Divine Catalysts: Religion and Portfolio Choices*

Maxime Bonelli Pulak Ghosh S. Lakshmi Naaraayanan Purnoor Tak

March 20, 2025

Abstract

Does religion shape individual portfolio decisions? To answer this question, we examine how the *same* individual changes investment behavior on significant religious days compared to other days, and assess the long-term impact on portfolio holdings and composition. Our setting exploits recurring stock trading sessions held during Diwali in India, a major festival rooted in beliefs about long-term wealth. We find that individuals who associate with beliefs about this event participate more actively and invest substantially larger amounts on the event day. 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 stock market investments and portfolio diversification post-event. These findings uncover a novel role for religion in shaping long-term investments and portfolio choices.

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

JEL Classification: G11, G50, Z12.

*Bonelli: London Business School (mbonelli@london.edu), Ghosh: Indian Institute of Management, Bangalore (pulak.ghosh@iimb.ac.in), Naaraayanan: London Business School (lnaaraayanan@london.edu), and Tak: London Business School (ptak@london.edu). For helpful comments and suggestions, we thank Steffen Andersen, Vimal Balasubramaniam, Laurent Calvet, João Cocco, Sam Hartzmark, Jingshi Liu, Abhiroop Mukherjee, Kasper Nielsen, Alessandro Previtero, Ashish Sahay, Oliver Spalt, and seminar participants at SKEMA Business School. We thank Ravi Varanasi from the National Stock Exchange for help in understanding the institutional details. Bonelli and Naaraayanan thank the Wheeler Institute for Business and Development, the AQR Asset Management Institute, and the Research and Materials Development Grant at London Business School for financial support. Yuan Gao provided excellent research assistance.

1 Introduction

Four out of five people worldwide identify with a religious group, with religion poised to play an outsized role in shaping socio-economic outcomes (Pew Research, 2012, 2022). A growing body of research shows that religion influences behaviors and outcomes (see Guiso et al., 2003; McCleary and Barro, 2006; Iyer, 2016; Bursztyn et al., 2019; Montero and Yang, 2022). Yet, despite its prevalence and importance in society, relatively little is known about whether and to what extent religion shapes individual investment decisions and long-term portfolio allocation—choices that have lasting implications for wealth accumulation (Bach et al., 2020; Campbell, 2006; Badarinza et al., 2019).

A key empirical challenge in isolating the role of religion in shaping individual portfolio choices is that religious affiliation is correlated with demographic characteristics and other background risk factors.[1] Put differently, the substantial selection on observable characteristics into religious affiliation raises concerns that selection on unobservable characteristics may also be significant (Altonji et al., 2005). In this paper, we address this challenge by examining how the same individual makes investment decisions differently on significant religious days compared to other days and assessing the impact on their long-term portfolio holdings and composition.

Our empirical setting leverages recurring trading sessions organized by stock exchanges during Diwali, a major festival culturally rooted in beliefs about long-term wealth and prosperity—a significance that applies to some groups but not others. We find that individuals who associate with these beliefs participate more actively and invest substantially larger amounts in the stock market on the event day. They favor new stock purchases over expanding existing holdings and avoid lottery-like stocks, aligning their investment behavior with a long-term wealth accumulation strategy. Moreover, they hold onto event-purchased stocks for longer, resulting in a persistent increase in equity investments and portfolio diversification post-event. These findings reveal a novel role for religion and its event-specific messaging in shaping individual investment behavior and long-term portfolio choices.

We focus on Diwali, known as the "Festival of Lights," a festival celebrated by over a billion people

[1] At the individual level, differences in religious background have been linked to variations in risk-taking (see, e.g., Barsky et al., 1997; Kumar et al., 2011; Benjamin et al., 2016). Proposed mechanisms include traits that promote economic success, such as diligence and trust (Iannaccone, 1998; Iyer, 2018), as well as positive effects on health, crime, substance use, income, and education (Gruber and Hungerman, 2008). Some argue that religiosity may hinder economic activity by emphasizing otherworldliness (Weber, 1905) or diverting time from productive labor (Barro and McCleary, 2003).

worldwide, which holds religious and cultural significance in Hindu tradition as a time of new beginnings and long-term wealth.[2] For Hindus, Diwali marks the beginning of the accounting year and is considered an auspicious time for financial investments, symbolizing an invocation for divine blessings for wealth accumulation and prosperity in the year ahead. In line with this belief, stock exchanges across India organize a special trading session, "Muhurat trading" (hereafter, the "event"), which predominantly attracts retail investors who view it as a symbolic start to a financially prosperous year. The trading session is widely advertised by stock exchanges, and individual banks and brokers. Given the strong emphasis on long-term economic well-being, it offers an ideal setting to examine whether, and to what extent, religion influences financial decision-making in equity markets and its implications for portfolio choices. Reflecting the significance of "Muhurat trading", aggregate trading data from the National Stock Exchange (NSE) suggests that retail investors dominate the session, accounting for approximately 87% of trades, and resulting in a pronounced retail buy-side imbalance in the market, a pattern not observed during secular and/or other religious events.[3]

Our empirical analysis leverages data from a major national brokerage firm, tracking all new account openings and clients' stock transactions from 2012 to 2019. Unlike previous studies that rely primarily on geographic variation in religious group concentrations, our dataset confers a unique advantage—the ability to infer an individual's religion. We exploit the fact that last names in India are strong indicators of both religion and caste, and that marriages in India are overwhelmingly intra-religious (Iyer, 2002; Banerjee et al., 2013; D'Acunto et al., 2024). To the best of our knowledge, we are the first to be able to infer religious identity of individual investors, allowing us to track their stock market participation, investment decisions, and equity portfolios over time. Specifically, we compare changes in equity investments for individuals likely influenced by the event ("treated" group), i.e., Hindu investors, with those of individuals from other religions ("control" group) who are unlikely to be influenced by the event and its messaging. This *within*-individual analysis allows us to isolate the

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

[3]We compare these results to retail buy-sell imbalance in the market around secular and other religious events, including other Hindu-related festivals, public holidays and earnings announcements. Consistently across the events, no comparable imbalance emerges, highlighting the unique influence of Diwali's cultural messaging and mitigating concerns regarding the role of general "sentiment" impacting market activity among retail investors (Da et al., 2015; Edmans et al., 2007; Baker and Wurgler, 2007).

impact of specific religious beliefs on individuals' financial decision-making, holding constant other fixed characteristics and demographics that might affect investment decisions.[4]

In the first part of the paper, we examine trading patterns on the event day, focusing on how investors' trading decisions on this day compare to their behavior on other days. Our empirical strategy leverages the *recurring* nature of the event over multiple years, enabling us to analyze within-investor changes in trading patterns on event days while also comparing these changes to those of a control group of non-Hindu investors. The presence of a control group mitigates at least two key concerns. First, this group of investors is unlikely to be influenced by the religious messaging specific to the event, allowing for a clearer comparison of trading behavior. Second, their presence helps address the possibility that increased trading activity on the event day is driven by market-wide factors, such as liquidity effects arising from the market being open on a holiday. Since the trading session is accessible to all investors regardless of religious identity, any differential behavior among treated investors can more directly be attributed to the event's religious significance. To further account for unobserved, time-varying local factors, we incorporate high-dimensional geography $\times$ day fixed effects. The combination of a control group, as well as individual and high-dimensional time-location fixed effects allows us to cleanly isolate the impact of religion on investment behavior and portfolio choices.

First, we find that treated individuals are significantly more active in the stock market on the event day compared to individuals from other religious groups.[5] Specifically, treated individuals are approximately 1.2 percentage point more likely to trade on the event—a 15% increase relative to the sample mean—compared to other days and relative to control individuals from the same region. Additionally, treated individuals trade significantly larger amounts, with transaction amounts increasing by 17% on the event day.

To better understand the nature of this increased activity, we examine whether Diwali's emphasis on long-term wealth and new beginnings differentially influences buying versus selling behavior. We find that the participation effect among treated investors is primarily driven by buying, with a 20%

[4]These include for example financial literacy and education (Bernheim and Garrett, 2003; Van Rooij et al., 2011; Cole et al., 2014), cognitive ability (Grinblatt et al., 2011), as well as political ideology (Kaustia and Torstila, 2011; Kaustia et al., 2016; Meeuwis et al., 2022; Ke, 2024).

[5]On the extensive margin, we provide suggestive evidence that treated individuals are more likely to open a brokerage account around Diwali and to trade on the event day for the first time.

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. This indicates that, relative to control individuals, treated investors are not only more likely to buy on the event day but also invest significantly larger amounts. Importantly, these effects are even stronger when restricting the sample to days when individuals trade. In other words, treated investors buy substantially larger amounts on the event day compared to their own buying activity on other trading days, relative to control individuals. This finding rules out the possibility that Diwali trades are merely symbolic or "token" transactions involving negligible amounts for the individual investors in our sample.

We further investigate the buying behavior of treated investors. Consistent with the event's emphasis on new beginnings, their 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. This pattern suggests that beliefs associated with Diwali's messaging on new beginnings encourage treated investors to actively reshape their portfolios by initiating new purchases, highlighting the role of event-specific beliefs in shaping investment decisions.

When analyzing the characteristics of stocks purchased by treated investors on event days, we find that their selections do not align with speculative or gambling-driven behavior. Instead, treated individuals predominantly buy stocks of well-established firms characterized by high market capitalization, firm age, and earnings per share, while avoiding speculative or lottery-like stocks. Notably, they exhibit a clear aversion to low-priced "penny" stocks and stocks with high return skewness or volatility, favoring instead low-skewness, low-volatility stocks. These findings are consistent with Diwali's messaging, which emphasizes long-term prosperity rather than gambling-like investment strategies.

To further examine the impact of event-specific messaging on long-term investment behavior, we study the holding duration of event-purchased stocks and the likelihood of liquidation. An intuitive implication of the event's emphasis on long-term prosperity is that treated investors should hold onto stocks purchased on Diwali for an extended period, rather than selling them shortly after. However, the surge in trading activity on the event day could also create a short-term trading "frenzy," potentially

leading investors to sell event-purchased stocks soon after the event. To distinguish between these possibilities, we analyze whether the event encourages more persistent stock holding among treated individuals or instead drives short-term selling. We estimate regression models of selling likelihood on a dummy variable indicating whether a stock was purchased on Diwali, incorporating individual $\times$ day and stock $\times$ day fixed effects. Our analysis also controls for key determinants of selling behavior, in particular whether the stock is trading at a paper gain relative to its purchase price (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 Diwali-purchased stocks trading at a paper gain. These findings indicate that Diwali's association with long-term prosperity influences investment horizons, encouraging treated investors to adopt a more long-term investment approach.

In the second part of the paper, we move beyond event-day trading activity to examine the long-term portfolio implications of these investment decisions. 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 total stock holdings, portfolio diversification, and volatility, compared to non-participants. To capture these dynamics, we construct stacked event windows around each Diwali trading session, 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 total stock portfolio value, a 10% expansion in the number of stocks held, and a significant decline in portfolio concentration, as measured by the portfolio Herfindahl index, 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. Additionally, we observe a gradual post-event decline in portfolio volatility, reinforcing the

idea that these investment choices affect portfolio composition. Taken together, our findings suggest that religious messaging associated with the event fosters lasting changes in individual portfolios well beyond the event itself.

Admittedly, alternative explanations beyond religion and its event-specific messaging could account for our findings. One potential explanation is that treated investors may experience a temporary rise in disposable income around Diwali, driven by cultural traditions such as gift-giving and bonuses, which could influence both stock market participation and investment horizons.[6] 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. Additionally, while we observe a slight increase in ATM withdrawals prior to Diwali, we find no meaningful 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, which are also commonly exchanged during Diwali.

To further rule out wealth effects and other broad explanations, we examine trading patterns around other religious events of similar significance that lack explicit associations with long-term wealth and prosperity. This approach allows us to hold religiosity constant for both (i) treated individuals and (ii) control religious groups, separately. Our estimates show that, if anything, treated individuals are less likely to trade on other major religious days, in terms of both buying and selling activity. Similarly, control group investors exhibit no significant increase in trading activity around their respective religious events. The distinct shift in trading behavior on the event day, characterized by increased stock market participation and larger buy trades combined with its persistent effects on individual portfolio diversification, strongly suggests that the key driver of these investment decisions is religious beliefs associated with specific messaging of the event.

Related Literature. Our primary contribution lies in isolating the impact of religion—separate from other correlated characteristics—by leveraging a within-individual analysis to document its effect on individual portfolio choices. In doing so, our findings contribute to the broader literature on religion

[6] See, for instance, Briggs et al. (2021); Andersen and Nielsen (2011) on the effect of wealth on stock market participation.

and economic behavior.[7] Prior research documents that local religious environment is correlated with the trading behavior of both retail and institutional investors (e.g., Kumar, 2009; Shu et al., 2012), corporate decision-making (e.g., Hilary and Hui, 2009; Jiang et al., 2018), and aggregate market outcomes (e.g., Kumar et al., 2011). On the household level, the evidence on religion's role in shaping financial behavior is mixed. For instance, Renneboog and Spaenjers (2012) find that religion is correlated with households' stock market participation decisions, while Hong et al. (2004) show that individuals who frequently attend religious services are more likely to invest in the stock market. Such mixed evidence likely reflects the challenge of disentangling religion's impact from other correlated background risk factors, a challenge we address through our within-individual research design.

Moreover, our financial market setting—critical for long-term wealth accumulation—allows us to study religion's impact in a domain where monetary incentives dominate, complementing research on non-monetary motivations (Frey, 1997; Akerlof and Kranton, 2000; Bénabou and Tirole, 2003; Gneezy, 2005; Bénabou and Tirole, 2006). Prior work shows that religiosity influences economic choices, including debt repayment, public goods contributions, and risk aversion (Iyer, 2002, 2016, 2018; Benjamin et al., 2016; Bursztyn et al., 2019; Fruehwirth et al., 2019; Sinding Bentzen, 2019). Religiosity also increases around economic shocks such as unemployment, divorce, declining social mobility, and income volatility (Clark, 2005; Binzel and Carvalho, 2017; Ager and Ciccone, 2018; Espín-Sánchez et al., 2023; Dehejia et al., 2007; Buser, 2015). Meanwhile, experimental and field studies explore normative appeals and their influence on behavior (Dal Bó and Dal Bó, 2014; Pruckner and Sausgruber, 2013; Berger et al., 2016; Hallsworth et al., 2017; Ito et al., 2018; Floyd et al., 2022).[8] This paper contributes to this literature by leveraging a quasi-natural experiment—Muhurat trading on Diwali in India—to identify the impact of religious beliefs on stock market investments and the role of religious messaging in shaping investment behavior.

Second, our findings also directly connect to the literature on individual trading behavior and

[7] Prior research has primarily focused on the Abrahamic faiths. On Christianity, see Barro and McCleary (2003), Benjamin et al. (2016), Caicedo (2019), Espín-Sánchez et al. (2023); on Judaism, see Pascali (2016), Johnson and Koyama (2017), Jha and Shayo (2019); on Islam, see Campante and Yanagizawa-Drott (2015), Bazzi et al. (2020), Demiroglu et al. (2021), Mehmood et al. (2023); and on Confucianism, see Kung and Ma (2014) and Chen et al. (2022). A nascent literature has recently begun to examine the economic implications of traditional African religions and ethnicity (Le Rossignol et al., 2022; Butinda et al., 2023; Hjort, 2021).

