Silencing the Noise, Amplified Effects: Causal Study on Price Efficiency

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Disclaimer: Motahhareh Moravvej-Hamedani acknowledges that this paper is exclusively dedicated to assessing the effects of internet disruption on the stock market, particularly exploring its impact on various stock market variables and their financial implications. The analysis does not venture into the political aspects or reasons behind internet disruptions. The objective is to provide an unbiased examination of the financial dynamics within the stock market context during such disruptions without delving into discussions regarding the triggers or political motivations. The findings and conclusions presented in this paper are derived solely from observed financial effects within the specified scope of stock market dynamics.

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Abstract

I study the causal effects of noise traders' removal on price efficiency. In September 2022, an unexpected internet disruption in Iran restricted noise traders, while informed traders maintained trading access through brokers. I document a 6.65-fold increase in the bid-ask spread and a 46.8% decrease in trade speed due to market access asymmetry. Social media censorship increased information asymmetry, leading to a substantial 7.2% price impact in affected regions. By conducting an extensive analysis of firm-specific characteristics, this study demonstrates the significant role noise traders play in market efficiency and provides novel insights into emerging markets through a natural experiment.

Keywords: Noise traders, Informed traders, Information asymmetry, Price efficiency, Causal study, Settlement microstructure, Differences-in-Differences(DiD), Social media, Sentiment analysis, Emerging markets

1 Introduction

In this paper, I make three significant contributions through examining the consequences of an unforeseen internet disruption on the stock market. First, I examine the impact of removing noise traders from the stock market, shedding light on their influence on price efficiency and market dynamics. Second, I investigate how social media disruption affects the price impact of trades, highlighting the role of information flow in trading decisions. Finally, I explore firm-specific characteristics and their resilience to noise trader activity, demonstrating how factors such as free-float, market capitalization, and earnings per share (EPS) influence a stock's stability in the face of market disruptions.

On September 16, 2022, Iranian authorities imposed the most severe nationwide internet and mobile network disruption to control the protests.[1] Traders using online platforms were unable to trade, while brokerage houses maintain stable connections to the trading engine via physical private networks. The market structure and connectivity is described in Section 3. The internet disruption, though varying in severity, remained in place for almost four weeks. This incident creates an unexpected market access asymmetry between noise traders (uninformed) and informed traders.

The market reacts significantly to this incident, as shown in Figure 1, with trade volume dropping by 39.55%. Online trading and retail trading decrease by 26.38% and 49.63%, respectively, in September compared to August 2022. The average daily bid-ask spread percentage spikes dramatically, increasing 6.64 times on the first trading day following the internet blockage and by 73.98% after the event, as illustrated in Figure 2. This incident marks the largest and most significant spike in the daily average bid-ask spread since 2018. The spread declines immediately after the internet disruption ends.

[1] A 22-year-old Iranian woman, Mahsa Amini, passes away under suspicious circumstances while in the custody of the morality police. Her death sparks a series of protests in Iran, estimated to be the largest ever. https://www.britannica.com/biography/death-of-Jina-Mahsa-Amini

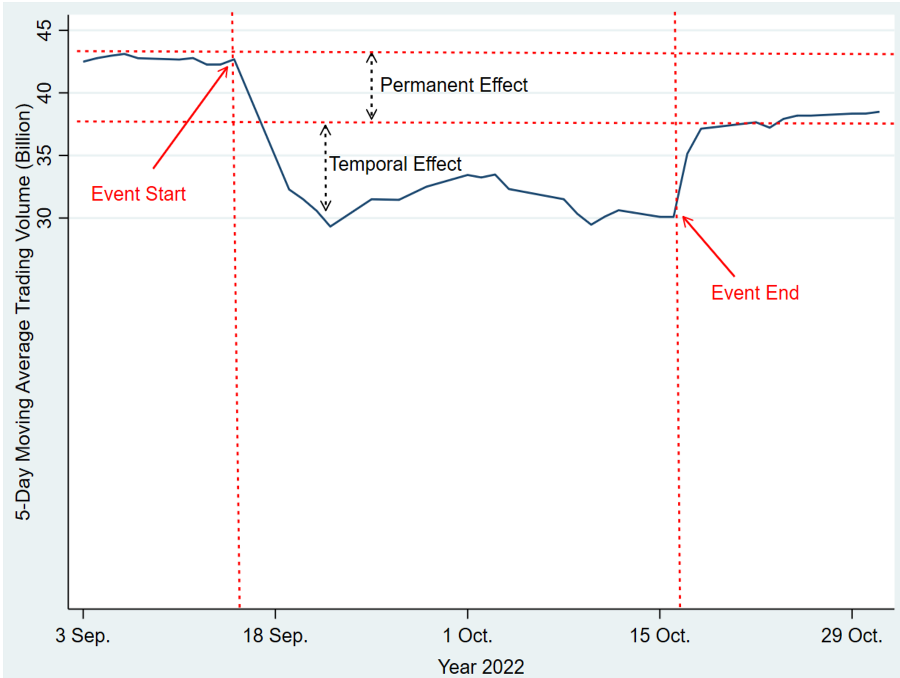


Figure 1. Market Reaction The TSE market reaction to internet disruption is depicted in this figure between Sep. 1st 2022 to Nov 1st 2022. The internet disruption starts in Sep. 16th 2022 and lasts till Oct 15th 2022. The 5-Day trading volume moving average reported in billion in y-axis.

I define noise traders as retail investors who rely on social media for trading signals and use online trading platforms to access the market, without intermediaries such as brokers or portfolio managers trading on their behalf. These traders, who often make decisions based on incomplete or noisy information, have been significantly empowered by fintech innovations, particularly online brokerage services that offer lower transaction costs and greater accessibility. By removing the need for intermediaries, fintech-driven platforms have democratized market access, allowing retail investors to trade directly and more frequently.

I apply two approaches for stock classification: one based on *Retail Trading Portion (RTP)* following Han and Kumar (2013), which identifies stocks that attract speculative retail trading, and another based on *social media attention* using Lopez Avila, Martineau, and Mondria (2024). High-RTP stocks tend to exhibit characteristics appealing to risk-seeking traders,

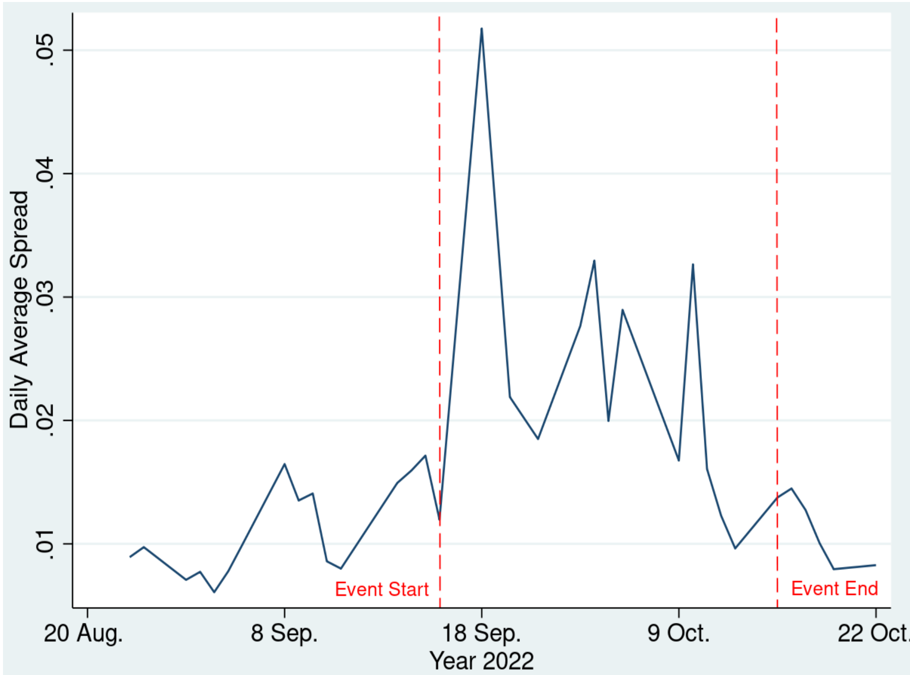


Figure 2. Average Daily Bid-Ask Spread In this figure, the average daily bid-ask spread (y-axis) is presented over time (x-axis). The data reveal a substantial spike of 73.98% in the average daily bid-ask spread. On Sep. 18th, the first trading day following the implementation of sudden internet blockage and the subsequent removal of noise traders from the market, the market witnessed a 6.64-fold increase in spread in one day. This pronounced increase in the bid-ask spread has a noteworthy adverse impact on market liquidity, with the number of submitted orders in the order book dropping by 11.16% in one day. The bid-ask Spread for TSE is calculated based on Equation (1) in which the value is multiplied by 100. The peak of this chart marks the greatest average daily bid-ask spread in 2022.

such as lottery-like payoffs. Similarly, high-attention stocks on social media platforms like Iranian StockTwits attract noise traders, amplifying their presence and influence. Using a causal Differences-in-Differences framework and an exogenous internet disruption shock, I measure how the absence of noise traders affects market outcomes such as liquidity, trade speed, order book imbalances, and abnormal returns. The results show that the trading speed and relative volume of informed traders decrease by 38.61% and 41.2%, respectively, during the disruption. Order book imbalances also decline, only to increase significantly post-disruption, indicating the return of noise traders to the market.

Social media platforms like WhatsApp, Telegram, Twitter, and Instagram were severely disrupted in specific regions facing fatal protests, particularly in the western and southern provinces. During these incidents, traders in affected regions struggled to receive timely information from their subscribed channels, leading to significant information asymmetry. I find that this temporal and spatial information asymmetry resulted in uninformed trading decisions, causing a 7.2% price impact and a 32.5% relative closing price gap in regions affected by the social media blackout, as discussed in Sections 9.1 and 11.4. These findings are consistent with Goettler, Parlour, and Rajan (2009), who analyze the limit order market under asymmetric information and show that it amplifies price distortions in markets with incomplete information. My results similarly demonstrate that microstructure noise increases the pricing gap in regions with limited access to social media, exacerbating uninformed trading.

While theoretical papers, such as De Long, Shleifer, Summers, and Waldmann (1990), have explored the concept of noise trader risk and its effect on asset prices, they do not directly measure firm-specific resiliency to noise trading. These works provide a foundation by suggesting that firms with certain characteristics may be better insulated from the volatility induced by noise traders. In contrast, my paper empirically measures the resiliency of firms by examining their performance during both the presence and absence of noise traders in the market, providing direct evidence of how firms withstand noise trader-induced volatility. My findings described in Section 10 and indicate that low free-float, small-cap, and low EPS stocks are significantly more sensitive to the presence and absence of noise traders, exhibiting substantial fluctuations in their abnormal returns.

I utilize a wide range of market and social media data, as described in Section 5. Beside order book and market data for this research, I utilize the *NetBlocks* worldwide internet monitoring service to record internet disruption incidents.[2] I gather and analyze data from *Telegram*, *Twitter*, Iranian *StockTwit*, and financial news-related channels to construct continuous mea-

[2]https://netblocks.org and https://t.me/netblocks

sures for internet disruption *(ID)*, daily sentiment, and attention. I use Armed Conflict Location and Event Data *(ACLED)* to measure the geographical fatality of the protests in the country and region to construct a robust *Political Unrest* measure through principal component analysis. [3]

2 Literature Review

Noise trading plays a prominent role in financial markets, especially with technological advancements and increased accessibility. According to JPMorgan data, noise trading hit its all-time high in February 2023, and this type of investor now accounts for an increasing percentage of the total trading volume for large-cap stocks. In financial literature, the role of noise traders remains a subject of debate. On one hand, Black (1986) argues that noise traders introduce inefficiencies into the market, distorting prices and leading to excess volatility. In contrast, Kyle (1985) suggests that the presence of noise traders enhance market liquidity by providing a counterparty for informed traders, thereby facilitating price discovery. Similarly, De Long, Shleifer, Summers, and Waldmann (1990) point out that while noise traders may increase short-term volatility, they do not necessarily destabilize the market in the long run.

A growing body of research supports the positive role of noise traders in financial markets. Peng and Xiong (2006), Da, Engelberg, and Gao (2011), and Barber and Odean (2008) examine attention-grabbing events to uncover trading and return patterns driven by retail buying pressure, though they do not focus on volatility or liquidity. Peress and Schmidt (2020) reports that liquidity declines when retail traders are distracted by major news broadcasts, suggesting that retail traders play a key role in maintaining liquidity. Noise traders ensure a sufficient number of buyers and sellers in the market, mitigating risks and preventing drastic price fluctuations Foucault, Sraer, and Thesmar (2011), while also reducing the impact of concentrated institutional trading (Gurrola-Perez, Lin, and Speth 2022). My findings support this view, showing

[3] https://acleddata.com

that noise traders play a positive role in improving market efficiency, particularly in emerging markets where they help reduce information asymmetry and foster liquidity.

The closest papers to my research empirically study the behavior of noise traders using the Robinhood trading platform as a proxy for inexperienced investors. Eaton, Green, Roseman, and Wu (2022) finds that the herding behavior of Robinhood users can create inventory risks that harm liquidity in stocks with high retail interest. Barber, Huang, Odean, and Schwarz (2022) presents findings suggesting that intense buying by Robinhood users forecasts negative returns, providing evidence that these users are more likely to engage in attention-induced trading, with their concentrated buying leading to large negative abnormal returns following herding episodes. While these studies contrast preannounced outages at Robinhood with outages at traditional retail brokers in non-overlapping periods, my paper examines the behavior of both noise traders and informed traders under the same market conditions, using a plausible exogenous shock.

Retail trading significantly impacts the information supply in financial markets (Martineau and Zoican 2023). In their study of a trading model with endogenous information supply, they suggest that sell-side analysts provide higher quality signals for stocks with large retail interest, as institutional investors can trade more aggressively without causing significant price impact. Building on their analysis, my research examines the causal effects of noise trader removal on stocks with large retail interest due to internet disruption. While their study focuses on the role of analysts in enhancing information supply for retail-heavy stocks, my work explores how the absence of noise traders—caused by an external shock like internet disruption—impacts liquidity and price dynamics, highlighting the significance of retail participation in market efficiency. Together, these studies offer a more comprehensive understanding of retail investors' influence on market behavior under different conditions.

