# How do Investors Manage Broker Misconduct Risk? *

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**Abstract**

Using proprietary records from 20 million Indian brokerage accounts and exploiting the suspension of a major broker (KSB) as a shock, we study how retail investors manage broker misconduct risk. We find that risk management strategies differ considerably across investors. Less active investors manage risk by moving towards better-regulated, thus perceived safer, bank-affiliated brokers (as opposed to FinTech brokers), or by moving out of the stock market completely. More active investors manage risk by diversifying across brokers while retaining their accounts with low-cost FinTech brokers. We also find spillover effects: areas with greater KSB presence subsequently exhibit lower entry and a higher number of brokerage accounts per investor. Overall, our results highlight the effect of broker misconduct risk on stock market participation and FinTech adoption.

*Keywords*: household finance; broker; FinTech; risk management; retail investors.

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# 1 Introduction

Brokers are a key link in the financial intermediation chain connecting retail investors to financial markets. In the absence of a perfect contract, the principal-agent problem between the investor and the broker creates broker misconduct risk, which can result in front-running (Fecht et al., 2018), re-routing the order flow to venues with worse execution terms (Battalio et al., 2016), or even in direct theft. While stock-specific risk can be easily diversified, broker misconduct exposes the investor's entire portfolio to a common shock. This risk is often inadequately insured in both developing and developed financial markets, leaving investors to manage it through several potentially costly strategies.[1] Facing broker misconduct risk, investors have three choices. First, they may accept it and take no action. Second, they may mitigate it, for example, by diversifying across brokers or by choosing brokers with a lower probability of misconduct. Finally, investors may avoid the risk altogether by refraining from direct participation in financial markets. The way in which investors address the broker misconduct risk can influence their choice of brokerage service, the number of brokers they use simultaneously, their trading activity, and even their decision to participate.

Despite the essential role of broker misconduct risk in household investing, empirical evidence on how investors address it is scarce. This scarcity is due to the lack of data that combines a salient broker misconduct event, where traders' broker choices and investment behavior are observable both in the cross-section and time-series. We overcome this challenge by 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 broker misconduct event. We show that investors affected by broker misconduct shift to better-regulated (e.g., bank-affiliated, non-FinTech) brokers and are more likely to diversify across brokers. We also find

[1] In many European countries, the maximal coverage of stock market losses due to broker 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.

evidence that a significant proportion of investors decided to completely avoid the risk by exiting the stock market.

Our analysis shows that the strategy an investor adopts is related to her trading intensity before the shock. Investors with pre-shock turnover above the median manage risk by diversifying across brokers. These investors open multiple accounts with different types of brokers, including both low-cost FinTech brokers and full-service brokers. In contrast, less active investors, for whom the fixed cost of establishing a new brokerage relationship is likely to be large relative to the expected benefits of market participation, either switch to bank-affiliated brokers, which may be perceived as safer, or avoid the risk altogether by exiting the market. Our results therefore suggest that a salient episode of broker misconduct does not merely reallocate investors across intermediaries; it also drives out the households whose attachment to the stock market is weakest.

To further understand the impact that broker misconduct has on financial markets, we ask whether such events can influence the behavior of investors who are not customers of the affected broker. We find that the KSB shock influenced brokerage choice even among individuals who were not directly affected (i.e., those without a KSB account): Within regions, zip codes with greater KSB presence subsequently show lower entry rates and a higher likelihood of holding multiple brokerage accounts per person.[2] Taken together, our results show that broker misconduct risk is an important determinant of brokerage choice, diversification across brokers, FinTech adoption, and retail stock market participation.

Brokers are a key link between households and stock markets. They provide access to trading, custody, information, and other services that determine how households participate in equity markets. Brokers also differ substantially in the services they offer and the fees they charge. For example, low-cost FinTech brokers provide inexpensive and convenient market access, while full-service brokers may offer extensive advice, support, and perceived security. The choice of broker can therefore affect not only households' trading costs and investment

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

behavior, but also their ability to build wealth over time. These consequences make the reliability of the broker essential for household investment decisions.

We define broker misconduct risk as the potential for a significant loss due to the broker's actions. Such a loss can happen when the broker fails to return funds on time (because of fraud or incompetence) or otherwise exploits the client, for example, by front-running, providing misleading trading recommendations, or routing orders to venues with lower execution quality (Battalio et al., 2016; Fecht et al., 2018). Experiencing or witnessing a fraud event involving one's own broker, followed by the broker's suspension from trading due to its inability to return investors' assets, arguably increases the subjective probability or salience of broker misconduct, amplifying the perceived risk.

Risk management can be approached in three broad ways: risk acceptance, risk mitigation, and risk avoidance. As the KSB shock did not lead to any major financial loss for investors, it is possible that some investors decided to accept the risk, and in that case, the KSB shock will have no effect on investor behavior. On the other hand, some investors may seek to mitigate broker risk by diversifying across brokers, choosing safer brokerage firms, or reducing their investment activity. Each of these strategies is costly: diversifying across brokers requires establishing and maintaining additional brokerage relationships, safer brokers charge higher commissions, and trading less entails forgone investment returns.[3] Investors therefore mitigate broker risk only when the expected benefits exceed these costs. Thus, some investors who don't benefit much from investing in the stock market may decide to completely avoid the risk by stopping direct trading in the stock market.

Immediately following the shock, all KSB brokerage accounts were suspended. The individuals who still had assets on their accounts were offered the option to transfer them to another broker. For the majority of investors who only had one account, this required establishing a relationship with one or several new brokers. We first document that KSB clients respond to the shock by increasing the number of brokers they use. Conditional on

[3] Under the Indian system, securities are held in dematerialized (demat) form, and each brokerage relationship is typically tied to a distinct demat account carrying its own annual maintenance charge.

the decision to accept or mitigate the risk, that is, opening at least one new account, we find that former KSB customers diversify across brokers, on average, opening 1.2 accounts per investor. Because each additional relationship is costly to form and maintain, holding more than one broker is a deliberate choice, and it reveals that affected investors are willing to pay the associated costs to limit their exposure to any single intermediary.

Since KSB was a large non-bank and non-FinTech broker, if individuals are willing to replace the closed account with a familiar broker type, they are more likely to choose another traditional non-bank 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 increased since they established their KSB account. Finally, if affected investors have a higher perceived risk of broker misconduct, 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 banking group is more likely to attract a regulator's attention, and therefore may appear 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 intermediaries.

Consistent with the latter hypothesis that the KSB default led to an increased subjective probability of broker misconduct, we find that, following the shock, affected investors are more likely to open accounts with bank-affiliated brokers rather than stand-alone brokerages, and they are less likely to open new accounts with FinTech brokers. These results hold when comparing affected individuals to clients of other brokers opening new accounts, as well as when comparing them to first-time entrants to the stock market. The latter comparison allows us to discriminate between the three explanations for broker choice set out above. New entrants open their accounts in the same calendar months as affected investors and therefore choose from an identical menu of brokerage services, which rules out the possibility that our results are driven by the composition of that menu at the moment of enrollment. Nor can the results be explained by a preference for a familiar broker type: KSB was itself a non-bank, non-FinTech broker, so investors seeking to replace it with a similar intermediary would have selected traditional stand-alone brokerages rather than bank-affiliated ones. What remains is the hypothesis that first-hand experience of the shock raised the perceived probability of broker misconduct and moved affected investors toward intermediaries they perceive to be better regulated and better capitalized.

The two effects differ significantly in their persistence. The migration toward bank-affiliated brokers is concentrated in the months immediately following the shock, peaking at 30 percentage points in the first month and decaying thereafter until it is no longer statistically distinguishable from zero by the end of our sample period. The avoidance of FinTech brokers does not fade: affected investors remain 25 to 50 percentage points less likely to open an account with a FinTech broker in every month through the end of the eighteen-month window. This asymmetry suggests that the shock produced two distinct responses. The flight toward safer intermediaries is transitory and recedes as the event loses salience (Bordalo et al., 2012, 2013; Dessaint and Matray, 2017), whereas the retreat from FinTech reflects a persistent revision in how affected investors evaluate the type of intermediary to which they entrust their assets.

Conditional on returning to the market, one can expect that affected individuals changed their trading behavior (Giannetti and Wang, 2016; Koudijs and Voth, 2016). For example, they can decrease their trading activity to minimize exposure to broker actions. In line with this conjecture, we find that investors respond to the KSB default with a decline in trading activity, including lower turnover, within-month trading frequency, and the number of different stocks traded monthly. However, this effect is only temporary: Within six months of the shock, individuals reach the same turnover and activity levels 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).