[8] Recent work has also examined ethnic divisions and resource allocation (Jha, 2013; Hjort, 2014; Iyer and Shrivastava, 2018; Fisman et al., 2020; Shayo, 2020; Bhalotra et al., 2023; Bharti and Roy, 2023).

performance (Barber and Odean, 2000, 2008; Grinblatt and Keloharju, 2000; Kaniel et al., 2008; Odean, 1998a; Seru et al., 2010).[9] One strand of this extensive literature identifies behavioral biases that shape retail investor activity (e.g., Daniel et al., 1998; Odean, 1998b; Ben-David et al., 2013; Da et al., 2021; Shefrin and Statman, 2000; Barberis and Huang, 2008). Particularly relevant to our setting, Anagol et al. (2021), Balasubramaniam et al. (2023), 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 and event-specific messaging in shaping investment decisions and portfolio allocations. Importantly, we show that spiritual influence can foster "non-speculative" behavior when its messaging emphasizes long-term prosperity.

Finally, we contribute to the literature examining the role of social factors as determinants of investor behavior in financial markets (see Hirshleifer, 2020). One strand of research examines how social interactions and peer effects influence household financial decisions (Hong et al., 2004; Ivković and Weisbenner, 2007; Brown et al., 2008; Kaustia and Knüpfer, 2012; Cannon et al., 2024; Gelman et al., 2024; Müller et al., 2024). In this paper, rather than treating religion as a broad proxy for social and cultural factors, we isolate the impact of a specific religious event and its associated beliefs on individual investor behavior over time. By leveraging within-individual variation, we provide a more precise understanding of how specific religious cues influence investment decisions, offering new insights into the mechanisms through which religion shapes financial decision-making.

2 Institutional Details

Our empirical analysis focuses on Diwali, a festival of cultural and religious significance in India, to examine the effects of religious beliefs on stock market behavior. In this section, we detail the institutional and cultural background of Diwali and its associated Muhurat trading session, emphasizing the festival's themes of prosperity and good fortune.

[9] A related literature in household finance examines stock market participation more broadly (Haliassos and Bertaut, 1995; Campbell, 2006; Guiso and Sodini, 2012; Ke, 2018, 2024; Gomes et al., 2021).

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.

Religion is also an important part of daily life in India, across religions. In Online Appendix Table IAA1, we study their importance using the World Value Survey. According to Wave 7 of the World Values Survey (2017-2022), 64% of individuals reported that religion is a "very important" part of their lives, while over 62% attend religious services at least once a month, highlighting the collective importance of religious engagement.

2.2 Cultural Significance and Symbolism of Diwali

Religious festival are prominent features of social life in India with Diwali being one of largest and most significant religious observance among Hindus.[10] Diwali marks the beginning of the New Year for many communities in India. Also known as the "Festival of Lights," it is one of the most celebrated Hindu festivals, symbolizing the triumph of light over darkness and good over evil. Observed by millions of individuals across India, Diwali typically spans five days, with the third day marking its peak. Families celebrate by illuminating homes with oil lamps, exchanging sweets, and setting off fireworks. The festival carries themes of new beginnings, prosperity, and spiritual renewal, as it commemorates the return of Lord Rama to his kingdom after exile, as described in Hindu epic lore. Diwali traditions focus on invoking blessings for wealth and fortune, making it a significant cultural moment linked to optimism and aspirations for prosperity in the year ahead.

[10] Often, they mark changes of season, occupations, the movements of stars and planets, or opportunities for expressing gratitude.

2.3 Muhurat Trading

Tradition. Since its inception in 1992, the National Stock Exchange has organized a special trading session known as "Muhurat Trading" to mark an auspicious start to the new financial year.[11] Muhurat trading takes place on the third day of Diwali, considered the most auspicious of the five days of the festival.[12] This tradition, deeply rooted in cultural and spiritual beliefs, invites investors to participate in the financial markets on a day that symbolizes prosperity and long-term economic well being. By merging financial transactions with religious customs, Muhurat Trading reinforces the hope for a prosperous year ahead.

Muhurat trading is considered as an auspicious way to start the new year, believed to bring wealth and prosperity. Rituals such as *Lakshmi Puja* and *Chopda Puja*, invoking blessings for success and abundance, are performed by stock brokers. Following this, the trading session primarily sees participation from retail investors, symbolizing a blend of spiritual tradition and financial optimism. These rituals, including placing a coin on account books to symbolize wealth, are a way to welcome prosperity, and traders and shopkeepers keep lights burning throughout the night in hopes that goddess of wealth will bring fortune in the year ahead.

Muhurat trading is advertised widely by both stock exchanges and individual banks and brokers in India. Alongside informational details on the date and timing of the trading session, the vast majority of advertising related to Muhurat trading heavily features religious messaging and imagery, highlighting the auspicious nature of the day and the trading session, alongside wealth and prosperity.[13] Da et al. (2011) propose that Google Search Volume Index (SVI) data serves as a direct measure of retail investor attention. Accordingly, we plot the online search interest for the term "Muhurat Trading" in India from 2012 to 2019 (our sample period, cf., Section 3) in Figure IAB4. The data show a pronounced peak in search interest each year precisely during the month of Diwali, indicating that retail interest in Muhurat trading sharply intensifies only around this time, underscoring its unique appeal

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

[12] The dates of Hindu festivals, including Diwali, are determined by the lunar calendar and therefore vary from year to year. Table IAD4 in the Internet Appendix lists the dates and timings of trading sessions at the National Stock Exchange.

[13] See Section B of the Online Appendix for more details on the advertising of Muhurat trading and examples of religious messaging in the marketing of the National Stock Exchange and brokers for the trading session, as well as examples of newspaper articles referencing and advertising the event.

to retail investors.

Implementation details. Muhurat trading follows a specific structure on Diwali, starting with a 15-minute block deal session where large, pre-arranged trades are executed between two parties at negotiated prices before the market opens to retail investors. This is followed by a 15-minute pre-open session, during which traders enter orders without executing trades, helping to establish the market's opening price. 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. Afterward, 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. Internet Appendix Table IAD4 lists the dates the Muhurat trading sessions occurred in our sample covering 2012 to 2019.

Aggregate retail activity. How does aggregate trading behavior change during Muhurat trading? To address this question, we collect comprehensive stock trading data from the Indian national stock exchange (NSE).[14] This dataset covers the entire universe of trading records from the NSE over the period from 2012 to 2019 (the sample period studied below). It provides detailed information for each transaction, including the trader's anonymized Permanent Account Number (PAN), the transaction date, the security ticker, the total number of shares bought or sold, and the execution price. Additionally, we observe the client type associated with each transaction, such as retail, institutional, overseas corporate bodies, statutory bodies, and unknown. For our analysis, we focus on transactions involving equities listed in the Prowess Database. We collapse transactions on the NSE by client type, state, stock, and day level 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.

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 Diwali compared to other significant event dates. Specifically, we compare average retail trading activity at the stock level during the five days preceding and following: (i) Di-

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

wali'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 IAB3 provides a list of these religious events along with their cultural significance.

Figure 1 presents the results. Panel A plots the average Diwali retail imbalance, calculated 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. This metric is a widely used proxy for retail order imbalance (see Barber et al., 2008; Barber and Odean, 2008). Panel B displays the share of retail trades made around Diwali.

The results in Panel A of Figure 1 reveal a significant retail buy order imbalance during Muhurat trading hours on Diwali, with no observable pre-trend or post-trend in the days preceding and following the event. By contrast, Figure IAD7 in the Online Appendix shows that the magnitude of the Muhurat trading effect on retail activity is significantly higher than, and not comparable to, trading activity observed around other Hindu religious events, non-Hindu religious events, national holidays, or informative days such as stock announcement dates.

3 Data and Summary Statistics

Our main empirical analysis leverages a unique proprietary dataset from a leading national brokerage firm in India, containing individual account-level trading records. Details on the dataset are provided below.

3.1 Brokerage Data

Our main dataset comes from a leading national brokerage firm in India, providing granular account-level information that allows us to examine retail investor trading in detail. This brokerage firm operates through more than 7,000 branches in all Indian states, giving our analysis a broad view of trading patterns in the country.

Data Overview. The primary component of this dataset is a trade file, which contains detailed transaction information, including an anonymized Permanent Account Number (PAN) as a unique identifier for each account, the last name and address of the account holder, the account opening date, the trans-

action date, the security name, the amount of shares bought or sold, 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, totaling 24,112 investors. Like others before us using Indian data, we focus on direct stockholdings (Campbell et al., 2014, 2019; Balasubramaniam et al., 2023).[15] Further, our data allow us to observe detailed attributes of the underlying investors such as gender, age at account opening, as well as a classification of their income and sector of employment.

For our analysis, we focus on transactions involving common stocks listed 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.[16] 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 observations from the brokerage data to the stock characteristics in Prowess, covering more than 88% of the transaction volume within our dataset.[17]

Another prominent feature of the dataset is that it enables us to link individual trading activity from the brokerage account to the individual's savings and checking account, ATM transactions, and credit card transactions within the same bank. This comprehensive view allows us to analyze changes in individuals' net wealth around the event in Section 6.

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-day 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

[15] Campbell et al. (2014) and Campbell et al. (2019) emphasize the very limited share held by mutual funds in India.

[16] Several prior studies on Indian firms have used this dataset, including Bertrand et al. (2002); Gopalan et al. (2007); Lilienfeld-Toal et al. (2012); Gopalan et al. (2016); Naaraayanan and Nielsen (2021); and Naaraayanan and Wolfenzon (2023).

[17] The match rate is effectively unchanged at 85% when we consider name changes of stocks.

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-day level to examine individual behaviors and portfolio-level characteristics.

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 data-driven 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 both religion, and that marriages in India, are overwhelmingly intra-religious. We utilize data from a major matrimonial website, which provides the first and last names of nearly six million users. This registry dataset includes self-reported demographic information about religion and caste elicited at marriage and includes names and surnames, date of marriage, state of birth, city of residence, height (in centimeters), religion, and caste. 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 state.

The religion split in our broker sample is largely consistent with the split across religious groups in the general Indian population. Specifically, we compare our sample to the the Population Census 2011, and find that our sample is tilted toward Hindus—90%, while just under 3% are Muslim.[18] Despite a smaller share of other religious groups (7% of the sample), the number of observations is large enough to allow a statistically meaningful analysis. We provide additional details in Online Appendix A.

To the best of our knowledge, we are the first to be able to link religion of individuals to their stock market transactions, allowing us to study how religiosity affects stock market participation and trading behavior at the individual-level.

[18]One potential reason for this imbalance is that Sharia principles condemn earning financial interest and discourage excessive risk-taking, which may deter Muslims from participating in the stock market (Naughton and Naughton, 2000).

3.2 Summary Statistics

Table 1 provides an overview of summary statistics for our brokerage dataset. Panel A details account-level demographics, indicating an average age of 43 years, with 73% of account holders being male and 90% being Hindu individuals (referred to as "Treated").

Panels B and C present statistics at the account-day level, where Panel B covers the entire sample and Panel C focuses on trading days only. Panel B shows that the average total (stock) portfolio value 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 C) 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).

Panels D and E provide account-stock-day level statistics for treated individuals, with Panel D showing unconditional statistics (entire sample) and Panel E focusing on sale-conditioned days (days with at least one sale in the individual portfolio). Panel D reveals that the frequency of trades at the account-stock-day level is 3% and that the average holding observation corresponds to a stock held for 147 days. The sale-conditioned sample (Panel E) shows that individuals trade 15% of their holdings on these days.

3.3 Additional Data

National Stock Exchange Data. We collect comprehensive trading data from the National Stock Exchange (NSE), one of the world's largest stock exchanges, spanning 2012 to 2019. This dataset includes detailed transaction-level information such as trader type (e.g., retail, institutional), security traded, volume, and execution price, covering over 2,200 unique stocks and approximately 70 million observations. By collapsing the data by client type, stock, and day, and merging it with stock characteristics and prices from the Prowess database, we construct a panel dataset capturing stock-level activity for different client types. Online Appendix Table IAD6 presents summary statistics in the NSE dataset aggregated at the stock-day level for retail investor trades. It presents the total number of buy and sell

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

transactions in a given stock on a particular day, as well as the corresponding transaction volumes in thousands of rupees. On average, for a particular stock, about 620 buy orders are submitted by retail investors, with an average daily total amount spent of ₹54,151,000, while about 580 sell orders are submitted, with an average total amount spent of ₹54,739,000. We also present trading imbalance measures at the stock-day level, calculated as the ratio of number of transactions $\frac{(buy-sell)}{(buy+sell)}$ submitted by retail investors.

World Values Survey. We use of Wave 7 of the World Values Survey, a survey measuring cross-country values and beliefs of individuals. Wave 7 covers over 60 countries and territories, asking questions collected over 2017 to 2022. We make use of questions relating to religiosity in India.

4 Empirical Analysis of Individual Trading Behaviors

In this section, we analyze the stock market participation and trading behavior of individuals. The objective of our empirical analysis is to determine whether individuals exposed to the religious messaging of the Diwali festival (referred to as the "Treated" group) participate more in financial markets and change their trading behavior around the Muhurat trading day compared to individuals who are not exposed to this messaging (the "Control" group). We define the treated group as individuals inferred to be Hindu based on their last names, while the control group comprises individuals inferred as belonging to other religions.

4.1 Trading around the Event

We examine changes in the trading activity among treated and control individuals around the event. To do so, we estimate panel regressions at the individual-day level. Our regression specification is as follows:

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

where the observations are at the account (i) and date (t) levels. The variable $Event_t$ is a dummy equal to 1 if day t corresponds to the Muhurat trading day, and $Treated_i$ is a dummy indicating

whether individual 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 day levels.

The dependent variable $Y_{i,t}$ is either a dummy variable indicating whether the individual trades, buys or sells on day t, or a continuous variable defined as the inverse hyperbolic sine (arcsinh) of the amount spent on trading, buying or selling on day t.[20] Importantly, for both types of dependent variable we include non-trading days in our sample.

To study the dynamics of trading behaviors around Diwali, we estimate the following specification:

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

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

Likelihood to Trade. Panel A of Table 2 presents estimation results of regression (1), when the dependent variable is a variable equal to 100 if the individual trades on that day, 0 otherwise. Column (1) includes only religion fixed effects. All 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, where state and district refers to the individual's registered address in India.[21] These specifications enable us to rule out the possibility that the effects we capture are solely driven by unobserved local factors.

The coefficient on $Event\ Day$, which can be estimated in specifications without date fixed effects (Columns (1) to (2)) is negative but statistically insignificant. If anything, this suggests a decrease in trading likelihood for control individuals on the event compared to other days, although standard

[20] We use the arcsinh transform to account for zeros, i.e., days when individuals do not trade.

[21] 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 across India. Each PIN code corresponds to a specific area, ensuring efficient mail distribution within districts, cities, towns, and even specific neighborhoods.

errors are large and comparable in magnitude to the coefficient itself.

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 Muhurat trading day compared to controls. The coefficient ranges from 1.1 to 1.28. Column (5) suggests that treated investors are approximately 1.21 percentage point (p.p.) more likely trade on the event (15% relative to the dependent variable's sample mean) compared to other days, relative to control individuals in the same district. Overall, these results suggest a strong, positive relationship between the event and trading activity among treated individuals.[22]

Amount Traded. Panel B of Table 2 presents the estimation results of regression (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. As in previous results, the coefficient on $Event\ Day$ is negative and insignificant (Columns (1) and (2)), suggesting that, if anything, control individuals tend to trade smaller amounts on Diwali.

The coefficient on the interaction term $Event\ Day \times Treated$ is positive and statistically significant across all specifications, with coefficients ranging from 0.15 to 0.16. Column (5) indicates that, on Diwali, treated individuals trade about 17% larger amounts compared to other days, relative to control individuals in the same district. These results confirm that the event fosters increased trading activity and volumes among treated individuals.

