Divine Catalysts: Religion and Portfolio Choices*

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Abstract

This paper examines how religious framing influences equity investment and portfolio diversification. To do so, we exploit religiously-framed trading sessions held during a major festival emphasizing new beginnings and long-term prosperity as a cue. Individuals whose religion is associated with the festival invest significantly more during these sessions and buy new stocks, while others do not respond. We rule out alternative explanations including gambling motives and sentiment effects. Consistent with the emphasis on long-term prosperity, these new positions are held longer than other portfolio holdings. Consequently, they lead to persistent increases in equity portfolio size and mechanically increase diversification, without reducing risk-adjusted returns. Our findings highlight that religious framing can nudge individuals towards long-term investments, with implications for wealth accumulation.

Keywords: Investment behavior, portfolio choice, household finance, retail trading activity, religion.

JEL Classification: G11, G50, Z12.

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1 Introduction

A widely documented pattern in household finance is that individuals underinvest in equities and hold poorly diversified portfolios (Badarinza et al., 2016). These behaviors play a key role in long-term wealth accumulation and, by extension, wealth inequality (Bach et al., 2020; Campbell et al., 2019). Traditional rational explanations emphasize information frictions, participation costs, and related constraints (Gomes et al., 2021; Campbell and Ramadorai, 2025). At the same time, another strand of work highlights the role of salience and framing in influencing investment decisions (Barber and Odean, 2008; Bordalo et al., 2013; Gennaioli et al., 2015; Hirshleifer, 2015; Bordalo et al., 2020). Yet, the role of religion in shaping equity participation and portfolio diversification remains poorly understood. This gap is surprising as religion is among the most deeply rooted systems of ideas influencing human behavior (Weber, 1905; Pope, 2024; Barro et al., 2025). Moreover, religious narratives often emphasize patience and long-term prosperity—motifs that plausibly affect financial decision-making (Guiso et al., 2003; Kumar et al., 2011; Renneboog and Spaenjers, 2012; Iyer, 2016).[1]

This paper studies whether religious framing influences investment in equity markets and portfolio diversification. We exploit a setting in which financial markets explicitly invoke a major religious festival emphasizing new beginnings and long-term prosperity to study how a religious cue can shift individual portfolio choices. Our empirical analysis leverages detailed account-level data from a large brokerage firm, which allow us to infer religious affiliation from last names with high accuracy and link this to investor's portfolio holdings and trading activity in equity markets. Using these data, we compare how the *same* individual adjust their portfolios on event days—when markets adopt an explicit religious framing—relative to non-event days, and contrast this shift between investors whose religion is associated with the festival and those for whom it is not. This within-individual design holds fixed all time-invariant characteristics and isolates trades driven by the religious cue from other individual characteristics correlated with religion that might affect trading behavior.[2]

[1] We acknowledge that disentangling religion from culture is inherently challenging, as religion is deeply embedded in local norms and traditions (Becker, 1996; Campante and Yanagizawa-Drott, 2015). Anthropological and sociological research emphasizes that religious worldviews are shaped by broader cultural contexts, making the separation of religion from culture challenging (Ver Beek, 2000), especially in economic domains, where religious events are often accompanied by financial behaviors (e.g., spending) tied to both cultural and religious practices (Montero and Yang, 2022).

[2] Potential characteristics correlated with religion include, for example, financial literacy and education (Cole et al., 2014), cognitive ability (Grinblatt et al., 2011), and political ideology (Kaustia et al., 2016; Meeuwis et al., 2022; Ke, 2024).

To provide intuition and guide our analysis, we embed cue theory into a standard intertemporal portfolio-choice framework (Laibson, 2001). In this setting, the religiously-framed trading session acts as a cue that raises the marginal utility of investing for some individuals, because it is symbolically linked to new beginnings and long-term prosperity. The cue temporarily raises the value of increasing equity positions. Although the cue itself is transitory, adjustment frictions make it costly to unwind these positions immediately, so the trades initiated on the event day can produce persistent changes in portfolio composition. We then examine trading sessions on a major festival emphasizing new beginnings and long-term prosperity. Consistent with the framework, we find that individuals whose religion is associated with the festival participate more actively and invest substantially larger amounts in the stock market on the event days relative to other days, while others do not respond. These individuals buy new stocks rather than increasing existing holdings, and hold onto these event-purchased stocks longer, leading to a persistent increase in the size of their equity account. These purchases mechanically increase portfolio diversification and do not lower risk-adjusted returns relative to a Capital Asset Pricing Model (CAPM)-implied optimally diversified portfolio.

Our empirical analysis leverages detailed data from a major national brokerage firm in India, covering all new account openings and clients' stock transactions linked to checking and savings accounts, between 2012 and 2019. The sample includes clients with above average income in the population and the account sizes are comparable to those studied in Campbell et al. (2019). Unlike prior studies that rely primarily on geographic variation in religious group concentrations, our data allow us to infer religious affiliation at the individual level using last names—a strong predictor of religion (Banerjee et al., 2013; Iyer, 2016; D'Acunto et al., 2024). In our data, over 92% of surname and state combinations can be assigned uniquely to one religion making the classification procedure highly accurate. To the best of our knowledge, we are the first to use such an approach to identify the religious affiliation of individual investors and to track their stock market activity and portfolio composition.

To identify religious-cue-driven investments, we exploit a stock market trading session—"Muhurat trading" (hereafter the *event*) held annually during a major religious festival—widely advertised and predominantly attended by retail investors. Specifically, this session is held during Diwali (the *festival*), known as the "Festival of Lights" and rooted in beliefs about new beginnings and long-term prosperity, which is celebrated by over a billion people worldwide and in Hindu tradition seen as an auspicious time for financial investments.[3] The recurring and predictable nature of the session, combined with its association with new beginnings and long-term prosperity, provides a near-ideal setting to isolate trades driven by religious cues and examine implications for individual portfolios.[4]

Our within-individual empirical design compares changes in investments for individuals likely influenced by the religious cue (the "treated" group, i.e., Hindus) with those of individuals from other religions (the "control" group), who are unlikely to be affected. Since the trading session is predictable and accessible to all investors regardless of their religion, the presence of a control group helps address the possibility that changes in trading activity could be driven by factors unrelated to the religious framing, such as liquidity effects arising from the market being open on a holiday. To further account for unobserved, time-varying local factors, we incorporate high-dimensional geography-by-date fixed effects. The combination of a control group, as well as individual and high-dimensional fixed effects, allows us to cleanly isolate religious-cue-driven trades and their impact on portfolios.

In the first part of the paper, we examine how investors' trading decisions on the event day compare to other days. We find that treated individuals are significantly more active in the stock market on the event day compared to individuals from other religious groups. Specifically, treated individuals are approximately 1.2 percentage points more likely to trade on the event day—a 15% increase relative to the sample mean—compared to other days and relative to control individuals from the same region. Additionally, we find that they trade significantly larger amounts, with transaction amounts increasing by 17% on the event day.[5]

In subsequent analysis, we find that the treated individuals are more likely to buy rather than sell, with a 20% increase in the likelihood of purchasing stocks and no significant change in selling likelihood. In terms of transaction amounts, treated investors spend 17% more on buy trades on the event day, while the amount spent on selling remains unchanged. Importantly, these effects are even larger when restricting the sample to days when individuals trade. In other words, treated investors

[3]Diwali is one of the most widely celebrated religious observances globally (Washington Post; NPR). According to Pew Research, seven in ten Asian Americans celebrate Diwali, and the festival is marked by a reception at the White House.

[4]Aggregate trading data from the National Stock Exchange (NSE) suggests that retail investors account for 87% of trades, and display a pronounced retail buy-side imbalance, which is met with abnormal sell-side imbalance by foreign entities. Moreover, we examine retail buy-side imbalance around secular and other religious events, including other Hindu-related festivals, public holidays and earnings announcements. Consistently, no comparable imbalance emerges, highlighting the unique influence of the event (see Da et al., 2015; Edmans et al., 2007, for events affecting retail investors' participation).

[5]We show that these results are robust to dropping one-event at a time from our estimation sample.

buy substantially larger amounts on the event day compared to their own buying activity on other trading days, relative to control individuals. This finding suggests that event-day trades are not merely symbolic or "token" transactions involving negligible amounts for the individuals in our sample.

We rule out wealth effects as a potential explanation for these findings.[6] Treated investors may experience a temporary rise in disposable income around the festival, driven by cultural traditions such as gift-giving and bonuses, which could influence equity investments. To assess this possibility, we analyze data from individuals' checking and savings accounts and find no significant changes in gross or net wealth around the event.[7]

In the second part of the paper, we then present several tests that validate the interpretation of the observed trading patterns as responses to the religious cue associated with the event. First, we show that treated individuals are *less* likely to trade—buy and sell—on other major religious days when financial markets do not explicitly invoke the festival or its associated emphasis on long-term prosperity, while control group investors exhibit no changes in trading activity around their respective religious events. This absence of trading activity on other religious days highlights that our results are not driven by sentiment effects, but are specific to the event's unique framing.

Second, we examine whether trading patterns on the event day align with the festival's emphasis on new beginnings and long-term prosperity. Specifically, we find that the increased buying activity is concentrated in new stocks rather than increasing positions in existing holdings. Treated individuals are 0.8 percentage points—30% relative to the sample mean—more likely to exclusively purchase new stocks that were not previously in their portfolios on the event day, while their likelihood of simply purchasing additional shares of their existing holdings remains unchanged. Further, we analyze the characteristics of stocks purchased by treated investors on event days relative to other days, and find that their stock selection does not reflect speculative or gambling behavior. Instead, on event days, treated individuals are *more* likely to buy stocks of well-established firms characterized by high market capitalization, firm age, and past-year performance, while there is no change in their tendency to buy stocks with lottery-like features such as skewness. Notably, treated individuals are *less* likely to buy

[6]See, for instance, Andersen and Nielsen (2011) on the effect of wealth on stock market participation.

[7]Additionally, while we observe a slight increase in ATM withdrawals (outflows) prior to the event, there are no significant differences in credit card transactions, suggesting that changes in liquidity are unlikely to be driving our results. However, a key limitation of this analysis is that we do not observe off-account physical cash and gold holdings.

stocks with high volatility and in addition, if anything, they are more likely to buy higher-share price stocks, as opposed to lower-share price "penny" stocks. Moreover, we show that they do not exhibit a higher likelihood of trading on event-day in the options market.

An intuitive implication of the festival's emphasis on long-term prosperity is that treated investors should hold onto stocks purchased on event days for an extended period. Therefore, we examine the likelihood of liquidation and the holding duration of event-purchased stocks. We estimate regressions of selling likelihood on a dummy variable indicating whether a stock was purchased on the event day, incorporating individual-date and stock-date fixed effects. Our analysis also controls for key determinants of selling behavior, in particular whether the stock is trading at a gain relative to its purchase price (see Odean, 1998; Ben-David and Hirshleifer, 2012).

We find that treated investors are significantly less likely to sell stocks purchased on the event day. On any given day, they are 10% less likely to sell an event-purchased stock, after accounting for time-varying individual and stock characteristics. When restricting the analysis to days when individuals sell at least one stock, treated investors are 30% less likely to sell an event-purchased stock, reinforcing the notion of longer holding horizons. Moreover, treated investors do not exhibit a stronger disposition effect for stocks purchased on the event, suggesting that, if anything, they are less prone to selling event-purchased stocks that are trading at a paper gain. In summary, our results on stock characteristics and holding period are inconsistent with gambling motives.

In further tests, we exploit heterogeneity in the intensity of the religious cue across individuals in two ways. First, across individuals in regions where the event is more or less salient, as proxied by Google Search Volume Index: greater salience is associated with a larger likelihood of trading and larger amounts on event days, whereas we do not observe any effects on other days. Second, we exploit variations across individuals in event-purchased stock returns. We find that participation in event-day trading is itself persistent: treated individuals are more likely to trade again on the event day in subsequent years when the stocks they purchased during the previous year's event had higher returns in the interim. These patterns reinforce the interpretation of the event as a religiously-framed cue where individuals are more likely to participate if the intensity of the cue is larger.

In the last part of the paper, we assess whether trading on the event day leads to persistent changes in the portfolios of treated individuals. Specifically, we investigate whether those who actively participate by purchasing stocks on the event day experience lasting effects on their equity account size, portfolio diversification, and risk-adjusted return, compared to non-participants. To capture these dynamics, we construct stacked event windows around each event, tracking portfolio evolution over three months before and three months after each event.

Our results show that, post-event, treated individuals who purchase stocks on the event day experience a 20% increase in the size of their equity account (i.e., increased participation in the equity market), a 10% expansion in the number of stocks held, and a significant decline in portfolio concentration, as measured by the portfolio Hirschman Herfindahl Index (HHI), relative to other treated individuals who do not participate. Importantly, these effects persist beyond the event, with no evidence of reversal in the months that follow, indicating that event-induced trading has lasting effects. The additional purchases mechanically increase portfolio diversification and do not lower risk-adjusted returns relative to a CAPM-implied optimally diversified portfolio. Moreover, while we do find evidence of a price impact from these purchases when comparing the returns of stocks on event days to those on other trading days, we do not observe significant price reversal in the following days, weeks or months. Taken together, our findings suggest that the religiously-framed cues have lasting effects on individual portfolios well beyond the event itself.

Finally, a growing literature documents substantial heterogeneity in investment returns across individual investors, with important implications for wealth inequality. Campbell et al. (2019), using Indian stock portfolio data, attribute rising return inequality to differences in diversification: larger accounts hold more diversified portfolios and earn higher risk-adjusted returns, while smaller accounts remain concentrated in a few stocks. Building on this insight, we examine whether event-driven stock purchases differ systematically by investor income and wealth. We find that event-driven purchases represent a significantly larger financial commitment for lower-income and smaller-account investors. These investors allocate a higher share of both income and account value to such purchases and end up with a greater portfolio share in event-purchased stocks—with these purchases contributing on average (median) to 25% (10%) increase in account size over the sample period. Taken together, our findings suggest that religiously-framed cues serve as a channel through which smaller investors engage in stock markets, increase their equity exposures, potentially mitigating return inequality for those most exposed to undiversified risk (Badarinza et al., 2019; Gomes et al., 2021).

Our results have broader implications for financial participation and inclusion. They show that religious framing can act as an economic force, shaping portfolio choices in ways that ultimately affect individuals' long-term wealth accumulation. More broadly, the evidence suggests that understanding financial participation requires attention not only to information and constraints, but also to the psychological and cultural frames through which individuals interpret investment opportunities. Relatedly, as financial institutions and policymakers seek to engage individual investors, religious cues—such as that embedded in Sharia-compliant funds, Catholic investment guidelines (e.g., the Vatican's 2022 *Mensuram Bonam*), and other faith-based financial products—could be leveraged to promote long-term investment and responsible financial decision-making.

Related Literature. First, we contribute to the household finance literature by showing that framing investments around religion can increase individuals' equity participation and portfolio diversification. One strand of the literature documents that individuals underparticipate in equity markets and hold highly undiversified portfolios (Grinblatt and Keloharju, 2001; Keloharju et al., 2012; Barberis and Huang, 2008; Badarinza et al., 2016; Campbell et al., 2019). On the other hand, existing work highlights the role of salience and framing in influencing investment decisions (Barber and Odean, 2008; Bordalo et al., 2013; Gennaioli et al., 2015; Hirshleifer, 2015). Our findings highlight that a religious cue can act as a nudge in affecting individual portfolio allocation. In doing so, our paper also contributes to the literature studying cues in the context of consumption by documenting the novel role played by religious cues in shaping equity investments (see, e.g., Laibson, 2001; Bernheim and Rangel, 2004; Bordalo et al., 2020; Allcott et al., 2022; Agarwal et al., 2025; Bordalo et al., 2025).

Second, we contribute to the literature on how religion shapes economic decision-making by isolating its impact on individual portfolio choices. While prior work documents correlations between group-level religiosity and the behavior of investors (e.g., Kumar, 2009; Shu et al., 2012), firms (e.g., Hilary and Hui, 2009; Schneider and Spalt, 2016; Jiang et al., 2018), and markets (e.g., Kumar et al., 2011), few studies directly link an individual's religion to their actual portfolio composition or returns. Existing evidence largely attributes religious effects to social interactions or communal norms (Hong et al., 2004; Renneboog and Spaenjers, 2012; Bender et al., 2022; Bazley et al., 2025) and shows that religion can shape lending and investment behavior via moral, cultural, or physiological mechanisms (e.g., Fisman et al., 2017, 2020; Demiroglu et al., 2021; D'Acunto et al., 2024). Complementing this literature, we identify a distinct channel through which religion affects financial decision-making: we exploit the unique context of religiously-framed trading sessions to cleanly isolate the effect of religious cues on portfolio allocation and long-term investment outcomes.

Finally, our findings also broadly connect to the literature on individual trading behavior and performance (see Barber and Odean, 2000, 2008; Grinblatt and Keloharju, 2000; Kaniel et al., 2008; Odean, 1998; Seru et al., 2010; Meyer and Pagel, 2022; Cookson et al., 2023).[8] One strand of this extensive literature identifies behavioral biases that shape retail investor activity (e.g., Daniel et al., 1998; Da et al., 2021; Barberis and Huang, 2008). Particularly relevant to our setting, Anagol et al. (2021), Balasubramaniam et al. (2023), Campbell et al. (2019), and Fisman et al. (2023) examine individual investor behavior in India, providing a contextual foundation for our study. Our contribution is to highlight a novel role for religion in shaping investments in this context.

2 Institutional Details

In this section, we discuss the background of the religious festival and institutional details of the associated trading session we exploit in our empirical analysis.

2.1 Religions in India

India is known for its significant religious diversity. According to the Population Census of 2011, approximately 79.8% of Indians identify as Hindu, making it the most prominent religious group in the country. Islam is the second-largest religion, with around 14.2% of the population, followed by Christianity at 2.3% and Sikhism at 1.7%. Other religious groups, including Buddhism, Jainism, and smaller indigenous faiths, together make up roughly 2% of the population.

In Online Appendix Table IAA1, we examine the importance of religion in India using the World Value Survey. According to Wave 7 of this survey, conducted between 2017 and 2022, 64% of individuals reported that religion is a "very important" part of their lives, while over 62% attend religious

[8] A related literature in household finance examines stock market participation more broadly (Haliassos and Bertaut, 1995; Campbell, 2006; Guiso and Sodini, 2012; Ke, 2024; Gomes et al., 2021).

services at least once a month, highlighting the importance of religious engagement.

2.2 Significance of Diwali

Religious festivals are prominent features of social life in India, with Diwali being one of the largest and most significant religious observances among Hindus. Diwali marks the beginning of the New Year for many communities in India. Also known as the "Festival of Lights," it symbolizes the triumph of light over darkness and good over evil. Observed by millions of individuals across India, Diwali typically spans five days with families celebrating by illuminating homes with oil lamps, exchanging sweets, and setting off fireworks. The festival carries themes of long-term prosperity and spiritual renewal.[9] Diwali traditions focus on invoking blessings for wealth and fortune, making it a significant event linked to optimism and aspirations for prosperity in the year ahead.

2.3 Muhurat Trading

Tradition. Since 1957, Indian stock exchanges have been organizing a special trading session known as "Muhurat Trading" to mark an auspicious start to the new financial year.[10] Muhurat trading takes place on the third day of Diwali, considered the most auspicious of the five days of the festival.[11] This session, rooted in cultural and religious beliefs, is open to all investors, allowing them to participate in financial markets on a day that symbolizes prosperity and long-term economic well-being.

Muhurat trading is widely advertised by stock exchanges, individual banks, and brokers in India. Alongside providing information on the date and timing of the trading session, the vast majority of advertising heavily features imagery highlighting the auspicious nature of the day.[12] Following Da et al. (2011), we use Google Search Volume Index (SVI) data as a proxy for retail investor attention and plot the online search interest for the term "Muhurat Trading" in India from 2012 to 2019 in Figure IAB4. The data show a pronounced peak in search each year precisely during the month of Diwali,

[9] Specifically, it commemorates the return of Lord Rama to his kingdom after exile, as described in Hindu epic lore.

[10] The term "Muhurat" signifies an opportune moment to start new projects or make financial decisions, and this special trading session for equities, marks the beginning of the traditional Hindu accounting year known as Samvat.

[11] The dates of Hindu festivals, including Diwali, are determined by the lunar calendar and therefore vary from year to year. Table IAE1 in the Online Appendix lists the dates and timings of trading sessions at the National Stock Exchange.

[12] See Section B of the Online Appendix for details on the advertising of Muhurat trading and examples of marketing content by the NSE and brokers for the trading session, as well as examples of newspaper articles referencing and advertising the event.

indicating that retail interest in Muhurat trading intensifies sharply only around this time.

Implementation details. Muhurat trading follows a specific structure on Diwali. The main event is the normal market session, lasting one hour, where continuous trading occurs, allowing investors to buy and sell stocks just like during regular market hours. Before the market opens to retail investors, a 15-minute block deal session takes place where large, pre-arranged trades are executed between two parties at negotiated prices. This is followed by a 15-minute pre-open session, during which traders enter orders without executing trades, helping to establish market opening prices. After the main event, there is a call auction session of 5 to 10 minutes, focused on trading illiquid securities, with prices determined by overall demand and supply. The day concludes with a 15-minute closing session, during which no new orders are accepted, but traders can square off existing positions at the closing price. Online Appendix Table IAE1 lists the dates the Muhurat trading sessions occurred in our sample covering 2012 to 2019.

Aggregate retail activity. We analyze the universe of stock trading data from the National Stock Exchange (NSE) to study aggregate retail trading activity on the event day.[13] This dataset covers the entire universe of trading records from the NSE over the period from 2012 to 2019. It provides detailed information for each transaction, including the client type such as retail, institutional, overseas corporate bodies, statutory bodies, and unknown. We collapse transactions to get a dataset of the total quantity and amount of shares bought and sold of each stock on each day by each client type. Online Appendix Table IAE2 presents summary statistics in the NSE dataset.

We then analyze the share of retail trades as well as the retail buy-side (vs. sell-side) order imbalance at the stock level on event days compared to other significant dates. Specifically, we compare average retail trading activity at the stock level during the five days preceding and following: (i) Diwali's Muhurat trading, (ii) other national Hindu religious events (excluding Diwali), (iii) non-Hindu religious events, (iv) national holidays, and (v) stock announcement dates. Online Appendix Table IAB1 provides a list of these religious events along with their cultural significance.

Online Appendix Figure IAE1 presents the results. Panel A plots the average retail buy-side im-

[13]NSE is the fifth largest stock exchange in the world by total market capitalization, exceeding $5 trillion, as of May 2024.

balance, calculated following Barber et al. (2008) as $\frac{(buy-sell)}{buy+sell}$ for the universe of retail trades on the NSE, where *buy* and *sell* represent the number of buy and sell trades, respectively. Panel B displays the share of trades accounted by retail investors. Panel A of Figure IAE1 reveals a significant retail buy-side imbalance on the event day, with no observable pre-trend or post-trend in the days preceding and following the event.[14] In contrast, Online Appendix Figure IAE2 shows no comparable spike in retail trading activity around other Hindu religious events, non-Hindu religious events, national holidays, or informative days such as stock announcement dates.

3 Conceptual Framework

To guide our empirical analysis, we embed cue theory into a simple intertemporal portfolio-choice model. Cue theory posits that environmental cues elicit temporary changes in preferences and behaviors, hence making cues and consumption complements by raising the marginal utility of consumption (Laibson, 2001; Pennesi, 2021; Apesteguia et al., 2023). When applied to our context, this framework can yield to predictions for trading and portfolio dynamics around the religiously-framed cue. In the framework, the cue generates a transient increase in the marginal utility of initiating equity purchases on event dates and induces a one-off increase in both the likelihood of buying and the average buy size concentrated on the event day itself, despite the timing being publicly known. Adjustment costs then make these event-initiated positions "sticky": once acquired, investors refrain from frequent rebalancing, implying persistence in post-event holdings.[15] The cue-based mechanism further delivers testable implications that help distinguish it from broader holiday or religiosity effects: trading should spike only on the specific event when stock markets invoke "new beginnings" and "long-term prosperity," (the cue) with null effects on other religious festivals, public holidays, or

[14] To shed light on the counterparties to this abnormal retail demand, we examine imbalances by client type. In particular, we find that overseas corporate bodies—typically foreign-incorporated investment companies—display an imbalance that turns significantly negative on the event day, suggesting that these entities accommodate the surge in retail demand.

[15] We do not take a stance on the specific nature of the cost. For example, event purchases could carry extra psychological value—anchored in the festival's auspicious framing—so giving them up feels especially regretful and could generate "realization disutility," which investors dislike (see for instance Barberis and Xiong, 2012). It could also be that investors mentally segregate event-purchases shares into a special "Diwali" account. Closing that account feels like "wasting" a cultural ritual, and raises the perceived cost of rebalancing these holdings (Thaler, 1999). At the same time, participating in Muhurat trading session could be a public/social ritual, and hence selling the event-purchased stocks may feel like reneging on a communal norm, imposing a reputational or identity cost (Akerlof and Kranton, 2000).

announcements that lack the same stock market framing. Moreover, the event-day response should be heterogeneous, concentrating in stocks for which the cue is most intense—especially new positions rather than existing holdings—and among individuals with higher cue salience, who should exhibit larger event-day spikes but no systematic differences on non-event days. Finally, the framework accommodates a reinforcement channel that implies persistence across years: investors who experience higher interim returns on event-purchased stocks should update upward the perceived potency of the cue and, as a result, be more likely to participate again in the next event's trading session, with no analogous relationship for trading on non-event days.

Overall, our conceptual framework highlights how an environmental cue—here, a religiously-framed trading session that ties participation in financial markets to new beginnings and long-term prosperity—can amplify the marginal utility from equity investing with implications for portfolio choices and wealth accumulation. In essence, the Muhurat session serves as a highly salient, attention-grabbing religious cue that draws some investors into the market, but not all. Even in the absence of new fundamental information, the religious framing and publicity surrounding the event focus investors' attention on equity investing, triggering trades that would not occur on a routine day absent the message and the cue. For a formal statement of the model, we refer to Appendix C.