Noise trading plays a significantly larger role in emerging markets compared to developed markets, largely due to the higher participation of retail investors who rely on non-fundamental information sources, such as social media and speculative signals. In markets like China and India, retail investors account for approximately 70-80% and 40-50% of daily trading volume, respectively, making these markets more prone to the volatility associated with noise trading Xiong and Yu (2011); Agarwal (2009). In contrast, developed markets like the United States and Europe see much lower retail participation, around 20-30%, where institutional investors dominate and reduce the impact of noise traders Barber, Odean, and Zhu (2009). This difference in market composition leads to higher volatility and inefficiencies in emerging markets, making the study of noise trading particularly relevant for understanding market stability and efficiency in these regions. Despite its significance, empirical research on noise trading in emerging markets remains relatively underexplored, highlighting the need for more focused studies in these contexts. This paper aims to fill this gap by providing new empirical evidence on the impact of noise trading in emerging markets.

Lopez Avila, Martineau, and Mondria (2024) studies the effect of social media attention before and after earnings announcements based on (Cookson, Mullins, and Niessner 2024), providing insights into the role of social media in price efficiency. They demonstrate that social media activity results in attention-based earnings announcements due to intermediary inventory risk, but the release of earnings news has an immediate price-correcting effect. I also applied the same classification for low- and high-attention stocks and found that the removal of noise traders from the market decreases liquidity for high-attention stocks. Crucially, my analysis shows that the removal of social media access itself in certain regions has a direct and significant price impact on the market. By comparing traders from regions with disrupted social media access to those from unaffected regions, I observe that social media disruptions lead to a positive price impact, further highlighting the role of social media in market dynamics.

Existing literature on noise traders in financial markets primarily focuses on their behavior and impact under normal market conditions. Studies such as (De Long, Shleifer, Summers, and Waldmann 1990) explore how noise traders, driven by irrational beliefs or incomplete information, affect market volatility, risk, and returns, often leading to mispricing and return reversals. Research by (Barber and Odean 2000) and (Tetlock 2007) further examines the role of investor sentiment and news media as noise, influencing stock price movements and market liquidity. While these studies provide valuable insights into the influence of noise traders in stable environments, my research expands this framework by evaluating noise trader behavior during periods of political unrest and internet disruption. I developed a measure for political unrest and controlled for it, studying various events with and without internet disruption in Section 11.1. In two cases where the internet was disrupted, the bid-ask spread increased significantly, suggesting that the removal of noise traders during political unrest and internet shutdowns leads to decreased market liquidity. These findings ultimately contribute to our understanding of market dynamics under extreme conditions.

3 The Market Structure

Iran, as an emerging market, presents a unique case for studying market structure. In particular, the Tehran Stock Exchange offers an ideal setting to investigate the impact of noise trading on price efficiency. A significant portion of trading—64.6% of the monthly volume—occurs online, driven by the education levels and preferences of local investors.[4] Additionally, the relatively isolated and disconnected nature of Iran's market from global economies ensures that external economic factors have minimal influence on the findings, making it a distinct environment for such analysis. Moreover, in emerging markets, social media access, noise trading, and digital market access play crucial roles in shaping market dynamics. Social media provides a vital source of information and sentiment for retail investors, often driving trading decisions (Black 1986). Additionally, the prevalence of noise trading—frequent, uninformed trades—can significantly influence price efficiency due to the less sophisticated investor base and height-

[4] https://rdis.seo.ir

ened market volatility. Digital market access further democratizes participation, expanding the investor pool and increasing liquidity, which is essential for the growth and stability of emerging markets (Chen, De, Hu, and Hwang 2014).

Iran's Stock market was founded in 1967. It currently consists of four primary exchanges, including the Tehran Stock Exchange (TSE), Iran Fara Bourse (IFB), Iran Energy Exchange (IEE) and Iran Mercantile Exchange (IME). In this research, I study the price efficiency in the TSE Market. In some cases, I utilize IFB market data as a robustness test. As of June 30th, 2023, the market value of TSE and IFB stands at 81,568,078B IR and 27,060,502B IR, respectively.[5] The trading hours in both exchanges are Saturday through Wednesday from 9:00 am to 12:30 pm Iran Standard Time (GMT+03:30).

The TSE and IFB are two separate stock exchanges in Iran, each serving distinct purposes. The TSE is the primary and larger stock exchange that handles the trading of a wide range of financial instruments, including stocks, Islamic bonds (Sukuk), and other securities. The TSE is more traditional and established, catering to a broader spectrum of companies. On the other hand, the IFB was established to provide a platform for trading securities that did not meet the requirements for listing on the TSE. The IFB focuses on smaller and newer companies, as well as specific financial instruments. The IFB aims to support the development of the Iranian Capital market by providing a space for a diverse range of securities and innovative ideas, such as crowdfunding or patent trading.

In Iran's stock exchange, position-keeping occurs at the account level under the central custodian, not with brokerage houses. Each trader is fully identified and assigned a unique trading code by the services provided for brokerage houses through the Central Securities Depository of Iran (CSDI). The CSDI functions as a prominent depository organization in the Iranian capital market, providing pre-trade and post-trade services across all exchanges. Established in 2005, the CSDI plays a crucial role in facilitating the central registration of exchange-traded securities

[5] The current exchange rate of IR to USD is 0.000042 on July 16th, 2023, based on https://www.cbi.ir.

and financial instruments. Its core functions include offering comprehensive clearing and settlement services to all exchanges. Additionally, the CSDI provides supplementary back-office services, such as electronic Know Your Customer (e-KYC) procedures and risk management initiatives. These initiatives aim to enhance settlement operations, including establishing credit limits and settlement guarantee funds. The institution also undertakes the critical task of maintaining up-to-date portfolio information through corporate action services, which involve activities like dividend distribution, rights issues, and capital increases. As a unique trustee within Iran's capital market, the CSDI extends its responsibilities to include governmental services such as overseeing the legal transfer or blockage of assets and facilitating collateral pledging.

Iran's Stock Exchange operates as a central limit order book (CLOB), a trading system used by most exchanges globally. This system utilizes an order book and a matching engine, specifically designed by ATOS-Euronext, to execute limit orders. Similar CLOB structures are observed in other financial markets, such as the Stockholm Stock Exchange and the Toronto Stock Exchange. It is a transparent system that matches traders' orders (e.g. bids and offers) on a price time priority basis. Figure 3 represent the basic architecture of connections to trade engine.

The trading platforms in the Tehran Stock Exchange consist of two main categories: Station-based and Internet-based. The station-based trading system involves a setup where trading terminals or stations are physically connected to the exchange's trade engine system through dedicated communication lines. This architecture is designed to provide a more secure and reliable connection compared to internet-based trading systems for 111 brokerage houses. Iran also has twenty three regional trading floors which are station-based and are equipped with the necessary hardware and software to facilitate trading activities. Station-based connections are on private networks and are not affected by internet disruption.

Fifteen licensed high-tech companies provide online trading services and are called, Order Management Systems (OMS). Online trading contributes to 65.2% of the total trading volume on the Tehran Stock Exchange. The *OMS* systems are not directly connected to the trade engine. They connect to brokers through a physical private network. The orders gathered through brokers, OMS systems, and regional trading floors are sent to the central order book system and then to the trade engine. During the internet disruption, the internet-based connection between users and OMS systems is disconnected, while users submitting orders on regional trading floors in person or by brokers through phone or in person can trade.

More than 70% of the Iranian population possess KYC-based trading codes, with over 53.2% actively participating in market trading.[6] Additionally, individuals engaged in daily buying and selling activities account for 66.38% of the total trading volume.[7] The increasing preference for online trading can be attributed to various factors, including cultural norms, educational attainment, and widespread smartphone usage. Institutional traders acquire specific trading codes through KYC. Typically, these traders engage portfolio managers and investment firms to protect assets and optimize risk management. Notably, 75 portfolio management companies and 176 licensed investment agencies specialize in advising substantial traders, particularly in the stock market domain. Institutional contribution to daily trading volume stands at 33.62%.

4 Internet Disruption

Internet shutdowns were imposed by 23 countries in 2022. Most of the shutdowns were triggered unexpectedly by protests, conflict, and allegations of human rights violations, with a smaller number being anticipated and announced in advance such as school exams and elections. The Guardian reported that access to internet services was restricted 187 times by 35 countries, according to new research, with India, Iran, and Myanmar repeatedly enforcing

[6]https://donyayebourse.com

[7]www.rdis.ir in July 2023

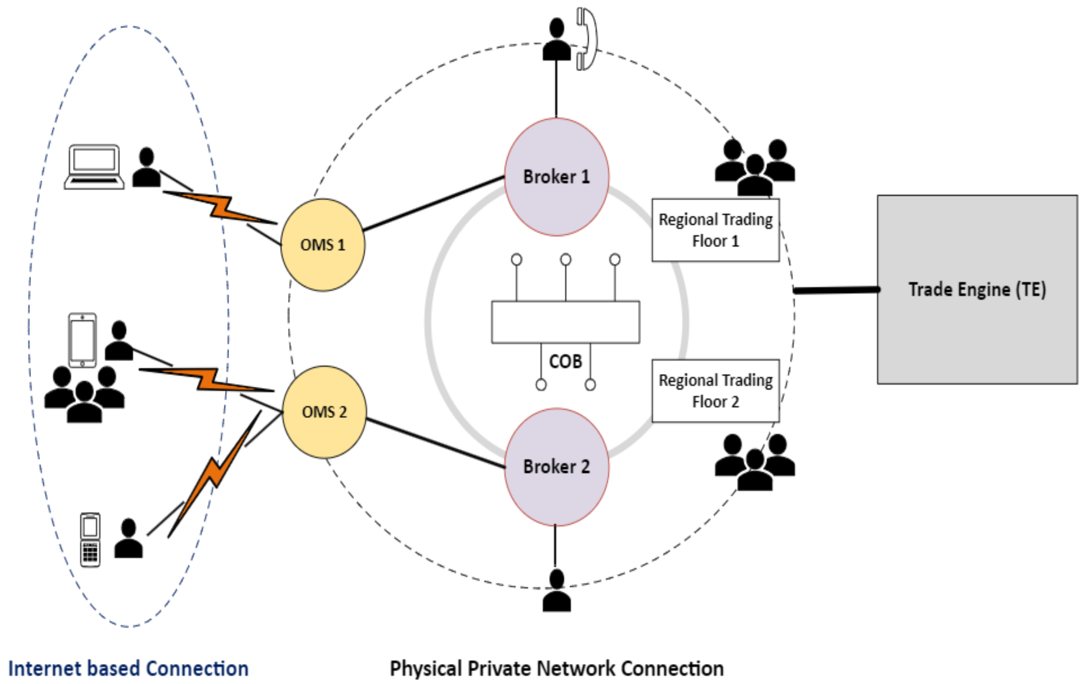


Figure 3. Connectivity in Market In this figure, the connectivity of trading venues, brokers, and *OMS* platforms is represented. The *OMS* stands for Order Management Systems, which provide online platforms for users to submit orders, access online brokerage services, and receive information dissemination. The *COB* stands for Central Limit Order Book. *Regional Trading Floors* are located in various provinces to facilitate in-person trading for users. The *OMS* systems are connected to the Trade Engine *TE* towards brokerage houses. Users can also send their orders directly to brokerage houses by phone or in person. Communication between users and *OMS* providers is based on Internet connections, while the connection between *OMS* systems, brokers, and regional trading floors is a physical private network. During governmental-imposed internet disruption in Iran, noise traders faced extreme limitations in accessing online trading platforms and social media. While noise traders had limited access to information broadcasting forums or signalling channels, informed traders maintained their ability to utilize established channels with brokerage agents. Institutional traders, who typically manage large portfolios, have implemented risk management protocols and trading agreements with their designated brokerage firms. Institutional traders commonly engage a single brokerage firm to safeguard their trading strategies and maintain confidentiality. Consequently, they maintain a close relationship with their designated agent, facilitating continuous communication even during internet disruptions. Given their authority to trade on behalf of informed investors, they are less vulnerable to Internet disruptions. Furthermore, they can engage in face-to-face or telephone consulting sessions to effectively interact with their agents.

blackouts since 2016.[8] Statista highlights that India had the most internet shutdowns in 2022, with 84 recorded shutdowns.[9]

NetBlocks tweeted on Sep. 21st, 2022, that "Iran is now subject to the most severe internet restrictions since Nov. 2019."[10] Reuters also reported that "The mobile internet was cut off for many users in Iran amid a new wave of protests and reports of casualties." The major disruption in internet service in Iran was confirmed by the NetBlocks internet monitor.[11] Wired also reported a drastic limitation on all digital communication in the country.[12] The U.S. Department of the Treasury stated that there was "systemic internet disruption by the Iranian regime" following Amini's death and the protests that ensued.[13] Additionally, a report from the Middle East Institute mentioned that "the Kurdistan Province in western Iran experienced a total internet shutdown, with targeted shutdowns on a geographical or linguistic basis", which were likely to be an effective means of suppressing opposition. [14]

Iran's Communications Minister, Issa Zarepour, is among the Iranian officials who have commented on the internet disruption in Iran. Zarepour stated that " the country had twice the internet access it needed and called for tougher measures to control online dissent". These statements reflect the Iranian government's position on internet disruption and its efforts to control online activities. [15]

I utilize the NetBlocks reporting service to attribute the accurate status of the internet disruption during the study period to analyse the date and location and severity of disruption.[16]

[8] https://www.theguardian.com/global-development/2023/feb/28/internet-shutdowns-record-number-countries-2022-report

[9] https://www.statista.com/chart/15250/the-number-of-internet-shutdowns-by-country/

[10] https://x.com/netblocks/status/1572651793355603972?s=20

[11] https://www.reuters.com/world/middle-east/major-disruption-internet-service-iran-netblocks-twitter-2022-11-21/

[12] https://www.wired.com/story/iran-internet-blackout-economy/

[13] https://home.treasury.gov/news/press-releases/jy1733

[14] https://www.mei.edu/publications/mahsa-amini-and-future-internet-repression-iran

[15] https://www.reuters.com/article/idUSL8N3AJ203/

[16] https://netblocks.org/

NetBlocks is an independent non-profit organization dedicated to monitoring and documenting instances of internet censorship, network disruptions, and cybersecurity concerns worldwide. NetBlocks employs diverse methodologies and tools to track internet connectivity and online freedom. NetBlocks measures and reports *Connectivity* which refers to the evaluation of the availability and performance of internet infrastructure within a region or country. This measure encompasses various indicators such as the accessibility of internet services, the presence of network disruptions or outages, and the overall quality of internet connectivity. NetBlocks typically uses real-time data and analysis tools to detect and report on internet disruptions, providing insights into how these disruptions affect communication, access to information, and overall digital connectivity.

