# The Impact of India's 2016 Demonetization on Stock Market Liquidity

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**Abstract**

This thesis examines whether a sudden, exogenous policy shock affects liquidity conditions in the equity markets using the 2016 Demonetization episode in India as a natural experiment. This policy rendered 86% of the cash in circulation ineffective overnight. I employ both a traditional event study and the generalized synthetic control method to assess the impact on three dimensions of stock market liquidity: market depth (trade quantity), market immediacy (execution speed) and market breadth (price impact). I find that market immediacy declined significantly after the event while market breadth remained stable. Market depth increased after the event but this result was not robust across both the methods. The increased trading activity suggests panic-driven liquidation rather than improved market functioning as trade execution slowed and no price impact was observed. The results highlight the multidimensional nature of liquidity, with different liquidity measures responding differently to the shock. The findings are consistent with market microstructure theory, where pressures on inventory and fear of adverse selection simultaneously drive reactions in liquidity provision.

**Keywords**: Liquidity, Demonetization, Event Studies, Generalized Synthetic Control
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# 1 Introduction

Demonetization refers to a government's decision to withdraw certain currency denominations from circulation, rendering them invalid for transactions. On November 8, 2016, the Government of India abruptly demonetized the highest denomination notes of INR 500 and 1000 (roughly equivalent to USD 7.50 and USD 15 respectively), deemed ineffective at midnight. This led to an overnight reduction in 86 percent of value of the currency in circulation. The Indian government justified this action by declaring an intention to reduce counterfeit currency, money laundering and corruption in the country. The announcement came without warning, even to most government officials and regulators. However, only the circulation of physical cash was affected and all digital operations functioned as usual. This was a severe shock to economic activity in a country where 90% of transactions took place in cash at that point of time (Rogoff 2016).

There have been previous demonetization initiatives around the world of course, for example on the introduction of the Euro in 2002. India itself has had two such exercises before, one in 1946 and one in 1978. However, the Indian demonetization of 2016 is of special interest due to the sudden nature of the announcement. It has been established that the general public did not know about the policy beforehand. Only 10 people out of a population of 1.20 billion were aware of the planned exercise.[1] Due to the unprecedented secrecy and scale of the action, this demonetization event serves as a natural experiment to examine how financial markets respond to a policy-induced disruption to liquidity.

This thesis investigates how market participants responded to the 2016 Demonetization event through changes in stock market liquidity. While prior research on demonetization has studied its impact on firm performance, exports, taxation and market returns, to the best of my knowledge, this is the first study which examines the impact on how trading conditions in the capital markets were affected. Conversely, few studies in the broader liquidity literature examine the impact of a large-scale, exogenous liquidity shock on trading activity. Methodologically, this study differs from previous studies in that I use two complementary methods to investigate my question. First, I conduct a traditional event study. To address the lack of a suitable control group which limits causal inference under the event study method, I

[1] See "Demonetisation: In the works for 6 months, 10 people in the loop, including Raghuram Rajan" at https://www.business-standard.com/article/economy-policy/demonetisation-in-the-works-for-6-months-10-people-in-the-loop-including-raghuram-rajan-116111000009_1.html

supplement with the generalized synthetic control method (GSCM).

Liquidity here refers specifically to liquidity related to trading conditions in the capital markets and not in the context of monetary policy. Liquidity in equity markets is important in that it affects the speed and cost of buying and selling securities. Brennan et al. (2012) defines stock market liquidity as the ability of the market to absorb a huge volume of securities at a lower execution cost within a short period without having a significant effect on security prices. Previous literature establishes liquidity as a priced factor affecting a firm's cost of capital. For example, Amihud and Mendelson 1986 have established the link between market returns and stock market liquidity. Previous studies have examined the impact of the demonetization on market returns. I seek to explore if the observed negative impact on stock returns after the event can be explained by the channel of stock market liquidity.

To assess stock market liquidity, I employ three different liquidity measures corresponding to varying dimensions of liquidity namely market depth (share turnover), market breadth (Amihud illiquidity) and market immediacy (coefficient of elasticity of trading or CET). These measures capture the quantity, price impact and speed of trading activity respectively. I find that the market immediacy declines significantly after the event, evidenced by both the methods used. According to the event study, CET declines to approximately 0.80 times its pre-event level in the post-event window of 14 to 90 days. Similarly, the GSCM analysis estimates a decline of 0.58% after the event. In contrast, I find that the market breadth remains largely unchanged. Both the methods show no statistically significant change in the Amihud illiquidity measure, suggesting that the price impact per unit of trading volume did not materially change following the policy. In case of the third aspect of market depth, the event study identifies a statistically significant increase in share turnover to approximately 1.60 times its pre-event level during the 7 to 30-day post-event window. However, this result is not corroborated by the second method of GSCM which does not detect a comparable change.

Thus, the results differ across the various liquidity measures, emphasizing the multidimensional nature of liquidity. They suggest that the policy may have triggered panic selling among institutional investors, leading to increased trading volumes and higher market depth. At the same time the trade execution speed, captured by market immediacy, slowed, likely due to the larger orders being placed. However, the price impact per unit of trading vol-

ume reflected by the market breadth remained stable, indicating that the market effectively absorbed the higher volumes. I discuss the potential mechanism behind the results in the Discussion section, focusing on two key sources of microstructure friction: market maker inventory costs and adverse selection risk. Furthermore, I also find that the movement in returns after the event cannot be explained by the channel of stock market liquidity alone.

The rest of the paper is organized as follows. Section 2 presents some further background and context regarding the demonetization event followed by a literature review in Section 3. Section 4 gives information on the data and variable construction for the empirical analysis and Section 5 elaborates on both the methodologies. Section 6 presents the two sets of results. Section 7 first discusses the results followed by the limitations of this study. Section 8 finally concludes.

# 2 Background and context

### 2.0.1 Policy announcement and implementation

The announcement of the demonetization was made by the Indian Prime Minister Narendra Modi via an unscheduled television announcement at 20:00 Indian Standard Time. India's central bank, the Reserve Bank of India (RBI), followed with a press release confirming the withdrawal of legal tender status of INR 500 and 1,000 denomination of banknotes. The explanation provided for this move was to tackle the rampant counterfeiting of Indian banknotes, to effectively nullify black money hoarded in cash and to curb the funding of terrorism with fake notes.[2] After some months, the government also gave additional reasons for the policy, including promoting a digital economy and payments system in the country, and bringing unaccounted money into the banking system by forcing people to deposit their cash holdings into bank accounts.

All members of the public, corporate firms, societies, trusts, etc. holding the concerned notes were provided an exchange facility from November 10, 2016 onwards, at any bank branch or office of the RBI, as credit to their respective bank accounts. This exchange facility was valid for 50 days up to December 30, 2016. For any immediate cash needs, notes up to the value of INR 4,000 could be exchanged for cash over the counter at bank branches.

[2]See Press Release : 2016-2017/1142 of the Reserve Bank of India

All ATMs and cash machines had restrictions on withdrawals up to INR 2,000 per day per card up to November 16, 2016 and the limits were raised to INR 4,000 from November 19, 2016 onwards.

In the years leading up to the demonetization, the Indian government had already been occupied in promoting several schemes to curb black money like attempts to increase the opening of bank accounts and track income through the linking of the national level identity cards ("Aadhaar" cards), tax identity cards (PAN cards) and bank accounts. This explains why once any cash is deposited in the banking system, it becomes difficult to use this cash for tax evasion or other illegal activities.

Whether the move achieved its stated objectives remains a matter of considerable debate. The RBI in its Annual Report for 2017-18 declared that it had completed counting the banned notes which were returned during the exchange window, stating that 99 percent of the demonetized notes were returned back to the banking system. [3]

### 2.0.2 Reactions

I explore the reported public and economic reactions to the policy in the months following the event. The policy led to widespread disruptions, as evidenced by the endless queues at banks, more than 100 reported deaths, [4] and a reported decrease in jobs in the Micro, Small and Medium Enterprises (MSME) sector. These events called into question the need, efficacy and collateral costs of this decision by the Indian government (Kazmin 2016).

The impact on the Indian stock market was considered to be short term in nature. The demonetization event coincided with the US presidential election in 2016. Both these events led to heightened volatility in the Indian market. The day after the event November 9, 2016, the Bombay Stock Exchange's premier index Sensex opened with a loss of 1300 points but recovered later.[5]. The premium valuation of the Indian stock market, compared to its peers

[3]See RBI's Annual Report 2017-18 at `https://rbidocs.rbi.org.in/rdocs/AnnualReport/PDFs/$0ANREPORT201718077745EC9A874DB38C991F580ED14242$.PDF`

[4]See "India's Demonetisation Kills 100 People Apparently - This Is Not An Important Number" at https://www.forbes.com/sites/timworstall/2016/12/08/indias-demonetisation-kills-100-people-apparently-this-is-not-an-important-number/

[5]See "How demonetisation and Donald Trump's victory impact your investments" https://economictimes.indiatimes.com/wealth/invest/how-demonetisation-move-and-donald-trumps-victory-impact-your-investments/articleshow/55384579.cms?from=mdr

in Asia, declined as a result of the demonetization. [6]

As per Rogoff 2016, the short term results of the demonetization were "catastrophic", knocking approximately 1-2 percent off GDP growth, with the heaviest burden falling on the middle class and poor. He also notes that the RBI had not printed nearly enough new notes to replace the old notes, further emphasizing the flawed execution of the policy. Considering the disruptive nature of the demonetization on the economy and public life, this thesis aims to examine its effects on stock market liquidity in India.

# 3 Literature review

## 3.1 Stock market liquidity and its determinants

Liquidity in its simplest form refers to the ability of a market to absorb large quantities of trades, without any delay, at lower transaction costs and minimal price impact. W. Liu 2006 suggests four main aspects of liquidity: price impact, trading quantity, execution time and transaction cost. The measures of liquidity are constructed to capture the following aspects: breadth which is a measure of price impact, depth which is a volume or quantity measure, immediacy which measures the speed of execution and tightness which measures the transaction cost or spread. Ellington 2018 also highlights the link between financial market liquidity shocks and macroeconomic parameters like GDP growth and inflation, documenting a substantial increase in these linkages during the Great Financial Crisis of 2008. Thus, we can conclude that liquidity is an important aspect of well-functioning financial markets and the economy as a whole.

Persaud 2003 argues that the key challenge of financial liquidity lies not in its average level but in its variability and uncertainty: "...there is also broad belief among users of financial liquidity—traders, investors and central bankers—that the principal challenge is not the average level of financial liquidity... but its variability and uncertainty.... ". This perspective is particularly relevant for assessing the impact of an exogenous shock like demonetization in the short term. As per Persaud 2002, if the market is illiquid consistently, market partici-

[6] See "The impact of demonetization on Indian market valuations" at https://www.livemint.com/Money/OGjBHqyXhelb1wQ8vpuT9J/The-impact-of-demonetization-on-Indian-market-valuations.html

pants demand a liquidity premium, as established in Amihud and Mendelson 1986. However, if the market is liquid at the time of entering into a hypothetical long position but becomes illiquid when the investor attempts to unwind his position, the uncertainty generated by this is disliked by market participants. Hence, Persaud 2002 defines these episodes where liquidity suddenly disappears as "liquidity black holes". These temporary but sudden shocks to liquidity are important to investigate and underscore the need to study not only the average level but also the volatility of liquidity.

