Journal of Behavioral and Experimental Economics 78 (2019) 121–137

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Economics

journal homepage: www.elsevier.com/locate/jbee

The High Holidays: Psychological mechanisms of honesty in real-life financial decisions

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ARTICLE INFO

Keywords:
Behavior
Beliefs
Decision-making
Honesty
Market anomalies
Mood
Religion
VIX
Volatility

JEL Classification:
D03
G02

ABSTRACT

Research in psychology has established that activation of religious ideas affects individuals' behavior. We hypothesize that religious and honesty mechanisms activated on the High Holidays, the ten days before Yom Kippur, when people seek repentance, amplify people's anxiety and affect their financial decision-making. We find that returns during the High Holidays are abnormally low; implied volatility, measured by VIX and VXO, as well as realized volatility estimates, are abnormally high; and the abnormal increase in implied volatility overshoots future volatility. Using these results, we devise a simple trading rule that investors may consider to maximize returns during the High-Holidays period.

1. Introduction

"IN GOD WE TRUST," the official U.S. national motto since the middle of the 20th century, has been decorating the American currency for many years.[1] As such, it is merely one reflection of religious standards serving as the basis of social norms and values, which are enforced by the threat of punishment by God (e.g., Johnson and Krüger, 2004). For instance, tradition in U.S. courts, as well as in numerous countries worldwide, dictates that people place their hands on the Bible before they give testimony, perhaps to obligate them to speak honestly for fear that not doing so might be followed by divine adverse retribution (e.g., Johnson and Bering, 2006).[2]

Miller and Hoffmann (1995) conceive of religious behavior as risk averse and nonreligious behavior as risk seeking, building on "Pascal's wager", a philosophical argument devised in the 17th century by Blaise Pascal, arguing that rational human beings should live as though God exists because if God does actually exist, they will have only a limited loss of some life's pleasures, whereas receive the infinite gains of eternity in Heaven. Osoba (2004) finds that individuals who exhibit risk-averse behavior are more likely to express stronger religious beliefs. Hilary and Hui (2009) report that firms in countries with higher religiosity levels display lower degrees of risk exposure, measured by variances in equity and asset returns. Moreover, they find that CEOs switching employers are more likely to join a firm with a religious environment, which is similar to the environment in their former firm. Hong and Kacperczyk (2009) suggest that social norms have an effect on financial markets by documenting that "sin" stocks, i.e., the stocks of alcohol, tobacco and gambling firms, have fewer analysts following them, lower institutional ownership, and higher expected returns, and are relatively inexpensive as reflected in their low price-to-book or price-to-earnings ratios. Kumar, Page, and Spalt (2011) document that in states with higher ratios of Catholics to Protestants (the former's attitude toward lotteries is considered more permissive), the legalization and early adoption of state lotteries are more likely, per-capita lottery sales are higher, and individual investors assign larger portfolio weights to lottery-type stocks. Moreover, Shu, Sulaeman, and Yeung (2012) examine the effects of county-level Protestant or Catholic ratios on return volatilities of mutual funds, establishing that Catholics exhibit less aversion to speculative risk than Protestants. Jiang, Jiang, Kim, and Zhang (2015) report that family firms with religious founders

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[1] In 1956, the United States Congress passed an act adopting "In God We Trust" as its official motto (Cf. Title 36 of the United States Code, Chapter 3, § 302).
[2] The notion of punishment for contravening God exists in ancient Greek culture, the three monotheistic religions and even in Eastern Asian and Indian religious traditions.

https://doi.org/10.1016/j.socec.2018.12.012
Received 12 August 2018; Received in revised form 13 December 2018; Accepted 31 December 2018
Available online 04 January 2019
2214-8043/

have less risk than other family companies. Benjamin, Choi, and Fisher (2016) show that primed Protestants increase voluntary contributions in a public goods game, whereas primed Catholics decrease their contributions. The literature also documents the effect of religious norms and beliefs on other firm and economic variables such as government performance, creditor protection, and economic growth (e.g., Guiso, Sapienza, and Zingales, 2003; Hooy and Ali, 2017; La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1999; Stulz and Williamson, 2003).

Psychological research reports that exposure to religious norms encourages moral behavior (e.g., Kirchmaier, Prüfer, and Trautmann, 2018; Norenzayan and Shariff, 2008). According to the objective self-awareness theory and the concept of mindlessness (see e.g., Langer, 1989; Mazar, Amir, and Ariely, 2008; Wicklund and Duval, 1972), there are relations between (dis)honesty and the attention paid to standards and values. For people concerned about their own moral standards, any dishonest action is more likely to be reflected in their self-concept, which in turn causes them to adhere to a stricter delineation between honest and dishonest behavior.

In the current study, we endeavor to shed light on the role of norms and standards of honesty using real-life financial data. To date, empirical corroboration of such behavior has been sought for only in the lab. Our study fills this gap by documenting that internal rewards based on faith, moral, and honesty affect individual behavior in real life financial situations.

Examining the effect of norms and standards of honesty on decision making in real financial markets, rather than in laboratories, has several benefits. First, in markets individuals are confronted with repeated situations, allowing them to learn from their own experience, as well as from the actions of others. Second, markets are presumed to produce an aggregate outcome in which individual violations of rational behavior wash out. Third, individuals may apply different decisions in real life than in the lab. Lastly, participating in market transactions, comparing to taking part in laboratory setups, involves considerable monetary stakes.

Our study employs market data from specific days on which investors are primed for honest behavior. Specifically, we focus on the ten days of the Jewish High Holidays. During the ten days between Rosh Hashanah, the Jewish New Year, and Yom Kippur, the day of atonement, Jews are granted the opportunity to ask for forgiveness and express regret for misdeeds, resulting in God's judging them favorably on Yom Kippur. The High Holidays are definitely unlike other holidays, secular or religious, which are generally considered joyous and festive days. In contrast, the focus during these "days of awe" is on atonement and self-reflection.

Although the finance literature has examined various issues with regard to holidays, there is only limited research related to the phenomenon we study here. Frieder and Subrahmanyam (2004) and Loughran and Schultz (2004) report reduced trading volume in the U.S. market on Yom Kippur, especially for companies based in cities with a relatively high percentage of Jewish residents (such as Boston, Los Angeles, Miami, New York City, and Philadelphia).[3] Kaplanski and Levy (2012) analyze two possibly conflicting sentiment effects around Kippur in the Tel Aviv Stock Exchange. The first is the positive holiday effect, and the second is the effect of the horrible war experienced on Yom Kippur in 1973. Their findings indicate that for the pre-war period (1967–1972), average abnormal rates of return on the two trading days after Yom Kippur were positive and relatively large. For the post-war period, they found that the negative sentiments of the war memory resulted in negative market returns for the two days after Kippur.

Overall, these studies focused on returns and trading volume, but overlooked volatility patterns and the High Holiday effect on investors' risk perception. To complete the picture, we suggest a novel examination of the interplay between religion, psychology, and financial markets. Relying on the literature from these three research fields, we devise and test the hypothesis that honesty mechanisms activated on the High Holidays amplify investors' anxiety and affect their financial decision-making. Corroborating our hypothesis, we find that returns during the High Holidays are abnormally low. Importantly, we also inspect second moments and find that implied volatility, measured by VIX and VXO, as well as realized volatility estimates, are abnormally high around the High Holidays. Moreover, we find that the abnormal increase in implied volatility overshoots future volatility. Using these results, we devise a simple trading rule that investors may consider to maximize returns during the High-Holidays period.

Fig. 1 depicts the average accumulated rates of change in implied and realized volatility measures around the High Holidays. We designate Yom Kippur as $t = 0$. The ten High Holidays, thus, fall between $t = -8$ or $t = -6$, depending on the weekends in each particular year, and $t = 0$. Specifically, the figure plots VIX, CBOE's Implied Volatility Index (a.k.a. "investors' fear gauge"), calculated using options on the S&P 500 index (the solid curve); its older counterpart, VXO, which employs S&P 100 index options (the dashed curve); and RV, a realized volatility estimate in the spirit of Carr and Wu (2006) complying with the implied volatility measures (the dotted curve).[4] As seen in the figure, the volatility measures increase towards Yom Kippur ($t = 0$), reach their peak roughly around that day, and then gradually descend back over a few weeks. We interpret these unusually high volatility levels as expressing people's amplified anxiety due to the activation of the honesty mechanisms in that time period.

In the sequel, we delve into detailed analysis of the abnormal volatility pattern around the High Holidays and suggest that the increased awareness to honesty and self-scrutiny at the forefront of investors' mind during this period affects their trading behavior. The picture emerging from the analysis corroborates the phenomenon captured in Fig. 1, even after controlling for seasonality and various well-known financial factors, suggesting thereby that heightened attention to honesty activated on the High Holidays indeed leaves an imprint in the financial market records.

The paper proceeds as follows. Section II details the scientific background of our research: we bring relevant accumulated experimental evidence, discuss the biological basis of the studied phenomenon, describe the role of VIX as investors' sentiment gauge, and show measures of public attention to the High Holidays, in the shape of Google's Search Volume Index; Section III describes the financial data; Section IV outlines the empirical analysis we conduct on actual- and implied-volatility dynamics; Section V provides further evidence, incorporating the analysis of returns; Section VI conducts some robustness tests and considers a possible trading strategy; and Section VII concludes.

2. Literature review

Based on the underlying assumption that economic agents are rational, classic economic analysis has neglected the role of psychological factors in asset pricing. However, recent financial research has challenged this perspective, providing accumulated evidence that links security market phenomena to investors' moods using proxies such as

[3] Following these studies, we focus on the U.S. market. Noteworthy, we have examined also the Tel Aviv Stock Exchange (TASE), although its implied volatility index, VIXTA, is available only from April 2000. Moreover, the economic activity in Israel, as well as the activity of the stock exchange and financial sector, are limited during the High Holidays. Using the resulting minuscule sample, we find that high holiday effects are present in TASE with respect to realized volatility, but merely weak evidence regarding returns and implied volatility.

[4] In Appendix A, Figure A1, we replicate the figure, excluding data from 2008, to eliminate the possibility of a spurious effect due to the subprime crisis.

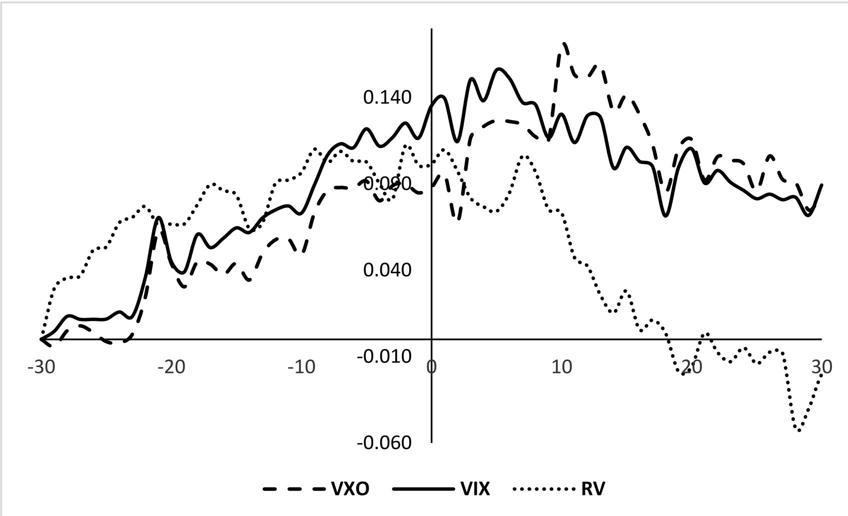

Fig. 1. Implied and realized volatility around the High Holidays
Fig. 1: The figure shows the accumulated rate of change in VIX, VXO and the to-be-realized volatility (RV) before, during, and after the High Holidays for the period 1990–2015. $t = 0$ is Yom Kippur. The ten High Holidays fall roughly between $t = -6$ and $t = 0$. RV is calculated in the spirit of Carr and Wu (2006): $RV_t = 100 \times \sqrt{\frac{252}{21} \times \sum_{i=1}^{21} R_t^2}$.

weather and seasonal biorhythms (e.g., Saunders, 1993; Kamstra, Kramer, and Levi, 2000 and 2003; Kliger and Levy, 2003a,b; Hirshleifer and Shumway, 2003; Dowling and Lucey, 2005; Kelly and Meschke, 2010; Kamstra, Kramer, and Levi, 2012; Kamstra, Kramer, and Levi, 2015, 2016, and 2017), holidays (e.g., Bergsma and Jiang, 2016; Yang; Fang, Lin, and Shao, 2018), air pollution (e.g., Yagil and Levy, 2011; Lepori, 2016), lunar phases (Dichev and Janes, 2003; Yuan, Lu, and Zhu, 2006; Yuan and Gupta, 2014), Sport outcomes (Edmans, Garćıa, and Norli, 2007) and even popular TV series finales and movies (Lepori, 2015a,b).[5]

Research has also provided mixed evidence on abnormal returns on Friday the 13th, compared with other Fridays (Kolb and Rodriguez, 1987; Dyl and Mabrel, 1988; and Lucey, 2001).

