In Stockbrokers We Trust? *

Dmitry Chebotarev[†] Pulak Ghosh[‡] Alexander Montag[§]

Varun Sharma[¶]

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Abstract

How does trust in stockbrokers affect brokerage choice, diversification across brokers, and market participation? Using proprietary records from 20 million Indian brokerage accounts and the default of a major broker (KSB) as a shock, we study investors' subsequent participation and trading. Over the 18 months following the shock, only half of affected clients returned. Returnees choose more (less) bank-affiliated (FinTech) brokers and diversify across brokers. Within regions, areas with greater KSB presence subsequently show lower entry and a higher per-person number of brokerage accounts. Overall, our results highlight the importance of trust for stock market participation and FinTech adoption.

Keywords: trust; broker; retail investors; stock market participation.

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[†]Indiana University Kelley School of Business. Email: dmchebot@iu.edu.

[‡]Indian Institute of Management Bangalore. Email: pulak.ghosh@iimb.ac.in.

[§]University of Warwick. Email: alexander.montag@wbs.ac.uk.

[¶]Corresponding author, Indiana University Kelley School of Business. Email: vs12@iu.edu.

1 Introduction

Stock market development is an important driver of economic progress (Bekaert et al., 2005; Gupta and Yuan, 2009; Rajan and Zingales, 1998). However, developing a well-functioning stock market requires a sufficient number of participants willing to entrust their money to the financial system. Lack of trust toward any link in the financial intermediation chain connecting the household to the asset would increase the investment risk, demotivating potential investors.

Since retail investors do not transact directly on exchanges, broker-dealers are their principal gateway to equity markets. Differential motivations between the broker and the client create a principal-agent problem, resulting in the broker taking advantage of its clients (Battalio et al., 2016; Fecht et al., 2018) or sometimes in direct fraud. Unlike stock-specific risk, broker's misconduct imposes a portfolio-wide shock, which is poorly insured in many developing as well as developed financial markets.[1] This "broker risk" is costly to diversify, which makes trust in the brokerage sector a necessary condition for broad stock-market participation. How does trust toward brokerage affect investors' participation, preferences across brokerage firms, and trading behavior?

To study the effect of trust on changes in client-broker relationships, granular data that not only contain retail investors' activity but also identify their associated brokerage accounts are necessary. We overcome this data challenge and study the research question using proprietary records on 20 million Indian brokerage accounts and the November 2019 default of a major broker, Karvy Stock Broking Ltd (KSB), as a trust shock. We show that over the 18 months (i.e., by the end of our sample window) following the shock, only half of affected clients returned. Those who returned shifted to safer (e.g., bank-affiliated, non-

[1]In many European countries, the maximal coverage of stock market losses due to broker's bankruptcy or financial distress is €20,000 (Germany, Italy, Netherlands, Denmark, etc). Some countries (Switzerland, South Korea, Mexico, etc) do not provide any insurance. In the US, SIPC insures investment amounts up to $500,000 per customer per firm. Similar to the US, Canada offers CAD 1 million coverage. While in India there is no SIPC equivalent at the national level, the National Stock Exchange at the moment of the incident covered up to ₹2,500,000 ($28,000) per investor.

FinTech) brokers and showed a higher likelihood to diversify across brokers. The KSB shock decreased the trust toward brokerage services even for individuals not directly affected (i.e., those without a KSB account): Within regions, zip codes with greater KSB presence subsequently show lower entry and a higher likelihood of having multiple brokerage accounts per person.[2] Taken together, our results show that trust is an important determinant of retail stock market participation and FinTech adoption.

We define lack of trust in a broker as the investor's subjective probability that the broker either fails to return funds on time (through fraud or incompetence) or otherwise exploits the client, for example, by frontrunning, providing misleading trading recommendations, or routing orders to venues with lower execution quality (Battalio et al., 2016; Fecht et al., 2018). Witnessing an event of fraud by one's own broker and its suspension from trading due to the inability to return investors' assets arguably decreases trust in brokerage. Since individuals are known to overweight personal experiences (Malmendier, 2021), we conjecture that even though the shock was public and was widely discussed in the news and social media, KSB clients were affected stronger than clients of other brokers or non-participants. Consistent with this conjecture, we find that the shock undermined the investment incentives of affected individuals: Half of directly affected market participants do not open any accounts 18 months after the event.[3] Importantly, when returning to the stock market, directly affected investors are likely to diversify across brokers, and this pattern is stronger among investors who were more active investors prior to the scandal.

Immediately following the shock, all KSB brokerage accounts were suspended. The individuals who still had assets on their accounts were offered to transfer them to another broker. For the majority of investors who only had one account, this required establishing a relationship with a new broker. Since KSB was a large non-bank and non-FinTech broker, if the individuals are willing to replace the closed account with a familiar broker type, they

[2]Zip codes in India are called pin codes; we refer to them as zip codes for ease of interpretability.

[3]This figure is likely an upper-bound estimate, as some individuals re-enter the market just to liquidate their portfolios. Only 23% of affected clients execute a new stock-purchase transaction following the scandal.

will be more likely to choose another traditional non-bank broker. By contrast, if investors' choice is shaped by the available menu of brokerage services at the moment of enrollment, they are more likely to choose a FinTech broker, because the popularity of FinTech has been increasing over time since they first established their KSB account. Finally, if affected investors have a lower trust level in brokerage services, they are more likely to choose a bank-broker for two reasons. First, bank-related brokers have access to the internal capital market of the financial group, which improves their ability to withstand shocks (Caglio et al., 2021; Gupta, 2021). Second, while brokers are relatively non-transparent intermediaries with little clarity of how they perform their activity (Battalio et al., 2016), banks are known to be well-regulated, which strongly affects their business (Buchak et al., 2018). Hence, a broker affiliated with a bank family is more likely to attract a regulator's attention, and therefore can appear to be safer. By contrast, FinTech brokers are relatively new entrants to the market and are not affiliated with large financial institutions; as a result, they may be perceived as riskier and less trustworthy intermediaries.

Consistent with the latter hypothesis that KSB default led to erosion of trust in brokers, we find that, following the shock, affected investors are more likely to open accounts with bank-affiliated brokers rather than with stand-alone brokerages. They are also less likely to open new accounts with FinTech brokers. These results hold when comparing affected individuals with first-time entrants to the stock market, as well as when comparing them with clients of other brokers opening new accounts. We conclude that affected individuals behave in a manner consistent with a lower level of trust toward brokerage after the KSB shock.

Conditional on returning to the market, one can expect that affected individuals change their trading behavior (Giannetti and Wang, 2016; Koudijs and Voth, 2016). For example, they can decrease their trading activity to minimize the exposure to broker's actions. In line with this conjecture, we find that investors respond to the KSB default with a decline in trading activity, decreasing their turnover, within-month trading frequency, and the number of different stocks traded monthly. However, this effect is only temporary: Within six months after the shock, individuals reach the same turnover and activity level as the control group. This suggests that those who return to active trading gradually revert to their usual behavior as the KSB default becomes less salient (Bordalo et al., 2012, 2013; Dessaint and Matray, 2017).

Finally, following the literature on social connections and investors' holdings (Hong et al., 2004, 2005; Ivković and Weisbenner, 2007; Pool et al., 2015), we ask whether the shock also affected individuals without a direct relationship with KSB. Similar to Giannetti and Wang (2016), we use the variation in KSB presence across zip codes as a measure of indirect exposure to the shock. In a difference-in-differences setting, we show that zip codes with a higher KSB market share experienced a decrease in the number of new entrants compared to control zips within the same region. Similar to directly affected peers, investors in high-presence areas are more likely to diversify across brokers, consistent with the shock being transmitted to unaffected individuals through social networks.

The presence of the indirect effect is especially important given the low stock market participation rate in India (9.5% of households), which is strikingly small compared to developed economies such as the United States (58% of households).[4] We find that shocks to trust toward brokerage can decrease the participation both directly and indirectly through social networks. This result is especially striking given that stock investments were insured up to ₹2,500,000 ($28,000) per investor.[5] Even though the majority of investors whose investment was below the limit received their money back, it took significant time and effort for some investors. Uncertainty about the implementation of the SIPC-type mechanism creates additional costs over and above the inability to respond to contemporary changes in stock market prices while (KSB) trading accounts are frozen. Our results call for considering the

[4]The information about US households' participation is available as of 2022 (The Federal Reserve, 2023), while for India as of 2025 (Reuters, 2025).

[5]SEBI's (the Indian stock market regulator) survey in 2025 highlights lack of awareness about the grievance redressal process among Indian retail investors. We confirm in private conversations with several former Karvy investors that they were unaware of the existence of the Investor Protection Fund.

effects of investors' trust in the brokerage system as a potential explanation for low stock market participation, especially in developing economies.

Our study speaks to several distinct literatures in financial intermediation and household finance. Our main contribution is to the literature on the relationship between brokers and their clients. Chen et al. (2007) document that mutual funds managed and cross-sold by insurance companies underperform peer funds. They find evidence consistent with agency problems skewing insurers' financial advice to their clients. Consistent with this view, Bergstresser et al. (2008) find that funds marketed by brokers have lower Sharpe ratios. Fecht et al. (2018) show that bank-brokers use their clients to unload own proprietary positions in stocks which subsequently underperform. Studying which funds brokers suggest to their clients, Christoffersen et al. (2013) document that brokers' incentive structures affect their clients' fund flows and investment performance. Of course, investors are aware of the principal-agent problem and internalize it in their decision making. Guiso et al. (2008) document that investors who do not find their bank-broker trustworthy invest less. We contribute to this literature by studying the effect of a shock to investors' trust in brokerage as an institution.

Our paper is also related to the growing literature on the effect of trust on financial decision making. Exploiting regional differences in Italy, Guiso et al. (2004) show that higher levels of social capital (and, as a result, of trust toward others) are associated with higher levels of stock market participation. Guiso et al. (2008), Georgarakos and Pasini (2011), and Balloch et al. (2015) further use levels of trust inferred from survey data, confirming the connection between trust and participation.[6] Gurun et al. (2018) show that the Bernard Madoff's Ponzi scheme significantly eroded investors' confidence in financial advisors. Giannetti and Wang (2016) study the response of investors to corporate scandals and find that they decrease their investments in affected and unaffected stocks, consistent with lower trust

[6] Gennaioli et al. (2014, 2015); Massa et al. (2022) highlight the importance of trust for delegated portfolio management; Gennaioli et al. (2022) show that higher levels of trust are associated with better performance of the insurance industry: fewer disputes regarding higher-to-verify claims, lower costs to firms, and higher profits.

in the issuer's solvency decreasing stock market participation.[7] In contrast to the existing literature, we study the effect of an exogenous shock to a brokerage firm. For most investors, who have just one brokerage account, this constitutes a shock to all equity investments. Unlike a shock to a relatively small subset of firms, a brokerage default cannot be easily mitigated through stock market diversification and thus poses a significant risk for retail investors.

