Smart(Phone) Investing?*

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Abstract

New technologies can change how we make financial decisions. Using transaction-level data from two large German retail banks, we study the effects of smartphones on investor behavior. To account for selection effects, we compare trades made by the same investor during the same month across different platforms. We find that smartphone trades increase the probability of buying risky assets, lottery-type assets, and the tendency to chase past returns. Using smartphones to purchase different asset classes or to trade during different hours does not fully explain our results. Smartphone trades do not substitute other trades. Investors also buy riskier and more lottery-type investments on other platforms. The effects of smartphones are not transitory. Our results suggest that the convenience of smartphone trading could come at the expense of investor portfolio efficiency.

Keywords: fintech, behavioral finance, smartphone trading, investment biases, preference for lottery-type assets, trend chasing.

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1 Introduction

New technologies can change the way households make economic decisions, from labor supply, to borrowing, to investor behavior.[1] Smartphones represent one of the most widely used technologies, with over 250 million devices in the US alone.[2] Ease of use, ubiquitous access to the web and speed of execution make the smartphones the preferred mean for many economic transactions. However, the increased convenience of using smartphones might come at a cost. For example, consumers are more inclined to make impulsive purchases such as ordering more unhealthy food when using mobile devices.[3] Large online brokers report that over 20% of all retail investor annual trades have been executed using mobile devices and estimate this percentage to double in the next few years.[4] Despite this trend, we know very little about how this technology affects investor behavior. This project aims to fill this void.

Using trade-level data from two large German retails banks, we investigate the effects of smartphones on investor behavior. We present three set of results. First, compared to trades done by the same investor in the same month across different platforms, smartphone trades increase the probability of buying risky assets and investments with higher volatility and more positive skewness. These first results are best summarized by investigating the tendency to buy lottery-type assets. In our preferred specification with investor by month fixed effects, smartphone trades increase the probability of purchasing lottery-type investments by eight percentage points or 67% of the unconditional mean for smartphone users. Second, smartphone trades increase also the tendency to chase

[1]For example, 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, Matvos, Piskorski and Seru (2018) and Fuster et al. (2018) document the effect of Fintech lending on borrowing decisions; and D'Acunto, Prahabala, and Rossi (2018) document the effect of robo-advising on investment decisions.

[2]Source: https://www.statista.com/topics/2711/us-smartphone-market/

[3]For a review of the effects of smartphones on consumer choices see Benartzi and Lehrer (2015).

[4]Source: https://www.cnbc.com/2018/11/29/td-ameritrade-sees-more-people-trading-on-their-phones.html

past returns and to buy investment that have performed in the top deciles of the return distribution. We find that smartphone trades increase the probability of buying in the top decile of past performers by 12 pp, or 35% of the unconditional mean. Third, we investigate the mechanisms that might drive these effects. The possibilities to trade specific asset classes or to trade during extended hours contribute, but do not entirely drive our results. Moreover, investors do not appear to use smartphones to substitute their risky, gambling-like trades. An analysis of spillover effects in fact suggests that risk-taking and lottery-type investments increase also in non-smartphone trades, after the investors start using smartphones. Last, the effects of smartphone are not transitory and driven by an initial excitement. They are relatively stable over time, in ten quarters after the adoption of smartphone trading.

The effects of smartphones on trading behavior is not obvious ex-ante. Smartphones can facilitate timely information acquisition, thus improving the quality of trades. At the same time, they also allow individuals to place trading orders at virtually anytime and from everywhere. This ability coupled with the speed of execution might foster more intuitive and impulsive actions. Psychologists hypothesize that we have two modes of thinking: system 1 is fast, instinctive and emotional while those system 2 is slower, more deliberative, and more logical (see Kahneman, 2011). Having the ability to almost instantaneously trade in more relaxed environments (e.g. during non-working hours at bars or restaurants) may potentially allow more impulsive, system 1 trades leading individuals to over-react to recent market trends and new information, or take on more risks than they should. By virtue of being a smaller screen, smart phones may also potentially exacerbate existing trading biases or create new ones (for a review see Benartzi and Lehrer, 2015).

To investigate the effects of smartphones, we use data from two large German retail banks that in the recent years have introduced applications that allow trading using mobile devices. We can observe all the holdings and transactions for 15,420 bank clients that have used mobile device applications in the period 2010 to 2017. More important for our research questions, we can observe the specific platform used for each trade. For example, the data record if a trade has occurred in-person, over an automated telephone service, a web-based interface, a desktop application, using an iPhone, an iPad or an Android device. The data also contain information on the exact time stamp (at the second) of each trade. In this draft we focus on smartphone vs. non-smartphone trades. In future drafts we plan to fully exploit the granularity of our data and to investigate the trades across different mobile devices (iPhone vs. iPads, iOS vs. Android devices).

Investigating the effects of the platform used on the trading activity poses significant identification challenges. Individuals who use smartphones to trade are different from those who use other platforms. For example, more active or sophisticated traders may be more likely to use smartphones while naïve traders may be more likely to trade in-person or using a web-based interface. Moreover, investor characteristics are also likely to change over time. For instance, individuals can become more sophisticated or start trading more actively over time. In our analyses, we address these concerns by exploiting within individual-by-time variation. In practice, we include individual-by-year or individual-by-month fixed effects in our estimations. These specifications will ensure that we compare trades made by the same individual within the same month or year, but using different platforms.

We conduct four sets of analyses. First, we document who are the adopters of smartphone trading applications. Compared to non-smartphone users, users trade more often (10 trades per month vs. five) and make larger trades ($44,815 vs. $20,284). They are also more likely to buy more volatile stocks and more past top performers. In this draft, we use only portfolio information. In future drafts we will be able to use also demographic characteristics such as age, gender, wealth and financial sophistication assessed by investigating trading patterns before the use of mobile trading (for some clients we observe the transactions history back to 1999). Moreover, for one bank we will have login activity information.

Second, we study if the use of smartphones induces differences in the riskiness of trades. There is no theoretical reason to expect that the trading platform might change the willingness to take financial risks. Nonetheless, if smartphones promote faster and more intuitive reasoning (more system 1 reasoning), it could be possible that investors might not fully appreciate the consequences of their trades and become more willing to bear risks. Conversely, the constant feedback available on smartphones might make investors more sensitive to their losses and make them over time more reluctant to invest in equities, as predicted by myopic loss aversion (Benartzi and Thaler, 1995).

Third, we examine if smartphones mitigate or exacerbate investor biases. By lowering the costs of information collection, smartphones might lead to more efficient portfolios and less investment mistakes. However, if smartphones promote more intutive reasoning, then investors might be more prone to biases (Kahneman, 2011). In this draft we examine only the well-documented investment bias to chase past returns. In future draft we plan to investigate also excessive turnover and fees.