4 Data and Summary Statistics

Our main empirical analysis leverages a unique dataset from a leading national brokerage firm in India, containing individual account-level trading records. This firm operates through more than 7,000 branches in all Indian states, giving our analysis a broad view of trading patterns in the country. Below, we provide details on the dataset.

4.1 Brokerage Data

Data Overview. The main dataset is a trade file, which contains detailed transaction information, including a tax identifier unique to each account, the last name and address of the account holder, the account opening date, the transaction date, the security name, and the total transaction value. Our sample covers trades from January 2012 through December 2019. Since we observe each account's opening date, we focus on accounts opened from January 2012 onward, allowing us to track the full evolution of each portfolio based on the trade data. In addition, we restrict the sample to trading accounts for which we also observe the linked checking and savings accounts, totaling 24,112 investors. This enables us to link individual trading activity from the brokerage account to the individual's savings and checking account, ATM (Automated Teller Machine) transactions, and credit card transactions within the same bank. Further, in the data we observe additional attributes of the underlying investors such as gender, age at account opening, as well as a classification of their income ranges.

Like others before us using Indian data, we focus on direct stock holdings (Campbell et al., 2014, 2019; Balasubramaniam et al., 2023).[16] For our analysis, we focus on transactions involving common stocks included in the Prowess Database, which is maintained by the Centre for Monitoring Indian Economy (CMIE) and is comparable to the CRSP database in the U.S.[17] We extract data from the latest vintage of Prowess, which is free from survivorship bias, as highlighted by Siegel and Choudhury (2012). We manually match stock name strings in the broker dataset to those in the Prowess dataset to extract stock identifiers and merge with stock prices and characteristics. This process allowed us to link over 85% of the observations from the brokerage data with the characteristics of the stocks in Prowess, covering more than 88% of the volume of transactions within our dataset.[18]

Construction of Holding Sample. We build a holding sample by following the methodology of Ben-David and Hirshleifer (2012). Specifically, we use the transaction dataset to construct a holding sample at the investor-stock-date level, where each observation represents an individual investor's holding of a particular stock on a given day. Investor-days on which an investor does not trade are included, allowing us to capture both trading and passive holding periods to accurately track portfolio composition over time. Purchases and sales are aggregated on a daily basis for each investor-stock combination. For instance, if an investor purchased a given stock on January 5, 2015, and held it until January 26, 2015, there would be 15 observations (15 business days) for that investor-stock holding duration. In some analyses, we also aggregate this holding sample at the investor-date level to examine individual behaviors and portfolio-level characteristics.

[16] Campbell et al. (2014) and Campbell et al. (2019) emphasize the very limited share held by mutual funds in India.
[17] Several prior studies have used this dataset (Bertrand et al., 2002; Gopalan et al., 2016; Naaraayanan and Nielsen, 2021).
[18] The match rate is effectively unchanged at 85% when we consider name changes of stocks.

Inferring Investors' Religion. A unique feature of our brokerage dataset is its inclusion of the account holder's last name, which we use to infer the individual's religion, similar to D'Acunto et al. (2024) and Bhagavatula et al. (2019). Specifically, we create a mapping of last names from our broker dataset into distinct religious groups by leveraging the fact that last names in India are strong indicators of religion, and that marriages in India, are overwhelmingly intra-religious. We utilize data from the largest matrimonial website, which provides the first and last names of nearly six million users. This registry dataset includes self-reported demographic information that includes names and surnames, date of marriage, state of birth, city of residence, and religion.

Given that the relationship between last name and religion is not always one-to-one, we assign probabilities indicating the likelihood that a particular last name corresponds to each religion within a specific state. The method yields a high degree of precision: on average, each unique state–surname combination is associated with only 1.09 religions, and in over 92% of cases, the assignment is made with 100% certainty. In addition, the uniqueness probability *across* religions is also similar, over 97% for all, so the risk of systematically matching some religions better or worse than others is low. This reflects the strong within-group concentration of religion in naming patterns. We provide details on the methodology, its accuracy and the religion split in our sample in Online Appendix A.

We match approximately 97% of individuals in our broker dataset to a religion, and focus our analysis on the five main religious groups: Hindu, Jain, Muslim, Sikh, and Christian. Individuals we are unable to match are excluded from the final analysis. To the best of our knowledge, we are the first to be able to link the religion of individuals to their stock market transactions.

4.2 Summary Statistics

Table 1 provides summary statistics for our brokerage dataset. Panel A details account-level demographics at the time of opening the account, indicating an average age of 43 years, with 73% of account holders being male and 90% being treated individuals. The median annual income is ₹300,000—where the values correspond to the midpoint of the income ranges provided by the brokerage firm. According to Bharti et al. (2024), the median (real) income observed in our sample is above the population average, with most of our sample lying between the 50th and 90th percentiles, and the largest belonging to the top 10% of the income distribution.

Panels B and C present statistics at the account-date level. Panel B shows that the average total portfolio value (size of the equity account) is around ₹1,070,000 (approximately $17,000) while the median is ₹185,000 ($3,000).[19] Panel B shows that 8% of account-day observations correspond to trading days, with 6% for buy and 3% for sell transactions. The trade-conditioned sample (Panel A of Online Appendix Table IAE3) shows a larger likelihood of buying (76%) compared to selling (36%) on active trading days, and an average buy amount (₹123,000, i.e., approximately $1,900) larger than the average sell amount (₹85,000, i.e., approximately $1,300).

Panel C provides account-stock-date level statistics for treated individuals, with Panel B of Online Appendix Table IAE3 focusing on sale-conditioned days (days with at least one sale in the individual portfolio). Panel C reveals that the frequency of trades at the account-stock-date level is 3% and that the average stock holding observation corresponds to 147 days. The sale-conditioned sample (Panel B) shows that individuals trade 15% of their holdings on these days.

5 Trading around the Event

We examine changes in the trading activity among treated and control individuals around the event, to test whether individuals change their investment behaviors when faced with the religious cue. To do so, we estimate panel regressions at the individual-date level including both trading and non-trading observations. Our regression specification is as follows:

$$Y_{i,t} = \beta \cdot Event_t \times Treated_i + \gamma_i + \delta_t + \epsilon_{i,t}, \tag{1}$$

where the observations are at the account (i) and date (t) levels. The variable $Event_t$ is a dummy equal to 1 if date t corresponds to the event day, and $Treated_i$ is a dummy indicating whether the individual holding the account i is inferred to be Hindu. γ_i and δ_t are individual and date fixed effects respectively. Standard errors are double-clustered at the individual and date levels.

The dependent variable $Y_{i,t}$ is either a dummy variable indicating whether the individual trades, buys or sells on date t, or a continuous variable defined as the inverse hyperbolic sine (arcsinh) of

[19]Over our sample window from 2012 to 2019, the average exchange rate is ₹64 to 1 USD.

the amount spent on trading, buying or selling on date t. We use the arcsinh transform to account for zeros, i.e., days when individuals do not trade.

To study the trading dynamics around the event, we estimate the following specification:

$$Y_{i,t} = \sum_{k=-5}^{5} \beta_k \cdot \{Day(k)_t \times Treated_i\} + \alpha_i + \delta_t + \epsilon_{i,t}, \tag{2}$$

where $Day(k)_t$ are dummy variables equal to one if date t correspond to k days before/after the event day (with $k \in \{-5, -4, ..., 0, ..., 4, 5\}$). Standard errors are double-clustered at the individual and date levels. The coefficients β_k in Equation (2) capture the differential effect for treated individuals on day k before/after the event relative to the baseline period outside the [-5, +5] window, compared to control individuals.

5.1 Trading

Likelihood to trade. Panel A of Table 2 presents results from estimating Equation (1), when the dependent variable is a dummy equal to 100 if the individual trades on that date, and 0 otherwise. Column (1) only includes religion fixed effects. Column (2) and remaining columns include individual fixed effects. Column (3) further include date fixed effects. In Columns (4) and (5), we include state $\times$ date fixed effects and district $\times$ date respectively.[20]

The coefficient on $Event\ Day$, which can be estimated in specifications without date fixed effects (Columns (1) to (2)) is statistically insignificant, suggesting no change in trading likelihood for control individuals on the event compared to other days. However, the coefficient on the interaction term $Event\ Day \times Treated$ is positive and statistically significant across all specifications, indicating that treated individuals are significantly more likely to trade on event days compared to other dates, relative to control individuals.[21] The coefficient ranges from 1.1 to 1.28. In the most stringent specification, i.e., Column (5), we find that treated investors are 1.21 percentage point (p.p.) more likely to trade

[20] State and district refers to the individual's registered address in India. A district, also known as revenue district, is an administrative division of an Indian state or territory. It is based on a PIN code, or Postal Index Number, which is a six-digit code used by India Post to uniquely identify and facilitate the sorting of mail in different geographic regions.

[21] In Appendix Section D, we show that treated individuals are more likely to open a brokerage account around the festival and tend to open an account with the intention of trading on the festival for the first time.

on event days— 15% relative to the dependent variable's sample mean.[22]

Amount traded. Panel B of Table 2 presents the estimation results of regression Equation (1), when the dependent variable is the inverse hyperbolic sine (arcsinh) of the amount traded. The results are consistent with the previous findings on trading likelihood. The coefficient on $Event\ Day$ is insignificant (Columns (1) and (2)), while the coefficient on the interaction term $Event\ Day \times Treated$ is positive and statistically significant across all specifications. The coefficients ranges from 0.15 to 0.16, with the most stringent specification (Column (5)) indicating that treated individuals trade about 17% larger amounts on event days.

Panel A of Figure 1 presents the estimated coefficients (β_k) and their corresponding 95% confidence intervals from Equation (2) where the dependent variable is the arcsinh of the amount traded, showing the dynamics of changes in traded amount around the event. We do not observe differences in the evolution of traded amounts between treated and control in the days leading up to the event (Day -5 to Day -1). Strikingly, on the event day we observe a clear spike in the amount traded for treated individuals relative to controls, while post-event (Day +1 to Day +5), the evolution of traded amounts does not exhibit any difference between treated and control. These patterns provide confidence that the differential increase in trading activity among treated individuals is driven by the event's religious cue, especially given that all event days are known in advance and participation in the trading session is open to all investors, regardless of religion.

5.2 Buying and Selling

Likelihood to buy and sell. Panel A of Table 3 presents the estimation results of regression Equation (1), where the dependent variable is equal to 100 if the individual buys (Columns (1)-(3)) or sells (Columns (4)-(6)) on that day, and 0 otherwise. All columns include individual fixed effects. Columns (1) and (3) include date fixed effects, Columns (2) and (5) further include state $\times$ date fixed effects, and Columns (3) and (6) include district $\times$ date fixed effects.

The coefficient on $Event\ Day \times Treated$ is positive and statistically significant in Columns (1),

[22] We also investigate the characteristics of treated individuals who trade on the event day in Online Appendix Table IAE4. Investor characteristics such as gender, age and income are uncorrelated with the likelihood to trade on the event among treated individuals, and whether they buy or sell.

(2) and (3), indicating that treated individuals are significantly more likely to buy stocks on event days compared to control individuals. The coefficient ranges from 1.18 to 1.29, suggesting an increase in buying activity of about 20% relative to the sample mean of 6.22. By contrast, the coefficients on $Event\ Day \times Treated$ in the sell specifications (Columns (4), (5) and (6)) are not statistically significant, implying that treated individuals are not more likely to sell stocks on the festival compared to controls. Overall, these results suggest that trading is concentrated on buying rather than selling.

Amount spent on buy and sell trades. Panel B of Table 3 presents the results of regressions where the dependent variable is the arcsinh of the amount spent on buy and sell trades. Consistent with the results in Panel A, the coefficient on $Event\ Day \times Treated$ is positive and statistically significant in the buy specifications (Columns (1), (2) and (3)), indicating that treated individuals spend significantly more on buy trades on the event day relative to other days, compared to control individuals. The coefficients are around 0.16, suggesting an increase of about 17% in the amount spent on buying relative to other days. In contrast, coefficients on $Event\ Day \times Treated$ in the sell specifications (Columns (4), (5) and (6)) are not statistically significant, suggesting no meaningful difference in changes in the amount spent on sell trades.

Importantly, these results hold even when restricting the sample to days on which individuals actively trade. In Online Appendix Table IAE5, we show that when considering only observations with non-zero trading activity, treated individuals spend at least 40% more on buy trades on the event day compared to other days on which they trade, relative to control individuals. In other words, treated investors engage in significantly larger trades on the event than on their other trading days, distinguishing their behavior from that of control individuals. The large magnitude suggests that buying behaviors on the event day are not merely "token" transactions involving negligible amounts.

Panel B of Figure 1 presents the estimated coefficients β_k in Equation (2), where the dependent variable is the arcsinh of the amount spent on buy trades (green) and sell trades (orange). The coefficient on the interaction term $Event\ Day \times Treated$ is positive and statistically significant for buy trades, indicating a clear spike in buying activity for treated individuals on the event day. In contrast, coefficients for sell trades are not statistically significant, confirming no notable change in selling behavior, consistent with the results in Table 3. As before, we find consistent patterns of a clear spike in buying but not selling on event days with no differential changes pre- and post-event, providing further evidence that these patterns are indeed attributable to religious motives.

Robustness. In Appendix D.3, we present additional robustness analyses that complement our baseline estimations. Specifically, we assess the sensitivity of the results to influential shocks by sequentially excluding one event at a time from the estimation sample. This leave-one-out exercise ensures that our findings are not driven by any single trading session or idiosyncratic episode.

5.3 Ruling out Wealth Effects

An alternative channel for our results is that treated investors may experience a temporary increase in wealth around the event, which could influence their investment decisions. Specifically, the festival is often associated with gifts and bonuses and perhaps such a change in liquidity and/or disposable income might lead them to be more willing to invest in equities.[23] Additionally, with greater perceived or actual wealth, they may be more inclined to hold onto investments for the long term. We attempt to directly mitigate concerns about wealth effects by leveraging our unique data linked to individual activity within the bank across their savings and checking accounts, and credit cards.

Specifically, we examine changes in daily balance across different accounts, ATM and credit card transactions for individuals around the events. We estimate Equation (2) and plots the coefficients (β_k) and their corresponding 95% confidence intervals on each day around the event in Online Appendix Figures IAE3, IAE4 and IAE5. We do not observe economically meaningful change in the amount of cash inflows and outflows, ATM withdrawal, or credit card transactions.[24]

A caveat of this analysis is that we do not have data on individuals' physical, off-account cash and commodity holdings. During the festival, it is common to receive, purchase, or exchange gold, considered as auspicious and associated with prosperity, which may lead to observable changes in

[23]Note that such argument(s) apply to religious festivals in general and should result in similar patterns of equity investments around religious events of similar cultural significance, unless the behavior is influenced by the messaging conveyed by the specific event. As we document in Section 6, we do not find evidence of changes in investment decisions around other religious events, thereby making general wealth effects an unlikely explanation for our results.

[24]Online Appendix Figure IAE4 shows that the likelihood to withdraw money jumps by 0.4% the day before the event for treated individuals. In Panel B, we find that the amount withdrawn jumps by less than 5%, which is substantially smaller than the 30% in the amount traded. In terms of magnitude, conditional on withdrawing, the median (average) withdrawn amount is ₹3,500 (7,141). In contrast, conditional on trading, the median (average) trading amount is ₹56,000 (207,000).

wealth not captured in our data.[25] While our empirical tests alleviate general concerns about wealth effects driving the results, our data do not permit a direct test of this specific channel. However, the tests in Section 6 help rule out this alternative explanation by examining trading behaviors on other religious event days and the types of stocks purchased by treated individuals on event days.

6 Isolating the Role of Religious Cues

In this section, we present several tests that validate the interpretation of the observed trading patterns as responses to the religious cue associated with the event. First, we test whether individuals trading behaviors differ on other religious event days that are not associated with a stock market session invoking a religious cue and the themes about wealth and long-term prosperity, for both the treated and control groups. Second, we characterize whether the trading activity on the event-days is aligned with the festival's emphasis on new beginnings and long-term prosperity.

6.1 Trading on Other Religious Events

We examine trading by investors on (i) other religious events of similar significance that lack the associated cue and themes and (ii) religious events of similar significance for the control religious groups. We follow Iyer (2018) to generate a list of religious events for the treated and control groups. They conducted a survey of 568 religious organizations in India and classify their largest religious gatherings which are festivals. These gatherings range from fewer than 1,000 to more than 500,000 devotees. We then hand-collect information on these events. Online Appendix Section A presents the list of events and their cultural significance. We estimate the following regression specification:

$$\begin{aligned} Y_{i,t} = \beta \cdot\ & Treated_i \times \{Other\ Hindu\ Event\}_t \\ & + \kappa \cdot\ Affected\,Control_i \times \{Non-Hindu\ Event\}_t + \gamma_i + \delta_t + \epsilon_{i,t}, \end{aligned} \tag{3}$$

[25] While it is clear that receiving or exchanging gold likely increases wealth and subsequent equity investments, the impact of gold *purchases* is more nuanced. Investors may perceive holding large quantities of gold (a traditional store of value) as having a higher opportunity cost, or have different return expectations on gold, compared to stocks. Consequently, they may reallocate their wealth into equities during the event, driven by the perception of better returns in stocks over gold. In theory, this shift could contribute to the observed increase in equity investment.

where the observations are at the account (i) and date (t) levels. The variable $\{Other\ Hindu\ Event\}_t$ is a dummy equal to 1 if date t corresponds to other Hindu religious events of similar significance (excluding Diwali) and $\{Non-Hindu\ Event\}_t$ is a dummy equal to 1 if date t corresponds to non-Hindu religious events of similar significance. $Treated_i$ is a dummy indicating whether individual i is inferred to be Hindu while $Affected\ Control_i$ is a dummy equal to one if individual i is affected by the non-Hindu religious event according to her inferred religion. γ_i and δ_t are individual and date fixed effects respectively. Standard errors are double-clustered at the individual and date levels.

The dependent variables $Y_{i,t}$ are either a dummy variable equal to 1 if the individual trades, buys or sells on date t, or a continuous variable defined as the inverse hyperbolic sine (arcsinh) of the amount spent on trading, buying or selling on date t. Importantly, for both types of dependent variable we include non-trading days in our sample.[26]

Online Appendix Table IAE7 presents the results. Compared to our baseline results, in Columns (1), (3), and (5), if anything, we see that individuals from the treated groups are less likely to trade—buy or sell, on other days of similar religious significance. In the second set of tests, in Columns (2), (4), and (6), we identify religious events of similar significance for the control group and find no effect. The benefit of this empirical specification is that it allows us to contrast the effects for individuals across religious groups, holding fixed the religion-specific cue of the events.

To examine the dynamics of trading activity around other religious events, we estimate event-study specification similar to Equation (2), replacing the Muhurat trading event with other religious events and where treated refers to individuals affected by their respective religious events. Figure 2 shows that, in contrast to our main findings, both treated and control investors are no more likely to trade—buy or sell—on their respective religious event-days.

6.2 Buying Behaviors: New vs. Existing Holdings

Next, we link buying behaviors to religious-cue-driven motives. Given the festival's emphasis on new beginnings and long-term prosperity, we examine buying behaviors with a focus on whether investors are more inclined to purchase new stocks—holdings not already in their portfolios— or whether they

[26] We exclude the festival itself from the set of events in the analyses. For events where the day of the event coincides with the closing of the stock market, we redefine the day of the event as the first day after the event the stock markets are open.

add additional shares to their existing holdings.

Panel A of Table 4 presents the estimation results of regression Equation (1), where the dependent variable is equal to 100 if the individual buys only new stocks (Columns (1)-(3)), only existing holdings (Columns (4)-(6)), or both (Columns (7)-(9)) on that day, and 0 otherwise. We find that treated investors tend to exclusively purchase new stocks, while they do not exclusively increase their holdings of existing stocks in their portfolio.

The estimates indicate that the interaction term *Event Day* $\times$ *Treated* is positive and statistically significant across Columns (1) to (3) for new holdings. These coefficients range from 0.76 to 0.84, representing more than 30% of the dependent variable's sample mean (2.38). Conversely, the coefficients for existing holdings in Columns (4) to (6) are statistically insignificant, indicating no significant change in the likelihood of simply purchasing additional shares of stocks already held. For individuals buying both new and existing holdings, in Columns (7) to (9), the interaction term is also positive and significant, although the effect size is smaller than for purely new holdings, suggesting that they predominantly focus on acquiring new stocks. Panel B examines the amount spent on buying trades and reinforces the findings in Panel A, suggesting that the increased spending by treated investors on the event day is primarily directed toward new acquisitions rather than augmenting existing positions. Overall, these patterns align with the religious cue around new beginnings and long-term prosperity influencing treated investors to expand their portfolios with new stocks.

6.3 Characteristics of Stocks Purchased on the Event

We next analyze the characteristics of stocks purchased by treated individuals on the event day. The goal of this exercise is two-fold. First, we aim to investigate whether the characteristics of the purchased stocks align with the cue associated with the festival. Second, it aims to shed light on whether treated individuals perceive the event as an opportunity for gambling and speculation.

Stock Characteristics. We construct an individual-date level dataset, restricted to days when an individual buys at least one stock ("buy-days"). For each treated investor on a buy-day, we compute the average percentile rank of the purchased stocks across a set of characteristics. Specifically, for each stock characteristic, we rank all listed stocks cross-sectionally on that day and compute the average percentile rank of the stocks purchased by individual i on date t. We estimate the following regression:

$$CharacteristicPercentile_{i,t} = \beta \cdot Event_t + \gamma_{i \times Year(t)} + \epsilon_{i,t}, \tag{4}$$

where $CharacteristicPercentile_{i,t}$ is the average percentile rank of the stocks purchased by individual i on date t, based on a given characteristic. The independent variable, $Event_t$, is a dummy equal to 1 if date t is an event day. The regression includes individual-year fixed effects ($\gamma_{i \times Year(t)}$) to control for time-varying individual-level preferences, allowing us to isolate changes in stock selection specific to the event day. Therefore, β in equation (4) captures whether treated individuals are more or less likely to buy stocks with certain characteristics on the event day, relative to the characteristics of the stocks they purchase on other days within the same year.[27] Standard errors are double-clustered at the individual and stock levels.

Figure 3 presents the estimated coefficients β from equation (4), along with 95% confidence intervals, across a range of stock characteristics. Panel A reports estimates for the following firm-level attributes: market capitalization, book-to-market ratio, firm age, past-year return, and past-year volatility. Market capitalization is measured as of the day prior to the transaction ($t - 1$). Book-to-market ratios are based on the most recently available book value from the previous fiscal year. Firm age is defined as the number of years since the stock's initial listing on either the NSE or BSE. Return and volatility are computed using daily returns over the year preceding day t. Summary statistics for stock-date level characteristics are provided in Online Appendix Table IAE8.

Treated individuals are significantly more likely to purchase stocks with higher market capitalization, with the estimated coefficient corresponding to approximately a 2.5 higher percentile rank. The second coefficient reveals a preference for growth stocks, as treated investors are more inclined to buy stocks with lower book-to-market ratios (coefficient of -1.4). Panel A also shows a clear tendency to purchase "older" firms, with a coefficient of 2.2, and a preference for stocks with stronger recent performance, reflected in a past-year return coefficient of 3.0. Finally, treated investors are significantly less likely to purchase stocks with high volatility (coefficient of -4.6).[28]

[27]In Online Appendix D.4, we examine the characteristics of the stocks purchased by treated individuals on event days, without comparing them to purchases made on non-event days.

[28]In Online Appendix Figure IAE6, we extend the analysis to include additional stock characteristics motivated by Balasubramaniam et al. (2023), who document their influence on stock holding behavior in India. The results indicate that

Lottery-like Characteristics. Next, we investigate whether treated individuals perceive the event as an opportunity for gambling-like behavior by examining their preferences for stocks with lottery-like characteristics. These characteristics, which appeal to speculative investors, include attributes such as high return skewness. Our hypothesis is that if treated individuals exhibit strong preference for these speculative features on event days, this would suggest that the event likely serves as an opportunity to gamble, inconsistent with the theme of long-term wealth associated with the festival.

We estimate the same regression specification as in Equation (4), focusing on the following stock attributes: share price on the day before the event and three measures of skewness, following Gao and Lin (2015), computed using daily data over the year before the event: conventional skewness, Pearson's skewness coefficient and up-to-down volatility.[29] Panel B of Figure 3 presents the estimated coefficients. The first coefficient shows that, if anything, treated individuals are more likely to purchase stocks with higher share price on event days. The other coefficients show that they exhibit no significant preference for stocks with higher skewness.

Options Trading. As an additional test of whether the event induces speculative or gambling-like behavior, we examine trading activity in margin derivative products (i.e., associated with leverage), such as options. Using our brokerage data, we construct individual-date-level indicators equal to 100 if an individual trades, buys, or sells any option contract on a given day. We then estimate regressions analogous to Equation (1), interacting the event-day indicator with the treated dummy, and including individual and date fixed effects. The results, reported in Online Appendix Table IAE9, show no statistically significant effect of the event on options trading among treated individuals. The coefficients on the interaction term *Event Day* $\times$ *Treated* are small in magnitude and statistically insignificant across specifications for trading, buying, and selling activity. These findings indicate that treated individuals do not increase their participation in leveraged or margin-based products on the event day.

treated individuals are not significantly more likely to purchase stocks paying dividends, or stocks with high turnover, EPS or market beta, on event days relative to other buy-days.

[29] Conventional skewness, is the third central moment of the return distribution divided by the cube of standard deviation. Pearson's skewness coefficient, is calculated as $3 \times$ (Mean $-$ Median)/Standard Deviation. Up-to-down volatility is computed as $-\log\left(\frac{(n_u-1)\sum_{\text{DOWN}} r_{it}^2}{(n_d-1)\sum_{\text{UP}} r_{it}^2}\right)$, where r_{it} represents the daily return for stock i, n_u (n_d) represents the number of days when the daily return is higher (lower) relative to the period mean, and $\sum_{\text{DOWN}} r_{it}^2$ ($\sum_{\text{UP}} r_{it}^2$) represents the sum of squared returns for days below (above) the period mean.