Another, and more extreme, way of managing broker misconduct risk is to completely avoid it by exiting the stock market. We proceed by looking at whether investors respond to the shock by withdrawing from the market, and whether this decision is related to their trading behavior before the shock. We find strong evidence of risk avoidance: half of directly affected market participants did not open any accounts within 18 months after the event and only a quarter of investors continue to purchase shares.[4]

Taken together, our mitigation and avoidance results show that the strategy an investor adopts is related to her trading activity before the shock. Investors with pre-shock turnover above the median are significantly more likely to return to the market: 61% of them hold a brokerage account eighteen months after the default, compared with 38% of investors with lower pre-shock activity. Conditional on returning, more active investors also open the largest number of new accounts. At the same time, active investors are the least likely to switch broker types, exhibiting an 11-percentage-point lower probability of reallocating toward bank-affiliated brokers than less active investors. Instead, they primarily mitigate broker misconduct risk by diversifying across brokers. In contrast, less active investors, for whom the fixed cost of establishing a new brokerage relationship is likely large relative to expected benefits, either switch to bank-affiliated brokers, which may be perceived as safer, or avoid the risk altogether by exiting the market. These results suggest that a salient episode of broker misconduct prompts households to evaluate their broker choice across multiple dimensions. Low-turnover investors who don't benefit much from low-cost trading offered by FinTech go to better-regulated bank-affiliated brokers. At the same time, high-turnover investors show less aversion to having an account with lower-cost, but potentially risky FinTech brokers.

[4]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.

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 zip codes 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 relative to developed economies such as the United States (58% of households).[5] We find that an increase in the salience of broker misconduct can decrease 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.[6] Even though the majority of investors received their investments back, some investors had to spend significant time and effort to recover their assets. Uncertainty about the implementation of the SIPC-type mechanism creates additional costs beyond the inability to respond to real-time changes in stock market prices while KSB trading accounts are frozen. Our results suggest that broker risk should be considered 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 prob-

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

[6]The 2025 survey by SEBI, the Indian stock market regulator, highlights a 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.

lems 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 showing how investors manage the broker misconduct risk.

Our paper is also related to the growing literature on the effect of social capital and 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.[7] 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 in the issuer's solvency decreasing stock market participation.[8] 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.

[7]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.

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

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 empirical strategy; Section 4 presents the evidence of risk mitigation strategies adopted by households; Section 5 discusses risk avoidance by not participating in the stock market; Section 6 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 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.[9]

Retail participation in India has been rising over time: Dematerialized (demat) accounts

[9]Source: fia.org.

reached 185.3 million at the end of 2024, which constitutes a 370% increase from the 2019 level.[10] 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 registration in 2023 as part of enforcement and investor-protection actions. Appendix A-2 provides additional details about the crisis.[11]

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

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

[11] 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.

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.[12] For retail 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

[12] 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).

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 June 2021. The raw data contain over 4 billion trades by more than 20 million investors in over 2,500 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).[13] 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.[14] The focus of our study is on households, and we therefore restrict the sample to retailers, which the NSE classification refers to as individuals.[15] Households represent 99% of unique investors and account for about 35% of equity trading turnover in our data.

[13] Badarinza et al. (2019) provides a survey of the literature on household finance in emerging economies.
[14] See, for example, note 1 on page 181 of the January 2024 NSE "Market Pulse" (nsearchives.nseindia.com).
[15] To be conservative, we exclude client IDs that are assigned to both retail and non-retail investor groups.

# 3 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 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 the shock. The table shows average values for a set of observable investor characteristics. 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 trends in outcomes prior to the shock (see Section 4.1), these descriptive statistics suggest that our control group provides a credible counterfactual for assessing the outcomes of investors with a Karvy brokerage account.

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:

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

where $\textit{Number of accounts}_{c,t}$ 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.[16] $\mathbb{1}_c^{Treated}$ is a dummy variable that equals 1 for Karvy customers and zero otherwise. $\alpha_c$ is the client fixed effect, and $\alpha_t$ 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 the treated and the control groups started with one account, which is due to the way we constructed 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

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

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 disentangle the effect of the number of returning clients from changes in the number of accounts per person, we examine each margin separately. Section 4 focuses on investors mitigating broker risk through diversification across brokers and safer broker choice, whereas Section 5 focuses on former Karvy clients avoiding the risk altogether by refraining from stock market participation.

# 4 Risk Mitigation

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 describe the effects on diversification across brokers in Section 4.1. In Section 4.2, we investigate the types of brokers Karvy customers choose to open an account with after the shock. In Section 4.3, we study how the Karvy scandal affected its customers' trading intensity (turnover, number of stocks traded, and trading frequency). Finally, in Section 4.4 we investigated the spillover effects in terms of diversification across brokers.

## 4.1 Diversification across brokers

Next, we investigate the risk mitigation 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 2 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 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 2 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 3 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 turnover (Figure A-1).

Taken together, the results in Figure 1 to 3 show that 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.

## 4.2 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.[17] 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 higher subjective probability of broker misconduct, 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

[17] 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.

attention, and therefore 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 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 4.2.1, we use existing non-Karvy customers as controls, whereas in Section 4.2.2, 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.

### 4.2.1 Non-Karvy clients as controls

To understand what type of brokers Karvy customers chose to open an account with, we construct a dataset at the client × brokerage account level. We denote by $t$ the calendar month in which client $c$ opened her account with broker $b$. We compare the types of brokers with which Karvy and non-Karvy customers open accounts using the following difference-in-differences (DiD) specification:

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

where $\mathbb{1}_{c,b,t}^{Broker\ Type}$ is a dummy that takes the value of 1 if broker $b$ is bank-affiliated and zero otherwise. $\mathbb{1}_t^{Post}$ is a dummy that takes the value of 1 if the account was opened after the Karvy scandal and zero otherwise. $\mathbb{1}_c^{Treated}$ is a dummy variable that equals 1 for Karvy customers and zero otherwise. $\alpha_t$ denotes month-of-account-opening FE and $\alpha_c$ denotes client FE; the level terms $\theta$ and $\gamma$ are absorbed by these FE where included, and we report Model

1 without fixed effects, Model 2 with month-of-account-opening fixed effects, and Model 3 with both. We cluster standard errors by client.

The coefficient of interest, $\beta$, has a compositional interpretation: it measures the change in the share of accounts opened by Karvy clients that are with a bank-affiliated or FinTech broker, relative to the corresponding change for accounts opened by non-Karvy clients.[18]

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, the fraction of accounts opened by treated investors contracting a bank-affiliated broker increased by 50 percentage points (pp).

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 20pp 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

[18] Because *Post* varies across accounts rather than within them, identification in Model 3 comes from clients who opened accounts both before and after the scandal, which reduces the estimation sample from 6,065,068 to 2,278,474 accounts.

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

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 10pp to 20pp 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 20pp to 40pp less likely to have an account with a FinTech broker after the Karvy scandal. In comparison, the fraction of FinTech accounts opened by Karvy customers was 2.5pp higher before the Karvy shock.

To examine how the effect of the Karvy scandal on broker choice evolves over time, we estimate Equation 2 in event time, replacing the *Post* indicator with a full set of month-of-account-opening dummies interacted with $\mathbb{1}_c^{Treated}$.[20] Figure 4 plots the resulting coefficients for bank-affiliated brokers. Panel A shows that, in the eleven months preceding the scandal, the estimated coefficients are small and statistically indistinguishable from zero, which supports the parallel trends assumption. In the first month after the scandal, the coefficient rises to 34 percentage points, its maximum over the sample period. It then declines steadily, reaching 20 percentage points by the fourth month and settling in a range of 10 to 17 percentage points from the fifth month onward. Panel C, which additionally includes individual fixed effects, displays the same pattern at a smaller magnitude: The coefficient peaks at 26 percentage points in the first month, falls to 13 percentage points by the fourth month, and is no longer statistically distinguishable from zero by the end of the sample period.

Figure 5 presents the corresponding estimates for FinTech brokers, and the pattern is markedly different. Panel A shows that the coefficient turns negative in the month of the

[20] Because we observe a single treatment event, calendar time and event time coincide, and the month-of-account-opening fixed effects of Model 2 are collinear with the event-time dummies of the specification itself. Models 1 and 2 therefore deliver identical estimates in event time, and we report both panels for consistency with the corresponding tables. The distinction between the two models remains informative in Table 3 through Table 5, where *Post* enters as a single indicator rather than as a full set of month dummies. Individual fixed effects are not absorbed in this way, and the estimates that include them are therefore reported separately. In the specifications that use the first and only account of each new entrant as the control group, individual fixed effects are not identified, as each control investor contributes a single observation.

scandal, reaches -28 percentage points in the following month, and then stabilizes between -33 and -43 percentage points for the remainder of the sample period. In contrast to the bank estimates, we observe no attenuation over the eighteen months following the scandal. Panel C confirms the persistence of the effect once individual fixed effects are included, with coefficients ranging from -10 to -27 percentage points and no discernible trend toward zero.[21]

Taken together, the two figures reveal an asymmetry that speaks to the underlying mechanism. The migration toward bank-affiliated brokers is concentrated in the months immediately following the scandal and dissipates thereafter, which mirrors the temporary decline in trading activity documented in Section 4.3 and is consistent with a salience effect that fades as the event recedes (Bordalo et al., 2012, 2013; Dessaint and Matray, 2017). Part of this front-loading also reflects the fact that suspended Karvy clients had to replace their only account without delay, so the urgency of the choice (and the weight placed on the perceived safety of the intermediary) was greatest at the moment of replacement. The avoidance of FinTech brokers, by contrast, does not fade: treated investors continue to steer away from FinTech brokers in every month through the end of our sample period. This persistence suggests that the scandal did not merely produce a transitory flight to safety but induced a durable revision in how affected investors evaluate broker types.