Our paper also contributes to the literature on the effects of personal experiences on economic behavior. Prior works have shown that people overweight personal experiences (Kaustia and Knüpfer, 2008), which affects risk taking (Andersen et al., 2016; Knüpfer et al., 2017; Koudijs and Voth, 2016; Malmendier, 2021; Malmendier and Nagel, 2011, 2016), investment preferences (Adib et al., 2024), house purchases (Happel et al., 2024), default and leverage decisions (Carvalho et al., 2023; Kalda, 2020; Kleiner et al., 2021). We add to this literature by studying the effect of first-hand — as well as indirect — experiences of a brokerage default on investors' stock market participation, brokerage choices, and trading behavior.

This paper proceeds as follows. Section 2 summarizes the Karvy scandal and describes the data; Section 3 discusses the main results for the directly affected individuals; Section 4 presents the evidence of indirectly affected individuals; Section 5 concludes.

2 Institutional details and data

2.1 Indian stock market

India has two nationwide exchanges — the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE). As of 2024, the NSE is the principal venue for equities. Within the NSE's cash market, non-institutional/retail investors accounted for 45–47% of turnover

[7] In a related paper, Bu et al. (2022) show that exposure to political corruption decreases the likelihood of stock market participation.

during 2024. Cash-market activity is large by international standards: The daily value traded during 2024 often fell in the ₹1.1–1.6 trillion ($13–19 billion). The World Federation of Exchanges lists the NSE among the busiest order-book equity venues in 2024, and the Futures Industry Association ranked the NSE as the world's largest derivatives exchange by contracts in 2023 according to the latest completed ranking.[8]

Retail participation in India has been rising over time: Dematerialized (demat) accounts reached 185.3 million at the end of 2024, which constitutes a 370% increase from the 2019 level.[9] Exchange trading is supervised by the Securities and Exchange Board of India (SEBI) under the SEBI Act, 1992. On the NSE, client compensation for broker failure is provided by the exchange-run Investor Protection Fund (IPF): the per-investor limit stood at ₹3.5 million at the end of 2024 ($42,000), raised from ₹2.5 million ($30,000) on August 13, 2024. The IPF pays only when a member is expelled or declared a defaulter and does not insure market losses. Before the transition to T+1 began in 2022, India operated a T+2 settlement cycle on both the NSE and the BSE.

2.2 Karvy scandal

Karvy Stock Broking Ltd (KSB), a business unit of the larger Karvy Group created in Hyderabad in 1983, grew into a prominent, diversified financial-services group in India offering broking, depository services, registrar & transfer agent work, wealth management and related services. Over decades, Karvy built wide geographic reach and business scale (large branch networks, substantial employee strength and a major presence in registrar/depository services). However, between 2019 and 2023 a major regulatory and enforcement case unfolded: SEBI concluded that Karvy had misused client securities (by pledging or transferring them without valid authorisation), imposed interim restrictions in 2019, issued final orders banning KSB and its promoters and levying penalties, and ultimately canceled its

[8] Source: fia.org.

[9] The total number of demat accounts reached 185.3 million in 2024 from 39.3 million in 2019 (business-standard.com).

registration in 2023 as part of enforcement and investor-protection actions. Appendix A-2 provides additional details about the crisis.[10]

Appendix A-2.1 provides the timeline of the KSB event. The active phase of the crisis unfolded on November 23, 2019, with SEBI issuing interim restrictions on KSB, which was widely covered in the popular press. At the moment of the interim order, Karvy was one of the major brokers in the Indian stock market, with a presence in all states and the vast majority of zip codes. Table 1 shows the distribution of active brokerage accounts of the investors in our sample across brokers. Out of the 6,179,805 accounts in our sample, 125,161 (2%) are with KSB.

As a consequence of the NSE's suspension of Karvy's trading rights across all market segments, retail clients found themselves unable to place new trades through Karvy, and faced restricted ability to transact until their holdings could be transferred or settled. This meant delays or constraints in selling securities, initiating fresh transactions, or executing derivative positions via Karvy. Retail investors were given the option to migrate their accounts/holdings from Karvy to other brokers. For example, some media reported that investors "will be able to migrate to other brokers" after the suspension (Economic Times India, 2025). The process required action by the client: selecting a new broker, initiating a transfer of their demat holdings or broking account, completing KYC, and making delivery instruction slips, or demat transfers. By December, 2 2019, around 93% of investors whose securities had been wrongly pledged by Karvy (≈83,000 clients) had had their securities worth ≈₹20.14 billion transferred back to their demat account (Sharma, 2019b). Thus, many retail clients recovered the actual holdings they had entrusted.

However, major news sources reported a loss of confidence in stock brokers.[11] For retail

[10]The text of the interim order is available on the official website of the Securities and Exchange Board of India: `https://www.sebi.gov.in/enforcement/orders/nov-2019/ex-parte-ad-interim-order-in-respect-of-karvy-stock-broking-limited_45049.html`.

[11]According to Reuters India, the Karvy case "has unnerved the country's retail investors" (Roy, 2019). The same conclusion is drawn by economictimes.com in an interview with Jaideep Hansraj, MD and CEO of Kotak Securities, a top-6 Indian stockbroker (Raj, 2019). Businesstoday.com states that "The Karvy case has dented investor confidence in the broking industry" (Sharma, 2019a).

clients, suspension meant uncertainty about the status of their holdings, possible loss of opportunity, inability to timely rebalance their portfolios, and psychological impact of having their broker under regulatory action. The event raised general investor concern about how safe their securities held with brokers are, and about brokers' power of attorney practices and pledging of client securities. In the aftermath of the KSB incident, SEBI initiated several reforms to safeguard client securities, for example, restrictions on pledging of client securities without explicit client consent, daily reporting of collateral, and enhanced transparency. For retail clients generally, these reforms boosted protection of assets held by brokers and reduced risks of future misuse.

2.3 Data

We draw our sample from proprietary data by the National Stock Exchange of India (NSE), which include all equity trades on the NSE between 2004 and 2017. The raw data contain 4 billion trades by 20.6 million investors in 2,558 stocks. The unit of observation is at the stock-investor-broker-day level. Specifically, the data include daily totals of buy and sale transactions (value, quantity, and average price) in a stock by a specific investor at a particular broker. Similar Indian data have been used to study related questions, such as stock market investors' behavior (Anagol et al., 2018, 2021; Campbell et al., 2014), returns (Campbell et al., 2019), and holdings (Balasubramaniam et al., 2023).[12] These similar data come from India's two share depositories and contain monthly stock holdings of investors. In contrast, our data come from the NSE and contain daily stock transactions of investors.

The NSE data that we use link each transaction to specific client and broker IDs, which is important in the context of our study because it allows us to characterize trading within and across different investors and broker types. The raw data also contain the official investor group classification by the NSE, which assigns each client ID to one of the following groups: individual, domestic institutional investor (DII), foreign, proprietary, corporate, and others.[13]

[12]Badarinza et al. (2019) provides a survey of the literature on household finance in emerging economies.
[13]See, for example, note 1 on page 181 of the January 2024 NSE "Market Pulse" (nsearchives.nseindia.com).

The focus of our study is on households, and we therefore restrict the sample to retailers, which the NSE classification refers to as individuals.[14] Households represent 99% of unique investors and account for 36% of equity trading turnover between 2004 and 2017.

3 Direct effects

We begin our analysis by studying the effect of the Karvy scandal on households that used Karvy as their broker, compared to households that did not have any brokerage account with Karvy. We first elaborate on our sample construction and empirical strategy in Section 3.1. We then describe the effects on stock market participation and diversification across brokers in Section 3.2. In Section 3.3, we investigate the types of brokers Karvy customers choose to open an account with after the shock. Finally, in Section 3.4, we study how the Karvy scandal affected its customers' trading intensity (turnover, number of stocks traded, and trading frequency).

3.1 Empirical strategy

We construct our analysis sample in the following way. Given that our identification strategy uses the collapse of Karvy in November 2019, we focus on investors who opened their brokerage accounts by the end of December 2018 and who traded at least once during 2019. The latter restriction ensures that our sample only includes active investors. We then aggregate the data at the investor-month level and restrict observations to twelve months before and eighteen months after the Karvy event (till June 2021, the last month for which we have data available). We further restrict the sample to investors with a single brokerage account in the first month of our pre-period. This ensures that our identifying variation primarily captures the effects of the broker default on Karvy clients, with both Karvy and non-Karvy clients starting out with identical numbers of brokerage accounts. Importantly, we place no

[14] To be conservative, we exclude client IDs that are assigned to both retail and non-retail investor groups.

further restriction on the number of brokerage accounts during the remainder of the sample period.

The final sample includes 149,282,949 investor-month observations for 4,815,579 unique investors. Out of these, 125,154 (3%) are Karvy clients, our directly treated group. The remaining 4,690,425 (97%) form our comparison group.

Table 2 presents descriptive statistics conducted one month before Karvy. The table shows average values for a set of observable investor characteristics, measured at event month minus one. Importantly, we use trading data for the first ten months of 2019 to construct the trades, stocks, turnover, and average trade size variables. Column (1) reports the averages for the full sample, Column (2) for investors with Karvy brokerage accounts, and Column (3) for the control group of investors with non-Karvy brokerage accounts. Column (4) shows the differences in means between the two investor groups, while Column (5) reports the statistical significance of these differences based on t-tests.

Although there are minor differences in means, the results indicate no economically significant differences in observable characteristics between investors with and without Karvy brokerage accounts. Statistical significance despite relatively small differences in means between treated and control groups is not particularly surprising given the size of our sample. Combined with the fact that we find parallel pre-trends in outcomes (see Section 3.2), these descriptive statistics suggest that our control group provides a credible counterfactual for assessing the outcomes of investors with a Karvy brokerage account.