Last, we evaluate what mechanism might drive smartphone effects. Do the ability to place trades anytime and everywhere entirely drive the effects of smartphones? To examine the importance of this channel, we repeat our analyses, including year-by-time-of-the-day fixed effects. Although our estimates become smaller, they are still economically and statistically significant. Analogously, the selection of riskier asset classes does not completely drive our results. After using smartphones, investors start buying higher volatility, higher skewness, more lottery-type assets also in their non-smartphone trades. This evidence seems to rule out substitution effects and the fact that investors might choose to allocate more gambling-type of trades to smartphones.

Overall, in this project we examine how smartphones, one of the most widespread technologies, affect investor behavior. The contribution of this study is twofold. First, our findings on investor behavior nicely dovetail with growing evidence on the effects of technology on household economic decisions. Second, our setting could provide a nice laboratory to understand what are the consequences of providing constant feedback and ease of execution of trades to retail investors and how this technology innovation might affect their risk-taking and, ultimately, the efficiency of their portfolios.

2 Data & Empirics

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

2.1 Data & Summary Statistics

Our analyses leverage transaction level data from two large German retail banks that cover all transactions done by banks' customers through their platforms. Along with transactions, this detailed data also provides customer level information across multiple dimensions. The transaction data includes information on securities traded, type of trades, day and time of trade execution, price and quantity of each transaction along with the device used for each trade among other variables. Since the customers in our data hold their primary accounts with these banks, most of them use the banks for all their transactions. This allows us to observe most transactions done by investors in our sample. This data covers about sixty five million transactions over the years from 1999 through 2017 related to over two hundred and twenty five thousand investors. The data from first bank covers information on over forty five million transactions related to over one hundred and ten thousand investors from 1999 through 2016 while that from second bank covers close to twenty million transactions related to over one hundred and sixteen thousand investors from 2003 through 2017. At the investor level, the data provides information on monthly snapshots of portfolio holdings along with demographic characteristics like gender, age, wealth, job etc.

Most of our analyses uses the transaction data where we impose three sample filters. First, we confine our sample from years 2010 through 2016 for the first bank and from years 2013 through 2017 for the second bank. This is because the first smartphone apps from respective banks were introduced in these years. Second, we drop trades associated with different savings plans and wealth management services because these are automated or regular trades that don't involve a choice from investors like active trades. Finally, we drop trades where either asset class or other information regarding the assets traded is not known. Applying these filters results in over twenty two million transactions related to about one hundred and eighty thousand investors. Over eighteen thousand of these investors use smartphone app to trade at least once.

We complement the proprietary data from banks with publicly available data on price dynamics, returns and characteristics for all securities traded within Germany to compute different risk and preference measures. Table 1 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 which occurred using smartphones. On average, 2% of trades in our sample use the smartphone technology with a standard deviation of 0.15. We define our first measure of risk taking as the probability of purchasing risky assets where risky assets are classified as equities, equity funds and similar assets. Mean probability of purchasing risky assets in our sample is 0.93 which is consistent with the overall trend in Germany. We use volatility of assets purchased as our second measure of risk taking which we define as the annualized standard deviation over trailing 12-month rolling window. The mean volatility in our sample is 17.27% with the standard deviation of 13.14%.

Our measures for gambling preference include skewness, calculated on a 12-month rolling window, and probability of purchasing lottery type assets. We follow Kumar (2009) and define lottery-type assets as those with below median price but above median skewness. The mean probability of purchasing a lottery-type asset within our sample is 7%. Our next set of measures help us examine trend chasing where we use the probability of purchasing top nth percentile performers based on returns that the asset earns during trailing 12-month window. The final set of outcomes we use include risk categories of assets purchased and probability of purchasing warrant or certificate. The banks assign risk categories that take integer values ranging from one through five to all assets within the data where higher value represents greater risk. Mean risk category of assets purchased in our sample is 3.99 while the mean probability of purchasing a warrant (certificate) is 9% (3%).

We next explore the use of smartphones within our sample over time in Figure 1. Panel A plots the percentage of trades that occur through smartphones on the Y-axis against calendar year on the X-axis. The use of smartphone begins in 2010 when the first smartphone app was launched by the first bank. It's use increases over time with over 2.5% of all trades occurring over the phone in 2017. The average usage drops in 2013 because of the addition of the second bank which launched it's app in 2013. Among investors within the first bank, the usage was close to 4% in 2017. Though the overall use is relatively small, the usage trend is increasing with over 10% of all investors using the smartphone technology in 2017. Similar to Panel A, Panel B plots the percentage of trades that occur through smartphones but confines to investors who use the phone. Among these investors, smartphone use is much higher, increasing at a faster rate with over 20% of all their trades using the technology. Thus, if smartphone trades differ from other trades, it's use might have a significant impact on the overall portfolio for these investors.

Since investors endogenously choose to use smartphones, those who use it may be inherently different from those who don't. Table 2 examines this plausibility by comparing trading behavior across phone users and non users. The mean and median for non users are computed using data on all years while those for phone users are computed using transactions until their first smart phone trade. This helps avoid any effects that phone trading itself may have on different trade characteristics. We find that phone users trade more frequently and higher volume than non users. Mean number (volume) of trades for phone users in a month is 10 trades (44,815 euros) compared to about 5 trades (20,284 euros) for non users. Phone users are also inclined to take more risks than non users. The mean probability of purchasing risky assets for phone users is 0.95 while mean volatility of assets purchased is 22% which are significantly higher than 0.92 and 16.52% for non users respectively. Finally, phone users exhibit greater gambling preference and are more likely to engage in trend chasing behavior as reflected by higher mean probability of purchasing both lottery type assets and assets in top 20 percentile based on returns over trailing 12-month period.

2.2 Empirical Methodology

OLS estimation of the effect of use of smartphones on trade characteristics may be biased by the endogenous choice that investors make to use the technology. As highlighted in the previous section, those investors who choose to use smart phones are inherently different from those who don't along several dimensions. Such unobserved heterogeneity across phone users and non users can potentially bias the estimates for the effect of smartphone use on trading behavior. Moreover, there maybe time varying differences even within the same individual that may affect both their decision to use smartphones and risk taking behavior. For example, investors may choose to use smartphones when their risk preferences change which may in turn bias any estimated effect that the use of smartphone may have on trade characteristics.

We overcome these potential threats by comparing trades done by the same investor during the same time period across platforms to estimate the association between the use of smartphones and trading behavior. 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 risk taking, gambling preference and likelihood of trend chasing behavior for trades done by investor i using platform j during year-month t. $Smartphone_{i,j,t}$ is a dummy variable that takes a value of one for investor i for trades that are done using smartphones during the month t. $\delta_{i,t}$ represents investor x month (year) fixed effects that control for time varying unobserved differences at the investor level. To evaluate the importance of across- and within- investor heterogeneity in our setting, we also estimate the model without any fixed effects and with the inclusion of investor fixed effects (δ_i) for all our main results. Robust standard errors are double-clustered at the investor and year-month level.