A large body of literature has established the link of liquidity and asset pricing, starting with Amihud and Mendelson 1986 and Acharya and Pedersen 2005. They establish that liquidity co-moves with contemporaneous returns as a negative shock to liquidity predicts high future illiquidity which raises the future expected return and lowers contemporaneous prices. Hence, liquidity becomes an important aspect for market participants to consider while determining their trading strategy. As per Amihud, Mendelson, and Pedersen 2005, if liquidity costs and risks affect the required return by investors, they affect corporations' cost of capital and, hence, the allocation of the economy's real resources. Bali et al. 2014 find that liquidity shocks are positively associated with contemporaneous returns and also predict future return continuations for up to six months. In the context of emerging markets, Bekaert et al. 2007 show that unexpected liquidity shocks are positively correlated with contemporaneous return shocks and that local market liquidity is an important driver of expected returns in emerging markets, and that the liberalization process has not fully eliminated this impact. This underscores the relevance of liquidity as a risk factor in emerging markets like India.

Studies commenting on market microstructure and systemic liquidity provide valuable insights into how liquidity behaves around policy shocks or systemic events. Chordia et al. 2000 empirically document the existence of commonality in liquidity, that is the phenomenon of individual stock liquidity measures to co-move even after controlling for firm-specific factors. They suggest that this commonality in liquidity can amplify financial distress during market-wide shocks, suggesting future areas for research for understanding this co-movement in times of macroeconomic shock and political events. While this study does not directly test for commonality, it contributes to the literature by examining the response of aggregate

liquidity to a market-wide shock, providing suggestive evidence to how market-wide liquidity may react under stress in the short term.

This study contributes to the empirical literature studying the impact of an exogenous shock, in the form of a certain event or policy, on stock market liquidity. One strand of literature covers the impact of stock index changes on the market liquidity. Jegadeesh and Subrahmanyam 1993 examines the effect on liquidity around the introduction of the Standard and Poor's (S&P) 500 index futures contract and find that the average bid-ask spreads of S&P 500 stocks increased significantly post the event. Hegde and McDermott 2003 study the impact on liquidity of stocks after index revisions and find an increased liquidity for added stocks and the opposite effect for deleted stocks. Wai Kong Cheung 2011 study the effects of index inclusions and exclusions of corporate sustainable firms on liquidity and find that liquidity deteriorates after the announcement day and bounces back significantly near the day of change.

Another strand of literature covers the impact of corporate actions like stock splits. Huang et al. 2015 examines the effect of stock splits on liquidity and find that most measures of liquidity increase around the stock split announcement but rebound after the ex-date, thereby documenting a short-lived effect.

A third section of the literature studies the impact of a change in the economic environment or news on liquidity dynamics. Yue et al. 2021 studies the effects of positive and negative news on the liquidity of the largest cryptocurrencies in an event study context and find that the liquidity of cryptocurrencies increases (decreases) after positive (negative) news announcement. G. Liu and B. Liu 2023 studies the impact of digital technology improvement on liquidity. Dash et al. 2021 studies the potential adverse effects of economic policies on stock market liquidity and find that a causal relationship exists between economic policy uncertainty and stock market liquidity.

This study takes into account the multidimensional nature of liquidity and studies three different liquidity measures in its investigation of the event's impact. Chai et al. 2010 argue that there is no single, definitive measure of market liquidity, as different measures capture various aspects of liquidity depending on the market structure and conditions. Similarly, Goyenko et al. 2009 emphasize that the choice of liquidity measure should be guided by

the specific objectives of the study. This has been elaborated on in the section on Variable construction

In summary, the existing literature establishes liquidity as a multidimensional, priced risk factor with both its level and variability playing a role in shaping the actions of market participants. While prior research has examined the response of liquidity to index composition changes, corporate actions and macroeconomic uncertainty, there is limited empirical evidence on how a sudden, exogenous policy shock affects liquidity in emerging markets. This study addresses that gap by analyzing the liquidity response across multiple dimensions of liquidity to India's 2016 demonetization policy. By doing so it contributes evidence on event-driven liquidity dynamics and insights into how policy-driven uncertainty might affect liquidity, especially in developing economies.

## 3.2 Demonetization

Demonetization refers to the act of stripping a currency unit of its status as a legal tender. It has historically been used as a tool to curb illicit activity, formalize the economy and implement monetary reforms. For example, Rogoff 2017 makes the case for a cashless or 'less-cash' economy based on the reasoning that large-denomination notes appear to support various forms of tax evasion and criminal activity. Furthermore, the presence of more cash also puts a lower bound on the nominal interest rate set by central banks.

This study is closely related to the literature studying the demonetization event in India. The 2016 demonetization in India has been the most extensively studied episode in the recent literature, which examines the short and medium-run effects on a variety of outcomes. For example, Chodorow-Reich et al. 2018 find that the Indian districts which experienced a more severe demonetization effect had relative reduction in economic activity, faster adoption of alternative payment technologies, and lower bank credit growth, thereby providing support for theoretical traditions that view money as essential. Other studies on demonetization study the impact on financial infrastructure and digital payments (see Aggarwal et al. 2023 and Crouzet et al. 2022) and tax compliance ( see Das et al. 2023).

In the context of financial markets, the literature on the effects of demonetization is

sparse. I summarize this below. Dharmapala and Khanna 2019 study the impact of the event on the Indian stock market and find little evidence that sectors thought to be associated with greater tax evasion or corruption experienced significantly different returns but find substantial positive returns for banks and state-owned enterprises. Lahiri and Deb 2022 study the impact on export performance and use the synthetic control method for their analysis. Sutar et al. 2023 implement an event study to find the impact of the event on stock market returns and find that the negative effect lasted for a short period of time and the market recovered within one month. This study aims to build on this work by proposing stock market liquidity as a potential mechanism underlying these return movements.

Although the Indian episode is the most recent prominent case, several other countries have implemented demonetization policies, each with their own unique motivations and consequences. In 2022, Nigeria implemented a demonetization to combat illicit activities such as vote-buying and kidnapping for ransom. However, the implementation led to significant challenges like widespread cash scarcity and the development of a new black market for selling naira notes, exacerbating the country's economic difficulties. This policy failure was the result of inadequate digital infrastructure in that it was insufficient to handle the increased digital transaction volume caused by the cash shortage. A low level of public trust in the digital alternatives also led to failure of the policy (Monye 2024).

Ghana demonetized its highest currency denomination in 1982. This move succeeded in reducing inflation temporarily but a loss of public faith in the country's currency led to Ghanians adopting foreign currency for several transactions and in some cases, even barter. This highlights the risk of currency substitution [7] when public confidence falters.

In December 2016, Venezuela abruptly withdrew its 100-bolívar note, triggering a severe liquidity crisis, public protests and commercial paralysis. The central bank's lack of preparedness and weak banking infrastructure undermined the policy outcome. The policy further destabilized an already fragile monetary system, highlighting the importance of institutional credibility and logistical capacity (Hurtado and Zerpa 2019).

In the context of developed economies, both the USA and the Eurozone have demonetized high denomination notes before to curb crime and money laundering. However, these phase-

[7]Currency substitution is when a country uses a foreign currency in lieu of, or in addition to, its domestic currency, primarily due to the greater stability of that foreign currency.

outs were gradual, well-communicated and planned, leading to minimal economic disruption.

Some theoretical models have been adopted to study demonetization's macroeconomic effects. Chodorow-Reich et al. 2018 model demonetization in an economy where agents hold cash both to satisfy a cash-in-advance constraint and for tax evasion purposes. Demonetization is modelled as a forced conversion of cash into less liquid bank deposits, which in the presence of downward wage rigidity predicts a decline in output, employment, and borrowing by firms. Their empirical findings using Indian data supports these predictions. Other models like in Crouzet et al. 2022 explore the effect on digital payments from the viewpoint of coordination failures in technology adoption.

In summary, the literature suggests that demonetization can have a range of outcomes depending on the nature of its implementation, the structure of the economy and institutional capacity. Well-planned demonetization policies in developed economies lead to minimal economic disruption whereas poorly executed ones in fragile economic or institutional settings lead to economic hardship. In India, the demonetization caused short-term disruptions in some outcomes and led to long-term positive effects in areas such as digital payments adoption. Hence, the Indian case stands out as an intermediate case to examine both disruptions and opportunities that such a policy can generate. This study contributes by studying the impact of the policy on financial market liquidity.

# 4 Data and Variable Construction

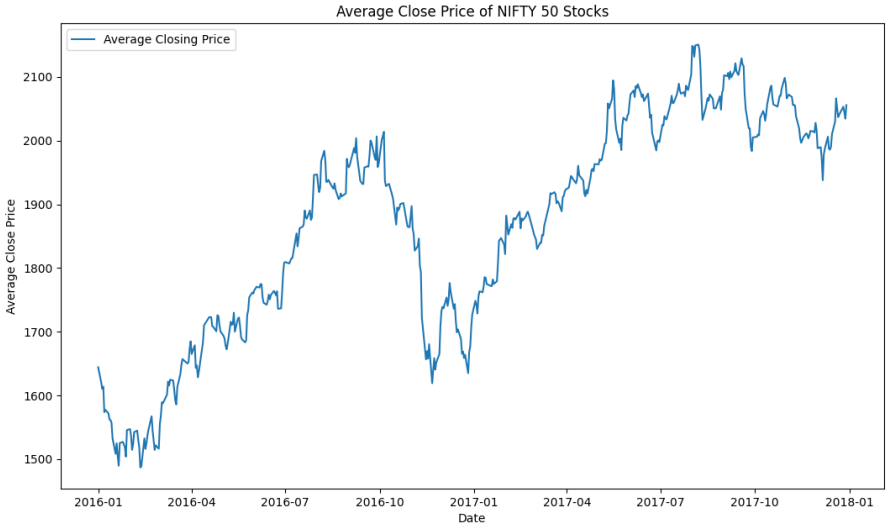
## 4.1 Data

I consider the NIFTY 50 index for the purpose of this study. It represents the weighted-average of the 50 largest companies listed on the National Stock Exchange (NSE) in India. The NIFTY 50 is a well-diversified index and represents major sectors of the Indian economy. The index represents approximately 60% of the free float market capitalization of the stocks listed on the NSE.

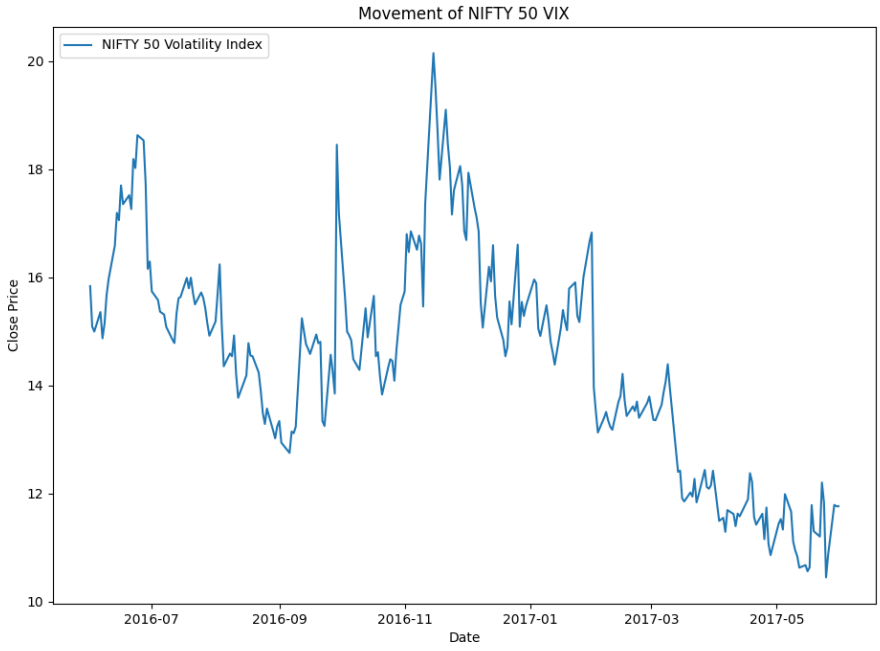
The composition of the NIFTY 50 index has been considered as of the end of October 2016 (calculated using data for the 12 month period from November 2015 to October 2016) [8]. In 2016, the NIFTY 50 index comprised 51 stocks. This is due to a 51st stock of Tata Motors DVR being added. This is a differential voting rights share of Tata Motors Limited which is also included in the Nifty 50 index. Refer Appendix A for the composition and industry-wise classification of the index during this period.