3.2 Participation and diversification across brokers

Using the sample described in the previous section, we start our analysis by looking at how the number of active brokerage accounts per investor evolved from January 2019 (11 months before Karvy's default in November 2019) to June 2021, at which point our data ends. Figure 1 displays the raw means for individuals directly affected by Karvy (treated) and those that are not (control) (Panel A) as well as DiD coefficients estimated by event time with 95% confidence intervals (Panel B). The estimating equation underlying the event time DiD coefficients in Panel B is:

$$Number\ of\ accounts_{c,t} = \sum_{n=-11}^{19} \beta_n \times (\mathbb{1}_t^n \times \mathbb{1}_c^{Treated}) + \alpha_c + \alpha_t + \epsilon_{c,t}, \tag{1}$$

where *Number of accounts*$_{c,t}$ is the number of brokerage accounts of client c in month t. $\mathbb{1}_t^n$ is an event-time dummy that takes the value of 1 if t=n and zero otherwise.[15] $\mathbb{1}_c^{Treated}$ is a dummy variable that equals 1 for Karvy customers and zero otherwise. α_c is the client fixed effect, and α_t is the month fixed effect. We cluster standard errors by client.

Figure 1 shows two noteworthy patterns. First, the evolution of the number of brokerage accounts of Karvy and non-Karvy customers looks similar in the pre-period. Both treated and control started with one account, which is due to the way we construct the sample. In addition, the number of new brokerage accounts opened by Karvy, as well as non-Karvy customers, increased only marginally before Karvy scandal. During the month of Karvy's default, the number of accounts for the control group remained essentially unchanged, whilst the treated group witnessed a reduction in the number of accounts by 1 due to Karvy's suspension by the regulator. As a result, the Karvy clients who did not open any new accounts from January 2019 to November 2019 (event months -11 to 0) had their account count dropped to zero.

The second noteworthy pattern is that the number of accounts by Karvy investors increased more steeply relative to the control group during the months following Karvy's default. This increase can be due to Karvy customers with only a single brokerage account before the default re-entering the stock market by opening a new account, or it can be due to some opening more than one account to diversify across brokers, or both.

To investigate these two potential channels, we focus on Karvy clients and first quantify how many of them re-entered the market after losing their primary and only brokerage

[15]Since we have only one treatment event, we use calendar time and event time interchangeably.

account due to Karvy's default by opening new accounts. To this end, we restrict the sample to Karvy clients with no other brokerage accounts as of November 2019 (event time 0) and create a dummy variable, $\mathbb{1}_{c,t}^{Account}$, that takes the value of 1 if client c has an active account in month t and zero otherwise. Panel A of Figure 2 plots monthly average values along with 95% confidence bands. It shows that all Karvy clients who had only one account ended up having no brokerage account immediately after Karvy defaulted ($t = 0$). Subsequently, some clients returned by opening new accounts with other brokers. By the end of our sample period, the coefficient estimate increased to 0.5, which shows that only 50% of former Karvy clients returned to the stock market by opening a brokerage account with a different broker.

It is possible that some of the investors who returned to the market with a new broker might have come to liquidate their pre-existent holdings.[16] We therefore create another dummy variable, $\mathbb{1}_{c,t}^{AccountWithBuy}$, that takes the value of 1 if client c has an active account with at least one buy transaction during the post-period in month t and zero otherwise. Panel B of Figure 2 plots monthly average values along with 95% confidence bands. It shows that only 23% of Karvy clients returned to the stock market by opening a brokerage account with a different broker with which they purchased new stocks during the eighteen months after the Karvy scandal. In addition, and in contrast to the relatively stable upwards trend in Panel A, the subset of Karvy clients in Panel B return to the market already within seven months.[17]

Next, we investigate the second potential channel by analyzing, conditional on having at least one brokerage account during the post-period, how many accounts Karvy clients opened after returning to the stock market. Panel A of Figure 3 shows the average number of brokerage accounts opened by investors who lost their primary and only brokerage account due to Karvy's default alongside 95% confidence bands. It shows that, conditional on having

[16]We condition our sample on investors who made at least one trade during the eleven months from January 2019 till the Karvy default. It is possible that some of these investors closed their accounts with Karvy before the scandal.

[17]However, it is possible that some of the Karvy clients who opened a new brokerage account after the scandal neither purchased new stocks nor liquidated their pre-existing holdings.

at least one brokerage account, Karvy clients opened more than one account. By the end of the sample period, the average Karvy client had 1.2 accounts after Karvy scandal. Panel B of Figure 3 shows that Karvy clients with at least one buy transaction during the post-period opened relatively more new brokerage accounts, with an average of 1.3 accounts by the end of the sample period.

Opening multiple accounts can be a sign of investors' attempt to diversify the brokerage risk. This diversification is likely to be more valuable to relatively more active clients who make more trades and take larger positions. Therefore, we proceed by analyzing how the post-scandal diversification across brokers is related to the client's pre-scandal trading behavior. We calculate for each client the total dollar-valued turnover during the ten months preceding the Karvy scandal and assign clients to "high" and "low" trading activity groups using the median value as a cutoff. Figure 4 displays the time series of average brokerage account numbers for both groups. It shows that Karvy investors that traded relatively more in the pre-period diversified more across brokers during the post-period by opening more new brokerage accounts. We find similar results when doing a median split by the number of trades, instead of dollars of turnover (Figure A-1).

Taken together, the results in Figure 1 to 4 show the following. Karvy and non-Karvy customers had similar numbers of brokerage accounts before Karvy scandal, however, Karvy investors opened relatively more brokerage accounts after the scandal. Only about 50% of Karvy investors re-entered the market by opening a brokerage account with a different broker during the eighteen months after the scandal. The Karvy clients who re-entered the market diversified across different brokers by opening, on average, 1.2 new brokerage accounts. In addition, Karvy investors, who traded relatively more in the pre-period, diversified even more during the post-period.

3.3 Broker choice

After Karvy scandal, all its brokerage accounts were suspended. For the majority of households, which had only one account, participating in the stock market post-scandal required establishing a relationship with a new broker. In this section, we investigate the types of brokers Karvy customers opened new accounts with. We start by classifying the brokers we have in our sample into three groups. The first group consists of brokers affiliated with a bank. The second group is FinTech brokers that are not affiliated with any bank and usually do not offer other services, such as equity research.[18] Such brokers are attracting new customers due to the low commission charged for trading. Our third category is traditional brokers that are not affiliated with any bank but are also not FinTech. Based on this classification, Karvy can be categorized as a large non-bank, non-FinTech broker.

If directly treated individuals prefer replacing their lost brokerage account with a familiar broker type, they will likely choose another traditional broker, similar to Karvy, that is, a large non-bank, non-FinTech broker. By contrast, if investors' choices are shaped by the available menu of brokerage services at the moment of enrollment, they are more likely to choose a FinTech broker, because the popularity of FinTech has been increasing over time. Finally, if affected investors have a lower trust level in brokerage services, they are more likely to choose a bank-broker for two reasons. First, bank-related brokers have access to the internal capital market of the financial group, which helps it withstand shocks (Caglio et al., 2021; Gupta, 2021). Second, while brokers are relatively non-transparent intermediaries with little clarity of how they perform their activity (Battalio et al., 2016), banks are known to be well-regulated, which strongly affects their business (Buchak et al., 2018). Hence, a broker affiliated with a bank family is more likely to attract the regulator's attention, and therefore

[18] We define as FinTech broker stockbroking firms whose primary customer experience is delivered through technology (web platforms, mobile apps, APIs), enabling investors to open accounts, place orders, fund accounts, and access analytics digitally and at scale. Table A-1 provides the list of FinTech brokers which we identify in our sample using the list provided by NSE supplemented by searching through publicly available data on individual brokers. Our results are robust to an alternative definition of FinTech as a broker, whose clients' trading activity on NSE is mostly (i.e., over 90%) online.

can appear to be safer. On the other hand, FinTech brokers are relatively new entrants to the market and are not affiliated with large financial institutions; as a result, they may be perceived as riskier and less trustworthy intermediaries.

One key challenge in this analysis is identifying a control group. Karvy customers, especially those with only one account, were forced to open a new account. Thus, they are not the same as other households that had accounts with other brokers and did not have any particular need to open a new account. We address this challenge by having two control groups. In Section 3.3.1, we use non-Karvy customers as controls, whereas in Section 3.3.2, we use new entrants as a control group. We argue that new entrants might be more similar to Karvy customers, as both had to open new brokerage accounts to enter the stock market.

3.3.1 Non-Karvy clients as controls

To understand what type of brokers Karvy customers chose to open an account with, we start by constructing a dataset at the client × brokerage account level. We then compare the probability of having an account with a bank-affiliated or FinTech broker by Karvy and non-Karvy customers using the following difference-in-differences (DiD) specification:

$$\mathbb{1}_{c,t}^{Broker\ Type} = \beta \times (\mathbb{1}_{t}^{Post} \times \mathbb{1}_{c}^{Treated}) + \alpha_c + \alpha_t + \epsilon_{c,t}, \tag{2}$$

where $\mathbb{1}_{c,t}^{Broker\ Type}$ is a dummy that takes the value of 1 if client c had an account with a bank-affiliated broker in month t and zero otherwise. $\mathbb{1}_{t}^{Post}$ is a dummy that takes the value of 1 for any period t after the Karvy scandal and zero otherwise. $\mathbb{1}_{c}^{Treated}$ is a dummy variable that equals 1 for Karvy customers and zero otherwise. α_c is the client fixed effect, and α_t is the month fixed effect. We cluster standard errors by client.

Panel A of Table 3 presents the results for the choice of bank-affiliated brokers. We find that Karvy clients were less likely to have an account with a bank-affiliated broker than the control group in the pre-period.[19] However, we also find that Karvy clients were more likely to have an account with a bank-affiliated broker than the control group after the scandal. The DiD coefficient suggests that compared to the control group, treated investors increased their probability of contracting a bank-affiliated broker by 50 percentage points.

Next, we explore the effect of having an account with a FinTech broker. We estimate the same specification as Equation 2, but we replace the dependent variable with a dummy that takes the value of 1 if client c had an account with a FinTech broker in month t and zero otherwise. Panel B of Table 3 presents the results. We find that the control group was more likely to have an account with a FinTech broker, which aligns with the growing popularity of FinTech brokers during our sample period. However, Karvy customers were around 20% less likely to have an account with a FinTech broker after the Karvy scandal. Taken together, these results suggest that first-hand experience of the scandal by treated investors led them to prefer safer brokers.