For estimating these regressions, we collapse our sample to the investor x month x trading platform level where trading platform has been categorized into two groups - smartphone and all other devices. Hence, the outcome variable in each observation is the mean value of all trades within the same investor x month x trading platform level. Our estimation strategy allows us to control for both across- and within- investor heterogeneity that may bias estimates while allowing trades within the same investor as well as within the same month to be correlated.

A potential concern with our analysis maybe that investors may choose to use smartphones to do certain types of trades over others. In particular, they may choose to substitute certain types of trades done over other platforms with smartphones. We evaluate this plausibility by examining the association between the use of smartphone and trading behavior on other platforms. Section 4 discusses this concern along with the analysis performed in detail.

3 Main Results

We examine the association between the use of smartphones and three trading behaviors: risk-taking, preferences for lottery-type assets (high volatility and high skewness), and trend chasing. The effects of smartphones on these behaviors is not obvious. Smartphones can facilitate more timely information acquisition. They can improve portfolio efficiency and reduce investment biases such as preferences for lottery stocks and trend chasing. Smartphones, however, can allow access to trading anytime and anywhere. This ubiquitous access coupled with the speed of execution of trades might foster more system 1 thinking (Kahneman,2011). System 1 has long been associated with more intuitive and impulsive actions, which can potentially increase risk-taking or exacerbate investment biases.

3.1 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. Our outcome variable is an indicator variable that captures the probability of purchasing risky assets. We define as risky assets equities and equity-based funds. Bonds, bond funds or gold-related funds are treated as non-equity investments. In Column (1) we do not include fixed effects. In this specification we find that the probability of purchasing risky assets is five percentage points (pp) higher for trades done using smartphones relative to other trades. This effect corresponds to an increase of 5.2% of the unconditional sample mean of 0.95 for smartphone users. However, heterogeneity in characteristics between smartphone users and non user 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 including year fixed effects. Consistent with these factors playing a role, our estimated effect of smartphone trading is smaller—2.11% of the sample mean—but still statistically significant at 1% level. However, within-investor time varying characteristics cans also bias our estimate in Column (2). For example, an investor's risk preferences and her use of smartphone may change simultaneously, thus impacting this estimate. We control for this plausibility in Column (3) where we include investor x year fixed effects on the right hand side 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 the same investor within the same year is 3pp more likely to purchase a risky asset while trading using smartphones versus not. Finally, in Column (4) we use our most stringent specification where we include investor x month fixed effects where we compare trades done by the same investor within the same year-month. This specification uses only those investor-month observations when the investor does multiple trades during the month. Hence, we lose a significant number of observations. Using this specification, we find that the probability of purchasing a risky asset is 4.3% greater for trades done by the same investor within the same month using smartphone versus other platforms.

Since the unconditional mean of purchasing risky assets for smartphone users is high (0.95), the magnitudes on the probability of purchasing risky assets might not fully capture the increased risk taking induced by smartphone use. Hence, we use volatility of assets purchased as our second measure of risk taking. We define volatility of assets purchased as the annualized standard deviation over trailing 12-month rolling window. Table 4 reports results for estimation using this outcome variable. As before, Column (1) does not include any fixed effects where we find that volatility of assets purchased using smartphones is 12.07pp higher than assets purchased using other platforms. This magnitude is economically large as it corresponds to 54.8% of the sample mean. However, this estimate maybe driven by both across- and within- investor heterogeneity. We control for time invariant across-investor heterogeneity in Column (2) and find that our estimates reduces to 4.43pp on inclusion of both investor and year fixed effects. In our most stringent specification in Column (4), we find that volatility of the assets purchased is 9.28pp higher for those purchased by the same investor within the same year-month using smartphones relative to other platforms. This magnitude is economically large as it corresponds to 42.2% of the unconditional mean.

3.2 Preferences for lottery-type stocks

We turn then to investigate the preferences for lottery-type assets. We start by investigating the skewness of assets purchased. Retail investors generally have preferences for positively skewed assets (e.g., Kumar, 2009). We present these results in table 5. In Column (1), we find that using smartphones increase the skewness of investments by 19.23pp, equal to approximately 33.4% of the standard deviation of the skewness for phone users of 57.58. This column does not include any fixed effects. When we add fixed effects, we find similar patterns like those in the previous tables. We estimate smaller, but still economically and statistically significant results. For example, in Column (4) we find that after controlling for investor X month fixed effects using smartphone increase skewness of asset purchased by 14.40, or 25% of standard deviation for the skewness for phone users.

In table 6, we measure more directly preferences for lottery-type assets. We compute the probability of purchasing lottery-type assets, defined as investments with below median prices, above median volatility and skewness in their asset classes (Kumar, 2009). In Column (1), we find that—without including fixed effects—smartphone trades increase the probability of purchasing lottery-type assets by 10 pp, or 83% of the unconditional mean for smartphone users. After including the same fixed effects used in the previous tables, we still find statistically and economically significant results. Under the most restrictive specification with investor X month fixed effects, smartphone trades increase the probability of purchasing lottery-type assets by 8 pp, or 67% of the unconditional mean.

3.3 Trend Chasing

Smartphones allow investors to access information on their investments on a more timely base. We investigate if smartphone influence the tendency of investors to buy "hot" investments, or asset that have performed unusually well in the recent past. For example, in our overall sample 68% of trades buy above median assets, based on past performance. Smartphone users have 34% of their trades concentrated in the top 20th percentiles of past performers. In table 7, panel A, we find that smartphone trades increase this tendency of purchasing assets from the top of the distribution of past performers. Without fixed effects, in Column (1), we find that the probability of buying these assets goes up by 11 pp, or 32.3% of the unconditional mean. After controlling for individual x month fixed effects, we still find an economically and statistically significant results. Smart phone trades increase the likelihood of purchasing in the top 20th percentile of past performers by 7.5pp or 22% of the unconditional mean. In penal B, we present as robustness check the effects of smartphones on the probability of purchasing at the top 50, 40, 30, 20, and 10 percent of the past return distribution. In all the specifications, we report results from our model that include investor x month fixed effects. Looking at this evidence, we can clearly see how the effect becomes economically and statistically significant above the 20th percentile. In Column (5), we document how smartphone trades increase the probability of buying in the top decile of past performers by 12 pp, or 35% of the unconditional mean.

Overall, our results provide evidence that support an effect of smartphones on investor trades. Even comparing trades within the same investor-month, we still find that investors buy more volatile and higher skewness assets using smartphones. These tendencies contribute to significantly increase the probability of purchasing lottery-type assets. Moreover, investors become significantly more likely to purchase top past performers. Previous research has documented that buying lottery-type stocks and chasing returns result in poorer portfolio performance. In future drafts of the paper we plan to directly investigate the effects of smartphone trading on performance, both net and gross of fees.