From Figure 1, we can observe the steep decline in closing price of the NIFTY 50 index after the end of the quarter ending October 31, 2016 and a recovery after January, 2017. A mirror image of the movement of the closing price is seen in the movement of the NIFTY 50 Volatility Index. We observe a sharp increase October, 2016 onwards and this upward trend is maintained till January, 2017. We can preliminarily conclude from these graphs that the stock markets faced a short-term impact after the demonetization.

[8] See https://www.niftyindices.com/reports/historical-data




**(a)** Movement of NIFTY 50 Closing Prices




**(b)** Movement of NIFTY 50 Volatility Index

**Figure 1:** NIFTY 50: Closing price and Volatility around November 8, 2016

The additional data for the generalized synthetic control method includes the country-wise index closing prices, trading volume, and currency exchange rates which have been sourced from Investing.com and Yahoo Finance. Data for the donor pool selection criteria has been sourced from the World Bank DataBank. Data for the monetary policy covariates has been sourced from the Bank for International Settlements 2025.

## 4.2 Liquidity measures

**Multidimensional nature of liquidity**

"Liquidity is inherently multidimensional." - Grossman and Miller 1988

Liquidity has three important dimensions namely price, quantity, and speed. A market is typically regarded as liquid when investors are able to execute large volumes at prices close to the underlying asset's fundamental value (Chacko et al. 2006). Despite its importance, especially after the Great Financial Crisis, liquidity remains an elusive concept as it is not observed directly but has a number of aspects that cannot be captured in a single measure. It is doubtful that there is one single measure that captures all its aspects (Amihud 2002).

Hence, I consider more than one measure of liquidity in this study. I consider share turnover and weighted log volume to measure depth/quantity, Amihud illiquidity to measure breadth/price and the coefficient of elasticity of trading (CET) to measure immediacy/speed.

### 4.2.1 Share turnover: a measure of depth

$$\text{Share Turnover} = \frac{VO_t}{SO_t}$$

Where $VO_t$ is the number of shares traded on day t and $SO_t$ is the number of shares outstanding on day t. A higher amount of share turnover indicates a deep market and represents higher liquidity. Depth refers to the availability of a fairly large amount of orders in the market such that it maintains equilibrium in a security's market price. Thus, the amount of securities traded in the market is a prerequisite for a deep market to exist and can be ascertained through the trading volume. The measure was first introduced by Datar 2000

as an intuitive measure of a stock's liquidity. One key benefit of using the share turnover rate as a liquidity proxy is its strong theoretical basis. As shown by Amihud and Mendelson 1986, liquidity is positively correlated with trading frequency in equilibrium. Therefore, when direct measures of liquidity are unavailable, turnover rate can serve as a substitute. Trading volume is market-capitalization weighted log trading volume.

#### 4.2.2 Coefficient of elasticity of trading (CET): a measure of immediacy

$$\text{CET} = \frac{\%\Delta T_s}{\%\Delta P}$$

Where $\Delta_T$ denotes the percentage change in the daily trading volume of a stock 's' and $\Delta_P$ denotes the percentage change in daily closing price. Immediacy indicates the execution time required for a transaction, which depends on the willingness of both the parties to a transaction to execute the stated quantity of a security at the quoted price without any delay in time. A larger CET indicates a higher immediacy and thereby confirms higher liquidity. Estimation of market immediacy by the CET was first propounded by Datar 2000 and further developed by Wanzala 2018. Hence, market immediacy is the ability or the speed with which transactions can be executed promptly at the prevailing price.

#### 4.2.3 Amihud illiquidity: a measure of breadth

$$\text{Amihud Illiquidity Ratio} = \frac{|R_{it}|}{Vol_{it}}$$

Where $|R_{it}|$ and $Vol_{it}$ are the absolute return and dollar volume on day t for stock i, respectively. Breadth refers to the ability of the market to smoothly enable trading of a given volume of securities without influencing the price. The Amihud metric can also be served as "a measure of consensus belief among investors about new information" as per Amihud 2002. A recent study by Coën and De La Bruslerie 2019 provides evidence that the Amihud ratio is a significant measure of the informativeness of the price. The Amihud measure as first given in Amihud 2002 does well measuring price impact in place of high frequency measures as per Goyenko et al. 2009. A lower Amihud illiquidity ratio depicts wider market breadth and thereby conveys the presence of higher liquidity.

For all of the above measures, to derive the aggregate market liquidity, the daily stock-specific measures were aggregated into cross-sectional averages that were weighted based on the daily market capitalization of these stocks. Next, to avoid any form of outliers, the monthly averages of liquidity measures were converted into natural log values, as per Naik et al. 2020.

**Table 1:** Descriptive Statistics of Liquidity Measures

| | **CET** | **Share Turnover** | **Amihud Illiquidity** | **Volume** |
|---|---|---|---|---|
| Mean | −0.01 | −6.48 | −18.42 | 21.23 |
| Median | 0.00 | −6.50 | −18.42 | 21.21 |
| Max | 0.25 | −5.40 | −18.42 | 22.08 |
| Min | −0.27 | −8.88 | −18.42 | 18.77 |
| Standard Deviation | 0.09 | 0.29 | 0.00 | 0.29 |
| Skewness | −0.28 | −1.40 | 4.13 | −1.74 |
| Kurtosis | 0.94 | 14.47 | 28.71 | 15.16 |

The descriptive statistics of the liquidity measures based on the NIFTY 50 index are given in Table 1. The mean value of the CET is close to zero, with an almost identical median, indicating a roughly symmetrical distribution. The share turnover and weighted log volume display the highest standard deviations indicating greater variation in trading activity over time. Amihud illiquidity remains constant in terms of mean and median with a standard deviation close to zero, but exhibits positive skewness and kurtosis, suggesting the presence of outliers.

Overall, the liquidity measures display a mild departure from normality, with a generally negative skewness and positive kurtosis. The proximity of mean values to the median suggests limited asymmetry. These statistics are broadly in line with previous studies which examine liquidity measures in the Indian stock market, such as Naik et al. 2020.

# 5 Methodology

## 5.1 Event study

To study the impact of demonetization on stock market liquidity, I first employ an event study methodology. While the majority of event studies in the finance literature are focused

on stock returns, as popularised by Ball and Brown 1968 and Fama et al. 1969, this paper applies them to liquidity measures. Event studies on stock returns calculate a measure known as cumulative abnormal returns and study the impact of the event on it. However, for the purpose of studying the impact on liquidity measures, it is important to calculate an outcome variable which captures the change from the pre-event period while isolating the impact of the event from changes in the overall market.

I follow Hegde and McDermott 2003 and Yue et al. 2021, where for a given event window, the Post/Pre ratio for a given liquidity measure is calculated as the ratio of the average of daily values of the liquidity measure for the post-event period to the corresponding average in the pre-event period. The null hypothesis that the population mean of the reported ratio is equal to 1, indicating no change in liquidity, is tested using a standard t-test:

$$H_0 : \mu_{\text{Post/Pre}} = 1 \quad \text{(No change in liquidity)}$$
$$H_1 : \mu_{\text{Post/Pre}} \neq 1 \quad \text{(Significant change in liquidity)}$$

The date of the event of demonetization is November 8, 2016. The announcement was made in the evening after closing of trading for the day. Hence, I take the event date as November 9, 2016. I use multiple event windows for the study being [-1,1], [-2,2], [-5, 5], [-7, 7], [-14, 14], [-30, 30], [-60, 60] and [-90, 90] trading days before and after the event.

Other literature has also adapted the event study methodology to examine liquidity changes. For example, Jegadeesh and Subrahmanyam 1993 examines the bid-ask spread around the introduction of S&P 500 index futures. To do this they employ a t-test examining the equality of mean percentage bid-ask spreads in the pre and post event periods. Wai Kong Cheung 2011 examines the impact of inclusion and exclusion of corporate sustainability related stocks on stock market liquidity by using Cumulative Abnormal Trading volume as a measure for the event study. The measure is constructed to remove market-wide changes in trading volume.[9]

A key limitation of the event study methodology conducted on liquidity measures is

[9]Boudt and Petitjean 2014 also study the dynamics of liquidity and news releases around jumps by identifying their intraday timing for the Dow Jones Industrial Average index constituents by constructing liquidity measures for both the event window and a non-event window. They standardize the liquidity measures by demeaning them by the median in the non-event window. Since this study does not capture intraday dynamics, I have not followed this method.

that it does not account for simultaneous macroeconomic changes which might affect the outcome variable. This serves as an impediment to determine causality and hence I employ a version of the synthetic control method as a complementary methodology to account for time-varying confounders.

## 5.2 GSCM

Synthetic control methodologies (SCM) (Abadie and Gardeazabal 2003 and Abadie, Diamond, et al. 2010) aim to estimate the effect of aggregate interventions on some aggregate outcome of interest. The method constructs a counterfactual by taking a weighted average of a group of control units, known as the donor pool, to recreate the trajectory of the treated unit in the absence of the intervention. The deviation between the actual trajectory of the treated unit and the constructed synthetic control is then interpreted as the estimated effect of the intervention.

Previous literature (Lahiri and Deb 2022) which studies the impact of demonetization on export performance using the synthetic control method outlines the suitability of the method in this particular context. First, it is difficult to determine a single country which can be considered as a control unit for India. Second, the SCM allows the policy effect to vary across post-treatment periods which enables us to distinguish between short-run and long-run impact. Third, if the policy is expected to have an impact on several variables, as in a research focus on the demonetization policy, then a DID estimation equation will suffer from endogeneity problems. The SCM, on the other hand, by matching countries on their pre-intervention characteristics minimizes this problem. The SCM is also especially suited for scenarios which are unanticipated such as the demonetization event.

This paper uses an extension of the basic SCM model outlined by Abadie and Gardeazabal 2003, known as the generalized synthetic control method (GSCM) introduced by Xu 2017. As per Xu 2017, the uncertainty estimates offered by the SCM are not easily interpretable. GSCM resolves this with one of the several advantages of the method being that it produces frequentist uncertainty estimates like standard errors and confidence intervals and improves efficiency under correct model specifications. The method is an extension of the SCM and builds on it further by using an interactive fixed effects model under a simple framework of which difference-in-difference (DiD) is a special case. Interactive fixed effects models account

for unobserved, time-varying confounders by modeling them as latent factors that interact with unit-specific loadings. The GSCM provides a flexible approach for causal inference in panel data settings where the parallel trends assumption of DiD may not hold due to time-varying confounders.