In summary, we find that treated individuals do not favor lottery-like stocks or options on event days, inconsistent with gambling behavior, a novel contribution relative to prior work that has used religion as a proxy for gambling propensity (see Kumar, 2009; Kumar et al., 2011).

Future Returns. Finally, we assess whether the stocks purchased by treated individuals on the event day tend to perform better or worse than those they buy on other days. To do so, we estimate the same regression specification as in Equation (4), using as the dependent variable the average percentile rank of the purchased stocks' returns over various future horizons: the next day, week, month, six months, and one year. Panel C of Figure 3 presents the estimated coefficients β from Equation (4), and suggests that treated individuals do not make poorer stock selection decisions on the event day.[30] We discuss the possibility of price impact affecting individuals' execution price in Section 7.3.

6.4 Likelihood to Sell Stocks Purchased on the Event

In this section, we conduct additional tests to tie the findings on trading patterns to the religious cue. An intuitive implication of the festival's emphasis on long-term prosperity is that treated investors should hold onto stocks purchased on the event day for an extended period, rather than selling them shortly after. Therefore, we examine the likelihood of liquidation of event-purchased stocks.

Empirical Specification. We use our holding sample at the investor-stock-date level to analyze differences in holding behavior between stocks purchased on the event and those bought on other days, while controlling for stock-level characteristics. We include all treated investors and the full set of trading days in our analysis, estimating the following specification:

$$Sell_{i,j,t} = \beta_1 \cdot \{Purchased\ on\ Event\}_{i,j,t} + \phi X_{i,j,t} + \gamma_{i,t} + \delta_{j,t} + \epsilon_{i,j,t} \quad (5)$$

where i, j, and t denote individual, stock, and date, respectively. The dependent variable $Sell_{i,j,t}$ equals 100 if individual i sells stock j on date t, fully or partially, conditional on it being in their

[30]The results indicate that event-day purchases tend to outperform other purchases over the medium to long run—specifically over the following six months and one year. This is consistent with the types of stocks treated individuals tend to buy on event days: large-cap, low-volatility stocks with strong recent performance, aligned with factors such as market, momentum, and low-volatility.

portfolio the previous day, and 0 otherwise. The variable $Purchased\ on\ Event$ is a dummy equal to 1 if some shares of stock j were purchased by individual i for the first time on event day. If the stock is fully sold and later repurchased, it is treated as a new position, resetting the dummy to zero.

The time-varying controls $(X_{i,j,t})$ include several variables known to influence selling behavior, as outlined in Ben-David and Hirshleifer (2012). First, we include a dummy for whether the stock is trading at a paper gain relative to its weighted-average purchase price, controlling for the well-documented disposition effect (e.g. Odean, 1998). Second, the square root of the number of days the stock has been held is included to account for the time structure of selling likelihood. We also include the return since purchase for stocks in paper loss (or gain) and zero otherwise, along with interactions between these returns and the square root of holding duration. Finally, the logarithm of the weighted-average purchase price is included. Individual $\times$ date fixed effects $(\gamma_{i,t})$ account for unobservable individual-specific factors that vary over time, such as personal liquidity shocks. Stock $\times$ date fixed effects $(\delta_{j,t})$ absorb time-varying stock-level factors, including news or changes in fundamentals. Standard errors are double-clustered at the individual and date levels.

Results. Table 5 presents the results. In Panel A, the sample includes days on which no trades occur, while in Panel B it consists only of days when the individual sells at least one stock. All columns include stock $\times$ date fixed effects. Columns (1) and (2) include individual fixed effects, while columns (3) and (4) incorporate individual $\times$ date fixed effects.

In Panel A, the coefficient on *Purchased on Event* is negative and highly significant (t-stat $\approx$ 4 across all columns), ranging from -0.13 to -0.25. The effect size represents 7% to 13% of the dependent variable's mean (2). In Panel B, we restrict the sample to sell days, with the coefficients on *Purchased on Event* being larger in magnitude, ranging from -1.5 to -1.7, and remain highly statistically significant (t-stat around 3 in all columns). The effect size is notable and approximately 30% of the dependent variable's mean in this sample (5). These results show that treated individuals exhibit a strong aversion to selling event-purchased stocks. As the empirical specifications control for time-varying individual and stock characteristics, it allows us to cleanly isolate *changes* driven by the religious cue.

Disposition Effect. The lower likelihood of selling event-purchased stocks raises the natural question of whether treated individuals are reluctant to realize their losses—the disposition effect—on these stocks (see, for instance, Odean, 1998). To test this, we estimate regression Equation (5), adding an interaction term between a dummy ($Gain$), which equals one if the stock's return since purchase is positive, and $Purchased\ on\ Event$ to assess whether the disposition effect differs for these stocks. These results are reported Online Appendix Table IAE10 and show that, if anything, treated individuals exhibit weaker disposition effect for event-purchased stocks.

6.5 Intertemporal Substitution: Shift in Trading vs. New Trades?

Online Appendix Figure IAE7 examines whether the event induces *new* investment or merely shifts investment timing. To examine this, we construct a matched sample that pairs each treated investor who ever trades during the event with a comparable treated investor who never traded on the event and based on the following characteristics: location, gender, income and occupation category, account opening year, and portfolio value at the end of the year, giving us one treated–control pair per cohort. We then define the event date for each treated investor as the first observed event-day trade, with the matched control investor inheriting the treated investor's event date. From the figure, we see there are significant differences in buying activity but not selling in the event-month but not before or after. This spike in differential buying activity suggests that treated investors who trade on event-days do not merely shift the timing of their investments. Put differently, the counterfactual treated investors who did not trade on event-day do not catch-up with the treated investors who do trade.

6.6 Heterogeneity Across Individuals

Having established that treated individuals substantially increase their equity purchases on the event day, we next examine how the magnitude and persistence of this response varies across investors. The theoretical framework predicts that heterogeneity in cue intensity and reinforcement from prior outcomes should generate systematic differences in event-day trading across individuals. In the following subsection, we test these predictions by exploiting cross-sectional variation in salience and by studying whether past positive returns on cue-induced investments strengthen future responsiveness.

Salience and Heterogeneous Trading Responses. Online Appendix Table IAE11 investigates whether variation in the intensity of the cue across individuals translates into differential trading responses. We measure salience using the Google Search Volume Index (SVI) for "Muhurat trading" and classify individuals residing in regions as high-salience every year if the index is in the top quartile across states. All regressions include individual and date fixed effects, so identification comes from individuals across regions with varying levels of salience.

Consistent with our framework, a larger $\delta_i^{(\text{Event})}$ amplifies the trading response, the interaction between *Event Day* and *High salience* is strongly positive for trading and buying outcomes. On event days, high-salience individuals are 1.24 percentage points more likely to trade and 1.25 percentage points more likely to buy—an economically meaningful increase relative to baseline frequencies. Importantly, the effect is concentrated entirely on the buy margin, further reinforcing the interpretation that the cue encourages the initiation of new positions rather than the liquidation of existing ones.

To isolate the cue-specific nature of this response, we also examine trading on non-event days. The main effect of *High salience* is small and statistically insignificant across all specifications, implying that high-salience individuals do not trade more during ordinary trading days. This absence of differences on non-event days is consistent with the model, which predicts that heterogeneity in $\delta_i^{(\text{Event})}$ matters only when the cue is active. It also helps rule out alternative explanations related to persistent regional differences in preferences, socioeconomic conditions, or general religiosity that could otherwise generate cross-sectional variation in trading. Thus, the observed heterogeneity reflects a cue-specific shift in intertemporal framing rather than stable preference heterogeneity.

Persistence in Participation. In additional tests, we next examine whether cue responses may be reinforced when past cue-induced actions yield favorable outcomes, leading to greater responsiveness in future periods. To examine this prediction, Online Appendix Table IAE12 focuses on whether individuals who experienced higher returns on event-day purchases in the previous year are more likely to participate again in subsequent events. We estimate panel regressions at the individual-year level, using an indicator for buying on the event day (Columns (1)–(3)) or the buy amount (Columns (4)–(6)) as the outcome. The key explanatory variables are returns on last year's event-day purchases measured at different horizons: one day, 21 trading days, and 252 trading days. All regressions include individual and year fixed effects, so identification comes from individuals observed in multiple events.

Only the longer-horizon return measure predicts future participation. A 10 percentage point increase in the prior year's 252-day return is associated with a 1.5 percentage point increase in the likelihood of buying again in the following event, with a similar pattern on the intensive margin. In contrast, short-run returns (one-day and 21-day) have no predictive power. This pattern suggests that individuals respond to the cue more strongly when past cue-induced investments have delivered longer-term gains—consistent with a reinforcement mechanism in which favorable outcomes strengthen the perceived meaning or potency of the cue.

7 Portfolio Implications and Account Size Inequality

In this last section, we examine whether the trading patterns observed on the event, along with the tendency of treated individuals to hold onto event-purchased stocks for longer, lead to persistent changes in their portfolios. While attributing long-term portfolio outcomes solely to trading decisions made on the event is inherently challenging, we can analyze individual portfolios over windows of several months around each event. Focusing on longer periods provides insight into the broader implications of religious cues on individuals' portfolios.

7.1 Portfolio Implications: Account Size and Diversification

Empirical Strategy. To trace the effects on individual portfolios, we construct six-month windows around each event, spanning three months before and three months after. Specifically, for each event in our sample (a "cohort"), we define a fixed-length window centered on the event date and track individual portfolio characteristics within this period. We then stack these event windows across all events, effectively creating a cohort-account-date level dataset that captures individual portfolio dynamics relative to the event, akin to a stacked difference-in-differences (Gormley and Matsa, 2011).

We focus on treated investors and examine how their portfolios evolve before and after each event, differentiating between those who actively participate by purchasing stocks on the event day and those who do not. We estimate the following regression:

$$Y_{i,c,t} = \beta \cdot \{Post_{c,t} \times EventBuyer_{i,c}\} + \gamma_{i,c} + \delta_{t,c} + \epsilon_{i,c,t}, \tag{6}$$

where c, i, and t denote cohort, individual and date respectively. The variable $Post_{c,t}$ is a dummy equal to 1 if date t falls on or after the event for cohort c. $EventBuyer_{i,c}$ is a dummy equal to 1 if individual i purchases stocks on the event day of cohort c. $\gamma_{i,c}$ and $\delta_{t,c}$ are individual-cohort and date-cohort fixed effects respectively. In some estimations, we further saturate the specification by adding trading intensity-date-cohort fixed effects. Trading intensity is defined at the individual-cohort level, classifying individuals into quartiles based on the number of trades they make over the cohort window. These fixed effects ensure that the estimated effects are not merely driven by individuals who trade more frequently, irrespective of whether it is an event day or not. In all specifications, standard errors are double-clustered at the individual and date levels.

Results. The estimation results are presented in Panel A of Table 6. The key coefficient of interest, $Post \times EventBuyer$, measures the change in portfolio outcomes after the event for treated individuals who purchase stocks on the event day, relative to those who do not. In Columns (1) and (2), the dependent variable is the logarithm of the individual's total stock portfolio value (i.e., equity account size). The coefficient on $Post \times EventBuyer$ is positive and statistically significant: 0.24 in Column (1) and 0.20 in Column (2), both significant at the 1% level. The post-event large and sustained increase of more than 20% in equity account size among participating treated individuals suggests that event-driven stock purchases lead to larger overall stock holdings. Columns (3) and (4) report the impact on portfolio diversification measured by the logarithm of the number of stocks held. The coefficients are positive and statistically significant (between 0.10 and 0.11, and significant at the 1% level), indicating that event-day buyers hold over 10% more stocks in their portfolios post-event compared to pre-event levels, relative to non-buyers. This suggests that event buyers expand their portfolios and maintain this diversification several months after the event. Consistent with the increase in the number of stocks, Columns (5) and (6) show that the HHI (defined as the sum of squared portfolio weights) decreases significantly post-event for event buyers (between -0.026 and -0.028).

Dynamics of the Effects. To better understand the evolution of portfolio characteristics around the event, we estimate an event-study specification similar to Equation (6), but replace the $Post$ indicator with a set of specific coefficients for each month before and after the event:

$$Y_{i,c,t} = \sum_{\tau=-3,\tau\neq-1}^{+3} \beta_\tau \left\{Month(\tau)_{c,t} \times EventBuyer_{i,c}\right\} + \gamma_{i,c} + \delta_{q,t,c} + \epsilon_{i,c,t}, \tag{7}$$

where $Month(\tau)_{c,t}$ is an indicator for month τ relative to the event, with $\tau = 0$ corresponding to the event month. The month immediately preceding the event ($\tau = -1$) serves as the baseline category and is omitted from the estimation. $\gamma_{i,c}$ and $\delta_{q,t,c}$ represent individual-cohort and trading intensity-date-cohort fixed effects, respectively. Standard errors are double-clustered at the individual and date levels. Figure 4 presents the estimated coefficients β_τ from Equation (7), along with 95% confidence intervals. In Panel A, the dependent variable is the logarithm of the individual's total stock portfolio value. Consistent with evidence from the previous section, we observe a clear jump in the value of stock holdings for event buyers in the event month, relative to other treated individuals. The coefficients remain positive and significant in the month following the event, suggesting a persistent increase in equity account size. In Panel B, we see a similar pattern, where the dependent variable is the logarithm of the number of stocks held. Panel C shows that portfolio HHI significantly decreases in the event month, reflecting a more diversified portfolio. Importantly, across the figures, we do not find a reversal in the months post-event, suggesting a lasting impact on individual portfolios.

7.2 Sharpe Ratio and CAPM-Implied Benchmark

We next examine whether the event-driven changes in portfolio diversification translate into variation in risk-adjusted performance. Specifically, we study how the Sharpe ratio of portfolios held by treated individuals who trade on the event day evolves in the post-event period. To do so, we proceed in two steps. First, we construct an *expected* Sharpe ratio for each individual portfolio based solely on its composition. For each stock held in the portfolio, we compute its Sharpe ratio based on the sample mean excess return and standard deviation over the full sample period. We then aggregate stock-level Sharpe ratios into a portfolio-level expected Sharpe ratio using the individual's portfolio weights. This measure reflects the portfolio's expected risk-adjusted return implied by its asset allocation. Then, we estimate Equation (6), using as the dependent variable the portfolio expected Sharpe ratio. The results, presented in Columns (1) and (2) of Panel B of Table 6, show a statistically significant increase of approximately 0.01 in the expected Sharpe ratio of event-day buyers' portfolios. This suggests that the stock selection described in Section 6.3, combined with the observed increase in diversification, is associated with an increase in risk-adjusted portfolio performance. Panel D of Figure 4 presents the estimated coefficients β_τ from Equation (7) and confirms that portfolio expected Sharpe ratio goes up for event buyers in the event month, relative to other treated individuals.

A natural question is whether this improvement simply reflects a mechanical effect of adding new stocks to the portfolio. To assess this, we construct a benchmark using the approach of Balasubramaniam et al. (2023). Under the CAPM assumption that the market portfolio delivers the highest Sharpe ratio, we compute the optimal Sharpe ratio achievable by a portfolio constrained to hold the same number of stocks as the individual's actual portfolio, with short sale constraint. We implement this optimization using LASSO regressions. Specifically, we regress weekly market returns on individual stock returns over our sample period and adjust the LASSO penalty to deliver portfolios with exactly N_h stocks. This method provides a feasible solution to the constrained maximization problem.[31]

For each individual portfolio, we then compute the difference between its expected Sharpe ratio (based on actual holdings) and the maximum CAPM-implied Sharpe ratio achievable with the same number of stocks. This difference captures how close the individual's portfolio is to the theoretical optimum, given their diversification level. We use this difference as the dependent variable in Equation (6). Results are presented in Columns (3) and (4) of Panel B of Table 6. The coefficients are statistically insignificant, indicating no systematic improvement in this difference. These results suggest that the observed increase in Sharpe ratios is driven primarily by the new stock purchased on event day that mechanically improve portfolio diversification and thus risk-adjusted performance, rather than improved investment skill. Overall, our results show that treated individuals who participate in the stock market on the event-day have lasting effects on their portfolios.

[31]Online Appendix Figure IAE8 shows the maximum achievable Sharpe ratio for portfolios of different sizes N_h, ranging from 1 to 100 stocks. As expected, achievable Sharpe ratios increase with portfolio size, and asymptotically approach the market Sharpe ratio.

7.3 Price Impact

Given the significant increase in individual buying activity documented in Section 5, along with the sizable retail buy-side imbalance reported in Figure IAE1, an important question is whether this surge in stock purchase generates temporary price pressure—potentially worsening execution prices for investors. To assess this, we study the market-level and stock-level price impact of the event. Panel A of Online Appendix Table IAE6 presents results from regressions of daily returns on the Indian stock market on an *Event Day* indicator, including year and day-of-year fixed effects. Column (1) shows that returns are significantly higher on event days, with a coefficient around 1%, suggesting that aggregate retail buying induces positive price pressure. However, Columns (2) through (4) include indicators for the day before the event, the day after, the week after, the month after, and the three months after. None of these coefficients are statistically significant, indicating no evidence of a reversal. Panel B confirms these results using a panel of individual stock returns. We find that while stock-level abnormal returns tend to be higher on the event day, they do not reverse in the days or weeks following. Taken together, these findings suggest that while the religiously-framed cue drives temporary price pressure through concentrated retail demand, there is no significant mean reversion in prices afterward. Combined with earlier evidence that treated investors tend to hold event-purchased stocks longer, and that the median holding period in our sample is approximately three months (Panel B of Online Appendix Table IAE3), these results alleviate concerns that event-day trades systematically lead to worse execution prices or erode subsequent returns through price reversal.

7.4 Aggregate Effects: Impact on Account Size Inequality

Finally, we examine how event-driven purchases shape patterns of wealth accumulation and account size inequality. A growing literature has documented substantial heterogeneity in returns across individual investors, with important implications for the distribution of wealth. Using data on Indian stock portfolios, Campbell et al. (2019) show that return heterogeneity is a key driver of rising inequality in risky asset ownership. They attribute this to differences in diversification: larger accounts tend to hold more diversified portfolios and earn higher risk-adjusted returns, while smaller accounts are more concentrated in a few stocks. This dynamic reinforces wealth inequality over time. Building on our previous findings, we ask whether event-driven stock purchases vary systematically across investors' account size, and if so, whether the associated improvements in portfolio diversification may help reduce disparities in long-term wealth accumulation.

To investigate whether event-driven stock purchases vary systematically by investor characteristics, we condition on investors who purchase at least one stock on the event day and examine heterogeneity across the income and wealth distribution in Online Appendix Figure IAE9. Panel (a) shows that the value of event-driven purchases, relative to reported income at account opening, declines monotonically across income buckets, indicating that lower-income investors commit a larger share of their income to stock purchases on event days. Panel (b) confirms a similar pattern when scaling the event-driven purchase amount by beginning-of-year account size, which controls for differences in investment scale within each income bucket.[32]

We then turn to account size as a proxy for wealth. Panel (c) shows that the ratio of event-driven purchases to total account value measured at year-end declines monotonically across account size quartiles (defined at the start of the year). Likewise, Panel (d) shows that the share of the portfolio held in event-purchased stocks by the end of the sample period is highest among the smallest accounts and declines across the distribution. These patterns show that event-driven purchases represent a relatively larger financial commitment for less affluent investors, suggesting that religion may play a more prominent role in shaping investment behavior and subsequent returns for this group. Together, these findings indicate that smaller investors respond more intensively to event-driven opportunities, both in terms of new investment flows and resulting portfolio composition.

Conclusion

This paper examines whether and to what extent framing investments around religion influences individual portfolio choices. In this paper, we combine individual trading account data allowing us to infer religious affiliation with a religiously-framed cue: trading sessions by stock exchanges in India invoking a major religious festival. We exploit a within-individual design, comparing treated

[32]Throughout this analysis, "year" refers to the Indian accounting year, which runs from April 1^{st} to March 31^{st} of the following calendar year.

investors to others less likely to be influenced by the religious cue, on event-days relative to other days. This isolates religious-cue driven trades, allowing us to trace their effects on subsequent portfolio outcomes.

We document a direct and novel role for religious cue in shaping portfolio choices and long-term investments. Treated individuals participate more actively and invest substantially larger amounts in the stock market on the event day, while others do not respond. They buy new stocks rather than increasing existing holdings, and avoid lottery-like stocks. Moreover, they hold onto event-purchased stocks longer, leading to a persistent increase in both the size of their equity account and portfolio diversification post-event, without reducing risk-adjusted returns. We also find that event-driven purchases represent a significantly larger financial commitment for lower-income and smaller-wealth investors. These investors also end up with a greater portfolio share in event-purchased stocks. Taken together, our findings suggest that religious framing can serve as a channel through which investors engage with financial markets, increase equity exposures, and thereby diversification.

Our results have broader implications for financial inclusion and faith-based investing. First, our findings highlight religious framing as an economic force that may have important implications for wealth accumulation and inequality. Specifically, our results suggest that framing investments around religion can benefit small investors and potentially reduce the growth of inequality, especially in emerging markets. Second, it highlights that understanding financial participation requires attention to the psychological and cultural frames through which individuals interpret investment opportunities. Relatedly, as financial institutions and policymakers seek to engage individual investors, culturally resonant messaging—such as that embedded in Sharia-compliant funds, Catholic investment guidelines (e.g., the Vatican's 2023 *Mensuram Bonam*), and other faith-based financial products—could be leveraged to promote long-term investment and responsible financial decision-making.

Figures

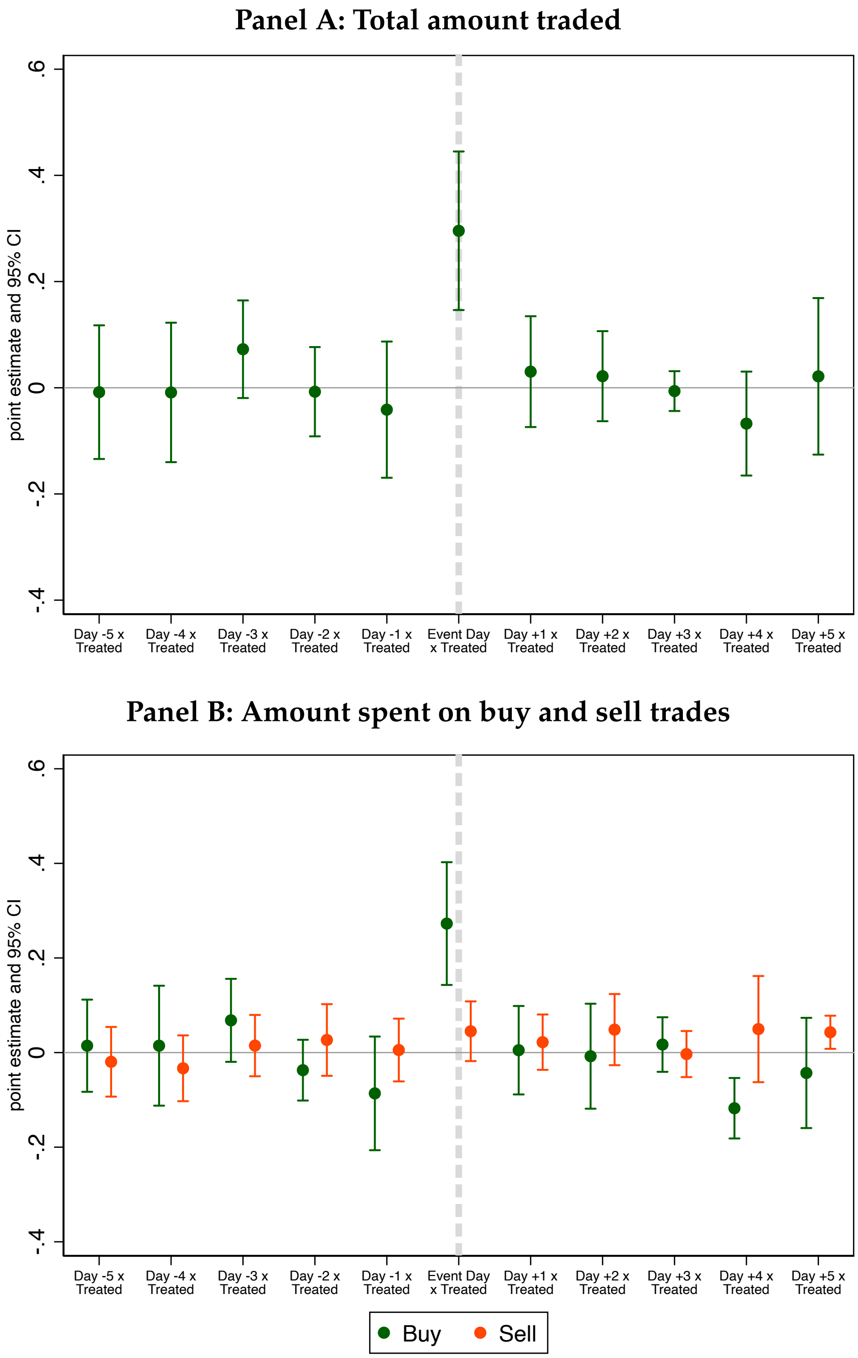
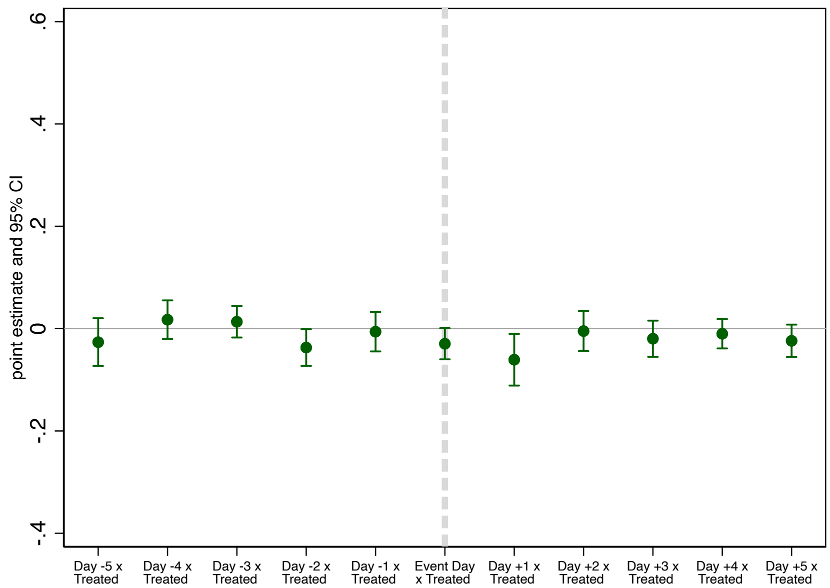


Figure 1: Dynamics of the traded amount around the events. This figure plots the coefficients β_k on each day in equation: $Y_{i,t} = \sum_{k=-5}^{5} \beta_k \{Treated_i \times Day(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the individual and date, and $Day(k)_t$ is a dummy equal to one if date t corresponds to k days before/after a Diwali day. $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. α_i and γ_t denote individual and date fixed effects respectively. The dependent variable is the arcsinh of the amount traded in Panel A, and the arcsinh of the amount spent on buy and sell trades in panel B. Horizontal bars correspond to 95% confidence intervals. Standard errors are double-clustered at the investor and date levels.