### 4.2.2 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

[21] The pre-period coefficients in Panel A are positive and, in several months, statistically significant, indicating that Karvy clients were somewhat more likely than the control group to open FinTech accounts before the scandal. This is consistent with the level estimates in Table A-2, where treated clients are 2.7 percentage points more likely to hold a FinTech account in the pre-period. The pre-trend is absorbed once individual fixed effects are included in Panel C, and it works against our finding: If anything, Karvy clients were on a path toward, rather than away from, FinTech brokers.

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 10-20pp more likely to have an account with bank-affiliated brokers and 25-50pp less likely to have an account with FinTech brokers after the Karvy shock.

We next estimate the specification with new entrants as the control group in event time. Figure A-2 plots the coefficients for bank-affiliated brokers. Panel A shows that, in the pre-period, Karvy clients were between 9 and 10 percentage points less likely than new entrants to open an account with a bank-affiliated broker, and that this gap narrows as the scandal approaches, becoming statistically indistinguishable from zero from the seventh month before the event onward. The coefficient then rises sharply, reaching 30 percentage points in the first month after the scandal, its maximum over the sample period. It declines to 18 percentage points by the fourth month and fluctuates between 10 and 18 percentage points thereafter. Panel C, which adds individual fixed effects, shows the same profile at a smaller magnitude: The pre-period coefficients are indistinguishable from zero, the effect peaks at 24 percentage points in the first month, and it is no longer statistically distinguishable from zero over the final five months of the sample period.

Figure A-3 presents the estimates for FinTech brokers. Panel A shows that, ten months before the scandal, Karvy clients were 24 percentage points more likely than new entrants to open an account with a FinTech broker, and that this gap declines steadily to 8 percentage points two months before the event. Immediately after the scandal, the coefficient turns negative, reaching -24 percentage points in the first month, and it continues to fall, stabilizing between -40 and -46 percentage points over the final ten months of the sample period. Panel C reproduces the pattern with individual fixed effects, with post-period coefficients between

-13 and -33 percentage points and no attenuation over time.[22]

Taken together, Figure A-2 and Figure A-3 allow us to discriminate between the hypotheses set out at the beginning of this section. New entrants choose from exactly the same menu of brokerage services as Karvy clients do at the moment of enrollment, since both groups open their accounts in the same calendar months. The relative shift of Karvy clients toward bank-affiliated brokers and away from FinTech brokers therefore cannot be attributed to the composition of the available menu, which is the second hypothesis we consider. Nor is it consistent with treated investors seeking to replace their lost account with a familiar broker type, which is the first hypothesis: Karvy was itself a non-bank, non-FinTech broker, and had familiarity governed the choice, we would observe treated investors selecting traditional stand-alone brokerages rather than bank-affiliated ones. Our results are most consistent with the third hypothesis, namely that first-hand experience of the scandal raised the subjective probability of broker misconduct and led affected investors toward intermediaries they perceive to be better regulated and better capitalized. The event-time analysis patterns reinforce the asymmetry documented in Figure 4 and Figure 5: the change toward bank-affiliated brokers is concentrated in the months immediately following the scandal and fades as the event loses salience, whereas the avoidance of FinTech brokers persists undiminished through the end of our sample period.

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

[22]The pre-period coefficients in Panel A are positive and declining, which reflects the fact that new entrants adopted FinTech brokers at a faster rate than incumbent Karvy clients over the course of 2019. This trend, however, is unlikely to account for the estimated effect. In the three months spanning the event, the coefficient moves by 32 percentage points, whereas the average monthly change over the pre-period is 2 percentage points, so the break at the event is an order of magnitude larger than the underlying drift. The estimates are also robust to including individual fixed effects, which absorb the level differences between the two groups, as Panel C shows. We nonetheless caution against interpreting the coefficients at the end of the sample period, where the cumulative pre-trend is largest, as purely treatment-driven.

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 4.2.1 and 4.2.2 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 higher perceived broker risk after the Karvy shock.

#### 4.2.3 Heterogeneous responses by trading behavior

The value of a safer intermediary need not be the same for all investors. Investors who trade frequently and take larger positions arguably have more at stake if their broker misappropriates their securities, which would lead them to shift toward safer brokers more strongly than less active investors. By contrast, active investors also derive the greatest benefit from the low commissions and the execution tools that FinTech brokers provide, so for them the safety of the intermediary trades off against the cost of trading. To distinguish between these possibilities, we split investors into "high" and "low" groups by the median of total turnover during the ten months preceding the scandal and re-estimate Equation 2 with a full set of interactions.

Table 6 presents the results. Panel A shows that, for investors with below-median pre-scandal turnover, the treatment effect on the probability of opening an account with a bank-affiliated broker is 54 percentage points, and it is stable across specifications. The triple interaction is negative and statistically significant at -10.5 to -12.1 percentage points, implying an effect of approximately 42 to 44 percentage points for investors with above-median turnover. Panel B shows the mirror image for FinTech brokers: The treatment effect is -22 percentage points for the low-turnover group, and the triple interaction is positive but small, ranging from 0.7 to 3.9 percentage points and statistically insignificant in Model 2. Both groups therefore move away from FinTech brokers and toward bank-affiliated brokers, but the reallocation is uniformly weaker among the investors who traded most before the scandal.

These results further describe how the two mitigation strategies are allocated across investors. Section 4.1 shows that the investors who traded most before the scandal open the largest number of new accounts, whereas the results here show that these same investors shift their broker type the least. Active investors thus appear to mitigate broker misconduct risk primarily on the diversification margin, spreading their assets across several brokers rather than abandoning the low-cost intermediaries on which their trading strategies depend. Less active investors, for whom diversification across brokers is less valuable relative to its fixed costs, instead mitigate the risk on the broker type margin, by contracting an intermediary they perceive to be safer. Both groups respond to the same shock, but they appear to manage the resulting risk through the instrument that is least costly to them.

## 4.3 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.[23] 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:

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

where $Trading\ activity_{c,t}$ 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 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. $\alpha_c$ is the client fixed effect, and $\mu_{z,b,t}$ is the zip-broker-month fixed effect. We cluster standard errors by client.

Figure 6 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 6 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 6 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

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

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.

### 4.4 Account diversification: spillover 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.[24] 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.

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.[25] 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

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

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.

We begin our investigation 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 $\textit{Number of accounts}_{c,t}$ 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. $\textit{Karvy fraction}_z$ is the fraction of clients with Karvy accounts in a zip code $z$. $\mu_{r,s,k,t}$ represents *region* × *stock market participants decile* × *Karvy presence decile* × *time* fixed effects, and $\alpha_c$ 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 7 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 7 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.

# 5 Risk Avoidance

After investigating the risk mitigation strategy of diversification and safer broker choice in the previous section, we next examine the risk avoidance strategy households can adopt by deciding to stop direct stock market participation. To this end, we focus on Karvy clients and quantify how many of them re-entered the market after losing their primary and only brokerage account due to Karvy's default by opening new accounts. 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 8 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 fraction of clients with an active brokerage account 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. 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 8 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 returns to the market already within seven months.[26]

The decision to abandon the stock market arguably depends on how much an investor expects to gain from participating in it. Re-establishing a brokerage relationship carries a fixed cost (selecting a new broker, completing the KYC procedure, and arranging the transfer of holdings) that is largely independent of how intensively the investor trades, whereas the benefit of doing so scales with expected trading activity. We therefore expect risk avoidance to be concentrated among investors who traded relatively little before the scandal. To test this conjecture, we split Karvy clients into "high" and "low" groups by the median of total turnover during the ten months preceding the scandal, and we plot re-entry separately for the two groups.

Figure 9 presents the results. Panel A shows that both groups start from a participation rate of one and fall to essentially zero in the month of the default, but that they recover at economically meaningfully different rates.[27] By the end of the sample period, 61% of Karvy clients with above-median pre-scandal turnover hold a brokerage account, compared with 38% of clients with below-median turnover. The gap opens immediately after the scandal, widens over the first year, and shows no sign of closing: Nearly two thirds of the less active investors have not opened a brokerage account eighteen months after the event, against roughly two fifths of the more active ones. Panel B restricts attention to the investors who purchase stocks at some point after the scandal and therefore speaks to the speed, rather

[26] 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.

[27] 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.

than the incidence, of re-entry. Among these investors, the more active group returns faster. 23% have an account one month after the default, compared with 15% of the less active group, and 78% compared with 67% after four months. Both groups have fully returned by the seventh month.

Taken together, these patterns show that the burden of risk avoidance falls disproportionately on marginal participants. The investors who leave the market are precisely those who traded least before the scandal; that is, those for whom the fixed cost of re-establishing a brokerage relationship is arguably largest relative to the benefits they expect from participating. Combined with the results of Section 4, this complements the mapping between pre-scandal trading activity and the choice of risk-management strategy: active investors remain in the market and mitigate broker misconduct risk, principally by diversifying across brokers, whereas less active investors avoid the risk altogether by ceasing to participate. This asymmetry is consequential for the aggregate effects of broker misconduct. The investors who exit are the ones whose participation is most fragile to begin with, and they are the ones the literature on stock market participation is most concerned with (Giannetti and Wang, 2016; Guiso et al., 2008). A salient episode of broker misconduct thus does not merely reallocate investors across intermediaries; it removes from the market those households whose attachment to it was weakest.