NetBlocks reports internet disruption incidents in real time and posts the state of internet connectivity during the incident on an hourly basis. There is no *API* available for receiving the connectivity data. To construct a daily average internet disruption measure for Iran, by collecting data, including images, texts, and descriptions, from the NetBlocks Telegram channel. [17] The connectivity is 100% when there is no incident reported for a specific hour and day by NetBlocks. The internet disruption measure *ID* is calculated by subtracting the daily average from 100%.

Figure 4 represents the daily average connectivity, which increases from 1.51 to 47.41 during the study period. Table 1 reports the analyzed NetBlocks connectivity. The average monthly number of disruptions in Iran is 11.19% higher than in other locations over a two-year average.[18]

[17] https://t.me/netblocks

[18] This period marks the highest number of internet disruption incidents broadcasts by NetBlocks at https://netblocks.org. See Appendix H for more information.

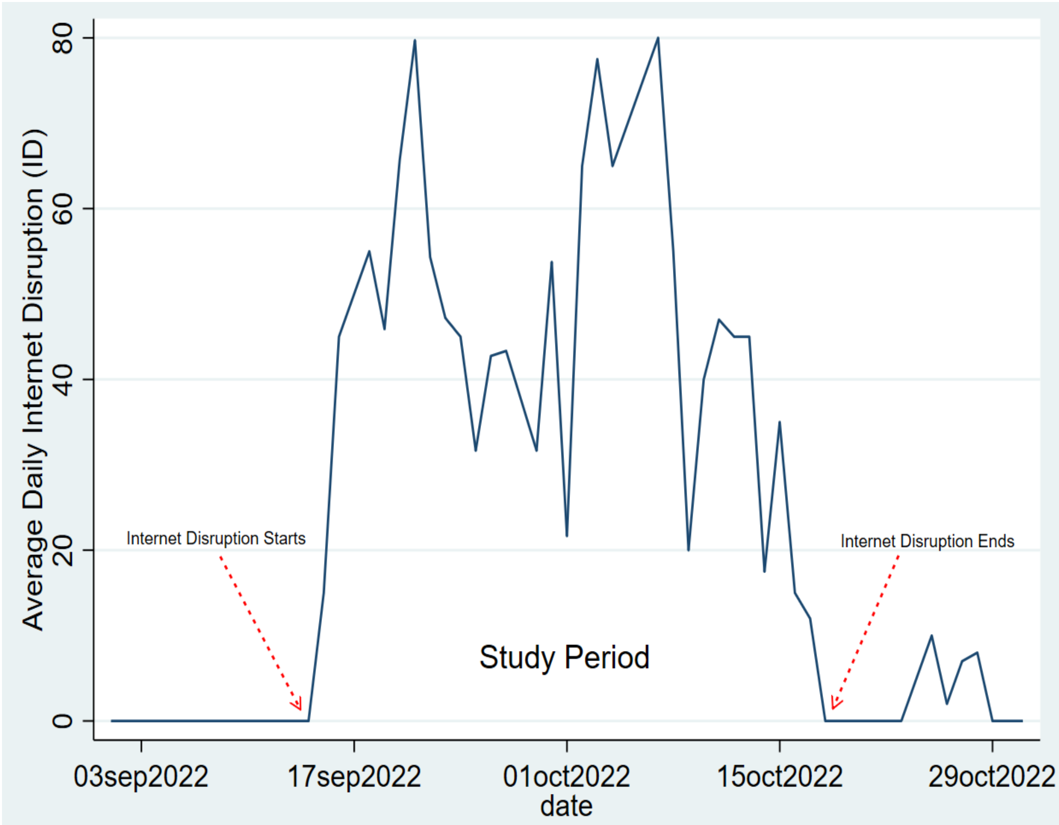


Figure 4. Daily Average Internet Disruption (ID) In this figure, the internet disruptions are analyzed based on NetBlocks' connectivity reports. The event study period spans from September 16th to October 16th, 2022, experiencing the highest*ID*.

Items	Classification	Period	2022	2023
Number of disruptions	*All*	*Yearly*	388	351
Number of disruptions	*Iran*	*Yearly*	30	41
Number of unique locations	*All*	*Yearly*	170	127
Avg. Number of disruptions	*Iran*	*Monthly*	2.5	1.9
Avg. Number of disruptions	*All*	*Monthly*	2.1	1.8

Table 1. Summary Statistics of Internet Disruption This table reports the summary of internet disruption in 2022 and 2023 all over the world based on the Netblocks Telegram channel. The *All* classification includes Iran.

5 Data and Stylized Facts

I collect public market data, including stock prices, companies' financial reports, market indices, and trading volume. Additionally, I gather non-public market data, such as live order books, from March 1st, 2022, to April 1st, 2023. Table 2 shows the summary statistics of the dataset. I collect the three best limits for each listed instrument trading in IFB and TSE markets for ten years as described in Table 3. In Appendix Section D I describe the parsing program to extract the three best limit values.

Items	**Value**
Trading Days	242
Listed Companies in TSE	381
Listed Companies in IFB	349
Suspended Tickers	125
Orders Count	7,966,343,286
Trades Count	447,367,588
Avg. Best Limit Change Flag	352 ms
Exchanges	2
Trading Floors	23
Online Platforms	15
Active Individual Traders	39,371,613
Active Institutional Traders	157,232
Total Trading Accounts	60,046,851
Avg. Order Frequency	1 ms
Market Value (TSE and IFB)	108,628,580B (IR)
Brokerage Houses	111

Table 2. Summary Statistics The dataset encompasses Tehran stock market and order book data from March 1st, 2013, to April 1st, 2023. The trading year in the Iranian market starts in March. The summary statistics for the year 2022 are reported in this table. The utilized market data measures are defined in Appendix Section A. The *IR* denotes the Iranian Rial. The exchange rate from IR to USD is 0.000042 as of July 16th, 2023, and fluctuates daily. The order book update messages are received in milliseconds, abbreviated as *ms*. I exclude suspended tickers from the sample. I address potential selection bias by excluding wholesale trades from the sample, considering the significant differences in the origin and motivations of wholesale trades compared to retail trades. To enhance the reliability of the findings, I also exclude 125 tickers under suspension status due to special financial reporting, under surveillance, general assembly, and other significant corporate actions from the sample in 2022.

The online trading volume substantially declined by 66.3% and 52% in Sep. and Oct. 2022, respectively.[19] In contrast, the offline trading volume remained relatively unchanged, experiencing only marginal growth. An alternative classification of trading types is based on account

[19]http://seo.ir/

Year	Observations	Min	Average	Max	Std. dev.
2013	27,707,769	0.0145	0.0498	0.0330	0.0433
2014	23,200,834	0.0207	0.0536	0.0359	0.0409
2015	32,352,625	0.0116	0.0432	0.0336	0.0382
2016	33,120,744	0.0105	0.0426	0.0241	0.0312
2017	44,623,425	0.0095	0.0382	0.0278	0.0341
2018	45,774,323	0.0086	0.0272	0.0298	0.0278
2019	126,924,776	0.0049	0.0180	0.0471	0.0212
2020	243,204,113	0.0096	0.0141	0.0205	0.0777
2021	134,717,603	0.0063	0.0127	0.0397	0.0915
2022	117,611,407	0.0041	0.0145	0.0528	0.0123

Table 3. Historical Spread The table summarizes the statistics for the average daily spread in the TSE Stock Market from 2013 to 2022. The bid-ask Spread is calculated based on Equation (1).

numbers. In the Tehran Stock Exchange, individual and institutional traders receive distinct trading codes after the initial KYC and trading code activation procedure. The Tehran Stock Exchange Index also *TEDPIX* declined more than 10% percent during the exogenous shock in the market. On the first trading day, seventy-five percent of the stocks closed in red at the end of the trading day. Almost $120 million in capital has been withdrawn from the Tehran Stock Exchange in ten days. It is also reported that the $28 million was pulled out of the Tehran Stock Exchange on Oct. 29, the highest daily amount in the past five months.

In times of political unrest, the bid-ask spread in financial markets may increase. This is because uncertainty and volatility rise, leading to greater risk perceptions among investors. As a result, market participants become more cautious, resulting in wider spreads between the prices at which they are willing to buy and sell assets. Through a robustness test, I exclude the hypothesis that the increase in bid-ask spread is solely due to political unrest by comparing six events of political unrest with and without internet disruption. I found that in two events where the internet was disrupted, leading to the removal of noise traders from the market, the bid-ask spread increased significantly. I control the regressions with a constructed continuous measures of political unrest to isolate the impact of the treatment from political uncertainty. The measure is created by principal component analysis (PCA) and is described in Section E.

The main components of creating this measure are sentiment analysis and fatality of protests. I also control the regression with USD-to-IRR exchange rate measure.[20] The USD-IRR exchange rate in Iran is a measure of political unrest because it reflects economic instability and public sentiment. During unrest, uncertainty rises, leading to currency depreciation as people seek safer assets like USD. Political instability often triggers capital flight, inflation, and reduced confidence in the government, all of which are captured by fluctuations in the exchange rate.

Items	**Telegram**	**Twitter**
Total Number of Posts	3,830,357	523,158
Total Number of Channels	56,142	48,477
Average Number of Posts per Year	1,720,225	338,515.70
Average Number of Posts per Month	212,319.40	57,958.52
Average Number of Posts per Day	8,107.39	2,543.95
Average Sentiment per Year	0.075	-0.054
Average Sentiment per Month	-0.033	-0.087
Average Sentiment per Day	-0.005	-0.007

Table 4. Social Media Summary Statistics The dataset encompasses Iran's stock market-related posts in *Telegram* and *Twitter* during four years starting from 2019.

I collect *Telegram* and *Twitter* posts related to Iran's stock market for four years, starting in 2019. Table 4 provides a summary of statistics for sentiment analysis. I measured sentiment based on six categories ranging from *very negative (-2)* to *very positive (+2)*. I report the weighted average daily sentiment, where posts with a greater number of likes and reposts, and those broadcast from channels with a higher number of followers, have higher weights. The average number of posts per day dropped by 34.63% and 62.78% on *Telegram* and *Twitter*, respectively, due to the internet disruption. [21]

[20]The daily USD-to-IRR exchange rate is available at https://www.bourseview.com/

[21]I use the nlptown/bert-base-multilingual-uncased-sentiment model. This model is a well-known for sentiment analysis and is based on the *BERT* (Bidirectional Encoder Representations from Transformers) architecture, which is a state-of-the-art model developed by Google. This specific model by *NLP Town* is trained on multilingual data and is designed to analyze sentiment in various languages, including Persian(Farsi).

6 Difference-in-Differences Analysis

In this section, I estimate the causal effect of the absence of noise traders, resulting from unexpected internet disruptions, on liquidity using a Difference-in-Differences framework. I am following the Han and Kumar (2013) and Barber, Odean, and Zhu (2006) approach to classifying stocks in Tehran Stock Exchange based on their retail trading level. Stocks with high retail trading proportion(*High-RTP*) have strong lottery features; they are overpriced and earn significantly negative alpha. The *RTP* of a stock is defined as the monthly dollar value of the buy and sell initiated small trades(bellow $5,000) divided by the dollar value of its total trading volume in the same month. The small trades are considered a proxy for retail trades. Intuitively, the traders buy and sell the stocks within their habitat more frequently. [22] They also show that retail traders predominately held and actively traded stocks with high idiosyncratic volatility (IVOL) and skewness or lower prices.

In this study, the exogenous shock refers to the abrupt disruption of internet services in the Tehran Stock Exchange. I classify the stocks into *High-RTP* and *Low-RTP* groups based on the monthly average of *RTP*, which was 19.84% in 2022. Table 5 reports the comparability of the treatment and control groups. The *High-RTP* stocks shape the treatment group as they are more affected by retail traders' removal from the market. The *Low-RTP* stocks are less affected since the institutional traders are trading them. Institutional traders are managing larger portfolios. Moreover, they have established communication channels with brokerage houses for risk management, trading on behalf and portfolio management.

The outcome variable is the average *Spread* per day for each group of stocks based on Equation (1). The spread serves as a proxy for average daily market liquidity. I assess the parallel trends assumption graphically by examining trends within both outcome groups. Figure **??** illustrates a similar bid-ask spread percentage trend for both groups before and after the

[22] The small-trades data measure is captured from the Institute for the Study of Security Markets(ISSM) and Trade and Quote(TAQ) based on (Han and Kumar 2013).

Items	**Treated** *(High-RTP)*	**Control** *(Low-RTP)*
Number of Tickers	184	157
Average Daily Trading Volume (M)	352.23	518.42
Number of Trading Days	252	252
Average RTP Level	27.73	14.21
Average Monthly Number of Trades	7,987.19	5,125

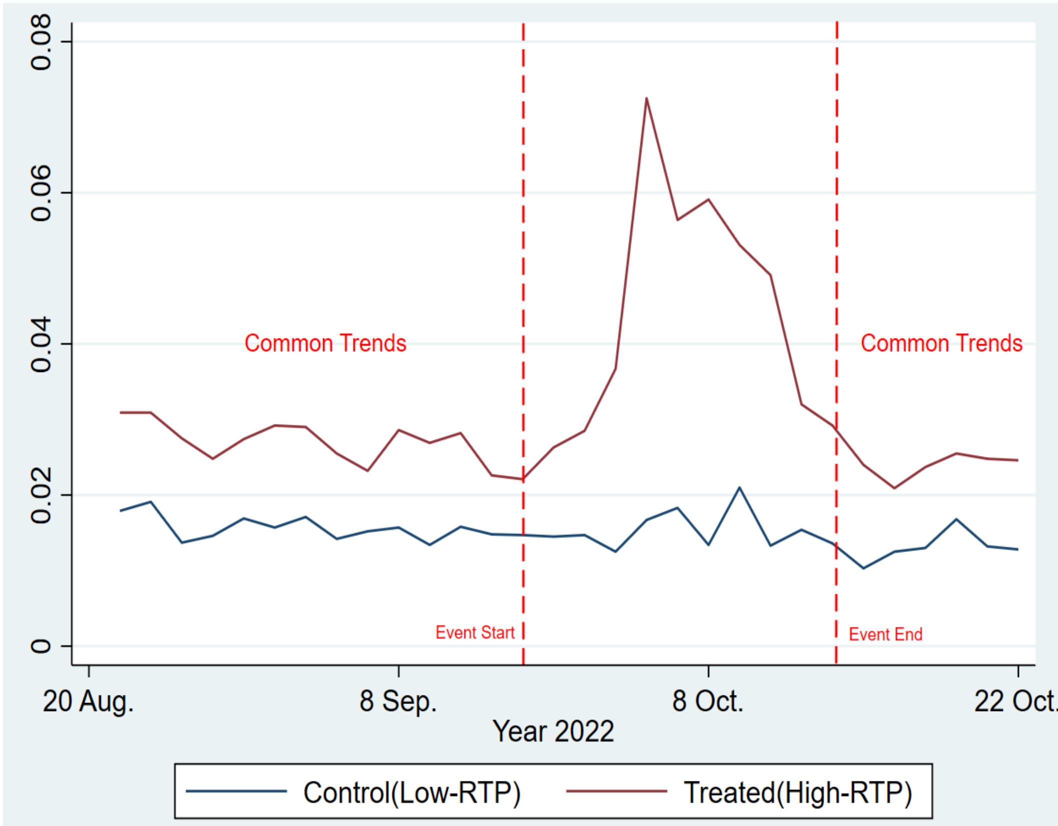
Table 5. Groups Comparability This table reports the comparability of treated and control groups created from trading stocks. The yearly average of *RTP* is 19.84%. I mark stocks with an RTP greater than the average as *High-RTP*. The treated group consists of stocks with a *High-RTP* level, while the control groups comprise stocks with *Low-RTP* levels. Forty eight tickers from TSE subject to specific supervisory suspensions, important announcements, or corporate actions in Sep. and Oct. 2022, are excluded from the sample. The study includes TSE stocks.