So far in the analysis, we have considered accounts that were opened by households at any point in time during the period for which we have the data, i.e., from January 2004 to June 2021. However, the composition of brokers can vary over time. For example, FinTech brokers started gaining popularity in India in 2010. To address this concern, we also perform an analysis similar to the one presented in Table 3, but we restrict our sample to the accounts that were opened by Karvy and non-Karvy customers starting from January 2019 (i.e., from 11 months before the Karvy scandal) onwards. Panel A of Table A-2 shows that Karvy customers were 10% to 20% more likely to have an account with a bank-affiliated broker after the Karvy scandal. On the other hand, Panel B of Table A-2 shows that Karvy customers were around 20% to 40% less likely to have an account with a FinTech broker after the Karvy scandal. In comparison, Karvy customers were 2.5% more likely to have a FinTech account before the Karvy shock.

[19] This result is expected given that Karvy itself was a non-bank broker.

3.3.2 New entrants as controls

Karvy customers, especially those with only one account, were forced to open a new account if they wanted to retain their ability to participate in the stock market. Thus, they are not the same as other households that had accounts with other brokers and did not have any need to open a new account. We argue that new entrants might be more similar to Karvy customers, as both opened new accounts to enter the stock market. Thus, we re-estimate the specification in Equation 2 but with new entrants as a control group.

Table 4 presents the results. Panels A and B show that new entrants were less likely to have an account with bank-affiliated brokers and more likely to have accounts with FinTech brokers. We also find that, in line with the results of Table 3 and Table A-2, Karvy customers were less likely to have an account with bank-affiliated brokers and more likely to have accounts with FinTech brokers in the pre-period. On the other hand, they were 10%-20% more likely to have an account with bank-affiliated brokers and 25%-50% less likely to have an account with FinTech brokers after the Karvy shock.

So far, our sample includes both the first and subsequent brokerage accounts opened by Karvy and non-Karvy clients. However, if a treated Karvy client had only one account pre-treatment, the Karvy suspension automatically closed her only trading account. Therefore, opening the first account after the treatment, Karvy brokers were not diversifying but rather replacing their closed accounts. As a result, their motivation to open a new account can be different from that of the control group who are more likely to open new accounts to diversify across brokers. To address this concern, we perform an additional test in which we restrict the sample to the first account of each new entrant. Table 5 presents the results. As we have only one observation per client for new entrants, we cannot include client fixed effects in these regressions. We find that the results are quantitatively and qualitatively similar to the estimates of Table 4.

Taken together, the results of Sections 3.3.1 and 3.3.2 show that, following the Karvy scandal, directly affected investors are more likely to open an account with a bank-affiliated broker rather than a stand-alone brokerage firm. We also find that they are less likely to open a new account with a FinTech broker. These results hold when comparing affected individuals with first-time entrants to the stock market, as well as when comparing them with clients of other brokers opening new accounts. Overall, these results point to affected individuals acting in a manner consistent with lower trust in brokerage after the Karvy shock.

3.4 Trading activity

The Karvy scandal could be a shock not only to participation but also to trading behavior. However, the direction of the effect is not clear ex-ante. We consider two hypotheses. First, experiencing the shock first-hand, investors compare the actual costs that they bore with the expected costs of a broker's insolvency. Since losses resulting from a broker's misconduct are insured, one can expect that investors who stayed in the market did not lose much and realized that trading is safer than they expected. In this case, one would anticipate an increase in trading activity among the returnees.[20] Second, it is possible that affected individuals decrease their trading activity to minimize the exposure to broker's actions (Giannetti and Wang, 2016; Koudijs and Voth, 2016).

To test these two hypotheses, we estimate Equation 3. Since we compare the trading activity of individuals across brokers and areas, we include zip–broker–month fixed effects in the regression. These fixed effects control for differences in trading conditions across brokers that may be implemented at different times and in different locations:

$$\textit{Trading activity}_{c,t} = \sum_{n=-9}^{9} \beta_n \times (\mathbb{1}_t^n \times \mathbb{1}_c^{Treated}) + \alpha_c + \mu_{z,b,t} + \epsilon_{c,t}, \tag{3}$$

where $\textit{Trading activity}_{c,t}$ is a metric of trading activity measured using *ln(turnover)*, number of stocks traded, or the number of trading days of client c in month t. $\mathbb{1}_t^n$ is a

[20] This logic is in line with the effect documented by Kleiner et al. (2021) among individuals who (indirectly) experienced the effects of bankruptcy protection.

dummy that takes the value of 1 if $t{=}n$ and zero otherwise. $\mathbb{1}_c^{Treated}$ is a dummy variable that equals 1 for Karvy customers and zero otherwise. α_c is the client fixed effect, and $\mu_{z,b,t}$ is the zip-broker-month fixed effect. We cluster standard errors by client.

Figure 5 plots the estimates of $\beta_{-9} - \beta_9$ in Equation 3. In line with the second conjecture, Panel A shows that individuals decrease their turnover by over 1% compared to the control group. This effect gradually disappears over time, becoming insignificant by April 2020. Similarly, Panel B of Figure 5 shows that post-crisis individuals trade less stocks than before. This finding resembles the effect documented by Guiso et al. (2008), who show that a shock to trust toward the stock market leads to lower portfolio diversification. However, as with turnover, the treatment effect reverts within five months. Finally, Panel C of Figure 5 suggests that investors spend less time on trading following the shock. In the first month after the shock, conditional on being present in the market, they trade 1.5 trading days less than an average investor in the control group. As with other variables, this effect is temporary.

These results suggest that investors who return to active trading gradually revert to their usual behavior as the Karvy shock becomes less salient (Bordalo et al., 2012, 2013; Dessaint and Matray, 2017). The final months of the sample period display an increase in trading activity compared to the pre-period, which suggests that, in the long run, investors who return to the market not only regain confidence but also get additionally encouraged by their relatively positive experience. Thus, our results support the temporary salience effect leading to less activity in the short run, which subsequently gives way to relatively more active behavior as the salience effect dissipates.

4 Indirect effects

While Karvy investors were directly affected by the shock, clients of other brokers and non-participating households could learn about Karvy's default from the news or through their social networks. To test for a possible indirect effect, we explore spatial variation in exposure to the Karvy shock. Following Giannetti and Wang (2016), we assume that within the same region, within a relatively homogeneous group of zip codes, zip codes with a relatively higher pre-treatment market share of Karvy are more exposed to the Karvy default.[21] An individual living in a more exposed zip code is more likely to learn about the difficulties faced by affected investors. Below we consider the indirect effect of the Karvy shock on the probability to diversify across brokerage accounts and the probability to enter the market.

A key challenge in analyzing indirect effects is finding an appropriate control group. While we want to compare areas with a high share of investors with Karvy accounts to low-share areas, these areas may differ along other dimensions as well. For example, high-Karvy areas might be more urban with higher stock market participation. To avoid bias in our estimates due to such omitted variables, we include high-density fixed effects. We classify zip codes into buckets using three parameters. The first parameter is the geographic region.[22] The second and third parameters are the number of stock market participants and the fraction of stock market participants with a Karvy account, respectively. We classify zip codes into 10 deciles in terms of stock market participation and Karvy presence. In our empirical specification, we control for time-varying region × stock market participation decile × Karvy presence decile fixed effects. This ensures that we compare zip codes within the same region and with similar participation in the stock market. This also ensures that we compare zip codes with high and low shares of Karvy investors within the decile band of Karvy presence. This approach avoids comparing, for example, a zip code with a very high Karvy presence located in a region with very high stock market participation, such as Mumbai or Delhi, with another zip code with minimal to nonexistent Karvy presence located in an underdeveloped, remote region with very low stock market participation.

[21] Zip codes in India are called pin codes; we refer to them as zip codes for ease of interpretability.
[22] In India, zip codes have six digits, with the first digit identifying a region.

4.1 Diversification across brokers

We begin our investigation of the indirect effect by considering whether a higher level of exposure to the shock affected the propensity to diversify across brokers. While directly affected individuals tend to open more accounts, investors who did not receive direct treatment are likely to be satisfied with the level of safety provided by their brokers.

To study the effect on diversification, we consider a sample of non-Karvy investors who had one account with a single broker in December 2018. We trace this sample of individuals over time in a DiD setting using the following specification:

$$\textit{Number of accounts}_{c,t} = \sum_{n=-9}^{9} \beta_n \times (\mathbb{1}_t^n \times \textit{Karvy fraction}_z) + \mu_{r,s,k,t} + \alpha_c + \epsilon_{c,t}, \qquad (4)$$

where *Number of accounts*$_{c,t}$ is the logarithm of the number of brokerage accounts of non-Karvy client c in month t. $\mathbb{1}_t^n$ is a dummy that takes the value of 1 if $t{=}n$ and zero otherwise. *Karvy fraction*$_z$ is the fraction of clients with Karvy accounts in a zip code z. $\mu_{r,s,k,t}$ represents *region* $\times$ *stock market participants decile* $\times$ *Karvy presence decile* $\times$ *time* fixed effects, and α_c is client fixed effects. The rich spatial variation in our sample and the granular fixed effects allow us to explore the variation within a region between comparable groups of zip codes, controlling for a variety of confounding spatial characteristics. We cluster standard errors by zip code.

Panel A of Figure 6 shows that after treatment, zip codes with higher Karvy presence experienced higher propensity to diversify across brokers. Furthermore, the effect is much stronger for the sample of most active investors (i.e., within the top 30% by trading activity) as Panel B of Figure 6 shows. We conclude that investors who were relatively more exposed to the shock through their social network are more likely to diversify across brokers, similar to directly affected investors.

4.2 Participation

Next, we consider whether a higher level of exposure to the shock affects the probability to enter the stock market for the first time. We regress the logarithm of the number of new entrants at the zip code level in Equation 4, using the same set of fixed effects as before, but replacing the client fixed effects with zip code fixed effects. We estimate the following specification:

$$\textit{Number of new entrants}_{z,t} = \sum_{n=-9}^{9} \beta_n \times (\mathbb{1}_t^n \times \textit{Karvy fraction}_z) + \mu_{r,s,k,t} + \alpha_z + \epsilon_{z,t}, \tag{5}$$

where $\textit{Number of new entrants}_{z,t}$ is the logarithm of the number of new entrants to the stock market in Zip code z in month t. $\mathbb{1}_t^n$ is a dummy that takes the value of 1 if t=n and zero otherwise. $\textit{Karvy fraction}_z$ is the fraction of clients with Karvy accounts in a zip code z. $\mu_{r,s,k,t}$ represents *region* $\times$ *stock market participants decile* $\times$ *Karvy presence decile* $\times$ *time* fixed effects, and α_z is the zip code fixed effect. The rich spatial variation in our sample and the granular fixed effects allow us to explore the variation within a region between comparable groups of zip codes, controlling for a variety of confounding spatial characteristics. We cluster standard errors by zip code.