4 Mechanism

Comparing trades done by the same investor in the same month, we find that investors are more likely to buy assets with higher volatility, higher skewness, more likely to be lottery-type investments. Moreover, investors engage more in trend chasing. In this section we investigate what drives these differential behaviors.

4.1 Do investor use smartphone to trade during different hours?

Smartphones potentially allow an immediate access to trading over an extended period of time. We first investigate trading hour dynamics in figure 2. In panel A we plot the density of trades per hour of the day for our entire sample, including also 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 we plot the same density separately for smartphone and non-smartphone users. The two density plot largely overlap, with smartphone users marginally more likely to trade around closing hours, compared to non-smartphone users. In plan C, we limit our analyses to smartphone users and we plot separately their smartphone vs. non-smartphone trades. Again, there is no apparent difference in the two density plots. Smartphone traders similarly use both platforms during the day.

In table 8, we investigate more formally if different trading hours drive our results. In addition to investor X month fixed effects, we include in our analyses also trading hour x year fixed effects. This specification will allow us to compare trades made during the same hour of the day (e.g., 9:00am), during the same year. All our previous results are robust to this additional specification. Investors on smartphone are more likely to buy risky assets and lottery-type assets, and invest in more volatile and higher skewness assets. Compared to our previous results in tables 3 to 6, the economic magnitudes are attenuated. They range from 35% of the previous estimate for the probability to purchasing risky assets (1.4pp to 4pp) to 52.6% for the volatility of the asset purchased (7.6% vs. 14.4)%). All the results remain economically significant. For example, the probability of buying lottery-type assets via smartphone increase by 3.2 pp, or 26.7% of the unconditional mean for smartphone users (12%).

Overall, these results suggest that there are important hours-of-the-day selection effects. Nonetheless, these effects do not fully account for our evidence.

4.2 Do investors use smartphones to trade different asset classes?

Other than using smartphone to trade during different hours, investors could use smartphones to trade different asset classes which could drive our results. To test for this possibility, we run additional specifications where we include asset class by year fixed effects. Assets in our sample can belong to six different asset classes namely stocks, bonds, funds, warrants, certificates and option bonds that could be converted to stocks. We find that our previous results survive the addition of this more restrictive set of fixed effects. As in the previous subsection, the economic magnitude are attenuated, but the effects of smartphones are present also in trades within the same asset class, in the same year. For example, the volatility of the assets purchased goes up by 2.5% or 11.4% of the unconditional mean for smartphone users (22%). Analogously, the probability of buying lottery-type assets increase by 2.4 pp, or 20.0% of the unconditional mean. These results suggest that even within the same asset class, investors are more likely to purchase assets which are riskier, have lottery-type characteristics, and those that have been recent top performers.

4.3 Do investors concentrate their "gambling" on smartphones?

Investors could use smartphones to trade at specific times specific asset classes. Previous evidence document that these effects do not entirely explain our results. Investors endogenously decide their trading platform. They can decide to predominantly execute on smartphones their high-volatility, high skewness, lottery-type of trades. In this case, smartphone trades are just substituting trades that would have occurred anyway in different platforms. If there are substitution effects, we should expect non-smartphone trades to display lower volatility, lower skewness, and less likely to involve lottery-type of assets. To identify these spill-over effects, we use a difference-in-differences approach. We estimate the following equation:

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

where y measures risk-taking, volatility, skewness and preferences for lottery-type assets for trades done in *non-smartphone platforms* by investor i during year-month t. $Afteruse_{i,t}$ is an indicator variable equal to one for investor i for trades that are done after she starts using the smartphone. 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 table 10. The coefficient of interest, $beta$, is not significant for the probability of purchasing risky assets. For all the other outcome variables—volatility, skewness, and probability of purchasing lottery-type assets—the coefficient for $Afteruse$ is positive and statistically significant. Smartphone users after they start trading on smartphones buy higher volatility and higher skewness assets, and become more likely to purchase lottery-type stocks on non-smartphone platforms. Therefore, we find positive spillover effects. This evidence goes against substitution effects and the hypothesis that smartphone users largely select smartphones to execute their high volatility, high skewness trades. In this empirical design, we compare early vs. late smartphone users. This design accounts for the potential selection effects between users and non-users. Nonetheless, also the timing of starting to use smartphone trading is endogenous and early users could be different from late users. In future drafts we plan to instrument the timing of first use with the date of the introduction of the smartphone applications. IOS and Android applications were introduced on different dates which we can exploit.

4.4 Are results transitory?

Last, we test if the effects of smartphones are short-lived. Do investors get excited about this new technology and temporarily change their behavior? Or are the effects of smartphone usage persistent over time. We provide a graphical representation of the results of this analysis in figure 3. We interact the variable of interest from equation 1, the indicator for smartphone trades, with indicator for the quarters after the first smartphone trades. We include in our specifications investor x month fixed effects. In panel A, we report results for the probability of buying risky assets. The effects of smartphones are stable from the first quarter of usage up to quarter nine or more. The effects on volatility of trades (panel B) and skewness (panel C) are also stable over time.

Overall, this evidence suggests that initial excitement or initial willingness take more risks/ more gambling via smartphones are not driving our results. And that the effect of smartphones could be more permanent than transitory.

5 Conclusion

The use of technology has a profound impact on the way we conduct economic transactions. Using a novel data set from two large German retail banks, we investigate the effects of smartphones on investor behavior. Comparing the trades done by the same investor in the same month across different platforms, we document that traders on smartphone buy more risky assets, chase higher volatility and higher skewness investments, and lottery-type of assets. Moreover, investors are more likely to engage in trend chasing. We conduct several additional analyses to better understand the mechanism behind these results. We first investigate if our results depend on the possibility of accessing investments/trading over extended hours. While important, timing of the day effects do not fully explain our results. Analogously, the selection of riskier asset classes does not completely drive our results. After using smartphones, investors start buying higher volatility, higher skewness, more lottery-type assets also in their non-smartphone trades. This evidence seems to rule out substitution effects and the fact that investors might choose to allocate more gambling-type of trades to smartphones. Taken altogether this evidence suggests that investors might perceive trading using smartphones more as a recreational or gambling-like activity. The ease of access to our portfolio and speed of execution of trades typical of smartphone trading might come at a cost for many retail investors. In future drafts of the paper we plan to investigate the effects of purchasing these assets on portfolio performance and efficiency. This would allow to better quantify the actual costs of the behaviors illustrated.