## 5.1 Risk avoidance: spillover effects

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 estimate a specification analogous to Equation 4, in which the dependent variable is the logarithm of the number of new entrants in a zip code and the client fixed effects are replaced with zip code fixed effects:

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

where *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. *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 $\alpha_z$ 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 10 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 broker misconduct risk as a potential explanation for low stock market participation, especially in developing economies.

# 6 Conclusion

In this paper, we study how broker risk affects diversification across brokers, brokerage choices, participation in the stock market, 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 the perceived level of broker risk. 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 broker risk 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 broker misconduct risk as a potential explanation for low stock market participation, especially in developing economies.

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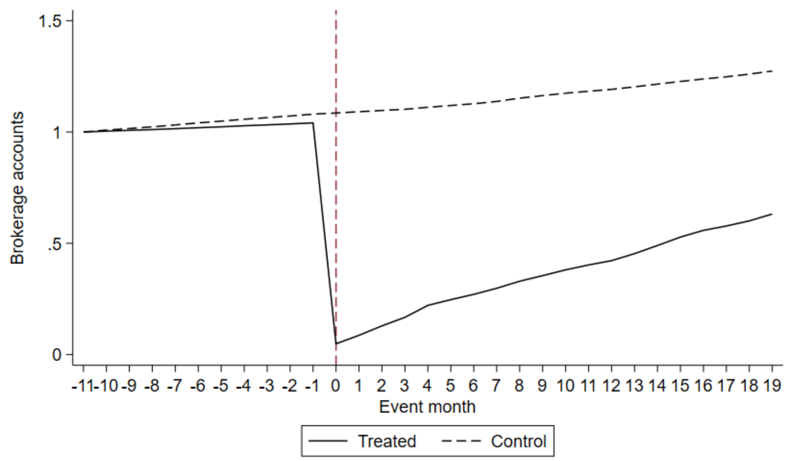
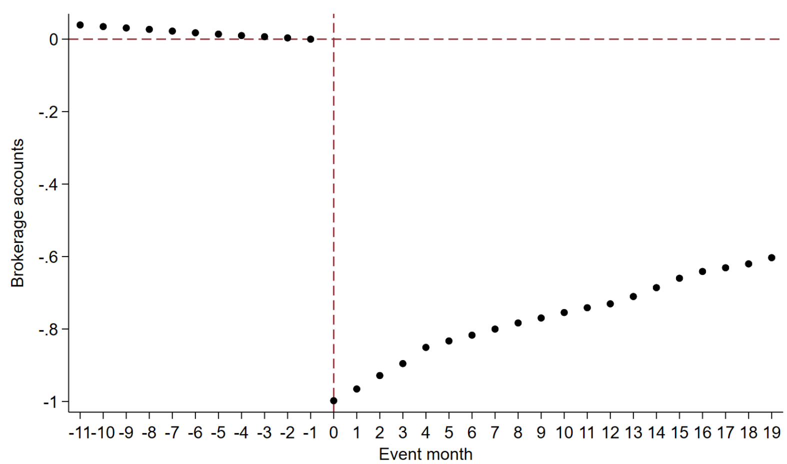
# Figures