Panel A: Total amount traded



Panel B: Amount spent on buy and sell trades

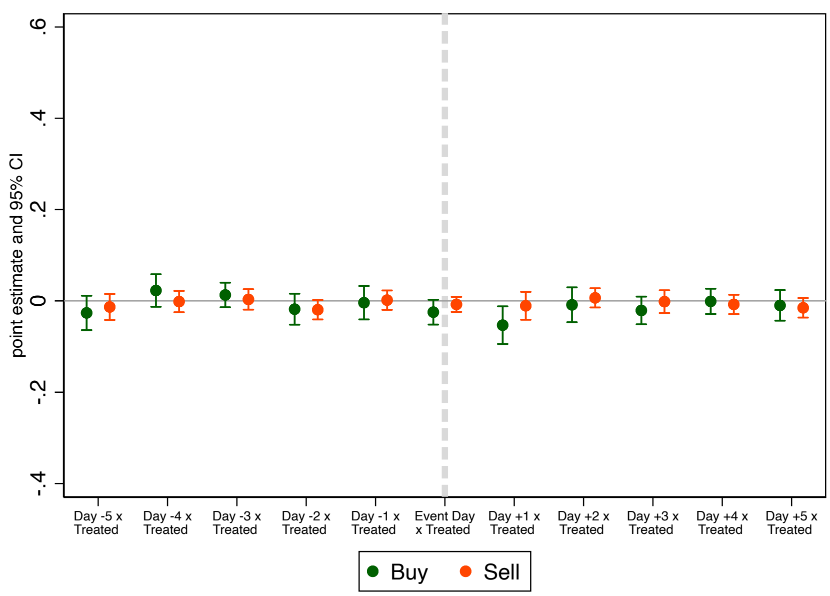


Figure 2: Dynamics of the traded amount around other religious events. This figure plots the coefficients β_k on each day in equation: $Y_{i,t} = \sum_{k=-5}^{5} \beta_k \{Affected_i \times Day(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the individual and date, and $Day(k)_t$ is a dummy equal to one if date t corresponds to k days before/after a religious event day (which is not Diwali). $Affected_i$ is a dummy variable equal to one if individual i is affected by the religious event according to her inferred religion. α_i and γ_t denote individual and date fixed effects respectively. The dependent variable is the arcsinh of the amount traded in Panel A, and the arcsinh of the amount spent on buy and sell trades in panel B. Horizontal bars correspond to 95% confidence intervals. Standard errors are clustered at the investor and date levels.

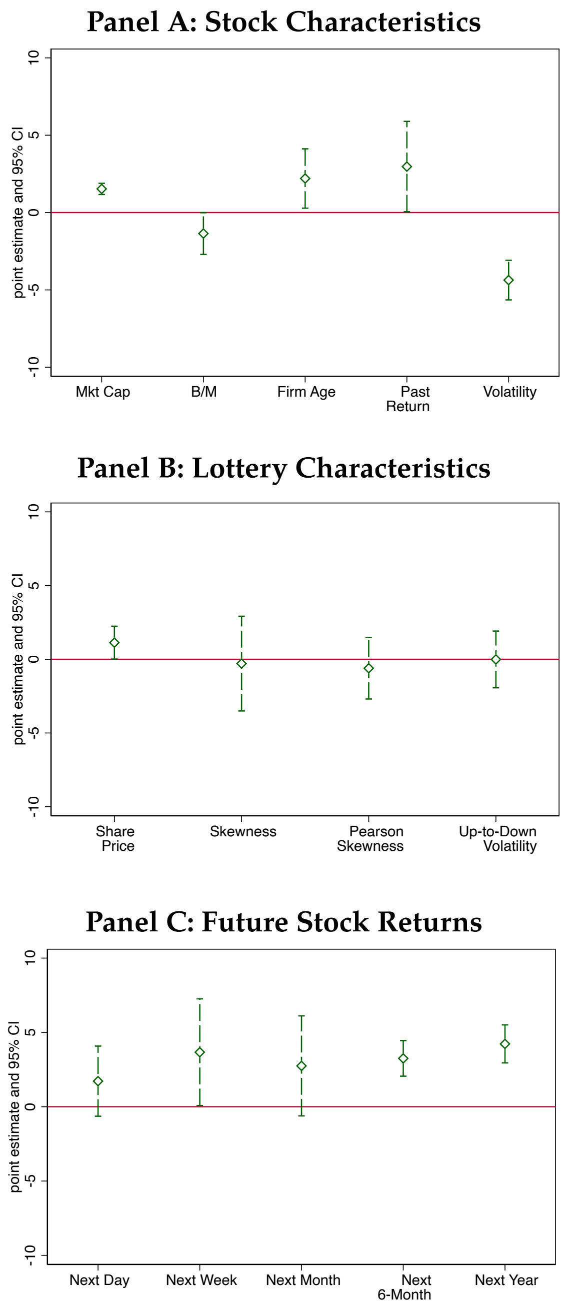


Figure 3: Characteristics of stocks purchased on event days vs. other days. This figure plots the estimated coefficients β from equation (4), which measures the change in the average percentile rank of stock characteristics on event days relative to other buy-days for treated individuals (Hindus). The dependent variable is the average percentile rank of the stocks purchased by individual i on day t, where the percentile is calculated daily based on the cross-sectional distribution of a given stock characteristic. The regression includes individual $\times$ year fixed effects. Standard errors are double-clustered at the individual and stock levels. Vertical lines represent 95% confidence intervals. Panel A presents results for firm-level characteristics: market capitalization, book-to-market ratio, firm age, past-year return, and past-year volatility. Panel B presents results for lottery-like characteristics: share price, skewness, Pearson skewness, and up-to-down volatility. Panel C presents results for stocks' future returns over the next day, week, month, six months and year.

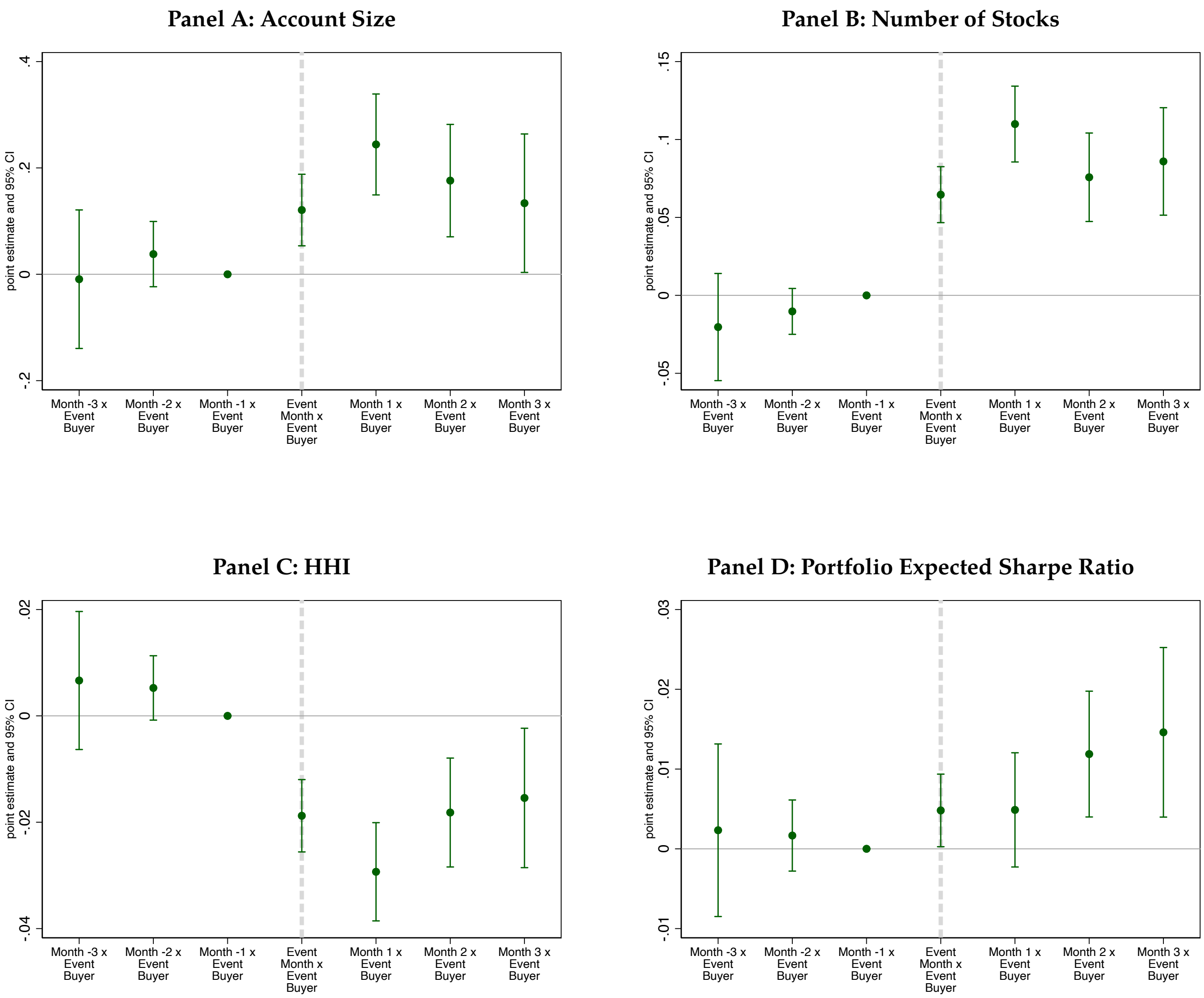


Figure 4: Dynamics of portfolio characteristics in the months before and after the events. This figure plots the estimated coefficients β_τ from Equation (7), capturing the evolution of portfolio characteristics before and after the event for treated individuals who purchase stocks on the event day, relative to other treated individuals. Regressions are estimated at the individual-date level for treated investors using stacked event windows around each Diwali event, where each cohort represents a separate event, and windows span three months before and three months after the event. The coefficients β_τ correspond to the interaction between a dummy indicating whether the individual purchases stocks on the event day of that cohort and a set of time-specific indicators for each of the three months before and after the event, with the month immediately preceding the event ($\tau = -1$) serving as the baseline category. The regression includes individual-cohort and trading intensity-date-cohort fixed effects. Panel A shows results for the logarithm of the individual's total stock portfolio value. Panel B examines the logarithm of the number of stocks held. Panel C uses the portfolio Herfindahl-Hirschman Index (HHI) as the dependent variable. Finally, Panel D studies portfolio expected Sharpe ratio, measured using the full-sample mean excess return and standard deviation of stocks held in the portfolio. Horizontal bars correspond to 95% confidence intervals. Standard errors are double-clustered at the investor and date levels.

Tables

Table 1: Broker Dataset Summary Statistics This table lists the account level (Panel A), account-date level (Panels B), and account-stock-date level (Panels C) summary statistics from our broker dataset. In Panel A, Age refers to age of the account holder as of June 2021, and income refers to the numeric midpoint in the income range given by the data provider. Panels C only includes the holdings of treated individuals (Hindus). "Unconditional sample" indicates that the sample is not restricted to trading days; it includes all account-date (or account-stock-date) observations, including those with no transactions. Over our sample window from 2012 to 2019, the average exchange rate is ₹64 to 1 USD.

Variable	Obs	Mean	Sd	5%	25%	50%	75%	95%
Panel A: Account level								
Age	24,112	42.77	13.75	27.00	32.00	38.00	51.00	70.00
Male	24,112	0.73	0.44	0.00	0.00	1.00	1.00	1.00
Income (₹100,000s)	24,112	8.12	10.84	3.00	3.00	3.00	7.00	23.00
Treated	24,112	0.90	0.30	0.00	1.00	1.00	1.00	1.00
Panel B: Account-date level (unconditional sample)								
Total Portfolio Value (₹1000s)	6,090,768	1,067.19	4,106.18	1.43	41.86	185.15	700.45	4,279.75
Nb. Stocks	6,090,768	5.22	7.96	1.00	1.00	3.00	6.00	18.00
Trade	6,090,768	0.08	0.27	0.00	0.00	0.00	0.00	1.00
Buy	6,090,768	0.06	0.24	0.00	0.00	0.00	0.00	1.00
Sell	6,090,768	0.03	0.17	0.00	0.00	0.00	0.00	0.00
Amount Traded (₹1000s)	6,090,768	16.52	223.12	0.00	0.00	0.00	0.00	33.76
Amount Buy Trades (₹1000s)	6,090,768	9.79	151.00	0.00	0.00	0.00	0.00	8.93
Amount Sell Trades (₹1000s)	6,090,768	6.73	136.58	0.00	0.00	0.00	0.00	0.00
Panel C: Account-Stock-date level (unconditional sample)								
Trade	28,587,808	0.03	0.16	0.00	0.00	0.00	0.00	0.00
Sell	28,587,808	0.02	0.13	0.00	0.00	0.00	0.00	0.00
Buy	28,587,808	0.01	0.09	0.00	0.00	0.00	0.00	0.00
Amount Traded (₹1000s)	28,587,808	3.10	69.15	0.00	0.00	0.00	0.00	0.00
Amount Buy (₹1000s)	28,587,808	1.84	52.90	0.00	0.00	0.00	0.00	0.00
Amount Sell (₹1000s)	28,587,808	1.26	44.59	0.00	0.00	0.00	0.00	0.00
Time Owned (Days)	28587808	146.70	158.61	5.00	34.00	93.00	204.00	481.00

Table 2: Trading behavior on Diwali day

Regressions are estimated at the individual-date level. In Panel A, the dependent variable is a variable equal to 100 if the individual trades on that day, 0 otherwise. In Panel B, the dependent variable is the arcsinh of the amount traded by the individual on that day. $Event$ is a dummy equal to 1 if the day corresponds to the Diwali's Muhurat trading day, and $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. Standard errors (in parentheses) are double-clustered at the individual and date level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Likelihood to trade

	Trade × 100				
	(1)	(2)	(3)	(4)	(5)
Event Day × Treated	1.185***	1.111***	1.099***	1.284***	1.211***
	(0.340)	(0.374)	(0.383)	(0.318)	(0.323)
Event Day	-0.711	-0.931			
	(1.285)	(0.951)			
Religion FE	Yes	No	No	No	No
Individual FE	No	Yes	Yes	Yes	Yes
Date FE	No	No	Yes	No	No
State × Date FE	No	No	No	Yes	No
District × Date FE	No	No	No	No	Yes
Observations	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768
R^2	0.00	0.11	0.12	0.13	0.16

Panel B: Amount traded

	Amount Traded				
	(1)	(2)	(3)	(4)	(5)
Event Day × Treated	0.158***	0.148***	0.147***	0.163***	0.154***
	(0.034)	(0.039)	(0.040)	(0.035)	(0.034)
Event Day	-0.142	-0.166			
	(0.141)	(0.106)			
Religion FE	Yes	No	No	No	No
Individual FE	No	Yes	Yes	Yes	Yes
Date FE	No	No	Yes	No	No
State × Date FE	No	No	No	Yes	No
District × Date FE	No	No	No	No	Yes
Observations	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768
R^2	0.00	0.11	0.12	0.13	0.16

Table 3: Buying and selling behaviors on Diwali day

Regressions are estimated at the individual-date level. In Panel A, in Columns (1) and (2) (resp. (3) and (4)), the dependent variable is a variable equal to 100 if the individual buys (resp. sells) on that day, 0 otherwise. In Panel B, in Columns (1) and (2) (resp. (3) and (4)), the dependent variable is the arcsinh of the amount spent on buy (resp. sell) trades by the individual on that day. $Event$ is a dummy equal to 1 if the day corresponds to the Diwali's Muhurat trading day, and $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. Standard errors (in parentheses) are double-clustered at the individual and date level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Likelihood to buy and sell

	Buy × 100			Sell × 100		
	(1)	(2)	(3)	(4)	(5)	(6)
Event Day × Treated	1.183***	1.286***	1.229***	-0.226	0.007	-0.005
	(0.330)	(0.271)	(0.301)	(0.158)	(0.168)	(0.142)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	No	No	Yes	No	No
State × Date FE	No	Yes	No	No	Yes	No
District × Date FE	No	No	Yes	No	No	Yes
Observations	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768
R^2	0.10	0.11	0.14	0.08	0.08	0.12

Panel B: Amount spent on buy and sell trades

	Amount Buy Trades			Amount Sell Trades		
	(1)	(2)	(3)	(4)	(5)	(6)
Event Day × Treated	0.158***	0.162***	0.157***	-0.019	0.006	0.004
	(0.034)	(0.030)	(0.031)	(0.017)	(0.019)	(0.016)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	No	No	Yes	No	No
State × Date FE	No	Yes	No	No	Yes	No
District × Date FE	No	No	Yes	No	No	Yes
Observations	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768
R^2	0.10	0.11	0.14	0.08	0.08	0.12

Table 4: Buying new versus existing holdings

Regressions are estimated at the individual-date level. In Panel A, in Columns (1) to (3) (resp. (4) to (6)), the dependent variable is a variable equal to 100 if the individual buys exclusively new stocks (resp. existing holdings) on that day, 0 otherwise. In Columns (7) to (9), the dependent variable is equal to 100 if the individual buys both new stocks and existing holdings on that day, 0 otherwise. In Panel B, in Columns (1) to (3) (resp. (4) to (6)), the dependent variable is the arcsinh of the amount spent by the individual when buying exclusively new stocks (resp. existing holdings). In Columns (7) to (9), the dependent variable is the amount spent by the individual when buying both new stocks and existing holdings. $Event$ is a dummy equal to 1 if the day corresponds to the Diwali's Muhurat trading day, and $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. Standard errors (in parentheses) are double-clustered at the individual and date level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Likelihood to buy

	Buy × 100								
	New Holdings			Existing Holdings			Both New and Existing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Event Day × Treated	0.844***	0.756***	0.758***	-0.023	0.168	0.114	0.362**	0.362**	0.357**
	(0.203)	(0.229)	(0.243)	(0.292)	(0.192)	(0.184)	(0.156)	(0.157)	(0.163)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	No	No	Yes	No	No	Yes	No	No
State × Date FE	No	Yes	No	No	Yes	No	No	Yes	No
District × Date FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768
R^2	0.04	0.05	0.09	0.10	0.10	0.13	0.03	0.04	0.07

Panel B: Amount spent on buy

	Amount Buy Trades								
	New Holdings			Existing Holdings			Both New and Existing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Event Day × Treated	0.096***	0.085***	0.084***	0.017	0.032	0.028	0.045**	0.046**	0.045**
	(0.023)	(0.027)	(0.027)	(0.027)	(0.021)	(0.020)	(0.018)	(0.018)	(0.019)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	No	No	Yes	No	No	Yes	No	No
State × Date FE	No	Yes	No	No	Yes	No	No	Yes	No
District × Date FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768
R^2	0.04	0.05	0.08	0.09	0.09	0.12	0.03	0.04	0.07

Table 5: Likelihood to sell stocks purchased on Diwali day

Regressions are estimated at the individual-stock-date level. For each trading day in our sample period, we include the holdings of treated investors (Hindus). In both panels, the dependent variable is a variable equal to 100 if the individual sells (fully or partially) the stock on that day. Panel A uses the unconditional sample, i.e., including days when no trading occurs. Panel B restricts the sample to observations where the individual sells on that day. $Purchased\ on\ Event$ is a dummy equal to 1 if some shares of the stock were purchased for the first time on Muhurat trading day. If the stock is sold off and repurchased later, it is considered a new position and the dummy is reset to zero. Control variables include a dummy indicating whether the stock is trading at a paper gain relative to its weighted-average purchase price, the logarithm of the weighted-average purchase price, the squared root of the number days the stock has been held, the return since purchase if the asset is in paper loss (gain) and zero otherwise, as well as their interactions with the squared root of the number days the stock has been held. Standard errors (in parentheses) are double-clustered at the individual and date level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Unconditional sample

	Sell × 100			
	(1)	(2)	(3)	(4)
Purchased on Event	-0.207***	-0.250***	-0.133***	-0.164***
	(0.049)	(0.057)	(0.037)	(0.041)
Control Variables	No	Yes	No	Yes
Individual FE	Yes	Yes	No	No
Individual × Date FE	No	No	Yes	Yes
Stock × Date FE	Yes	Yes	Yes	Yes
Observations	28,587,808	28,587,808	28,587,808	28,587,808
R^2	0.072	0.074	0.295	0.296

Panel B: Sale-conditioned sample

	Sell × 100			
	(1)	(2)	(3)	(4)
Purchased on Event	-1.593***	-1.696***	-1.463***	-1.631***
	(0.525)	(0.530)	(0.525)	(0.537)
Control Variables	No	Yes	No	Yes
Individual FE	Yes	Yes	No	No
Individual × Date FE	No	No	Yes	Yes
Stock × Date FE	Yes	Yes	Yes	Yes
Observations	2,122,229	2,122,229	2,122,229	2,122,229
R^2	0.322	0.327	0.396	0.401

Table 6: Individual Portfolio Implications

Regressions are estimated at the individual-date level for treated investors using stacked event windows constructed around each Diwali event, where each cohort represents a separate event, and windows span three months before and three months after the event. In Panel A, the dependent variables capture portfolio size, diversification, and concentration. Columns (1)–(2) examine the logarithm of the individual's total stock portfolio value, Columns (3)–(4) consider portfolio diversification, measured by the logarithm of the number of stocks held, and Columns (5)–(6) analyze portfolio concentration, proxied by the Herfindahl-Hirschman Index (HHI). In Panel B, ithe dependent variables are the expected Sharpe ratio of the portfolio based on its composition in Columns (1)-(2); and the difference between the portfolio expected Sharpe ratio and the maximum CAPM-implied Sharpe ratio achievable with the same number of stocks in Columns (3)-(4). The key independent variable is $Post \times EventBuyer$, where $Post$ is a dummy equal to 1 if the day falls on or after the event for that cohort and $EventBuyer$ is a dummy equal to 1 if the individual purchases stocks on the event day of that cohort. Columns (1), (3), and (5) include individual-cohort and date-cohort fixed effects, while Columns (2), (4), and (6) include individual-cohort and trading intensity-date-cohort fixed effects, where trading intensity is measured at the individual-cohort level and classifies investors into quartiles based on their trading frequency within the cohort window. Standard errors (in parentheses) are double-clustered at the individual and date levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Account Size and Diversification

	Total Portfolio Value		Nb. Stocks		HHI	
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Event Buyer	0.240***	0.204***	0.107***	0.098***	-0.028***	-0.026***
	(0.041)	(0.042)	(0.012)	(0.011)	(0.004)	(0.004)
Individual × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Date × Cohort FE	Yes	No	Yes	No	Yes	No
Trading Intensity × Date × Cohort FE	No	Yes	No	Yes	No	Yes
Observations	3,154,360	3,154,360	3,154,360	3,154,360	3,154,360	3,154,360
R^2	0.86	0.86	0.93	0.93	0.88	0.89

Panel B: Portfolio Sharpe Ratio

	Sharpe Ratio		Sharpe Ratio relative to CAPM-Implied	
	(1)	(2)	(3)	(4)
Post × Event Buyer	0.010***	0.007**	0.005	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Individual × Cohort FE	Yes	Yes	Yes	Yes
Date × Cohort FE	Yes	No	Yes	No
Trading Intensity × Date × Cohort FE	No	Yes	No	Yes
Observations	3,146,386	3,146,386	3,146,386	3,146,386
R^2	0.90	0.90	0.89	0.89

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Online Appendix
FOR ONLINE PUBLICATION

A Religion in India

Table IAA1: World Values Survey - Religious Life in India This table presents (weighted) tabulations of two questions related to religion asked in Wave 7 of the World Values Survey in India, for which data was collected over 2017 to 2022. Panel A presents tabulations of a question asking survey respondents how important religion is in their lives, while Panel B presents a tabulation of a question asking the frequency with which respondents attend religious service.

	Frequency (1)	Percent (2)
	Panel A: Question 6 - "Important in life: Religion"	
Don't know	12.22	0.72
Very important	1,086.11	64.19
Rather important	363.58	21.49
Not very important	150.75	8.91
Not at all important	79.35	4.69
	Panel B: Question 171 - "How often do you attend religious service?"	
Don't know	11.25	0.66
More than once a week	391.50	23.14
Once a week	410.81	24.28
Once a month	258.20	15.26
Only on special holy days	357.89	21.15
Once a year	43.89	2.59
Less often	152.82	9.03
Never, practically never	65.64	3.88

Inferring Religion from Last Names. We follow Bhagavatula et al. (2019); D'Acunto et al. (2024) and create a data-driven mapping of last names into distinct cultural groups. To identify religion, we leverage the fact that last names in India are strong indicators of both religion and caste, and that marriages in India are overwhelmingly intra-religious.