Internet disruption, with the treated group experiencing an increase during the event, while the control group maintains its trend.

$$Spread_i = ((AskPrice_i - BidPrice_i)/AskPrice_i) \tag{1}$$

The $HRTP$ is a dummy variable set to one if the observation is related to the group exposed to the internet disruption treatment in period t, and set to zero if the observation belongs to the control group in period t. The treated group consists of stocks with high retail trader levels. The variable $Event = 0..1$ indicates the respective periods before and after the event. The $Event$ is a dummy variable set to zero if the observation is in the pre-event or post-event period, and set to one if it is in the event period. I estimate the treatment effect through α_3. Table 6 reports that the average daily bid-ask spread increases significantly for the treated group after the event.

$$\mathit{Spread} = \alpha_0 + \alpha_1 \mathit{HRTP} + \alpha_2 \mathit{Event} + \alpha_3(\mathit{HRTP} * \mathit{Event}) + \alpha_4 \mathit{Controls} \tag{2}$$



7 Attention

Social investment networks have emerged as the main source of investment advice for numerous retail investors (Cookson, Mullins, and Niessner 2024). They have also been identified as a catalyst for ongoing non-fundamental trading motives (Pedersen 2022) and as a mechanism that generates systematic noise trading (Barber, Huang, Odean, and Schwarz 2022).

I construct daily stock noisy *attention* based on the approach of Lopez Avila, Martineau, and Mondria (2024).[23] I measure how much attention a stock receives on social media by dividing the total number of posts for a stock on a given day by the total number of posts on the platform on that day Equation (5). I compute *Sahamyab* stock attention, which is an Iranian platform

[23] https://www.sahamyab.com/

Table 6. Differences-in-Differences Analysis The left-hand-side variable represents the average daily bid-ask spread measured per stock. The variable denoted as *Event* is a binary dummy variable, taking a value of one if the observation occurs after the specified event, namely the internet disruption. The *HRTP* dummy variable is set to one for observations related to the high retail trading level and zero otherwise. The interaction term captures the treatment effect. The regressions in columns (2) and (3) are controlled for political unrest with the *USD-IRR* exchange rate and its weekly volatility with *Vol-USD-IRR*, respectively. The regression in column (4) is controlled for political unrest through the proxy measure created using PCA and is named *PoliticalUnrest*. The standard errors in all columns are clustered by date.

	(1)	(2)	(3)	(4)	(5)
	Spread	*Spread*	*Spread*	*Spread*	*Spread*
High Retail Trading Portion (HRTP)	0.431***	0.372***	0.452***	0.339***	0.209***
	(21.36)	(21.46)	(21.26)	(21.42)	(22.12)
Event Dummy	0.101*	0.105*	0.108*	0.103**	0.092**
	(1.19)	(1.15)	(1.14)	(1.75)	(1.86)
*HRTP * Event*	0.231***	0.237***	0.224***	0.256***	0.204***
	(2.88)	(2.63)	(2.72)	(2.70)	(2.58)
USD to IRR Ex. Rate		0.0023*			0.0011*
		(1.62)			(1.55)*
Political Unrest				0.053 ***	0.041 ***
				(2.78)	(2.65)
Log(Size)			-0.017***		-0.008
			(-4.22)		(-4.01)
Free Float			-0.031***		-0.028***
			(-3.25)		(-3.22)
B/M			0.012***		0.011***
			(2.75)		(2.56)
Constant	0.516***	0.651***	0.328***	0.403***	0.311***
	(39.36)	(39.12)	(38.44)	(38.73)	(42.21)
Observations	29,403	29,403	29,403	29,403	29,403
R^2	0.562	0.571	0.586	0.582	0.561

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

similar to *StockTwits*, as follows:

$$\text{StockAtt}_{i,t} = \frac{\text{posts}_{i,t}}{\sum_{i=1}^{N} \text{posts}_{i,t}} \tag{3}$$

where $\text{posts}_{i,t}$ is the number of posts for stock i on date t. The denominator is the sum of posts for all stocks on StockTwits on date t.

Then, I classify stocks into daily high and low attention categories based on daily average attention. The *HATT* is a dummy variable set to on if the daily stock attention of a particualr stock is greater than the average of the daily attention. This dummy variable serves as a proxy for stocks appealing to noise traders. *ID* is the continuous measure of internet disruption and is calculated based on Equation (4) as described in Section 4. For each day, I construct the average connectivity based on analyzing NetBlocks' connectivity graphs.

$$ID = 100\% - Connectivity\% \tag{4}$$

$$Spread = \beta_0 + \beta_1 HATT + \beta_2 ID + \beta_3 (HATT * ID) + \beta_4 Controls \tag{5}$$

I run the regression analysis based on 5. The findings are reported in Table 7. As expected, β_1 is negative and significant suggesting the fact that stocks with a higher level of attention are more liquid. the β_2 coefficient is positive and significant which is supporting the fact that higher disruption leads to more noise traders crowded out which result in higher spread resulting lower liquidity. The β_3 coefficient captures the interaction effect and is significantly positive. Liquidity is marginally more affected by internet disruption in stocks with high attention.

8 Impact on Informed Trading

In this section, I analyze the impact of the absence of noise traders on the *Relative Trading Volume* of a group of informed traders. I use the trading codes associated with portfolio management contracts as a proxy for informed trading. [24] Notably, portfolio managers have access to private network trading platforms, which remain unaffected by the Internet disruption.

[24] The CSDI company issues unique codes beginning with the letters *PRX* for all such contracts. The assets under these codes belong to investors but are managed by portfolio managers.

Table 7. Stock Attention The left-hand-side variable represents the average daily bid-ask spread measured per stock. The variable denoted as *ID* is the continuous measure of internet disruption. The *HATT* dummy variable is set to one for stocks having higher-than-daily average attention. The interaction term, *HATT*ID*, captures the treatment effect. The regressions in columns (2) and (3) are controlled for political unrest using the *USD-IRR* exchange rate and its weekly volatility, *Vol-USD-IRR*, respectively. The regression in column (4) is controlled for political unrest through the proxy measure created using PCA, named *PoliticalUnrest*. The standard errors in all columns are clustered by date. Stocks with a history of fewer than five days of discussion during the study period are excluded from the observations. The study period is from September 1st to November 1st, 2022.

	(1)	(2)	(3)	(4)	(5)
	Spread	*Spread*	*Spread*	*Spread*	*Spread*
High Attention Stocks (HATT)	-0.512***	-0.522***	-0.452***	-0.511***	-0.305***
	(-2.72)	(-2.83)	(-3.02)	(-3.14)	(-3.02)
Internet Disruption Measure (ID)	0.122***	0.112***	0.108***	0.103***	0.082***
	(3.19)	(4.05)	(4.14)	(3.75)	(4.22)
*HATT * ID*	0.422***	0.433***	0.421***	0.376***	0.314***
	(3.18)	(3.62)	(3.82)	(3.44)	(3.11)
USD to IRR Ex. Rate		0.004*			0.002*
		(1.64)			(1.67)
Political Unrest			0.062		0.055 ***
			(2.46)		(2.44)
Log(Size)			-0.022***		-0.016
			(-3.28)		(-3.12)
Free Float			-0.025***		-0.019***
			(-3.16)		(-3.18)
B/M			0.006**		0.004***
			(1.95)		(2.02)
Constant	1.263***	1.233***	1.338***	1.423***	1.044***
	(3.61)	(3.52)	(3.46)	(3.75)	(3.22)
Observations	18,235	18,235	18,235	18,235	18,235
R^2	0.522	0.532	0.452	0.475	0.423

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The relative trade volume (RTV) is calculated using Equation (6). A RTV value greater than one suggests higher-than-average volume, indicating increased interest or participation. Conversely, a RTV value less than one implies lower-than-average volume. Where n is the total number of trading days in the six-week period starting on Sep. 7th, 2022. The V_i represents the trading volume on day i within the six-week history. The V_{current} is the trading volume on the current day.

$$RTV = \frac{V_{\text{current}}}{\frac{1}{n}\sum_{i=1}^{n} V_i} \tag{6}$$

I run the regression based on Equation (7), and the findings are reported in Table 8. The results show that the relative daily trade volume of informed traders decreases significantly during the absence of noise traders from the market. This finding can be interpreted in three ways. First, the absence of noise traders may result in fewer counterparties for informed traders, reducing overall market liquidity. This lack of liquidity can discourage informed traders from executing large trades, as such trades could have a more pronounced impact on prices. Second, the absence of noise traders can lead to wider bid-ask spreads and higher transaction costs, as fewer participants are available to absorb trades. This increase in trading costs may further disincentivize informed traders from engaging in the market. Third, the decrease in informed traders' activity might suggest that their ability to trade optimally is compromised without the presence of noise traders. Informed traders often rely on noise traders to mask their trades, thereby reducing the risk of moving the market. Without this "cover," informed traders may become more hesitant to trade, potentially impairing price discovery and market efficiency.

$$\textit{RelativeTradingVolume (RTV)} = \alpha_0 + \alpha_1 \textit{Event} + \alpha_2 \textit{Controls} \tag{7}$$

9 Price Efficiency

In this section, I study the effect of noise trader elimination from the market on price efficiency through two channels. The first analysis highlights that information asymmetry due to severe social media disruption in certain regions results in a wider closer price gap. The second analysis suggests that the speed at which information is incorporated into prices is slower after noise trader removal from the market. The third test studies the abnormal return of the stocks

Table 8. Informed Traders Behaviour Analysis The variable denoted as *Event* is a dummy variable, taking a value of one if the observation occurs during the internet disruption. The *RTV* is the relative trading volume calculated by dividing the daily trade volume of PRX codes by the six-week average trading volume of PRX. The observations are related to the TSE over six weeks, of which two weeks experienced internet disruption. The regressions in columns (2) and (3) are controlled for political unrest with the *USD-IRR* exchange rate and its weekly volatility with *Vol-USD-IRR*, respectively. The regression in column (4) is controlled for political unrest through the proxy measure created using PCA and is named *PoliticalUnrest*.

	(1)	(2)	(3)	(4)
	RTV	*RTV*	*RTV*	*RTV*
Event Dummy	- 0.412**	- 0.3320**	- 0.432**	- 0.381**
	(-2.12)	(-3.01)	(-3.25)	(-3.53)
USD to IRR Ex. Rate		-0.3320*		
		(-1.72)		
Political Unrest				0.0132***
				(2.83)
Constant	0.36	0.41	0.46	0.38
	(0.22)	(0.12)	(0.31)	(0.28)
Observations	1,873,552	1,873,552	1,873,552	1,873,552
R^2	0.374	0.561	0.462	0.662

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

among high and low retail trading percentage stocks. The findings suggest that noise traders' elimination from the market, degrades price efficiency.

9.1 Price Impact

I examine the effect of social media disruptions on price impact by comparing trades initiated from regions experiencing social media disruptions, referred to as *SMRegions*, with those from non-disrupted regions. I hypothesize that regions with social media restrictions will exhibit *blind* trading behavior, characterized by a higher relative price gap in order submissions, which in turn leads to a greater price impact due to reduced access to information and increased uncertainty.

$$Price\ Impact = \frac{P_{post\text{-}trade} - P_{pre\text{-}trade}}{P_{pre\text{-}trade}} \tag{8}$$

where:

- $P_{\text{pre-trade}}$ is the price of the asset before the trade.
- $P_{\text{post-trade}}$ is the price of the asset immediately after the trade.

I attribute trades to locations based on the locations of their brokerage houses.[25] I define a dummy variable *SMRegion* to mark regions with social media restrictions during the internet disruption. Regions such as Western, Southern provinces and Tehran experienced the highest social media disruption due to the nature of the protests in my analysis as depicted in Appendix Figure 9. This variable is set to one if the region meets three conditions: first, the *Fatalities* measure is greater than average; second, the Internet disruption *(ID)* measure is greater than average; and third, the Netblocks' textual analysis includes *restriction* remained, applied or aggravated along with the words *Telegram*, *Instagram*, *Twitter*, *Social Media*, and *Whatsapp*.