Panel A of Figure 2 presents the estimated coefficients β_k in (2) when the dependent variable is the arcsinh of the amount traded, showing the dynamics of changes in trading activity around the event. The coefficient on the interaction term $Event\ Day \times Treated$ is positive and statistically significant, indicating a clear spike in trading activity on the event for treated individuals relative to controls. In the days leading up to the event (Day -5 to Day -1), there is no significant difference in the evolution of traded amounts, as the coefficients are close to zero and statistically insignificant. Similarly, post-event (Day +1 to Day +5), the evolution of traded amounts exhibit does not exhibit significant differences between treated and control. These results suggest that the increase in trading

[22]We also investigate the characteristics of treated individuals who trade on the event day in Internet Appendix Table IAD10. 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.

is concentrated specifically on the Muhurat trading day, reinforcing the role of the event for stock market participation among treated individuals.

Likelihood to Buy and Sell. Panel A of Table 3 presents the estimation results of regression (1), when 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), (2) and (3), indicating that treated individuals are significantly more likely to buy stocks on Diwali 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 dependent variable's sample mean (6.22). By contrast, the coefficient on $Event\ Day \times Treated$ in the sell specifications (Columns (4), (5) and (6)) is close to zero and not statistically significant. This implies that treated individuals are not significantly more likely to sell stocks on Diwali compared to controls. Overall, these results suggest that the baseline effect is concentrated on buying behavior rather than selling.[23]

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. 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.

Consistent with the results presented in Panel A of Table 3 and discussed above, 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, the coefficient on $Event\ Day \times Treated$ in the sell specifications (Columns (4), (5) and (6)) is small and not statistically significant, suggesting no meaningful difference in changes in the amount spent

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

on sell trades between treated and control individuals on the event day.

Importantly, these results hold even when restricting the sample to days on which individuals actively trade. In Online Appendix Table IAD7, we show that when considering only observations with non-zero trading activity, treated individuals spend between 40% to 80% 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. This finding rules out the possibility that Diwali trades are merely symbolic or "token" transactions involving negligible amounts.

Panel B of Figure 2 presents the estimated coefficients β_k in (2), when 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, the coefficient for sell trades is close to zero and not statistically significant, confirming no notable change in selling behavior, consistent with the results in Table 3.

In the days leading up to the event (Day -5 to Day -1), there is no significant change in the evolution of buying or selling activity between treated and controls, as the coefficients are close to zero and statistically insignificant. Similarly, post-event (Day +1 to Day +5), the evolution of both buying and selling activities are not different. Although we observe a small negative coefficient on Day +4 for buying and a positive coefficient on Day +5 for selling, the magnitude is smaller compared to the event day.

4.2 Buying Behaviors: New vs. Existing Holdings.

Given Diwali's emphasis on new beginnings, we further study the buying behavior of treated investors on the event day, with a focus on whether they are more inclined to purchase new stocks (holdings not already in their portfolios) or to add additional shares to their existing holdings.

Panel A of Table 4 presents the estimation results of regression (1), when 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. All columns include individual

fixed effects. Columns (1), (4) and (7) include date fixed effects, Columns (2), (5) and (8) further include state $\times$ date fixed effects, and Columns (3), (6) and (9) include district $\times$ date fixed effects. The estimates indicate that treated individuals are significantly more likely to exclusively purchase new stocks on the event day compared to other days relative to controls, with coefficients for the interaction term *Event Day* $\times$ *Treated* being 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 smaller in magnitude and 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, the interaction term is also positive and significant, although the effect size is smaller than for purely new holdings, suggesting a predominant focus on acquiring new stocks.

Panel B of Table 4 examines the (arcsinh) amount spent on buying trades and reinforces the findings in Panel A. The interaction term *Event Day* $\times$ *Treated* is again positive and statistically significant across Columns (1) to (3) for new holdings, with coefficients ranging from 0.08 to 0.1, indicating that treated individuals also tend to spend significantly more on new stock purchases on the event day. For existing holdings, the coefficients in Columns (4) to (6) are again small and statistically insignificant, showing no significant change in the amount invested in previously held stocks. For buy trades involving both new and existing holdings, the coefficients are positive and significant but smaller than for new holdings alone, suggesting that the increased spending by treated investors on the event day is primarily directed toward new acquisitions rather than augmenting existing positions.

Overall, the results suggest that the increased buying behavior by treated investors on the event day is primarily concentrated on acquiring new stocks rather than expanding existing holdings. This pattern aligns with the hypothesis that Diwali's cultural emphasis on new beginnings and long-term wealth influences treated investors to expand their portfolios with new assets rather than simply reinforcing prior investments.

4.3 Characteristics of Stocks Purchased on the Event

We analyze the characteristics of stocks purchased by treated individuals (Hindus) during Muhurat trading on Diwali. By examining stock attributes, our goal is twofold. First, we aim to uncover patterns in the types of stocks purchased on this day and determine whether these characteristics align with the cultural messaging of Diwali. Second, we aim to assess whether treated individuals perceive Muhurat trading as an opportunity for gambling and speculative behavior. To do so, we examine two groups of stock characteristics: (i) traditional stock characteristics, such as for instance market capitalization, and (ii) lottery-like characteristics, such as return skewness.

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

$$Buy_{i,j,t} = \beta_h HighCharacteristic_{j,t-1} + \beta_l LowCharacteristic_{j,t-1} + \gamma_{i,t} + \epsilon_{i,j,t}, \tag{3}$$

where i, j, and t denote individual, stock, and day, respectively. The dependent variable, $Buy_{i,j,t}$, is a variable equal to 10,000 if individual i buys stock j on day 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 Muhurat trading day t. The omitted baseline category comprises 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 $\times$ day fixed effects ($\gamma_{i,t}$) to control for unobservable individual-specific factors that vary over time, such as personal liquidity. These fixed effects absorb all individual-level variation on a given day, allowing us to focus on the relative attractiveness of stock characteristics within each individual-day. Stock fixed effects are not included as the stock characteristics analyzed here are relatively persistent and our sample includes only eight

trading sessions. Standard errors are double-clustered at the individual and stock levels.

In Panel A of Table 5, we examine the following stock characteristics: market capitalization, book-to-market ratio, firm age, earnings per share (EPS), and past-year returns. Market capitalization is measured on the day before the event. The book-to-market ratio is calculated using the latest available book values from the previous calendar year-end. Firm age corresponds to the number of years since listing. EPS is based on the latest available year-end figures, while past-year returns correspond to returns over the previous year ending the day before the event. Stock-day level summary statistics are presented in Online Appendix Table IAD8.

The results in column (1) of Panel A show that treated individuals are significantly more likely to purchase large-cap stocks, i.e., stocks in the top quintile for market capitalization. The coefficient on the high market capitalization dummy is approximately 2 basis points (b.p.), representing more than 300% of the mean of the dependent variable (0.64 b.p.). Conversely, treated individuals are less likely to buy small-cap stocks (those in the bottom quintile for market capitalization), with a smaller effect of -0.13 b.p.

Column (2) indicates a preference for growth-oriented stocks, as treated individuals are more likely to purchase stocks in the bottom quintile of the book-to-market ratio and less likely to purchase value stocks in the top quintile of the book-to-market ratio. The magnitude of the coefficients are respectively 0.73 and -0.88 b.p. Columns (3) reveals a clear preference for "old firms". The coefficient on the high firm age dummy is 1.2 b.p., representing close to 200% of the mean of the dependent variable (0.64 b.p.). Columns (4) and (5) reveal a preference for stocks with high earnings per share (0.7 b.p.), as well as a mild preference for high-performing stocks based on past-year returns but the magnitude (0.15 b.p.) and statistical significance (10%) are lower.

When all independent variables are included simultaneously in column (6), high market capitalization stands out as the dominant characteristic favored by treated individuals, with a coefficient of 2 basis points (b.p.). Preferences for stocks of older firms, as well as for stocks with high (and low) past-year returns, persist but are smaller in magnitude. Treated individuals also exhibit an aversion to stocks with high book-to-market ratios.

Overall, these findings suggest that during Muhurat trading, treated individuals primarily focus on stocks of well-established companies, characterized by high market capitalization and, to a lesser ex-

tent, high earnings per share (EPS). This investment behavior is plausibly consistent with an emphasis on long-term wealth and prosperity.

In Online Appendix Table IAD9, we extend the analysis to include additional stock characteristics. 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. These characteristics are motivated by Balasubramaniam et al. (2023), who document their strong influence on stockholding behavior in India. The results in Online Appendix Table IAD9 indicate that treated individuals are significantly more likely to purchase stocks that pay dividends and are highly liquid (high turnover). These findings further align with a preference for large companies with strong fundamentals.

Lottery-like Characteristics In addition to traditional stock characteristics, we investigate whether treated individuals perceive Muhurat trading 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 for instance high return skewness. Our hypothesis is that if treated individuals exhibit strong preferences for these speculative stocks, it would suggest that Muhurat trading may serve as a gambling-like opportunity, inconsistent with the cultural theme of long-term wealth conveyed by Diwali.

For this analysis, we estimate the same regression specification as in equation (3), 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. The first measure, conventional skewness, is the third central moment of the return distribution divided by the standard deviation cubed, which provides a measure of the asymmetry in returns. The second measure, Pearson's skewness coefficient, is calculated as $3 \times (\text{Mean} - \text{Median})/\text{Standard Deviation}$ and captures the degree of asymmetry relative to the center of the distribution. The third measure, up-to-down volatility, reflects the relative frequency and magnitude of positive versus negative daily returns and is computed as:

$$-\log\left(\frac{(n_u-1)\sum_{\text{DOWN}} r_{it}^2}{(n_d-1)\sum_{\text{UP}} r_{it}^2}\right), \tag{4}$$

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. This measure is derived from Chen et al. (2001) and is the negative of their $DUVOL$ metric, where higher values indicate greater relative volatility in negative returns compared to positive returns. 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, indicating whether a stock falls in the top or bottom quintile for each characteristic on the day before the Muhurat trading day. Stocks in the middle 60% of the distribution serve as the baseline category. As before, the regression includes individual $\times$ day fixed effects to account for time-varying, individual-specific factors, allowing us to focus on the relative attractiveness of lottery-like characteristics within each individual-day. Standard errors are double-clustered at the individual and stock levels.

Panel B of Table 5 presents the results. Column (1) shows that treated individuals are significantly more likely to purchase stocks in the top quintile for share price, with a coefficient of 0.69 basis points (b.p.), representing over 100% of the mean of the dependent variable (0.64 b.p.). Conversely, treated individuals are less likely to buy low-priced stocks, as indicated by the negative coefficient of -0.44 b.p. for the bottom quintile of share prices. This suggests that treated individuals tend to avoid low-priced, or so-called "penny," stocks.

Columns (2) to (4) examine preferences for skewness. Treated individuals exhibit a significant aversion to stocks with high past-year return skewness and Pearson skewness, as evidenced by negative coefficients of -0.22 b.p. and -0.21 b.p., respectively. In contrast, they are more likely to purchase stocks in the bottom quintile for skewness, with coefficients of 0.72 b.p. and 0.64 b.p., respectively. These findings indicate that treated individuals do not favor stocks with lottery-like payoffs, which are often associated with speculative or gambling-like behavior. Column (4) also shows a mild aversion to stocks with high up-to-down volatility, as indicated by a negative coefficient of -0.14 b.p. for the top quintile. There is also some preference for stocks in the bottom quintile of up-to-down volatility (the magnitude of this effect is 0.53 b.p.). Finally, column (5) shows that treated individuals exhibit a clear preference for low-volatility stocks, with a coefficient of 1.2 b.p., nearly 200% of the mean of the

dependent variable. When all independent variables are included in column (6), we observe that the preferences for low-skewness and low-volatility stocks persist, while treated individuals also exhibit a significant aversion to stocks with low share price.

Overall, these findings suggest that treated individuals do not favor lottery-like stocks during Muhurat trading. Instead, their stock selection aligns with a preference for low-skewness and low-volatility. This pattern appears consistent with the cultural messaging of Diwali, which emphasizes stability and long-term wealth, not speculative or gambling-like behavior.

4.4 Likelihood to Sell Stocks Purchased on the Event

It remains an open question whether treated individuals sell the stocks they purchase on the event shortly after or retain them for a longer period. Previous results indicate that treated individuals predominantly buy stocks of large, well-established companies, with a preference for low skewness and low volatility during Muhurat trading. This behavior suggests an investment approach aligned with long-term wealth rather than speculative tendencies. However, the increased market activity on Muhurat trading day could still reflect a short-term trading "frenzy". We empirically assess whether the religious context of Diwali encourages more persistent stock holding among treated individuals or leads to short-term selling behavior.

Empirical Specification. To test whether treated individuals tend to retain stocks bought on the event for an extended period, we use our holding sample at the investor-stock-day level (see Section 3 for construction details). This approach enables us 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 regression specification at the individual-stock-day level:

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

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

previous day, and 0 otherwise. This variable is thus expressed in percentage points. 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 a Muhurat trading 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 indicating whether the stock is trading at a paper gain relative to its weighted-average purchase price, controlling for the well-documented disposition effect among individual investors (e.g. Odean, 1998a). 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 $\times$ day fixed effects ($\gamma_{i,t}$) account for unobservable individual-specific factors that vary over time, such as personal liquidity shocks. Stock $\times$ day 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 day levels.

Empirical Results. Table 6 presents the regression results. In Panel A, the sample is unconditional, i.e., it includes investor-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 $\times$ day fixed effects. Control variables are included in Columns (2) and (4).

In Panel A, the coefficient on *Purchased on Event* is negative and highly significant (t-stat ≈ 4 across all columns), ranging from -0.13 to -0.25. This suggests that, after controlling for individual-day and stock-day characteristics, individuals who purchased stocks on the event are significantly less likely to sell these stocks later. The effect size represents 7% to 13% of the dependent variable's mean (2), indicating a strong tendency for treated individuals to retain stocks bought on the event.

In Panel B, where the sample is restricted to sell days, the coefficients on *Purchased on Event* are larger in magnitude, ranging from -1.5 to -1.7, and remain highly statistically significant (t-stat around 3 in all columns). These coefficients suggest that, on days when treated individuals sell stocks, they

are much less likely to sell those purchased on Diwali. The effect size represents approximately 30% of the dependent variable's mean in this sample (5), reinforcing the finding that treated individuals exhibit a strong aversion to selling event-purchased stocks. Overall, this behavior aligns with the cultural emphasis on long-term wealth and suggests that Diwali is associated with a tendency toward stock retention rather than short-term trading.

Disposition Effect. In Table 6 discussed above, we account for the well-documented disposition effect by including a control variable indicating whether a stock is trading at a paper gain relative to its weighted-average purchase price. We now examine whether treated investors exhibit a stronger or weaker disposition effect specifically for stocks purchased on the event day. To do so, we estimate regression (5), adding an interaction term between a dummy variable ($Gain$), 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.

The results in Internet Appendix Table IAD5 confirm a strong disposition effect, as evidenced by the highly significant coefficients on $Gain$, which range from 0.64 to 0.75 in Panel A (unconditional sample) depending on the specification, and is approximately 7 in Panel B (sale-conditioned sample). This indicates that investors are substantially more likely to sell stocks when they are trading at a gain. The interaction term $Purchased\ on\ Event \times Gain$ is consistently negative across all specifications, although its statistical significance varies: it is significant in Panel A but not in Panel B. This suggests that the disposition effect is not stronger for event-purchased stocks; if anything, it appears to be weaker. Overall, these findings indicate that Diwali's cultural association with long-term wealth does not reinforce investors' tendency to feel more comfortable selling at a gain. Instead, it appears to mitigate their propensity to sell winners.

5 Individual Portfolio Implications

In this 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. By focusing on these periods, we assess whether meaningful shifts in portfolio composition occur and whether these changes persist over time, providing insight into the broader implications of religious messaging on individuals' portfolios.

5.1 Empirical Strategy

To assess the persistence of portfolio changes, we construct six-month event windows around each event, spanning three months before and three months after. This approach allows us to track how individual portfolios evolve relative to the event and determine whether observed trading patterns lead to lasting changes. 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-day level dataset that captures individual portfolio dynamics relative to the event.