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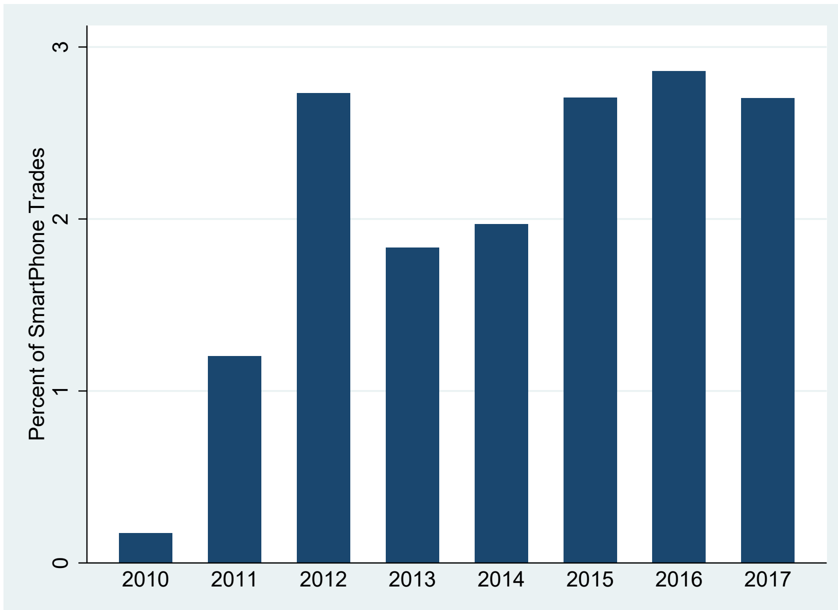
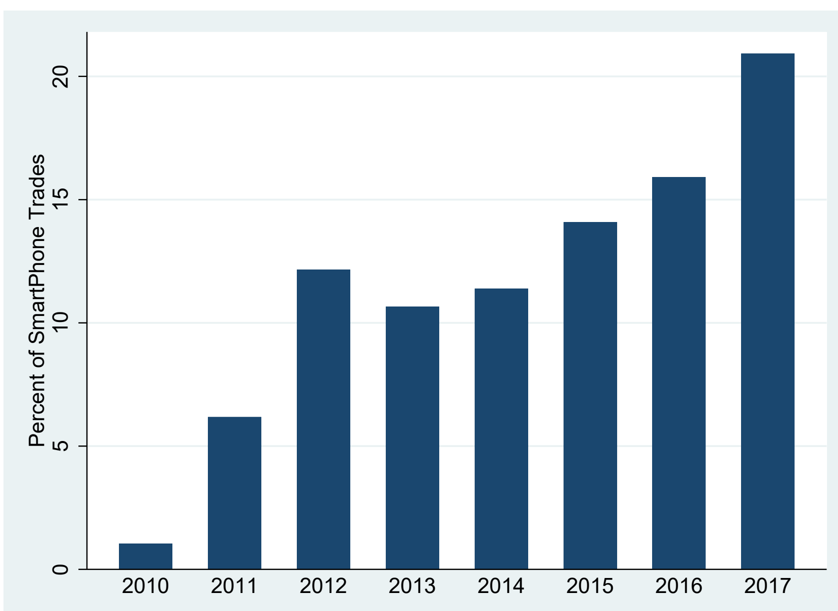
Figure 1:
Smartphone Usage
This figure plots the fraction of trades that occur over smartphones through time. Panel A plots this usage for the entire sample while Panel B plots this conditional for investors who use the smartphone.