I measure the immediate price impact based on the change in stock price resulting from trades 8. I run the regression based on Equation (9). The sign of β_1 indicates the effect of social media absence on trading dynamics in Province A. Table 9 reports the findings. A significantly positive price impact is observed from trades initiated in regions where social media is disrupted. The results suggest that social media censorship leads to a higher price impact of trades compared to other regions. This can be attributed to two interpretative channels. First, reduced information flow: traders in social media-restricted regions have less access to real-time information, leading to more uninformed or speculative trades, which could cause larger

[25]Traders initiate KYC process with a brokerage house opening a trading account. Regardless of whether traders submit orders online or offline, these orders are routed to the trade engine using their brokers back-office. Traders typically maintain a financial relationship with the same brokerage house unless they move to a different location or switch brokers. While this method is not entirely accurate, as traders can trade online while in a different physical location or traveling, it largely matches traders with their locations for the purposes of my research.

price movements for a given trade volume. Second, increased uncertainty: the absence of social media causes prices to react more strongly to trades, as market participants may interpret these trades as signals of significant new information.

$$\mathit{PriceImpact} = \beta_0 + \beta_1 \mathit{SMRegion} + \beta_2 \mathit{OrderVolume} + \beta_3 \mathit{Spread} + \beta_4 \mathit{Volatility} + \beta_5 \mathit{PoliticalUnrest} \tag{9}$$

Table 9. Price Impact The dependent variable is *Price Impact*, representing the immediate percentage change in stock price resulting from trades. The variable *SMRegion* is a dummy variable indicating whether the order is submitted by investors facing social media disruption, including those from Western or Southern provinces and Tehran (set to one) or not (set to zero). The variable *Order Volume* represents the volume of orders placed per stock per day. The variable *Spread* serves as a proxy for measuring liquidity per stock per day. The variable *Volatility* captures the daily stock price volatility. The regression in column (2) includes a control for political unrest through a proxy measure created using PCA, referred to as *Political Unrest*. The sample comprises four weeks of observations, spanning from September 16th to October 16th, 2022. The standard errors are clustered at the date level.

	(1) *Price Impact*	(2) *Price Impact*
Social Media Restricted Region (SMR)	0.075 ***	0.072 ***
	(5.43)	(5.12)
Order Volume	0.012 ***	0.013 ***
	(4.25)	(3.82)
Spread	0.030***	0.026***
	(3.02)	(3.83)
Volatility	0.0082***	0.0075***
	(4.12)	(4.03)
Political Unrest		0.0211**
		(1.83)
Constant	0.51	0.44
	(0.22)	(0.42)
Observations	121,323,401	121,323,401
R^2	0.562	0.533

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

9.2 Price Update Frequency

In this test, I calculate the price update frequency of each stock per day as a proxy for measuring how fast information is incorporated into prices. The stocks with a higher number of price update messages in the specific trading volume range, referred to as the *base volume*, exhibit a higher frequency of price updates during the day. I calculate the price update frequency for *HRTP* and *LRTP*. The formula for price updates in the Tehran Stock Exchange is described in Equation (10). After each price update, a message is sent to the trading engine. The price update itself is related to the trade volume of each stock, which is comparable to the base volume for each stock.

$$ClosePrice_t = \begin{cases} VWAP = (Price_i * Volume_i)/\Sigma_{i=1}^{t} Volume_i, & \text{if } Volume_i <= BaseVolume_t \\ ClosePrice_{t-1} + ((\Sigma_{i=1}^{t} Volume_i)/BaseVolume_t) * (VWAP - ClosePrice_{t-1})), & \text{Otherwise} \end{cases} \tag{10}$$

I set the dummy variable *Blackout* to one for regions experiencing connectivity bellow 50%. Using Equation (11), I study the effect of internet disruption on the frequency of price updates for *HRTP* stocks which are appealing to noise traders. As reported in Table 10, *HRTP* stocks have a lower frequency of price updates during the blackout, leading to a slower incorporation of information into prices at 46.8% due to the elimination of noise traders from the market.

$$PriceUpdateFreq. = \alpha_0 + \alpha_1 HRTP + \alpha_2 Blackout + \alpha_3 (HRTP * Blackout) + \alpha_4 Controls \tag{11}$$

9.3 Abnormal Return

Abnormal returns *AR* represent the excess return that an investment or portfolio generates over a predicted rate of return. I calculate this measure based on the *TEDPIX* market index. The formula for calculating abnormal return involves comparing the actual return generated by the

Table 10. Price Update Frequency The observations are balanced for two weeks before and after the internet disruption on Sep. 16th, 2022. The *Price Update Freq.* variable represents the daily frequency of price updates for each stock, recorded as a percentage of the total updates for all stocks. The stocks are classified based on high and low retail trading types. The *HRTP* dummy variable is set to one if the stock is of high retail trading type. The *Blackout* variable is a dummy set to one if the trading location experienced more than 80% internet disruption based on the NetBlocks report. The regression in column (2) is controlled for political unrest through the proxy measure created using PCA and is named *PoliticalUnrest*.

	(1)	(2)
	Price Update Frequency(%)	*Price Update Frequency(%)*
High Retail Trading Portion (HRTP)	0.121 **	0.112 **
	(1.83)	(2.04)
Blackout Dummy	-0.203 ***	-0.185 ***
	(-2.22)	(-2.45)
*HRTP*Blackout*	-0.386***	-0.422***
	(-2.82)	(-3.01)
Political Unrest		0.032 **
		(1.89)
Constant	0.31	0.21
	(0.14)	(0.54)
Observations	6,014,752	6,014,752
R^2	0.345	0.671

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

investment with the expected return based on market performance. I also calculate the Cumulative Abnormal Return *CAR* over several periods, including 1 day, 3 days, 1 week, 2 weeks and 1 month after the incident. This provides insights into how an investment performs relative to overall market conditions or its expected performance.

The Cumulative Abnormal Return CAR_t at time t is calculated using Equation (12). The R_{it} is the actual return of stock i at time t, the $beta_i$ is the Beta (systematic risk measure) of stock i and the R_{mt} is the Return of the market or benchmark at time t which in this analysis is the market index.

$$CAR_t = \sum_{i=1}^{t}(R_{it} - \beta_i R_{mt}), \tag{12}$$

By regression Equation (13), I study the effect of removing noise traders from the market by examining the *CAR* of *HRTP* stocks. As reported in Table 11, when noise traders are removed from the market due to internet disruptions, the *CAR* decreases significantly for *HRTP* stocks. This highlights the fact that noise traders consistently lose in the market, especially in their preferred types of stocks.

$$CAR = \alpha_0 + \alpha_1 HRTP + \alpha_2 Event + \alpha_3 (HRTP * Event) + \alpha_4 Controls \tag{13}$$

Table 11. Cumulative Abnormal Return The observations are balanced for four weeks including two weeks before and after the internet disruption on Sep. 16th, 2022. The *CAR* is the cumulative abnormal return variable calculated in 1 day, 3 days, 1 week, and one month for each stock. The stocks are classified based on high and low retail trading types. The *HRTP* dummy variable is set to one if the stock is greater than the average high retail trading percentage in the 2022 sample. The *Event* variable is a dummy set to one if the observation falls in the event period. The *HRTP*Event* is the interaction term capturing the effect. The regressions are controlled for political unrest through the proxy measure created using PCA and are named *PoliticalUnrest*.

	(1)	(2)	(3)	(4)	(5)
	1 day CAR	*3 days CAR*	*1 Week CAR*	*2 Weeks CAR*	*1 Month CAR*
High Retail Trading Portion (HRTP)	0.0522	0.0412***	0.0619***	0.0537***	0.0273***
	(1.43)	(2.36)	(2.34)	(2.31)	(3.30)
Event Dummy	0.0712	-0.0928**	-0.0190**	-0.0417***	-0.0872***
	(0.44)	(2.13)	(2.41)	(2.60)	(2.69)
*HRTP*Event*	-0.0019	-0.0095**	-0.0721***	-0.0861***	-0.0640*
	(-0.99)	(-1.88)	(-2.88)	(-3.94)	(-1.76)
Political Unrest	0.0241***	0.0245***	0.0237***	0.0312***	0.0212***
	(3.02)	(4.12)	(2.82)	(2.63)	(4.03)
Constant	0.0005	0.0056*	0.0113**	0.0253**	0.0534**
	(0.05)	(1.90)	(2.23)	(2.45)	(2.55)
Observations	7,253	7,253	7,253	7,253	7,253
R^2	0.301	0.243	0.512	0.262	0.352

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

10 Firm Specific Analysis

In this section, I evaluate firm-specific features such as free float, firm size, earnings per share (EPS), and book-to-market ratio (B/M) on one-week and two-week abnormal returns before and after the internet disruption. The findings are summarized in Table 12.

1-week CAR	**Before**	**During**	**After**
Free Float			
Low	0.0421 (5.22)	-0.0009 (-6.34)	-0.0014 (-7.14)
High	0.0018 (4.11)	0.0002 (1.91)	0.0003 (2.63)
Observations	1,892	2,809	1,167
R^2	0.31	0.22	0.45
EPS			
Low	0.0385 (2.44)	-0.0052 (3.52)	0.00 49 (1.35)
High	0.0083 (3.15)	-0.0081 (1.22)	-0.0085 (-1.41)
Observations	2,412	3,425	2,352
R^2	0.42	0.36	0.37
Log (Size)			
Low	0.0312 (4.52)	-0.0208 (-1.72)	-0.0315 (-3.25)
High	0.0115 (3.61)	0.0147 (1.95)	0.0127 (3.89)
Observations	2,321	2,912	3,041
R^2	0.38	0.33	0.41
B/M			
Low	0.0252 (2.75)	-0.0174 (-3.11)	0.0247 (2.63)
High	0.0411 (3.25)	0.0325 (1.23)	0.0462 (3.42)
Observations	1,712	2,812	2,115
R^2	0.37	0.44	0.52

Table 12. Firm Specification Analysis The *Before* period is one week before Sep. 16, 2022. The *During* period starts on Sep. 16, 2022, when noise traders were removed. The *After* period starts on Oct. 16, 2022, when noise traders return to the market. The coefficients of regressions are reported in each cell. The left-hand side variable is the 1-week CAR. The right-hand side variables are *Free Float*, *EPS*, *Log(Size)* and *B/M*. The numbers reported in parentheses indicate the significance of the analysis.

Noise traders are more attracted to markets or stocks where they can generate volatility, often seen in lower free-float stocks due to their higher price sensitivity and limited liquidity. The findings show that low free-float stocks had a significant positive CARs of 4.21% before noise traders were removed, which turned slightly negative to -0.09% during their absence and further declined to -0.14% after their return. High free-float stocks, in contrast, consistently exhibited positive CARs before, during, and after the periods of noise trader activity. This suggests that low free-float stocks are more sensitive to the presence and absence of noise traders, showing significant fluctuations in their abnormal returns, while high free-float stocks maintain stable, albeit smaller, positive returns regardless of noise trader activity.

Noise traders tend to prefer small-cap stocks over large-cap stocks. This preference is driven by several factors, including the higher potential for price movement and the greater impact of their trades on smaller, less liquid stocks. The results indicate that smaller companies, *Low log(size)*, had significant positive CARs of 3.12% before noise traders were removed, which turned negative to -2.8% during their absence and further decreased to -3.5% after their return. In contrast, larger companies, *High log(size)*, consistently exhibited positive CARs before, during, and after the periods of noise trader activity. This suggests that smaller companies are more sensitive to noise trader presence, while larger companies maintain stable, positive returns regardless of noise trader activity.

Noise traders tend to prefer stocks with lower earnings per share *EPS*. This is supported by the fact that small-cap firms, which typically have *Low EPS* and less analyst coverage, offer greater earnings surprise potential and are more attractive to noise traders. These stocks have more opportunities for unexpected gains, drawing in noise traders who often look for under-researched or less popular stocks where their trading activities can have more significant impacts. The results show that *Low EPS* stocks had significant positive CARs before noise traders were removed, which turned negative to -0.52% during their absence, and remained slightly positive at 0.49% after their return. *High EPS* stocks, in contrast, exhibited a positive CARs of 0.83% before, turned negative to -0.81% during, and further declined to -0.85% after the periods of noise trader activity.

These findings suggest that *Low B/M* stocks are more susceptible to noise trader influence, experiencing overvaluation in their presence and correction in their absence, while *High B/M* stocks exhibit greater resilience to changes in noise trader activity, maintaining positive returns throughout all periods. *Low B/M* stocks (growth stocks) are often more volatile, receive more media attention and hype and are associated with trending sectors, which aligns with the speculative and often irrational behavior of noise traders. *High B/M* stocks (value stocks) tend to be less attractive to noise traders because they offer fewer opportunities for speculative gains. *Low B/M* stocks exhibit positive and significant CARs of 2.52% when noise traders are present in the market. However, upon the removal of noise traders, these stocks experience a stark reversal, with negative CARs of -1.74%, indicating a substantial correction in their valuation. The return of noise traders to the market restores the positive CARs for *Low B/M* stocks to 2.47%, nearly identical to the initial period. In contrast, *High B/M* stocks demonstrate more stability across all periods. They show positive and significant CARs of 4.11% with noise traders present, maintain positive but insignificant CARs of 3.25% when noise traders are removed, and experience the highest CARs of 4.62% upon the return of noise traders.

11 Robustness Tests

I conduct four tests to evaluate the robustness of my findings. The first test examines changes in the bid-ask spread during unrest incidents, comparing periods with and without internet disruptions. The second test investigates whether in-person trade submissions increase following an internet disruption. The third test assesses the effect of internet disruption on order imbalance in the market, using it as a proxy to highlight the removal of noise traders. The fourth test measures the price impact by analyzing the relative closing price gap between social media-restricted regions and those unaffected.

11.1 Unrest Incidents

In this section, I investigate the significance of the average daily bid-ask spread change following six major political unrest events in Iran. Table 13 presents the findings. In two instances where internet connectivity is disrupted, the average daily bid-ask spread increases significantly. This analysis rejects the hypothesis that the observed rise in the bid-ask spread solely stems from political unrest and not from the noise traders' removal from the market.

Table 13. Unrest Incidents The regression results for six event studies are reported in this table. For each event, the average daily bid-ask spread, *Avg Daily Spread* is calculated for three consecutive trading days, including one day before the event, the event day, and the day after. The event is represented by a dummy variable set to one on the day of the event or the first trading day if the event occurs on a non-trading date and time. Internet disruption in Iran for *Sep.2022Event* and *GasPrice2019Event* is reported in the related time period, while it is not reported for the other ones. (see Appendix F).

	(1) *Spread*	(2) *Spread*	(3) *Spread*	(4) *Spread*	(5) *Spread*	(6) *Spread*
Sanction 2018	-1.78 (-0.79)					
Trump 2019		2.327 (0.47)				
GasPrice 2019			0.596*** (2.82)			
Strike 2020				1.23 (0.34)		
Flight 2020					-3.01 (-0.34)	
September 2022						6.63*** (12.05)
Constant	2.69 (1.06)	2.63 (1.08)	2.31 (0.23)	3.05 (0.53)	5.04 (1.04)	7.28 (1.26)
Observations	1,227	1,311	1,284	1,403	1,385	1,470
R^2	0.432	0.643	0.897	0.532	0.534	0.681

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

11.2 User Response to Internet Disruption

I study the user response to internet disruption through two channels. The first channel is the change in user behavior by evaluating a shift from online to in-person order submissions through relative trading volume. The second channel involves counting the number of daily posts and likes on social media platforms before and after the incident to measure the severity of the internet disruption.