The method models the following functional form:

$$Y_{it} = \delta_{it} D_{it} + x'_{it}\beta + \lambda'_i f_t + \epsilon_{it} \tag{1}$$

where the treatment indicator $D_{it}$ equals 1 if unit i has been exposed to the treatment prior to time t and equals 0 otherwise. $\delta_{it}$ is the heterogeneous treatment effect on unit i at time t; $x'_{it}$ is a (k $\times$ 1) vector of observed covariates, $\beta$ is a (k $\times$ 1) vector of unknown parameters, $f_t$ is an (r $\times$ 1) vector of unobserved common factors, $\lambda_i$ is an (r $\times$ 1) vector of unknown factor loadings, and $\epsilon_{it}$ represents unobserved idiosyncratic shocks for unit i at time t and has zero mean. The method accounts for unobserved heterogeneities by modeling them as interactive fixed effects through the factor structure $\lambda'_i f_t$, thereby generalizing both the fixed effects and synthetic control methods.

The model is estimated in three stages. First, I estimate the interactive fixed effects model using the control group data to obtain the latent factors $\hat{f}_t$ and covariate coefficients $\hat{\beta}$. Next, the treated unit's pre-treatment outcomes are projected onto the factor space to obtain each unit's factor loadings $\hat{\lambda}_i$. Using the estimated factors $\hat{f}_t$, factor loadings $\hat{\lambda}_i$ and covariate coefficients $\hat{\beta}$, the model predicts the untreated counterfactual outcomes $\hat{Y_{it}}(0)$ for treated units in the post-treatment period. The treatment effects are then estimated as:

$$\hat{\delta_{it}} = Y_{it} - \hat{Y_{it}}(0) \tag{2}$$

The outcome of interest, average treatment effect on the treated (ATT) for each post-intervention period is then computed by averaging $\hat{\delta_{it}}$ across treated units.

The number of latent factors is selected via a cross-validation procedure that minimizes the mean-squared prediction error by holding back a small amount of data (e.g. one pre-treatment period) and using the rest of the data to predict the held-back information. The model assesses the statistical significance of the estimated treatment effects using parametric model-based inference. Standard errors, confidence intervals and p-values are computed based on the assumption that the estimator of the treatment effect follows an asymptotic

normal distribution.

### 5.2.1 Contextual requirements and assumptions

I summarise the contextual requirements as per Abadie 2021 and Xu 2017 necessary to implement the generalized version of the synthetic control method.

**Size of the Effect and Volatility of the Outcome** As per Abadie 2021, small effects to the treated unit will be indistinguishable from the other shocks to the treated unit if the outcome variable of interest is highly volatile. In cases where substantial volatility is present in the outcome variable, it is advised to remove it via filtering. To address this concern, I use monthly averages of the liquidity measures in order to de-noise the data instead of the daily values which have been used for the event study. This issue of noise vis-à-vis aggregation is covered in subsequent sections.

**Table 2:** List of Donor Pool Countries

| Unit | Country |
|---|---|
| 1 | Australia |
| 2 | Belgium |
| 3 | Canada |
| 4 | China |
| 5 | France |
| 6 | Greece |
| 7 | Hong Kong |
| 8 | Japan |
| 9 | Philippines |
| 10 | Saudi Arabia |
| 11 | South Korea |
| 12 | UK |
| 13 | US |

**Donor pool** Apart from data availability, I consider the following criteria in the selection of the donor pool countries as per Abadie 2021.

First, countries which may be affected by the intervention in the 'treated' country should be excluded from the sample. As per Q. Liu et al. 2024, emerging economies' stock markets exhibit a relatively weaker external influence and are more susceptible to external influence, making them net recipients of risk. Hence, I include developed economies in the donor pool but exclude surrounding smaller South Asian economies like Sri Lanka and Bangladesh which could be affected by the intervention in India.

Second, it is also important to eliminate from the donor pool any units that may have suffered large idiosyncratic shocks to the outcome of interest during the study period, if it is judged that such shocks would not have affected the outcome of the unit of interest in the absence of the intervention. An example of this is the reaction of the US markets to the 2016 presidential elections, where Trump's victory might have triggered short-term fluctuations in market liquidity around the election day which was November 8, 2016, November 9 (when Trump was informally projected to win) and January 6, 2017 (when the results were formally counted). However, this concern is mitigated for two reasons. A temporary shock such as this would affect both the treated unit and the donor pool and would therefore be a time-varying common trend. As in a difference-in-difference estimation, such shocks would be differenced out which allows us to attribute any deviations between the treated unit and synthetic control to the intervention itself. Also, while Trump's election is politically significant, it is not a systemic financial shock, and the impact on liquidity, if any, will not be persistent.

Third, it is important to restrict the donor pool to units with characteristics that are structurally similar to the affected unit. To make meaningful comparisons, I consider two criteria to capture similarities at the market-level. First, I limit the donor pool to the largest stock indices in the world by market capitalization. Since India's NIFTY 50 which is the treated unit is among these top indices, this would ensure that the donor pool indices operate under comparable regulatory frameworks, market depth and institutional settings. As a secondary filter, I apply a structural similarity filter. Specifically, I consider market indices in economies which fall within +- 10% of the treated unit's value on two dimensions: i) Market capitalization of domestic listed companies as a percent of GDP, and ii) Share turnover ratio (trading volume as a percent of market capitalization). These indicators serve as proxies for the relative size, importance and depth of the equity markets.

Abadie, Diamond, et al. 2010 also suggest restricting the donor pool if there exist countries in the donor pool whose trajectory in the pre-intervention periods was significantly

different from the trajectory of India. The inclusion of such donors would make it difficult to disentangle whether a difference in post-intervention match quality is attributable to the lack of fit or to the demonetization policy. To address this concern, it is important to check the pre-intervention fit for each measure while interpreting the results.

The list of countries in the donor pool is presented in Table 2.

**No Anticipation** As in any research design that exploits time variation in the outcome variable to estimate the effect of an intervention, synthetic control estimators may be biased if forward-looking economic agents react in advance of the policy intervention under investigation. As per Dharmapala and Khanna 2019, the announcement of demonetization was very much a surprise which provides a rare opportunity to test the effects of this initiative under this method. Hence, this condition is satisfied.

**No Interference** Abadie 2021 mentions that units' outcomes should be invariant to other units' treatments and assuming that such spillover effects do not exist is a strong restriction that must be accounted for in the analysis of the results. In accordance with this, I exclude neighbouring units (here other South Asian countries) from the donor pool to ensure the spillover effects from the event, if any, do not bias the synthetic control.

**Convex Hull condition** This condition is based on the idea that a combination of unaffected units can approximate the pre-intervention characteristics of the affected unit. This is ensured in the synthetic control method by constraining all weights to be non-negative and the sum of weights to be one. However, in the use of GSCM the weights are not subject to the restriction of summing to one and hence this condition does not apply.

**Time Horizon** This condition is related to the concern that the effect of some interventions may take time to emerge or be of sufficient magnitude to be detectable in the data. As detailed before, both the price and volatility impact on the NIFTY 50 index appear to be short-term from a visual examination. Furthermore, the analysis has to be restricted to June 2017 in the post-intervention period due to a new tax regime introduced in India during that month, which could confound the effects observed after this period.

**No Structural Breaks** The GSCM requires that there be no structural breaks, i.e. the treated and control units should be affected by the same set of factors and there is no change in the number of factors during the observed time periods. I discuss this condition further in the Limitations section and in Appendix B.

**Strict Exogeneity** The GSCM requires that the idiosyncratic errors $\epsilon_{it}$ are independent of the treatment assignment, observed covariates, and unobserved cross-sectional and temporal heterogeneities of all units at all periods. While the strict exogeneity assumption cannot be formally tested, Xu 2017 recommends testing its plausibility through diagnostic checks like evaluating pre-treatment fit by comparing actual outcomes with predicted counterfactuals and conducting placebo tests.

Other assumptions which are common with regular difference-in-difference with fixed effects models include weak serial dependence of the error terms, regularity conditions and cross-sectionally independent and homoscedastic error terms.

### 5.2.2 Choice of variables

The choice of outcome variables is the same as in the set-up of the event study. It involves the three liquidity measures namely market immediacy (CET), market depth (share turnover) and market breadth (Amihud illiquidity).

I first consider a baseline model with the only predictor variable being the same as the outcome variable but restricted to the pre-intervention period. As a robustness check, I add covariates to the model in the form of policy rates set by central banks across the donor pool countries. Having no substantial differences between both results, I only present the results from the model with the covariates added. The pre-intervention period is considered from March, 2016 to October, 2016 i.e. 8 months.

The post-intervention period was cut off at May, 2017 to prevent exposure to subsequent policies that involved a change in the indirect taxation system in India, that were anticipated in June, 2017 and implemented in July, 2017 in accordance with Lahiri and Deb 2022.

# 6 Results

## 6.1 Event study

The results of the event study are given in Table 3.

We find that the CET decreases significantly in the post-event period to approximately 0.80 times its pre-event level. The effect is statistically significant at the 1% level in the 14 to 90-day window following demonetization. This decline in CET indicates a notable reduction in trading elasticity, suggesting slower trade execution in the months after demonetization, potentially reflecting increased market frictions or execution delays.

In contrast, the second measure of share turnover increases to approximately 1.60 times its pre-event level after the event. The effect is statistically significant at all conventional significance levels from 7 to 30 days post the event. Not surprisingly, we observe a similar increase in traded volume up to 30 days post the event. These findings point to a short-term spike in liquidity immediately after the event.

The third measure, Amihud illiquidity, remains largely unchanged with post/pre ratios being close to 1 and statistically indistinguishable from the pre-event levels. This shows that the price impact per unit of trading volume, a proxy for market breadth, was not materially affected by the event.

Thus, the results differ among the various liquidity measures. Taken together, the evidence indicates that the demonetization led to increased market depth, evidenced by the higher share turnover and volumes and a decline in market immediacy as indicated by a lower CET. However, there is no evidence of change in market breadth as indicated by the unchanged Amihud illiquidity. One plausible mechanism is that the policy induced panic selling among institutional investors, leading to large trading volumes. However, trade execution has slowed, probably due to the larger orders being placed while the price impact (breadth) remains stable, suggesting that the market is effectively absorbing these higher volumes. This has been elaborated on in the subsequent section.

That said, the above causal attribution requires caution. While these effects are consistent with a policy shock to liquidity in the stock market, the observed effects could also be the result of some concurrent macroeconomic shock or other structural change in the market. To establish that the observed changes were driven by the demonetization policy and not by

other confounding factors affecting the liquidity measures at the same time, one must control for alternate drivers of the liquidity measures. Hence, I use a control sample and relevant covariates to construct a feasible counterfactual, by using a synthetic control approach within a fixed effects framework, that is the generalized synthetic control approach, in the next subsection.