Honesty is considered a cornerstone in creating trust relationships. The psychological literature argues that the greater the external rewards of being dishonest, the more likely people will engage in dishonest behavior (e.g., Mazar and Ariely, 2006). For instance, brokers have tempting incentives for acting dishonestly: being rewarded, inter-alia, based on volume of transactions, they may favor personal gains over the interests of their clients (McDonald, 2002; Davis, 2004).

2.1. Experimental evidence

The psychological literature reports that thoughts about supernatural agents drive people to curb dishonest behavior and increase pro-social behavior. For example, Bering, McLeod, and Shackelford (2005) document that college students who were casually told that a ghost of a dead graduate student had been spotted in their private testing room were less willing to cheat on a computerized spatial-reasoning task than were students in a benchmark group who were told nothing; Shariff and Norenzayan (2007) establish that mentioning God in an experiment increases pro-social behavior. They report that implicitly activating the concept of God increases monetary allocations to strangers in the anonymous dictator game; and Van Beest and Williams (2010) find that the prospect of being excluded by God reduces well-being and pro-social behavior, particularly for individuals deeply involved in their faith.

Mazar et al. (2008) consider the self-concept maintenance theory according to which people allow themselves to engage in some level of dishonest behavior, thereby benefiting from such activities while maintaining their positive view of themselves as honest individuals. Inter alia, they show that causing people to become more aware of their internal standards of honesty reduces their tendency for deception.

An additional driver of honest behavior could be the timing of exposing the individual to the attention to self. Based upon the theory of objective self-awareness (Wicklund and Duval, 1972), Shu, Mazar, Gino, Ariely, and Bazerman (2012) find that signing written forms of self-reports makes ethics salient and reduces dishonest reporting.

Prior works about self-concept and standards of honesty report that people value honesty, believe in their own morality, and want to maintain this aspect of their self-concept (Greenwald, 1980; Sanitioso, Kunda, and Fong, 1990; Griffin and Ross, 1991). In addition, they are often torn between the two competing motivations of benefitting from cheating and maintaining a positive self-concept as honest individuals (Aronson, 1969; Harris, Mussen, and Rutherford, 1976).

There is some experimental evidence that activating religious thinking can encourage pro-social behavior. For example, implicitly priming religious thoughts increases generosity in anonymous economic games, even though trait religiosity is unrelated to generosity (Shariff and Norenzayan, 2011). According to this study, participants were less likely to cheat in a game when they were primed with the concept of an angry, punishing God than when they were primed with the concept of a loving and forgiving God. In addition, in a series of experiments, Rounding, Lee, Jacobson, and Ji (2012) document that people tend to exercise greater self-control when religious themes are made implicitly salient. Mazar et al. (2008) test whether increased awareness to honesty leads to more honest behavior. In an experimental setup, participants were instructed to write down either as many of the Ten Commandments as they could recall (increased self-awareness) or the names of ten books that they have read in high school (the control group). Their findings support the hypothesis that dishonesty declines as attention to standards of honesty increases.

2.2. Biological basis

Sasaki et al. (2013) delved into the genetic foundations of religion priming effects on pro-social behavior by examining on the role of the dopamine D4 receptor (DRD4) gene. Given that some variants of DRD4 are more susceptible to environmental influence than others and that religion may increase pro-social behavior, they query whether an environmental input in the form of religion priming interacts with the gene. Their results show that participants with a DRD4 gene variant that is susceptible to environmental influences do indeed behave in a more pro-social manner when implicitly primed with religion, whereas such priming has no effect on those without such a gene.

Inzlicht and Tullett (2010) investigate the effect of priming with

[5] Lucey and Dowling (2005) provide a comprehensive literature review on affect and decision-making.

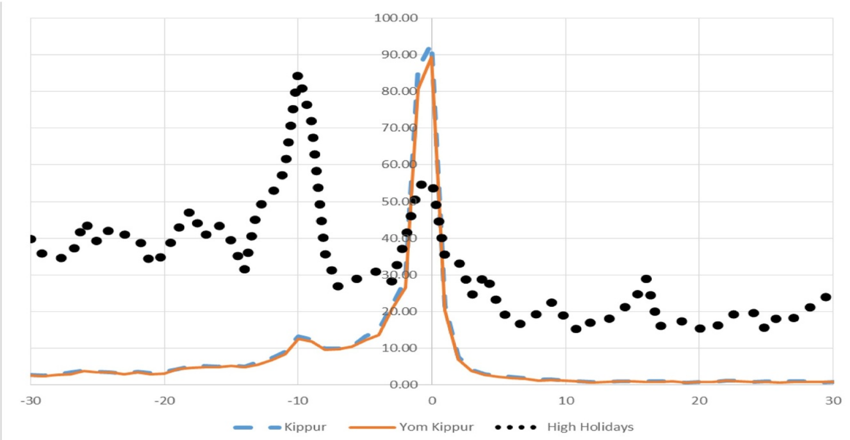

Fig. 2. Graphical output for search queries
Notes: The graph plots the output of Google's SVI for the terms "Kippur" (broken line), "Yom Kippur" (solid line), and "High Holidays" (dotted line) on a daily basis for 2007–2014. The numbers on the graph represent the average relevant search volume and are presented on a scale from 0–100. $t = 0$ is Yom Kipper, and t-10 is ten days before Yom Kippur.

religion cues on brain activity related to people's feelings of anxiety and distress. They posit that religion may have an anxiolytic effect, because it is associated with a sense of meaning and order. Error-related negativity is a neural signal from the anterior cingulate cortex that is associated with defensive responses to errors. The experimental findings of Inzlicht and Tullett (2010) suggest that religion primes a decline (increase) in the amplitude of the believers' (nonbelievers') error-related negativity signal, attenuating (enhancing) their anxiety and feelings of distress.

2.3. VIX and investor sentiment

Baker and Wurgler (2007) propose implied volatility, measured by VIX and VXO, as a potential proxy for market sentiment. VIX, also known as the market's "fear gauge" (Whaley, 2000), is considered a tool for predicting the future volatility of the market. The ability of VIX to express investors' fears is key element in our research. We investigate VIX during the High Holidays, a period in which people reflect on their deeds and seek repentance. Principally, we suggest that investors' increased awareness to honesty and self-scrutiny during the High Holidays affects their trading behavior.

VIX is calculated based on the S&P 500 put and call options traded on the Chicago Board Options Exchange. It differs from historical volatility estimators in that it is a forward-looking forecast, while the latter are based on historical market price volatility. Prior research has shown that VIX can reflect information that a historical volatility forecasts cannot convey (Fleming, 1998; Blair, Poon, and Taylor, 2001; Jiang and Tian, 2005; Becker, Clements, and White, 2006). For instance, while VIX usually fluctuates around 20 (percent per annum), it reached a peak score of 80 in the subprime crisis (October 2008), indicating the related major market panic.

2.4. Public attention to the high holidays

The literature provides plenty of classical and neoclassical proxies for investor attention. The classical proxies, generally stemming from trading and regular media variables, include extreme returns (e.g., Barber and Odean, 2008); inflated trading volume (e.g., Gervais, Kaniel, and Mingelgrin, 2001); an abundance of news and headlines (Tetlock, 2007); and price limit hits (Seasholes and Wu, 2007).

The neoclassical proxies for attention arise from web searches and social media activity. In that avenue, Google Trends (https://www.google.com/trends/) provides Search Volume Index (SVI) information for queries in Google, starting from January 2004. Aggregate search intensity as reflected in Google's SVI may be a better measure of attention than counting news articles in the press, because the latter does not take into account the extent to which readers actually notice each article. The underlying assumption is that if people are searching for some term in Google, they are paying attention to it. Choi and Varian (2012) provide evidence that search engine results can forecast near-term economic indicators such as home and automotive sales, tourism activity, and consumer confidence; and finally, Da, Engelberg, and Gao (2011) propose a direct measure of investor attention based on Google's search volume.

For our analysis, we use daily SVI of specific terms related to our study: "Kippur," "High Holidays" and "Yom Kippur." Google Trends has recently allowed the downloading of daily search data for consecutive periods of six months. Fig. 2 provides the graphical output for these search queries. As expected, the graphs demonstrate a peak in search volume around Yom Kippur. Moreover, corroborating our assertion that the High Holidays gain special public attention, the search volume of the "High Holidays" term manifests its highest peak 10 days before Yom Kippur. Most of the queries on these terms come from the U.S. As illustrated by Fig. 3, they are heavily concentrated in states with relatively high percentage of Jewish residents. This observation is commensurate with the findings by Loughran and Schultz (2004), of reduced trading volume on Yom Kippur for companies based in such areas.

In this spirit, Fig. 4 demonstrates that attention to Yom Kippur is translated into a reduction in the trading volume. We use two series of data to reflect the change in trading around Yom Kippur. The first is the trading volume in the S&P 500 index, and the second is the Russell 2000 index, which is composed of small caps that are not among the largest 1000 stocks in the US.

2.5. Anecdotal evidence

Earlier evidence on the non-typical behavior of exchange markets appears in the following cases. On September 19, 1915, The New York Times published one of the earliest stories on the effect of the Jewish High Holidays on stock market trading. In an article entitled "The London Market Quiet – Jewish Holidays Cause Small Attendance on the Exchange," the newspaper reported that money and discount rates on the London Stock Exchange were "easy today" and attendance at the exchange was low due to the Jewish holiday of Rosh Hashanah. On September 27, 1935, the Altoona Mirror in Pennsylvania referred to a Wall Street adage, "Sell before Rosh Hashana, and buy before Yom Kippur." On September 17, 1936, the Chester Times in Pennsylvania stated that some of the previous session's selling on the New York Stock Exchange came from Jewish traders who wanted to get out of the market before the Rosh Hashana holiday. On September 11, 2007, The Wall Street Journal discussed the conventional explanation that traders close out positions prior to Rosh Hashanah "in advance of spending the holidays with family," but noted that other latent factors may be present.

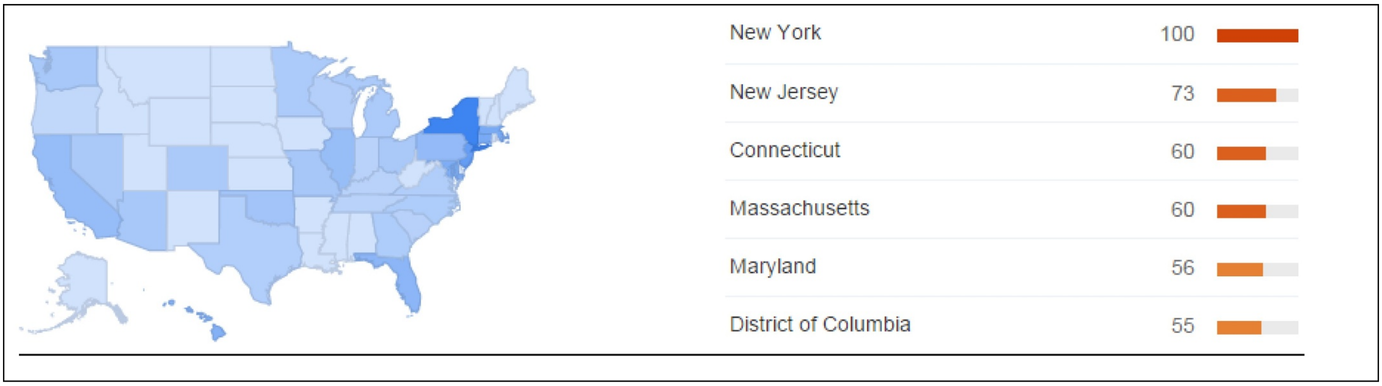

Fig. 3. Regional interest for "Kippur"
Notes: Fig. 3 displays that, for example, the query "Kippur" is mainly searched using Google search-engine in New York State.