**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).



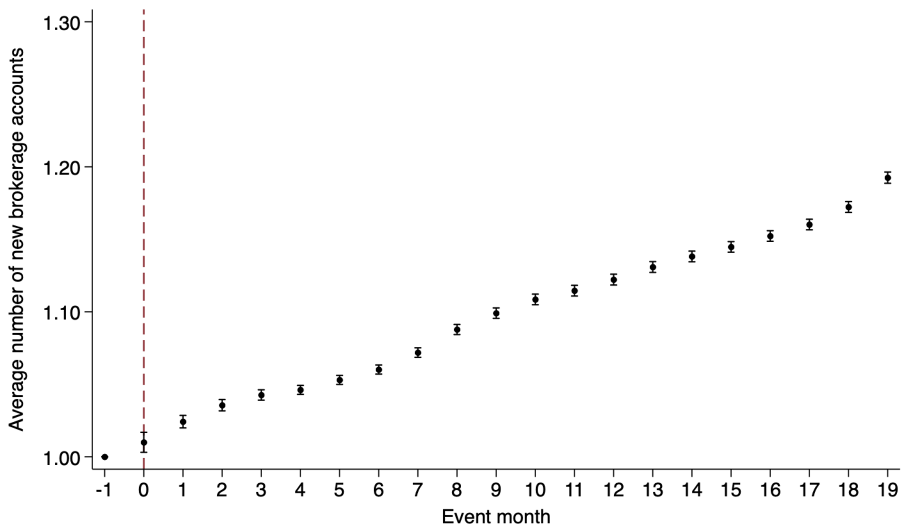

**a** Raw means.



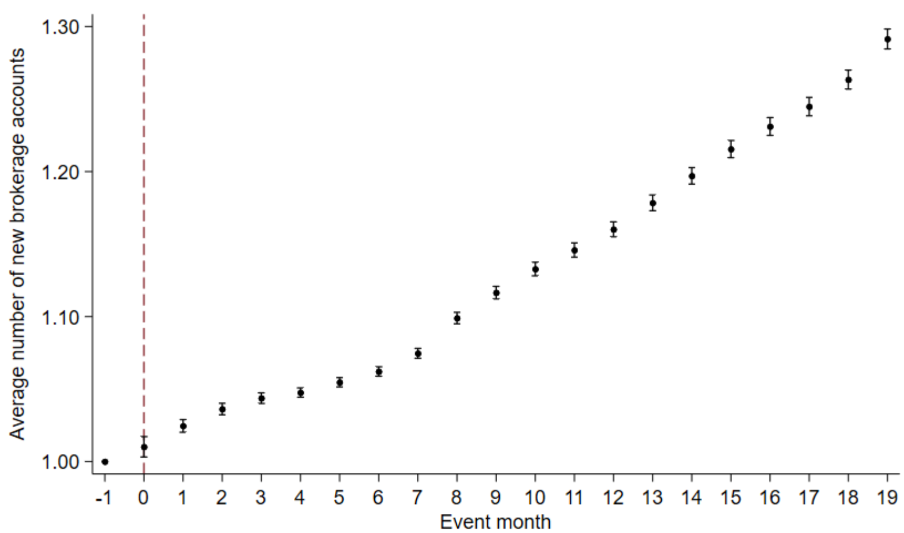

**b** DiD coefficients.

**Figure 2.** 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.



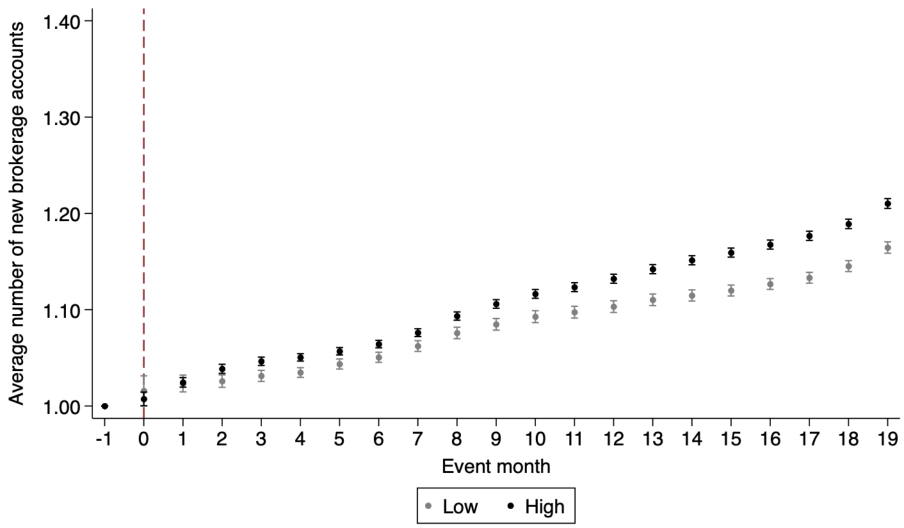

**a** All individuals.



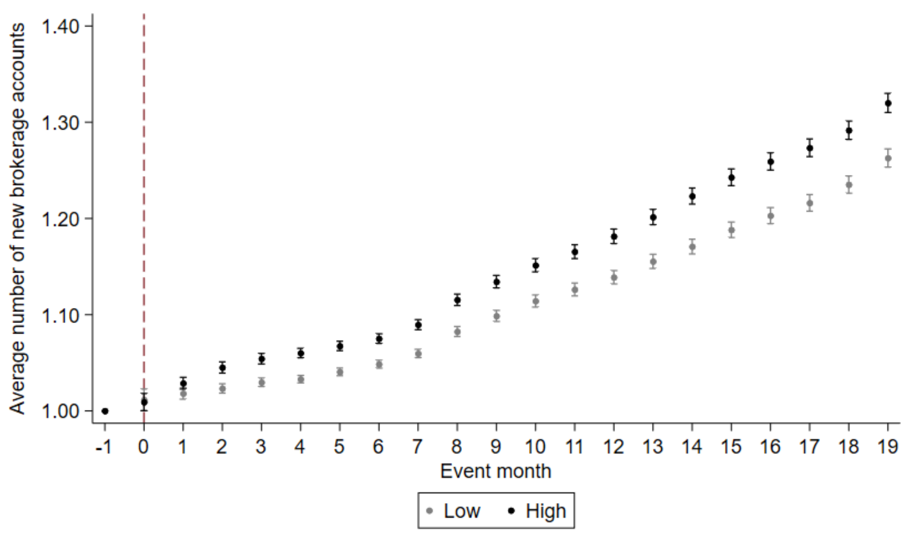

**b** Individuals with a buy transaction post-Karvy.

**Figure 3.** 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.



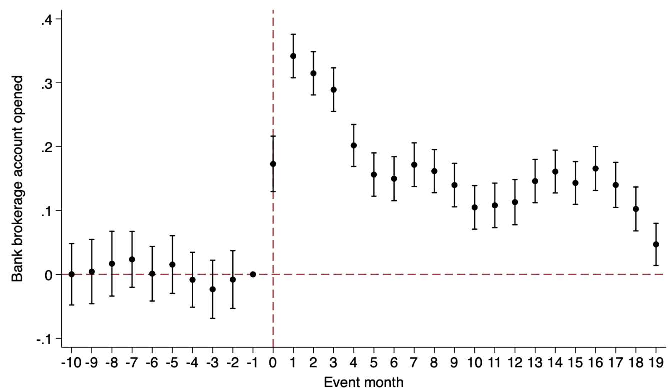

**a** All individuals.



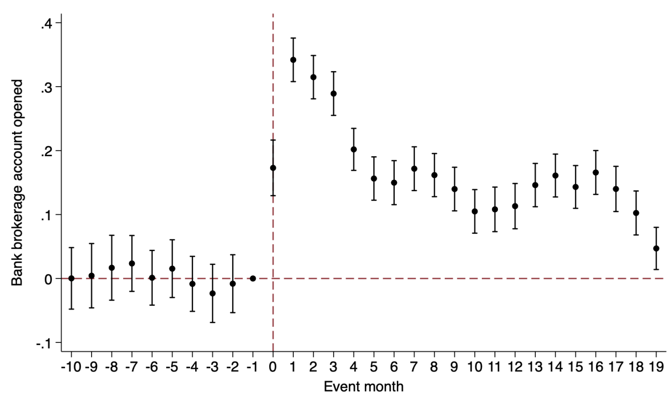

**b** Individuals with a buy transaction post-Karvy.

**Figure 4.** Bank brokerage accounts opened: non-Karvy customers as control

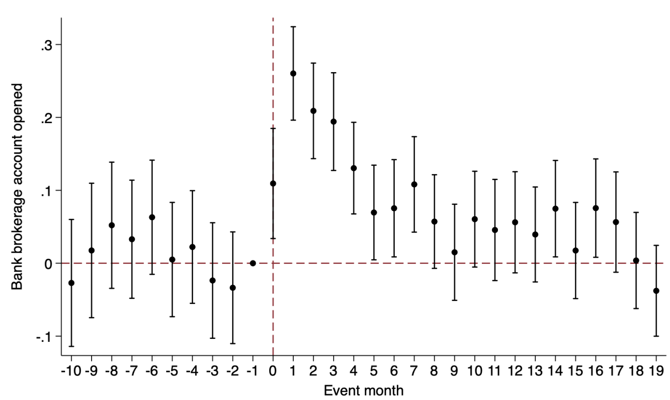
This figure shows the effects of Karvy on opened bank-affiliated brokerage accounts around Karvy. It displays DiD coefficients estimated by event time with 95% confidence intervals. The dependent variable is a dummy with a value of one if the broker is a bank. The unit of analysis is at the individual-broker level. Model 1 in Panel A includes no FE. Model 2 in Panel B includes the month-of-account-opening FE. Model 3 additionally includes individual FE. Standard errors are clustered by individual.




**a** Model 1.



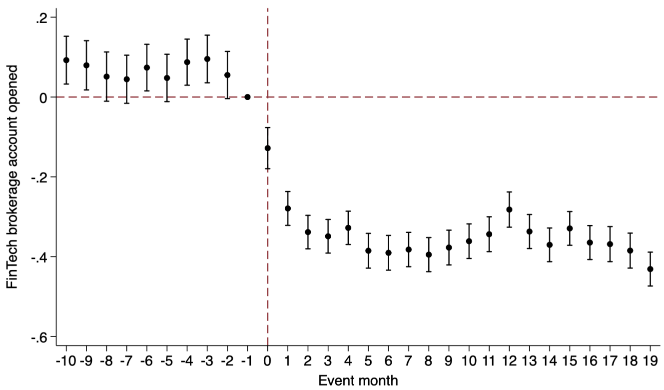

**b** Model 2.



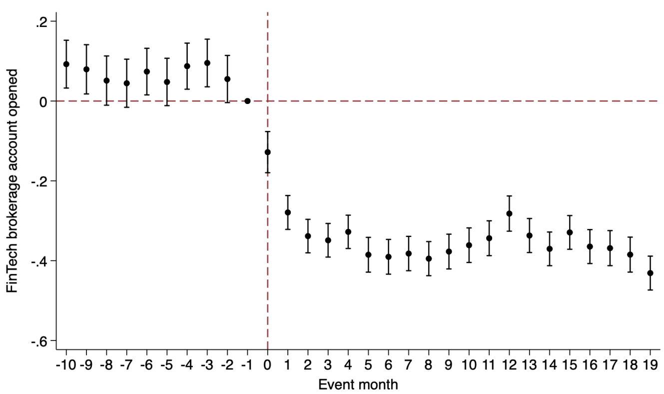

**c** Model 3.

**Figure 5.** FinTech brokerage accounts opened: non-Karvy customers as control

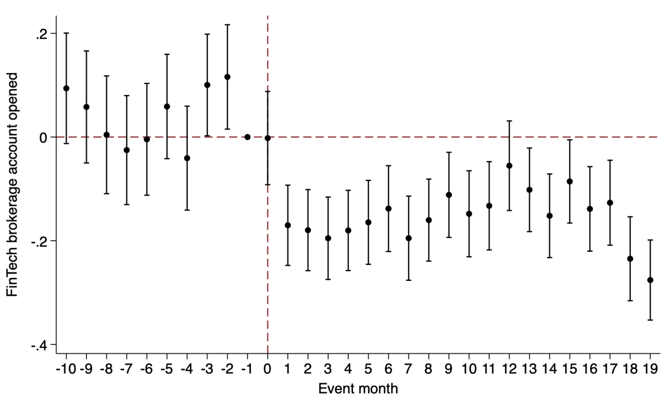
This figure shows the effects of Karvy on opened FinTech brokerage accounts around Karvy. It displays DiD coefficients estimated by event time with 95% confidence intervals. The dependent variable is a dummy with a value of one if the broker is a FinTech. The unit of analysis is at the individual-broker level. Model 1 in Panel A includes no FE. Model 2 in Panel B includes the month-of-account-opening FE. Model 3 additionally includes individual FE. Standard errors are clustered by individual.




**a** Model 1.



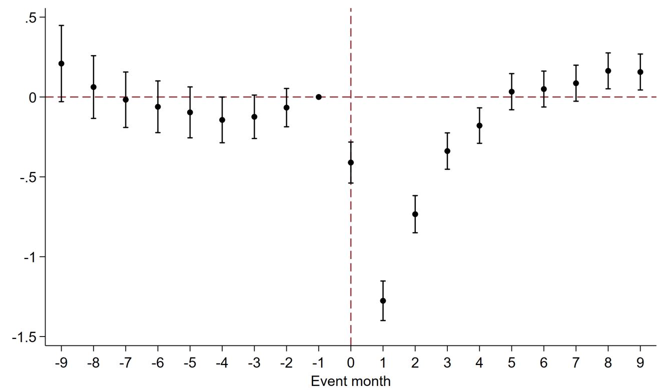

**b** Model 2.



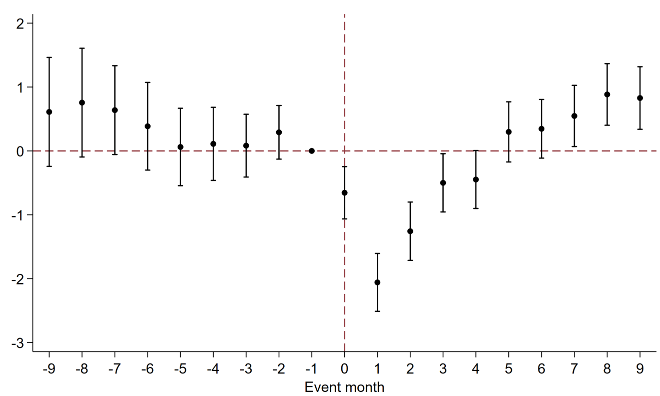

**c** Model 3.

**Figure 6.** Trading behavior of individuals directly affected by Karvy

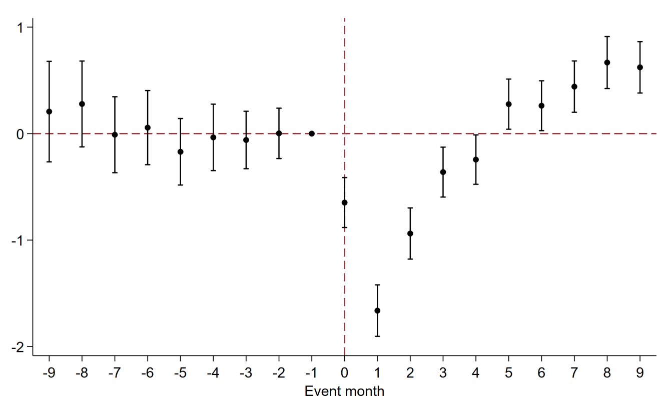
This figure shows the effects of Karvy default on the trading intensity of the Karvy investors compared to non-Karvy investors. It displays monthly $ln(turnover)$ (Panel A), number of stocks traded (Panel B), and number of days traded (Panel C) by event time with 95% confidence intervals. Standard errors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