**Table 3:** Event Study results: Post/Pre ratios, T-statistics, and P-values across different event windows and liquidity measures

| **Window** | **CET** | | | **Share Turnover** | | | **Amihud Illiquidity** | | | **Volume** | | | **Avg. Trade Size** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ratio | T-stat | P-val | Ratio | T-stat | P-val | Ratio | T-stat | P-val | Ratio | T-stat | P-val | Ratio | T-stat | P-val |
| (-1,1) | 0.9306 | -0.405 | 0.755 | 1.6574 | 3.914 | 0.159 | 1.0001 | 0.280 | 0.826 | 1.7221 | 3.232 | 0.191 | 1.2501 | 1.411 | 0.393 |
| (-2,2) | 0.9422 | -0.577 | 0.622 | 1.6005 | 5.712** | 0.029 | 1.0003 | 1.109 | 0.383 | 1.6200 | 4.206* | 0.052 | 1.2101 | 1.912 | 0.196 |
| (-5,5) | 0.9904 | -0.094 | 0.934 | 1.5162 | 5.056** | 0.037 | 1.0003 | 1.164 | 0.364 | 1.5627 | 3.892* | 0.060 | 1.2178 | 1.969 | 0.188 |
| (-7,7) | 1.1194 | 1.822 | 0.143 | 1.6860 | 7.319*** | 0.002 | 1.0000 | 0.180 | 0.866 | 1.6822 | 6.363*** | 0.003 | 1.1803 | 2.413* | 0.073 |
| (-14,14) | 0.7665 | -8.091*** | 0.000 | 1.5955 | 5.498*** | 0.000 | 0.9998 | -2.090* | 0.066 | 1.6218 | 5.774*** | 0.000 | 1.0404 | 0.966 | 0.359 |
| (-30,30) | 0.8702 | -6.478*** | 0.000 | 1.3059 | 4.143*** | 0.000 | 0.9999 | -1.500 | 0.148 | 1.2932 | 4.077*** | 0.001 | 0.9673 | -1.030 | 0.315 |
| (-60,60) | 0.9268 | -5.590*** | 0.000 | 1.0303 | 0.619 | 0.540 | 1.0001 | 1.267 | 0.212 | 1.0064 | 0.138 | 0.891 | 0.9337 | -3.305*** | 0.002 |
| (-90,90) | 0.9478 | -4.765*** | 0.000 | 1.0193 | 0.510 | 0.612 | 1.0001 | 1.497 | 0.140 | 1.0041 | 0.113 | 0.910 | 0.9889 | -0.635 | 0.528 |

Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## 6.2 GSCM

**Table 4:** Summary of ATT Estimates and Covariate Effects for CET, Share Turnover, and Amihud Illiquidity

| Outcome | Estimate | S.E. | CI Lower | CI Upper | p-value | Covariate Effect (Policy Rate) |
|---|---|---|---|---|---|---|
| **CET** | -0.0058* | 0.0032 | -0.0120 | 0.0004 | 0.0646 | -0.0058 (p = 0.0044)*** |
| **Share Turnover** | -0.0386 | 0.0866 | -0.2083 | 0.1311 | 0.6556 | -0.1141 (p = 0.2597) |
| **Amihud Illiquidity** | 0.0011 | 0.5312 | -1.0400 | 1.0420 | 0.9983 | 0.0089 (p = 0.0000)*** |

**Table 5:** Period-by-Period ATT Estimates for CET, Share Turnover, and Amihud Illiquidity

| Period | CET | | | Share Turnover | | | Amihud Illiquidity | | |
|---|---|---|---|---|---|---|---|---|---|
| | ATT | S.E. | p-value | ATT | S.E. | p-value | ATT | S.E. | p-value |
| -8 | 0.0041 | 0.0081 | 0.6081 | 0.1415 | 0.1261 | 0.2616 | -0.0005 | 0.0247 | 0.9826 |
| -7 | 0.0047 | 0.0084 | 0.5766 | -0.0162 | 0.1422 | 0.9095 | -0.0002 | 0.0429 | 0.9971 |
| -6 | 0.0010 | 0.0083 | 0.9033 | 0.0250 | 0.1463 | 0.8640 | 0.0009 | 0.0312 | 0.9774 |
| -5 | -0.0017 | 0.0081 | 0.8322 | -0.0977 | 0.1187 | 0.4105 | 0.0000 | 0.0307 | 0.9993 |
| -4 | -0.0023 | 0.0086 | 0.7894 | -0.1308 | 0.1024 | 0.2012 | -0.0003 | 0.0392 | 0.9942 |
| -3 | -0.0038 | 0.0109 | 0.7285 | 0.0366 | 0.1759 | 0.8351 | 0.0005 | 0.0341 | 0.9889 |
| -2 | -0.0036 | 0.0100 | 0.7156 | 0.0448 | 0.1225 | 0.7145 | -0.0017 | 0.0377 | 0.9637 |
| -1 | -0.0006 | 0.0084 | 0.9406 | -0.0252 | 0.1256 | 0.8407 | 0.0004 | 0.0171 | 0.9827 |
| 0 | 0.0023 | 0.0071 | 0.7504 | 0.0219 | 0.1444 | 0.8793 | 0.0010 | 0.0302 | 0.9738 |
| 1 | 0.0004 | 0.0365 | 0.9903 | -0.3180* | 0.1699 | 0.0613 | 0.0046 | 0.2436 | 0.9850 |
| 2 | -0.0565 | 0.0441 | 0.2000 | -0.0442 | 0.1436 | 0.7584 | 0.0006 | 0.3376 | 0.9987 |
| 3 | 0.0347*** | 0.0077 | 0.0000 | 0.1402 | 0.1184 | 0.2365 | -0.0005 | 0.3733 | 0.9989 |
| 4 | 0.0051 | 0.0134 | 0.7011 | 0.0891 | 0.1741 | 0.6090 | 0.0010 | 0.5690 | 0.9987 |
| 5 | -0.0258 | 0.0201 | 0.1991 | -0.1383 | 0.1752 | 0.4301 | 0.0011 | 0.5699 | 0.9985 |
| 6 | 0.0070 | 0.0200 | 0.7248 | 0.0395 | 0.1915 | 0.8367 | 0.0003 | 1.1486 | 0.9998 |

### 6.2.1 Market immediacy/ CET

Table 4 shows the ATT coefficients for all the liquidity measures of interest. Table 5 presents the period-wise ATT estimates.

The estimated ATT coefficient for CET is -0.0058. This indicates that the demonetization event resulted in a decrease in CET by 0.58%.[10] This estimate is statistically significant at

[10]Because the dependent variable is log transformed, the estimated coefficients can be approximately interpreted as percentage changes.

the 90% confidence level.

Table 5 indicates a negative impact on CET in the second post-treatment period followed by a positive impact in the third post-treatment period, which is statistically significant at all conventional significance levels.

Figure 2 represents the ATT of the demonetization event on the CET over time. The ATT moves close to zero before the event and is fairly volatile after the event takes place. It slopes sharply downward one month after the event but recovers in the subsequent month to higher than pre-event levels. Thus, there is a lag of one month after the event in the reaction of the CET. From a visual interpretation, we can observe a short-term decrease in CET after the event.

From Figure 3, we observe that the treated and estimated counterfactual closely follow each other in the pre-intervention period and even one month after the event. This implies a good pre-intervention fit for the measure. Two months after the event, the treated average drops significantly for a short period of time and then makes a V-shaped recovery. On the other hand, the estimated counterfactual displays a relatively gentler slope in its decline after the event. Thus, this departure of the treated unit's path from the estimated counterfactual serves as evidence of a negative impact of the demonetization on the CET.

I perform a robustness test to assess this result by adopting an in-space placebo test, a method adapted from the SCM literature and applied here to the GSCM framework. This approach enhances the credibility of the causal inference framework by systematically reassigning the treatment to each unit in the donor pool as if they were exposed to the intervention. Doing so generates a distribution of placebo treatment effects which serves as a benchmark against the estimated effect for the treated unit. By comparing the true ATT to the placebo distribution, we can evaluate whether the observed effect is statistically different to pure chance.

Figure 4 displays the results of the in-space placebo test. In the pre-treatment period, all units show very similar ATT trajectories near zero. This suggests the method constructs a precise counterfactual with limited divergence between the placebo runs. The black line indicating the treated unit India shows a clear dip right after the event and a subsequent rebound. Though the placebo units exhibit more volatility as compared to the treated unit, none of them follow the same pattern as the treated unit in that none of them exhibit a steep decline immediately after the event. India's ATT path is distinguishable from other

units particularly in the two months immediately following the event. Hence, the result for the treated unit does not appear to be random noise.