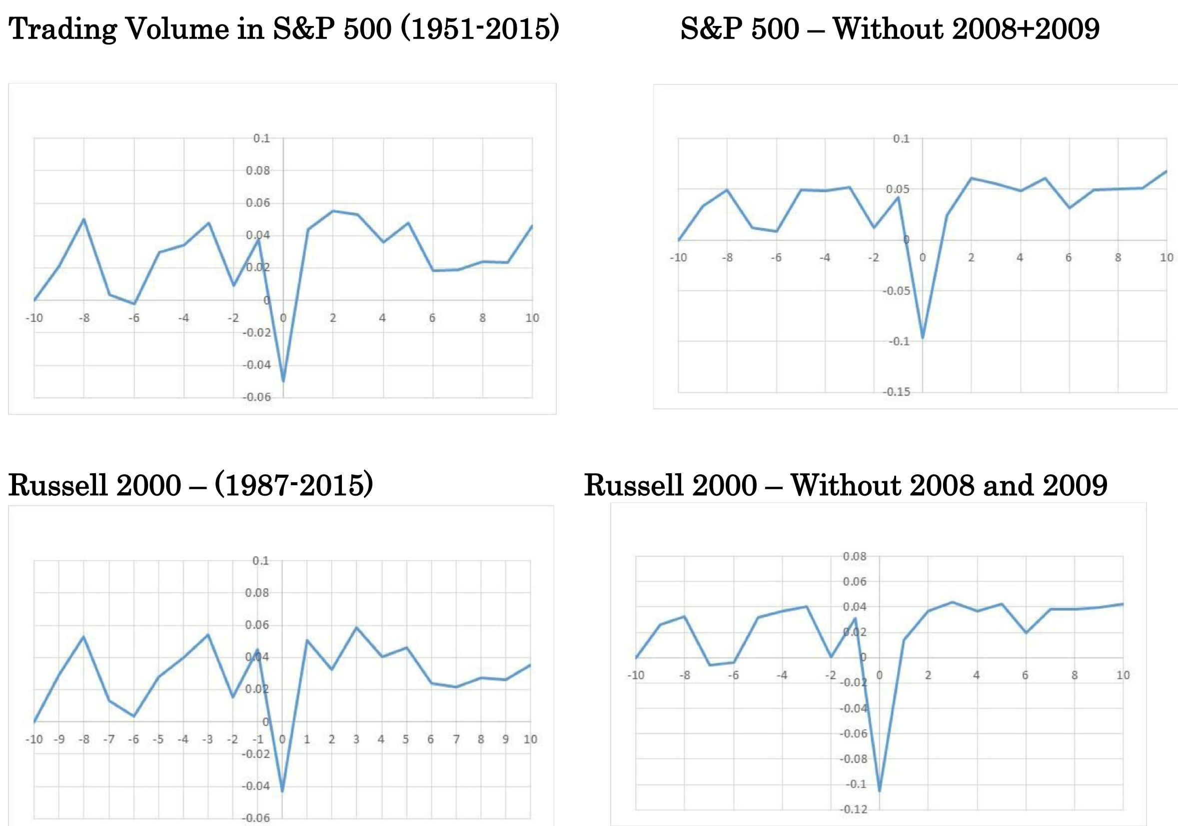

Fig. 4. Trading volume around Kippur
Notes: The figures depict the cumulative average rate of change in trading volume in a window that accounts for two weeks around Yom Kippur (each week is comprised of five trading days). $T = 0$ is the day of Yom Kippur and is associated with a significant decrease in the trading volume. Rosh Hashanah (6–8 trading days before Yom Kippur) is also associated with reduced trading volume.

Finally, the Pew Research Center estimates that religious Jews account for about 1.8% of the total U.S. adult population.[6] As of 2016, about 1.1 million residents of New York City, or about 12% of its residents, were Jewish.[7] According to the 2000 National Jewish Population Survey, 59% of American Jews fast on Yom Kippur.[8] A survey conducted in Israel in 2013 indicated that 73% of Israeli Jews fast.[9]

2.6. Religion and risk tolerance

The literature has established that race and religion appear to affect risk aversion. Barsky, Juster, Kimball, and Shapiro (1997) find noticeable differences in risk tolerance by the race and religion of the respondent. Whites are the least risk tolerant, Blacks and Native Americans somewhat more risk tolerant, and Asians and Hispanics the most risk tolerant. Risk tolerance also varies significantly by religion.

[6] http://www.pewforum.org/2013/10/01/chapter-1-population-estimates/
[7] Heilman, Uriel (April 18, 2016). "7 things to know about the Jews of New York for Tuesday's primary". Jewish Telegraphic Agency. Retrieved June 17, 2018.
[8] https://www.quora.com/What-percent-of-U-S-Jews-go-to-the-synagogue-on-Yom-Kippur-What-percent-of-them-fast
[9] https://www.ynetnews.com/articles/0,7340,L-4428978,00.html.

Table 1
Descriptive Statistics in (%) for daily data for January 2, 1990 to May 6, 2015.

Panel A: Entire sample	VIX	VXO	B	R_M	PV	RV	Day Light
Mean	19.89	20.31	−0.001	0.03	15.55	15.54	12.21
Median	18.08	18.20	0.00	0.06	13.24	13.21	12.22
Max	80.86	87.24	0.38	11.58	84.85	84.85	15.10
Min	9.31	8.51	−0.47	−9.03	4.72	4.72	9.25
Std. Dev.	7.97	8.74	0.06	1.14	9.20	9.21	1.99
Skewness	2.08	1.95	0.16	−0.06	2.97	2.97	−0.02
Kurtosis	10.50	9.68	5.37	11.87	16.99	16.98	1.57
n	6379	6381	6324	6381	6381	6381	6381
Panel B: The High Holiday days	**VIX**	**VXO**	**B**	**R_M**	**PV**	**RV**	**Day Light**
Mean	22.63	23.28	−0.001	−0.14	17.49	19.24	12.08
Median	19.51	19.80	−0.01	−0.02	14.29	13.64	12.08
Max	63.92	75.96	0.20	5.42	59.04	84.85	12.92
Min	11.53	10.29	−0.21	−7.62	6.14	6.37	11.23
Std. dev.	10.47	12.23	0.06	1.38	11.85	16.17	0.41
Skewness	1.32	1.55	0.43	−0.14	1.77	2.74	0.03
Kurtosis	4.34	5.49	4.58	−0.02	5.73	11.17	2.07
N	177	177	175	177	177	177	177
Panel C: Non-High Holiday days	**VIX**	**VXO**	**B**	**R_M**	**PV**	**RV**	**Day Light**
Mean	19.81	20.22	−0.001	0.04	15.50	15.43	12.22
Median	18.05	18.19	0.00	0.06	13.22	13.18	12.27
Max	80.86	87.24	0.38	11.58	84.85	82.06	15.10
Min	9.31	8.51	−0.47	−9.03	4.72	4.72	9.25
Std. dev.	7.88	8.61	0.06	1.13	9.11	8.91	2.02
Skewness	2.11	1.95	0.16	0.00	3.03	2.83	−0.03
Kurtosis	10.87	9.82	5.40	11.86	17.70	15.77	1.53
N	6202	6204	6149	6204	6204	6204	6204
Panel D: Differences in means between High Holiday and Non-High Holiday days	**VIX**	**VXO**	**B**	**R_M**	**PV**	**RV**	**Day Light**
Mean Diff.	2.82***	3.06***	0.000	−0.18**	1.99***	3.81***	−0.14

Notes: The values are reported in percentages, except for the Day Light variable, which is reported in hours. The one-month-previous volatility (PV), as well as to-be-realized volatility (RV) are denominated in annual terms. Panel A provides the statistics for the entire sample; Panels B and C report the statistics for the High Holiday and non-High Holiday subsamples, respectively; and Panel D provides the differences between the means reported in Panels B and C (*** and ** indicate statistical significance at the levels 1% and 5%, respectively).

Protestants are the least risk tolerant, Jews the most, and Catholics are about halfway between Protestants and Jews. Halek and Eisenhauer (2001) use data about households' life insurance and estimate the Pratt-Arrow coefficient of relative risk aversion. Their findings indicate that both Blacks and Hispanics are significantly less risk averse than Whites and other races, and that the only religion that appears to affect risk aversion is not Catholicism, but Judaism. Catholics and Jews are more averse to taking risks than members of other faiths to pure risk (as measured by their coefficient of relative risk aversion in a model of life insurance demand), but more tolerant of 'speculative' risk taking (as measured by the willingness to accept a job with equal chances of doubling or reducing the household income).[10] Finally, and as previously indicated, Osoba (2004) claims that individuals who exhibit risk-averse behavior are more likely to express stronger religious beliefs.

3. Data

Our financial data consist of daily records of VIX from January 3, 1990 to May 6, 2015 and VXO from January 3, 1986 to May 6, 2015. We also use U.S. market-value- and equal-weighted returns, including and excluding dividends, resulting in four (2 × 2) indices for January 1926 through May 2015. In addition, the data include Fama and French's (1992) ten value-weighted portfolios extracted from Kenneth French's website.[11]

Table 1 presents the main descriptive statistics of our data. Panel A of the table contains summary statistics of the key variables, VIX; VXO; daily difference in 10-year bond market yields, as recorded by the St. Louis Federal Reserve (B); S&P 500 index return (R_M); one-month previous volatility (PV); and to-be-realized volatility (RV). The latter two variables (as well as VIX and VXO) are denominated in annual terms. The mean values for the volatility variables are 19.89% for VIX, and 20.31% for VXO; 15.55% for PV, and 15.56% for RV. In line with known empirical evidence, the financial variables in the table are leptokurtic, as evident in their kurtosis values that exceed 3, the kurtosis of the normal distribution. The rightmost column of the table provides summary statistics of the daylight hours variable.

Panels B and C of Table 1 provide the same information, partitioned for the High Holiday and non-High Holiday days in our sample, and Panel D designates the differences in means between High Holiday and Non-High Holiday days. Note that the High Holidays follow the Jewish calendar, which is lunar and adjusted for the sun, so they do not occur at fixed Gregorian calendar dates, but rather are scattered variably over

[10] We would like to thank an anonymous referee for raising this point.

[11] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 1.1
Market Portfolio Statistics in (%) (1926–2015).