We utilize data from three major matrimonial websites, which provide the first and last names of approximately 26,700,000 users, along with their self-reported religions. Given that the relationship between last name and religion is not always one-to-one, we employ these data to assign probabilities indicating the likelihood that a particular last name corresponds to each religion within a specific region. The matrimonial dataset decomposes religion into the following seven categories: Hindu, Jain, Muslim, Sikh, Christian, Buddhist and Parsi.

Our last name to religion mapping strategy proceeds in three steps. First, we for each last name in the matrimonial database, we compute the count of the last name by state and religion, and calculate the probability of religion by last name and religion within state. We then select the most likely religion for each last name and state combination and assign that last name and state combination this most likely religion. If multiple religions are equally likely for a particular last name and state combination, we do not assign a religion. Within this dataset, we can assign a religion for approximately 98% of last name and state combinations. Finally, we match the most likely religion for each last name and state combination with the accounts in the broker dataset.

The strength of our surname- and state-based matching strategy to assign religious affiliation probabilities to individuals lies in the high degree of uniqueness and certainty it yields in assigning religion. Across all unique combinations of state and surname in our data, the average number of distinct religions observed is only 1.09, indicating that the vast majority of combinations are associated with a single religious group. This narrow distribution is visually summarized in Figure IAA1, which shows that most state–surname pairs are linked to just one religion, and very few have more than two. Further confirming the precision of our matching, we find that the average probability of the most likely religion assigned to a state–surname pair is 98.3%. This implies that in nearly all cases, one religion overwhelmingly dominates within a given state–surname group. As shown in Table IAA2, over 92.9% of all combinations are assigned to a single religion with 100% certainty, while 96.4% exceed an 80% confidence threshold, and virtually all cases (99.9%) exceed 50%. Finally, in IAA3, we tabulate the average probability that a given surname-state combination is assigned to the ultimate religion it is categorized as. This table indicates that across all religions, the probability of the surname-state combination belonging to the ultimate assignment religion is greater than 97%.

Among the 27,250 account holders in the broker dataset, we can match around 97% with a last name and state in the matrimonial database with an assigned religion. Given the low sample size of Buddhist and Parsi populations in our broker dataset, we focus on the following five main religious groups for our analysis: Hindu, Jain, Muslim, Sikh and Christian. Finally, we drop any account holders which we cannot match to a religion, arriving at a database of accounts of 26,353 individuals. The distribution of religion in our final sample of account holders is indicated in Table IAA4.

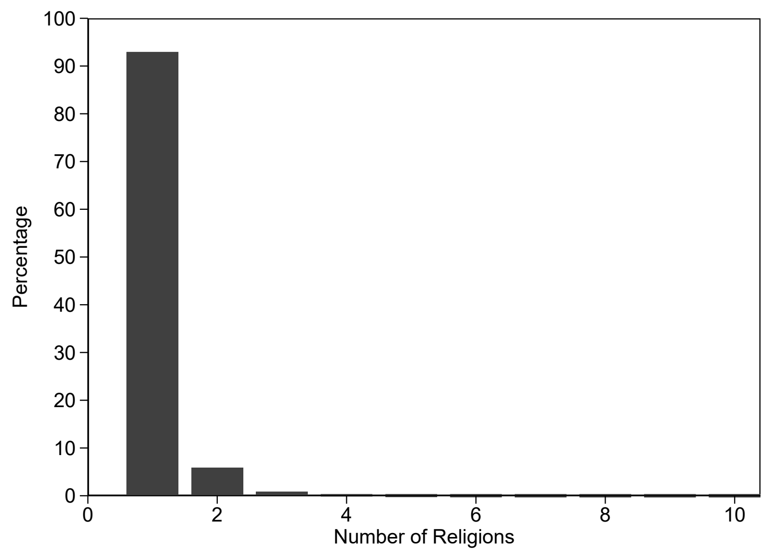


Figure IAA1: Share of State-Surname Combinations Assigned to a Religion This figure plots a histogram of the number of religions a given state-surname pair is assigned to in our matrimonial dataset.

Table IAA2: Percent of State–Surname Combinations by Religion Assignment Certainty
This table presents the proportion of state-surname combinations that are assigned to a single religion with 100% probability, with $\geq 80\%$ probability, and with $\geq 50\%$ probability in our matrimonial dataset.

Assignment Certainty	Percent
100% assigned	92.97
$\geq$ 80% assigned	96.42
$\geq$ 50% assigned	99.88

Table IAA3: Average Probability by Ultimate Assignment
This table presents the average of the probability of a surname and state assigned to the religion that it is categorized as from the matrimonial dataset.

Religion	Percent
Hindu	99.41
Jain	97.00
Muslim	99.41
Sikh	97.87
Christian	99.10

Table IAA4: Distribution of Religion in Broker Dataset
This table presents the distribution of religion for each account holder in the broker dataset.

Religion	Count	Percent
Hindu	21,705	90.02
Jain	1,056	4.38
Muslim	617	2.56
Sikh	491	2.04
Christian	243	1.01

B Religious Events and Messaging

The Muhurat trading session, organized by the Bombay Stock Exchange and the National Stock Exchange, is advertised widely by both exchanges and individual brokers. The largest newspapers in India, including *The Times of India* and *Hindustan Times*, publish announcements of the date and time of the Muhurat trading session each year.[33] Figure IAB2 also presents examples of newspaper articles over our sample period referencing Muhurat trading, with references to the "auspicious" nature of the event, as well as "wealth and prosperity." The salience of the event and religious messaging are featured prominently in both the announcements and advertising. For example, many articles indicate this is an "auspicious" trading session, and including other religious messaging and imagery to accompany the announcements. Advertisements by the National Stock Exchange also reflects this sentiment, as Figure IAB1 demonstrates. In particular, these advertisements reference the auspicious nature of the trading session in addition to wealth and prosperity, with religious imagery.

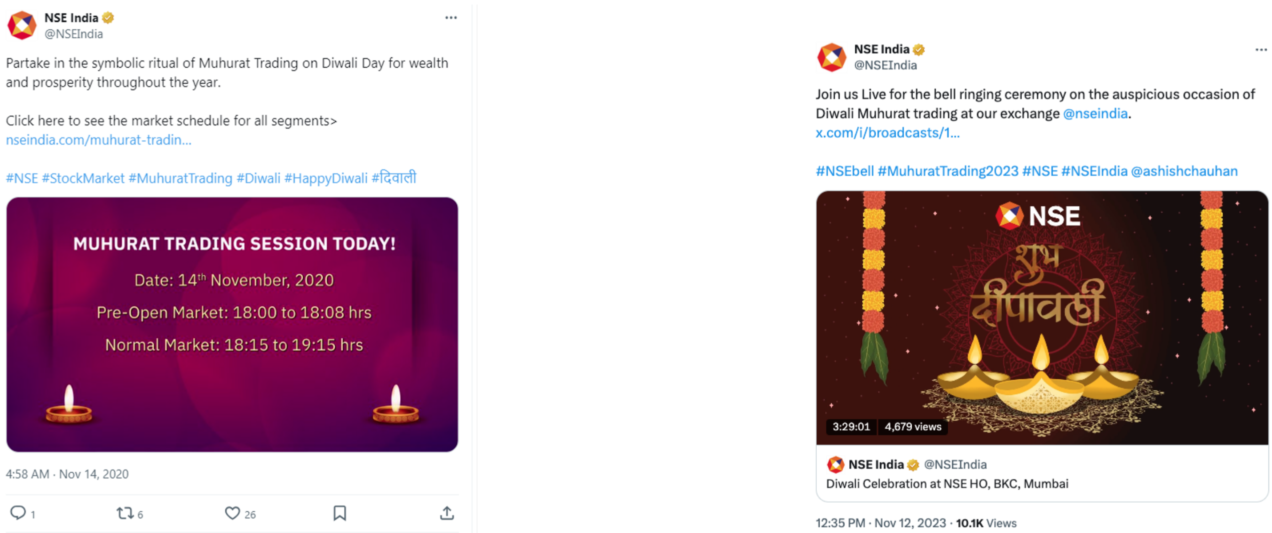
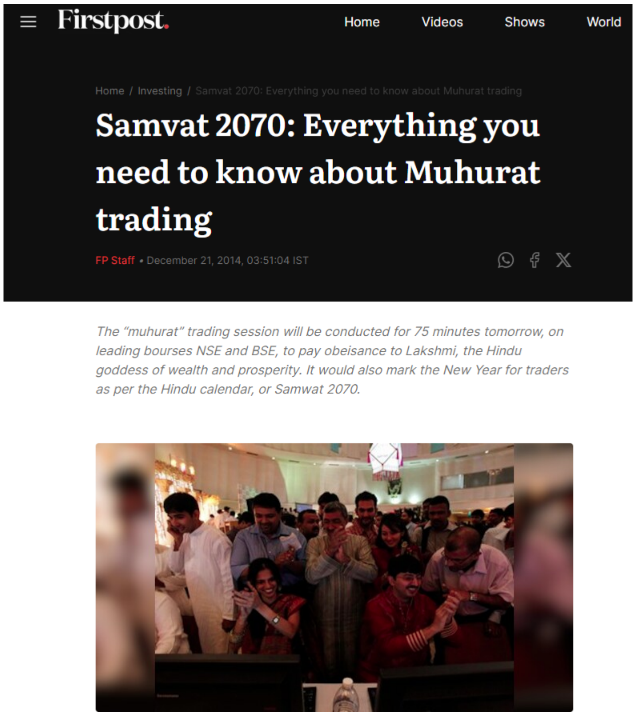


Figure IAB1: National Stock Exchange Muhurat Trading Advertising. This figure presents examples of Muhurat trading advertising on Twitter by the National Stock Exchange. The Tweets are available at https://x.com/NSEIndia/status/1327476084028260352 and https://x.com/NSEIndia/status/1723680845830168685.

[33]See, for example, https://timesofindia.indiatimes.com/business/india-business/muhurat-trading-2019-all-you-need-to-know/articleshow/71775284.cms and https://economictimes.indiatimes.com/markets/stocks/news/nse-bse-to-conduct-60-minute-muhurat-trading-on-diwali/articleshow/49616210.cms?from=mdr.

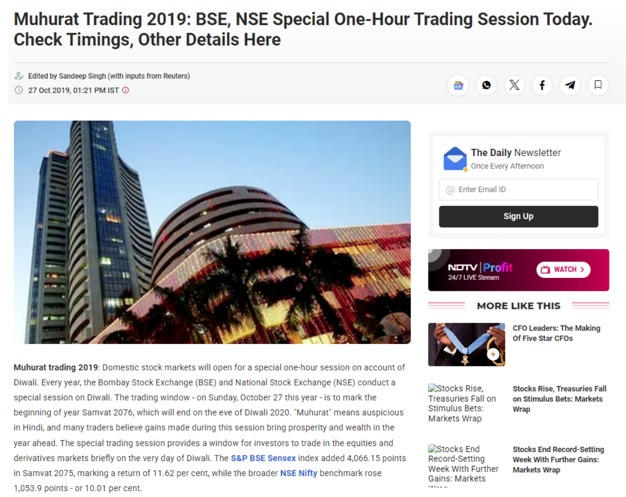

Home Videos Shows World

Home / Investing / Samvat 2070: Everything you need to know about Muhurat trading

Samvat 2070: Everything you need to know about Muhurat trading

FP Staff • December 21, 2014, 03:51:04 IST

The "muhurat" trading session will be conducted for 75 minutes tomorrow, on leading bourses NSE and BSE, to pay obeisance to Lakshmi, the Hindu goddess of wealth and prosperity. It would also mark the New Year for traders as per the Hindu calendar, or Samwat 2070.


Muhurat Trading 2019: BSE, NSE Special One-Hour Trading Session Today. Check Timings, Other Details Here

Edited by Sandeep Singh (with inputs from Reuters)

27 Oct 2019, 01:21 PM IST

Muhurat trading 2019: Domestic stock markets will open for a special one-hour session on account of Diwali. Every year, the Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) conduct a special session on Diwali. The trading window - on Sunday, October 27 this year - is to mark the beginning of year Samvat 2076, which will end on the eve of Diwali 2020. "Muhurat" means auspicious in Hindi, and many traders believe gains made during this session bring prosperity and wealth in the year ahead. The special trading session provides a window for investors to trade in the equities and derivatives markets briefly on the very day of Diwali. The S&P BSE Sensex index added 4,066.15 points in Samvat 2075, marking a return of 11.62 per cent, while the broader NSE Nifty benchmark rose 1,053.9 points - or 10.01 per cent.

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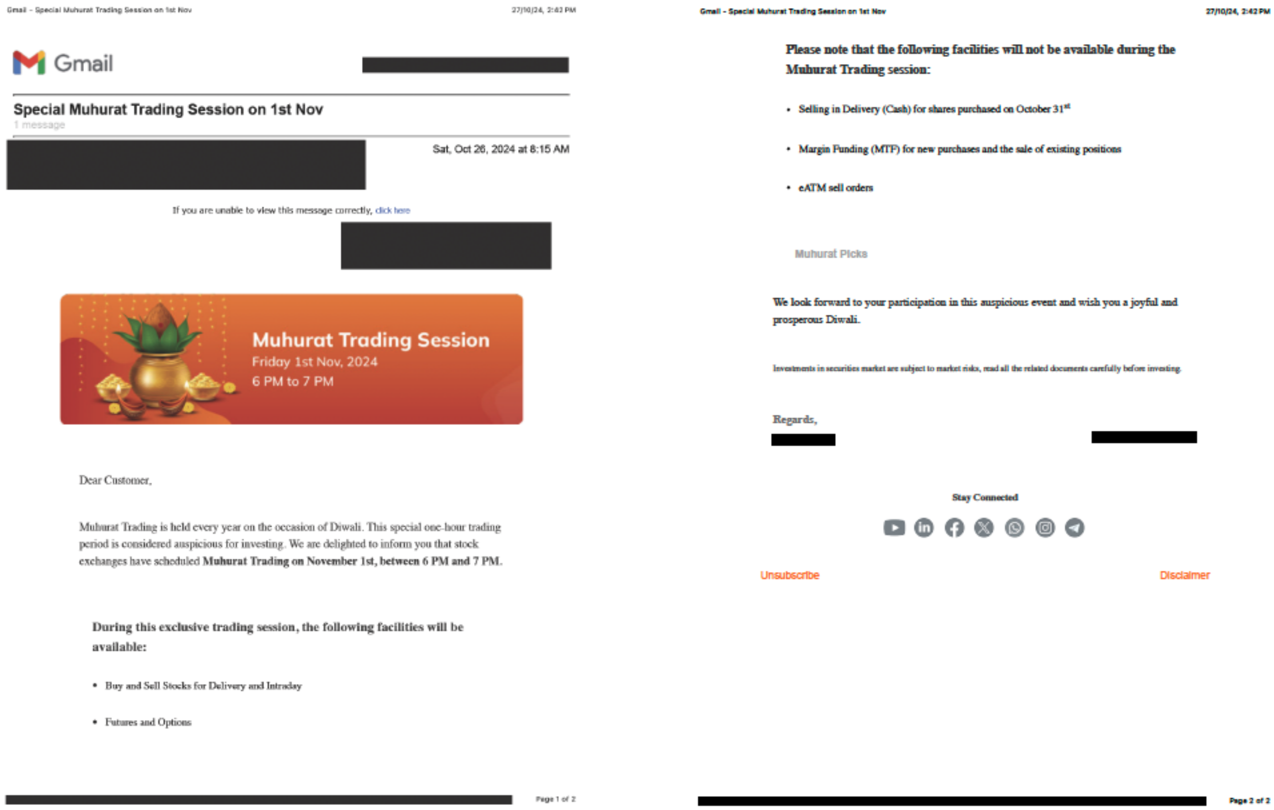
Stocks Rise, Treasuries Fall on Stimulus Bets: Markets Wrap

Stocks End Record-Setting Week With Further Gains: Markets Wrap

Figure IAB2: Newspaper References to Muhurat Trading. This figure presents examples of newspapers articles announcing Muhurat Trading. These articles are available at https://www.firstpost.com/investing/samvat-2070-everything-you-need-to-know-about-muhurat-trading-1207861.html and https://www.ndtvprofit.com/business/muhurat-trading-timings-2019-diwali-bse-nse-to-conduct-special-muhurat-trading-today-diwali-2019-2123294.

The particular broker for which we have data for also sends emails to clients indicating the date and time of Muhurat trading, while referencing the religious significance of the event. Figure IAB3 is an example of an email sent by the broker to advertise the 2024 Muhurat trading session.



Gmail - Special Muhurat Trading Session on 1st Nov 27/10/24, 2:42 PM

Gmail [redacted]

Special Muhurat Trading Session on 1st Nov
1 message

[redacted] Sat, Oct 26, 2024 at 8:15 AM

If you are unable to view this message correctly, click here

[redacted]

Dear Customer,

Muhurat Trading is held every year on the occasion of Diwali. This special one-hour trading period is considered auspicious for investing. We are delighted to inform you that stock exchanges have scheduled **Muhurat Trading on November 1st, between 6 PM and 7 PM.**

During this exclusive trading session, the following facilities will be available:

- Buy and Sell Stocks for Delivery and Intraday
- Futures and Options

[redacted] Page 1 of 2

Gmail - Special Muhurat Trading Session on 1st Nov 27/10/24, 2:42 PM

Please note that the following facilities will not be available during the Muhurat Trading session:

- Selling in Delivery (Cash) for shares purchased on October 31st
- Margin Funding (MTF) for new purchases and the sale of existing positions
- eATM sell orders

Muhurat Picks

We look forward to your participation in this auspicious event and wish you a joyful and prosperous Diwali.

Investments in securities market are subject to market risks, read all the related documents carefully before investing.

Regards,
[redacted] [redacted]

Stay Connected

Unsubscribe Disclaimer

[redacted] Page 2 of 2

Figure IAB3: Muhurat Trading Announcement Email. This figure presents an example of an email sent out by the broker for which we have individual retail trading data to clients for the 2024 Muhurat trading session.

Interest in the term "Muhurat Trading" in online searches also peaks during the month of Diwali when the special trading session takes place. Figure IAB4 plots the search interest in "Muhurat Trading" over our sample period, with the vertical dashed lines representing the month of Diwali and the trading sessions.

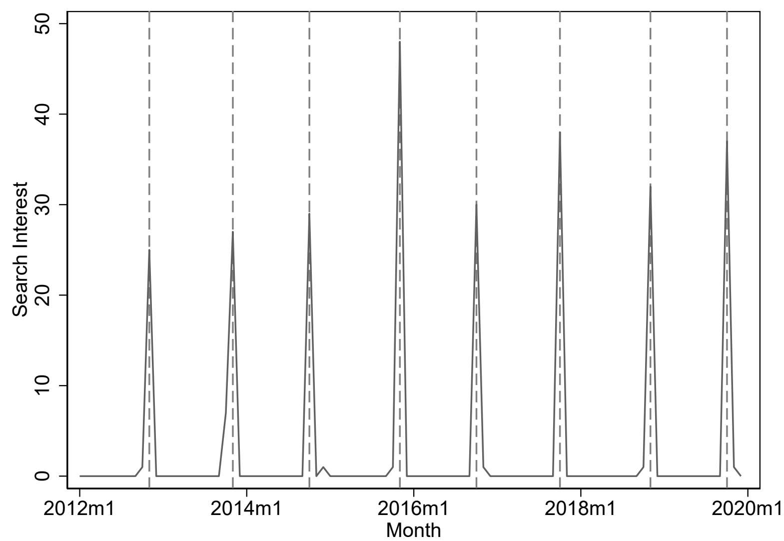


Figure IAB4: Google Trends Search Interest for "Muhurat Trading." This figure plots the time series of Google Trends search interest for the term "Muhurat Trading" from 2012 to 2019 in India nationally. The vertical dashed lines represent the month of the Muhurat trading session each year.

Table IAB1: Festivals, Religion, and Cultural Significance

SI No	Festivals	Religion	Cultural Significance
1	Diwali	Hindu, Jain	Celebrates the victory of light over darkness and good over evil, associated with the return of Lord Rama to Ayodhya.
2	Holi	Hindu	Festival of colors, celebrating the arrival of spring and the triumph of good over evil.
3	Navaratri	Hindu	A nine-day festival honoring the goddess Durga and symbolizing the triumph of good over evil.
4	Onam	Hindu	Harvest festival celebrated in Kerala, marking the return of the legendary King Mahabali.
5	Ganesh Chaturthi	Hindu	Celebration of the birth of Lord Ganesha, the remover of obstacles.
6	Ram Navami	Hindu	Marks the birth of Lord Rama, the seventh avatar of Vishnu.
7	Janmashtami	Hindu	Celebrates the birth of Lord Krishna, the eighth avatar of Vishnu.
8	Dussehra	Hindu	Commemorates the victory of Lord Rama over the demon king Ravana.
9	Mahavir Jayanti	Jain	Celebrates the birth of Lord Mahavira, the 24th Tirthankara in Jainism.
10	Vaisakhi	Sikh	Harvest festival and also marks the Sikh New Year and the formation of the Khalsa.
11	Guru Gobind Singh Sahib	Sikh	Observes the birth anniversary of Guru Gobind Singh, the tenth Sikh Guru.
12	Bandi Chhor Divas	Sikh	Celebrates the release of Guru Hargobind and his followers from imprisonment.
13	Guru Nanak Gurpurab	Sikh	Celebrates the birth of Guru Nanak, the founder of Sikhism.
14	Ramadan	Muslim	Holy month of fasting, prayer, and reflection, culminating in Eid al-Fitr.
15	Eid al-Fitr	Muslim	Festival marking the end of Ramadan, with feasts and celebrations.
16	Muharram	Muslim	Observance of the Islamic New Year and a period of mourning for the martyrdom of Imam Hussain.
17	Christmas	Christian	Celebrates the birth of Jesus Christ.
18	Good Friday	Christian	Observes the crucifixion of Jesus Christ, leading to Easter celebrations.
19	Republic Day	Holiday	Marks the day India became a republic with the adoption of its constitution on January 26.
20	Independence Day	Holiday	Celebrates India's independence from British rule on August 15.
21	Gandhi Jayanti	Holiday	Observes the birth of Mahatma Gandhi, the leader of India's independence movement.

C Conceptual Framework

To guide our empirical analysis, we embed cue theory into a simple intertemporal portfolio-choice model. Cue theory posits that environmental cues elicit temporary changes in preferences and behaviors, hence making cues and consumption complements by raising the marginal utility of consumption (Laibson, 2001; Pennesi, 2021; Apesteguia et al., 2023). Our conceptual framework highlights how an environmental cue—here, a religiously-framed trading session that ties participation in financial markets to new beginnings and long-term prosperity—can amplify the marginal utility from equity investing with implications for portfolio choices and wealth accumulation. In essence, the Muhurat session serves as a highly salient, attention-grabbing event that draws investors into the market (Barber and Odean, 2008). Even in the absence of new fundamental information, the auspicious framing and publicity surrounding the event focus investors' attention on equity investing, triggering trades that would not occur on a routine day absent the message and the cue.

C.1 Baseline Portfolio-Choice Model

Consider an investor i who, in each period t, chooses consumption c_t and a portfolio adjustment Δh_t of a broadly diversified equity holding h_t. Wealth evolves according to:

$$W_{t+1} = (1+r)\big(W_t - c_t - \Delta h_t\big) + h_t \pi_t, \tag{C.1}$$

where r is the risk-free rate, π_t is the stochastic per-unit return (including dividends), and $\Delta h_t = h_t - h_{t-1}$ captures net purchases. The investor maximizes expected lifetime utility (until time T):

$$\max_{c_t, \Delta h_t} \ \mathbb{E}\left[\sum_{t=0}^{T} \beta^t u(c_t, h_t)\right], \tag{C.2}$$

subject to the budget constraint (C.1) and a discount factor β. Under usual assumptions (e.g., CRRA over consumption and wealth), this model predicts smooth adjustments in holdings—absent shocks—since each trade incurs fixed costs or adjustment frictions (see Campbell, 2006, and below).

C.2 Introducing the Cue

We model the Muhurat trading session as a *cue*—a predictable environmental signal that temporarily raises the perceived marginal utility of investing in equities.[34] Let $\mathcal{D}$ denote the discrete set of dates corresponding to the event. We modify per-period utility to include a cue-driven term on those dates:

$$U_{i,t}(c_t, h_t) = u(c_t, h_t) + \mathbf{1}_{t\in\mathcal{D}} \cdot \delta_i \cdot v(\Delta h_t). \tag{C.3}$$

[34] Note that much of literature discusses cues in the context of temptation goods. However, one does not need "lottery-type" payoffs to treat a good as a temptation. Even safe, low-volatility stocks can function as temptation goods when a cue temporarily boosts their perceived value, raising short-run utility (Bernheim and Rangel, 2004).

Here, $\delta_i > 0$ measures investor i's sensitivity to the cue, and $v(\Delta h_t)$ is an increasing function capturing the immediate utility gain from trading (Bernheim and Rangel, 2004; Loewenstein, 1996). On non-event dates the cue term vanishes, reducing the model to the standard intertemporal choice problem; on event-day, the cue acts like a temporary utility subsidy to expanding equity positions. Importantly, $\delta_i > 0$ only for investors who recognize the event as an auspicious time for wealth (e.g., those of the relevant religious affiliation); for others, δ_i is effectively zero. Thus, only the "treated" investors experience the utility boost on event days, consistent with our empirical design comparing religiously affected vs. unaffected individuals.

Trading Frictions. We assume the trading-cost function to depend both on the sign and size of the trade. Specifically, we decompose the net portfolio change as

$$\Delta h_t \;=\; \Delta h_t^+ - \Delta h_t^-,$$

where $\Delta h_t^+ = \max\{\Delta h_t, 0\}$ and $\Delta h_t^- = \max\{-\Delta h_t, 0\}$.