We focus on treated individuals 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. This approach is similar to a stacked difference-in-differences (as in Gormley and Matsa, 2011; Cengiz et al., 2019) and allows us to assess whether trading on the event day leads to persistent portfolio changes. Specifically, we estimate the following regression:

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

where c, i, and t denote cohort, individual and day respectively. The variable $Post_{c,t}$ is a dummy equal to 1 if day 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. Standard errors are double-clustered at the individual and day levels.

We consider several dependent variables. First, to assess whether the increased stock market participation and buying behavior observed on the event translates into a larger total investment in the stock market, we use the logarithm of the individual's total stock portfolio value. Second, to examine whether the purchase of new stocks increases diversification, we consider two measures

of portfolio diversification: (i) the logarithm of the number of stocks in the portfolio and (ii) the portfolio's Herfindahl index (HHI), defined as the sum of squared portfolio weights, ranging between 0 and 1. Finally, to test whether this potential diversification leads to lower portfolio volatility, we compute portfolio volatility as the rolling (annualized) standard deviation of portfolio returns over the past 21 days (approximately one month).

5.2 Empirical Results

The estimation results are presented in Table 7. The key coefficient of interest, $Post \times EventBuyer$, measures the change in portfolio outcomes after the event for treated individuals who participated by purchasing stocks on the event day, relative to treated individuals who did not. In the odd-numbered columns, we include individual-cohort and date-cohort fixed effects. In the even-numbered columns, 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 Columns (1) and (2), the dependent variable is the logarithm of the individual's total stock portfolio value. The coefficient on $Post \times EventBuyer$ is positive and highly significant: 0.24 in Column (1) and 0.20 in Column (2), both significant at the 1% level. This indicates that treated individuals who purchase stocks on the event day experience a sustained increase of more than 20 in total portfolio value post-event, relative to other treated individuals. These results suggest that event-driven stock purchases are not merely short-term trading activity but contribute 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 decreases significantly post-event for event buyers (between -0.026 and -0.028, significant at the 1% level). This confirms that event-driven purchases lead to greater portfolio diversification relative to other treated individuals, reinforcing the idea that event buyers allocate funds across a broader set of stocks.

The impact of event-day stock purchases on portfolio volatility is negative, but its statistical significance varies. In Column (7), where date-cohort fixed effects are included, the coefficient is negative and significant (-0.735, significant at the 5% level), suggesting that portfolio volatility decreases by nearly one percentage point for event buyers relative to non-buyers. However, in Column (8), when controlling for trading intensity, the coefficient remains negative but is no longer statistically significant.

5.3 Dynamics of the Effects

To better understand the evolution of portfolio characteristics around the event, we estimate a specification similar to equation (6), but replace the $Post$ indicator with a set of time-specific coefficients for each month before and after the event. This approach allows us to track the dynamics of the effect over time, identifying whether portfolio characteristics change immediately in the event month and whether these changes persist in the long run. Specifically, we estimate the following regression:

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

where $Month(\tau)_{c,t}$ is an indicator for month τ relative to the event, with $\tau = 0$ corresponding to the event month. This specification allows us to estimate a separate coefficient, β_τ, for each of the three months before and three months after the event, enabling us to assess both observable pre-trends and post-event dynamics. 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, where trading intensity is defined as described above (quartiles based on the individual's number of trades over the cohort window). Standard errors are double-clustered at the individual and day levels.

Figure 3 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. 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 stock market investments. In Panel B, the dependent variable is the logarithm of the number of stocks held. The pattern is similar, with a clear increase in diversification for event buyers during the event month, relative to other treated individuals. Importantly, there is no observable reversal in the months post-event, indicating that individuals maintain their broader portfolios over time. Consistent with the increase in the number of stocks, Panel C shows that portfolio HHI significantly decreases in the event month, reflecting a more diversified portfolio. This effect does not revert post-event, suggesting a lasting impact on portfolio concentration. Finally, Panel D shows that portfolio volatility declines slowly in the months following the event for individuals who purchased stocks on the event day, relative to non-buyers. This delayed effect is expected, given that volatility is measured using a rolling 21-day window, requiring time for recent trading to influence observed portfolio volatility.

Taken together, these results indicate that treated individuals who actively participate in the stock market on the event-day experience lasting effects on their portfolios. They maintain their overall investment levels, hold more stocks, reduce portfolio concentration, and exhibit lower volatility in the months following the event. These findings suggest that event-driven trading has persistent implications for individual portfolios.

6 Mechanism and Alternative Explanations

So far, we have established that individuals from treated group are significantly more active in the stock market on Muhurat trading day relative to other days, compared to investors from other religions. These investors are also more likely to buy rather than sell. Notably, treated investors are less likely to sell the stocks purchased on Diwali, suggesting that the cultural association with long-term prosperity influences their selling decisions and thus their investment horizon. Finally, among treated individuals, those who participate on the event day experience lasting portfolio changes relative to their non-participating counterparts. However, there may be potential alternative explanations

unrelated to the religious messaging during the events for these findings, which we consider in this section.

6.1 Wealth Effects

A primary alternative explanation for our results is that individuals in the treated group may experience a temporary increase in wealth around the event, which could influence their stock market participation and investment decisions. Specifically, Diwali is often associated with gifts and bonuses and perhaps such a change in liquidity or disposable wealth might lead them to be more willing to participate in the stock market. Additionally, with greater perceived or actual wealth, they may be more inclined to hold onto investments for the long term, driven by a sense of abundance or optimism about future returns.[24]

Since our data links individual activity within the bank across their savings and checking accounts, and credit cards, we examine changes in net wealth of individuals around the events. Across the different accounts, we estimate:

$$Y_{i,t} = \sum_{k=-5}^{5} \beta_k \left\{ Treated_i \times Day(k)_t \right\} + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{8}$$

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 Diwali's Muhurat trading day. α_i and γ_t denote individual and date fixed effects respectively. Standard errors are clustered at the investor and day levels. We consider various dependent variables described below.

Online Appendix Figure IAD8 plots the coefficients (β_k) and their corresponding 95% confidence intervals on each day around the event. In Panel A, the dependent variable is the arcsinh of the individual's checking account balance. We see that prior to the event, the average checking account balances are slightly higher while after the event they become close to zero, with both sets of coefficients statistically indistinguishable from zero. In Panel B, the dependent variable is the arcsinh of the difference

[24]Note that such argument(s) apply to religious festivals in general and should result in similar patterns of stock market participation around religious events of similar cultural significance, unless the behavior is influenced by the messaging conveyed by the specific event. In the subsequent subsection, we formally test for changes in investment decisions around other religious events driving our results.

between credit and debit amounts, further breaking down the amounts received or transferred (net credit-debit). We again see that there is no change in the amount of cash received or transferred to other accounts.

Next, in Online Appendix Figure IAD9, we examine ATM transactions. In Panel A, the dependent variable is a dummy equal to one if we observe an ATM withdrawal on the individual's account on that day. It shows that the likelihood to withdraw money from ATM jumps by 0.4% the day before Diwali for treated individuals. Moreover, in Panel B, where the dependent variable is the arcsinh of the withdrawn amount, 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 economic magnitude, conditional on withdrawing, the median withdrawn amount is ₹3,500 with the average being ₹7,141. In contrast, conditional on trading, the median trading amount is ₹56,000 with the average being ₹207,000 (cf. Table 1).

Lastly, in Online Appendix Figure IAD10, we examine credit card transactions. Approximately 1.2% of individual-days observations correspond to day with credit card transaction. Conditional on a day with transaction, the median daily amount is ₹1,231 with the average being ₹50,007. In Panel A, the dependent variable is a dummy variable equal to one if we observe a credit card transaction on the individual's account on that day. In Panel B, the dependent variable is the arcsinh of the transaction amount. Across both panels, we do not see a change in credit card transaction activities.

An important caveat of this analysis is that we do not have data on individuals' physical off-account cash and commodity holdings. It is common for people to purchase gold, silver, and other metals around this time, as it is considered auspicious and are associated with prosperity and good fortune. At the same time, 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 Diwali, driven by the perception of better returns in stocks over gold. This shift, in theory, could increase stock market participation.

Unfortunately, while our tests assuage general concerns regarding wealth effects driving our results, the data do not allow us to test these specific explanations. Therefore, in the subsequent section, we perform additional tests to rule out these and other such broader alternative explanations for our main findings.

6.2 Trading around Other Religious Events

As a reminder, our baseline tests show a differential propensity in stock market investments among treated and control groups, around Diwali. Therefore, if the increased activity of the treated group on Muhurat trading day is indeed driven by Diwali's specific religious messaging, we should not observe similar patterns on (i) other religious events of similar significance that lack this specific messaging, and (ii) religious events of similar significance among 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 Table IAB3 presents the list of events and their cultural significance) and estimate the following regression specification:

$$Y_{i,t} = \beta\, Treated_i \times \{Other\ Hindu\ Event\}_t + \kappa\, Affected\, Control_i \times \{Non-Hindu\ Event\}_t + \gamma_i + \delta_t + \epsilon_{i,t}, \tag{9}$$

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 day t corresponds to other Hindu religious events of similar cultural significance (excluding Diwali) and $\{Non-Hindu\ Event\}_t$ is a dummy equal to 1 if day t corresponds to non-Hindu religious events of similar cultural significance. $Treated_i$ is a dummy indicating whether individual i is inferred to be Hindu while $Affected\ Control_i$ is a dummy variable 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 day levels.

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

Internet Appendix Table IAD11 presents the results from this exercise. Compared to our baseline results, in Columns (1), (3), and (5), if anything, we see that individuals from the treated groups are

less likely trade—buy or sell, on other days of similar religious significance.[25] In the second set of tests, in Columns (2), (4), and (6), we identify religious events of similar significance for the control religious group. The benefit of this empirical specification is that it allows us to contrast the effects for individuals across religious groups, holding fixed the religious significance of the events to them. Our estimates suggest, in contrast to our baseline findings that individuals from treated group are significantly more active in the stock market on Muhurat trading day, that individuals in the control group are no more likely to trade—buy or sell, on their respective religious event days.

Note that these tests help assuage additional concerns that investors in the treated group might be influenced by peers within their community, which could lead to increased market activity. If other investors in their social circles are actively trading, they might feel compelled to trade as well. In contrast our results suggest that on these "neutral" days of similar religious significance but absent the specific messages, we do not find evidence that treated group exhibits significantly more active trading than the control group.

Taken together, our results are most consistent with the explanation that the effects on stock market investments that we document in our baseline likely stem from religious messaging associated with Diwali.

Conclusion

This paper examines whether and to what extent religion influences financial decision-making and affect long-term portfolio choices. While prior research has documented correlations between religiosity and economic behavior, establishing a direct link remains challenging due to confounding factors. We provide novel evidence that religion and its event-specific messaging on event days influence stock market investments, encouraging long-term investment rather than short-term speculation. Our findings reveal a previously unexplored channel through which religion shapes individual economic behavior, demonstrating that its effects persist well beyond the religious event itself and have potential implications for wealth accumulation and inequality.

[25]Note that we exclude Diwali itself from the set of events in the analyses. Furthermore, 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.

To identify the effects, we exploit Muhurat trading during Diwali, a recurring stock market trading session held during a festival culturally rooted in beliefs about long-term prosperity. This setting, combined with a unique dataset from a major national brokerage firm, allows us to compare how the same individual makes investment decisions on religiously significant days versus other days, isolating the impact of religious messaging from fixed individual characteristics. Using last names to infer religious affiliation, we find that individuals who associate with these beliefs increase their stock market participation, invest substantially larger amounts, and favor new stock purchases over expanding existing holdings on the event day. They also avoid speculative, lottery-like stocks and hold onto event-purchased stocks for longer, leading to persistent increases in stock market participation and portfolio diversification. Importantly, these effects are exclusive to Diwali and do not appear around other religious or secular events, ruling out alternative explanations related to liquidity shocks, wealth effects, or peer influence.

Our results have broader implications for faith-based investing, financial inclusion, and the intersection of religion and economic behavior. 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. More broadly, our findings highlight religion as an economic force, shaping investment behavior in ways that persist well beyond the religious event itself.

Figures

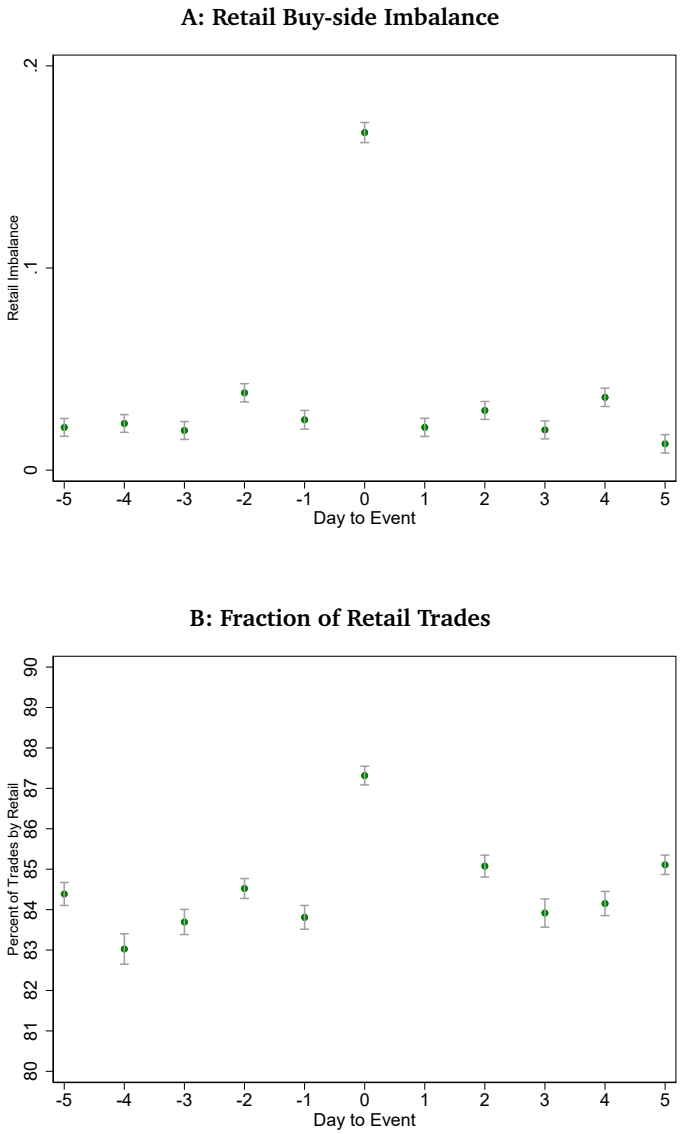
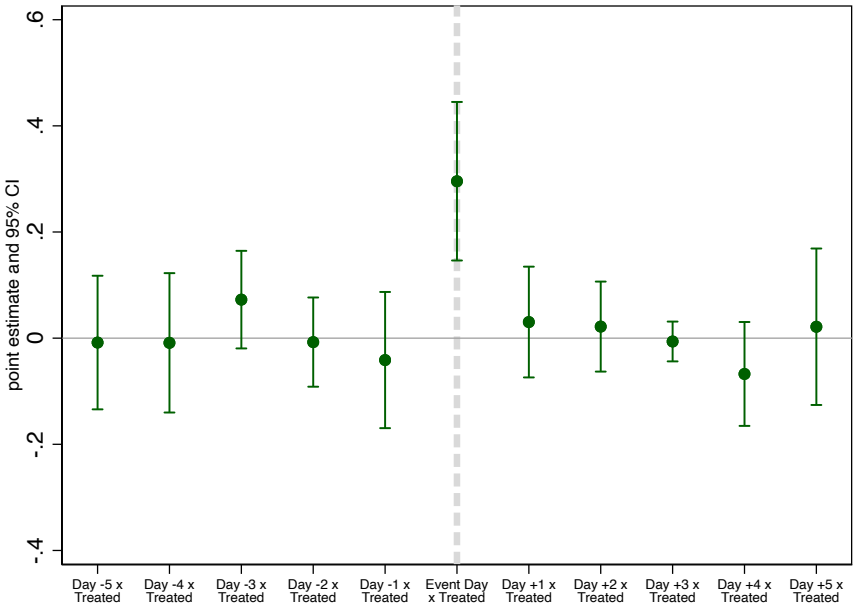


Figure 1: Aggregate retail imbalance and share of retail trades around Diwali. This figure plots the retail imbalance and share of retail trades means with 95% confidence intervals around the 5 days before and after Diwali for stocks trading on the National Stock Exchange (NSE). Retail imbalance is computed as $\frac{(buy+sell)}{buy-sell}$, where *buy* and *sell* are the number of buy and sell trades, respectively.