Panel A: Entire sample	MP1	MP2	MP3	MP4
Mean	0.04	0.03	0.08	0.07
Median	0.07	0.06	0.12	0.10
Max	15.68	15.30	20.30	20.18
Min	−18.10	−18.10	−14.19	−14.20
Std. dev.	1.06	1.06	1.07	1.07
Skewness	−0.16	−0.17	0.33	0.32
Kurtosis	21.12	20.92	29.78	29.64
n	23,595	23,595	23,595	23,595
Panel B: The High Holiday days	MP1	MP2	MP3	MP4
Mean	−0.09	−0.10	−0.09	−0.10
Median	0.02	0.01	0.04	0.04
Max	4.50	4.50	5.30	5.21
Min	−7.77	−7.77	−7.45	−7.46
Std. dev.	1.23	1.23	1.28	1.28
Skewness	−1.56	−1.57	−1.50	−1.51
Kurtosis	12.03	12.03	11.91	11.89
n	659	659	659	659
Panel C: Non-High Holiday days	MP1	MP2	MP3	MP4
Mean	0.045	0.03	0.08	0.07
Median	0.08	0.06	0.12	0.11
Max	15.68	15.30	20.30	20.18
Min	−18.10	−18.10	−14.19	−14.20
Std. dev.	1.05	1.05	1.06	1.06
Skewness	−0.09	−0.11	0.42	0.42
Kurtosis	21.52	21.30	30.67	30.52
n	22,936	22,936	22,936	22,936
Panel D: Differences in means between High Holiday and Non-High Holiday days	MP1	MP2	MP3	MP4
Mean	−0.13***	−0.12***	−0.17***	−0.16***

Notes: MP1 and MP2 are the value-weighted index returns, including dividends and excluding dividends, respectively. MP3 and MP4 are market equal-weighted index returns, including dividends and excluding dividends, respectively.

September and October. According to Panel B, there have been 177 High Holiday trading-days since 1990.[12] This number spikes to 659 if we consider the period beginning in January 1926. While traditionally the High Holidays encompass ten days, nowadays they usually include six to eight trading days. However, earlier in the twentieth century, they encompassed nine trading days, because the New York Stock Exchange was open six days a week during the 1920s until May 1952. We note that the returns on the High Holiday days tend be negative, and positive on the non-High Holiday days in our sample. The differences in means presented in Panel D are in accordance with our hypotheses: the mean implied volatility measures (VIX and VXO) during the High Holidays are higher than during non-High holidays (2.82, $p = 0.000$ and 3.06, $p = 0.000$, respectively); the mean one-month-previous volatility and to-be-realized volatility (PV and RV) during the High Holidays are higher, as well (1.99, $p = 0.004$, and 3.81, $p = 0.000$); and the mean High Holiday return during the High Holidays is lower than the mean during the non-High Holiday days (difference of −0.18, $p = 0.041$), as well.

Table 1.1 presents descriptive statistics of four different proxies of the market index: (i) market value-weighted index returns, including dividends (MP1); (ii) market value-weighted index returns, excluding dividends (MP2); (iii) market equal-weighted index returns, including dividends (MP3); and (iv) market equal-weighted index returns, excluding dividends (MP4). Panel A describes the whole period, from 1926 to 2015, and Panels B and C, respectively, provide partitioned descriptive statistics for the High Holiday and non-High Holiday days. Panel D shows the differences in means between High Holiday and Non-High Holiday days. The overall findings of this table indicate that the returns are significantly lower during High Holidays, for the four different proxies of the market index.

We construct a measure of the one-month previous volatility, PV, and to-be-realized volatility, RV, in the spirit of Carr and Wu (2006). Specifically, we calculate the monthly average of the squared logarithmic returns assuming 21 trading days in a month, and adjust it to annual terms assuming 252 trading days in a year:

$$RV_t = 100 \times \sqrt{\frac{252}{21} \times \sum_{j=1}^{21} (Ln(s_{t+j}/s_{t+j-1}))^2}; \tag{1}$$

and

$$PV_t = 100 \times \sqrt{\frac{252}{21} \times \sum_{j=-21}^{-1} (Ln(s_{t+j}/s_{t+j-1}))^2}, \tag{2}$$

where s_t is the value of the S&P500 index on trading-day t, and j counts the trading days in the relevant estimation window.

To test whether the financial data satisfy the stationary assumption, we conduct two Augmented Dickey-Fuller (1979) (ADF) tests, one with a constant and the other with a constant and linear time trend. We also use the Phillips-Perron (1988) (PP) parametric test in two similar forms. The results, presented in Table 2, are of a statistically significant rejection of the null hypothesis of non-stationarity, suggesting that the

[12] There are 204 High Holiday trading-days in the period from January 1986 to May 2015.

Table 2
Dickey–Fuller and Phillips–Perron tests for unit root.

	ADF with intercept	with intercept and trend	Phillips–Perron with intercept	with intercept and trend
VIX	−5.05***	−5.09***	−6.02***	−6.06***
VXO	−6.42***	6.43***	−8.92***	−8.89***
ΔVIX	−27.69***	−26.69***	−94.76***	−94.75***
ΔVXO	−35.48***	−35.48***	−132.06***	−132.06***
PV	−5.48***	−5.57***	−5.63***	−5.73***
RV	−5.49***	−5.57***	−5.63***	−5.72***
R_M	−60.26***	60.26***	−84.60***	−84.60***
B	−76.75***	−76.63***	−76.75***	−76.75***

Notes: Table 2 describes the unit root tests for the variables of interest using the Augmented Dickey–Fuller (ADF) and the Phillips–Perron (PP) tests. VIX denotes the volatility index, PV denotes the one-month previous volatility; RV denotes (future) realized volatility; R_M denotes market portfolio returns; and B denotes the change in the 10-year bond rates. ΔVIX and ΔVXO are the rate of change (the first difference) in the VIX and VXO, respectively. The t-statistic for each of the two tests is according to MacKinnon's (1996) one-sided *p*-values. In both test formats, data are stationary, and (***) indicates a significance level of 1%.

Table 3
Estimation Results for Eq. (3).

	MP1	MP2	MP3	MP4
d_H	**0.072***	**0.073***	**0.083***	**0.083***
intercept	0.676***	0.675***	0.653***	0.651***
AR(1)	29.617***	29.711	37.711***	37.771***
R^2	0.088	0.089	0.142	0.143
D.W	2.155	2.155	2.188	2.188
N	23,594	23,594	23,594	23,594

Notes: The table reports the estimation results for Eq. (3) estimated as an autoregressive, AR(1), model. MP1 and MP2 are the value-weighted index returns, including and excluding dividends, respectively. MP3 and MP4 are market equal-weighted index returns, including and excluding dividends, respectively. This equation tests whether instantaneous volatility in returns proxied by the absolute values of the returns is higher during the High Holidays. The estimated coefficients are presented in percentage terms. (***), (**) and (*) indicate significance at the levels of 1%, 5% and 10%, respectively. Eq. (3) is given by: $\sqrt{R_t^2} = d_1 \cdot d_{H,t} + d_0 + \psi_t$, where $\psi_t = \rho\psi_{t-1} + u_t$.

financial variables, as well as the first differences of VIX and VXO, are stationary.

4. Actual- and implied-volatility dynamics

Henceforth, we specify and test empirical specifications aimed at measuring the effect of the High Holidays on actual- and implied-volatility dynamics. We begin this section with estimating simple actual- and implied-volatility regressions (Subsections A and B); continue with devising and estimating augmented implied volatility models (Subsection C); and conclude with accounting for possible intervention of lagged explanatory variables and seasonality patterns (Subsections D and E). The bottom line of the analysis presented in this section is that High Holidays have a significantly positive impact on the actual- and implied-volatilities.

4.1. Simple actual volatility models

We begin the analysis about High Holidays effects on volatility by conditioning instantaneous volatility and variance measures on the High Holiday dummy variable. The literature proposes to proxy instantaneous volatility by absolute-returns (see e.g., Andersen, Bollerslev, Diebold, and Ebens, 2001). Accordingly, we employ the following model:

Table 4.1
Estimation results for Eqs. (4) and (6).

High-Holiday Dummy (d_H)	**2.82***	**1.28***	**1.13***	**1.16***
Intercept	19.81***	7.92***	7.94***	7.95***
Previous volatility (PV)		0.77***	0.77***	0.77***
S&P500 return (R_M)			−0.85***	−0.85***
Change in bond yield (B)				−0.15
Adj-R^2	0.003	0.79	0.80	0.80
F	20.54***	11782***	8600***	6400***
N	6379	6379	6379	6323

Notes: The table reports the estimation results of Eq. (6). The dependent variable in these estimations is the VIX. The equation is estimated gradually using four different forms that appear in the columns of the table. The α coefficient captures the systematic effect of the High Holiday days on the VIX. (***) and (**) indicate significance at the levels of 1% and 5%, respectively. Eq. (6) is given by: $VIX_t = \alpha_0 + \alpha_1 d_{H,t} + \beta_1 PV_t + \beta_2 R_{M,t} + \beta_3 B_t + \varepsilon_t$.

$$\sqrt{R_t^2} = d_1 \cdot d_{H,t} + d_0 + \psi_t. \tag{3}$$

where the absolute value of the return, $\sqrt{R_t^2}$, proxies for the instantaneous volatility, R is the market return, and $d_{H,t}$ is a dummy variable indicating the days in the High Holidays period.

We note that the above simple instantaneous variance and volatility specifications may be oversimplified, inter alia because they do not account for heteroscedasticity. Thus, and in order to prevent variance instability problems, we allow, in the sequel, the variance to vary over time by using the GARCH(*p,q*) specifications.

We employ four different proxies for the market index, provided by the CRSP database: (i) market value-weighted index returns, including dividends (MP1); (ii) market value-weighted index returns, excluding dividends (MP2); (iii) market equal-weighted index returns, including dividends (MP3); and (iv) market equal-weighted index returns, excluding dividends (MP4). Each of these four variables are used, in its turn, as the dependent variable in the regression analysis.

We estimate Eq. (3) to determine whether volatility is higher during the High Holidays, relatively to the rest of the trading days, using each of the market return variables described above. The regression results of Eq. (3) estimated as an autoregressive, AR(1), model are reported in Table 3. As seen in the table, the estimated coefficients of d_H are positive in all of the tested specifications and are statistically significant at the 10% significance level in all of them. The estimated coefficients range from 0.072% (for MP1) to 0.083% (for MP3 and MP4).

The findings so far, which report a rise in instantaneous volatility during the High Holidays, support our hypothesis about the special volatility pattern during these days. We turn now to the basic analysis of the implied volatility measures.

4.2. Simple implied volatility models

In order to assess the impact of the High Holidays on VIX, we estimate the following simple regression:

$$VIX_t = \alpha_1 \cdot d_{H,t} + \alpha_0 + \varepsilon_t, \tag{4}$$

where α_0 is an intercept; $d_{H,t}$ is a dummy variable indicating the days in the High Holiday period; α_1 is the High Holidays' effect on VIX, and ε_t is an error term. The estimation results, appearing in the first column of Table 4.1, reject the null hypothesis that the High Holidays have no effect on VIX. Specifically, α_1, the estimated coefficient of $d_{H,t}$, capturing the effect of the High Holidays on VIX, equals 2.82, and is significant at the 1% significance level.

For robustness, we estimate a similar regression with VXO as the dependent variable and obtain corroborating results:

$$VXO_t = \alpha_1 \cdot d_{H,t} + \alpha_0 + \varepsilon_t, \tag{5}$$

The regression results appear in the first column of Table 4.3. As seen there, the estimated effect of the High Holidays on VIX, as captured by, α_1, is even higher than in the case of VIX as dependent

Table 4.2
Estimation Results for Eq. (6a).

High-Holiday Dummy (d_H)	**0.19**	**0.67******	**0.60****	**0.63*****
Intercept	9.23***	6.92***	7.01***	7.01***
Previous volatility (PV)		0.57***	0.59***	0.59***
S&P500 return (R_M)			−0.65***	−0.66***
Change in Bond Yield (B)				0.55
Realized volatility (RV)	0.68***	0.25***	0.23***	0.24***
Adj-R^2	0.63	0.82	0.83	0.84
F	5388***	10079***	8034***	6402***
N	6359	6359	6359	6303

Notes: The table presents the estimation results for Eq. (6a). Unlike Table 4.1, we added the realized volatility (RV) to the explanatory variables. Gradually estimating this equation when RV is retained allows us to capture the additional effect of the High Holidays under the many specifications proposed. In other words, the α_1 coefficient (of d_H) in the previous estimate (Table 4.1) reflects the systematic effect on the VIX, but α_1 in the current specification captures the overreaction effect of the High Holidays on the VIX. (***) and (**) indicate significance at the levels of 1% and 5%, respectively.

variable, 3.06, and is significant at the 1% significance level, as well.