The cost function is given by

$$C\big(\Delta h_t\big) \;=\; C^+\big(\Delta h_t^+\big) \;+\; C^-\big(\Delta h_t^-\big)\;, \tag{C.4}$$

where: $C^+(\cdot)$ and $C^-(\cdot)$ are convex and differentiable functions for purchases and sales, respectively.

Investor's Objective Function. The objective then becomes

$$\max_{\{c_t, h_t\}} \sum_{t=0}^{T} \beta^t \Big[u(c_t, h_t) + \mathbf{1}_{t\in\mathcal{D}} \cdot \delta_i \cdot v(\Delta h_t)\Big] \;-\; \sum_{t=1}^{T} \beta^t \, C\big(\Delta h_t\big),$$

subject to the usual budget constraint. Under this specification, on the event date ($t \in \mathcal{D}$), the term $\delta_i \, v(\Delta h_t)$ can outweigh $C^+(\Delta h_t^+)$, inducing new purchases. After the event date, reversing those positions ($\Delta h_t^- > 0$) incurs the sale cost $C^-(\Delta h_t^-)$, generating post-event inertia.[35]

C.3 Implications for Trading Behavior

C.3.1 Main Predictions.

1. **Trading Activity.** On dates $t \in \mathcal{D}$, the first-order condition equating marginal utility of consumption and investment shifts. The investor's first-order condition (FOC) for $\Delta h_t > 0$ is

$$u_h(c_t, h_t) + \mathbf{1}_{t\in\mathcal{D}} \cdot \delta_i \cdot v'(\Delta h_t) = \lambda_t \, (1 + r) + C'(\Delta h_t),$$

[35] We do not take a stance on the specific nature of the cost. For example, event purchases could carry extra psychological value—anchored in the festival's auspicious framing—so giving them up feels especially regretful and could generate "realization disutility," which investors dislike (Loomes and Sugden, 1982; Barberis and Xiong, 2012). It could also be that investors mentally segregate event-purchases shares into a special "Diwali" account. Closing that account feels like "wasting" a cultural ritual, and raises the perceived cost of rebalancing these holdings (Thaler, 1999). At the same time, participating in Muhurat trading session could be a public/social ritual, and hence selling the event-purchased stocks may feel like reneging on a communal norm, imposing a reputational or identity cost (Akerlof and Kranton, 2000).

where λ_t is the marginal utility of wealth. On cue-dates $t \in \mathcal{D}$, the extra $\delta_i \cdot v'(\Delta h_t)$ term raises the marginal benefit of buying, inducing a one-off spike in both the probability of buying and the average trade size. Although the timing of $t \in \mathcal{D}$ is public knowledge, it is important to note that the preference shock is transient—investors derive the extra utility only by trading on the event day.

2. **Persistence in Holdings.** Once established, holdings are adjusted infrequently due to adjustment costs. Once event-purchased holdings are in place, selling them incurs a sale cost $C^-(\Delta h_t^-)$, so it is optimal to leave holdings unchanged rather than pay the adjustment costs.

C.3.2 Additional Predictions.

Beyond the main predictions, our stylized model can generate additional predictions about the heterogeneity in the trading response depending on intensity of the religious cue.

3. **Placebo.** First, we exploit non-event religious days as a validation of the cue-specificity built into our model and allow the utility function to respond to multiple potential cues indexed by k. Specifically,

$$U_{i,t}(c_t, h_t) = u(c_t, h_t) + \sum_k \mathbf{1}_{t \in \mathcal{D}} \cdot \delta_i^{(k)} \cdot v\big(\Delta h_t\big),$$

where each $\mathcal{D}_k$ is the date of a different event, and $\delta_i^{(k)}$ measures how potent that cue is for investor i. We posit that only events tied to religiously-framed trading sessions linked to themes about new beginnings and long-term prosperity will have

$$\delta_i^{(\text{Event})} > 0,$$

while for all other events— religious festivals, national holidays, public announcements etc.

$$\delta_i^{(k \neq \text{Event})} \approx 0.$$

Empirically, this generates the following prediction: treated investors spike in trading only when $\mathbf{1}\{t \in \mathcal{D}_{\text{Event}}\} = 1$. If we observe a zero-effect on other days that lack the associated framing, this will rule out broader "holiday" or "religiosity" explanations and confirm that it is the religiously-framed cue—captured by $\delta_i^{(\text{Event})}$—that is driving the transient increase in marginal utility and thus the observed trading patterns.

4. **Heterogeneity across Stocks**. Second, we exploit heterogeneity in the intensity of the religious cue across stocks. If $\delta_i^{(\text{Event})}$ varies across stocks, then we expect the trading activity on the event-days to be concentrated on the stocks that align with festival's emphasis on new beginnings and long-term prosperity. In particular, the cue is likely larger for new stocks rather than existing holdings in the portfolio, in line with the emphasis on new beginnings.

5. **Heterogeneity across Individuals**. Third, we exploit heterogeneity in the trading response across individuals depending on the strength of the religious cue, captured by $\delta_i^{(\text{Event})}$. Because $\delta_i^{(\text{Event})}$ reflects the intensity of salience to investor i, individuals with higher cue salience should exhibit larger increases in marginal utility from initiating new

equity positions on the event day. Formally, when $\delta_i^{(\text{Event})} > \delta_j^{(\text{Event})}$, we expect investor i to display a larger trading spike than investor j when $\mathbf{1}\{t \in \mathcal{D}_{\text{Event}}\} = 1$, but no corresponding differences on non-event days.

In addition, the framework naturally accommodates a reinforcement mechanism: if the returns on event-purchased stocks in the interim period validate the underlying association with long-term prosperity, then investors update the perceived potency of the cue. This can be captured by a simple mapping,

$$\delta_{i,t+1}^{(\text{Event})} = \delta_{i,t}^{(\text{Event})} + \gamma \cdot R_{i,t}^{\text{Event}}, \qquad \gamma > 0,$$

where $R_{i,t}^{\text{Event}}$ is the interim return on the stock(s) purchased during the previous year's event. Positive returns thus increase future sensitivity to the cue, making participation itself persistent across years. Consequently, investors experiencing higher post-event returns should be more likely to trade again on the next event day, whereas we expect no relation between interim returns and trading on non-event days.

Together, these two forces imply that heterogeneity in both initial cue salience and post-event reinforcement generates predictable cross-sectional variation in event-day participation.

D Stock Market Participation

D.1 Brokerage Account Opening

In this appendix, we extend our analysis by studying decisions of individuals to open a brokerage account. To do so, we aggregate the number of accounts opened by individuals in our brokerage dataset across treated and non-treated groups and region. Specifically, we estimate:

$$naccounts_{imst} = \exp\left\{\beta_0 + \beta_1 Event_t + \beta_2 (Treated_i \times Event_t) + \gamma_{ims} + \varepsilon_{imst}\right\}, \tag{D.1}$$

where $naccounts_{ismt}$ is the number of brokerage accounts opened by individuals of treated group i on date t in state s and month-of-year m. Given the count nature of our dependent variable, we estimate a Poisson specification and control for treated × state × month-of-year fixed effects, allowing us to rule out concerns about differences in region-specific seasonality in account opening across treated and control groups. We cluster standard errors at the state-level.

Figure IAD1 presents the estimated coefficients β_1 and β_2, labeled as "Event" and "Event × Treated", respectively. Note that the base effect on "Treated" is subsumed by the fixed effects, and hence not displayed. The figure shows that individuals in the control group are not significantly more likely to open an account in the month of Diwali, with β_1 close to zero and statistically insignificant. The coefficient β_2, is positive and statistically different from zero, indicating that number of accounts opened are larger for individuals from the treated group relative to control group, controlling for seasonality and trends across groups. The coefficient estimate suggests that treated group opens 1.14 ($e^{0.133}$) accounts more in the month of Diwali compared to control group. Relative to the average of 1.43 new accounts opening on a daily basis, the estimate suggests a doubling in account opening. While the effect size is modest, this finding supports the hypothesis that treated individuals tend to open accounts with the intention of trading on Diwali. We formally test this in the subsequent section.

D.2 Likelihood to Trade for the First Time on Diwali

To assess whether treated individuals open their accounts with the intention of trading specifically on Muhurat trading day, we examine the likelihood of first-time trading occurring on Diwali. For each individual, we record the account opening date and the first observed trade date. We construct an individual-day dataset including the days between these two events. Using a hazard model, we estimate the probability of trading for the first time on Diwali, conditional on not having traded prior to that day.

The hazard model we estimate takes the form:

$$h_i(t) = h_0(t) \exp\left\{\beta_0 + \beta_1 Event_t + \beta_2 Treated_i + \beta_3 Event_t \times Treated_i + \epsilon_{i,t}\right\}, \tag{D.2}$$

where observations occur at the account (i) and date (t) levels. The variable $h_i(t)$ represents individual i's probability of trading on date t, conditional on not having traded before. $h_0(t)$ is the baseline hazard. The variable $Event_t$ is a dummy

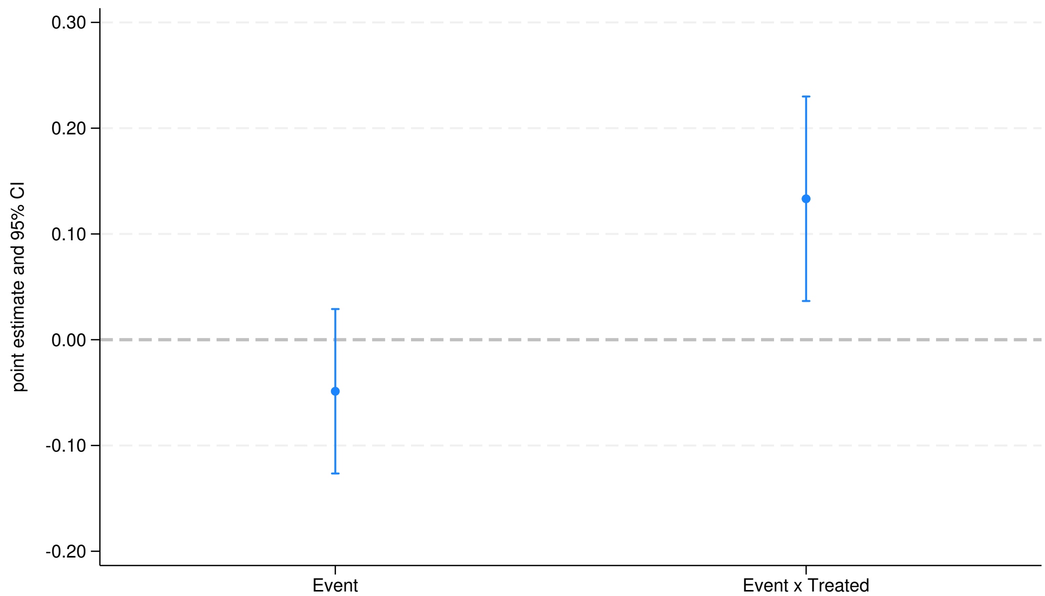


Figure IAD1: New brokerage account openings around Diwali events. This figure plots the estimates β_1 ("Event") and β_2 ("Event $\times$ Treated") of a $naccounts_{imst} = \exp\{\beta_0 + \beta_1 Event_t + \beta_2 (Treated_i \times Event_t) + \gamma_{ims} + \varepsilon_{imst}\}$, where $naccounts_{ismt}$ is the number of brokerage accounts opened by individuals of treated group i on date t in state s and month-of-year m. Given the count nature of our dependent variable, we estimate a Poisson specification and control for treated $\times$ state $\times$ month-of-year fixed effects, allowing us to rule out concerns about differences in region-specific seasonality in account opening across treated and control groups.

equal to 1 if date t corresponds to the Diwali Muhurat trading day, and $Treated_i$ is a dummy indicating whether individual i is inferred to be Hindu.

With this structure, the hazard ratio, $exp(\beta_1)$, measures the ratio of the probability of trading for the first time on Diwali versus the probability of trading for the first time on another day. Our main coefficient of interest in Equation (D.2) is β_3, the coefficient on the interaction term. This coefficient measures the difference in the (log) hazard ratio between treated and control individuals for trading on Diwali. More specifically, e^{β_3} represents the relative change in the hazard (or likelihood) of trading for the first time on Diwali for treated individuals compared to control individuals. Standard errors are clustered at the date level.[36]

Figure IAD2 presents the estimated coefficients β_1, β_2 and β_3, labeled as "Event," "Treated" and "Event $\times$ Treated" respectively. The results show that control individuals are not significantly more likely to trade for the first time on Diwali, with β_1 close to zero and statistically insignificant. The coefficient β_2, while small in magnitude, is significantly negative, indicating that treated individuals are 7% less likely to trade for the first time on any given day than controls (the hazard ratio is equal to 0.93 = $e^{-0.07}$). However, our main coefficient of interest β_3 is positive and statistically significant, with a magnitude of approximately 0.5. This indicates that the hazard (or likelihood) of treated individuals trading for the first time on Diwali is 1.65 ($= e^{0.5}$) higher than for control individuals. This implies that treated individuals are 65% more likely to trade for the first time on Diwali compared to controls. This finding supports the hypothesis that treated individuals tend to open accounts with the intention of trading on Diwali.

[36]The hazard model does not allow to cluster standard errors across multiple dimensions. We choose to cluster by day (rather than by investor) to adopt a conservative approach, as the number of trading days in our sample is smaller than the number of investors.

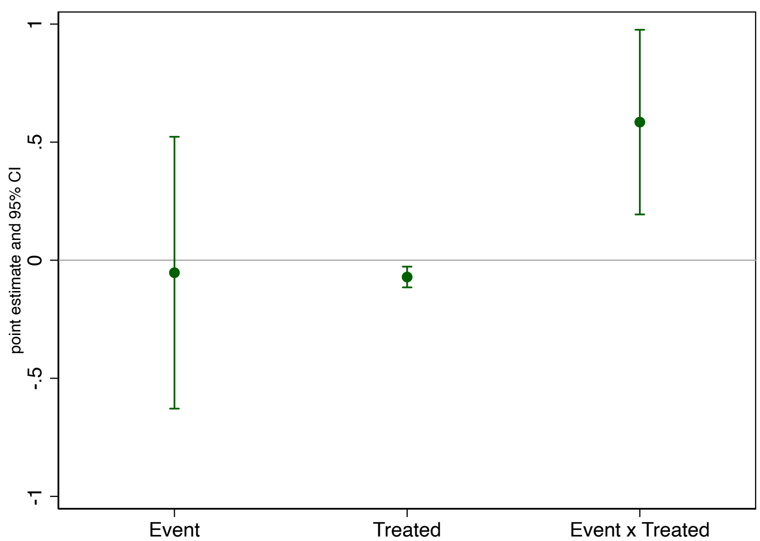


Figure IAD2: Likelihood to trade for the first time on Diwali event. This figure plots the estimates β_1 ("Event"), β_2 ("Treated") and β_3 ("Event $\times$ Treated") of a Cox hazard model of the form $h_i(t) = h_0(t)\exp\{\beta_0 + \beta_1 Event_t + \beta_2 Treated_i + \beta_3\{Event_t \times Treated_i\} + \epsilon_{i,t}\}$, where observations are at the account (i) and date (t) level, between the account opening date and the first trade date. For every account-day, $h_i(t)$ is investor i's probability of trading for the first time on date t conditional on not having traded prior to date t, and $h_0(t)$ is the baseline hazard. $Event$ is a dummy equal to 1 if the day corresponds to the Diwali's Muhurat trading day, and $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. Horizontal bars correspond to 95% confidence intervals. Standard errors are clustered at the date level.

D.3 Additional Robustness

In this Appendix, we show further robustness to our baseline estimations. Specifically, we show robustness to dropping one-event at a time.

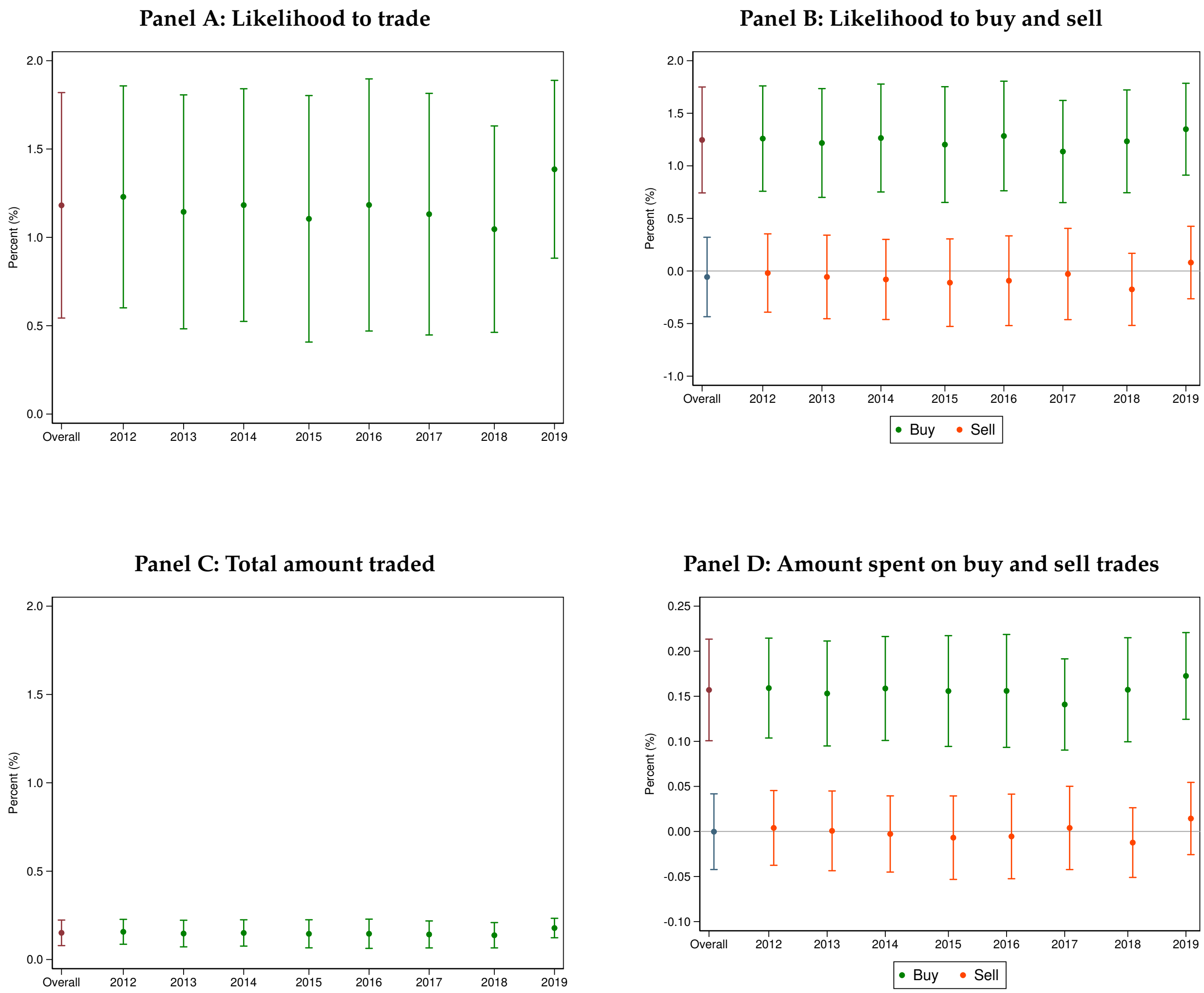


Figure IAD3: One leave-out estimations by event. This figure plots the estimated coefficients β after dropping one event at a time alongside the overall coefficient in maroon. Panel A presents results for likelihood of trade expressed in percent. Panel B presents results for the likelihood of buy and sell trade, both expressed in percent. Panel C presents results for total amount traded. Panel D presents results for the amount of buy and sell trades. All regressions include individual and state $\times$ date fixed effects as in specification Column (4) of Table 2.

D.4 Characteristics of Stocks Purchased on the Event

In this Appendix, we further analyze the characteristics of stocks purchased by treated individuals (Hindus) on the event day.

Stock Characteristics. For each event-day in our sample (eight trading days), we build a dataset at the individual-stock-date level. We include all treated investors and the full set of stocks traded on these days. For a given treated individual on an event-day, the dataset includes both the stocks the individual holds and those they do not. We then estimate the following empirical specification:

$$Buy_{i,j,t} = \beta_h \cdot HighCharacteristic_{j,t-1} + \beta_l \cdot LowCharacteristic_{j,t-1} + \gamma_{i,t} + \epsilon_{i,j,t}, \quad \text{(D.3)}$$

where i, j, and t denote individual, stock, and date, respectively. The dependent variable, $Buy_{i,j,t}$, is a variable equal to 10,000 if individual i buys stock j on date t, and 0 otherwise (i.e., it is expressed in basis points). The independent variables, $HighCharacteristic_{j,t-1}$ and $LowCharacteristic_{j,t-1}$, are dummies indicating whether a stock falls in the top or bottom quintile (i.e., top or bottom 20%) of the distribution for a given characteristic on day $t-1$, i.e., the last trading day before the event date t. The omitted baseline category comprises of stocks in the middle 60% of the distribution. In our results, we also report the p-value of a t-test comparing the coefficients on the top (β_h) and bottom (β_l) quintile dummies. The regression includes individual $\times$ date fixed effects $(\gamma_{i,t})$ to control for unobservable individual-specific factors that vary over time and focus on the relative attractiveness of stock characteristics for buying within each individual-day.[37] Standard errors are double-clustered at the individual and stock levels.

In Panel A of Table IAD1, we examine the following stock characteristics: market capitalization, book-to-market ratio, firm age, earnings per share (EPS), and past-year returns (all computed as described in Section 6.3 of the main text). The results in column (1) show that treated individuals are significantly more likely to purchase large-cap stocks with the coefficient on the high market capitalization dummy being approximately 2 basis points (b.p.). This represents a more than 300% increase compared to the mean of the dependent variable (0.64 b.p.). Conversely, treated individuals are significantly less likely to buy small-cap stocks with a smaller effect size of -0.13 b.p.

Column (2) indicates a preference for growth-oriented stocks, as treated individuals are more likely to purchase low book-to-market stocks (0.73 b.p.) and are less likely to purchase value stocks (-0.88 b.p.). Column (3) reveals a clear preference for "old firms" (1.2 b.p.) while Columns (4) and (5) reveal a preference for stocks with high earnings per share (0.7 b.p.). In Column (6), when we include all the characteristics simultaneously, we find that large market capitalization is the dominant characteristic favored by treated individuals, with a coefficient of 2 basis points (b.p.). Preference for stocks of older firms and stocks with high (and low) past-year returns, persist but are smaller in magnitude.

Overall, these findings suggest that on event days, treated individuals primarily purchase stocks of well-established companies, characterized by high market capitalization and, to a lesser extent, high earnings per share (EPS). This invest-

[37]Stock fixed effects are not included as the stock characteristics analyzed here are relatively persistent and our sample includes only eight trading sessions.

ment behavior aligns with the event's emphasis on long-term wealth and prosperity.

In Table IAD2, we extend the analysis to include additional stock characteristics motivated by Balasubramaniam et al. (2023), who document their strong influence on stock holding behavior in India. Specifically, we examine whether stocks paid dividends in the past year, have high (vs. low) average turnover over the past year, and exhibit high (vs. low) market beta, computed using the Indian Fama-French factors based on daily returns over the past year. The results indicate that treated individuals are significantly more likely to purchase stocks that pay dividends and are highly liquid (high turnover), confirming the findings above on the preference for large companies with strong fundamentals among treated investors on event days.

Lottery-like Characteristics. Next, we investigate whether treated individuals purchase stocks with lottery-like characteristics. We estimate the same regression specification as in Equation (D.3), focusing on the following stock attributes: share price on the day before the event and three measures of skewness: conventional skewness, the Pearson's skewness coefficient, the up-to-down volatility (all computed as described in Section 6.3 of the main text). Additionally, we include conventional return volatility, computed over the year preceding the event. The variables $HighCharacteristic_{j,t-1}$ and $LowCharacteristic_{j,t-1}$ are defined as in the previous analysis. Standard errors are double-clustered at the individual and stock levels.

Panel B of Table IAD1 presents the results. Column (1) shows that treated individuals are significantly more likely to purchase stocks in the top quintile for share price while they are less likely to buy low-priced stocks. Moreover, Column (2) shows that they exhibit a significant aversion to stocks with high past-year return skewness and Pearson skewness. In contrast, they are more likely to purchase stocks with low skewness. Column (4) also shows a mild aversion to stocks with high up-to-down volatility while Column (5) shows that treated individuals exhibit a clear preference for low-volatility stocks. In Column (6), when we include all independent variables, we find that the preferences for low-skewness and low-volatility stocks persist, together with a significant aversion to stocks with a low share price. Overall, these findings suggest that treated individuals do not favor lottery-like stocks on event days. Instead, their stock selection appears tilted towards low-skewness and low-volatility characteristics, inconsistent with speculative and gambling behavior.

