterogeneity by Investor Age
This table reports estimates from regressing investor behaviors on smartphone use for investors in different age groups.The outcome variables include the volatility of assets purchased, the skewness of assets purchased, the probability of purchasing lottery-type assets, the probability of purchasing under-diversifying assets, the probability of purchasing past winners, and the probability of purchasing past losers. In Column 1, we report results for the sub-sample of investors younger than 30 years old. Analogously, in Column 5, we report results for those investors that are older than 60 years. 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)

Smart(Phone) Investing?

Appendix for Online Publication

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

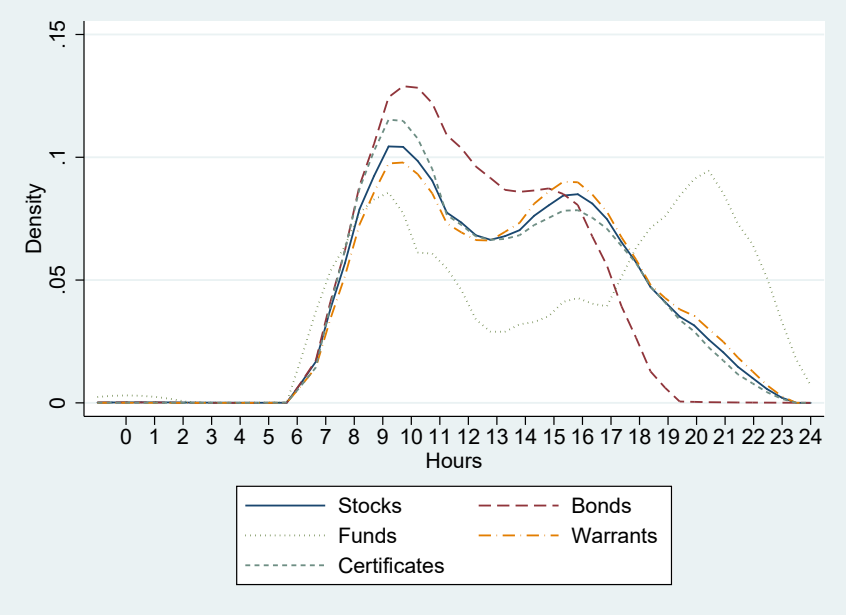


Table A1:
Riskiness of Assets Purchased

This table reports estimates from regressing risk-taking on the use of smartphones. We measure risk-taking by the risk categories assigned by the banks with one indicating the lowest risk and five indicating the highest risk. Each observation corresponds to a purchase trade, and different columns include different fixed effects 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 of Assets Purchased			
	(1)	(2)	(3)	(4)
Smartphone	0.209***	0.020***	0.051***	0.085***
	(8.69)	(3.05)	(8.01)	(11.41)
Individual FE	No	Yes	No	No
Year FE	No	Yes	No	No
Individual x Year FE	No	No	Yes	No
Individual x Month FE	No	No	No	Yes
Observations	9,502,255	9,492,588	9,473,450	9,229,168
R^2	0.001	0.406	0.410	0.449

Table A2:
Probability of Purchasing Warrants or Certificates
This table reports estimates from regressing the probability of purchasing warrants or certificates on the use of smartphones. The outcome variable for Panel A is the probability of purchasing a warrant. The outcome in Panel B is the probability of purchasing a certificate. Each observation corresponds to a purchase trade, and different columns include different fixed effects 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: Warrants

	Probability of Purchasing a Warrant			
	(1)	(2)	(3)	(4)
Smartphone	0.137***	-0.002	0.037***	0.056***
	(6.11)	(-0.35)	(9.64)	(7.33)
Individual FE	No	Yes	No	No
Year FE	No	Yes	No	No
Individual x Year FE	No	No	Yes	No
Individual x Month FE	No	No	No	Yes
Observations	9,064,832	9,055,122	9,036,386	8,798,775
R^2	0.002	0.696	0.715	0.724

Panel B: Certificates

	Probability of Purchasing a Certificate			
	(1)	(2)	(3)	(4)
Smartphone	0.010**	0.008***	0.006***	0.007***
	(2.32)	(3.27)	(3.53)	(3.48)
Individual FE	No	Yes	No	No
Year FE	No	Yes	No	No
Individual x Year FE	No	No	Yes	No
Individual x Month FE	No	No	No	Yes
Observations	9,064,832	9,055,122	9,036,386	8,798,775
R^2	0.000	0.311	0.365	0.431

Table A3:
Robustness Test: Value-weighted Outcome Measures
This table reports estimates of the smartphone effects on our main outcomes, measured after accounting for value of trades. Each observation corresponds to a purchase trade. We exclude from this analysis our measure of underdiversification because it already accounts for 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)
Ind x Month 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:
Robustness Test: Investors Trading Using Their Main Accounts
This table reports estimates of the smartphone effects on our main outcomes for those investors that have their primary account with the two banks in our sample. Each observation corresponds to a purchase trade. 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)
Ind x Month 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:
Robustness Test: Investor-by-Day Fixed Effects
This table reports estimates of the smartphone effects on our main outcomes after including investor-by-day fixed effects. Each observation corresponds to a purchase trade. 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	Underdiversification	Top 10 Pctl Performers	Bottom 10 Pctl Performers
	(1)	(2)	(3)	(4)	(5)	(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)
Individual 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 A6:
Choice of Trading Hours and Asset Classes

This table reports estimates from regressing investor behaviors of the use of smartphones after controlling for time-varying effects of trading hours and asset classes. We exclude from this table our measure of underdiversification because diversifying trades belong to only one specific asset class (i.e., mutual funds). Each observation corresponds to a purchase trade. 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)
Ind x Month 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 A7:
Device Screen Size
This table reports estimates from regressing investor behaviors on the use of smartphones and iPads. Each observation corresponds to a purchase trade. 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)
Individual 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 A8:
Performance: Market Adjusted Returns
This table reports estimates from regressing market adjusted returns of the assets purchased on the use of smartphones. The returns in different columns are computed assuming different holding periods of the assets purchased. Each observation corresponds to a purchase trade. 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)
Ind x Month 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