Panel A: Total amount traded



Panel B: Amount spent on buy and sell trades

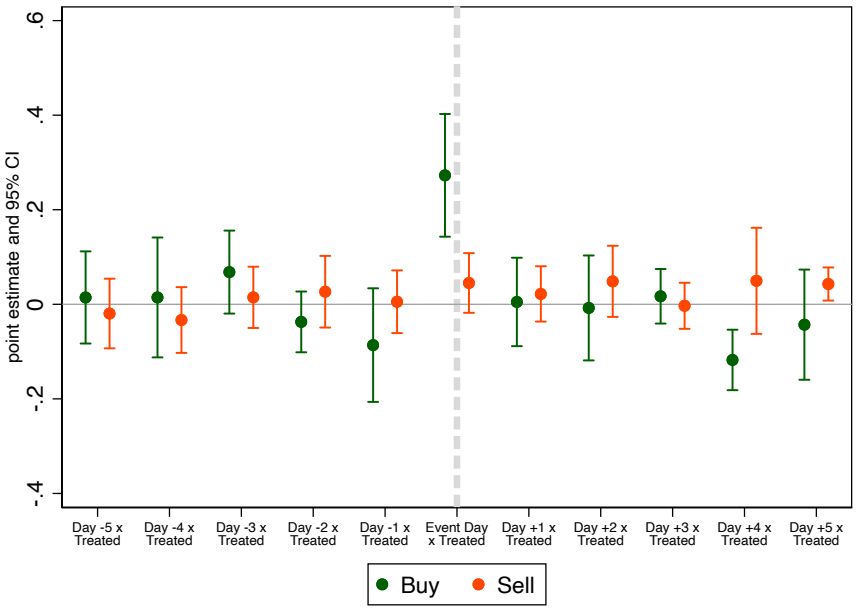


Figure 2: Dynamics of the traded amount around the events. This figure plots the coefficients β_k on each day in equation: $Y_{i,t} = \sum_{k=-5}^{5} \beta_k \{Treated_i \times Day(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the individual and date, and $Day(k)_t$ is a dummy 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 day levels.

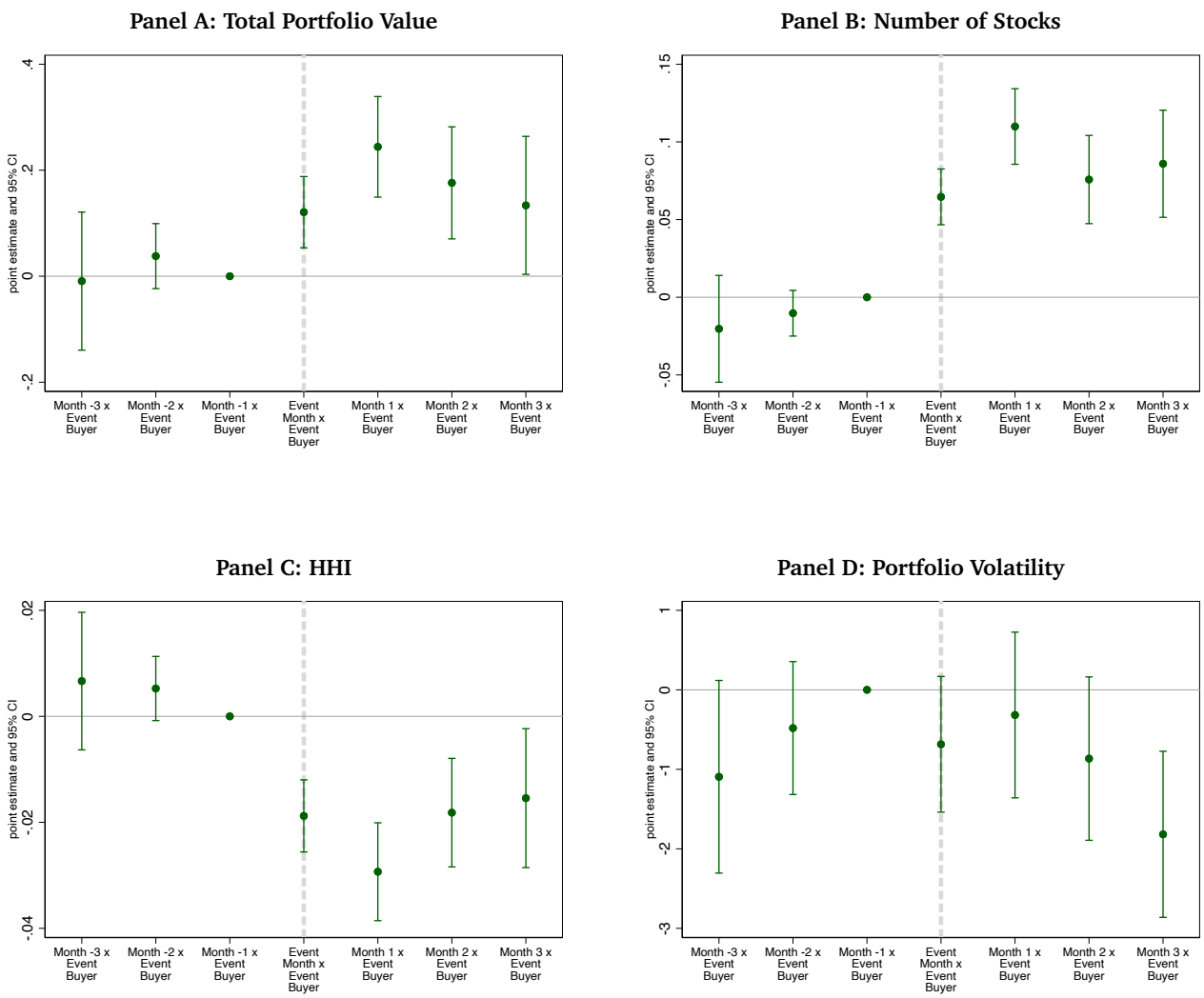


Figure 3: Dynamics of portfolio characteristics in the months before and after the events. This figure plots the estimated coefficients β_τ from equation (7), capturing the evolution of portfolio characteristics before and after the event for treated individuals who purchase stocks on the event day, relative to other treated individuals. Regressions are estimated at the individual-day 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 volatility, measured as the standard deviation of portfolio returns over the past 21 days. Horizontal bars correspond to 95% confidence intervals. Standard errors are double-clustered at the investor and day levels.

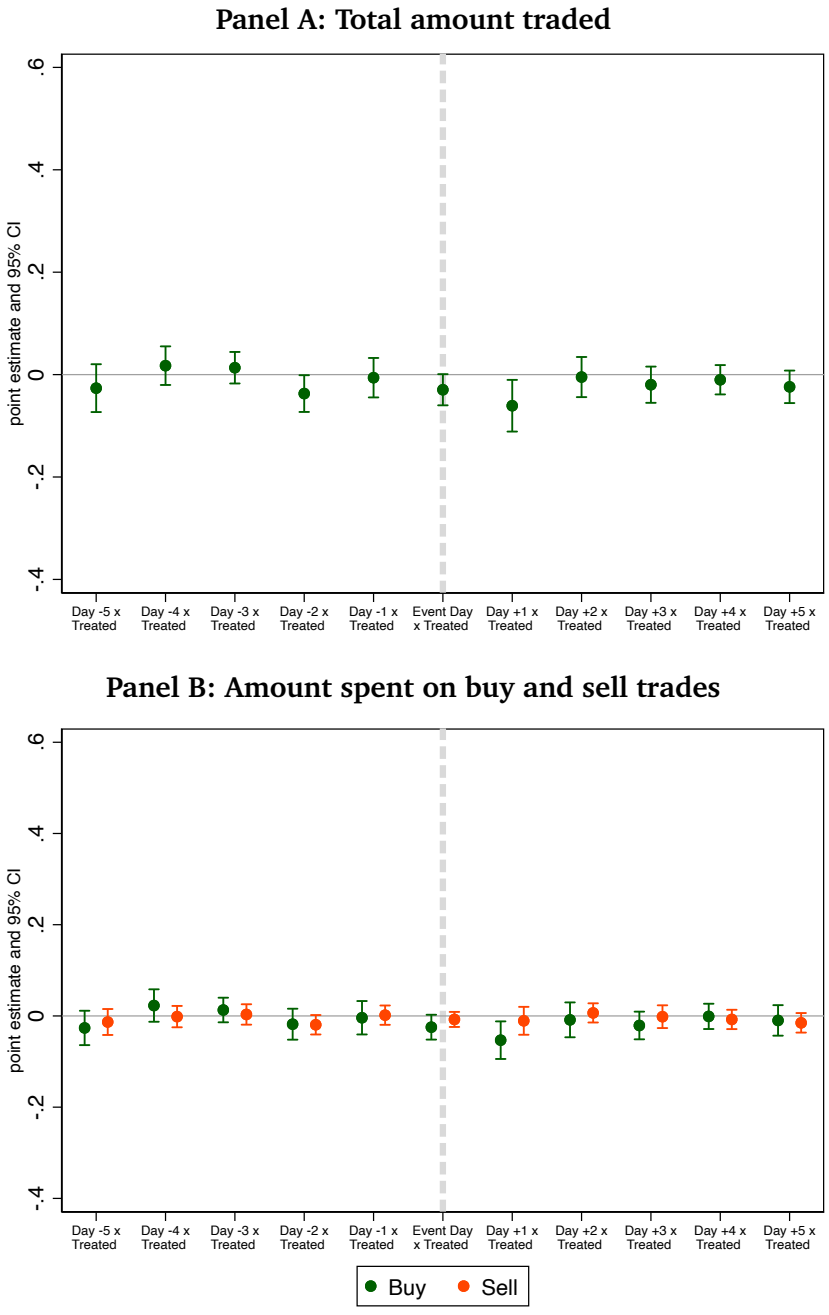


Figure 4: Dynamics of the traded amount around other religious events. This figure plots the coefficients β_k on each day in equation: $Y_{i,t} = \sum_{k=-5}^{5} \beta_k \{Affected_i \times Day(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the individual and date, and $Day(k)_t$ 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 day levels.

Tables

Table 1: Broker Dataset Summary Statistics This table lists the account level (Panel A), account-day level (Panels B and C), and account-stock-day level (Panels D and E) summary statistics from our broker dataset. In addition, 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. Panel C restricts the account-day sample to observations on days when individuals trade at least one stock. Panels D and E only include the holdings of treated individuals (Hindus). Panel E 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 rupees 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)	24112	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-Day level (unconditional sample)								
Total Portfolio Value (₹1000s)	6090768	1,067.19	4,106.18	1.43	41.86	185.15	700.45	4,279.75
Nb. Stocks	6090768	5.22	7.96	1.00	1.00	3.00	6.00	18.00
Trade	6090768	0.08	0.27	0.00	0.00	0.00	0.00	1.00
Buy	6090768	0.06	0.24	0.00	0.00	0.00	0.00	1.00
Sell	6090768	0.03	0.17	0.00	0.00	0.00	0.00	0.00
Amount Traded (₹1000s)	6090768	16.52	223.12	0.00	0.00	0.00	0.00	33.76
Amount Buy Trades (₹1000s)	6090768	9.79	151.00	0.00	0.00	0.00	0.00	8.93
Amount Sell Trades (₹1000s)	6090768	6.73	136.58	0.00	0.00	0.00	0.00	0.00
Panel C: Account-Day 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

Continued next page

Summary statistics (continued)

Variable	Obs	Mean	Sd	5%	25%	50%	75%	95%
Panel D: Account-Stock-Day level (unconditional sample)								
Trade	28587808	0.03	0.16	0.00	0.00	0.00	0.00	0.00
Sell	28587808	0.02	0.13	0.00	0.00	0.00	0.00	0.00
Buy	28587808	0.01	0.09	0.00	0.00	0.00	0.00	0.00
Amount Traded (₹1000s)	28587808	3.10	69.15	0.00	0.00	0.00	0.00	0.00
Amount Buy (₹1000s)	28587808	1.84	52.90	0.00	0.00	0.00	0.00	0.00
Amount Sell (₹1000s)	28587808	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
Panel E: Account-Stock-Day level (sale-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 2: Trading behavior on Diwali day

Regressions are estimated at the individual-day 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 day 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-day 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 day 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-day 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 hodlings). 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 day 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: Characteristics of stocks purchased on Diwali day

Regressions are estimated at the individual-stock-day 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-day 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 6: Likelihood to sell stocks purchased on Diwali day

Regressions are estimated at the individual-stock-day 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 day 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	28587808	28587808	28587808	28587808
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 7: Individual Portfolio Implications

Regressions are estimated at the individual-day 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. The dependent variables capture portfolio size, diversification, concentration, and volatility. 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). Columns (7)–(8) estimate the impact on portfolio volatility, defined as the rolling (annualized) standard deviation of portfolio returns over the past 21 days. 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), (5) and (7) include individual-cohort and date-cohort fixed effects, while Columns (2), (4), (6) and (8) further include 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 day levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Total Portfolio Value		Nb. Stocks		HHI		Volatility (%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × Event Buyer	0.240***	0.204***	0.107***	0.098***	-0.028***	-0.026***	-0.735**	-0.348
	(0.041)	(0.042)	(0.012)	(0.011)	(0.004)	(0.004)	(0.332)	(0.322)
Individual × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date × Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No
Trading Intensity × Date × Cohort FE	No	Yes	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	2,956,799	2,956,799
R^2	0.86	0.86	0.93	0.93	0.88	0.89	0.50	0.50

References

Abadie, A., S. Athey, G. W. Imbens, and J. Wooldridge (2017). When should you adjust standard errors for clustering? Technical report, National Bureau of Economic Research.

Ager, P. and A. Ciccone (2018). Agricultural risk and the spread of religious communities. *Journal of the European Economic Association 16*(4), 1021–1068.

Akerlof, G. A. and R. E. Kranton (2000). Economics and identity. *Quarterly Journal of Economics 115*(3), 715–753.

Altonji, J. G., T. E. Elder, and C. R. Taber (2005). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of Political Economy 113*(1), 151–184.

Anagol, S., V. Balasubramaniam, and T. Ramadorai (2021). Learning from noise: Evidence from india's ipo lotteries. *Journal of Financial Economics 140*(3), 965–986.

Andersen, S. and K. M. Nielsen (2011). Participation constraints in the stock market: Evidence from unexpected inheritance due to sudden death. *Review of Financial Studies 24*(5), 1667–1697.

Bach, L., L. E. Calvet, and P. Sodini (2020). Rich pickings? risk, return, and skill in household wealth. *American Economic Review 110*(9), 2703–2747.

Badarinza, C., V. Balasubramaniam, and T. Ramadorai (2019). The household finance landscape in emerging economies. *Annual Review of Financial Economics 11*(1), 109–129.

Baker, M. and J. Wurgler (2007). Investor sentiment in the stock market. *Journal of economic perspectives 21*(2), 129–151.

Balasubramaniam, V., J. Y. Campbell, T. Ramadorai, and B. Ranish (2023). Who owns what? a factor model for direct stockholding. *Journal of Finance 78*(3), 1545–1591.