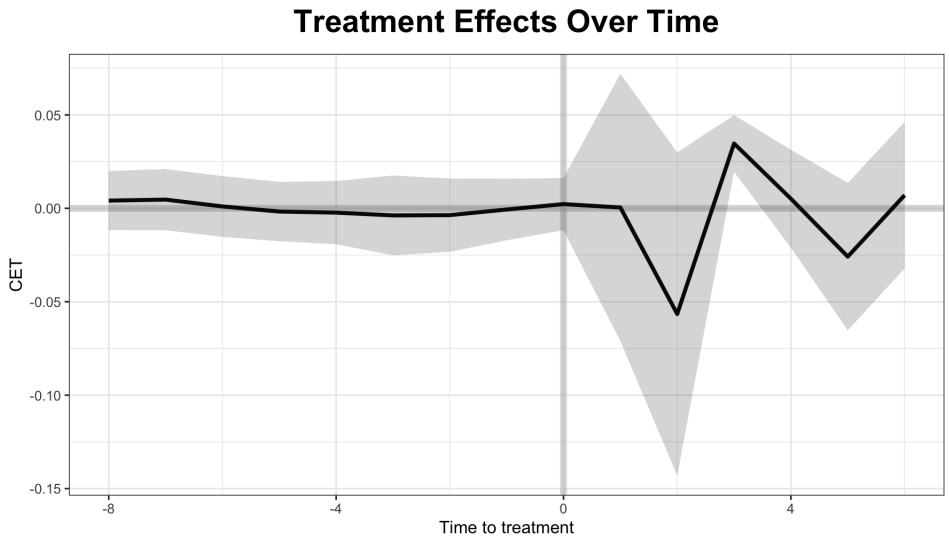



**Figure 2:** CET: Treatment effects over time

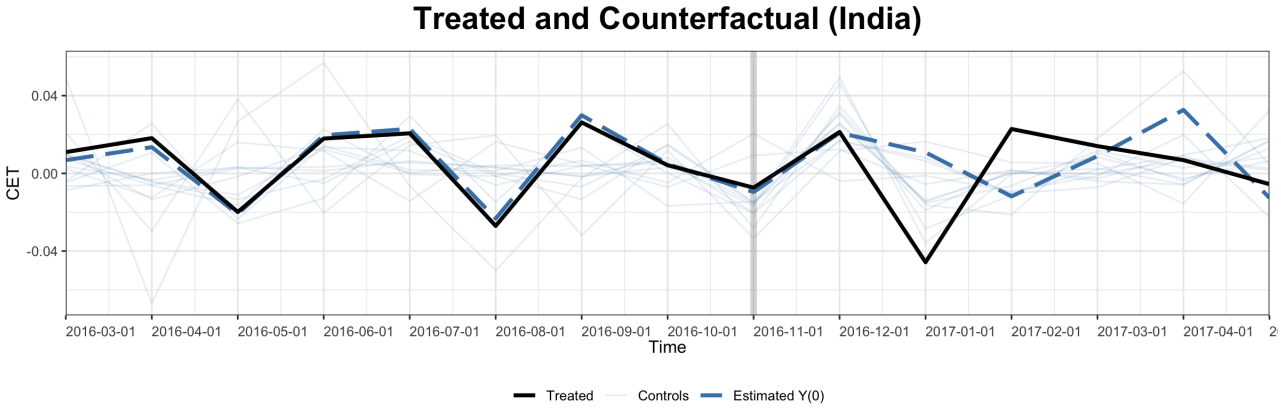



**Figure 3:** CET: Treated vs Counterfactual for India with raw data

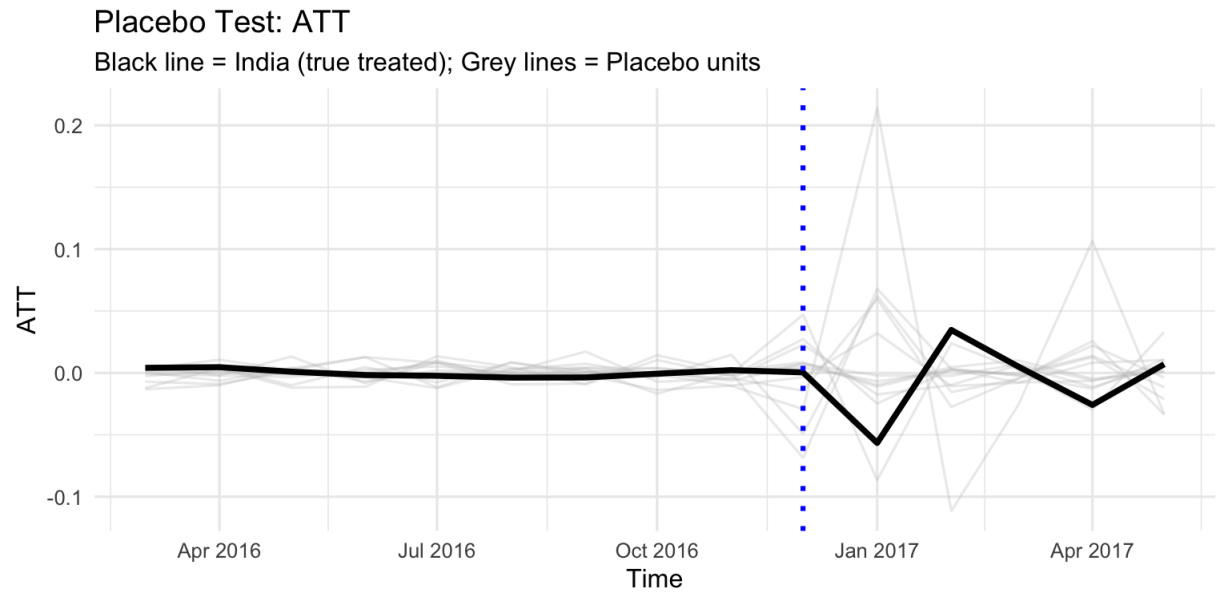



**Figure 4:** CET: In-space Placebo Test

### 6.2.2 Market depth/ Share turnover

The estimated ATT coefficient for share turnover is -0.0386. This indicates that the demonetization event resulted in a decrease in average share turnover by 3.86%. However, this estimate is statistically insignificant at all conventional significance levels as indicated by the p-value of 0.6556.

Table 5 indicates a negative impact on share turnover in the first post-treatment period, which is statistically significant at the 90% confidence level. No further robustness tests have been performed due to the insignificant result.

As per Abadie 2021, the credibility of the SCM depends on the extent to which the synthetic control can fit the trajectory of the treated unit for an extended pre-event period. If the fit is poor, they recommend against using synthetic control.

Figure 5 represents the ATT of the demonetization event on the share turnover over time. The ATT slopes downward immediately after the event but recovers after one month to higher than pre-event levels. From a visual interpretation, we can observe a short-term decrease in share turnover after the event.

From Figure 6, we observe that the treated and estimated counterfactual follow each

other albeit not precisely in the pre-intervention period. This serves as a diagnostic check to check pre-intervention fit as per Xu 2017. After the event, the treated average drops significantly for a short period of a month and makes a V-shaped recovery. On the other hand, the estimated counterfactual displays a relatively stable movement after the event. Thus, the figure lends credence to the notion that the share turnover faced a short-term decrease post the event but is not statistically significant. Overall, the result of decreased share turnover after the event is only weakly significant.

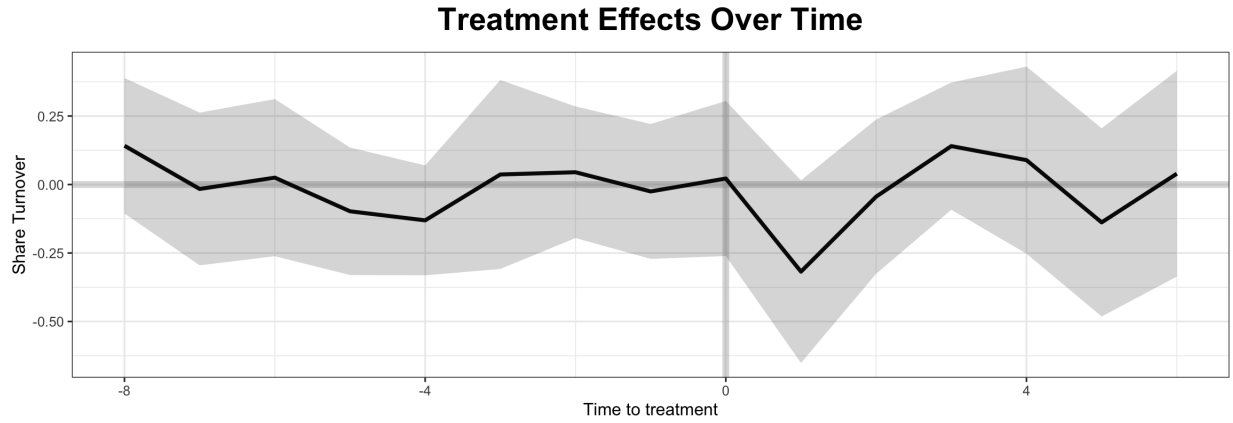



**Figure 5:** Share Turnover: Treatment effects over time (monthly)

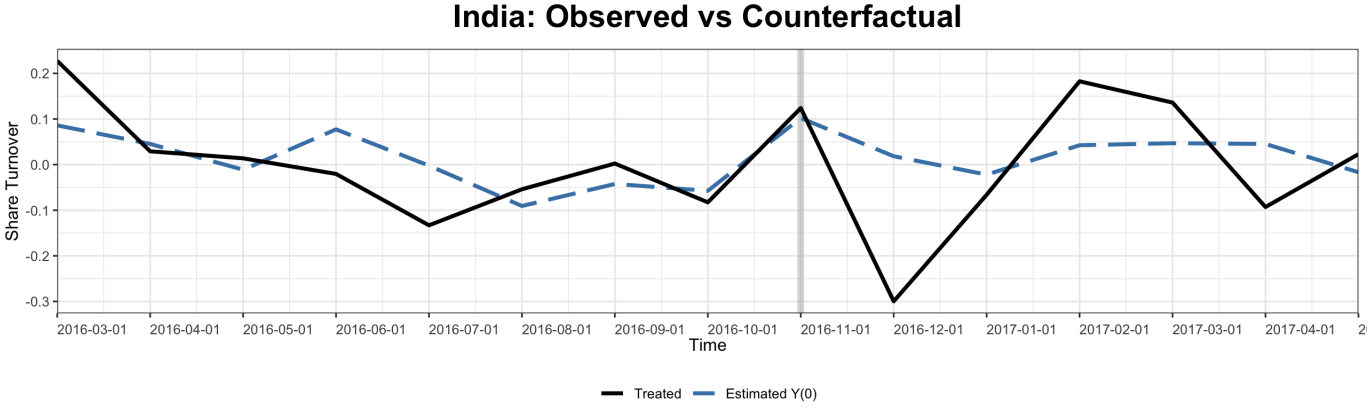



**Figure 6:** Share Turnover: Treated vs Counterfactual for India

### 6.2.3 Market breadth/ Amihud illiquidity

The estimated ATT coefficient for Amihud illiquidity is 0.0011. This indicates that the demonetization event resulted in an increase in Amihud illiquidity by 0.11%. However, this estimate is not statistically significant at any conventional significance level.

Table 5 indicates a negligible impact on Amihud illiquidity in all post-treatment periods. No further robustness tests have been performed because of the insignificance of the results.

Figure 7 represents the ATT of the demonetization event on the Amihud illiquidity over time. The ATT moves close to zero before and after the event. We observe an increase in the confidence interval after the event. From a mere visual interpretation, we can observe no impact of the event on the Amihud illiquidity.

From Figure 8, we observe that the paths of the treated unit and estimated counterfactual do not follow each other both before and after the event. This implies a poor pre-intervention fit for the measure. The path of the treated unit deviates from the counterfactual some months before the event takes place. As such, we cannot attribute the deviation between the two to the event itself. Thus, there is no evidence of a significant treatment effect on the meausure of Amihud illiquidity, suggesting that the event did not substantially impact liquidity as measured by this metric.

The discussion of the results is covered in the subsequent section.

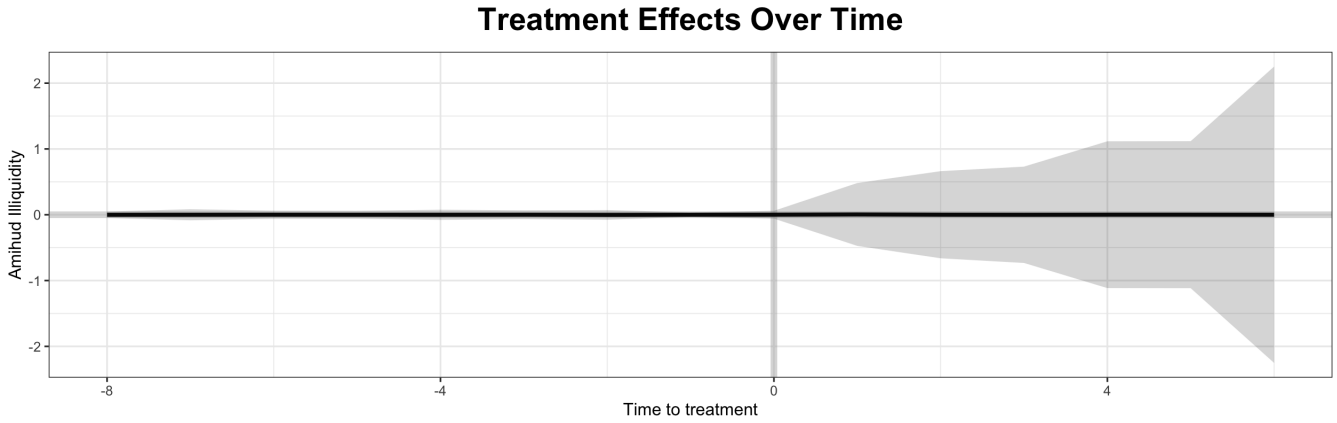



**Figure 7:** Amihud Illiquidity: Treatment effects over time

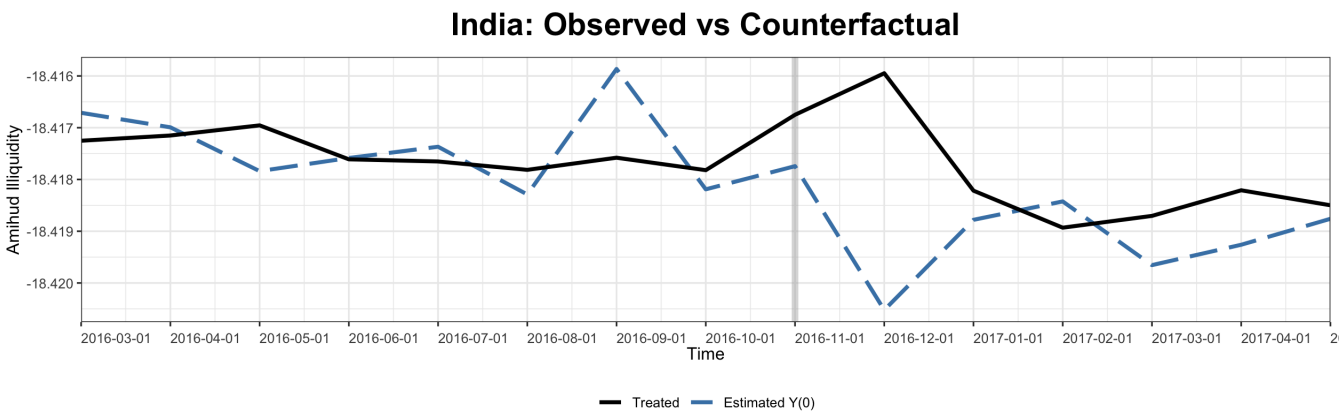



**Figure 8:** Amihud Illiquidity: Treated vs Counterfactual for India

# 7 Discussion and Limitations

## 7.1 Discussion of results

### 7.1.1 Impact on market depth and trading volumes

I measure market depth by the measure of share turnover. For the financial year 2016-17, non-promoter holdings of the NIFTY 50 index amounted to approximately 55% of the total market capitalization. Of this, nearly 30% was held by Domestic Mutual Funds (DMFs) [11]. Institutional investors, such as DMFs, tend to exhibit pro-cyclical flows meaning that they tend to sell during periods of market uncertainty (Sirri and Tufano 1998). At the time of bad news, these funds face redemption pressures and are forced to liquidate holdings. This can contribute to increased trading activity. In the case of the demonetization event, more than half of the index's holding was owned by investors prone to panic selling in case of bad news and uncertainty which likely exacerbated the market's response to the policy shock.