Table IAD1: Characteristics of stocks purchased on Diwali day

Regressions are estimated at the individual-stock-date level. For each Muhurat trading day in our sample period, we include treated investors (Hindus) and all stocks in our dataset. The dependent variable is a dummy equal to 10,000 if the individual buys the stock on that day, and 0 otherwise. In Panel A, the independent variables are dummies indicating whether a stock is, on that day, in the top ("High") or bottom ("Low") quintile based on market capitalization (column (1)), book-to-market ratio (column (2)), earnings per share (column (3)), or past-year return (column (4)). Column (5) includes all these variables simultaneously. In Panel B, the independent variables are dummies for whether a stock is in the top or bottom quintile based on share price (column (1)), past-year skewness (column (2)), past-year Pearson skewness coefficient (column (3)), or past-year up-to-down volatility (column (4)). Column (5) includes all these variables simultaneously. For both panels, p-values of t-tests comparing coefficients on "High" vs. "Low" dummies are reported. All regressions include individual-date fixed effects, and standard errors (in parentheses) are double-clustered at the individual and stock levels. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock Characteristics

	Buy (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
High Mkt Cap	2.012***					1.962***
	(0.248)					(0.270)
Low Mkt Cap	-0.128***					-0.193*
	(0.012)					(0.099)
High B/M		-0.877***				-0.210**
		(0.170)				(0.105)
Low B/M		0.730**				0.447
		(0.286)				(0.285)
High Firm Age			1.202***			0.874*
			(0.453)			(0.509)
Low Firm Age			0.097			-0.177
			(0.177)			(0.188)
High EPS				0.704**		-0.001
				(0.280)		(0.340)
Low EPS				-0.324**		-0.026
				(0.128)		(0.147)
High Return					0.150*	0.421**
					(0.088)	(0.187)
Low Return					-0.144*	0.377**
					(0.082)	(0.152)
Individual × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64451478	29697371	38286959	37755688	62486079	29366207
R^2	0.002	0.003	0.002	0.002	0.001	0.003
High = Low (p-value)	0.000	0.000	0.017	0.000	0.004	

(*Continued from previous page*)

Panel B: Lottery-like Characteristics

	Buy (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
High Share Price	0.688***					0.264
	(0.162)					(0.175)
Low Share Price	-0.436***					-0.395***
	(0.077)					(0.081)
High Skewness		-0.221***				-0.106
		(0.076)				(0.071)
Low Skewness		0.716***				0.478***
		(0.164)				(0.118)
High Pearson Skewness			-0.205***			-0.010
			(0.059)			(0.048)
Low Pearson Skewness			0.643***			0.468**
			(0.206)			(0.203)
High Up-to-Down Volatility				-0.144**		0.103
				(0.071)		(0.068)
Low Up-to-Down Volatility				0.527***		0.133
				(0.155)		(0.117)
High Volatility					-0.050	-0.043
					(0.064)	(0.068)
Low Volatility					1.203***	0.999***
					(0.235)	(0.242)
Individual × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64500399	62431074	62431074	62331150	62486079	62331150
R^2	0.001	0.001	0.001	0.001	0.001	0.002
High = Low (p-value)	0.000	0.000	0.000	0.000	0.000	

Table IAD2: Additional characteristics of stocks purchased on Diwali day

Regressions are estimated at the individual-stock-date level. For each Muhurat trading day in our sample period, we include treated investors (Hindus) and all stocks in our dataset. The dependent variable is a dummy equal to 10,000 if the individual buys the stock on that day, and 0 otherwise. The independent variables are dummies indicating whether a stock is, on that day, in the top ("High") or bottom ("Low") quintile based on firm age, i.e., the number of years since listing (column (1)), whether the stock paid a dividend in the past year (column (2)), average turnover over the past year (column (3)), market beta (column (4)), or past-year volatility (column (5)). Column (6) includes all these variables simultaneously. p-values of t-tests comparing coefficients on "High" vs. "Low" dummies are reported. All regressions include individual-date fixed effects, and standard errors (in parentheses) are double-clustered at the individual and stock levels. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Buy (bps)			
	(1)	(2)	(3)	(4)
Paid Dividend	0.946***			0.774***
	(0.180)			(0.184)
High Turnover		0.717***		0.549**
		(0.147)		(0.224)
Low Turnover		-0.475***		-0.360***
		(0.082)		(0.092)
High Beta			0.256***	0.179
			(0.085)	(0.127)
Low Beta			-0.432***	-0.099
			(0.095)	(0.239)
Individual × Date FE	Yes	Yes	Yes	Yes
Observations	38305868	64451478	64454545	38243133
R^2	0.002	0.001	0.001	0.002
High = Low (p-value)		0.000	0.000	

E Additional Figures and Tables

E.1 Tables

Table IAE1: List of Muhurat trading dates and timings
This table lists the dates and timings of Muhurat trading session on account of Diwali covered in our sample. All trades executed in the trading session result in settlement obligations. They are available at Circulars.

Year	Date	Timings
2012	November 13, 2012	15:30 to 17:20
2013	November 3, 2013	18:00 to 19:50
2014	October 23, 2014	18:15 to 19:50
2015	November 11, 2015	17:30 to 19:05
2016	October 30, 2016	18:15 to 19:50
2017	October 19, 2017	18:15 to 19:50
2018	November 7, 2018	17:00 to 18:50
2019	October 27, 2019	17:45 to 19:40

Table IAE2: National Stock Exchange Summary Statistics
This table presents summary statistics of daily transactions aggregated at the stock-date level, on the National Stock Exchange over our sample period covering 2012 to 2019 for all retail trades.

Variable	Obs	Mean	Sd	5%	25%	50%	75%	95%
Buy	2,816,089	619.06	2,129.21	3.00	23.00	86.00	371.00	2,913.00
Sell	2,816,089	584.49	2,067.89	3.00	22.00	78.00	333.00	2,781.00
Amount Buy (₹1000s)	2,816,089	54,150.56	263,175.37	8.42	312.07	2,619.61	17,243.68	244,377.64
Amount Sell (₹1000s)	2,816,089	54,738.50	267,882.73	8.94	321.60	2,712.23	17,473.94	247,097.69
Retail imbalance	2,816,089	0.03	0.25	-0.36	-0.11	0.02	0.17	0.42

Table IAE3: Broker Dataset Summary Statistics Conditional on Trading This table lists the account-date level (Panel A), and account-stock-date level (Panel B) summary statistics from our broker dataset. Panel A restricts the account-day sample to observations on days when individuals trade at least one stock. Panel B only includes the holdings of treated individuals (Hindus) and restricts the holdings sample to observations on days when individuals sell at least one stock. Over our sample window from 2012 to 2019, the average exchange rate is ₹64 to 1 USD.

Variable	Obs	Mean	Sd	5%	25%	50%	75%	95%
Panel A: Account-date level (trade-conditioned sample)								
Total Portfolio Value (₹1000s)	484,500	2,296.89	6,469.26	13.52	149.87	560.83	1,911.40	9,430.40
Nb. Stocks	484,500	11.45	15.71	1.00	3.00	7.00	14.00	37.00
Buy	484,500	0.76	0.43	0.00	1.00	1.00	1.00	1.00
Sell	484,500	0.36	0.48	0.00	0.00	0.00	1.00	1.00
Amount Traded (₹1000s)	484,500	207.64	765.61	1.92	19.51	55.91	158.88	772.01
Amount Buy Trades (₹1000s)	484,500	123.05	522.21	0.00	0.30	24.16	88.35	486.02
Amount Sell Trades (₹1000s)	484,500	84.59	477.42	0.00	0.00	0.00	37.27	358.34
Panel B: Account-Stock-date level (trade-conditioned sample)								
Trade	2,122,229	0.15	0.36	0.00	0.00	0.00	0.00	1.00
Sell	2,122,229	0.05	0.21	0.00	0.00	0.00	0.00	0.00
Buy	2,122,229	0.11	0.31	0.00	0.00	0.00	0.00	1.00
Amount Traded (₹1000s)	2,122,229	23.16	187.37	0.00	0.00	0.00	0.00	92.04
Amount Buy (₹1000s)	2,122,229	6.12	93.83	0.00	0.00	0.00	0.00	0.00
Amount Sell (₹1000s)	2,122,229	17.04	162.83	0.00	0.00	0.00	0.00	59.09
Time Owned (Days)	2,122,229	111.33	144.72	2.00	17.00	57.00	148.00	411.00

Table IAE4: Diwali trades and Hindu investor characteristics

This table presents investor-date level summary statistics and t-tests of differences for Hindus who trade or do not trade on Diwali for investor characteristics. Characteristics include an indicator variable for male, the age as of the trading day, and income. Column (7) presents a t-test of the difference between the "No Trade" group and the "Any Trade" group, with the t-statistic in brackets. Column (8) refers to the buy vs. sell difference, conditional on any trade. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	No Trade *N=34,812*			Any Trade *N=1,094*			Mean Difference	Conditional Difference: Mean Difference - Buy vs. Sell
	Mean (1)	**Sd (2)**	**Median (3)**	**Mean (4)**	**Sd (5)**	**Median (6)**	**(7)**	**(8)**
Male	0.72	0.45	1.00	0.71	0.46	1.00	0.01	-0.04
							[0.93]	[-0.96]
Age	40.94	13.86	36.42	41.37	13.36	38.33	-0.43	1.97
							[-1.05]	[1.46]
Income	9.29	12.18	3.00	8.89	11.65	3.00	0.40	-0.69
							[1.10]	[-0.57]

Table IAE5: Amount spent on buy and sell trades on Diwali day conditional on trading Regressions are estimated at the individual-date level, restricting the sample to observations where trading occurs. In Columns (1) to (3) (resp. (4) to (6)), the dependent variable is the arcsinh of the amount spent on buy (resp. sell) trades by the individual on that day. $Event$ is a dummy equal to 1 if the day corresponds to the Diwali's Muhurat trading day, and $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. Standard errors (in parentheses) are double-clustered at the individual and date level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Amount Buy Trades			Amount Sell Trades		
	(1)	(2)	(3)	(4)	(5)	(6)
Event Day × Treated	0.583***	0.388**	0.308*	-0.458***	0.070	0.193
	(0.137)	(0.167)	(0.180)	(0.172)	(0.242)	(0.163)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	No	No	Yes	No	No
State × Date FE	No	Yes	No	No	Yes	No
District × Date FE	No	No	Yes	No	No	Yes
Observations	484,500	484,500	484,500	484,500	484,500	484,500
R^2	0.14	0.18	0.26	0.20	0.24	0.31

Table IAE6: Market Return and Stock Abnormal Return on Event Days Regressions are estimated at the daily level. In Panel A, the dependent variable is the daily return (in percent) of the Indian stock market. In Panel B, the dependent variable is the daily CAPM-implied abnormal return (in percent) at the stock-day level. *Event Day* is a dummy equal to 1 if the day corresponds to the Diwali Muhurat trading session. Columns (2) through (4) include indicators for the day before the event, the day after, the week after, the month after, and the three months after. All specifications include year and day-of-year fixed effects. Panel B further includes stock fixed effects. Robust standard errors (in parentheses) are adjusted to be heteroscedasticity-consistent in Panel A. In Panel B, standard errors are double-clustered at the stock and date levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Market Return

	Market Return (%)			
	(1)	(2)	(3)	(4)
Day before Event			0.059	0.062
			(0.241)	(0.243)
Event Day	0.964^{***}	0.966^{***}	0.966^{***}	0.970^{***}
	(0.197)	(0.198)	(0.198)	(0.200)
Day after Event		0.426	0.426	0.396
		(0.459)	(0.460)	(0.523)
Week after Event				0.095
				(0.315)
Month after Event				-0.106
				(0.221)
3-Month after Event				0.045
				(0.137)
Year FE	Yes	Yes	Yes	Yes
Day of Year FE	Yes	Yes	Yes	Yes
Observations	1,979	1,979	1,979	1,979
R^2	0.182	0.182	0.182	0.182

Panel B: Stock Abnormal Return

	Stock Abnormal Return (%)			
	(1)	(2)	(3)	(4)
Day before Event			-0.222	-0.207
			(0.298)	(0.299)
Event Day	1.331^{***}	1.332^{***}	1.331^{***}	1.346^{***}
	(0.103)	(0.103)	(0.103)	(0.105)
Day after Event		0.098	0.097	-0.264
		(0.160)	(0.160)	(0.233)
Week after Event				0.207
				(0.215)
Month after Event				0.137
				(0.173)
3-Month after Event				0.033
				(0.077)
Year FE	Yes	Yes	Yes	Yes
Day of Year FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Observations	5,708,179	5,708,179	5,708,179	5,708,179
R^2	0.005	0.005	0.005	0.005

Table IAE7: Likelihood to trade, buy and sell on other religious-event days

Regressions are estimated at the individual-date level. In Panel A, in Columns (1) and (2), the dependent variable is a variable equal to 100 if the individual trades on that day, 0 otherwise; in Columns (3) and (4), it is a variable equal to 100 if the individual buys any stock on that day, 0 otherwise; in Columns (5) and (6), it is a variable equal to 100 if the individual sells any stock on that day, 0 otherwise. In Panel B, in Columns (1) and (2), the dependent variable is the arcsinh of the amount traded by the individual on that day; in Columns (3) and (4), it is the arcsinh of the amount spent on buy trades by the individual on that day; in Columns (5) and (6), it is the arcsinh of the amount spent on sell trades by the individual on that day. $Other\ Hindu\ Religious\ Event$ is a dummy equal to 1 if the day corresponds to an Hindu religious event except Diwali, and $Non\ Hindu\ Religious\ Event$ is a dummy equal to 1 if the day corresponds to religious event for non-Hindu religions. $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. $Affected\ Control$ is a dummy indicating whether the individual is inferred to be of the religion associated with $Non\ Hindu\ Religious\ Event$. Standard errors (in parentheses) are double-clustered at the individual and date level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Likelihood to trade

	Trade × 100		Buy × 100		Sell × 100	
	(1)	(2)	(3)	(4)	(5)	(6)
Other Hindu Religious Event × Treated	-0.277*	-0.277*	-0.227	-0.227	-0.038	-0.038
	(0.163)	(0.163)	(0.149)	(0.149)	(0.087)	(0.087)
Non-Hindu Religious Event × Affected Control		0.012		-0.027		0.002
		(0.225)		(0.208)		(0.111)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768
R^2	0.12	0.12	0.10	0.10	0.08	0.08

Panel B: Amount spent on trades

	Amount Traded		Amount Buy Trades		Amount Sell Trades	
	(1)	(2)	(3)	(4)	(5)	(6)
Other Hindu Religious Event × Treated	-0.034*	-0.034*	-0.027	-0.027	-0.005	-0.005
	(0.019)	(0.019)	(0.017)	(0.017)	(0.011)	(0.011)
Non-Hindu Religious Event × Affected Control		-0.004		-0.010		-0.000
		(0.026)		(0.023)		(0.013)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768	6,090,768
R^2	0.12	0.12	0.10	0.10	0.08	0.08

Table IAE8: Stock Summary Statistics This table lists the stock-date level summary statistics. Firm age corresponds to the number of years since listing. Skewness, Pearson Skewness, Up-to-down Volatility and Volatility are computed using daily data over the preceding year. Skewness is the third central moment of the return distribution divided by the standard deviation cubed. Pearson's skewness coefficient, is calculated as $3 \times (\text{Mean} - \text{Median})/\text{Standard Deviation}$. Up-to-down volatility, reflects the relative frequency and magnitude of positive versus negative daily returns, where higher values indicate greater relative volatility in negative returns compared to positive returns. Paid Dividend is a dummy equal to one if the stock paid dividend over the preceding year. Turnover is the fraction of shares outstanding traded on the day. Beta is the market beta computed using the Indian Fama French factor, using daily returns over the preceding year.

Variable	Obs	Mean	Sd	5%	25%	50%	75%	95%
Mkt Cap (₹mio)	6445793	34,529.81	213094.77	33.44	196.20	947.76	6,438.62	115135.65
Book-to-market (B/M)	2270893	11.95	28.18	1.43	2.54	4.78	10.64	40.46
Firm Age (Years)	3136599	34.10	22.06	10.00	21.00	28.00	40.00	81.00
Earnings-per-share (EPS)	3112099	9.94	85.42	-34.51	-1.55	2.75	14.47	63.86
Past-year Return (%)	5266427	20.94	191.40	-72.23	-34.08	-4.55	37.57	172.00
Share Price (₹)	6447262	246.60	1,271.53	1.60	12.27	42.72	157.70	906.83
Skewness	5263726	0.42	1.59	-0.67	0.03	0.41	1.01	2.04
Pearson Skewness	5263726	0.15	0.35	-0.28	0.00	0.15	0.31	0.55
Up-to-down Volatility	5228729	0.40	0.76	-0.57	0.04	0.39	0.78	1.37
Volatility	5266295	0.04	0.18	0.02	0.03	0.03	0.04	0.06
Paid Dividend	3232424	0.64	0.48	0.00	0.00	1.00	1.00	1.00
Turnover (bps)	6445793	0.23	1.59	0.00	0.01	0.03	0.13	0.90
Beta	6430216	0.85	11.62	-0.33	0.37	0.83	1.31	2.01

Table IAE9: Likelihood to trade margin products such as options on event days

Regressions are estimated at the individual-date level. In Columns (1), (2) and (3), the dependent variables are dummies indicating whether the individual trades, buy, or sell, respectively, any margin products such as options. $Event$ is a dummy equal to 1 if the day corresponds to the Diwali's Muhurat trading day, and $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. Standard errors (in parentheses) are double-clustered at the individual and date level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Trade × 100	Buy × 100	Sell × 100
	(1)	(2)	(3)
Event Day × Treated	0.046	0.076	-0.064
	(0.166)	(0.151)	(0.166)
Individual FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Observations	6,090,768	6,090,768	6,090,768
R^2	0.242	0.223	0.225

Table IAE10: Disposition Effect

Regressions are estimated at the individual-stock-date level. For each trading day in our sample period, we include the holdings of treated investors (Hindus). In both panels, the dependent variable is a variable equal to 100 if the individual sells (fully or partially) the stock on that day. Panel A uses the unconditional sample, i.e., including days when no trading occurs. Panel B restricts the sample to observations where the individual sells on that day. $Purchased\ on\ Event$ is a dummy equal to 1 if some shares of the stock were purchased for the first time on Muhurat trading day. If the stock is sold off and repurchased later, it is considered a new position and the dummy is reset to zero. $Gain$ is a dummy indicating whether the stock is trading at a paper gain relative to its weighted-average purchase price. Control variables include the logarithm of the weighted-average purchase price, the squared root of the number days the stock has been held, the return since purchase if the asset is in paper loss (gain) and zero otherwise, as well as their interactions with the squared root of the number days the stock has been held. Standard errors (in parentheses) are double-clustered at the individual and date level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Unconditional sample

	Sell × 100			
	(1)	(2)	(3)	(4)
Purchased on Event	-0.149***	-0.202***	-0.059	-0.101**
	(0.054)	(0.069)	(0.042)	(0.049)
Gain	0.639***	0.684***	0.683***	0.754***
	(0.020)	(0.020)	(0.021)	(0.023)
Purchased on Event × Gain	-0.170***	-0.148**	-0.206***	-0.196***
	(0.065)	(0.071)	(0.060)	(0.062)
Control Variables	No	Yes	No	Yes
Individual FE	Yes	Yes	No	No
Individual × Date FE	No	No	Yes	Yes
Stock × Date FE	Yes	Yes	Yes	Yes
Observations	28,587,808	28,587,808	28,587,808	28,587,808
R^2	0.073	0.074	0.296	0.296

Panel B: Sale-conditioned sample

	Sell × 100			
	(1)	(2)	(3)	(4)
Purchased on Event	-1.322**	-1.455**	-1.144**	-1.368**
	(0.586)	(0.630)	(0.580)	(0.639)
Gain	6.694***	7.044***	6.957***	7.185***
	(0.231)	(0.246)	(0.253)	(0.266)
Purchased on Event × Gain	-0.767	-0.745	-0.812	-0.811
	(0.886)	(0.889)	(0.970)	(0.956)
Control Variables	No	Yes	No	Yes
Individual FE	Yes	Yes	No	No
Individual × Date FE	No	No	Yes	Yes
Stock × Date FE	Yes	Yes	Yes	Yes
Observations	2,122,229	2,122,229	2,122,229	2,122,229
R^2	0.326	0.327	0.400	0.401

Table IAE11: Heterogeneity by Salience

Regressions are estimated at the individual-stock-date level. For each trading day in our sample period, we include the holdings of treated investors (Hindus). Columns (1), (2), and (3) the dependent variable is a variable equal to 100 if the individual trades, buys, or sells on that day, respectively, and 0 otherwise. In Columns (4) and (5), the dependent variable is the arcsinh of the amount spent on buy and sell trades by the individual on that day. The sample includes days when no trading occurs. $High\ Salience$ is a dummy equal to 1 if the Google Search Volume Index within a year in the top quartile across states. $Event\ Day$ is a dummy equal to 1 if the day corresponds to the Diwali's Muhurat trading day. Standard errors (in parentheses) are double-clustered at the individual and date level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	Trade × 100	Buy × 100	Sell × 100	Buy amount	Sell amount
	(1)	(2)	(3)	(4)	(5)
High salience	0.076	0.049	0.069	0.005	0.007
	(0.135)	(0.113)	(0.069)	(0.013)	(0.008)
Event Day × High salience	1.240***	1.251***	-0.056	0.138***	-0.011
	(0.252)	(0.205)	(0.107)	(0.028)	(0.012)
Individual FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
R^2	0.12	0.10	0.08	0.10	0.08
Observations	6,197,490	6,197,490	6,197,490	6,197,490	6,197,490

Table IAE12: Persistence in Participation Conditional on Performance Regressions are estimated at the individual-year level, including only treated individuals (Hindus). The dependent variable in Columns (1)–(3) is an indicator equal to 100 if the individual buys on the event day in a given year, and 0 otherwise. In Columns (4)–(6), the dependent variable is the inverse hyperbolic sine (arcsinh) of the total amount spent on buy trades on the event day. The key independent variables measure the returns earned on stocks purchased on the previous year's event day, computed over three horizons: 1 day, 21 trading days (approximately 1 month), and 252 trading days (1 year). All specifications include individual and year fixed effects. Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Buy × 100			Amount Buy		
	(1)	(2)	(3)	(4)	(5)	(6)
1-Day Return Post-Event Last Year	-65.298			-9.152		
	(115.392)			(13.077)		
21-Day Return Post-Event Last Year		36.727*			3.053	
		(19.181)			(2.182)	
252-Day Return Post-Event Last Year			15.328***			1.795***
			(5.536)			(0.617)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,874	1,874	1,874	1,874	1,874	1,874
R^2	0.458	0.461	0.465	0.469	0.471	0.476

E.2 Figures

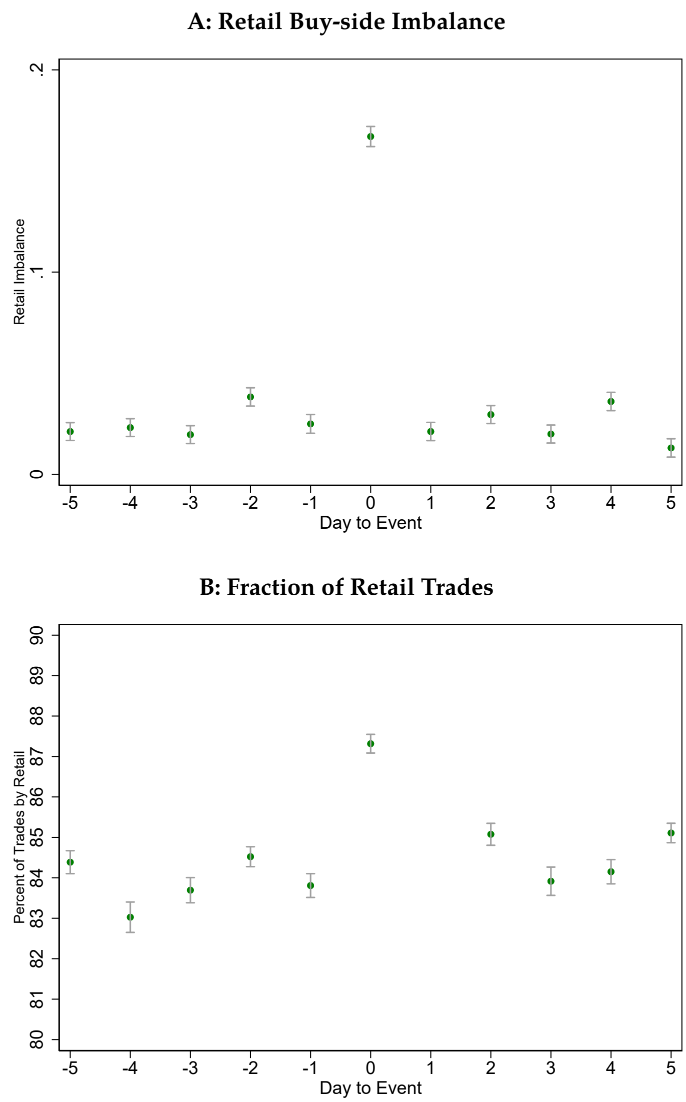


Figure IAE1: Aggregate retail imbalance and share of retail trades around the event. This figure plots the retail imbalance and share of retail trades means with 95% confidence intervals around the 5 days before and after Diwali for stocks trading on the National Stock Exchange (NSE). Retail imbalance is computed as $\frac{(buy+sell)}{buy-sell}$, where *buy* and *sell* are the number of buy and sell trades, respectively.