Banerjee, A., E. Duflo, M. Ghatak, and J. Lafortune (2013). Marry for what? caste and mate selection in modern india. *American Economic Journal: Microeconomics 5*(2), 33–72.

Barber, B. M. and T. Odean (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The journal of Finance 55*(2), 773–806.

Barber, B. M. and T. Odean (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies 21*(2), 785–818.

Barber, B. M., T. Odean, and N. Zhu (2008). Do retail trades move markets? *Review of Financial Studies 22*(1), 151–186.

Barberis, N. and M. Huang (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review 98*(5), 2066 – 2100.

Barro, R. J. and R. M. McCleary (2003). Religion and economic growth across countries. *American sociological review 68*(5), 760–781.

Barsky, R. B., F. T. Juster, M. S. Kimball, and M. D. Shapiro (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *Quarterly Journal of Economics 112*(2), 537–579.

Bazzi, S., G. Koehler-Derrick, and B. Marx (2020). The institutional foundations of religious politics: Evidence from indonesia. *Quarterly Journal of Economics 135*(2), 845–911.

Ben-David, I., J. R. Graham, and C. R. Harvey (2013). Managerial miscalibration. *The Quarterly Journal of Economics 128*(4), 1547 – 1584.

Ben-David, I. and D. Hirshleifer (2012). Are investors really reluctant to realize their losses? trading responses to past returns and the disposition effect. *Review of Financial Studies 25*(8), 2485–2532.

Bénabou, R. and J. Tirole (2003). Intrinsic and extrinsic motivation. *Review of Economic Studies 70*(3), 489–520.

Bénabou, R. and J. Tirole (2006). Incentives and prosocial behavior. *American Economic Review 96*(5), 1652–1678.

Benjamin, D. J., J. J. Choi, and G. Fisher (2016). Religious identity and economic behavior. *Review of Economics and Statistics 98*(4), 617–637.

Berger, M., G. Fellner-Röhling, R. Sausgruber, and C. Traxler (2016). Higher taxes, more evasion? evidence from border differentials in tv license fees. *Journal of Public Economics 135*, 74–86.

Bernheim, B. D. and D. M. Garrett (2003). The effects of financial education in the workplace: Evidence from a survey of households. *Journal of Public Economics 87*(7-8), 1487–1519.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics 119*(1), 249–275.

Bertrand, M., P. Mehta, and S. Mullainathan (2002). Ferreting out Tunneling: An Application to Indian Business Groups. *Quarterly Journal of Economics 117*(1), 121–148.

Bhagavatula, S., M. Bhalla, M. Goel, and B. Vissa (2019). Cultural diversity on corporate boards and firm outcomes. Technical report, Working paper.

Bhalotra, S., I. Clots-Figueras, L. Iyer, and J. Vecci (2023). Leader identity and coordination. *Review of Economics and Statistics 105*(1), 175–189.

Bharti, N. K. and S. Roy (2023). The early origins of judicial stringency in bail decisions: Evidence from early childhood exposure to hindu-muslim riots in india. *Journal of Public Economics 221*, 104846.

Binzel, C. and J.-P. Carvalho (2017). Education, social mobility and religious movements: The islamic revival in egypt. *Economic Journal 127*(607), 2553–2580.

Briggs, J., D. Cesarini, E. Lindqvist, and R. Östling (2021). Windfall gains and stock market participation. *Journal of Financial Economics 139*(1), 57–83.

Brown, J. R., Z. Ivković, P. A. Smith, and S. Weisbenner (2008). Neighbors matter: Causal community effects and stock market participation. *Journal of Finance 63*(3), 1509–1531.

Bursztyn, L., S. Fiorin, D. Gottlieb, and M. Kanz (2019). Moral incentives in credit card debt repayment: Evidence from a field experiment. *Journal of Political Economy 127*(4), 1641–1683.

Buser, T. (2015). The effect of income on religiousness. *American Economic Journal: Applied Economics 7*(3), 178–195.

Butinda, L. D., A. A. Lameke, N. Nunn, M. Posch, and R. S. de la Sierra (2023). On the importance of african traditional religion for economic behavior. Technical report, National Bureau of Economic Research.

Caicedo, F. V. (2019). The mission: Human capital transmission, economic persistence, and culture in south america. *Quarterly Journal of Economics 134*(1), 507–556.

Campante, F. and D. Yanagizawa-Drott (2015). Does religion affect economic growth and happiness? evidence from ramadan. *Quarterly Journal of Economics 130*(2), 615–658.

Campbell, J. Y. (2006). Household finance. *Journal of Finance 61*(4), 1553–1604.

Campbell, J. Y., T. Ramadorai, and B. Ranish (2014). Getting better or feeling better? how equity investors respond to investment experience. Technical report, National Bureau of Economic Research.

Campbell, J. Y., T. Ramadorai, and B. Ranish (2019). Do the rich get richer in the stock market? evidence from india. *American Economic Review: Insights 1*(2), 225–240.

Cannon, B., D. Hirshleifer, and J. Thornton (2024). Friends with benefits: Social capital and household financial behavior. Technical report, National Bureau of Economic Research.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics 134*(3), 1405–1454.

Chen, J., H. Hong, and J. C. Stein (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of financial Economics 61*(3), 345–381.

Chen, Z., C. Ma, and A. J. Sinclair (2022). Banking on the confucian clan: why china developed financial markets so late. *Economic Journal 132*(644), 1378–1413.

Clark, A. (2005). Deliver us from evil: Religion as insurance.

Cole, S., A. Paulson, and G. K. Shastry (2014). Smart money? the effect of education on financial outcomes. *Review of Financial Studies 27*(7), 2022–2051.

Da, Z., J. Engelberg, and P. Gao (2011). In search of attention. *Journal of Finance 66*(5), 1461–1499.

Da, Z., J. Engelberg, and P. Gao (2015). The sum of all fears investor sentiment and asset prices. *Review of Financial Studies 28*(1), 1–32.

Da, Z., X. Huang, and L. J. Jin (2021). Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics 140*(1), 175 – 196.

D'Acunto, F., P. Ghosh, and A. G. Rossi (2024). How costly are cultural biases? evidence from fintech. *Journal of Financial Economics*, Forthcoming.

Dal Bó, E. and P. Dal Bó (2014). "do the right thing:" the effects of moral suasion on cooperation. *Journal of Public Economics 117*, 28–38.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam (1998). Investor psychology and security market under- and overreactions. *Journal of Finance 53*(6), 1839 – 1885.

Dehejia, R., T. DeLeire, and E. F. Luttmer (2007). Insuring consumption and happiness through religious organizations. *Journal of Public Economics 91*(1-2), 259–279.

Demiroglu, C., O. Ozbas, R. C. Silva, and M. F. Ulu (2021). Do physiological and spiritual factors affect economic decisions? *The Journal of Finance 76*(5), 2481–2523.

Edmans, A., D. Garcia, and Ø. Norli (2007). Sports sentiment and stock returns. *The Journal of finance 62*(4), 1967–1998.

Espín-Sánchez, J.-A., S. Gil-Guirado, and N. Ryan (2023). Praying for rain. *Working Paper*.

Fisman, R., P. Ghosh, A. Sarkar, and J. Zhang (2023). Dirty air and green investments: The impact of pollution information on portfolio allocations. Technical report, National Bureau of Economic Research.

Fisman, R., A. Sarkar, J. Skrastins, and V. Vig (2020). Experience of communal conflicts and intergroup lending. *Journal of Political Economy 128*(9), 3346–3375.

Floyd, E., M. Hallsworth, J. A. List, R. D. Metcalfe, K. Rotaru, and I. Vlaev (2022). The role of enforcement action uncertainty on tax compliance: Evidence from three experiments. *Working Paper*.

Frey, B. (1997). Not just for the money. *An Economic Theory of Personal Motivation/Edward Elgar Publishing*.

Fruehwirth, J. C., S. Iyer, and A. Zhang (2019). Religion and depression in adolescence. *Journal of Political Economy 127*(3), 1178–1209.

Gao, X. and T.-C. Lin (2015). Do individual investors treat trading as a fun and exciting gambling activity? evidence from repeated natural experiments. *The Review of Financial Studies 28*(7), 2128–2166.

Gelman, M., D. Hirshleifer, Y. Levi, and L. Reiter-Gavish (2024). Social interaction intensity and investor behavior. Technical report, National Bureau of Economic Research.

Gneezy, U. (2005). Deception: The role of consequences. *American Economic Review 95*(1), 384–394.

Gomes, F., M. Haliassos, and T. Ramadorai (2021). Household finance. *Journal of Economic Literature 59*(3), 919–1000.

Gopalan, R., A. Mukherjee, and M. Singh (2016). Do debt contract enforcement costs affect financing and asset structure? *Review of Financial Studies 29*(10), 2774–2813.

Gopalan, R., V. Nanda, and A. Seru (2007). Affiliated firms and financial support: Evidence from Indian business groups. *Journal of Financial Economics 86*(3), 759–795.

Gormley, T. A. and D. A. Matsa (2011). Growing out of trouble? corporate responses to liability risk. *The Review of Financial Studies 24*(8), 2781–2821.

Grinblatt, M. and M. Keloharju (2000). The investment behavior and performance of various investor types: a study of finland's unique data set. *Journal of Financial Economics 55*(1), 43–67.

Grinblatt, M., M. Keloharju, and J. Linnainmaa (2011). Iq and stock market participation. *Journal of Finance 66*(6), 2121–2164.

Gruber, J. and D. M. Hungerman (2008). The church versus the mall: What happens when religion faces increased secular competition? *Quarterly Journal of Economics 123*(2), 831–862.

Guiso, L., P. Sapienza, and L. Zingales (2003). People's opium? religion and economic attitudes. *Journal of Monetary Economics 50*(1), 225–282.

Guiso, L. and P. Sodini (2012). Household nance: An emerging eld. *Handbook of the Economics of Finance. Vol*.

Haliassos, M. and C. C. Bertaut (1995). Why do so few hold stocks? *Economic Journal 105*(432), 1110–1129.

Hallsworth, M., J. A. List, R. D. Metcalfe, and I. Vlaev (2017). The behavioralist as tax collector: Using natural field experiments to enhance tax compliance. *Journal of Public Economics 148*, 14–31.

Hilary, G. and K. W. Hui (2009). Does religion matter in corporate decision making in america? *Journal of financial economics 93*(3), 455–473.

Hirshleifer, D. (2020). Presidential address: Social transmission bias in economics and finance. *The Journal of Finance 75*(4), 1779–1831.

Hjort, J. (2014). Ethnic divisions and production in firms. *Quarterly Journal of Economics 129*(4), 1899–1946.

Hjort, J. (2021). Ethnic investing and the value of firms. *CEPR Discussion Paper No. DP16316*.

Hong, H., J. D. Kubik, and J. C. Stein (2004). Social interaction and stock-market participation. *Journal of Finance 59*(1), 137–163.

Iannaccone, L. R. (1998). Introduction to the economics of religion. *Journal of economic literature 36*(3), 1465–1495.

Ito, K., T. Ida, and M. Tanaka (2018). Moral suasion and economic incentives: Field experimental evidence from energy demand. *American Economic Journal: Economic Policy 10*(1), 240–267.

Ivković, Z. and S. Weisbenner (2007). Information diffusion effects in individual investors' common stock purchases: Covet thy neighbors' investment choices. *The Review of Financial Studies 20*(4), 1327–1357.

Iyer, S. (2002). *Demography and religion in India*. Oxford University Press.

Iyer, S. (2016). The new economics of religion. *Journal of Economic Literature 54*(2), 395–441.

Iyer, S. (2018, 12). The economics of religion in india.

Iyer, S. and A. Shrivastava (2018). Religious riots and electoral politics in india. *Journal of Development Economics 131*, 104–122.

Jha, S. (2013). Trade, institutions, and ethnic tolerance: Evidence from south asia. *American political Science review 107*(4), 806–832.

Jha, S. and M. Shayo (2019). Valuing peace: the effects of financial market exposure on votes and political attitudes. *Econometrica 87*(5), 1561–1588.

Jiang, F., K. John, C. W. Li, and Y. Qian (2018). Earthly reward to the religious: religiosity and the costs of public and private debt. *Journal of Financial and Quantitative Analysis 53*(5), 2131–2160.

Johnson, N. D. and M. Koyama (2017). Jewish communities and city growth in preindustrial europe. *Journal of Development Economics 127*, 339–354.

Kaniel, R., G. Saar, and S. Titman (2008). Individual investor trading and stock returns. *Journal of Finance 63*(1), 273–310.

Kaustia, M. and S. Knüpfer (2012). Peer performance and stock market entry. *Journal of Financial Economics 104*(2), 321–338.

Kaustia, M., S. Knüpfer, and S. Torstila (2016). Stock ownership and political behavior: evidence from demutualizations. *Management Science 62*(4), 945–963.

Kaustia, M. and S. Torstila (2011). Stock market aversion? political preferences and stock market participation. *Journal of Financial Economics 100*(1), 98–112.

Ke, D. (2018). Cross-country differences in household stock market participation: The role of gender norms. In *AEA Papers and Proceedings*, Volume 108, pp. 159–162. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Ke, D. (2024). Left behind: Partisan identity, stock market participation, and wealth inequality. *Journal of Banking & Finance 164*, 107201.

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

Kumar, A., J. K. Page, and O. G. Spalt (2011). Religious beliefs, gambling attitudes, and financial market outcomes. *Journal of financial economics 102*(3), 671–708.

Kung, J. K.-s. and C. Ma (2014). Can cultural norms reduce conflicts? confucianism and peasant rebellions in qing china. *Journal of Development Economics 111*, 132–149.

Le Rossignol, E., S. Lowes, and N. Nunn (2022). The social consequences of traditional religion in contemporary africa. Technical report, National Bureau of Economic Research.

Lilienfeld-Toal, U. v., D. Mookherjee, and S. Visaria (2012). The distributive impact of reforms in credit enforcement: Evidence from Indian debt recovery tribunals. *Econometrica 80*(2), 497–558.

McCleary, R. M. and R. J. Barro (2006). Religion and economy. *Journal of Economic perspectives 20*(2), 49–72.

Meeuwis, M., J. A. Parker, A. Schoar, and D. Simester (2022). Belief disagreement and portfolio choice. *Journal of Finance 77*(6), 3191–3247.

Mehmood, S., A. Seror, and D. L. Chen (2023). Ramadan fasting increases leniency in judges from pakistan and india. *Nature human behaviour 7*(6), 874–880.

Montero, E. and D. Yang (2022). Religious festivals and economic development: Evidence from the timing of mexican saint day festivals. *American Economic Review 112*(10), 3176–3214.

Müller, K., Y. Pan, and C. Schwarz (2024). Social media and stock market participation. *Working Paper*.

Naaraayanan, S. L. and K. M. Nielsen (2021). Does personal liability deter individuals from serving as independent directors? *Journal of Financial Economics 140*(2), 621–643.

Naaraayanan, S. L. and D. Wolfenzon (2023). Business group spillovers. *Review of Financial Studies Forthcoming*.

Naughton, S. and T. Naughton (2000). Religion, ethics and stock trading: The case of an islamic equities market. *Journal of Business Ethics 23*, 145–159.

Odean, T. (1998a). Are investors reluctant to realize their losses? *Journal of Finance 53*(5), 1775–1798.

Odean, T. (1998b). Volume, volatility, price, and profit when all traders are above average. *Journal of Finance 53*(6), 1887 – 1934.

Pascali, L. (2016). Banks and development: Jewish communities in the italian renaissance and current economic performance. *Review of Economics and Statistics 98*(1), 140–158.

Pruckner, G. J. and R. Sausgruber (2013). Honesty on the streets: A field study on newspaper purchasing. *Journal of the European Economic Association 11*(3), 661–679.

Renneboog, L. and C. Spaenjers (2012). Religion, economic attitudes, and household finance. *Oxford economic papers 64*(1), 103–127.