According to the event study results, the share turnover and volume increased to 1.60/1.70 times the pre-event mean in the window of 7 days and 14 days after the event. This sharp increase in market depth and trading volume immediately after the event indicates a significant rise in market liquidity. However, this is of the "distress liquidity" nature and not indicative of improved market functioning. Hence, this jump in volume and depth can plausibly be attributed to institutional investors' pro-cyclical behaviour and forced liquidation during times of market uncertainty.

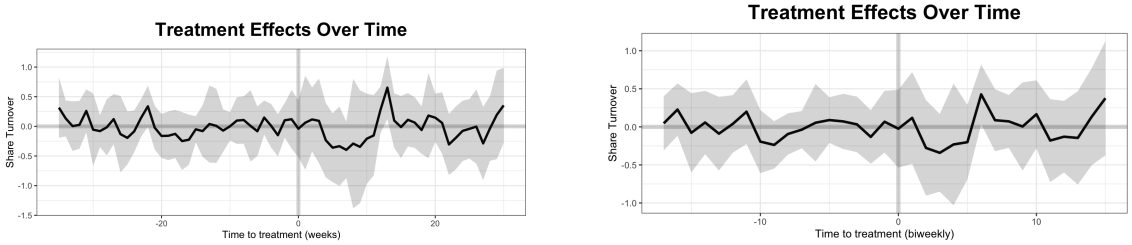
However, the above result is not supported by the GSCM result at the monthly frequency level. There are two issues at play here which contribute to the deviation in results. One is of noise or high volatility and the other is of coarse temporal aggregation.

Abadie 2021 suggest denoising the data in case the outcome variable is highly volatile since in such a case it will be difficult to distinguish the effects of the treatment on the outcome unit from its natural fluctuations. Outcome variables that include substantial random noise elevate the risk of overfitting. In such cases, it is advisable to filter out the volatility in both the treated unit and the donor pool before applying synthetic control techniques. Following this guidance, I do not use daily data in the GSCM framework since

[11] See India Ownership Tracker, Q4 FY24 — Vol. 5, Issue 4, National Stock Exchange

it is highly noisy and this presence of excessive randomness makes it difficult to construct a reliable counterfactual for the treated unit under the method.

On the other hand, monthly aggregation while reducing volatility may be too coarse to capture short-lived effects. The event study, using daily data, detects a significant increase in share turnover immediately following the event whereas the GSCM, using monthly data, fails to detect significant changes, likely because the effect is diluted over the longer aggregation window.




**(a)** Share Turnover: Treatment effects over time (weekly)

**(b)** Share Turnover: Treatment effects over time (biweekly)

**Figure 9:** Share Turnover: Treatment effects over time (weekly and biweekly)

To address this mismatch, it is worth referencing Figure 9 which displays the GSCM results for share turnover at the weekly and biweekly aggregation levels. These more granular aggregation levels serve as a compromise between denoising and the ability to detect short-term movements. The results show that the ATT increases slightly after the treatment date and fluctuates thereafter. While most effects are statistically insignificant (the detailed results for the weekly and bi-weekly aggregation are given in Appendix A), we observe a significant positive effect on the share turnover 6 fortnights (0.426) and 13 weeks (0.6526) after the event, suggesting a delayed but short-lived response.

In summary, the only significant effect on the share turnover detected by the GSCM occurs approximately 3 months after the event. The divergence between the event study and GSCM findings can therefore be attributed to the combination of noise in high-frequency data which hampers counterfactual construction and loss of information due to coarse aggregation at the monthly level.

### 7.1.2 Impact on immediacy

As detailed above, I measure market immediacy by the CET which is essentially the log price elasticity of trading volumes. A higher CET indicates a more liquid market where volume changes are more sensitive to price changes. Conversely, a lower CET suggests lower liquidity indicating that volume changes would be less sensitive to price changes.

The average trade/order size is calculated as:

$$\text{Avg Trade Size} = \frac{T_s}{\text{Total Trades}}$$

where $T_s$ is the total trading volume of the stock and Total Trades is the number of trades executed.

An increase in average trade size implies larger orders, which are likely to take more time to execute indicating reduced market immediacy. As per Table 3, we observe a statistically significant increase in the average trade size in the 7 day post-event window. This finding is consistent with prior evidence that at the order-level, execution tends to take longer on larger orders (Garvey and Qin 2022).

Given the consistent results observed under both the event study and the GSCM framework, the findings suggest a significant impact of the demonetization event on trading behaviour. The increase in average trade size suggests that market participants are placing larger orders which generally require more time to execute. The simultaneous decline in CET reflects a deterioration in liquidity, meaning that price changes have a lesser impact on traded volume. In such conditions, the execution of larger orders takes longer as market participants trade more cautiously in order to execute the orders without significantly impacting the price. Thus, the combined effect of larger orders and reduced liquidity leads to slower trade execution in the post-event period.

### 7.1.3 Impact on market breadth

Market breadth, as measured by the Amihud illiquidity ratio, is defined as the absolute return divided by dollar volume. Both the event study and GSCM results show that there

was no significant change in the Amihud illiquidity measure after the event. We also know from the results that trading volume has increased post the event, hence the stability of the Amihud illiquidity measure can only be explained in two ways:

- Lower percentage price change movements: If the percentage price change (i.e., $\frac{P_t - P_{t-1}}{P_{t-1}}$) decreases, it offsets the increased volume, keeping the illiquidity measure stable. This would suggest that despite higher trading activity, price movements are less pronounced.

- Percentage price change remain same: Then, for the product $(P_t * Qty)$ (dollar volume) to increase while keeping the ratio unchanged, the current price would need to decrease. A lower price compensates for the increase in quantity, maintaining a stable denominator in the Amihud formula.

However, from Sutar et al. 2023, we know that within a 30 day post-event window the market reacted negatively to the event with negative CARs observed. Hence, the first option of lower percentage price changes outlined above seems more plausible. This suggests that the market absorbed the additional volume after the event without significant price impact. Supporting this, Anand et al. 2013 show that participation by liquidity supplying institutions can ameliorate illiquidity, while participation by liquidity demanding institutions can exacerbate illiquidity. This implies that the type of institutional participation may influence the extent of illiquidity observed in the market.

### 7.1.4 Correlation to returns movement

Demonetization led to a short-term economic slowdown and a decrease in the GDP growth rate (Chodorow-Reich et al. 2018). Sutar et al. 2023 find that the stock market initially viewed the announcement of demonetization to be disruptive to the entire market but the market bounced back after one month. It is interesting to note that within a 30-day post event window, the cumulative abnormal returns (CAR) reduced but the market liquidity depth (share turnover and volume) increased while market immediacy reduced.

From a theoretical standpoint, one would hypothesize that the drop in CAR would be associated with a reduction in liquidity. A decrease in contemporaneous returns would

indicate higher future returns and lower contemporaneous liquidity as liquidity co-moves with contemporaneous returns as per Acharya and Pedersen 2005. Yet, the findings suggest that despite the reduction in CAR, the market depth and trading volume increased.

This suggests that although the market's reaction was negative, the increased volume was likely due to heightened trading activity, possibly driven by panic selling or liquidation in response to the uncertainty caused by the demonetization event. The reduced immediacy (slower execution of trades) aligns with this, as larger trades took longer to execute in a less liquid environment. Hence, I find that the movement in stock returns after the demonetization event is not explained by the mechanism of stock market liquidity.

### 7.1.5 Theoretical interpretation of liquidity effects

The results of increased market depth (share turnover) but reduced market immediacy (CET) can be interpreted through the lens of market microstructure theory. Two sources of market friction offer competing, yet complementary explanations: inventory costs and adverse selection.

As given by Stoll 1978, Amihud and Mendelson 1980, T. Ho and Stoll 1981 and T. S. Y. Ho and Stoll 1983, the inventory cost paradigm suggests that market makers manage their inventory of positions by adjusting their quotes. If they are long, that is holding too many shares, they lower ask prices to offload their positions. If they are short, they raise bid prices to buy shares.

The second paradigm of adverse selection refers to the idea that trading with better-informed investors leads to losses for market makers. The market makers thus widen spreads or reduce the number of quotes they post to compensate for these losses. Hence, spreads increase with adverse selection (Glosten and Milgrom 1985 and Kyle 1985).

Panic selling by institutional investors generated large sell-order flows. This shows up in the results as an increase in share turnover. Market makers who absorb these orders end up in a net long position and lower their ask quotes to attract buyers and rebalance their inventory. At the same time, an event like demonetization triggers economic uncertainty which makes it difficult for market makers to judge whether they are trading with informed or uninformed investors. Fearing adverse selection, market makers adjust their bid/ask quotes (or shrink their order sizes), effectively widening the spread. The net result is an order book which

has shifted downwards on the sell-side but has become more expensive for new buyers and sellers in the market (due to the wider spreads). We observe that market makers, fearing informed or forced trades, pull back liquidity resulting in increased trading activity but at a higher implicit cost signalled by the reduced CET. This aligns with the pattern reflected in the results of increased market depth with reduced market immediacy.

In summary, the demonetization generated distress liquidity, in that there was an increased trading activity but at worse terms but without any price impact. The results are consistent with a market microstructure environment in which pressures on inventory and fear of adverse selection simultaneously drive reactions of liquidity provision.

## 7.2 Limitations of the study

In this section, I highlight some limitations of this study which are important to consider while interpreting the results.

First is a methodological consideration. As per Xu 2017, modelling assumptions play an important role in the GSCM. One such assumption is that the treated and control units must be affected by the same set of factors, sharing common support in factor loadings, during the observed time periods. However, since the method uses extrapolation to impute the treated counterfactual, any erroneous estimation of factor loadings may lead to misleading results since the accuracy of the results is heavily dependent on the chosen factor loadings. I examine the factors and factor loadings estimated by the GSCM for the three liquidity measures in Appendix B and find robust results for CET and share turnover but weak overlap in the factor loadings for Amihud illiquidity.