**a** Log of turnover



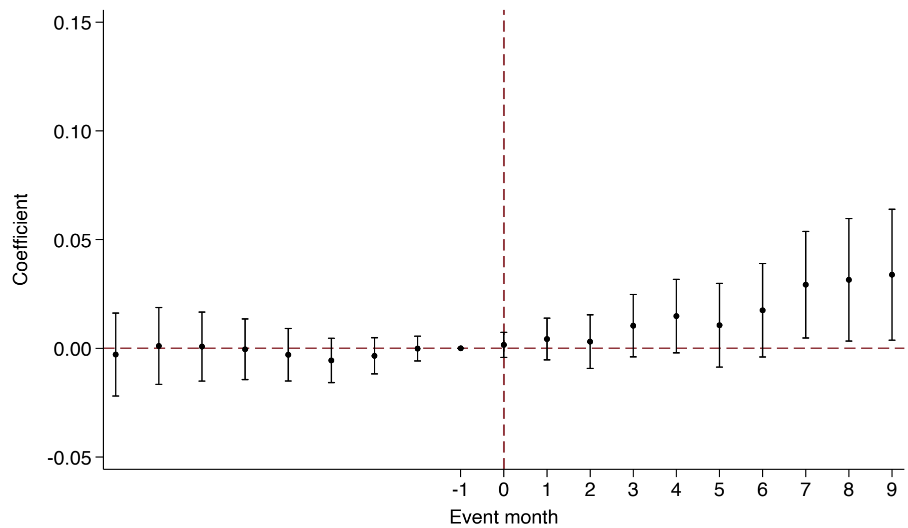

**b** Number of stocks traded



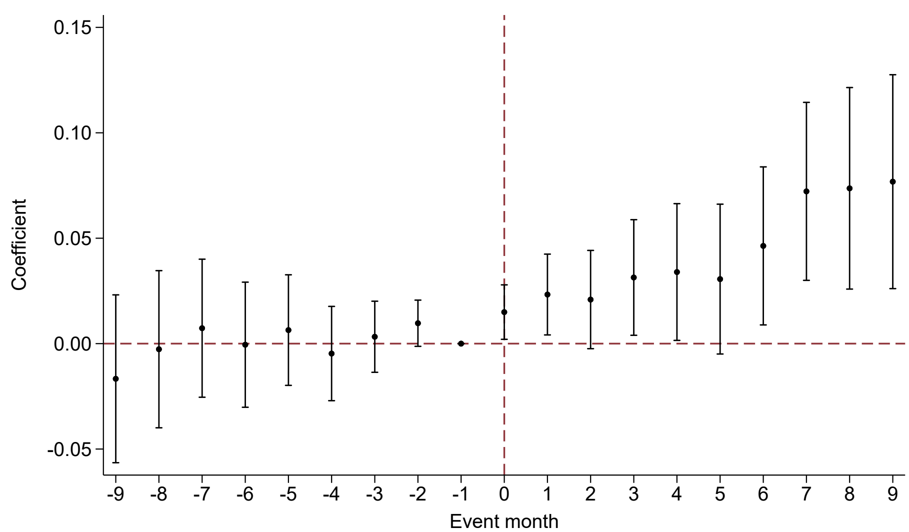

**c** Number of days traded

**Figure 7.** 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.



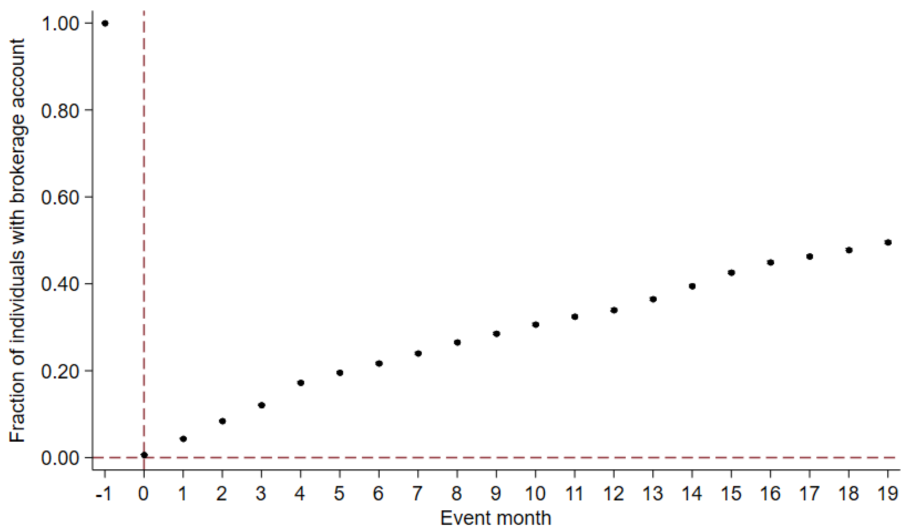

**a** All retail market participants.



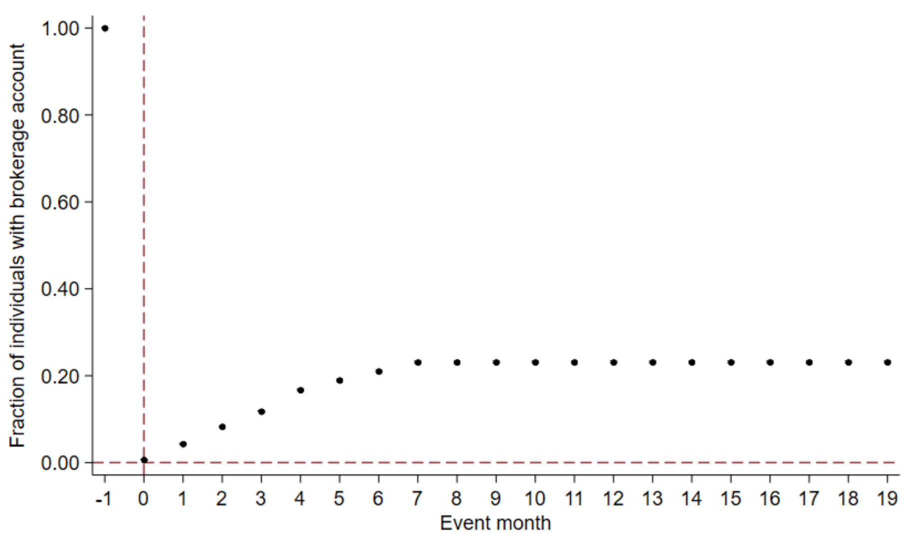

**b** More active retail market participants.

**Figure 8.** 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.



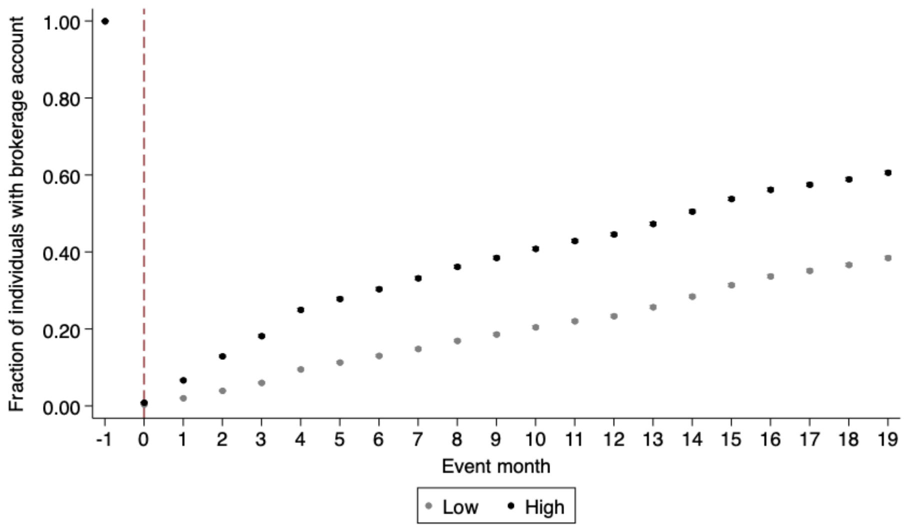

**a** All individuals.



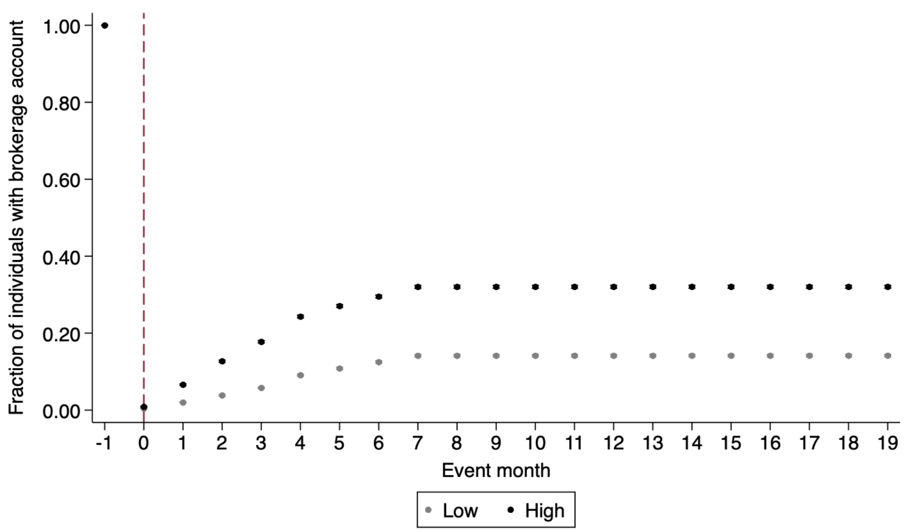

**b** Individuals with a buy transaction post-Karvy.

**Figure 9.** Market participation of individuals directly affected by Karvy by trading behavior

This figure shows the effects of Karvy on the market participation of directly affected individuals split by their trading behavior. It displays the fraction of individuals by low/high turnover (i) with an active brokerage account (Panel A) or (ii) with at least one buy transaction (Panel B) in event time with 95% confidence intervals. We classify individuals into low- and high-turnover groups based on a median split of total turnover over the ten months preceding the Karvy event.



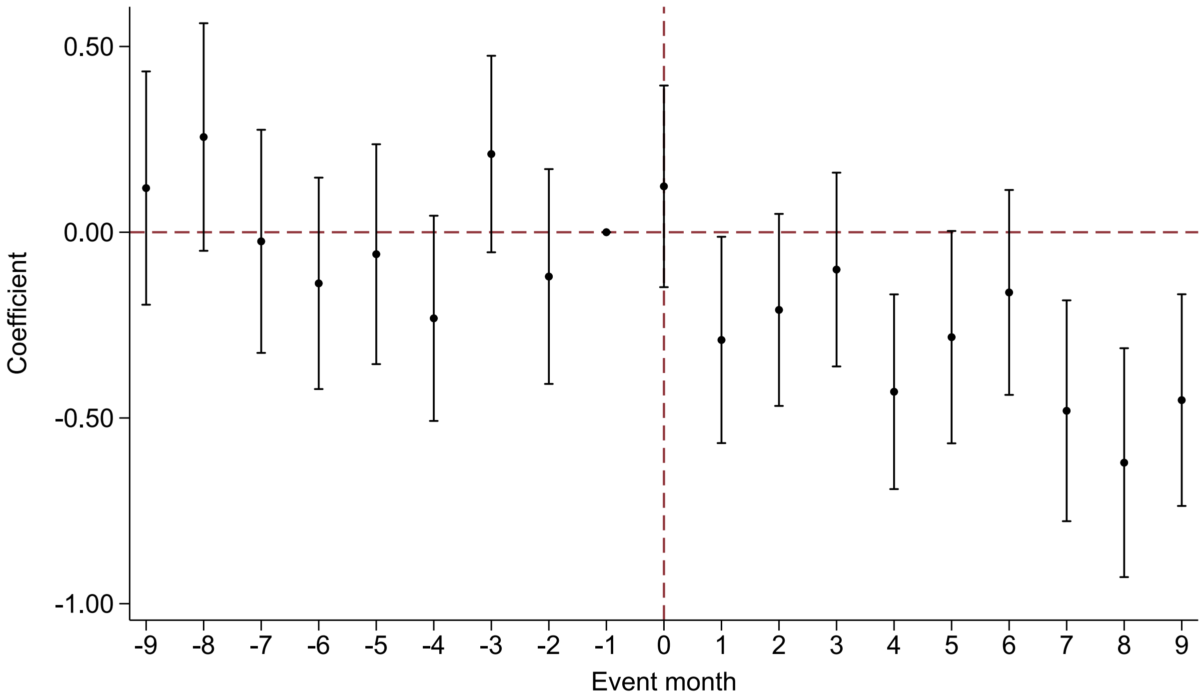

**a** All individuals.




**b** Individuals with a buy transaction post-Karvy.

**Figure 10.** 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)<br>Account opened | (2)<br>Account opened | (3)<br>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)<br>Account opened | (2)<br>Account opened | (3)<br>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)<br>Account opened | (2)<br>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)<br>Account opened | (2)<br>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 |

**Table 6.** Brokerage accounts type by trading behavior: non-Karvy customers as control

This table presents results for regressions of opened brokerage accounts around Karvy by broker type and trading behavior. 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. We split individuals into low/high by median turnover in the ten months prior to the Karvy shock. 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)<br>Account opened | (2)<br>Account opened | (3)<br>Account opened |