Roberts, M. R. and T. M. Whited (2013). Endogeneity in empirical corporate finance1. In *Handbook of the Economics of Finance*, Volume 2, pp. 493–572. Elsevier.

Seru, A., T. Shumway, and N. Stoffman (2010). Learning by trading. *The Review of Financial Studies 23*(2), 705–739.

Shayo, M. (2020). Social identity and economic policy. *Annual Review of Economics 12*(1), 355–389.

Shefrin, H. and M. Statman (2000). Behavioral portfolio theory. *Journal of Financial and Quantitative Analysis 35*(2), 127 – 151.

Shu, T., J. Sulaeman, and P. E. Yeung (2012). Local religious beliefs and mutual fund risk-taking behaviors. *Management Science 58*(10), 1779–1796.

Siegel, J. and P. Choudhury (2012). A reexamination of tunneling and business groups: New data and new methods. *Review of Financial Studies 25*(6), 1763–1798.

Sinding Bentzen, J. (2019). Acts of god? religiosity and natural disasters across subnational world districts. *Economic Journal 129*(622), 2295–2321.

Van Rooij, M., A. Lusardi, and R. Alessie (2011). Financial literacy and stock market participation. *Journal of Financial Economics 101*(2), 449–472.

Weber, M. (1930[1905]). The protestant ethic and the spirit of capitalism.

Internet 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, Bhalla, Goel, and Vissa (2019); D'Acunto, Ghosh, and Rossi (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, Muslin, 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.

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 IAA2.

Table IAA2: 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	23,729	90.04
Jain	1,149	4.36
Muslim	681	2.58
Sikh	534	2.03
Christian	260	0.99

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.[26] 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.

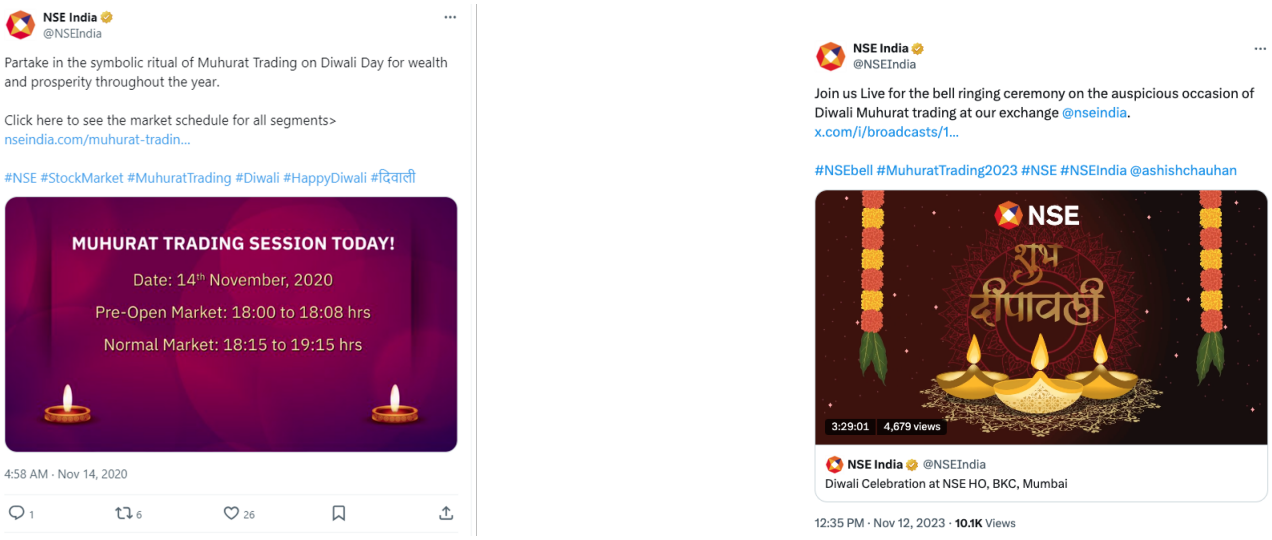


Figure IAB1: National Stock Exchange Muhurat Trading Advertising. This figure presents examples of Muhurat trading advertising on Twitter by the National Stock Exchange. The Tweets are available at https://x.com/NSEIndia/status/1327476084028260352 and https://x.com/NSEIndia/status/1723680845830168685.

[26] 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.

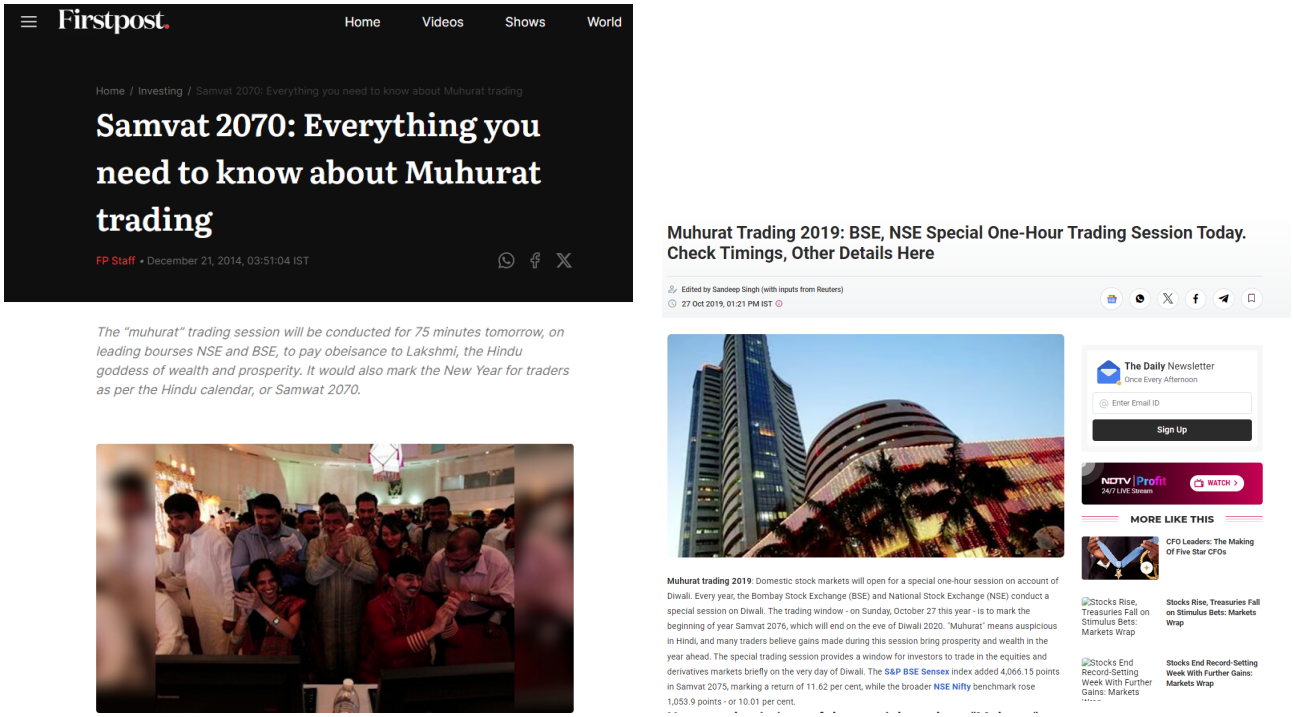


Figure IAB2: Newspaper References to Muhurat Trading. This figure presents examples of newspapers articles announcing Muhurat Trading. These articles are available at https://www.firstpost.com/investing/samvat-2070-everything-you-need-to-know-about-muhurat-trading-1207861.html and https://www.ndtvprofit.com/business/muhurat-trading-timings-2019-diwali-bse-nse-to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

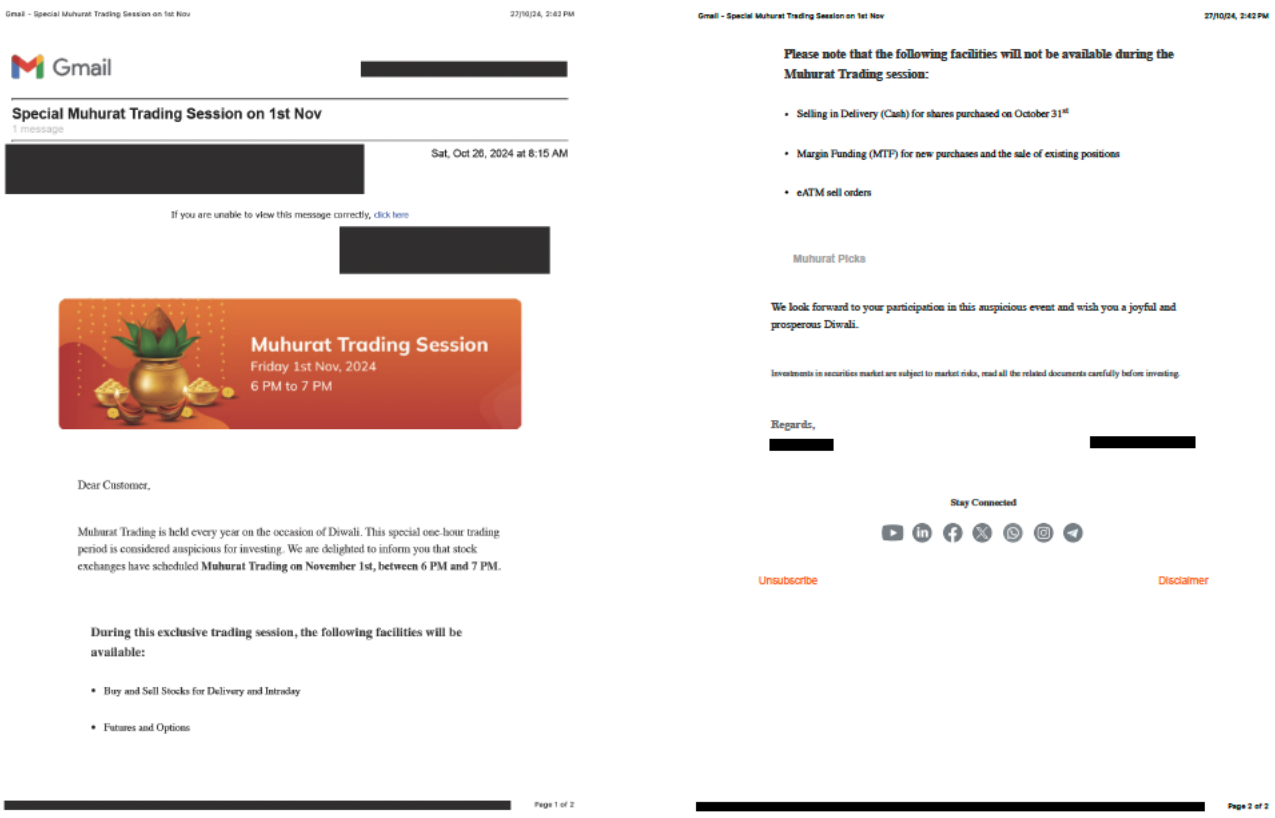


Figure IAB3: Muhurat Trading Announcement Email. This figure presents an example of an email sent out by the broker for which we have individual retail trading data to clients for the 2024 Muhurat trading session.

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.

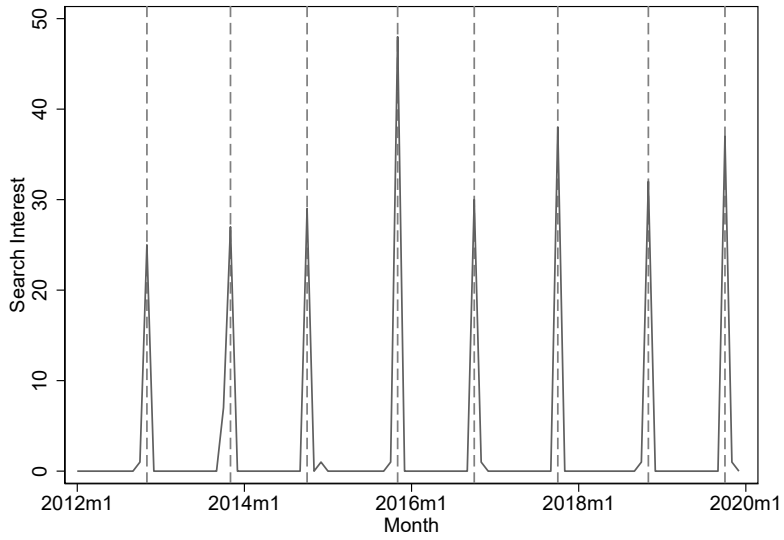


Figure IAB4: Google Trends Search Interest for "Muhurat Trading." This figure plots the time series of Google Trends search interest for the term "Muhurat Trading" from 2012 to 2019 in India nationally. The vertical dashed lines represent the month of the Muhurat trading session each year.

Table IAB3: 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 Stock Market Participation

C.1 Brokerage Account Opening

We begin 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:

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

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 $\times$ 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. We cluster standard errors at the state-level (Bertrand, Duflo, and Mullainathan, 2004; Roberts and Whited, 2013; Abadie, Athey, Imbens, and Wooldridge, 2017).

Figure IAC5 presents the estimated coefficients β_1 and β_2, labeled as "Event" and "Event $\times$ 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 opening 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.

C.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:

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

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

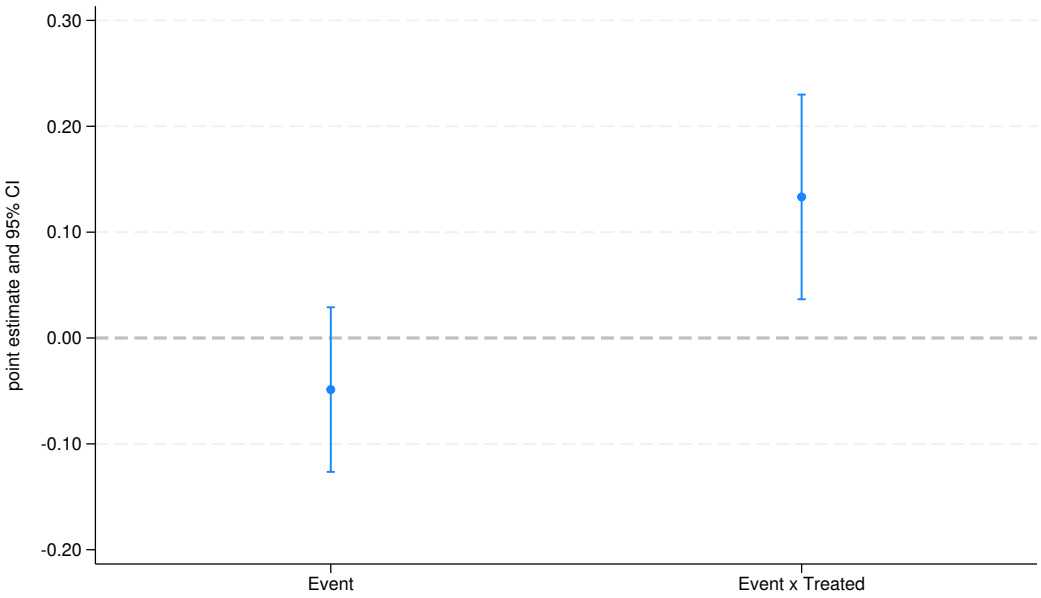


Figure IAC5: New brokerage account openings around Diwali events. This figure plots the estimates β_1 ("Event") and β_2 ("Event $\times$ Treated") of a $naccounts_{imst} = \exp\{\beta_0 + \beta_1 Event_t + \beta_2(Treated_i \times Event_t) + \gamma_{ims} + \varepsilon_{imst}\}$, where $naccounts_{ismt}$ 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 day 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 (C.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 day level.[27]

Figure IAC6 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.

[27]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.