Iran has twenty-three regional trading floors. These in-person trading venues are open to both individual and institutional traders for in-person order submissions. Following an internet disruption, I expect a noteworthy surge in trading volume on these floors, as online trading channels were disrupted. To evaluate this hypothesis, I measure the relative trading volume of each trading venue based on Equation (6).

$$\textit{Relative Trading Volume (RTV)} = \beta_0 + \beta_1 \textit{West} + \beta_2(\textit{West} * \textit{Event}) + \beta_3 \textit{PoliticalUnrest} \quad (14)$$

Table 19 reports the trading venue classification in Iran in Appendix Section B. To examine whether the location-spread relation varies geographically with the location of the trading venue, I include a *West* dummy variable and its interaction with Event as regressors in Equation (14). The *West* dummy variable takes the value of one if the trade is initiated from the western provinces of Iran.[26]

Table 14 reports evidence indicating that following the internet disruption, the western provinces experienced a significant increase in relative trading volume compared to the other four zones during the event. As depicted in Figure 5, full internet blockage is reported in Kurdistan by NetBlocks. This supports the hypothesis that investors had limited access to online trading platforms during the event.[27] On the other hand, trading venues situated on the west

[26] Because Mahsa Amini was born and raised in a Kurdish family in Saqqez, Kurdistan Province, on the west side of Iran. https://www.theguardian.com/world/2022/sep/17/iran-protests-death-kurdish-woman-mahsaa-amini-morality-police

[27] https://netblocks.org/reports/internet-disrupted-in-iran-amid-protests-over-death-of-mahsa-amini-X8qVEwAD

side exhibit a non-significant and positive influence on overall trading volume before the event for 3.346%. However, during the study period, the contribution of in-person trade submission increases significantly to 29.99%. This finding supports the hypothesis that internet disruption affects user behaviour because of market access disruption and prompts traders to participate in the nearest trading venue for order submissions.

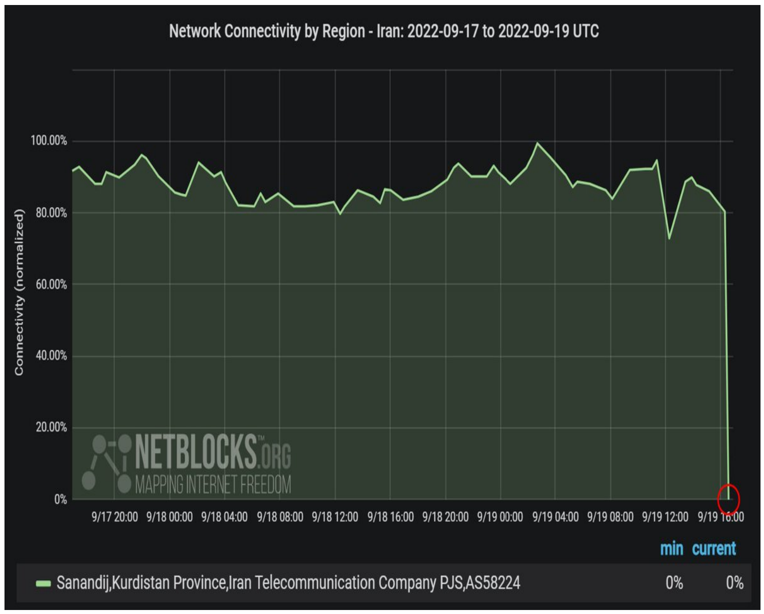


Figure 5. Internet Blockage in Western Regions The NetBlocks real-time network connectivity by region data reveals near-total disruption in the western provinces of Iran due to the protests in this location. Kurdistan is a western province in Iran that witnessed the first and largest protests with the least internet access.

To evaluate the user response to internet disruption, I measure the daily number of likes and posts on *Telegram* and *Twitter* to study the severity of internet disruption on social media activity. The average number of posts per day dropped by 34.63% and 62.78% on Telegram and Twitter, respectively, due to the internet disruption. Table 15 reports the regression analysis based on Equations (15) and (16). As reported, after the internet disruption, the number of posts and likes dropped significantly on both platforms.

$$DailyPosts = \gamma_0 + \gamma_1 Event \tag{15}$$

Table 14. Location-based Relative Trading Volume The dependent variable is the daily *In-person Relative Trading Volume* of orders submitted across various trading venues. Online trading orders are excluded from this analysis. The nationwide trading venues are categorized into North, East, West, South, and Center. To highlight the West trading venues, a *West* dummy variable is employed, set to one and zero otherwise. The *Event* is a dummy variable set to one during the event. The interaction term *West*Event* captures the coefficient of interest. Observations are selected from a two-week balanced sample before and after the event. The regression in column (2) is controlled for political unrest through the proxy measure created using PCA and is named *PoliticalUnrest*.

	(1)	(2)
	In-person RTV	*In-person RTV*
West Dummy	0.334^{*}	0.283^{*}
	(1.23)	(1.42)
*West*Event Dummy*	0.29^{***}	0.31^{***}
	(3.21)	(3.45)
Political Unrest		0.023^{*}
		(1.45)
Constant	8.26^{*}	7.21
	(1.35)	(0.72)
Observations	1,080	1,080
R^2	0.524	0.455

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$$\mathit{DailyLikes} = \beta_0 + \beta_1 \mathit{Event} \tag{16}$$

11.3 Order Book Imbalance

Order imbalance in the stock market refers to a situation where there is an unequal distribution of buy and sell orders at a particular price level or for a specific security (Chordia, Roll, and Subrahmanyam 2002). This imbalance occurs when the quantity of buy orders (demand) significantly exceeds or falls short of sell orders (supply), or vice versa. Order imbalances often reflect shifts in sentiment and noise trading behavior. When there is a significant imbalance in

Table 15. Social Media Reaction In this table, the number of daily likes and posts before and after the internet disruption is studied through regression analysis. The observations cover a four-week period: two weeks before Sep. 16th, 2022, and two weeks after, with the *Event Dummy* set to one. The standard errors are clustered at the date level. Columns (1) and (2) pertain to the daily number of likes and posts on *Telegram*, while columns (3) and (4) pertain to *Twitter*.

	(1)	(2)	(3)	(4)
	Telegram Daily Likes	*Telegram Daily Posts*	*Twitter Daily Likes*	*Twitter Daily Posts*
Event Dummy	-7,334,135***	-1,728.10***	-8.36e+07***	3,061.12***
	(-3.97)	(-4.94)	(-2.96)	(-2.73)
Constant	1.60e+07***	4825.84***	3061.12***	2,922.08***
	(9.36)	(14.88)	(6.51)	(9.68)
Observations	308,053	308,053	115,440	115,440
R^2	0.212	0.233	0.221	0.233

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

buy or sell orders, it indicates a potential mismatch in supply and demand at current price levels. This imbalance can lead to price adjustments as market participants react to the perceived value and sentiment-driven trading (Barber, Odean, and Zhu 2006).

In this test, I study the effect of noise traders removal from the market through *Order Book Imbalance(OBI)*. Noise traders can cause increased market volatility and significant price movements due to their irrational trading behavior. When noise traders exit the market a significant drop in order imbalance indicates that the market is returning to a state where buy and sell pressures are more evenly matched, reflecting more rational trading based on fundamental values. I test this fact through the regression in Equation (17). Table 16 reports the findings that during the internet disruption and noise traders' removal from the market, the average daily OBI decreases significantly.

$$OBI = \beta_0 + \beta_1 Event + \beta_2 PoliticalUnrest \tag{17}$$

Table 16. Order Book Imbalance The *Daily Average OBI* is the average daily OBI in a three-best limit order book. The *Event* is a dummy variable set to one during the event. The regression in column (2) is controlled for political unrest through the proxy measure created using PCA and is named *PoliticalUnrest*. The standard errors are reported at the date level.

	(1)	(2)
	Daily Average OBI	*Daily Average OBI*
Event	-0.0013***	-0.0011***
	(-58.36)	(-48.32)
Political Unrest		0.102*
		(1.42)
Constant	0.670***	0.023***
	(3.13)	(2.31)
Observations	13,343,515	13,343,515
R^2	0.032	0.041

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

11.4 Relative Price Gap

This test aims to analyze the temporal and spatial variations in internet and social media disruptions during the study and their impact on investor behavior and price discovery. I hypothesize that social media-restricted regions will exhibit *blind* trading behavior, evidenced by a higher relative price gap in order submissions.

I define a dummy variable *SMRegion* to mark the most social media affected regions during the event. This variable is set to one if the region meets three conditions: first, the *fatalities* measure is greater than average; second, the Internet disruption *(ID)* measure is greater than average; and third, the Netblocks' textual analysis includes *restriction* remained, applied or aggravated along with the words *Telegram*, *Instagram*, *Twitter*, *Social Media*, and *Whatsapp*. Regions such as Western, Southern provinces and Tehran experienced the highest social media disruption due to the nature of the protests as depicted in Appendix Figure 9.

I measure the relative close price gap per stock between orders submitted by investors in regions experiencing the highest social media disruption, where *SMRegion* is equal to one, and other regions, where *SMRegion* is equal to zero. The *Relative Close Price Gap* is the difference between each individually submitted order and the final closing price of the stock at the end of the trading day, as defined by Equation (18).

$$RelativePriceGap_i = (|DailyClosePrice_i - OrderPrice_i|)/DailyClosePrice_i \tag{18}$$

I use this proxy to measure the inability of traders to gain investment insights due to internet disruption, which potentially impacts their trading decisions. I run the regression based on Equation (19). Table 17 reports the findings. A significantly wider close price gap is observed in regions where *SMRegion* is equal to one, compared to regions where *SMRegion* is equal to zero. This aligns with the hypothesis that social media disruption leads to information asymmetry, resulting in less efficient trading decisions.

$$\mathit{RelativePriceGap} = \alpha_0 + \alpha_1 \mathit{SMRegion} + \alpha_2 \mathit{Event} + \alpha_3 (\mathit{SMRegion} * \mathit{Event}) + \alpha_4 \mathit{PoliticalUnrest} \tag{19}$$

12 Conclusion

This study represents the first empirical contribution to address the theoretical debate about the role of noise traders in market efficiency within a causal framework, focusing on two key channels: market access asymmetry and geographical information asymmetry. By systematically investigating the impact of noise trading in emerging markets, this research explores the causal link between the absence of noise traders and its effect on fair market pricing. It also advances our understanding of how information asymmetry influences price formation, contributing sig-

Table 17. Relative Close Price Gap The table reports results from a regression analysis where the dependent variable is the daily percentage of *Relative Gap*, representing the relative close price difference between the order and the daily closing price of a specific stock. The sample comprises orders placed between September 16th and October 16th, 2022. The variable *SMRegion* is a dummy variable indicating whether the order is submitted by investors facing social media disruption, such as those in the Western or Southern provinces and Tehran (set to one) or not (set to zero). *SMRegion* is set to one if the location meets three conditions: *fatalities* greater than average, Internet disruption *(ID)* greater than average, and the Netblocks' textual analysis includes restrictions along with the words *Telegram*, *Instagram*, *Twitter*, *Social Media*, and *Whatsapp*. Similarly, *Event* is a dummy variable set to one for observations during the event and zero otherwise. The coefficient of interest pertains to the interaction term between *SMRegion* and *Event*. The regression in column (2) is controlled for political unrest through a proxy measure created using PCA, named *PoliticalUnrest*. The observations are only for in-person (offline) orders during the event analysis.

	(1)	(2)
	Relative Gap(%)	*Relative Gap(%)*
Social Media Restricted Region (SMR)	0.543 *	0.410 *
	(1.13)	(1.22)
Event Dummy	0.152 ***	0.143 ***
	(3.23)	(3.62)
*SMR*Event*	0.352***	0.314***
	(3.02)	(3.83)
Political Unrest		0.281**
		(1.87)
Constant	0.52	0.54
	(0.24)	(0.42)
Observations	24,425,322	24,425,322
R^2	0.463	0.427

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

nificantly to the empirical market microstructure literature.

Utilizing a Differences-in-Differences (DiD) framework, this paper examines the causal effects of unforeseen internet disruptions on market efficiency through the lenses of information asymmetry and market access asymmetry. The findings show that the absence of noise traders slows the incorporation of information into prices, leading to decreased liquidity and reduced market depth. Additionally, firm-specific analysis reveals that stocks with a lower free float percentage are less impacted by these disruptions. Social media censorship further exacerbates information asymmetry, widening the relative closing price gap in regions affected by internet disruptions.

This research provides valuable insights into the dynamics of emerging markets, offering practical implications for both academic researchers and policymakers. It contributes to the understanding of the market-priced risks associated with access disruptions in a causal empirical context.

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A Variable Definition

#	Variables	Description
1	Bid-ask spread	The amount by which the asking price exceeds the bid price for an asset in the market.
2	Free float	Those shares are readily available for trading in the stock market and are not restricted by the government or specific shareholders.
3	Market liquidity	Refers to the ease with which a security can be converted into ready cash without affecting its market price.
4	Price volatility	Represents how large an asset's prices swing around the mean price—it is a statistical measure of its dispersion of returns.
5	Market depth	Refers to the market liquidity for a security based on the number of standing orders to buy (bids) and sell (offers) at various price levels
6	Market fair price	The price security would sell in an open and competitive market where the buyer and seller have adequate information and reasonable time to complete a deal.
7	Buying power	The total buy value of the individuals is divided by the number of individual buyers.
8	RTP level	The monthly dollar value of the buy and sell initiated small trades(trade size bellow \$5,000) divided by the dollar value of its total trading volume in the same month.
9	West dummy	The dummy variable is set to one if the trading venue is related to the western provinces of Iran.
10	Political unrest	The constructed measure based on the PCA analysis has a threshold higher than 80%.
11	Financial unrest	The USD-IRR exchange rate and its weekly volatility serve as proxies for financial unrest.
12	SM regions dummy	The dummy variable is set to one if the trading regions in the country experienced social media disruption, based on the Net Blocks report.
13	Blackout dummy	The dummy variable is set to one for regions experiencing internet disruption of more than 80% based on the Net Blocks report.
14	Price update frequency	The daily frequency of price updates for each stock is recorded as a percentage of the total number of updates for all stocks. This measure is calculated based on 5j messages sent to trade engine after each trade.
15	Week i dummy	The dummy variable is set to one if the observation belongs to week number i and zero otherwise.
16	Relative trading volume	The trading volume of a trading account in each week is divided by its total trading over six weeks.
17	Close price gap	The difference between each individual submitted order price and the final closing price of the stock at the end of the trading day.
18	PRX code	The trading account is assigned to portfolio management companies. Each PRX code is created based on a financial contract between a broker and a customer.