|---|---|---|---|
| Treated | -0.402*** | -0.402*** | |
| | (0.000) | (0.001) | |
| Post | -0.275*** | | |
| | (0.001) | | |
| High | -0.131*** | -0.120*** | |
| | (0.000) | (0.000) | |
| Treated × Post | 0.548*** | 0.542*** | 0.538*** |
| | (0.004) | (0.004) | (0.004) |
| Treated × High | 0.136*** | 0.133*** | |
| | (0.001) | (0.001) | |
| Post × High | 0.135*** | 0.120*** | 0.130*** |
| | (0.001) | (0.001) | (0.001) |
| Treated × Post × High | -0.105*** | -0.106*** | -0.121*** |
| | (0.004) | (0.004) | (0.004) |
| Constant | 0.405*** | 0.360*** | 0.189*** |
| | (0.000) | (0.000) | (0.000) |
| Individual FE | No | No | Yes |
| Month FE | No | Yes | Yes |
| Observations | 6,065,068 | 6,065,068 | 2,278,474 |
| Adj. $R^2$ | 0.050 | 0.078 | 0.077 |

Panel B: FinTech brokers

| | (1) Account opened | (2) Account opened | (3) Account opened |
|---|---|---|---|
| Treated | -0.154*** | -0.147*** | |
| | (0.000) | (0.001) | |
| Post | 0.509*** | | |
| | (0.001) | | |
| High | 0.074*** | 0.045*** | |
| | (0.000) | (0.000) | |
| Treated × Post | -0.220*** | -0.217*** | -0.215*** |
| | (0.004) | (0.004) | (0.004) |
| Treated × High | -0.054*** | -0.022*** | |
| | (0.001) | (0.001) | |
| Post × High | -0.137*** | -0.103*** | -0.108*** |
| | (0.001) | (0.001) | (0.001) |
| Treated × Post × High | 0.035*** | 0.007 | 0.039*** |
| | (0.004) | (0.004) | (0.004) |
| Constant | 0.160*** | 0.249*** | 0.428*** |
| | (0.000) | (0.000) | (0.000) |
| Individual FE | No | No | Yes |
| Month FE | No | Yes | Yes |
| Observations | 6,065,068 | 6,065,068 | 2,278,474 |
| Adj. $R^2$ | 0.133 | 0.210 | 0.243 |

# 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

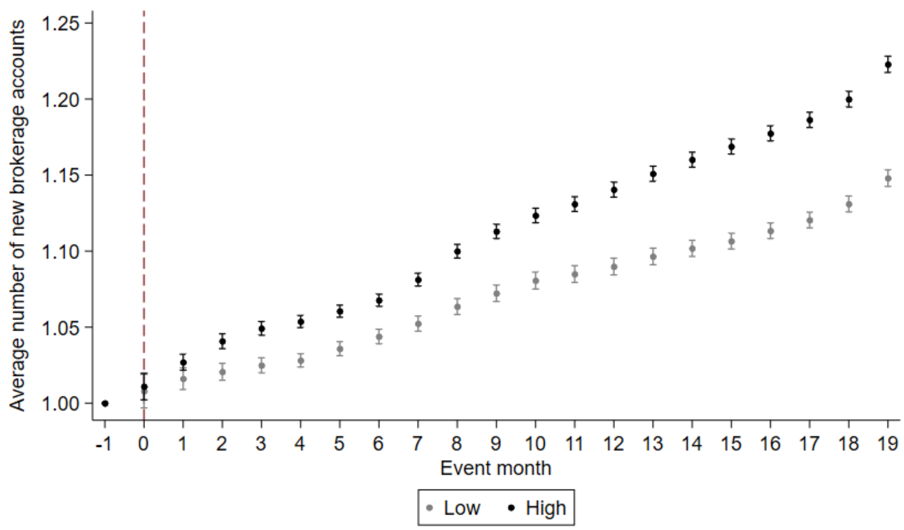
| | (1) Account opened | (2) Account opened | (3) Account opened |
|---|---|---|---|
| Treated | -0.013** | -0.013** | |
| | (0.005) | (0.005) | |
| Post | -0.063*** | | |
| | (0.001) | | |
| Treated × Post | 0.184*** | 0.174*** | 0.076*** |
| | (0.006) | (0.006) | (0.012) |
| Constant | 0.195*** | | |
| | (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