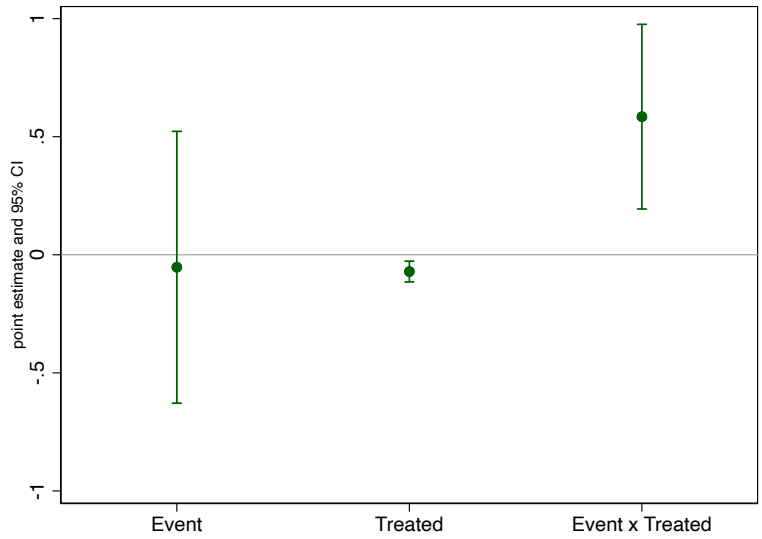


Figure IAC6: Likelihood to trade for the first time on Diwali event. This figure plots the estimates β_1 ("Event"), β_2 ("Treated") and β_3 ("Event $\times$ Treated") of a Cox hazard model of the form $h_i(t) = h_0(t) \exp\{\beta_0 + \beta_1 Event_t + \beta_2 Treated_i + \beta_3\{Event_t \times Treated_i\} + \epsilon_{i,t}\}$, 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 day t conditional on not having traded prior to day 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 day level.

D Additional Figures and Tables

Table IAD4: 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

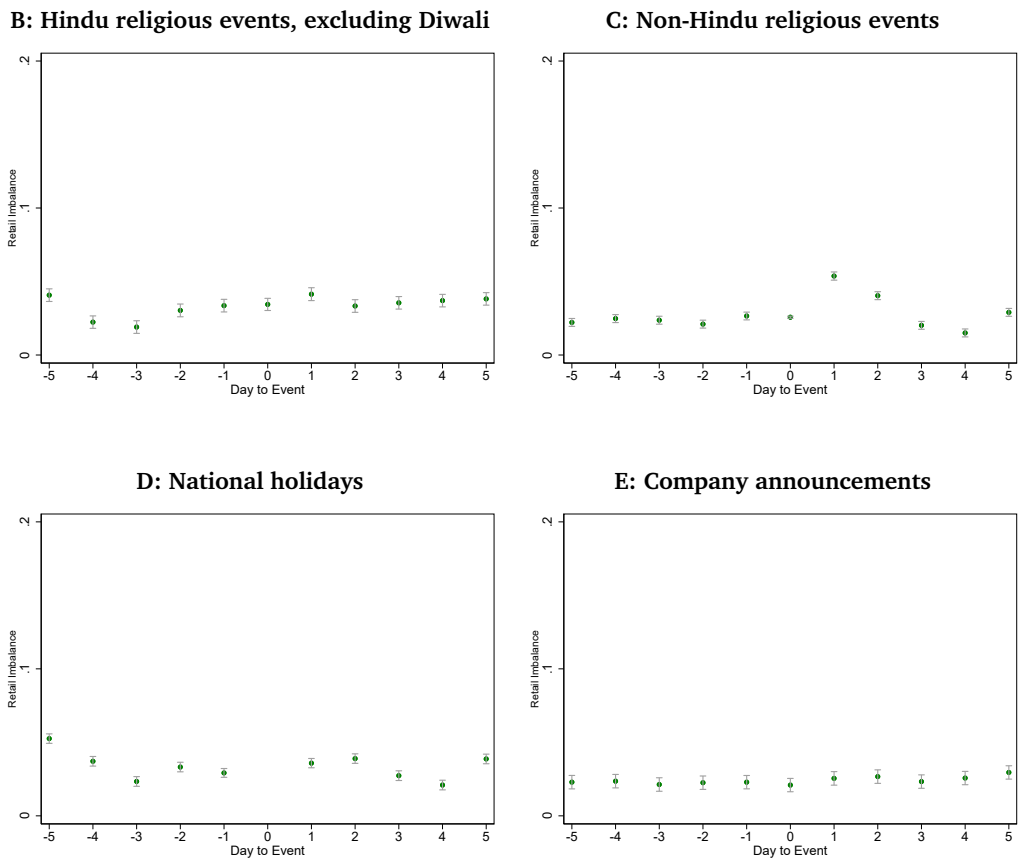


Figure IAD7: Aggregate retail imbalance around other events. This figure plots the retail imbalance mean with 95% confidence intervals around the 5 days before and after a particular event for stocks trading on the National Stock Exchange (NSE). Retail imbalance is computed as $\frac{(buy+sell)}{buy-sell}$, 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.

Table IAD5: Disposition Effect

Regressions are estimated at the individual-stock-day 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 day level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

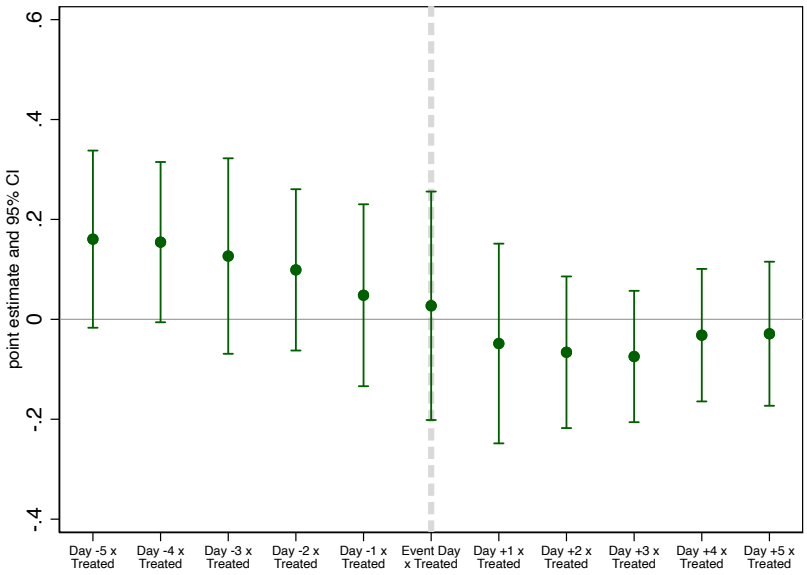
Panel A: Unconditional sample

	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	28587808	28587808	28587808	28587808
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

Panel A: Checking Account Balance



Panel B: Credit-Debit Net Amount

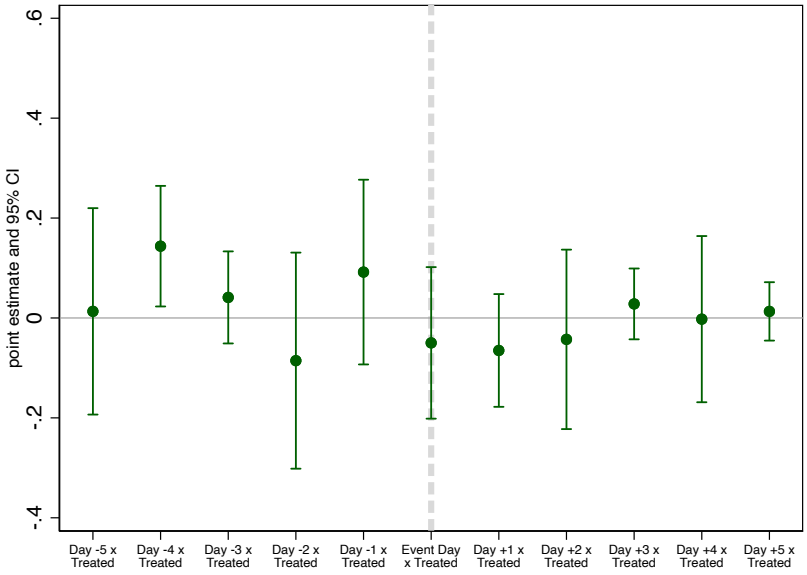
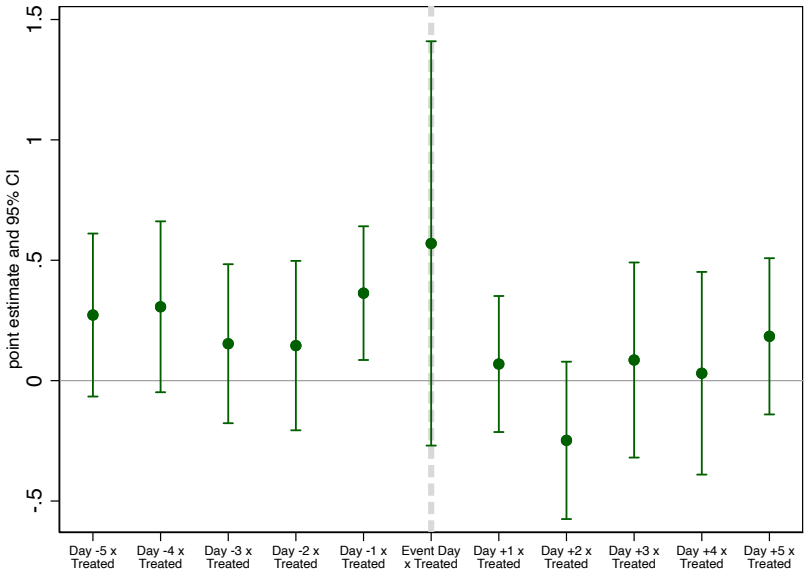


Figure IAD8: Dynamics of account balance and credit-debit net amount. This figure plots the coefficients β_k on each day in equation: $Y_{i,t} = \sum_{k=-5}^{5} \beta_k \{Treated_i \times Day(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the individual and date, and $Day(k)_t$ 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 day levels.

Panel A: Likelihood of an ATM Transaction



Panel B: ATM Transaction Amount

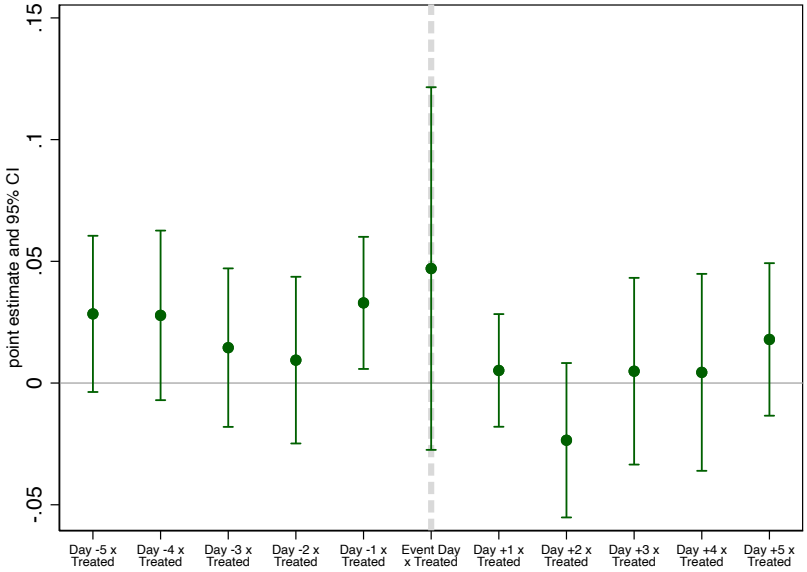
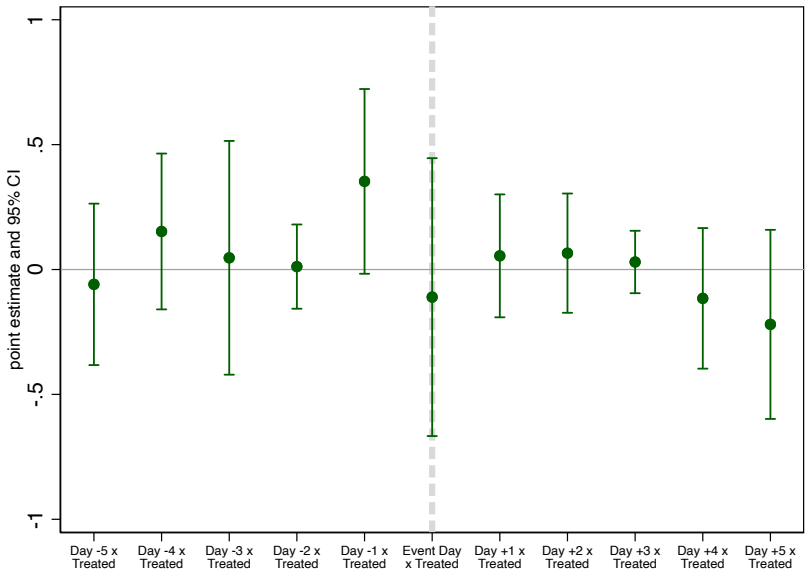


Figure IAD9: Dynamics of ATM transactions. This figure plots the coefficients β_k on each day in equation: $Y_{i,t} = \sum_{k=-5}^{5} \beta_k \{Treated_i \times Day(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the individual and date, and $Day(k)_t$ is a dummy equal to one if 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 day levels.

Panel A: Likelihood of a Credit Card Transaction



Panel B: Credit Card Transaction Amount

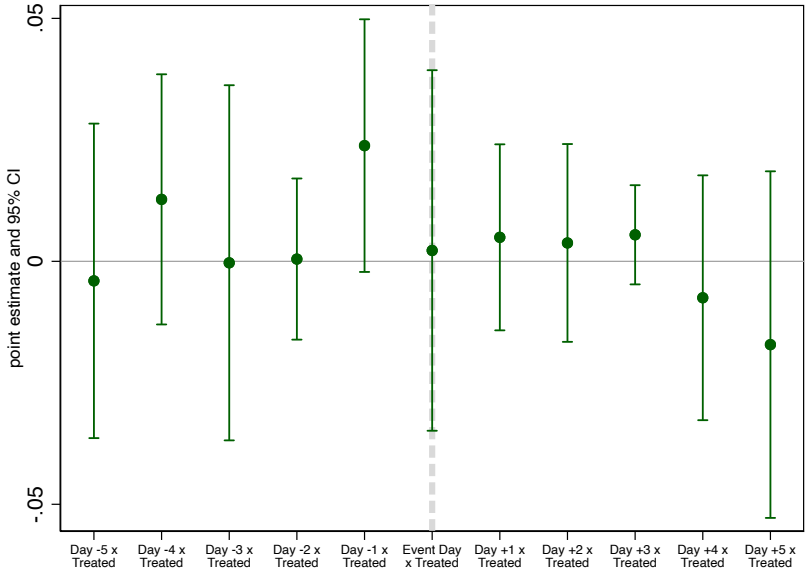


Figure IAD10: Dynamics of credit card transactions. This figure plots the coefficients β_k on each day in equation: $Y_{i,t} = \sum_{k=-5}^{5} \beta_k \{Treated_i \times Day(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the individual and date, and $Day(k)_t$ is a dummy equal to 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 day levels.

Table IAD6: National Stock Exchange Summary Statistics

This table presents summary statistics of daily transactions aggregated at the stock-day 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 IAD7: Amount spend on buy and sell trades on Diwali day conditional on trading Regressions are estimated at the individual-day 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 day 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 IAD8: Stock Summary Statistics This table lists the stock-day 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 IAD9: Additional characteristics of stocks purchased on Diwali day

Regressions are estimated at the individual-stock-day 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-day 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	

Table IAD10: Diwali trades and Hindu investor characteristics

This table presents investor-day 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 IAD11: Likelihood to trade, buy and sell on other religious-event days

Regressions are estimated at the individual-day 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 day 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