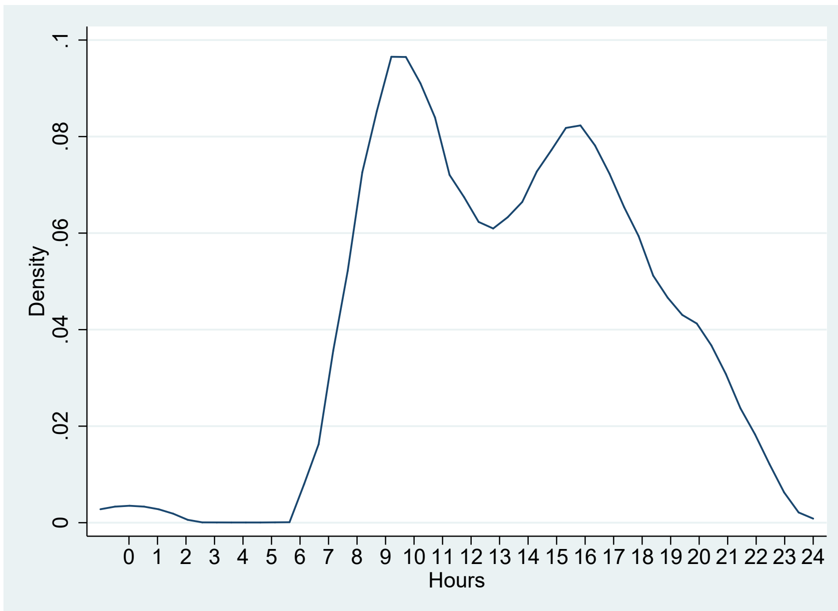


Panel A

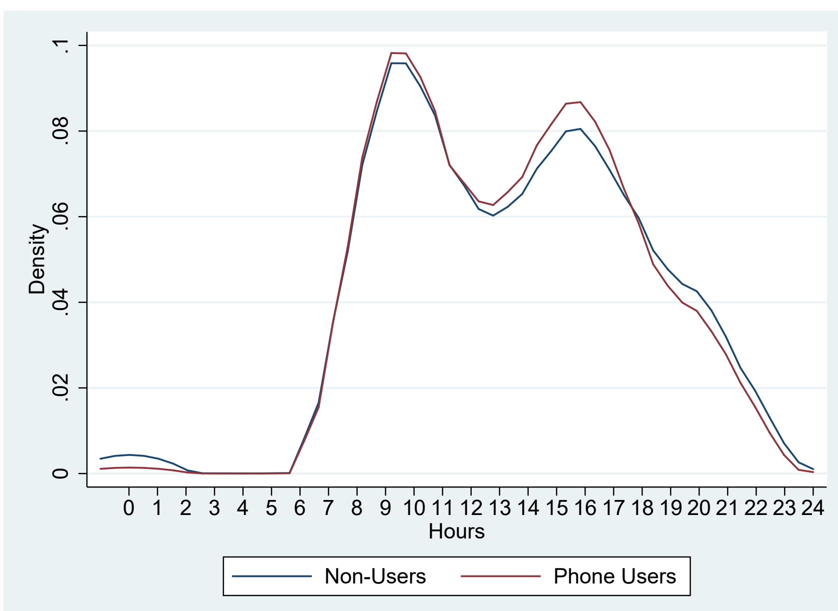


Panel B

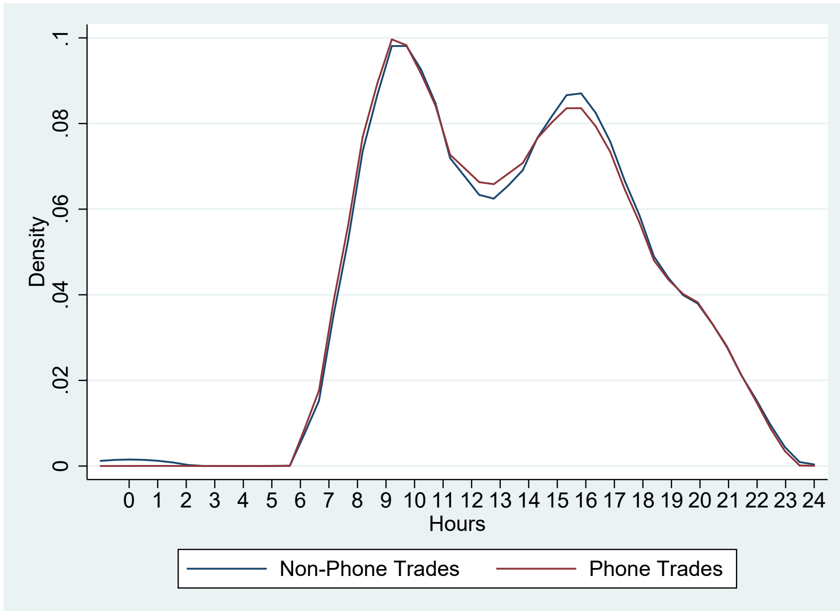
Figure 2:
Trading Hour Density
This figure plots density for hour of the day that trade occurs. Panel A plots this for the sample while Panel B compares this density for phone users versus non-users. Panel C plots this density for phone users and compares smartphone and non-phone trades.



Panel A

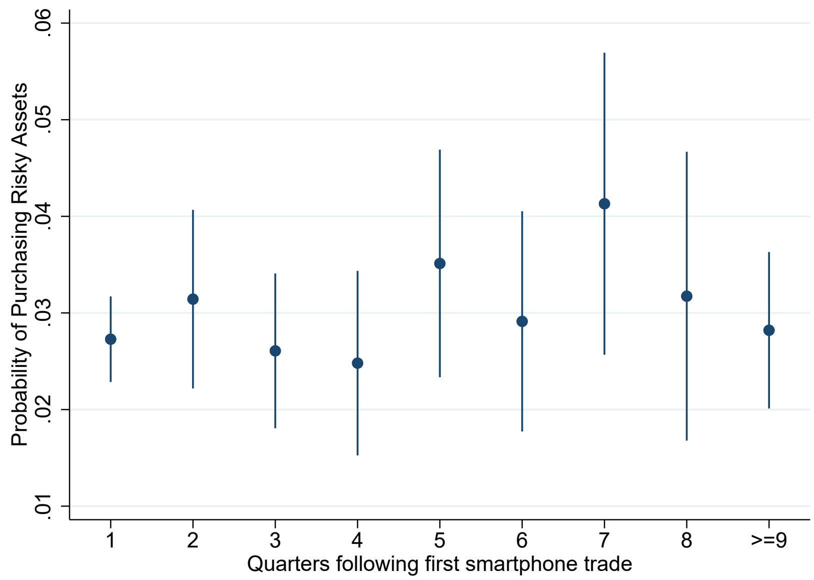


Panel B

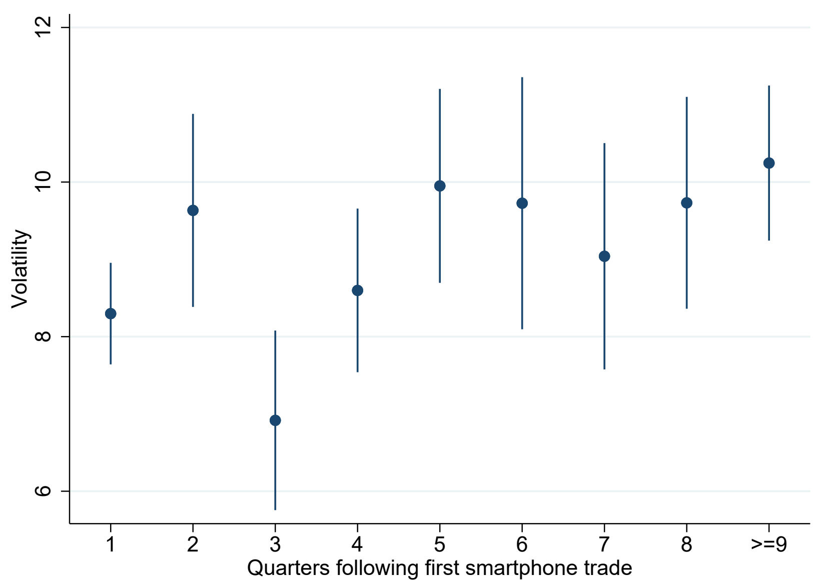

Density
0
.02
.04
.06
.08
.1
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hours
Non-Phone Trades
Phone Trades

Panel C

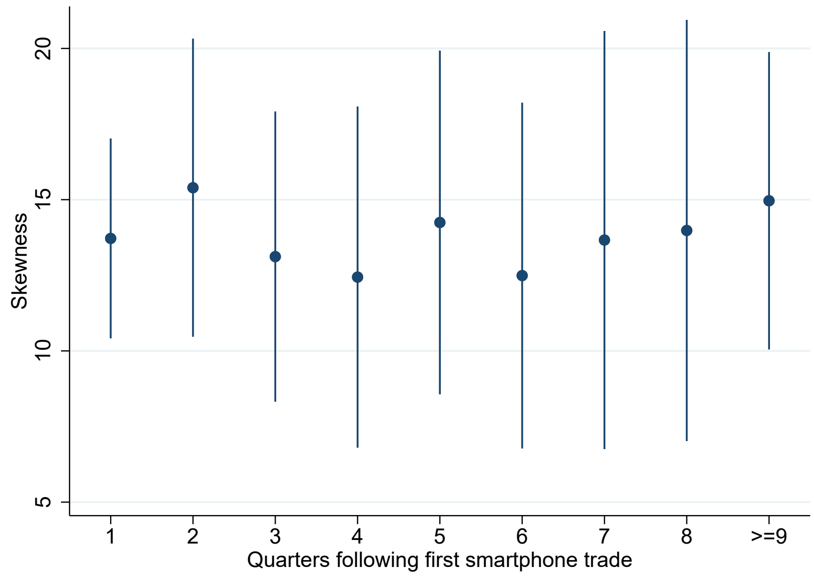
Figure 3:
Dynamics
This figure plots the dynamics of our effects relative to the first use of smartphone. Each coefficient represents the effect of the use of smartphone on risk taking for different quarters relative to the first use. The outcome variables include Probability of purchasing risky assets (panel A), volatility (panel B) and skewness (panel C) of assets purchased. The confidence intervals are plotted at 5% levels.