4.3. Augmented implied volatility models

We candidate three control variables that may explain VIX in an augmented setup, and step-wise append them to the regression: (i) the previous month's volatility (PV); (ii) the daily contemporaneous rate of return of the stock market (R_M); and (iii) the contemporaneous change in the yield of 10-year bonds (B):

$$VIX_t = \alpha_1 \cdot d_{H,t} + \alpha_0 + \beta_1 \cdot PV_t + \beta_2 \cdot R_{M,t} + \beta_3 \cdot B_t + \varepsilon_t. \tag{6}$$

As in the previous specifications, the effect of the High Holidays on VIX is estimated by α_1. We gradually estimate Eq. (6) to determine whether the addition of variables makes any qualitative changes to the estimated High Holiday effect. The regression results appear in the second to fourth columns of Table 4.1. As seen in the table, α_1 ranges from 1.13 to 1.28, and is always significant at the 1% significance level, thus the effect of the High Holidays on VIX is robust to the inclusion of PV, R_M, and B.

Further, the sign of the estimated coefficient of PV is positive, proposing that VIX is positively correlated with historical volatility levels; the sign of the estimated coefficient of R_M is negative, implying a reverse relation between VIX and market returns; and the sign of the estimated coefficient of B is negative, though insignificantly so, implying that, if at all, VIX is negatively related to changes in bond yields.

The estimation results of Eq. (6) with VXO as the dependent variable appear in the second to fourth columns of Table 4.3. The results are very much alike those of the corresponding VIX specifications: α_1 ranges from 1.20 to 1.38, and is always significant at the 1% significance level; the sign of the estimated coefficient of PV is positive; the sign of the estimated coefficient of R_M is negative; and the sign of the estimated coefficient of B is negative. Unlike the VIX regression, however, the latter coefficient is significant, implying that, VXO is negatively related to changes in bond yields. Thus, the effect of the High Holidays is robust to the inclusion of PV, R_M, and B, also for the case of VXO as the implied volatility measure.

Having estimated the effect of the High Holidays on VIX, we turn to measuring the extent to which the High Holidays cause overreaction in VIX, relatively to future volatility levels.[13] To do so, we include the next month's to-be-realized volatility (RV) as an explanatory variable into the analysis:

$$VIX_t = \alpha_0 + \alpha_1 \cdot d_{H,t} + \beta_1 \cdot PV_t + \beta_2 \cdot R_{M,t} + \beta_3 \cdot B_t + \beta_4 \cdot RV_t + \varepsilon_t. \tag{6a}$$

[13] For literature on the relation between RV and VIX see, e.g., Christensen and Prabhala (1998); and Becker, Clements, and White (2007).

Table 4.3
Estimation Results for (5) and (6) with VXO.

High-Holiday Dummy (d_H)	**3.06*****	**1.38*****	**1.20*****	**1.23*****
Intercept	20.22***	7.24***	7.26***	7.27***
Previous Volatility (PV)		0.84***	0.84***	0.84***
S&P500 Return (R_M)			−1.00***	−1.00***
Change in Bond Yield (B)				−0.32***
Adj-R^2	0.003	0.78	0.80	0.80
F	21***	11364***	8391***	6244***
N	6381	6381	6381	6325

Notes: The table reports the estimation results of Eq. (6) where the VXO is regressed gradually against several control variables. (***) indicates significance at the levels of 1%. Eq. (6) is regressed as follows. $VXO_t = \alpha_1 d_{H,t} + \alpha_0 + \beta_1 PV_t + \beta_2 R_{M,t} + \beta_3 B_t + \varepsilon_t$.

Table 4.4
Estimation Results for Eq. (6a) with VXO.

High-Holiday Dummy (d_H)	**0.15**	**0.67****	**0.58****	**0.60****
Intercept	8.49***	6.05***	6.15***	6.15***
Previous volatility (PV)		0.61***	0.63***	0.62***
S&P500 return (R_M)			−0.77*	−0.77***
Change in bond yield (B)				0.51
Realized volatility (RV)	0.76***	0.31***	0.29***	0.29***
Adj-R^2	0.64	0.82	0.84	0.84
F	5727***	10148***	8160***	6495
N	6361	6361	6361	6305

Notes: The table reports the estimation results of Eq. (6a) where the VXO is regressed gradually against several control variables. (***) and (**) indicate significance at the levels of 1% and 5%, respectively. Eq. (6a) is regressed as follows. $VXO_t = \alpha_1 d_{H,t} + \alpha_0 + \beta_1 PV_t + \beta_2 R_{M,t} + \beta_3 B_t + \beta_4 RV_t + \varepsilon_t$.

The regression results appear in Table 4.2. We estimate Eq. (6a) in four steps. As seen in the first column of the table, without any control variables, α_1 is positive (equals 0.19), but insignificant. However, when the cumulative effects of PV, R_M, and B are controlled for, α_1 ranges from 0.60 to 0.67, and is significant at 5% or lower, suggesting that the High Holidays cause overreaction in VIX relatively to future volatility levels. Further, the estimated coefficients of PV, R_M, and B, possess similar values and significance levels as in the previous set of regressions, reported in Table 4.1. Lastly, the estimated coefficient of the to-be-realized volatility, RV, is positive and significant at the 1% significance level, capturing the High Holidays' effect on VIX, which is also realized in future volatility levels. Recall that the regressions of Eq. (6), i.e., without the inclusion of RV, capture the systematic impact of the High Holidays on VIX, whereas the regressions of Eq. (6a), i.e., including RV in the regressions, capture the overreaction effect of the High Holidays on VIX.

The estimation results of Eq. (6a) with VXO as the dependent variable appear in the second to fourth columns of Table 4.4. The results are qualitatively similar to those of the corresponding VIX specifications: without any control variables, α_1 is positive (equals 0.15), but insignificant; after the inclusion of PV, R_M, and B, α_1 ranges from 0.58 to 0.67, and is significant at 5%, corroborating that the High Holidays cause overreaction in VXO relatively to future volatility levels. Thus, the overreaction effect of the High Holidays on VIX is replicated also with VXO as the implied volatility measure.

In the next subsection, we re-conduct the analysis with several modifications, for robustness. Specifically, we introduce lagged explanatory variables and replace the market index with various alternatives.

4.4. Augmented implied volatility models: lagged explanatory variables

In order to test the robustness of the results with regard to serial correlation, we run two additional augmented specifications, respectively controlling for lagging changes in VIX, and for lagging market

Table 4.5
Estimation Results for Eq. (6b).

High-Holiday Dummy (d_H)	**1.16*** **	**1.07*** **	**0.98*** **	**0.91*** **
Intercept	7.95***	7.91***	7.88***	7.86***
Previous volatility (PV)	0.77***	0.77***	0.77***	0.77***
S&P500 return (R_M)	−0.85***	−0.88***	−0.89***	−0.89***
Change in bond yield (B)	−0.15	−0.22	−0.34	−0.20
ΔVIX_{t-1}		0.12***	0.13***	0.13***
ΔVIX_{t-2}			0.11***	0.11***
ΔVIX_{t-3}				0.09***
Adj-R^2	0.80	0.81	0.82	0.82
F	6400***	5406***	4715***	4180***
n	6323	6317	6314	6311

Notes: The table reports the estimation results of Eq. (6b) without the realized volatility variable (RV). ΔVIX_{t-k} is the k-th lagging variable of the VIX's rate of change. The lagging changes in the VIX are included to control for any serial correlation in the VIX. (***), (**) and (*) indicate significance at the levels of 1%, 5% and 10%, respectively. By Eq. (6b): $VIX_t = \alpha_0 + \alpha_1 d_{H,t} + \beta_1 PV_t + \beta_2 R_{M,t} + \beta_3 B_t + \sum_{k=1}^{K} \vartheta_k \Delta VIX_{t-k} + \varepsilon_t$.

returns:

$$VIX_t = \alpha_0 + \alpha_1 d_{H,t} + \beta_1 PV_t + \beta_2 R_{M,t} + \beta_3 B_t + \beta_4 RV_t + \sum_{k=1}^{K} \vartheta_k \Delta VIX_{t-k} + \varepsilon_t, \quad (6b)$$

$$VIX_t = \alpha_0 + \alpha_1 d_{H,t} + \beta_1 PV_t + \beta_2 R_{M,t} + \beta_3 B_t + \beta_4 RV_t + \sum_{k=1}^{K} \phi_k R_{M,t-k} + \varepsilon_t, \quad (6c)$$

The estimation results for Eq. (6b) are reported in Tables 4.5 (without RV) and 4.6 (with the inclusion of RV). This equation differs from Eq. (6a) in that it includes lagging changes in VIX to control for any serial correlation in the VIX. Using four steps, we include additional lags of the variable ΔVIX_t. Since there is no clear-cut rule for the lag length, we arbitrary use up to three lags; the results of each lagged variables set are presented in a separate column in the table. After accounting for serial correlation in this manner, the overall picture does not change, and the signs and significance of the coefficients are hardly changed. Specifically, α_1 remains positive and highly significant. In other words, VIX exhibits above-average values during the High Holidays, even after controlling for serial correlation in its values. A similar picture emerges from the estimations based on Eq. (6c) which incorporates further lags of R_M to control for serial correlation in the S&P 500 index (Tables 4.7 and 4.8).

Table 4.6
Estimation Results for Eq. (6b).

High-Holiday Dummy (d_H)	**0.63** **	**0.59** **	**0.54*** **	**0.50** **
Intercept	7.02***	7.03***	7.05***	7.07***
Previous volatility (PV)	0.59***	0.60***	0.60***	0.61***
S&P500 return (R_M)	−0.66***	−0.69***	−0.70***	−0.72***
Change in bond yield (B)	0.55	0.47	0.35	0.44
Realized volatility (RV)	0.24***	0.23***	0.22***	0.21***
ΔVIX_{t-1}		0.09***	0.10***	0.10***
ΔVIX_{t-2}			0.08***	0.09***
ΔVIX_{t-3}				0.07***
Adj-R^2	0.84	0.84	0.84	0.85
F	6402***	5532***	4880***	4362***
n	6303	6297	6294	6291

Notes: The table reports the estimation results of Eq. (6b) without omitting any of the explanatory variables as was done in the table above. ΔVIX_{t-k} is the k-th lagging variable of the VIX's rate of change. The alpha coefficient in this case reflects systematic changes in the excess VIX due to the High Holidays. (***) and (**) indicate significance at the levels of 1% and 5%, respectively. The equation is given by: $VIX_t = \alpha_0 + \alpha_1 d_{H,t} + \beta_1 PV_t + \beta_2 R_{M,t} + \beta_3 B_t + \beta_4 RV_t + \sum_{k=1}^{K} \vartheta_k \Delta VIX_{t-k} + \varepsilon_t$.

Table 4.7
Estimation Results for Eq. (6c).

High-Holiday (d_H)	**1.16*** **	**0.97*** **	**0.82*** **	**0.75*** **
Intercept	7.95***	7.98***	8.01***	8.05***
Previous volatility (PV)	0.77***	0.77***	0.77***	0.77***
S&P500 (R_M)	−0.85***	−0.90***	−0.93***	−0.93***
Bond yield change (B)	−0.15	−0.15	−0.35	−0.29
$R_{M,t-1}$		−0.78***	−0.82***	−0.84***
$R_{M,t-2}$			−0.66***	−0.70***
$R_{M,t-3}$				−0.56***
Adj-R^2	0.80	0.81	0.82	0.83
F	6400**	5539***	4901***	4389***
N	6323	6323	6323	6323

Notes: The table reports the estimation results of Eq. (6c). We did not include RV in the explanatory variables in order to capture the systematic impact of the High Holidays on the VIX. This equation is estimated using three different lags of market returns. The selected lags are $k = 1$, $k = 2$ and $k = 3$. (***) and (**) indicate significance at the levels of 1% and 5%, respectively.

Table 4.8
Estimation Results for Eq. (6c).