Results in Figure 7 show that the number of new entrants significantly decreases for the areas with a higher Karvy presence following the shock. Similar to the diversification result, this finding is consistent with non-participants getting information through social networks, or, alternatively, with a wider coverage of the Karvy scandal in local media in relatively more affected areas.

The presence of indirect effects is especially important given the low stock market participation rate in India (9.5% of households), which is strikingly small compared to developed economies such as the US (58% of households). This result is all the more surprising given that stock investments were insured up to ₹2,500,000 ($28,000) per investor at the time of the Karvy scandal. Our findings call for considering the effects of investors' trust toward the brokerage system as a potential explanation for low stock market participation, especially in developing economies.

5 Conclusion

In this paper, we study how trust in stockbrokers affects participation, diversification across brokers, and trading behavior. Using proprietary data on the brokerage accounts of 20 million investors in the Indian stock market and a default by one of the largest brokers, Karvy, we find that the default had a sizable direct and indirect effect on stock market participation. After the shock, half of Karvy customers do not return to the stock market within 18 months, and those who do diversify across brokers with 1.2 accounts per investor. Similarly, individuals in areas with higher Karvy presence experienced a relative drop in the number of new entrants and an increase in the propensity to diversify across brokerage firms.

We show that affected investors, compared to other brokers' clients or new entrants, are more likely to open brokerage accounts with traditional bank-affiliated brokers rather than FinTech brokers, which is consistent with investors' preference for safe intermediaries following a shock to trust. Affected investors also decrease their trading activity (turnover, trading frequency, and number of securities traded). However, this effect is temporary: Investors who stay in the market recover their trading activity within six months after the shock.

Taken together, our results highlight the importance of trust in determining the adoption of FinTech and stock market participation. The presence of the indirect effect is especially important given the low stock market participation rate in India (9.5% of households as of 2025). Our results call for considering the effects of investors trust toward the brokerage system as a potential explanation for low stock market participation, especially in developing economies.

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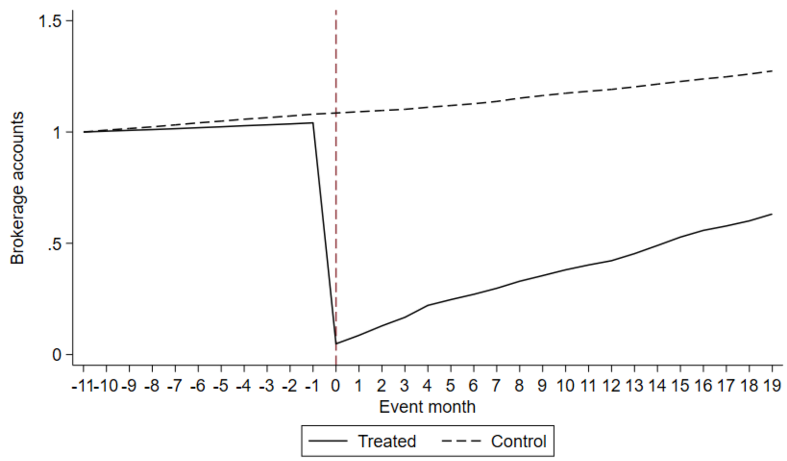
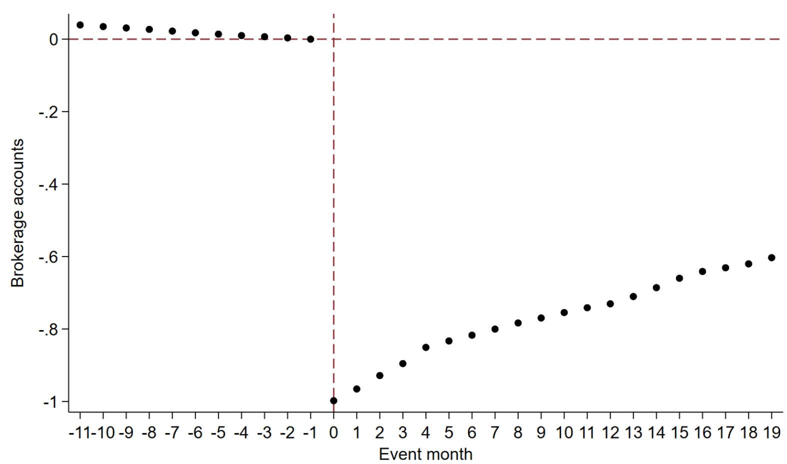
Figures

Figure 1. Number of active brokerage accounts around Karvy

This figure shows the effects of Karvy on the number of active brokerage accounts. It displays the raw means for individuals directly affected by Karvy (treated) and those that are not (control) (Panel A) as well as DiD coefficients estimated by event time with 95% confidence intervals (Panel B).



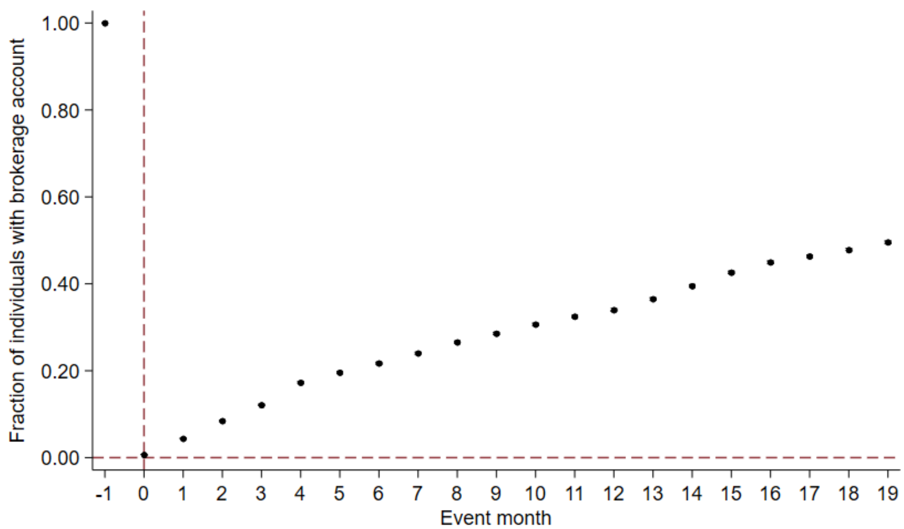
a Raw means.



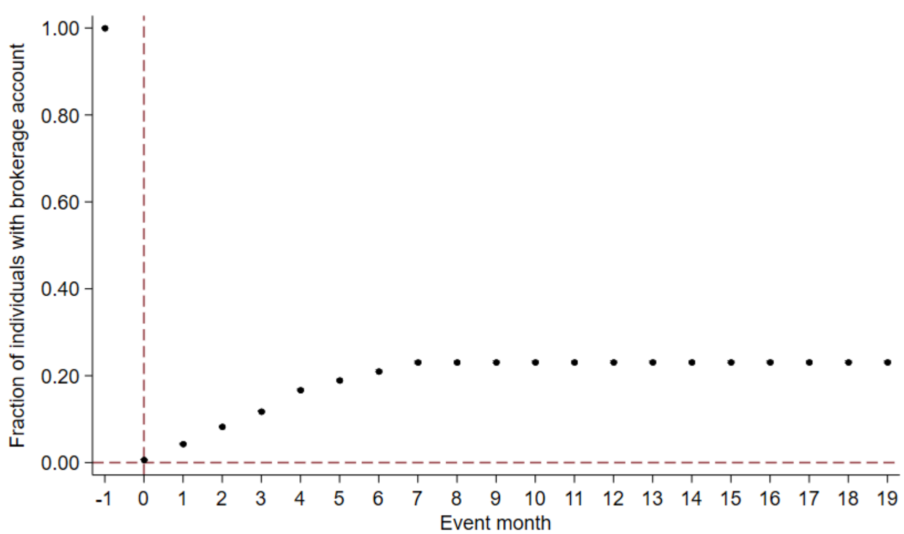
b DiD coefficients.

Figure 2. Market participation of individuals directly affected by Karvy

This figure shows the effects of Karvy on market participation of directly affected individuals. It displays the fraction of individuals with an active brokerage account (Panel A) and with at least one buy transaction (Panel B) by event time with 95% confidence intervals.



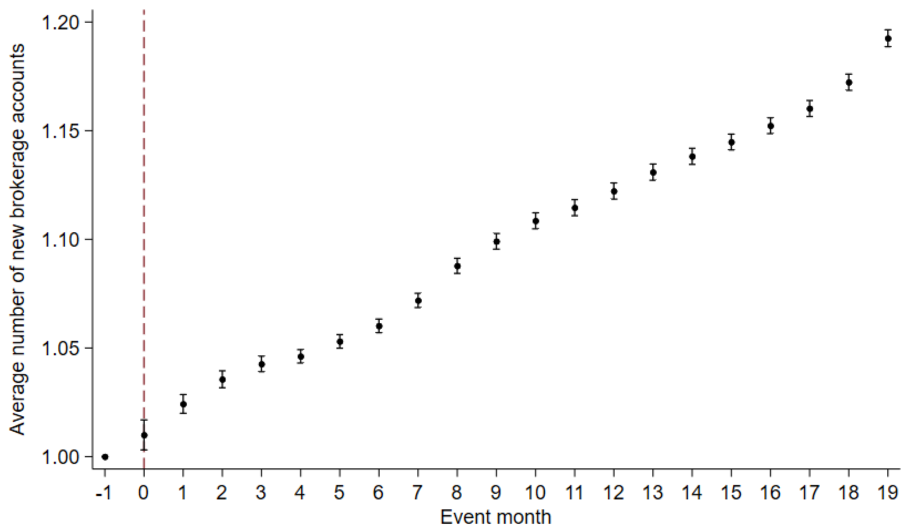
a All individuals.