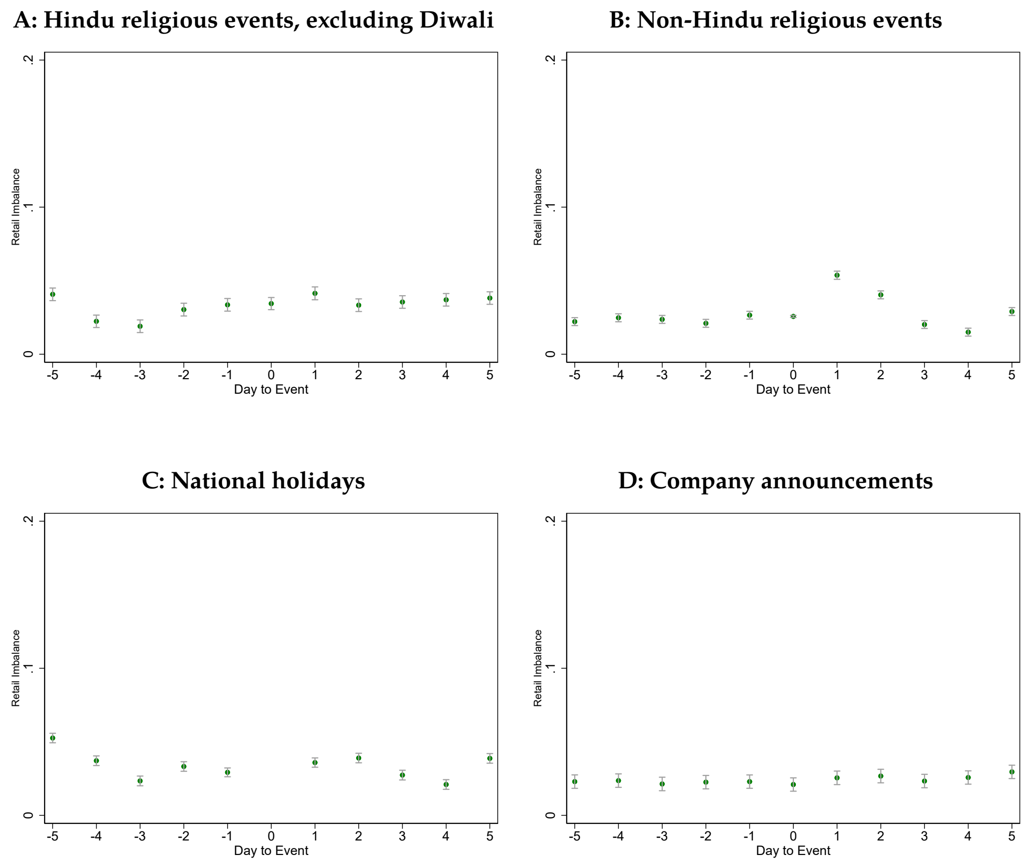


Figure IAE2: Aggregate retail imbalance around other events. This figure plots the retail imbalance mean with 95% confidence intervals around the 5 days before and after a particular event for stocks trading on the National Stock Exchange (NSE). Retail imbalance is computed as $\frac{(buy+sell)}{buy-sell}$, where *buy* and *sell* are the number of buy and sell trades, respectively. The event date refers to Hindu national religious events excluding Diwali, non-Hindu religious events, national holidays and firm announcement dates in Panels A-D, respectively.

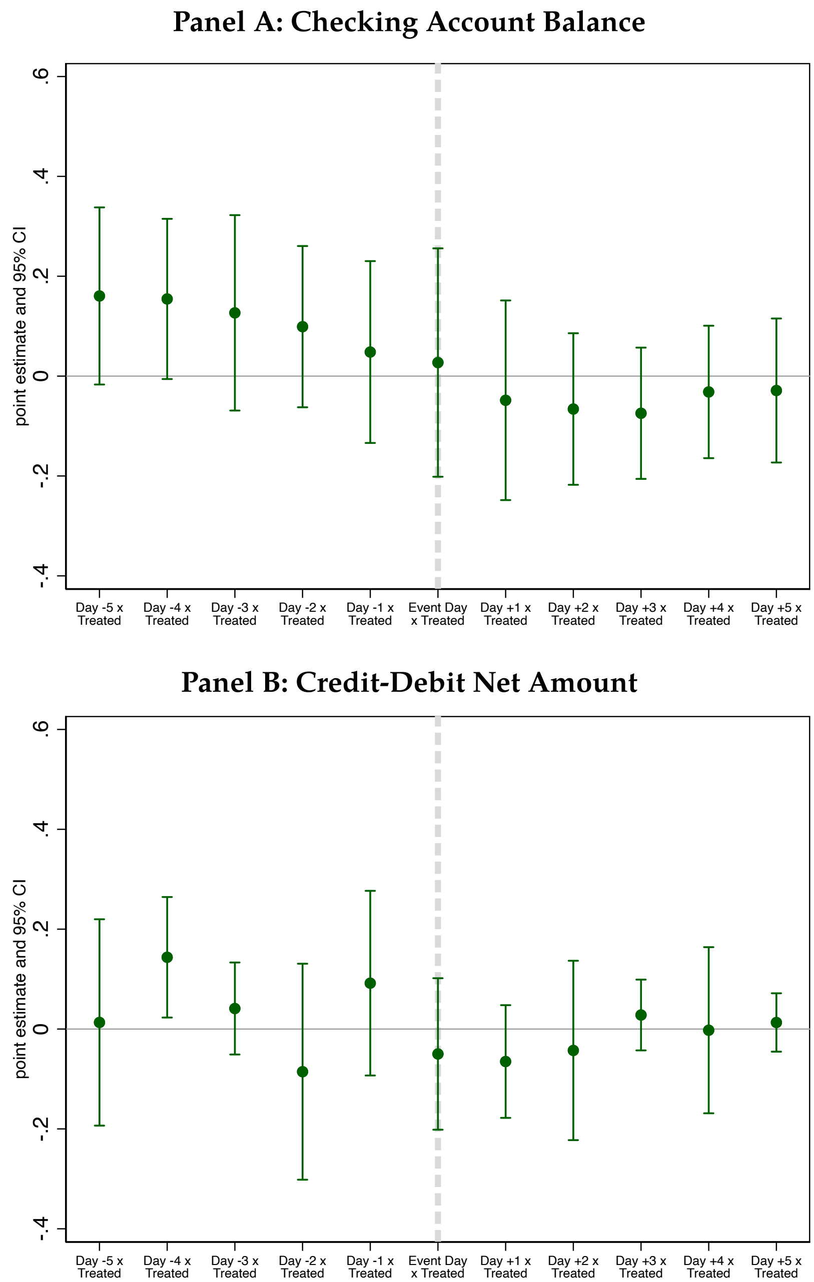


Figure IAE3: Dynamics of account balance and credit-debit net amount. This figure plots the coefficients β_k on each day in equation: $Y_{i,t} = \sum_{k=-5}^{5} \beta_k \{Treated_i \times Day(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the individual and date, and $Day(k)_t$ is a dummy equal to one if date t corresponds to k days before/after a Diwali day. $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. α_i and γ_t denote individual and date fixed effects respectively. The dependent variable is the arcsinh of the individual's checking account balance in Panel A, and the arcsinh of the difference between credit and debit amounts in Panel B. Horizontal bars correspond to 95% confidence intervals. Standard errors are double-clustered at the investor and date levels.

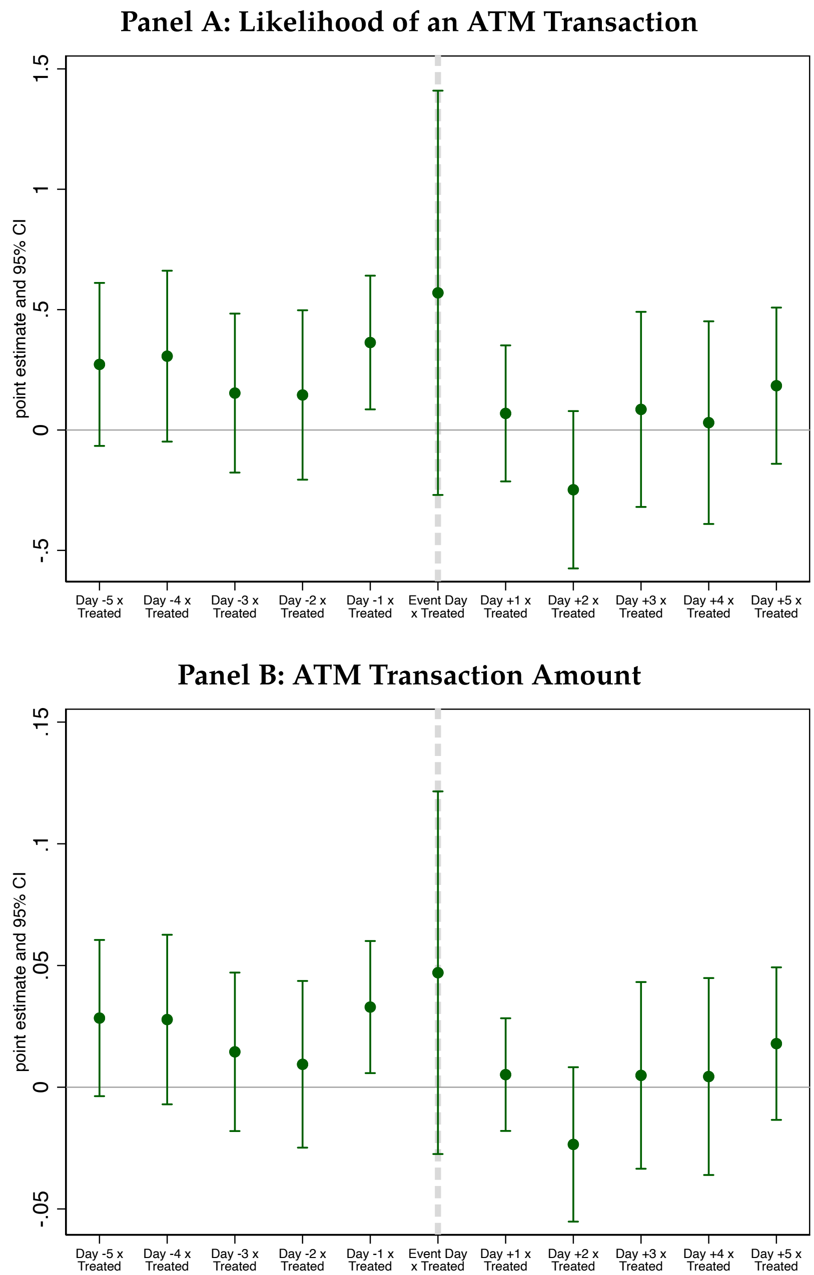


Figure IAE4: Dynamics of ATM transactions. This figure plots the coefficients β_k on each day in equation: $Y_{i,t} = \sum_{k=-5}^{5} \beta_k \{Treated_i \times Day(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the individual and date, and $Day(k)_t$ is a dummy equal to one if date t corresponds to k days before/after a Diwali day. $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. α_i and γ_t denote individual and date fixed effects respectively. The dependent variable is a dummy equal to one if we observe an ATM withdrawal on the individual's account on tha day, and is the arcsinh of the individual's ATM transaction amount in Panel B. Horizontal bars correspond to 95% confidence intervals. Standard errors are double-clustered at the investor and date levels.

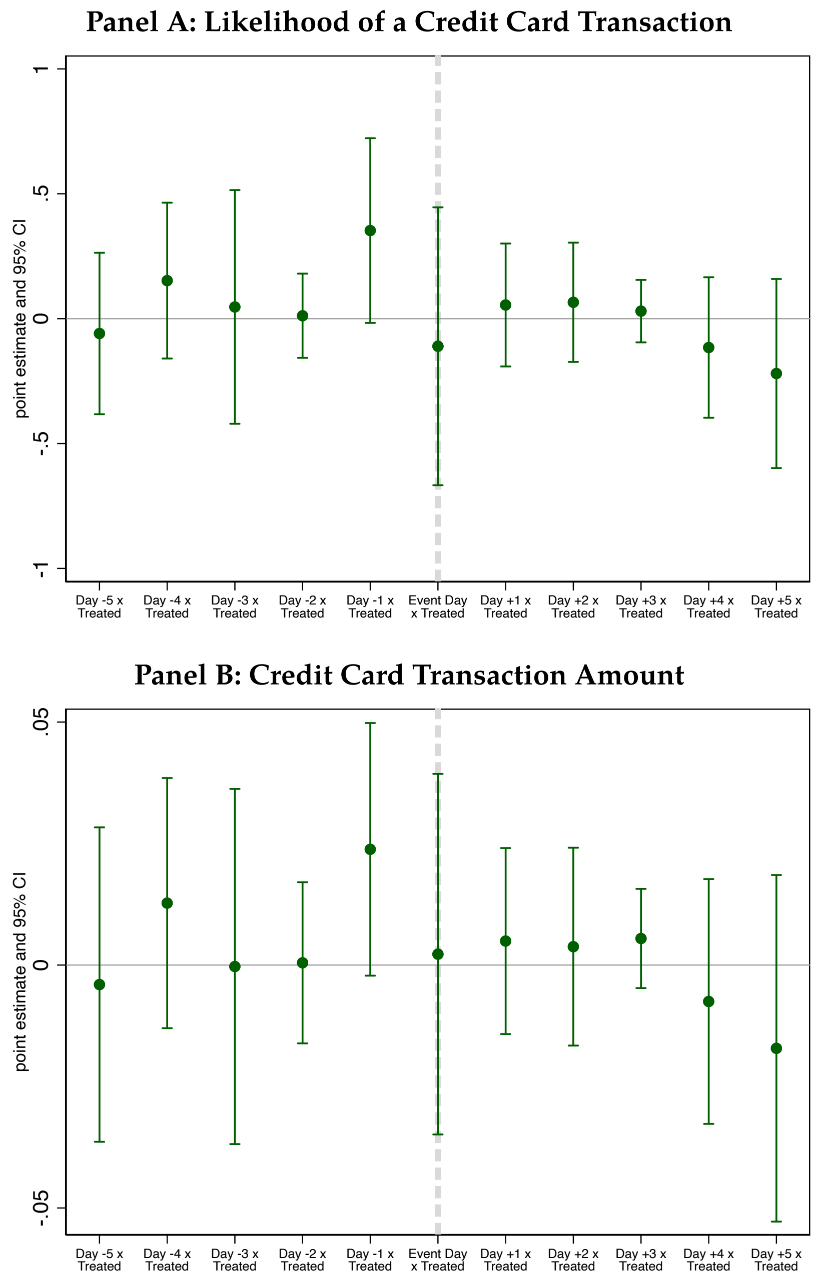


Figure IAE5: Dynamics of credit card transactions. This figure plots the coefficients β_k on each day in equation: $Y_{i,t} = \sum_{k=-5}^{5} \beta_k \{Treated_i \times Day(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the individual and date, and $Day(k)_t$ is a dummy equal to one if date t corresponds to k days before/after a Diwali day. $Treated$ is a dummy indicating whether the individual is inferred to be Hindu. α_i and γ_t denote individual and date fixed effects respectively. The dependent variable is a dummy equal to one if we observe a credit card transaction on the individual's account on that day in Panel A, and is the arcsinh of the individual's credit card transaction amount in Panel B. Horizontal bars correspond to 95% confidence intervals. Standard errors are double-clustered at the investor and date levels.

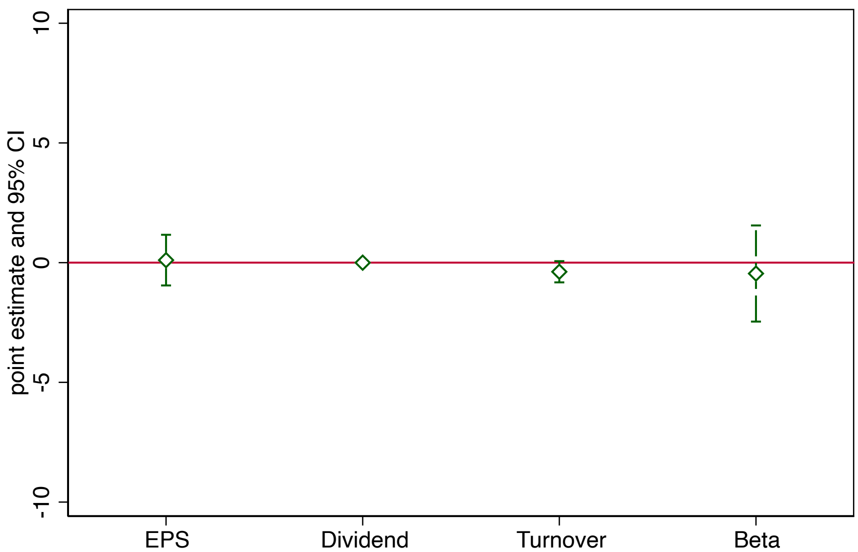
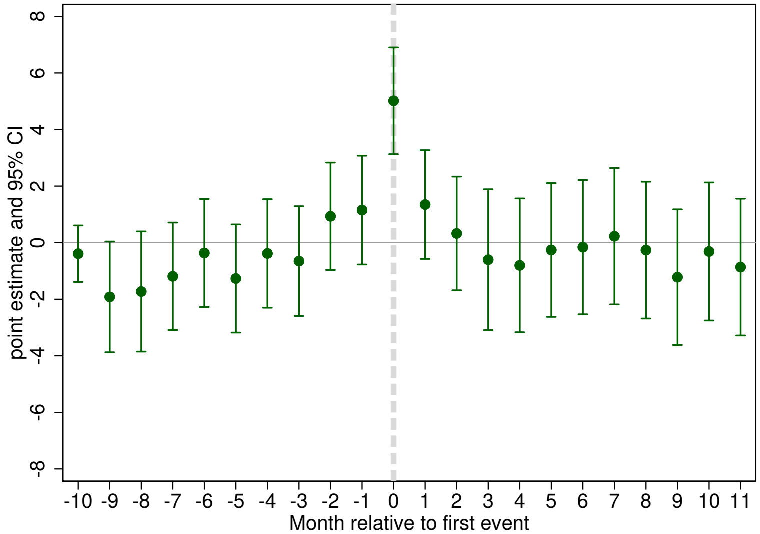


Figure IAE6: Other characteristics of stocks purchased on event days vs. other days. This figure plots the estimated coefficients β from equation (4), which measures the change in the average percentile rank of stock characteristics on event days relative to other buy-days for treated individuals (Hindus). The dependent variable is the average percentile rank of the stocks purchased by individual i on day t, where the percentile is calculated daily based on the cross-sectional distribution of a given stock characteristic. The regression includes individual $\times$ year fixed effects. Standard errors are double-clustered at the individual and stock levels. Vertical lines represent 95% confidence intervals. The figure presents results for firm-level characteristics: earning-per-share, whether the firm paid dividend over the past year, turnover, and stock market beta.

Panel A: Amount spent on buy trades



Panel B: Amount spent on sell trades

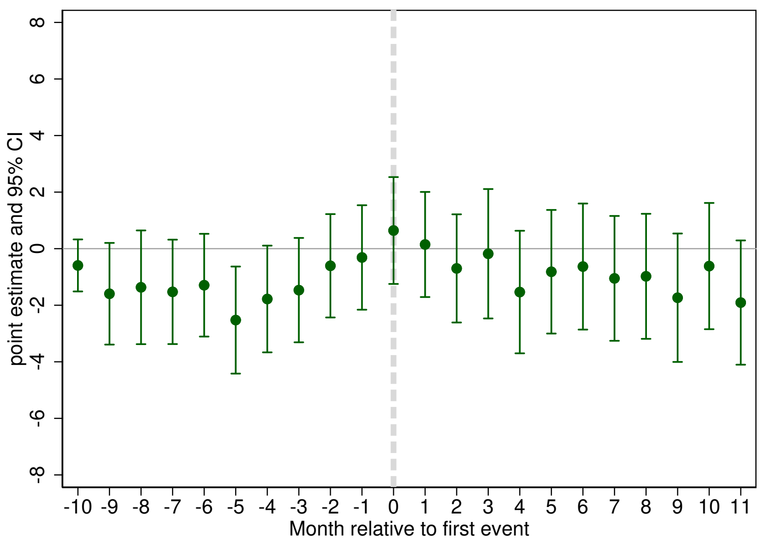


Figure IAE7: Dynamics of traded amount within treated on event. This figure plots the coefficients β_k and the corresponding 95% confidence intervals estimated from: $Y_{i,t} = \sum_{k=-10}^{11} \beta_k \{Treated_i \times Month(k)_t\} \alpha_{p(i)\,c(i)\,y(t)} + \delta_{p(i)\,s(i)\,ym(t)} + \varepsilon_{i,t}$, where i and t denote the individual and time, and $Month(k)_t$ is a dummy equal to one if time t corresponds to k months before/after the event day. $Treated_i$ is a dummy variable equal to one if individual i is affected by the religious event according to her inferred religion, while the control group consists of matched control investors from the same religion but who did not participate on the day and matched using pre-event covariates— state of tax registration (s), gender, broad income group, occupation, and account opening year. We then assign the same event date as the treated investor in the pair as the pseudo event date for the control group. The dependent variable is the arcsinh of the amount spent on buy (sell) trades in panel A (panel B). The fixed effects are α_{pcy} for cohort-pair $\times$ investor $\times$ event-year and $\delta_{ps\,ym}$ for cohort-pair $\times$ state $\times$ year-month. Standard errors are clustered at the cohort-pair $\times$ investor level.

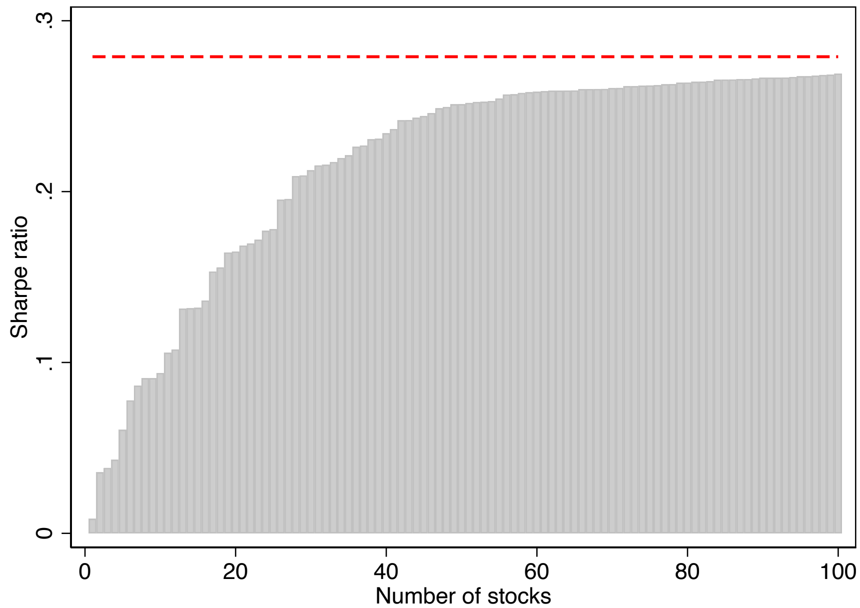
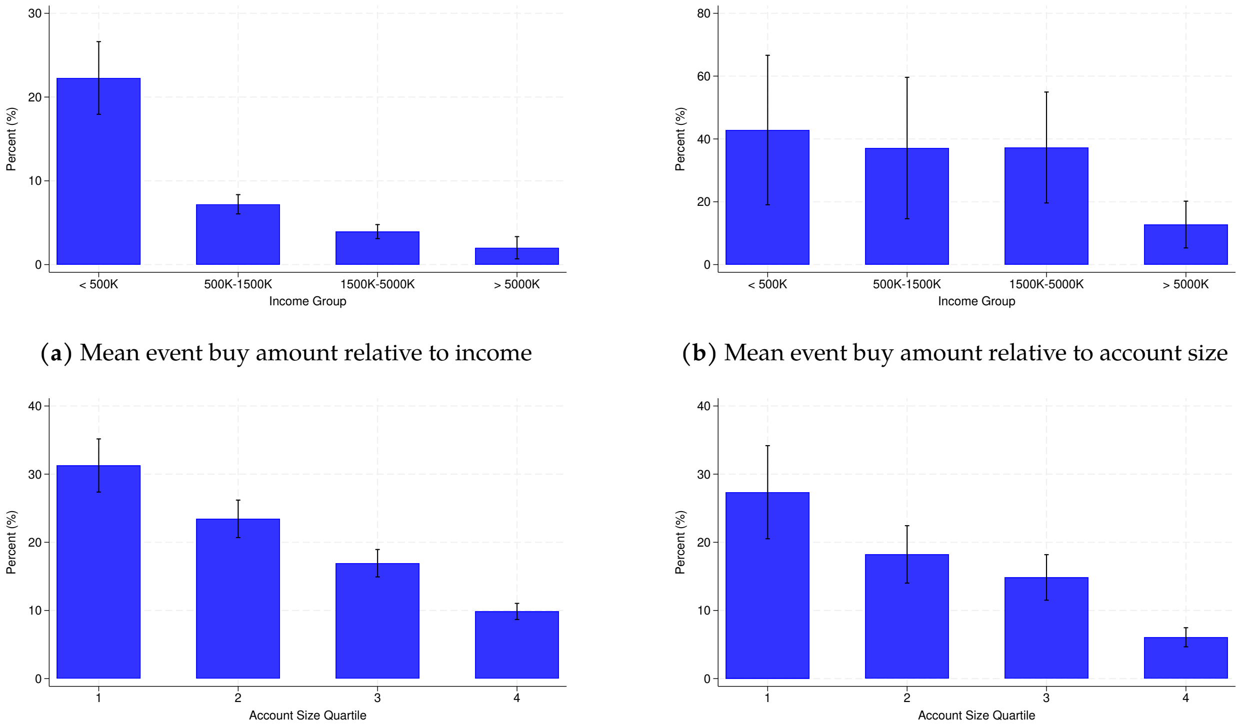


Figure IAE8: CAPM-implied Sharpe ratio estimates. This figure presents the annualized Sharpe ratio from the best N (between 0 and 100) stock CAPM-implied portfolio. The x-axis represents the number of stocks in the portfolio. The horizontal dashed line corresponds to the Sharpe ratio of the market portfolio. The Sharpe ratio estimates are based on weekly returns data for our sample period, solving a constrained optimization using LASSO regression. Specifically, following Balasubramaniam et al. (2023), we regress weekly market returns on individual stock returns over our sample period and adjust the LASSO penalty to deliver portfolios with exactly N stocks.



(a) Mean event buy amount relative to income

(b) Mean event buy amount relative to account size

(c) Fraction of event buy amount relative to account size

(d) Fraction of portfolio value in event-purchased stocks

Figure IAE9: Aggregate Effects on Account Size Inequality. The figures presents sample means with standard errors across measures of income and wealth, both in nominal '000 ₹ values. Panel (a) presents the average across individuals of the event-purchased amount relative to the income reported at the time of opening the account by income buckets, while panel (b) presents the average across individuals of the event-purchased amount relative to the size of the equity account at the end of year by income buckets. Panel (c) presents the average across individuals of the event-purchased amount relative to the size of the equity account by quartiles of account size defined based on the beginning of the year values. Panel (d) presents the fraction of the portfolio value in event-purchased stocks by quartiles of account size defined based on the beginning of the year values.