	Reg. 1	**Reg. 2**	**Reg. 3**	**Reg. 4**
High-Holiday (d_H)	**0.63** **	**0.53** **	**0.45***	**0.42***
Intercept	7.02***	7.11***	7.20***	7.27***
Previous volatility (PV)	0.59***	0.60***	0.61***	0.62***
S&P500 (R_M)	−0.66***	−0.71***	−0.74***	−0.75***
Bond yield change (B)	0.55	0.50	0.31	0.33
Realized volatility (RV)	0.24***	0.22***	0.21***	0.20***
$R_{M,t-1}$		−0.57***	−0.62***	−0.65***
$R_{M,t-2}$			−0.49***	−0.52***
$R_{M,t-3}$				−0.41***
Adj-R^2	0.84	0.84	0.85	0.85
F	6402***	5595***	4969***	4464***
n	6303	6303	6303	6303

Notes: The table reports the estimation results of (6c) . This equation is estimated using three different lags of market returns. The selected lags are $k = 1$, $k = 2$ and $k = 3$. (***), (**) and (*) indicate significance at the levels of 1%, 5% and 10%, respectively. The equations is given by: $VIX_t = \alpha_0 + \alpha_1 d_{H,t} + \beta_1 PV_t + \beta_2 R_{M,t} + \beta_3 B_t + \beta_4 RV_t + \sum_{k=1}^{K} \phi_k R_{M,t-k} + \varepsilon_t$.

4.5. Augmented implied volatility models: accounting for seasonality

Prior works have shown that stock returns are lower when there are fewer hours of daylight. In this subsection, we investigate the effect of adding seasonality control variables to the main equation, Eq. (6).[14] The control variables include dummy variables that capture possible intraweek patterns in VIX, daylight hours, days after non-weekend holidays, and the first five days of the new tax year (cf. Kamstra, Kramer, and Levi, 2003). We include these variables in the matrix Z_t in the following equation:

$$VIX_t = \alpha_0 + \alpha_1 d_{H,t} + \beta_1 PV_t + \beta_2 R_{M,t} + \beta_3 B_t + \beta_4 RV_t + M'Z_t + \varepsilon_t. \quad (6d)$$

Table 5 reports the estimation results for Eq. (6d). This equation is an extension of the model presented in Eq. (6). It incorporates additional seasonal variables, the number of daylight hours ($DayLight_t$); day-of-the-week dummy variables, Mondays (M_t), Tuesdays (T_t), Wednesdays (W_t) and Thursdays (TH_t); non-weekend holidays (NWH_t); and

[14] We calculate the number of daylight hours using a formula that takes into consideration the latitude and the day of the year in New York City (see, e.g., Kamstra, Kramer, & Levi, 2003).

Table 5
. Estimation Results for Eq. (6d).

High-Holiday (d_H)	**0.59****	**0.59****	**0.60****
Intercept	9.69***	9.53***	9.46***
Previous volatility (PV)	0.58***	0.58***	0.58***
S&P500 (R_M)	−0.66***	−0.66***	−0.66***
Change in bond yield (B)	0.47	0.47	0.43
Realized volatility (RV)	0.24***	0.24***	0.24***
Daylight hours (Daylight)	−0.21**	−0.21***	−0.21***
Monday (M)		0.39***	0.39***
Tuesday (T)		0.18	0.18
Wednesday (W)		0.12	0.13
Thursday (TH)		0.14	0.14
Non-weekend holidays (NWH)			0.29
First 5 days in new tax year (NTY)			0.19
Adj-R^2	0.83	0.84	0.84
F	5499***	3273***	2278***
N	6303	6303	6303

*Notes:*The table reports the estimation results for Eq. (6d). This equation is an extended version of Eq. (6). It accounts for several additional control variables: the to-be-realized volatility (RV), number of daylight hours (Daylight) and dummy variables to capture the day of the week seasonality: Monday (M), Tuesday (T), Wednesday (W) and Thursday (TH), non-weekend holidays (NWH), and the first five days of the new tax year (NTY). (***), (**) and (*) indicate significance at the levels of 1%, 5% and 10%, respectively.
By Eq. (6d): $VIX_t = \alpha_1 d_{H,t} + \alpha_0 + \beta_1 PV_t + \beta_2 R_{M,t} + \beta_3 B_t + \beta_4 RV_t + \mu_2 M_t + \mu_3 T + \mu_4 W_t + \mu_5 TH_t + \mu_6 NWH_t + \mu_7 NTY_t + \varepsilon_t$.

Table 6
Estimation Results for Eq. (7) for January 1926–March 2015.

	MP1	MP2	MP3	MP4
d_H	**−0.123*****	**−0.120*****	**−0.133*****	**−0.132****
Intercept	0.0417***	0.028***	0.066***	0.056***
R_{t-1}	6.997***	6.968***	20.889**	20.886***
R^2	0.006	0.005	0.044	0.044
D.W	1.994	1.994	1.980	1.979
N	23,595	23,595	23,595	23,595

Notes: The table reports the estimation results of Eq. (7). The dependent variable in this equation is the U.S. market portfolio return–MP_t. This variable varies depending on the regression. MP1 is the market value-weighted index returns, including dividends; MP2 is the market value-weighted index returns, excluding dividends; MP3 is the market equal-weighted index returns, including dividends; and MP4 is the market equal-weighted index returns, excluding dividends. The coefficients a, a1 and b1 are reported in percentage terms. The coefficients a1 and b1 are statistically significant for all four regressions. (***) denotes significance at the levels of 1%. Eq. (7) is given by: $R_t = a_0 + a_1 d_{H,t} + \sum_{k=1}^{K} b_k R_{t-k} + \xi_t$.

the first five days in the new tax year (NTY_t). The overall results show that the High Holidays have a significantly positive impact on VIX, as evident in the α_1 coefficient estimates in Table 5. In addition, the number of daylight hours has a negative effect on VIX, suggesting that the fear index is lower during summer. The results also show that, among all weekdays, Mondays have the highest positive effect on VIX, a finding that accords with prior studies (e.g., Harvey and Whaley, 1992; Fleming, Ostdiek, and Whaley, 1995).[15] Lastly, controlling for differential effects on trading days after non-weekend holidays and on the five days of new tax years hardly influences the estimated positive impact of the High Holidays on VIX.

5. Volatility and return dynamics

In this subsection, we incorporate the inspection of returns around the High Holidays into the analysis. First, we test simple return autoregression models (Subsection A); and then we investigate simultaneous return and volatility specifications (Subsection B).

5.1. Simple return models

As documented in prior research, investors tend to take less risk when they are fearful or depressed (see e.g., Molin, Mellerup, Bolwig, Scheike, and Dam, 1996; Gavriilidis, Kallinterakis, and Tsalavoutas, 2016; Harding and He, 2016; Sun et al., 2016; Smales, 2017). We conjecture, therefore, that if investors' fears increase on the High Holidays, they will be less willing to take risks on these days, thus cause a decline in stock prices. For investigating return dynamics around the High Holidays, we estimate the following regression:

$$R_t = a_0 + a_1 \cdot d_{H,t} + \sum_{k=1}^{K} b_k \cdot R_{t-k} + \xi_t, \tag{7}$$

where R_t is the rate of return of the market portfolio, $d_{H,t}$ is a dummy variable that receives the value 1 for High Holidays and 0 otherwise, R_{t-k} is the k^{th}-order lagging variable of R_t, and ξ_t is a random error. The inclusion of K lagged regressors accounts for possible autocorrelation that might distort the results. Recall that this equation is a first attempt to characterize the type of impact the High Holidays have on market returns. In the sequel, we estimate regression specifications that simultaneously consider return and volatility dynamics.

The estimation results of Eq. (7), using each of the different proxies for the market index, MP1 to MP4, and $K = 1$, are reported in Table 6.[16] Corroborating our hypotheses, the regressions display significantly negative coefficients for d_H, indicating that the High Holidays negatively affect market returns, reflecting the relative unwillingness of investors to take risks during the High Holidays. In addition, the coefficients of R_{t-1} are positive and statistically significant, capturing the first-order serial correlation in returns, and the values of the Durbin–-Watson statistic for serial correlation are very close to 2, indicating the absence of first-order serial autocorrelation in the regressions' residuals.

5.2. Joint return-volatility models

In this subsection, we jointly estimate the effects of the High Holidays on returns and volatility, by using GARCH(*p,q*) specifications. Specifically, we utilize the maximum likelihood function to jointly estimate the coefficients of the following generalized specification:

$$R_t = a_1 \cdot d_{H,t} + a_0 + \sum_{k=1}^{K} b_k \cdot R_{t-k} + \nu_t, \tag{8}$$

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{P} \gamma_i \nu_{t-i}^2 + \sum_{j=1}^{q} \delta_j^2 \sigma_{t-1}^2. \tag{9}$$

Eq. (8) is the mean equation, corresponding with Eq. (7), and Eq. (9) is the variance equation. The term "*p*" in Eq. (9) is the order of the ARCH terms, while "*q*" is the order of the GARCH terms. The variance specification that we have chosen for the regressions is GARCH (2,1). We select this specification because other basic specifications, such as GARCH(1,1), show correlated squared errors (see, e.g., Bae and Karolyi, 1994).

Table 7 reports the estimation results of the mean- and variance-

[15] Note the weekday dummies report differences from Friday.

[16] Selecting k = 1 is in line with prior works reporting positive autocorrelations at lag 1 for U.S. indices (e.g., Schwert, 1990). Moreover, it is in accordance with the obtained values of the information criteria of Akaike, Schwarz and Hannan-Quinn. The results for other values of K, as well as for separating the sample into two equal periods, or considering the period 1962 to 2015 (Frieder & Subrahmaniam, 2004), portray a similar picture regarding the effect of the High Holidays on the returns, and are available as supplementary material in the online appendix.

Table 7
Estimations results for Eqs. (8) and (9) for various proxies of market portfolios.

	MP1	MP2	MP3	MP4
$\mathbf{d_H}$	**−0.174*****	**−0.169*****	**−0.221*****	**−0.219*****
Intercept	0.060***	0.048***	0.074***	0.064***
R_{t-1}	13.387***	13.339***	24.971***	24.918***
Intercept	0.000***	0.000***	0.000***	0.000***
u_{t-1}^2	11.548***	11.490***	17.493***	17.342***
u_{t-2}^2	−1.649***	−1.607***	−3.218***	−3.107***
σ_{t-1}^2	89.307***	89.323***	85.405***	85.433***
$Q_{LB}(K=1)$	1.031	1.033	0.145	0.162
$Q_{LB}(K=5)$	4.582	4.770	3.086	3.167
$Q_{LB}(K=10)$	9.051	9.501	11.612	11.716

Notes: The table illustrates the estimation results of Eqs. (8) and (9). The definitions of market portfolios 1 –4 are as described above in Table 3. The coefficients a0, a1, b1, γ0, γ1, γ2 and δ1 are reported in percentage terms. QLB(k) is the Ljung-Box Q-statistics. The period covered is January 1926 to March 2015, yielding 23,594 observations. (***), (**) and (*) indicate significance at the levels of 1%, 5% and 10%, respectively. Eqs. (8) and (9) are given by: $R_t = a_1 \cdot d_{H,t} + a_0 + \sum_{k=1}^{K} b_k \cdot R_{t-k} + v_t$, and $\sigma_t^2 = \gamma_0 + \sum_{i=1}^{P} \gamma_i v_{t-1}^2 + \sum_{j=1}^{q} \delta_j \sigma_t^2$, respectively.

Table 8
Estimations results for Eqs. (8) and (10) for various proxies of market portfolios.