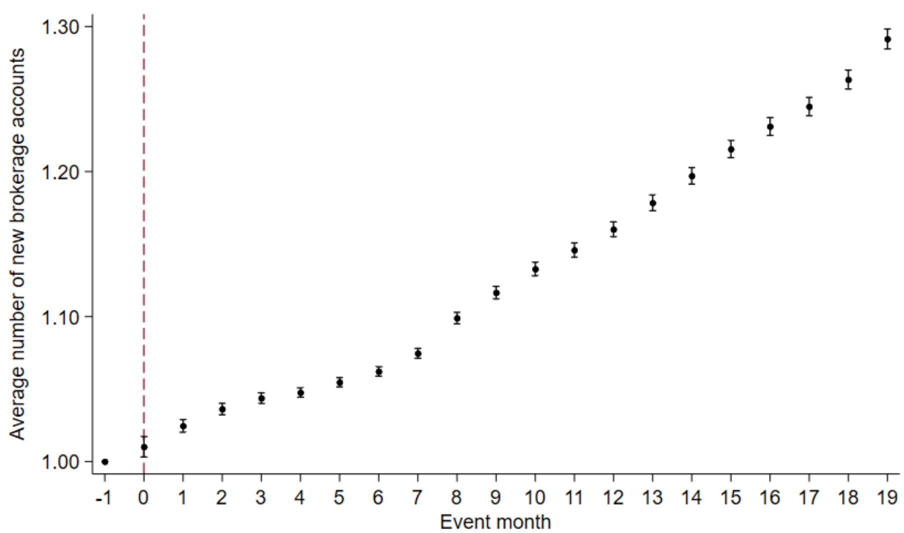
b Individuals with a buy transaction post-Karvy.

Figure 3. Brokerage account diversification of individuals directly affected by Karvy

This figure shows the effects of Karvy on brokerage account diversification of directly affected individuals. It displays the average number of new brokerage accounts conditional on participating in the market (Panel A) and conditional on at least one buy transaction (Panel B) by event time with 95% confidence intervals.



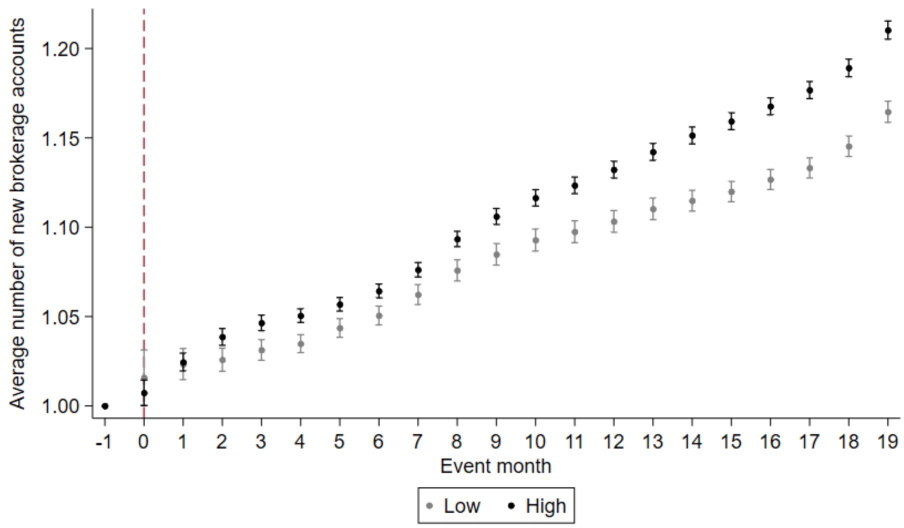
a All individuals.



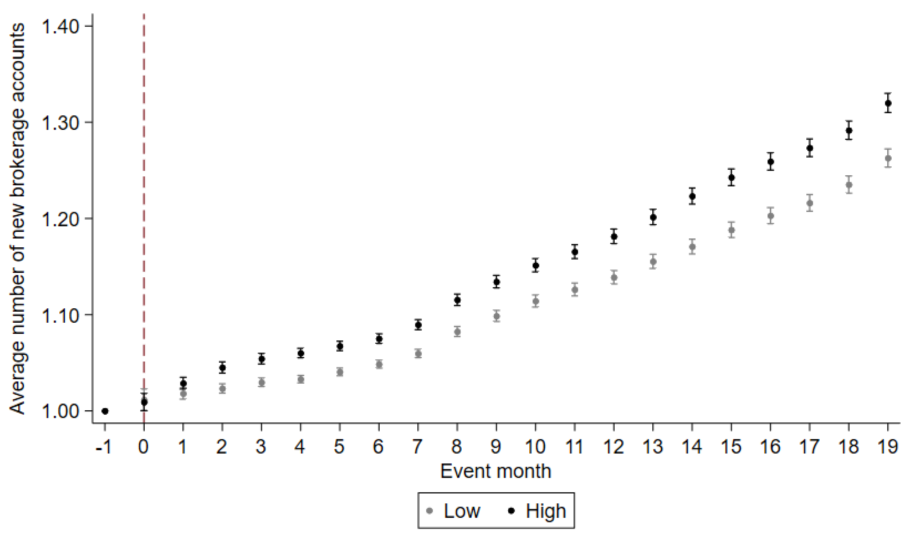
b Individuals with a buy transaction post-Karvy.

Figure 4. Brokerage account diversification of individuals directly affected by Karvy by trading behavior

This figure shows the effects of Karvy on brokerage account diversification of directly affected individuals by trading behavior. It displays the average number of new brokerage accounts by low/high turnover conditional on participating in the market (Panel A) and conditional on at least one buy transaction (Panel B) by event time with 95% confidence intervals. We assign individuals to low/high groups by median splitting total turnover during the ten months before Karvy.



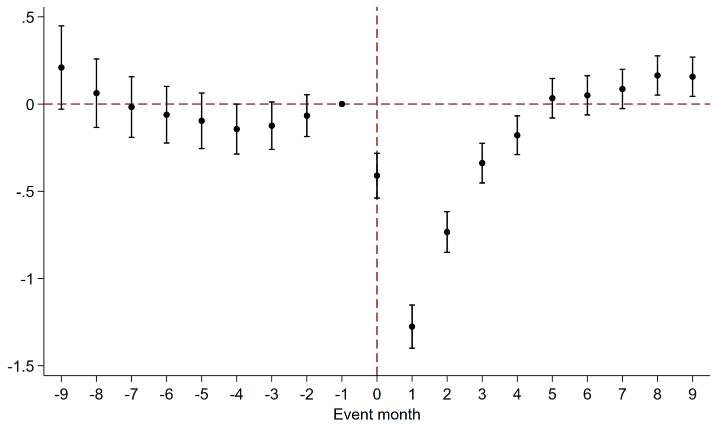
a All individuals.



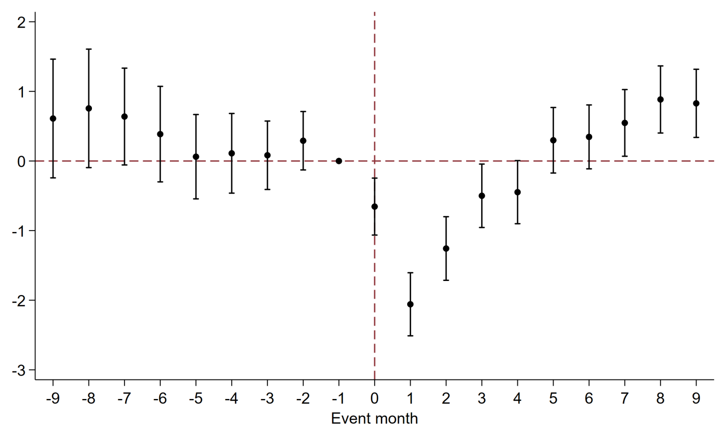
b Individuals with a buy transaction post-Karvy.

Figure 5. Trading behavior of individuals directly affected by Karvy

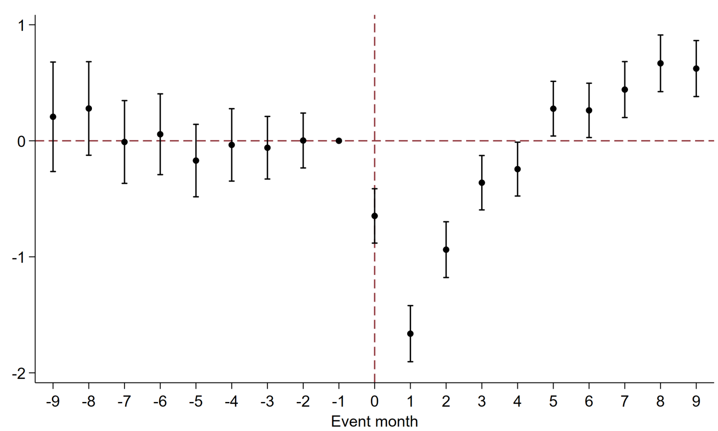
This figure shows the effects of Karvy default on the trading intensity of the Karvy investors compared to non-Karvy investors. It displays monthly $ln(turnover)$ (Panel A), number of stocks traded (Panel B), and number of days traded (Panel C) by event time with 95% confidence intervals. Standard errors are clustered by client.



a Log of turnover



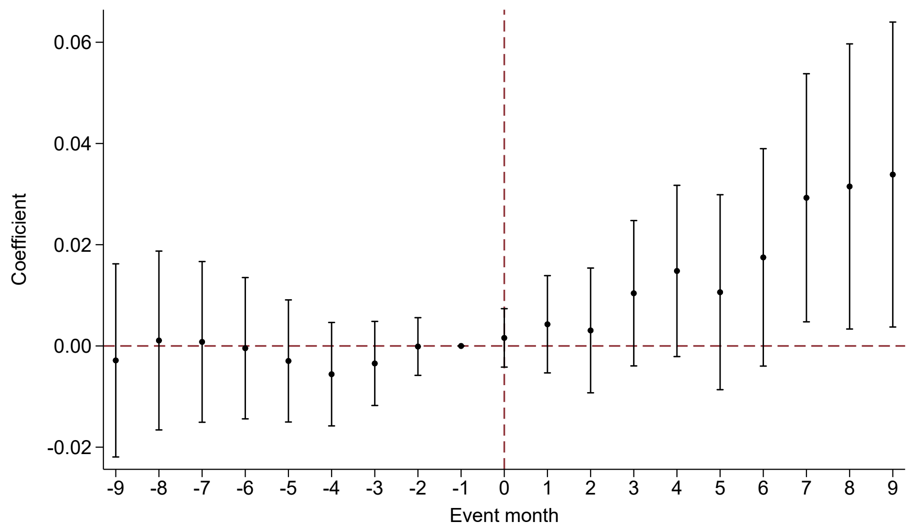
b Number of stocks traded



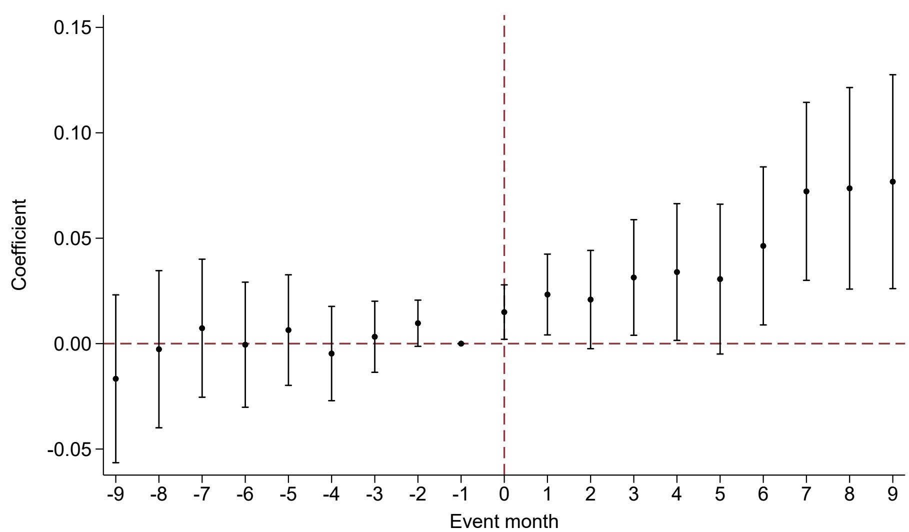
c Number of days traded

Figure 6. Brokerage account diversification of retail investors in high Karvy areas