Panel A



Panel B



20
15
10
5
Skewness
1
2
3
4
5
6
7
8
>=9
Quarters following first smartphone trade

Panel C

Table 1:
Summary Stats
This table reports the summary statistics of variables used in our analysis.

	Mean	Std.Dev.	p25	Median	p75
Smartphone	0.02	0.15	0.00	0.00	0.00
Prob of Purchasing Risky Assets	0.93	0.23	1.00	1.00	1.00
Volatility of Assets Purchased	17.27	13.14	8.71	13.70	21.32
Skewness of Assets Purchased	-7.92	55.56	-38.64	-7.46	24.16
Prob of Purchasing Lottery type Assets	0.07	0.23	0.00	0.00	0.00
Prob of Purchasing Top 50 pctl performers	0.68	0.40	0.38	1.00	1.00
Prob of Purchasing Top 40 pctl performers	0.61	0.42	0.00	0.75	1.00
Prob of Purchasing Top 30 pctl performers	0.46	0.42	0.00	0.50	1.00
Prob of Purchasing Top 20 pctl performers	0.29	0.38	0.00	0.00	0.50
Prob of Purchasing Top 10 pctl performers	0.11	0.27	0.00	0.00	0.00
Risk Categories of Assets Purchased	3.99	0.72	3.50	4.00	4.50
Prob of Purchasing a Warrant	0.09	0.26	0.00	0.00	0.00
Prob of Purchasing a Certificate	0.03	0.16	0.00	0.00	0.00

Table 2:
Who uses Smartphones?
Table description goes here Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at 10%, 5% and 1% level, respectively. *, ** and *** represent significance at 10%, 5% and 1% level, respectively.

	Phone Users		***Non Users***	
	Mean	Median	Mean	Median
Avg No of Trades per Month	10.01	3.00	5.32	2.00
Volume of Trades per Month	44815.85	5687.70	20284.60	2000.00
Prob of Purchasing Risky Assets	0.95	1.00	0.92	1.00
Volatility of Assets Purchased	22.01	17.78	16.52	13.13
Skewness of Assets Purchased	-5.61	-5.09	-9.02	-8.48
Prob of Purchasing Lottery type Assets	0.12	0.00	0.07	0.00
Prob of Purchasing Top 20 pctl performers	0.34	0.17	0.28	0.00
Risk Categories of Assets Purchased	4.12	4.00	3.97	4.00
Prob of Purchasing a Warrant	0.19	0.00	0.07	0.00
Prob of Purchasing a Certificate	0.04	0.00	0.03	0.00

Table 3:
Probability of Purchasing Risky Assets
This table reports estimates of the regressions that examine the effect of the use of smartphones on risk taking as measured by the probability of purchasing risky assets. Each observation corresponds to individual x month x trading device level where trading device has been categorized into two groups - smartphone and all other devices. All outcome variables are aggregated from the trade-level data to the observation-level as average values 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 10%, 5% and 1% level, respectively.

	Probability of Purchasing Risky Assets			
	(1)	(2)	(3)	(4)
Smartphone	0.05***	0.02***	0.03***	0.04***
	(20.22)	(13.07)	(15.54)	(17.73)
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	1595097	1575443	1524956	636922
R^2	0.001	0.684	0.670	0.499

Table 4:
Volatility of Assets Purchased
This table reports estimates of the regressions that examine the effect of the use of smartphones on risk taking as measured by the volatility of purchased assets calculated using 12-month rolling window as annualized standard deviation. Each observation corresponds to individual x month x trading device level where trading device has been categorized into two groups - smartphone and all other devices. All outcome variables are aggregated from the trade-level data to the observation-level as average values 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 10%, 5% and 1% level, respectively.

	Volatility of Assets Purchased			
	(1)	(2)	(3)	(4)
Smartphone	12.07***	4.43***	6.66***	9.28***
	(10.62)	(10.00)	(16.05)	(12.19)
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	2326852	2309186	2270342	1320533
R^2	0.012	0.633	0.560	0.479

Table 5:
Skewness of Assets Purchased
This table reports estimates of the regressions that examine the effect of the use of smartphones on risk taking as measured by the skewness of purchased assets calculated using 12-month rolling window. Each observation corresponds to individual x month x trading device level where trading device has been categorized into two groups - smartphone and all other devices. All outcome variables are aggregated from the trade-level data to the observation-level as average values 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 10%, 5% and 1% level, respectively.

	Skewness of Assets Purchased			
	(1)	(2)	(3)	(4)
Smartphone	19.23***	5.13**	10.19***	14.40***
	(3.67)	(2.81)	(4.90)	(3.71)
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	2326695	2309032	2270186	1320331
R^2	0.002	0.281	0.392	0.503

Table 6:
Probability of Purchasing Lottery type Assets
This table reports estimates of the regressions that examine the effect of the use of smartphones on risk taking as measured by the probability of purchasing assets with below median prices but above median volatility and skewness. Each observation corresponds to individual x month x trading device level where trading device has been categorized into two groups - smartphone and all other devices. All outcome variables are aggregated from the trade-level data to the observation-level as average values 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 10%, 5% and 1% level, respectively.

	Prob of Purchasing Lottery Type Assets			
	(1)	(2)	(3)	(4)
Smartphone	0.10***	0.03***	0.05***	0.08***
	(7.32)	(7.53)	(10.72)	(12.93)
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	2361188	2343582	2305258	1362141
R^2	0.003	0.331	0.379	0.497

Table 7:
Trend Chasing
This table reports estimates of the regressions that examine the effect of the use of smartphones on trend chasing. The outcome variable in Panel A is the probability of purchasing an asset that belongs to the top quintile based on past 12-month performance while the outcome variables in Panel B include the probability of purchasing an asset that belongs to the top 50, 40, 30, 20 and 10 percentiles respectively. Each observation corresponds to individual x month x trading device level where trading device has been categorized into two groups - smartphone and all other devices. All outcome variables are aggregated from the trade-level data to the observation-level as average values 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 10%, 5% and 1% level, respectively.

Panel A

	Purchasing Top 20 pctl Performers			
	(1)	(2)	(3)	(4)
Smartphone	0.110***	0.039**	0.055***	0.075***
	(5.70)	(3.43)	(4.71)	(5.50)
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	2313256	2295587	2256415	1304401
R^2	0.001	0.294	0.404	0.499

Panel B

	Prob of Purchasing Top Performers				
	(1)	(2)	(3)	(4)	(5)
	Top 50	Top 40	Top 30	Top 20	Top 10
Smartphone	-0.005	-0.003	-0.001	0.075***	0.120***
	(-1.36)	(-1.42)	(-0.39)	(5.50)	(8.52)
Individual x Month FE	Yes	Yes	Yes	Yes	Yes
Observations	1304401	1304401	1304401	1304401	1304401
R^2	0.500	0.500	0.501	0.499	0.497

Table 8:
Are Results driven by Trading Hours?
This table reports estimates of the regressions that examine the effect of the use of smartphones on risk taking and trend chasing within the same trading hour. The outcome variables include probability of purchasing a risky assets, volatility of purchased assets, skewness of purchased assets and probability of purchasing lottery type assets. Each observation corresponds to individual x month x trading device level where trading device has been categorized into two groups - smartphone and all other devices. All outcome variables are aggregated from the trade-level data to the observation-level as average values 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 10%, 5% and 1% level, respectively.