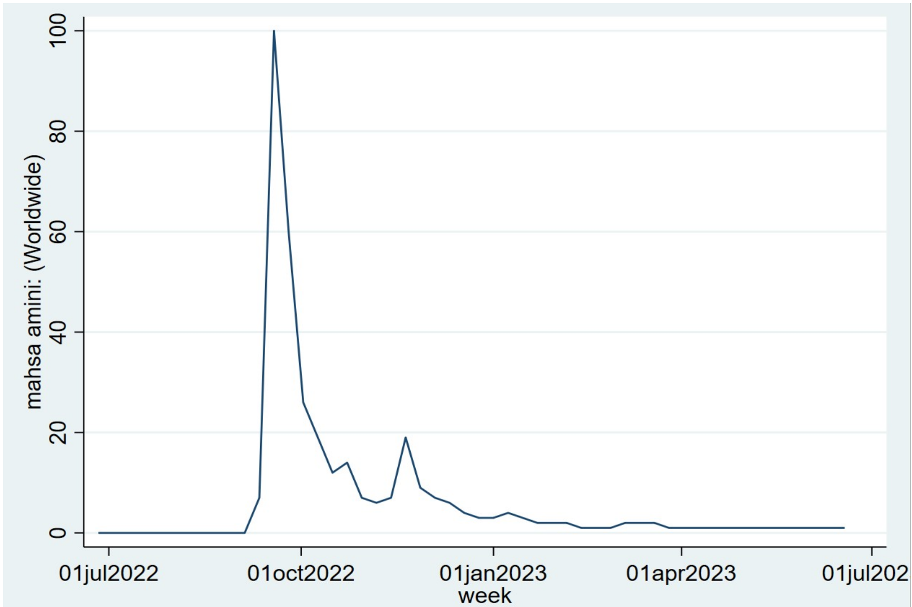
Table 18. Variables Definition The description of the variables utilized in this study is provided in this table.

B Regional trading floors

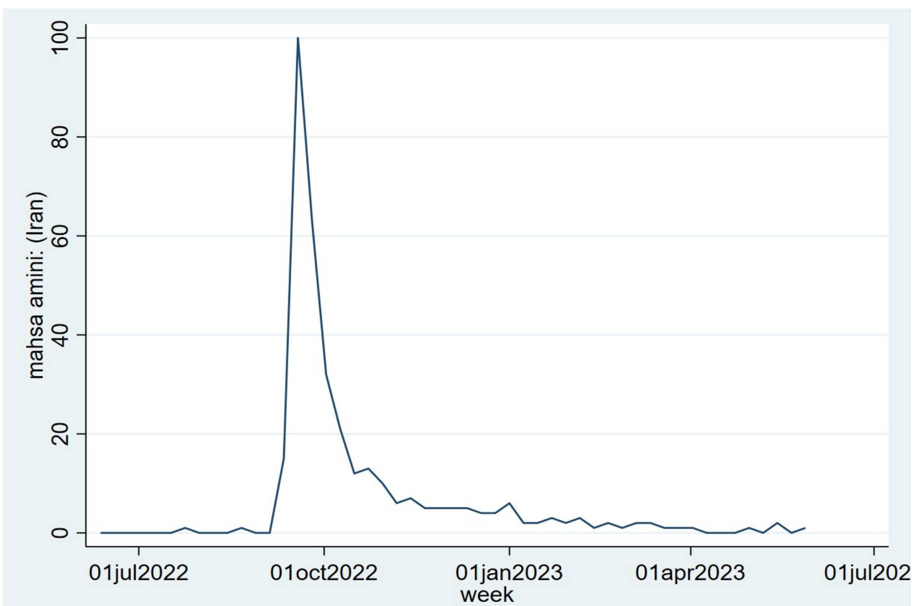
	Province (City)	Location	Zone
1	Alborz (Karaj)	West	West
2	Ardabil (Ardabil)	North-West	North
3	Azarbaijan, East (Tabriz)	North-West	North
4	Azarbaijan, West (Urmia)	North-West	North
5	Fars (Shiraz)	Center	Center
6	Gilan (Rasht)	North	North
7	Hamedan (Hamedan)	West	West
8	Hormozgan (Bandar Abbas)	South	South
9	Hormozgan (Kish)	South	South
10	Isfahan (Isfahan)	Center	Center
11	Kerman (Kerman)	East	East
12	Kermanshah (Kermanshah)	West	West
13	Khorasan, Rasavi (Mashhad)	East	East
14	Khorasan, South (Birjand)	East	East
15	Khuzestan (Ahvaz)	West	West
16	Mazandaran (Sari)	North	North
17	Qazvin (Qazvin)	West	West
18	Qom (Qom)	West	West
19	Semnan (Semnan)	Center	Center
20	Sistan and Baluchestan (Zahedan)	South-East	East
21	Tehran(Tehran)	North	North
22	Yazd (Yazd)	Center	Center
23	Zanjan (Zanjan)	West	West

Table 19. Regional Trading Floors The regional trading venues are sorted alphabetically in this table. In this study, I classified these 23 floors into five main zones: North, East, West, South and Center. The West zone is of paramount importance because of the severity of the internet blockage during Sep. 2022. The dummy variable *WestD* is set to one if the trade is initiated from the West trading floor.

C Attention



((**a**)) World-wide Attention



((**b**)) Country-wide(Iran) Attention

Figure 6. Google Trends Google Trends show the greatest attention to the death of Mahsa Amini in Sep. 2022, both worldwide and nationwide. The search for the name *Mahsa Amini* is depicted in this graph.

D Best limit analysis

In this section, I document the procedure for parsing the RLC04 message. The RLC version 1.8 message specification was published in December 2006 for the Atos Euronext trade engine. In general, only normal orders are used in calculating the best limits; that is, all orders except non-triggered Stop orders.

The limits for orders in the order book can be ranked in terms of their interest to a counterparty, with the most interesting orders listed first: 1) buy orders in descending order by price; 2) sell orders in ascending order by price. The ”best limit with a rank of N” is a summary of the buy orders and the sell orders present in the order book at the Nth best limit, as depicted in Figure 7. Therefore The ”best limit with a rank of N” is a summary of the buy orders and the sell orders present in the order book at the Nth best limit.

Best limit N is characterized by: 1) it is rank N, 2) for buy orders: the price limit for rank N, the number of orders at this limit, and the total quantity that can be executed; 3) for sell orders: the price limit for rank N, the number of orders at this price, and the total quantity that can be executed. Any change to the value of any of the above data items results in the sending of a Best Limits message.

RLC04 message is sent in three cases: 1) when one or more of the five best limits for trading instruments has changed or 2) during the pre-opening phase, or 3) when the market summary of the instrument has changed. In this research, I am focusing on the best limit messages as of modification in the order book. The place of each best limit is indicated with a flag from 1 to 5, and the market summary presence is marked with a flag 6. The rank N in the order book of the best limit with the position X in the message is equal to the position in the flags table of the Xth flag with the value of 1. For example, if the flags are 001000, the message has only one best limit, and its rank is 3.

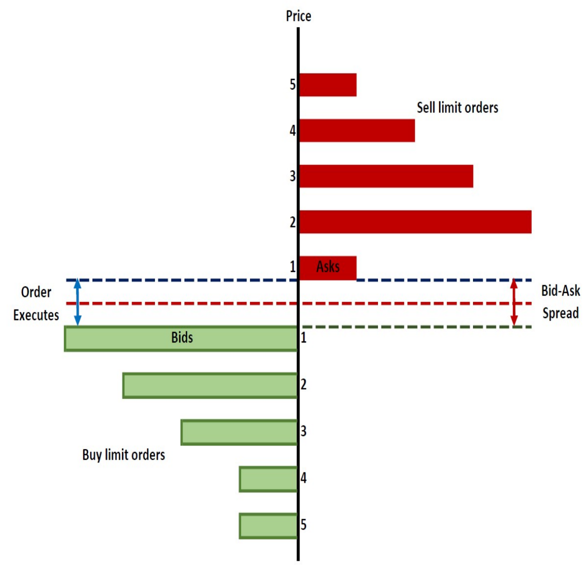


Figure 7. Bid-Ask Spread This figure shows the 5-best limits for bid-ask spread. The orders executed in the bid-ask spread limit.

{ "_id" : { "$oid" : "64b21bde54eab662626f0b6c" }, "type" : "RLC", "title" : "Best Limits", "header" : {
"RLCMessageType" : "04", "RLCHeaderType" : "1", "RLCSendingAppID" : "00",
"InstrumentMarketPlaceID" : "362", "RLCGroupCode" : "NO", "RLCSubGroupCode" : "N4",
"InstrumentID" : "IRB5SQ010341", "InstrumentMnemonicCode" : "SQ1Q1", "RLCEventDate" :
"20230715", "RLCEventTime" : "06012700" }, "content" : { "Type of orders at the origin of a trade" : "B",
"Filler" : "   ", "Change of best limit flag" : ["1", "1", "1", "1", "1", "1"], "Best limit aggregate" : [{ "Best
buy limit quantity" : "000000006000", "Number of orders at a best buy limit" : "0001", "Best buy limit
price" : "00001000000.00", "Best sell limit price" : "00001010000.00", "Number of orders at a best sell
limit" : "0001", "Best sell limit quantity" : "000000000080", "Filler" : " " }, { "Best buy limit quantity" :
"000000000000", "Number of orders at a best buy limit" : "0000", "Best buy limit price" :
"0000000000000", "Best sell limit price" : "0000000000000", "Number of orders at a best sell limit" :
"0000", "Best sell limit quantity" : "000000000000", "Filler" : " " }, { "Best buy limit quantity" :
"000000000000", "Number of orders at a best buy limit" : "0000", "Best buy limit price" :
"0000000000000", "Best sell limit price" : "0000000000000", "Number of orders at a best sell limit" :
"0000", "Best sell limit quantity" : "000000000000", "Filler" : " " }, { "Best buy limit quantity" :
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"0000", "Best sell limit quantity" : "000000000000", "Filler" : " " }, { "Best buy limit quantity" :
"000000000000", "Number of orders at a best buy limit" : "0000", "Best buy limit price" :
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"0000", "Best sell limit quantity" : "000000000000", "Filler" : " " }, { "Best buy limit quantity" :
"000000000000", "Number of orders at a best buy limit" : "0000", "Best buy limit price" :
"0000000000000", "Best sell limit price" : "0000000000000", "Number of orders at a best sell limit" :
"0000", "Best sell limit quantity" : "000000000000", "Filler" : " " }] }, "sequenceID" : { "$numberLong" :
"11916" }, "messageID" : { "$numberLong" : "11918" }, "messageDate" : 14020424, "timestamp" :
"1402/04/24-07:39:02.575" }

Figure 8. RLC04 Best Limits Messages The format of RLC04 trade engine message is depicted in this figure. Each message contains the type of the order, order origin, best limit flag change, the number of orders at the best buy limit, best buy limit quantity, best buy limit price, amount, best sell limit price, number of orders at the best sell limit, best sell limit quantity, instrument name and market.

E Principal component analysis

PCA is widely used in data analysis and machine learning for predictive models. This statistical technique achieves dimensionality reduction through three main mathematical steps, including standardizing the data, covariance matrix calculation, and Eigenvectors and Eigenvalues calculations. PCA is particularly applicable when multi-collinearity exists between the features(variables). Since political unrest is not measurable directly, I attribute six main categories of explanatory variables describing political unrest features including protest fatality, scale, war and conflicts in the region, USD-IRR exchange rate and sentiment as described in Table 20. [28] Figure 9 represents the Fatality of the protests during the study period.

In order to choose the best descriptive measure for political unrest among the predicted principal components, I follow the threshold approach as described in Jolliffe (2002) approach by setting an 80% to 90% cumulative threshold. I use this constructed and selected component in regressions as a control variable called *PoliticalUnrest*.

#	Measure	Description
1	Fatality	This is a continuous measure created based on factors such as the number of deaths, levels of violence, interventions, and strategic developments such as arrests.
2	Scale	This is a continuous measure of the number of people attending protests or demonstrations.
3	Regional Unrest	This is a binary variable set to one if there is a war or conflict in the Middle East.
5	USE-IRR Exchange Rate	The dollar-to-rial exchange rate is an indicator of political unrest, signifying a lack of trust in the national currency among users who seek to hedge their assets by holding USD.
6	Sentiment	The daily aggregated sentiment analysis of social media including Telegram and Twitter calculating based on *BERT* (Bidirectional Encoder Representations from Transformers).

Table 20. PCA Main Measures The main components of PCA analysis are described in this table.

[28] I utilize ACLED crisis data for constructing my measure available at https://acleddata.com/.