This figure shows the effects of Karvy on brokerage account diversification of individuals in regions with higher Karvy presence. It displays the average number of new brokerage accounts conditional on participating in the market for all retail investors (Panel A) and a subset of more active retail investors (Panel B) by event time with 90% confidence intervals. More active retail investors are defined as investors with top decile turnover. Standard errors are clustered by zip code.



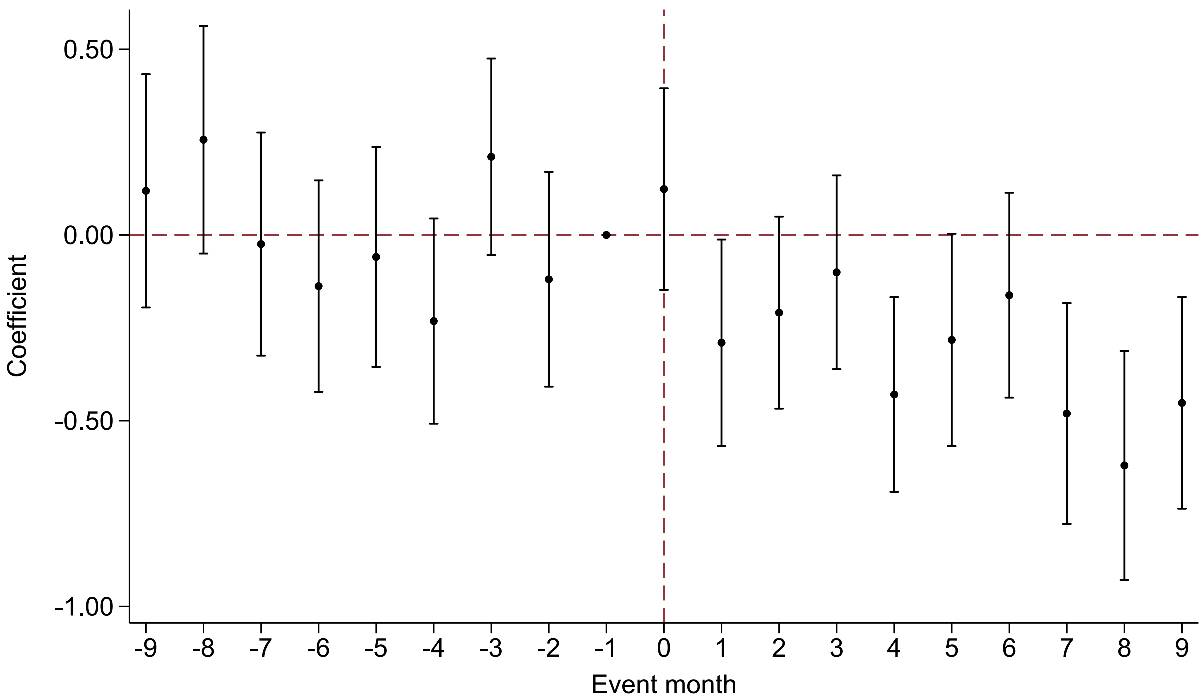
a All retail market participants.



b More active retail market participants.

Figure 7. New entrants in high Karvy areas

This figure shows the effects of Karvy on the stock market participation in regions with higher Karvy presence. The stock market participation is measured as the number of new retail investors that enter the market in a given month. It displays the log of the number of New entrants by event time with 90% confidence intervals. Standard errors are clustered by zip codes.



Tables

Table 1. Distribution of investors' accounts across brokers

This table presents the distribution of active brokerage accounts of the investors in our sample across brokers.

Broker name	Accounts	Accounts (%)	Accounts (cum %)
ZERODHA BROKING LIMITED	741,288	12	12
ICICI SECURITIES LIMITED	658,648	10.66	22.65
HDFC SECURITIES LTD.	482,795	7.81	30.47
SHAREKHAN LTD.	360,262	5.83	36.3
ANGEL ONE LIMITED	328,668	5.32	41.61
KOTAK SECURITIES LTD.	290,406	4.7	46.31
MOTILAL OSWAL FINANCIAL SERVICES LIMITED	235,632	3.81	50.13
AXIS SECURITIES LIMITED	200,710	3.25	53.37
RKSV SECURITIES INDIA PRIVATE LIMITED	187,397	3.03	56.41
IIFL SECURITIES LIMITED	152,123	2.46	58.87
SBICAP SECURITIES LIMITED	146,870	2.38	61.24
KARVY STOCK BROKING LTD.	**125,161**	**2.03**	**63.27**
GEOJIT FINANCIAL SERVICES LIMITED	95,845	1.55	64.82
5PAISA CAPITAL LIMITED	94,341	1.53	66.35
RELIGARE BROKING LIMITED	83,710	1.35	67.7
RELIANCE SECURITIES LIMITED	77,870	1.26	68.96
MARWADI SHARES AND FINANCE LIMITED	76,060	1.23	70.19
SMC GLOBAL SECURITIES LTD.	66,928	1.08	71.28
NUVAMA WEALTH AND INVESTMENT LIMITED.	58,786	.95	72.23
NIRMAL BANG SECURITIES PVT. LTD.	57,586	.93	73.16
REMAINING BROKERS COMBINED	1,658,719	26.84	100
Total	6,179,805	1	–

Table 2. Descriptive statistics

This table presents descriptive statistics by comparing investors with a Karvy account (treated) and those without (control) a month before Karvy. We require investors to have opened their brokerage account by the end of December 2018 and to have traded at least once during 2019.

	(1) Full	(2) Treated	(3) Control	(4) Difference	(5) t-statistic
Stocks traded	6.90	9.24	6.83	2.41***	(56.91)
Turnover (mil INR)	2.23	2.52	2.23	0.30***	(10.40)
Avg trade size (mil INR)	0.04	0.04	0.04	-0.00***	(-11.36)
Female	0.27	0.26	0.27	-0.01***	(-8.73)
Observations	4,815,579	125,154	4,690,425	4,815,579	

Table 3. Brokerage accounts type: non-Karvy customers as control

This table presents results for regressions of opened brokerage accounts around Karvy by broker type. The dependent variable in Panel A is a dummy with a value of one if the broker is a bank, whereas in Panel B it is a dummy with a value of one if the broker is a FinTech company. The unit of analysis is at the individual-broker level. Model 2 includes the month-of-account-opening FE. Model 3 additionally includes individual FE. Standard errors clustered by individual are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bank brokers

	(1) Account opened	(2) Account opened	(3) Account opened
Treated	-0.331***	-0.331***	
	(0.000)	(0.000)	
Post	-0.206***		
	(0.000)		
Treated × Post	0.502***	0.492***	0.473***
	(0.002)	(0.002)	(0.002)
Individual FE	No	No	Yes
Month FE	No	Yes	Yes
Observations	6,065,068	6,065,068	2,278,474
Adj. R^2	0.033	0.064	0.070

Panel B: FinTech brokers

	(1) Account opened	(2) Account opened	(3) Account opened
Treated	-0.179***	-0.155***	
	(0.000)	(0.000)	
Post	0.438***		
	(0.001)		
Treated × Post	-0.224***	-0.234***	-0.208***
	(0.002)	(0.002)	(0.002)
Individual FE	No	No	Yes
Month FE	No	Yes	Yes
Observations	6,065,068	6,065,068	2,278,474
Adj. R^2	0.126	0.208	0.240

Table 4. Brokerage accounts type: New entrants as control

This table presents results for regressions of opened brokerage accounts around Karvy by broker type. The dependent variable in Panel A is a dummy with a value of one if the broker is a bank, whereas in Panel B it is a dummy with a value of one if the broker is a FinTech company. The unit of analysis is at the individual-broker level. We restrict the sample to brokerage accounts opened from 2019 onward. In addition, we use individuals opening their first brokerage account as controls. Model 2 includes the month-of-account-opening FE. Model 3 additionally includes individual FE. Standard errors clustered by individual are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bank brokers

	(1) Account opened	(2) Account opened	(3) Account opened
Treated	-0.099***	-0.098***	
	(0.005)	(0.005)	
Post	-0.100***		
	(0.000)		
Treated × Post	0.221***	0.205***	0.107***
	(0.006)	(0.006)	(0.012)
Individual FE	No	No	Yes
Month FE	No	Yes	Yes
Observations	15,599,467	15,599,467	4,453,879
Adj. R^2	0.007	0.022	-0.015

Panel B: FinTech brokers

	(1) Account opened	(2) Account opened	(3) Account opened
Treated	0.071***	0.071***	
	(0.007)	(0.007)	
Post	0.229***		
	(0.000)		
Treated × Post	-0.502***	-0.471***	-0.263***
	(0.007)	(0.007)	(0.015)
Individual FE	No	No	Yes
Month FE	No	Yes	Yes
Observations	15,599,467	15,599,467	4,453,879
Adj. R^2	0.027	0.049	0.035

Table 5. Brokerage accounts type: New entrants as control (Only first account)

This table presents results for regressions of opened brokerage accounts around Karvy by broker type. The dependent variable in Panel A is a dummy with a value of one if the broker is a bank, whereas in Panel B it is a dummy with a value of one if the broker is a FinTech company. The unit of analysis is at the individual-broker level. We restrict the sample to brokerage accounts opened from 2019 onward. In addition, we use individuals opening their first and only brokerage account as controls. Model 2 includes the month-of-account-opening FE. Standard errors clustered by individual are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bank brokers

	(1) Account opened	(2) Account opened
Treated	-0.160***	-0.156***
	(0.005)	(0.005)
Post	-0.149***	
	(0.000)	
Treated × Post	0.269***	0.243***
	(0.006)	(0.006)
Month FE	No	Yes
Observations	9,915,361	9,915,361
Adj. R^2	0.014	0.034

Panel B: FinTech brokers

	(1) Account opened	(2) Account opened
Treated	0.105***	0.103***
	(0.007)	(0.007)
Post	0.273***	
	(0.000)	
Treated × Post	-0.546***	-0.505***
	(0.007)	(0.007)
Month FE	No	Yes
Observations	9,915,361	9,915,361
Adj. R^2	0.039	0.066

Appendix

A-1 Additional tables and figures

Table A-1. List of FinTech brokers

This table provides a list of Indian brokers registered at NSE during our sample period, which are identified as FinTech.