	Risky Asset	Volatility	Skewness	Lottery Type Asset
	(1)	(2)	(3)	(4)
Smartphone	0.014***	3.475***	7.573***	0.032***
	(4.58)	(9.23)	(5.84)	(5.27)
Individual x Month FE	Yes	Yes	Yes	Yes
Trading Hour x Year FE	Yes	Yes	Yes	Yes
Observations	33689	48879	48865	51441
R^2	0.547	0.630	0.565	0.580

Table 9:
Are Results driven by Choice of Asset Classes?
This table reports estimates of the regressions that examine the effect of the use of smartphones on risk taking and trend chasing within the same asset class. Assets can belong to six different asset classes namely stocks, bonds, funds, warrants, certificates and option bonds that could be converted to stocks. The outcome variables include probability of purchasing a risky assets, volatility of purchased assets, skewness of purchased assets and probability of purchasing lottery type assets. Each observation corresponds to individual x month x trading device level where trading device has been categorized into two groups - smartphone and all other devices. All outcome variables are aggregated from the trade-level data to the observation-level as average values 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 10%, 5% and 1% level, respectively.

	Risky Asset	Volatility	Skewness	Lottery Type Asset
	(1)	(2)	(3)	(4)
smartphone	0.004	2.536***	3.146***	0.024***
	(1.46)	(13.80)	(3.96)	(6.01)
Individual x Month FE	Yes	Yes	Yes	Yes
Asset Class x Year FE	Yes	Yes	Yes	Yes
Observations	636922	1304450	1304252	1344679
R^2	0.652	0.722	0.579	0.555

Table 10:
Spillover Effects on Other Trades
This table reports estimates of difference-in-differences regressions that examine the association between the use of smartphones and riskiness of assets traded by the same individual on other platforms. The outcome variables include probability of purchasing a risky assets, volatility of purchased assets, skewness of purchased assets and probability of purchasing lottery type assets. Each observation corresponds to individual x month level and captures average risk taking on devices other than smartphones. Standard errors are double-clustered at individual and month level, and t-statistics are reported in parentheses. *, ** and *** represent significance at 10%, 5% and 1% level, respectively.

	Risky Asset	Volatility	Skewness	Lottery type Asset
	(1)	(2)	(3)	(4)
$\text{Afteruse}_{i,t}$	0.002	0.529***	4.787***	0.005***
	(1.37)	(5.75)	(9.44)	(2.64)
Individual FE	Yes	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	302278	427665	428285	287169
R^2	0.507	0.540	0.093	0.306

Smart(Phone) Investing?

Appendix for Online Publication

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

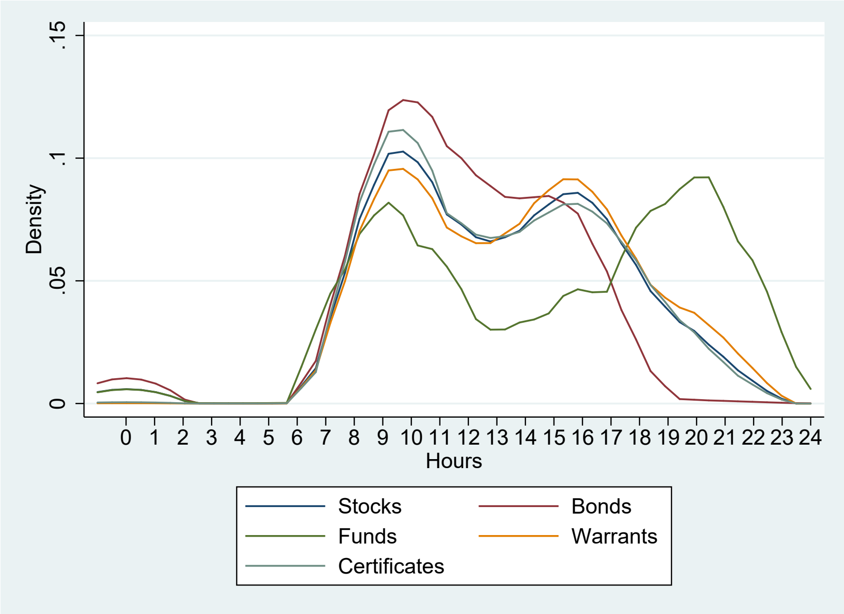


Table A1:
Riskiness of Assets Purchased
This table reports estimates of the regressions that examine the effect of the use of smartphones on risk taking as measured by measured by the risk categories assigned by the banks (which classify all assets into five risk categories). Each observation corresponds to individual x month x trading device level where trading device has been categorized into two groups - smartphone and all other devices. All outcome variables are aggregated from the trade-level data to the observation-level as average values 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 10%, 5% and 1% level, respectively.

	Risk Categories of Assets Purchased			
	(1)	(2)	(3)	(4)
Smartphone	0.248***	0.049***	0.098***	0.163***
	(16.02)	(7.59)	(11.89)	(14.32)
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	2551671	2535135	2500436	1610230
R^2	0.002	0.567	0.548	0.501

Table A2:
Probability of Purchasing Warrants/Certificates
This table reports estimates of the regressions that examine the effect of the use of smartphones on risk taking as measured by the probability of purchasing warrants/certificates. The outcome variable for Panel A (B) includes the probability of purchasing warrants (certificates). Each observation corresponds to individual x month x trading device level where trading device has been categorized into two groups - smartphone and all other devices. All outcome variables are aggregated from the trade-level data to the observation-level as average values 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 10%, 5% and 1% level, respectively.

Panel A

	Probability of Purchasing a Warrant			
	(1)	(2)	(3)	(4)
Smartphone	0.16***	0.03***	0.07***	0.12***
	(5.01)	(3.98)	(9.35)	(8.13)
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	2589595	2573148	2539461	1657381
R^2	0.007	0.689	0.597	0.493

Panel B

	Probability of Purchasing a Certificate			
	(1)	(2)	(3)	(4)
Smartphone	0.02*	0.01**	0.01**	0.01**
	(2.04)	(3.25)	(2.57)	(2.19)
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	2589595	2573148	2539461	1657381
R^2	0.000	0.468	0.502	0.505