	MP1	MP2	MP3	MP4
$\mathbf{d_H}$	**−0.105*****	**−0.102*****	**−0.103*****	**−0.102*****
Intercept	0.061***	0.048***	0.073***	0.063***
R_{t-1}	13.577***	13.517***	25.151***	25.091***
Intercept	0.000***	0.000***	0.000***	0.000***
v_{t-1}^2	11.222***	11.173***	16.731***	16.578***
v_{t-2}^2	−1.383***	−1.360***	−2.970***	−2.844***
σ_{t-1}^2	89.411***	89.437***	85.995***	86.009***
$\mathbf{d_H}$	**0.00039*****	**0.00039*****	**0.00046*****	**0.00046*****
$QLB(K=1)$	1.421	1.409	0.312	0.342
$QLB(K=5)$	7.529	7.825	6.335	6.430
$QLB(K=10)$	13.890	14.494	18.775**	18.811**

Notes: The table presents the estimation results of the Eqs. (8) and (10). The coefficients a0, a1, b1, γ0, γ1, γ2, δ1 and λ are reported in percentage terms. The definitions of market portfolios MP1–MP4 are as described above in Table 6. The period covered is January 1926 to March 2015, yielding 23,594 observations. (***) and (**) indicate significance at the levels of 1% and 5%, respectively. Eq. (10) is given by: $\sigma_t^2 = \gamma_0 + \sum_{i=1}^{P} \gamma_i v_{t-i}^2 + \sum_{j=1}^{q} \delta_j \sigma_{t-1}^2 + \lambda d_{H,t}$.

equation system, Eqs. (8) and (9). In support of the previous findings presented in Table 6, the estimated coefficients of $d_{H,t}$ are negative for all of the four market index proxies. The suitability of the GARCH specification we have selected is corroborated by the Ljung-Box (1978) Q-statistic, $Q_{LB}(k)$, presented for different lags ($k = 1, k = 5, k = 10$) at the bottom three rows of Table 7.

Next, we extend Eq. (9) by adding a dummy variable to the variance equation. The new specification allows us to test whether the High Holidays also affect conditional volatility. The extended equation is given by:

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{P} \gamma_i v_{t-i}^2 + \sum_{j=1}^{q} \delta_j \sigma_{t-1}^2 + \lambda d_{H,t}, \tag{10}$$

where d_H is a dummy variable that receives the value of 1 if trading day t is a High Holiday. A significant λ indicates that the High Holidays have an impact on the variance. Table 8 reports the estimation results of equation system composed of Eqs. (8) and (10). The findings are in line with those reported in Table 7. The estimated coefficients of $d_{H,t}$ in Eq. (8) are negative and significant for all of the four market index proxies, though are roughly half in magnitude, and the λ coefficients of $d_{H,t}$ in Eq. (10) are all positive and statistically significant, confirming our hypothesis of increased volatility during the High Holidays.

6. Robustness and trading strategy

In this section, we test the robustness of the results to estimation with various capitalization-based portfolios (Subsection A). Then, we present a possible trading strategy (Subsection B).[17]

6.1. Various capitalization-based portfolios

In this subsection, we employ ten different capitalization-based portfolios, to assess the impact of the High Holidays on market capitalizations of varying sizes.[18]

The estimation results for Eq. (7) with respect to these ten cap-based portfolios are reported in Table 9. As previously described, our model tests whether returns behave differently during the High Holidays. As in the case of the four different proxies of market portfolios, the coefficients of the High Holidays dummies have negative values in all ten portfolios, indicating that, on average, the High Holidays are accompanied by negative returns. The reported coefficients of d_H exhibit a significantly negative monotonic effect over the cap-based portfolios, with the strongest negative effect for the smallest portfolio (p1). Note that the coefficients of the lagged returns are positive, indicating a degree of serial correlation, and their inclusion in the equation results in Durbin–Watson values that are close to 2.

Next, we report the High Holidays' effect on instantaneous volatility for the ten capitalization-based portfolios. Tables 10 presents the estimation results of Eq. (3), for the period from January 1926 to May 2015. We find that instantaneous volatility during the High Holidays tend to be higher for each of the ten capitalization based portfolios. These findings are evident in the positive coefficients of d_H, illustrated in the Table 10.

Tables 11 and 12 provide the estimation results of Eqs. (8) and (9), and Eqs. (8) and (10), respectively, for the ten capitalization-based portfolios. Both tables show that the coefficients of d_H for the return equation are negative, indicating that these portfolios have lower returns during the High Holidays. In addition, the results in Table 12 document a positive hike in the conditional variance, evident in the estimated coefficients of d_H for the variance equation. Thus, the overall picture indicates a robust High Holidays effect on returns and variances across the ten capitalization-based portfolios.

Overall, the evidence we have demonstrates that small cap stocks reveal a systematic pattern during the High Holidays. In many of the specifications proposed (e.g., Tables 9 and 11 in the manuscript, and S4 and S5 in the online appendix), there is a clear tendency of small cap firms to shrink during the High Holidays. This tendency is weak for large cap stocks. One explanation for this finding corresponds with the evidence established in the financial literature that individual investors tend to trade small cap stocks. Taking this information together, we can make a reasonable guess that Jewish households are deeply involved in the trading of small cap stocks and feel pressure to sell during the High Holiday period.

6.2. Sin stocks

As stated in the article's introduction section, the literature labels

[17] We also estimated the regression models after dropping the data around the crises of 1929, 1973, 1987 and 2008. With the exception of some minor quantitative changes, the overall results are very similar to the results reported above. These results are available upon request.

[18] All NYSE securities are ranked into decile portfolios on the last trading day of each quarter.

Table 9
Estimation Results for Eq. (7) for Cap-based Portfolios, January 1926–May 2015.

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10
$\mathbf{d_H}$	**−0.250a**	**−0.205b**	**−0.191b**	**−0.185b**	**−0.172b**	**−0.147b**	**−0.119b**	**−0.115b**	**−0.106b**	**−0.088b**
Intercept	0.100a	0.084a	0.078a	0.076a	0.073a	0.073a	0.070a	0.063a	0.057a	0.073a
R_{t-1}	16.28a	14.45a	13.44a	14.32a	14.28a	14.23a	15.23a	16.31a	18.42a	17.84a
R^2	0.027	0.021	0.019	0.021	0.021	0.021	0.024	0.027	0.035	0.032
D.W	1.985	1.988	1.990	1.986	1.987	1.989	1.988	1.985	1.991	2.010

Notes: The coefficients a0, a1 and b2 are reported in percentage terms. P_i (i = 1, 2, …, 10) denotes the i-th number of the portfolio with p1 as the smallest size portfolio and p10 as the largest. By Eq. (7): $R_t = a_0 + a_1 \cdot d_{H,t} + \sum_{k=1}^{K} b_k \cdot R_{t-k} + \xi_t$. The number of observations used is 23,635 for the period between January 1926 and May 2015. Due to space considerations, significance levels are presented using (a), (b) and (c) which indicate significance at the levels of 1%, 5% and 10%, respectively

Table 10
Estimation Results for Eq. (3) for Cap-based Portfolios, January 1926–May 2015.

Portfolio	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
$\mathbf{d_{H,t}}$	**0.100**	**0.109**	**0.132b**	**0.100c**	**0.128b**	**0.120b**	**0.099b**	**0.092b**	**0.086b**	**0.035**
Intercept	1.255a	1.057a	0.951a	0.866a	0.801a	0.723a	0.651a	0.571a	0.476a	0.458a
AR(1)	34.76a	35.46a	35.33a	36.32a	35.98a	36.65a	38.06a	39.81a	39.66a	36.24a
R^2	0.121	0.126	0.125	0.132	0.130	0.135	0.145	0.159	0.158	0.131
D.W	2.158	2.184	2.192	2.193	2.203	2.190	2.210	2.224	2.221	2.178

Notes: This table reports the estimation results for Eq. (3). The dependent variable is the actual volatility proxied by the absolute rate of return. The table provides further evidence of the significant increase in the instantaneous volatility of ten size based-capitalization portfolios during the High Holidays. The rest of notations are as in previous tables. By Eq. (3): $\sqrt{R_t^2} = d_1 \cdot d_{H,t} + d_0 + \psi_t$. where $\psi_t = \rho\psi_{t-1} + u_t$.

Table 11
Estimation results for Eqs. (8) and (9) for January 1926–May 2015.

Portfolio	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
$\mathbf{d_{H,t}}$	**−0.275a**	**−0.250a**	**−0.308a**	**−0.279a**	**−0.227a**	**−0.185a**	**−0.179a**	**−0.185a**	**−0.158**	**−0.071a**
Intercept(α_0)	0.105a	0.089a	0.088a	0.083a	0.083a	0.080a	0.078a	0.073a	0.065	0.077a
R_{t-1}	19.10a	18.12a	18.37a	19.70a	19.57a	20.46a	21.08a	21.56a	23.16	18.56a
Intercept(γ_0)	0.00a	0.00a	0.00a	0.00a	0.00a	0.00a	0.00a	0.00a	0.00	0.00a
v_{t-1}^2	14.05a	14.04a	15.02a	14.47a	13.86a	16.57a	15.09a	16.42a	18.08	20.56a
v_{t-2}^2	−2.68a	−2.98a	−2.96a	−2.66a	−1.11a	−5.26a	−2.84a	−4.83a	−6.24	−7.12a
σ_{t-1}^2	88.22a	88.68a	87.73a	87.98a	87.19a	88.67a	87.37a	88.19a	88.00	86.16a
QLB(K = 1)	0.33	0.35	0.07	0.27	0.31	0.11	0.98	0.52	0.10	0.05
QLB(K = 5)	7.75	6.78	4.90	6.24	5.21	7.86	6.19	5.56	6.03	13.34b
QLB(K = 10)	16.16c	17.26	12.82	13.93	17.02	15.17	12.11	10.45	10.10	21.29b

Notes: The table reports the estimation results for Eqs. (8) and (9). QLB(K) is the Q-statistic of Ljunk-Box (1978). The conditional volatility function follows GARCH (2,1). The terms "a", "b", and "c" indicate significance at the 1%, 5% and 10% levels, respectively. Eqs. (8) and (9) are given by: $R_t = a_1 \cdot d_{H,t} + a_0 + \sum_{k=1}^{K} b_k \cdot R_{t-k} + v_t$, and $\sigma_t^2 = \gamma_0 + \sum_{i=1}^{P} \gamma_i v_{t-i}^2 + \sum_{j=1}^{q} \delta_j^2 \sigma_{t-1}^2$, respectively.

Table 12
Estimation Results for Eqs. (8) and (10) for Ten Different Capitalization Based Portfolios for January 1926–May 2015.

Portfolio	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
$\mathbf{d_{H,t}}$	**−0.156b**	**−0.146a**	**−0.144a**	**−0.133a**	**−0.115a**	**−0.109a**	**−0.091a**	**−0.091a**	**−0.070a**	**−0.063a**
Intercept(α_0)	0.106a	0.089a	0.088a	0.084a	0.082a	0.079a	0.079a	0.073a	0.065a	0.078a
R_{t-1}	19.12a	18.23a	18.62a	19.96a	19.73a	20.53a	21.09a	21.72a	23.22a	18.43a
Intercept(γ_0)	0.000a	0.000a	0.000a	0.000a	0.000a	0.000a	0.000a	0.000a	0.000a	0.000a
v_{t-1}^2	13.73a	13.70a	14.26a	14.14a	13.71a	15.41a	15.08a	15.75a	17.84a	20.42a
v_{t-2}^2	−2.42a	−2.90a	−2.58a	−2.58a	−1.50a	−4.27a	−3.01a	−4.30a	−6.55a	−7.32a
σ_{t-1}^2	88.44a	89.02a	88.15a	88.30a	87.75a	88.78a	87.62a	88.33a	88.60a	86.48a
$\mathbf{d_{H,t}}$	**0.001a**	**0.001a**	**0.001a**	**0.001a**	**0.001a**	**0.000a**	**0.000a**	**0.000a**	**0.000a**	**0.000a**
QLB(K = 1)	0.37	0.42	0.17	0.38	0.49	0.22	1.37	0.87	0.14	0.05
QLB(K = 5)	12.01b	10.55b	8.25	11.05b	8.78	11.19b	13.04b	9.85c	13.31b	16.79a
QLB(K = 10)	25.11	24.45a	19.04b	22.28b	24.14a	20.93b	23.82a	16.98c	20.49b	26.36a

Notes: The table reports the estimation results of Eqs. (8) and (10). The estimation addresses the returns and volatility of the ten capitalization based decile portfolios. The coefficients a0, a1, b1, γ0, γ1, γ2, δ1 and λ are reported in percentage terms. The terms "a", "b", and "c" indicate significance at the 1%, 5% and 10% levels, respectively. The rest of the notations are as described above. Eq. (8) and (10) are given by: $R_t = a_1 \cdot d_{H,t} + a_0 + \sum_{k=1}^{K} b_k \cdot R_{t-k} + v_t$, and $\sigma_t^2 = \gamma_0 + \sum_{i=1}^{P} \gamma_i v_{t-i}^2 + \sum_{j=1}^{q} \delta_j^2 \sigma_{t-1}^2 + \lambda d_{H,t}$, respectively.