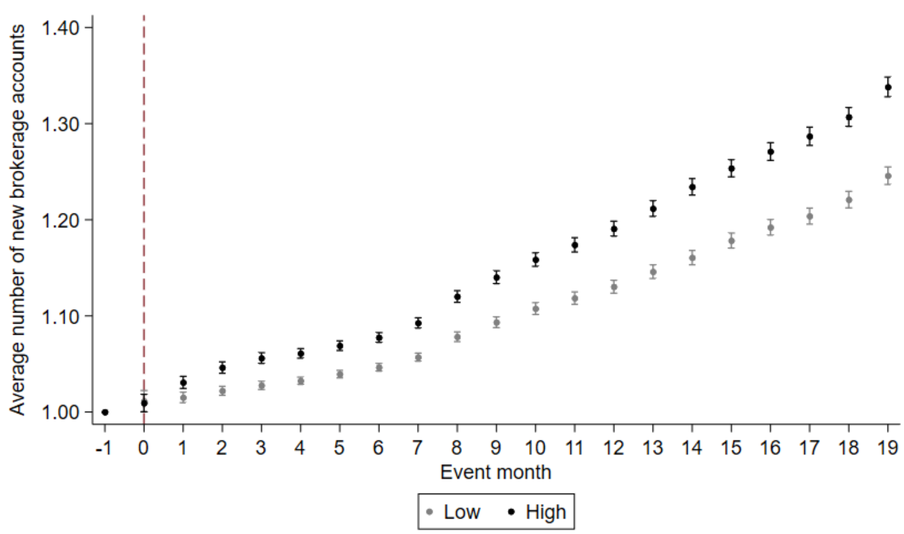
| | (1) Account opened | (2) Account opened | (3) Account opened |
|---|---|---|---|
| Treated | 0.027*** | 0.026*** | |
| | (0.007) | (0.007) | |
| Post | 0.156*** | | |
| | (0.001) | | |
| Treated × Post | -0.430*** | -0.414*** | -0.188*** |
| | (0.007) | (0.007) | (0.015) |
| Constant | 0.480*** | | |
| | (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.



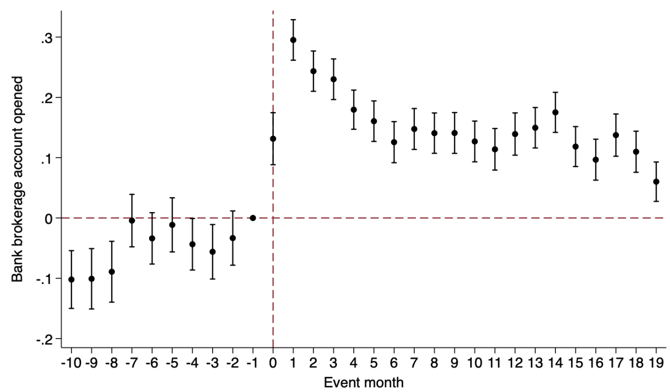

**a** All individuals.



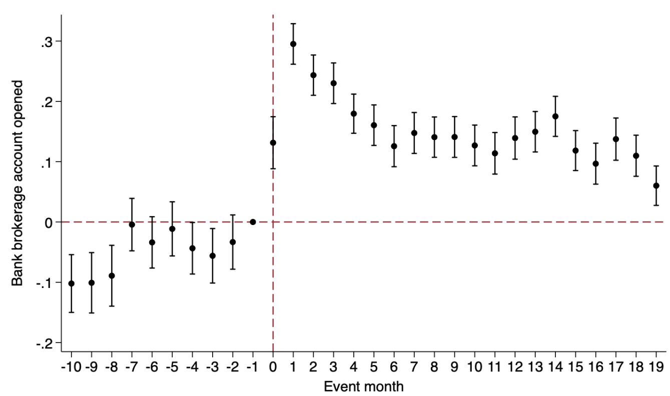

**b** Individuals with buy transaction post-Karvy.

**Figure A-2.** Bank brokerage accounts opened: New entrants as control

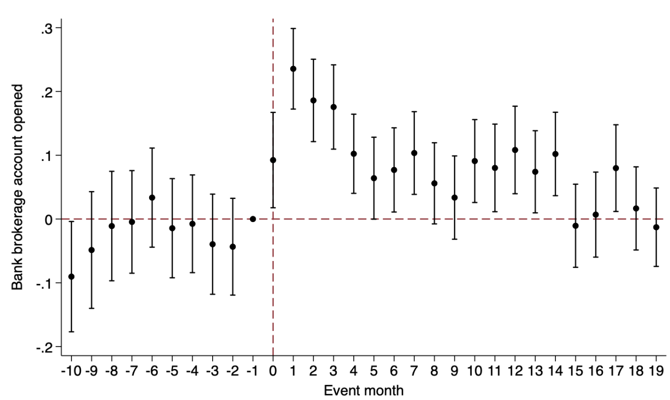
This figure shows the effects of Karvy on opened bank-affiliated brokerage accounts around Karvy. It displays DiD coefficients estimated by event time with 95% confidence intervals. The dependent variable is a dummy with a value of one if the broker is a bank. The unit of analysis is at the individual-broker 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 1 in Panel A includes no FE. Model 2 in Panel B includes the month-of-account-opening FE. Model 3 additionally includes individual FE. Standard errors are clustered by individual.




**a** Model 1.



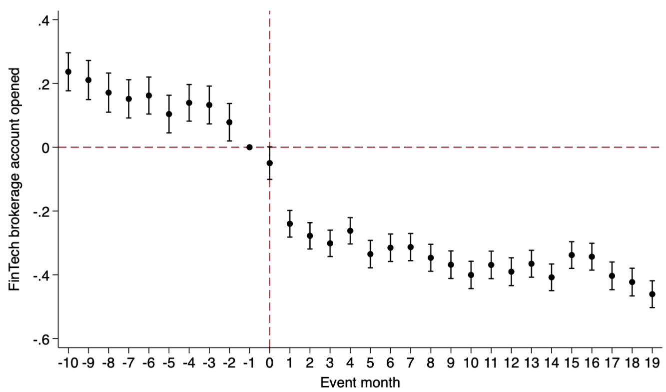

**b** Model 2.



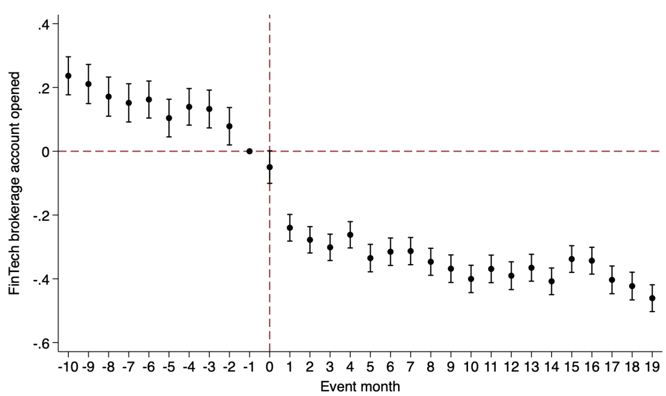

**c** Model 3.

**Figure A-3.** FinTech brokerage accounts opened: New entrants as control

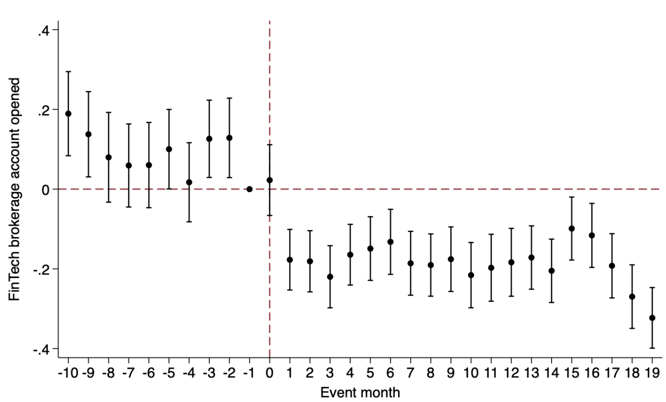
This figure shows the effects of Karvy on opened FinTech brokerage accounts around Karvy. It displays DiD coefficients estimated by event time with 95% confidence intervals. The dependent variable is a dummy with a value of one if the broker is a FinTech. The unit of analysis is at the individual-broker 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 1 in Panel A includes no FE. Model 2 in Panel B includes the month-of-account-opening FE. Model 3 additionally includes individual FE. Standard errors are clustered by individual.




**a** Model 1.




**b** Model 2.




**c** Model 3.

## 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.