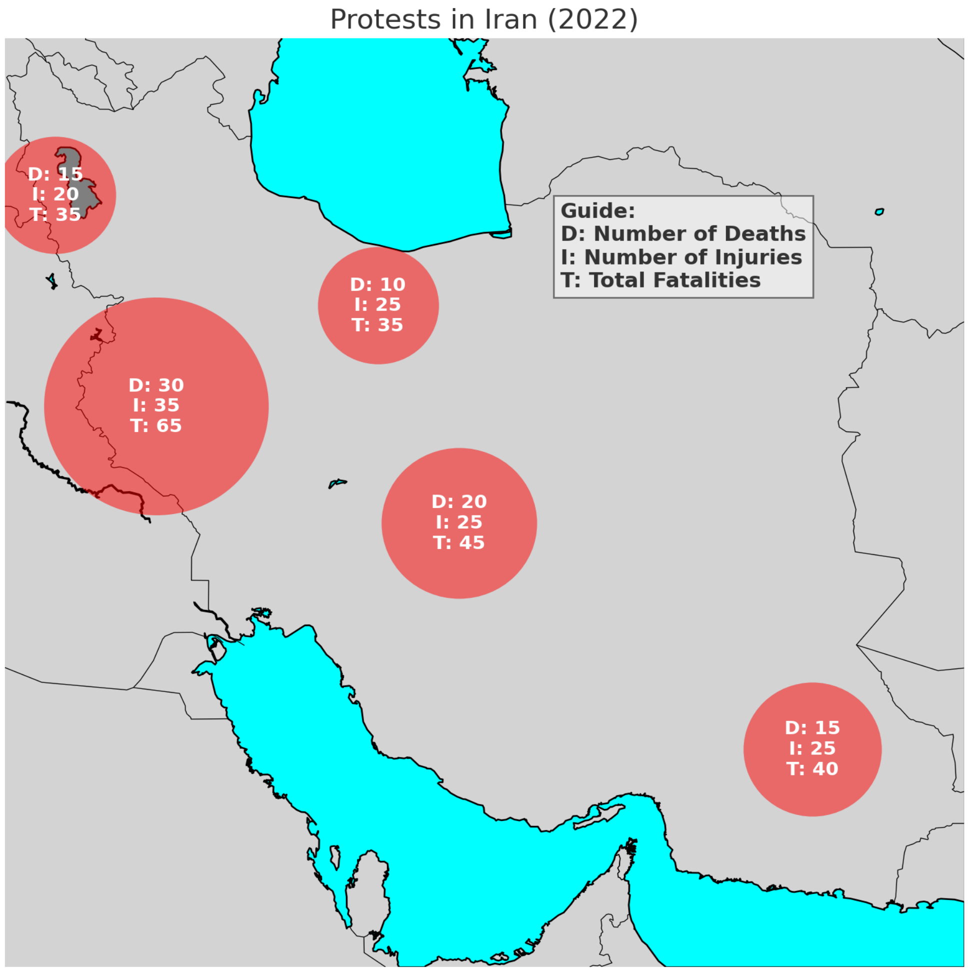


Figure 9. Fatalities of Protests in Iran The graph shows the fatalities of the protests based on the number of deaths (*D*), the number of injured (*I*), and the total number of deaths and injured (*F*). These figures are attributed to each location based on an analysis of the *ACLED* dataset during Sep. 15th 2022 to Nov 1st 2022.

F Political unrest events

The list of political unrest studied in the robustness section is provided in Table 21.

#	Event	Description
1	Sanction 2018	U.S. President Donald Trump signs a document reinstating sanctions against Iran after announcing the U.S. withdrawal from the Iran nuclear deal at the White House in Washington on May 8, 2018.
2	Trump 2019	By the time President Trump met with congressional leaders on the afternoon of June 20, 2019, he had already decided to retaliate against Iran for shooting down an American surveillance drone.
3	Gas Price 2019	Iran abruptly raised gasoline prices as much as 200 percent early Friday, Nov 15th, 2019 and imposed a strict rationing system, and within hours protests erupted across the country. In this event, the internet is disrupted.
4	Strike 2020	U.S. came to strike and kill a top Iranian General Ghasem Soleimani in Baghdad on January 4th, 2020.
5	Flight 2020	The Boeing 737-800 flying the route was shot down by the Islamic Revolutionary Guard Corps (IRGC) shortly after takeoff, killing all 176 occupants on board on January 8th, 2020.
6	Sep. 2022	The death of Mahsa Amini on 16 Sep. 2022 after being detained by Iran's morality police sparked protests unlike any the country had seen before. In this event, the internet is disrupted.

Table 21. Political Unrest Events The description of the political unrest events in this study is provided in the following table. The events are listed chronologically.

G Free Float Dynamics

Free float refers to the portion of a company's shares available for trading in the open market. It excludes shares held by insiders, controlling stakeholders, and shares not available for trading. Generally, stocks with lower free float tend to experience larger daily price changes compared to stocks with higher free float because they have fewer shares accessible for trading.

$$DailyPriceChange = \gamma_0 + \gamma_1 LFFS + \gamma_2 Event + \gamma_3 (LFFS * Event) + \gamma_4 PoliticalUnrest \quad (20)$$

The summary statistics are presented in Table 22 for two main stock exchanges in Iran. I designate stocks with lower than average free float as *LFFS* which is the dummy variable set to one. I investigate the correlation between the free float percentage of stocks and the daily price change following an exogenous shock, as illustrated in Equation (20). As indicated in Table 23, the *LFFS* stocks exhibit negative and insignificant daily price changes, attributed to a lack of liquidity. One interpretation of these findings can be attributed to the fact that *LFFS* stocks are less attracted to noise and retail traders and usually controlled by strategic investors.

Exchange	*Count*	*Average*	*Std.Dev*	*Min*	*Max*
Both	532	29.12	20.2	0	100
IFB	152	26.43	17.92	0.042	98.81
TSE	380	30.2	20.96	0	100

Table 22. Free Float Summary Statistics The summary statistics for free float percentage in IFB and TSE exchanges are reported at the end of August 2022.

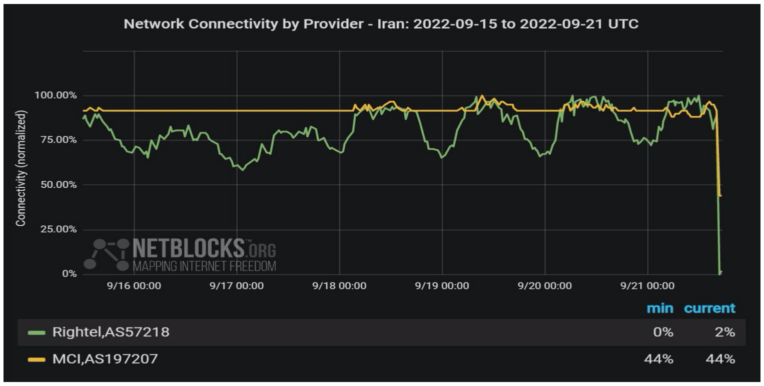
Table 23. Free Float Stocks The *DailyPriceChange* is the percentage of the daily price change and the dependent variable. The *LFFS* is a dummy variable set to one for stocks with lower than average free float in each market including TSE. The *LFFS* is an independent variable. The *Event* is a dummy variable set to one during the event. The interaction term *LFFS*Event* captures the coefficient of interest for low free float stocks after the event. The regression in column (2) is controlled for political unrest through the proxy measure created using PCA and is named *PoliticalUnrest*.

	(1)	(2)
	Daily Price Change %	*Daily Price Change %*
LFFS	13.32***	14.15***
	(3.21)	(4.22)
Event	12.2**	10.3**
	(1.81)	(1.78)
*LFFS*Event*	-14.76	-9.32
	(-0.95)	(-0.72)
PoliticalUnrest		11.5*
		(1.62)
Constant	-1.307***	-1.016**
	(-3.93)	(-1.81)
Observations	7,832	7,832
R^2	0.569	0.742

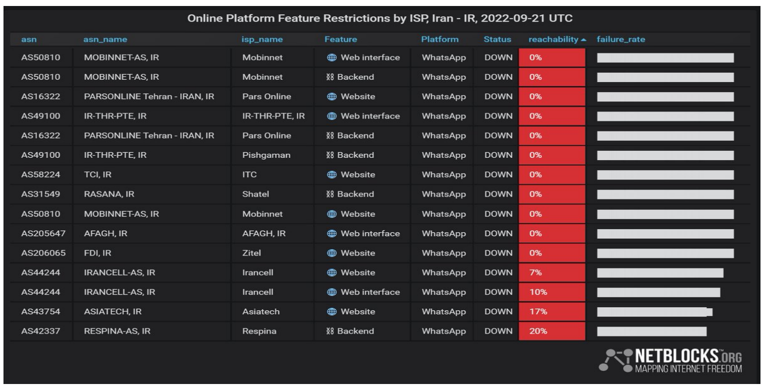
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

H NetBlocks

Figure 10 presents NetBlocks' network data, illustrating a significant disruption in internet service after Sep. 16th, 2022. This disruption subsequently extended to mobile networks, affecting MCI, Iran's predominant cellular operator. As a result, a considerable number of internet users within the country experienced a state of complete offline connectivity, particularly in the capital city, as well as in the west and south provinces. This period earned significant attention both nationwide and worldwide, as depicted in Figure 6 in Appendix Section C.



((**a**)) Nation-scale loss of connectivity on MCI(first and leading mobile operator)


Online Platform Feature Restrictions by ISP, Iran - IR, 2022-09-21 UTC

asn	asn_name	isp_name	Feature	Platform	Status	reachability	failure_rate
AS50810	MOBINNET-AS, IR	Mobinnet	Web interface	WhatsApp	DOWN	0%	
AS50810	MOBINNET-AS, IR	Mobinnet	Backend	WhatsApp	DOWN	0%	
AS16322	PARSONLINE Tehran - IRAN, IR	Pars Online	Website	WhatsApp	DOWN	0%	
AS49100	IR-THR-PTE, IR	IR-THR-PTE, IR	Web interface	WhatsApp	DOWN	0%	
AS16322	PARSONLINE Tehran - IRAN, IR	Pars Online	Backend	WhatsApp	DOWN	0%	
AS49100	IR-THR-PTE, IR	Pishgaman	Backend	WhatsApp	DOWN	0%	
AS58224	TCI, IR	ITC	Website	WhatsApp	DOWN	0%	
AS31549	RASANA, IR	Shatel	Backend	WhatsApp	DOWN	0%	
AS50810	MOBINNET-AS, IR	Mobinnet	Website	WhatsApp	DOWN	0%	
AS205647	AFAGH, IR	AFAGH, IR	Web interface	WhatsApp	DOWN	0%	
AS206065	FDI, IR	Zitel	Website	WhatsApp	DOWN	0%	
AS44244	IRANCELL-AS, IR	Irancell	Website	WhatsApp	DOWN	7%	
AS44244	IRANCELL-AS, IR	Irancell	Web interface	WhatsApp	DOWN	10%	
AS43754	ASIATECH, IR	Asiatech	Website	WhatsApp	DOWN	17%	
AS42337	RESPINA-AS, IR	Respina	Backend	WhatsApp	DOWN	20%	

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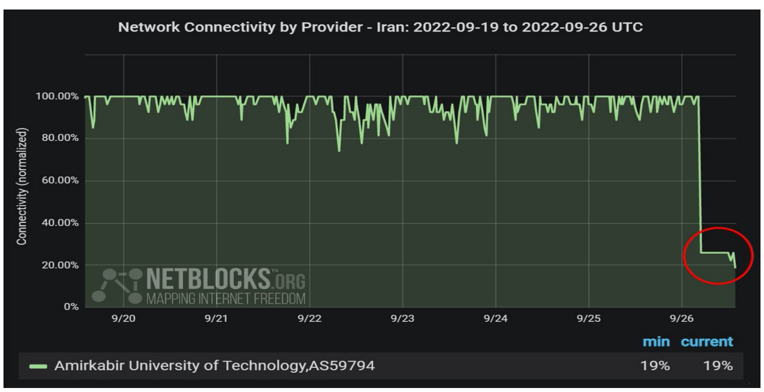
((**b**)) Wide disruption on multiple popular internet providers



((**c**)) Social media restrictions specifically on Instagram, Telegram and WhatsApp

Figure 10. Internet Disruption in Iran Examples of NetBlocks' report on Internet disruption in Iran in Sep. 2022 is depicted in these figures. Panel *a* represents the nationwide scale of connectivity disruption on the first and leading mobile network operator in Iran. Panel *b* displays zero connectivity for popular internet providers. Panel *c* depicts the social media restrictions exceeding 80%, affecting platforms such as Instagram, Telegram, and WhatsApp in specific region in Tehran.

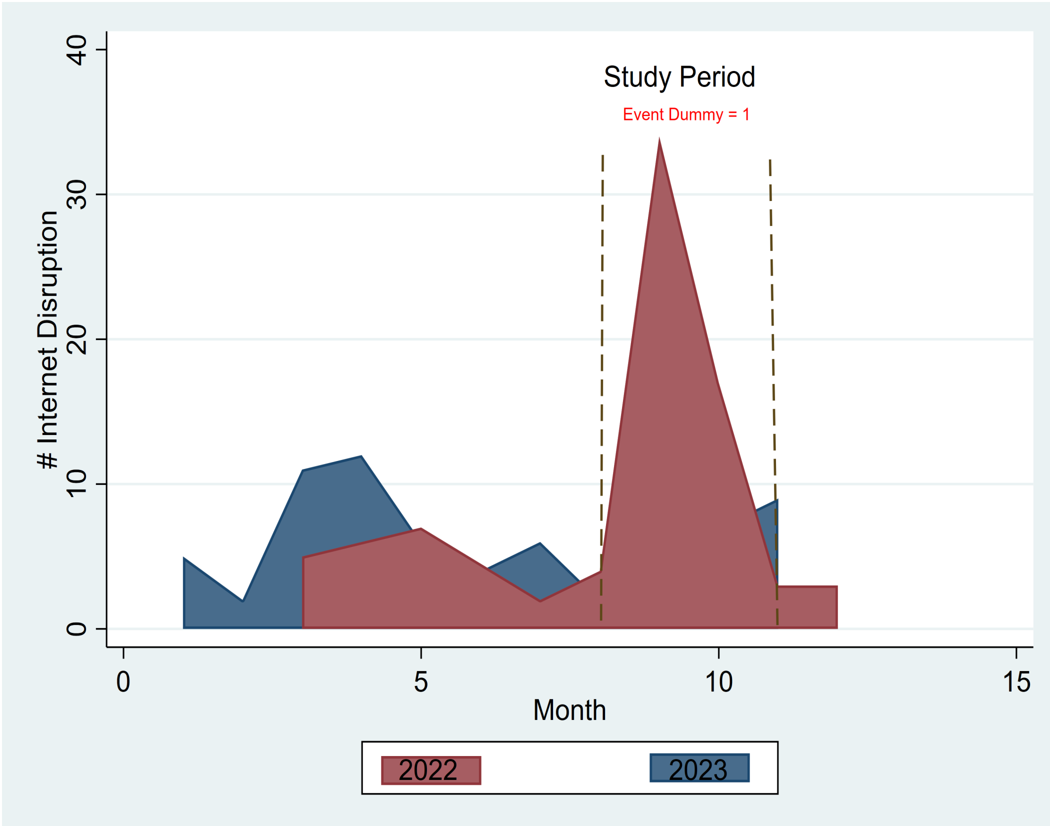


Figure 11. Internet Disruption in Iran The y-axis represents the number of internet disruptions per day. The event study period spans from September 16th to October 16th, 2022, marking the greatest number of incidents in 2022 and 2023.