#	Registration num	NSE member code	Name
1	INZ000010231	14300	5paisa Capital Limited
2	INZ000156038	90112	Alice Blue Financial Services Private Limited
3	INZ000161534	12798	Angel One Limited
4	INZ000245435	09946	Angel Securities Limited
5	INZ000160131	13773	Choice Equity Broking Private Limited
6	INZ000008524	90061	Fyers Securities Private Limited
7	INZ000177036	90097	Goodwill Wealth Management Private Limited
8	INZ000006031	90133	Moneylicious Securities Private Limited
9	INZ000095034	07708	Navia Markets Limited
10	INZ000240532	90165	Paytm Money Limited
11	INZ000174330	06537	Religare Broking Limited
12	INZ000315837	13942	RKSV Securities India Private Limited
13	INZ000002535	12135	Samco Securities Limited
14	INZ000194736	07604	Ventura Securities Limited
15	INZ000031633	13906	Zerodha Broking Limited

Table A-2. Brokerage accounts type: non-Karvy customers as control (Only accounts opened after 2018)

This table presents results for regressions of opened brokerage accounts around Karvy by broker type. The dependent variable in Panel A is a dummy with a value of one if the broker is a bank, whereas in Panel B it is a dummy with a value of one if the broker is a FinTech company. The unit of analysis is at the individual-broker level. We restrict the sample to brokerage accounts opened from 2019 onward. Model 2 includes the month-of-account-opening FE. Model 3 additionally includes individual FE. Standard errors clustered by individual are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bank brokers

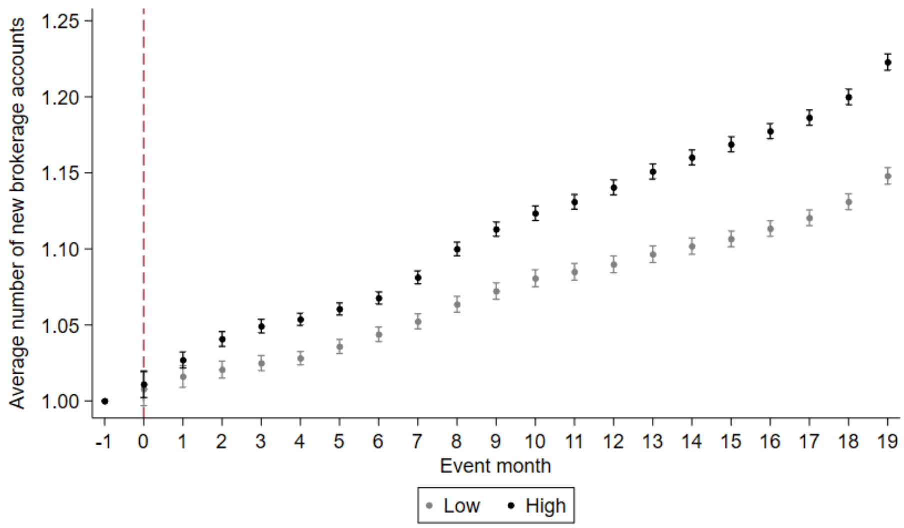
	(1) Account opened	(2) Account opened	(3) Account opened
Treated	-0.013**	-0.013**	
	(0.005)	(0.005)	
Post	-0.063***		
	(0.001)		
Treated × Post	0.184***	0.174***	0.076***
	(0.006)	(0.006)	(0.012)
Constant	0.195***		
	(0.001)		
Individual FE	No	No	Yes
Month FE	No	Yes	Yes
Observations	1,290,212	1,290,212	435,524
Adj. R^2	0.015	0.023	0.046

Panel B: FinTech brokers

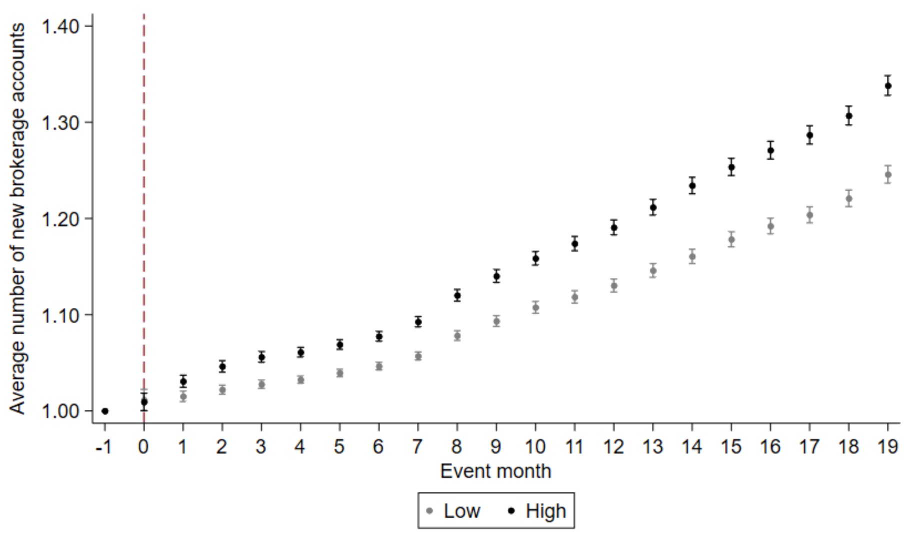
	(1) Account opened	(2) Account opened	(3) Account opened
Treated	0.027***	0.026***	
	(0.007)	(0.007)	
Post	0.156***		
	(0.001)		
Treated × Post	-0.430***	-0.414***	-0.188***
	(0.007)	(0.007)	(0.015)
Constant	0.480***		
	(0.001)		
Individual FE	No	No	Yes
Month FE	No	Yes	Yes
Observations	1,290,212	1,290,212	435,524
Adj. R^2	0.047	0.057	0.102

Figure A-1. Brokerage account diversification of individuals directly affected by Karvy by trading behavior

This figure shows the effects of Karvy on brokerage account diversification of directly affected individuals by trading behavior. It displays the average number of new brokerage accounts by low/high trades conditional on participating in the market (Panel A) and conditional on at least one buy transaction (Panel B) by event time with 95% confidence intervals. We assign individuals to low/high groups by median splitting the number of trades during the ten months before Karvy.



a All individuals.



b Individuals with buy transaction post-Karvy.

A-2 Additional details on the Karvy crisis

The Karvy scandal erupted in late 2019 when the National Stock Exchange (NSE), during a routine inspection, discovered that Karvy Stock Broking Ltd had been illegally using and pledging client securities to raise loans for its own purposes and to fund other Karvy Group companies. Instead of keeping client shares in demat accounts, Karvy allegedly transferred them to its own accounts, pledged them with banks, and raised billions of rupees in loans—without informing investors or obtaining proper consent. SEBI's forensic review found that Karvy had created layers of transactions, diverted funds to related entities such as Karvy Realty, and concealed certain demat accounts from exchanges to avoid scrutiny. The value of client securities misused was widely reported to be around ₹20–28 billion, making it one of the largest broker violations in Indian market history. On 22 November 2019, the Securities and Exchange Board of India (SEBI) issued an ex-parte interim order barring Karvy Stock Broking Ltd from taking on new clients and executing trades after a preliminary report from the National Stock Exchange of India (NSE) found that Karvy had misused clients' securities — specifically, transferring or pledging shares held in demat accounts without valid authorisation and diverting funds to group entities. The NSE audit had discovered that between January and August 2019 Karvy failed to report certain DP (depository participant) accounts and had transferred excess securities of several billion rupees to related clients. In the immediate aftermath, on 26 November 2019, Karvy's chairman and promoter, C. Parthasarathy, resigned from the board of one of its listed group companies in the wake of the disclosures. By 2 December 2019, under SEBI's directions the depository National Securities Depository Limited (NSDL) and the exchanges were facilitating the transfer of securities worth around ₹20 billion back into the accounts of about 83,000 investors whose holdings were allegedly mis-pledged. The scandal prompted SEBI to broaden its probe to the exchanges' oversight of brokers, with a report on 27 November 2019 questioning why the NSE and others failed to spot the irregularities earlier. Thus, within a short span in late 2019 Karvy moved from being a prominent broker to being under a major regulatory ban, sparking widespread investor concern and reshaping how pledging of client securities was regulated in India.

A-2.1 Timeline of the Karvy crisis

1. **20 June 2019:** Securities and Exchange Board of India (SEBI) issues a circular barring brokers from pledging client securities and instructs segregation by September — the regulatory backdrop to the Karvy matter.

2. **19 August 2019:** National Stock Exchange of India (NSE) conducts a "limited purpose inspection" of Karvy Stock Broking covering January 1, 2019 onward; preliminary findings of misuse of client securities emerge.

3. **22 November 2019:** SEBI issues an ex-parte interim order barring Karvy Stock Broking from onboarding new clients for its broking business, after NSE's report flagged alleged misuse of client securities (reportedly ≈₹20 billion).

4. **23 November 2019:** Media reports publish that SEBI has banned KSB for suspected ₹20 billion fraud and misuse of client shares; depositories asked not to act on any Power of Attorney instruction from Karvy.

5. **29 November 2019:** SEBI publishes its "Order dated November 29 2019 in respect of Karvy Stock Broking Ltd." formalising its interim directions.

6. **2 December 2019:** Karvy's trading rights across various market segments (equity, currency, debt) were suspended by NSE as part of the steps following the investigation.