Table 13
Sin stocks behavior during High Holidays.

	Beer	Smoking	Gaming	Guns	Market index
Sample: 1926–2015					
Intercept	0.057***	0.055***	0.052***	0.058***	−0.045***
	(0.009)	(0.007)	(0.011)	(0.012)	(0.007)
HH	−0.091	**−0.087***	**−0.223*****	**−0.120***	**−0.134*****
	(0.058)	(0.047)	(0.068)	(0.071)	(0.041)
Sample: 1926–1971					
Intercept	0.055	0.038***	0.048***		0.042***
	(0.015)	(0.008)	(0.017)		(0.010)
HH	−0.071	−0.049	**−0.270*****		**−0.156*****
	(0.092)	(0.051)	(0.102)		(0.059)
Sample: 1972–2015					
Intercept	0.058***	0.073***	0.054***	0.066***	0.047***
	(0.011)	(0.013)	(0.014)	(0.013)	(0.059)
HH	−0.106	−0.122	**−0.159***	**−0.158****	**−0.103***
	(0.069)	(0.083)	(0.088)	(0.081)	(0.059)

Notes: The table reports the estimation results for $R_{it} = \beta_0 + \beta_1 d_{H,t} + u_{it}$. R is the daily return of the i-th economic sector index. $d_{H,\ t}$ is a dummy variable indicating the days in the High Holiday period. The data are extracted from Kenneth French's library website. Data about guns are available since July 1, 1963. The stocks of companies in gaming and guns are strongly negative compared with those of other sectors. The numbers in parentheses are standard errors. The market index used is the market value-weighted index returns, including dividends.

the stocks of alcohol, tobacco, weapons and gambling firms as sin stocks. Norm-influenced (in this case Jewish) investors may tend to sell these sin stocks as the High Holidays approach, yielding strong negative shifts in their prices.

We tracked the returns of these economic sectors and found results corroborating our contention. As reported in Table 13, stocks in companies related to the gambling and gun industries are the most vulnerable industries during the High Holiday period. These companies demonstrate strong negative returns compared with those of other sectors (Beer, Smoking, and the market portfolio). The sin stocks, particularly those of gaming and guns, provide strong results in terms of both the intensity of the decline in price and statistical significance. The results hold true of the entire sample (1926 to 2015), and for the subsamples 1926 to 1971 and 1972 to 2015, respectively.

6.3. Trading strategy

Henceforth, we propose a simple trading rule that investors may consider. Specifically, we examine buying the VIX index "*t*" days before the High Holiday period starts and selling it on the last High Holiday day. The results, for a range of starting points, are presented in Table 14. The leftmost column ($t = 0$) considers buying the index on the first High Holiday day and selling it on the last High Holiday day of that year. The second column ($t = -6$) suggests buying the index six trading

Table 14
Trading rules using the VIX for 1990–2015.

Panel A- Entire Sample (1990–2015)

	$t = 0$	$t = -6$	$t = -7$	$t = -8$	$t = -9$	$t = -10$	$t = -11$	$t = -12$	$t = -13$
Mean	0.041	0.094	0.107	0.111	0.105	0.119	0.130	0.155	0.138
Stdev	0.172	0.233	0.246	0.224	0.226	0.287	0.296	0.361	0.365
Max	0.623	0.888	0.993	0.931	0.765	1.110	1.016	1.491	1.621
Min	−0.233	−0.227	−0.197	−0.187	−0.242	−0.202	−0.278	−0.169	−0.233
t-stat	1.182	2.004	2.177	2.484	2.318	2.080	2.197	2.143	1.893
" + " Ratio	0.56	0.60[c]	0.72[a]	0.72[a]	0.68[b]	0.52	0.60[a]	0.60[a]	0.56

	$t = -14$	$t = -15$	$t = -16$	$t = -17$	$t = -18$	$t = -19$	$t = -20$	$t = -21$
Mean	0.130	0.166	0.186	0.169	0.151	0.163	0.181	0.185
Stdev	0.364	0.331	0.393	0.386	0.376	0.437	0.422	0.452
Max	1.607	1.510	1.823	1.772	1.660	1.983	1.907	2.095
Min	−0.215	−0.240	−0.248	−0.278	−0.366	−0.384	−0.381	−0.314
t-stat	1.785	2.497	2.364	2.195	2.001	1.861	2.140	2.041
" + " Ratio	0.56	0.84[a]	0.76[a]	0.72[a]	0.76[a]	0.68[a]	0.76[a]	0.76[a]

Panel B- Sample without 2000 and 2008

	$t = 0$	$t = -6$	$t = -7$	$t = -8$	$t = -9$	$t = -10$	$t = -11$	$t = -12$	$t = -13$
Mean	0.011	0.056	0.065	0.071	0.071	0.073	0.084	0.090	0.066
Stdev	0.125	0.171	0.168	0.148	0.185	0.207	0.238	0.235	0.197
Max	0.332	0.472	0.414	0.374	0.484	0.556	0.654	0.725	0.529
Min	−0.233	−0.227	−0.197	−0.187	−0.242	−0.202	−0.278	−0.169	−0.233
t-stat	0.437	1.580	1.858	2.311	1.838	1.702	1.702	1.827	1.613
" + " ratio	0.52	0.57	0.70[b]	0.70[b]	0.65[c]	0.48	0.57	0.57	0.52

	$t = -14$	$t = -15$	$t = -16$	$t = -17$	$t = -18$	$t = -19$	$t = -20$	$t = -21$
Mean	0.059	0.101	0.109	0.097	0.085	0.081	0.097	0.091
Stdev	0.197	0.180	0.199	0.200	0.215	0.226	0.224	0.212
Max	0.515	0.559	0.571	0.589	0.578	0.626	0.660	0.665
Min	−0.215	−0.240	−0.248	−0.278	−0.366	−0.384	−0.381	−0.314
t-stat	1.427	2.687	2.637	2.319	1.888	1.730	2.087	2.053
" + " ratio	0.52	0.83[a]	0.74[a]	0.70[b]	0.74[a]	0.65[c]	0.74[a]	0.74[a]

Notes: The table reports the returns achieved by applying the simple trading strategy of buying the VIX index (t) trading days before the beginning of the High Holiday period (on $t = 0$) and selling it on the last High Holiday day. The " + " ratio is the number of positive returns achieved by applying this strategy to the total number of returns. In Panel B, we excluded the years 2000 and 2008 for the sake of robustness checks. Panel A demonstrates that except for the $t = 0$ (buying the VIX index on the first High Holiday day and selling it on the last day) case, the other cases provide statistically significant positive returns. The terms "a", "b", and "c" indicate significance at the 1%, 5% and 10% levels, respectively, for the sign test.

days before the first High Holiday day and selling it on the last High Holiday day, and so on, up to $t = -21$. Panel A of the table illustrates the average returns resulting from utilizing this strategy during the entire sample period (from 1990, when VIX was introduced, until May 2015). The highest average return achieved is 18.6%, which occurs if investors buy the VIX 16 days before the first High Holiday day. The maximal rate of return for a single trading position is obtained for $t = -21$ with 209.5%, while the lowest occurs for $t = -19$ with −38.4%. As the *t*-statistic values reported in the table indicate, the trading strategy provides significant positive returns for all of the "*t*" values except for $t = 0$. The transaction costs that one would need to take into account are dwarfed by the significant high returns. Furthermore, outliers do not appear to have a strong influence on the results of the trading strategy, because the ratio of positive returns (denoted by " + " ratio in the table) to the overall returns exceed 50% in most cases, as given in the bottom of the table. For example, employing the strategy when $i = 15$ provides a return of 16.60% on average using 25 observations: 21 positive cases and 4 negative ones, yielding 84% as a positive return ratio. The returns range from 150.1% to −24%, and the sign test reinforces these results.

To check the robustness of our results even further, we created Panel B, which accounts for the dotcom and subprime crises during which the VIX leaped to exceptional levels. In this panel, we excluded the observations from both years (2000 and 2008). The results, nevertheless, remain qualitatively unchanged.

7. Conclusion

In this study, we suggested a novel examination of the interplay between religion, psychology, and financial markets. Recent literature in psychology emphasizes that exposure to religious norms and values may elevate individuals' attention to moral standards and increase the likelihood of behavior that is consistent with these standards. Motivated by this literature, we investigate whether such exposure has impact on the trading activity in real capital-markets. Using data from the U.S. from 1926 to May 2015, and from 1990 to May 2015, we find evidence of systematic patterns of return and volatility behavior on the ten days commonly known in Jewish tradition as the High Holidays or the Days of Awe. We hypothesize that honesty mechanisms activated on the High Holidays amplify people's anxiety and affect their financial decision-making. Corroborating our hypothesis, we find that returns in the U.S. capital markets during the High Holidays are abnormally low; implied volatility, measured by VIX and VXO, as well as realized volatility estimates, are abnormally high; and the abnormal increase in implied volatility overshoots the future volatility level. Using these results, we devise a simple trading rule that investors may consider to maximize returns during the High-Holidays period. Future research with access to the actual trading records of investors that are matched to their religious affiliation would be a major help in understanding the interplay between implicitly priming religious thoughts and investor trading decisions.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.socec.2018.12.012.

Appendix A

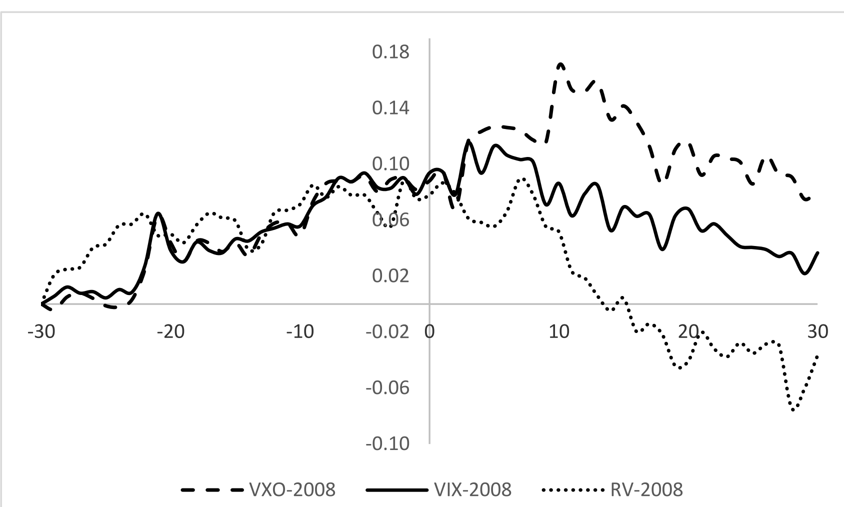

Fig. A1. Implied and realized volatility around the High Holidays, excluding 2008
Notes: The figure shows the accumulated rate of change in the VIX, VXO and the to-be-realized volatility (RV) before, during, and after the High Holidays for the period 1990–2015. The window starts 30 trading days before Yom Kippur and ends 30 trading days after it. $t = 0$ is Yom Kippur day. Data from 2008 is excluded, to eliminate the possibility of a spurious effect of due to the subprime crisis. RV is calculated in the spirit of Carr and Wu (2006): $RV_t = 100 \times \sqrt{\frac{252}{21} \times \sum_{t=1}^{21} R_t^2}$.

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