Second, Xu 2017 also notes that when the number of pre-treatment periods is small, incidental parameters can lead to biased estimates of the treatment effects. However, the risk of bias in the estimates is seemingly low when the treatment units comprise approximately one fifth of the total number of units in the sample. In this study, I consider one treated unit (India) and a donor pool comprising more than ten countries. This satisfies the recommendation suggesting that the estimates are unlikely to be biased.

Third, I would like to point out the exclusion of an important measure of liquidity in the study which is the bid-ask spread. Due to a lack of reliable data on bid-ask rates across countries, this measure which is a proxy for market tightness could not be included in the

analysis. It would be interesting to study how this measure evolved in the wake of the demonetization, given that it is the amount of cost incurred by an investor for transacting a security. However, as noted by Persaud 2002, bid-ask spreads are a good measure of liquidity only during good liquidity conditions and not during poor conditions of liquidity, wherein price and quantity offer a better picture of market conditions.

Fourth, I would like to highlight the issue of measurement error in the liquidity measures. As per Amihud, Mendelson, and Pedersen 2005, any sole liquidity measure measures liquidity imperfectly because it cannot encompass all the dimensions of liquidity, its empirical estimate is noisy and the use of low-frequency data increases the measurement noise. Hence, the measures used are widely accepted but imperfect proxies of the liquidity in the equity markets. Though each measure captures a different dimension of liquidity, it may not fully reflect the entire spectrum of trading frictions faced by market participants. Additionally, differences in market microstructure across the world might lead to different reactions to such an event in different countries.

Despite its limitations, this study examines unanswered questions about the event of demonetization and provides a possible explanation for the mechanism behind the observed results. It also provides some insights to policymakers interested in the impact of such policy shocks on stock market liquidity.

# 8 Conclusion

This thesis sets out to investigate the effect of an exogenous liquidity shock, the 2016 Indian demonetization, on stock market liquidity. I find that the market immediacy/speed (CET) declined and the market breadth/price impact (Amihud illiquidity) remained unchanged after the event. These results are consistent across both empirical frameworks. However, the market depth/quantity (share turnover) showed an increase after the event under one of the methodologies and not the other, indicating a mixed response. The findings reflect the multidimensional nature of liquidity and hint at the inventory cost and adverse selection frictions at play.

This study points towards some questions which remain unanswered. First, how do the measures respond on a second-by-second basis after the announcement? Second, how does heterogeneity among market participants affect the responses? The difference in reactions of high-frequency traders vis-à-vis traditional market makers would also contribute to the knowledge on the expectation formation process of investors. How would the aforementioned findings differ across various asset classes like fixed income, foreign exchange and alternatives? Hence, future research on high-frequency, granular data with disaggregated investor information could generate additional insights on the response of various liquidity measures.

While this study comments on how policy shocks affect various aspects of liquidity, some of its limitations merit a mention such as the GSCM being based on an extrapolation of factor loadings, the non-availability of bid-ask data potentially leading to missing important insights on market tightness and that though the liquidity measures used are standard across the literature, they remain noisy and imperfect measures of the true market liquidity.

Overall, this thesis has tangible policy implications. It points to the need of a planned and phased implementation of a large-scale policy intervention such as this, to reduce informational shocks that drive institutional panic trading. Arguably, the negative effects of the policy would have been reduced if the government had carried out well-communicated staggered roll-outs of the demonetization, thereby limiting uncertainty in the capital markets.

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# Appendix

## A. Additional tables and figures

### NIFTY 50

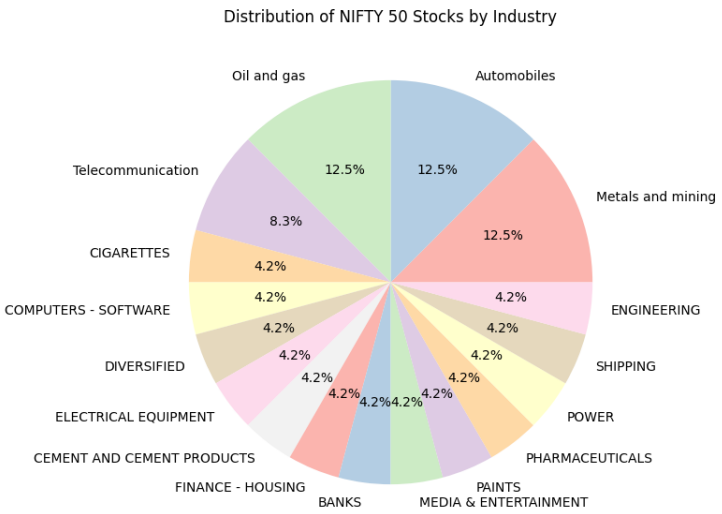


**Figure 10:** NIFTY 50: Classification by Industry

**Table 6:** NIFTY 50 Composition as of October, 2016

| Sr. No | Security Symbol | Security Name | Industry | Equity Capital (In Rs.) | Free Float Market Capitalisation (Rs. Crores) | Weightage (%) | Beta | Volatility (%) | Monthly Return |
|---|---|---|---|---|---|---|---|---|---|
| 1 | ACC | ACC Ltd. | CEMENT AND CEMENT PRODUCTS | 1877871730.00 | 14250.70 | 0.45 | 0.88 | 1.27 | -5.13 |
| 2 | ADANIPORTS | Adani Ports and Special Economic Zone Ltd. | SHIPPING | 4141903522.00 | 27187.25 | 0.86 | 1.46 | 3.18 | 18.91 |
| 3 | AMBUJACEM | Ambuja Cements Ltd. | CEMENT AND CEMENT PRODUCTS | 3971290458.00 | 18601.13 | 0.59 | 0.95 | 1.41 | -4.59 |
| 4 | ASIANPAINT | Asian Paints Ltd. | PAINTS | 959197790.00 | 48497.28 | 1.53 | 0.64 | 1.54 | -7.32 |
| 5 | AUROPHARMA | Aurobindo Pharma Ltd. | PHARMACEUTICALS | 585169586.00 | 22020.11 | 0.69 | 1.18 | 1.48 | -4.37 |
| 6 | AXISBANK | Axis Bank Ltd. | BANKS | 4776106626.00 | 81525.75 | 2.57 | 1.26 | 2.16 | -9.91 |
| 7 | BAJAJ-AUTO | Bajaj Auto Ltd. | AUTOMOBILES | 2893670200.00 | 38494.15 | 1.21 | 0.89 | 1.38 | 0.10 |
| 8 | BANKBARODA | Bank of Baroda | BANKS | 4608319196.00 | 14704.34 | 0.46 | 1.66 | 1.75 | -7.02 |
| 9 | BHEL | Bharat Heavy Electricals Ltd. | ELECTRICAL EQUIPMENT | 4895200000.00 | 12588.01 | 0.40 | 1.52 | 1.39 | 3.19 |
| 10 | BPCL | Bharat Petroleum Corporation Ltd. | OIL AND GAS | 14461684960.00 | 34842.54 | 1.10 | 0.71 | 1.37 | 9.25 |
| 11 | BHARTIARTL | Bharti Airtel Ltd. | TELECOMMUNICATION | 19987000510.00 | 42041.06 | 1.33 | 0.69 | 1.33 | 1.50 |
| 12 | INFRATEL | Bharti Infratel Ltd. | TELECOMMUNICATION | 18966670690.00 | 18454.57 | 0.58 | 0.61 | 2.03 | -4.87 |
| 13 | BOSCHLTD | Bosch Ltd. | AUTOMOBILES | 313989000.00 | 19919.77 | 0.63 | 0.86 | 1.08 | -4.04 |
| 14 | CIPLA | Cipla Ltd. | PHARMACEUTICALS | 1607220942.00 | 29300.64 | 0.92 | 0.61 | 1.27 | -0.22 |
| 15 | COALINDIA | Coal India Ltd. | METALS & MINING | 63163644000.00 | 41106.90 | 1.30 | 0.69 | 1.15 | 0.96 |
| 16 | DRREDDY | Dr. Reddy's Laboratories Ltd. | PHARMACEUTICALS | 853489715.00 | 41997.70 | 1.32 | 0.74 | 1.31 | 7.00 |
| 17 | EICHERMOT | Eicher Motors Ltd. | AUTOMOBILES | 271980830.00 | 32007.53 | 1.01 | 0.87 | 1.48 | -3.27 |
| 18 | GAIL | GAIL (India) Ltd. | OIL & GAS | 12684774000.00 | 20270.65 | 0.64 | 1.02 | 1.75 | 15.28 |
| 19 | GRASIM | Grasim Industries Ltd. | CEMENT AND CEMENT PRODUCTS | 933482020.00 | 31255.08 | 0.99 | 0.74 | 1.17 | 0.33 |
| 20 | HCLTECH | HCL Technologies Ltd. | COMPUTERS - SOFTWARE | 2821680788.00 | 43326.91 | 1.37 | 0.70 | 1.52 | -4.02 |
| 21 | HDFCBANK | HDFC Bank Ltd. | BANKS | 5076901034.00 | 251333.76 | 7.93 | 0.78 | 0.91 | -1.54 |
| 22 | HEROMOTOCO | Hero MotoCorp Ltd. | AUTOMOBILES | 399380176.00 | 42840.39 | 1.35 | 0.95 | 1.34 | -1.80 |
| 23 | HINDALCO | Hindalco Industries Ltd. | METALS & MINING | 2065007832.00 | 19172.57 | 0.60 | 1.96 | 1.53 | -1.93 |
| 24 | HINDUNILVR | Hindustan Unilever Ltd. | DIVERSIFIED | 2164245676.00 | 59932.18 | 1.89 | 0.59 | 1.10 | -3.31 |
| 25 | HDFC | Housing Development Finance Corporation Ltd. | FINANCE - HOUSING | 3164952360.00 | 217986.09 | 6.88 | 1.07 | 1.82 | -1.14 |
| 26 | ITC | I T C Ltd. | CIGARETTES | 12090430722.00 | 204515.68 | 6.45 | 0.94 | 1.03 | 0.12 |
| 27 | ICICIBANK | ICICI Bank Ltd. | BANKS | 11635133120.00 | 161175.68 | 5.08 | 1.66 | 2.76 | 9.88 |
| 28 | IDEA | Idea Cellular Ltd. | TELECOMMUNICATION | 36009152400.00 | 9679.26 | 0.31 | 0.74 | 2.58 | -2.91 |
| 29 | INDUSINDBK | IndusInd Bank Ltd. | BANKS | 5964716540.00 | 59161.04 | 1.87 | 0.96 | 1.07 | -0.08 |
| 30 | INFY | Infosys Ltd. | COMPUTERS - SOFTWARE | 11484723320.00 | 200253.84 | 6.32 | 0.84 | 1.16 | -3.28 |
| 31 | KOTAKBANK | Kotak Mahindra Bank Ltd. | BANKS | 9179988890.00 | 94807.16 | 2.99 | 0.91 | 1.11 | 5.49 |
| 32 | LT | Larsen & Toubro Ltd. | ENGINEERING | 1863945430.00 | 120990.56 | 3.82 | 1.41 | 1.26 | 2.94 |
| 33 | LUPIN | Lupin Ltd. | PHARMACEUTICALS | 901962150.00 | 36288.01 | 1.14 | 0.77 | 1.38 | 2.15 |
| 34 | M&M | Mahindra & Mahindra Ltd. | AUTOMOBILES | 3105461920.00 | 61348.40 | 1.94 | 0.91 | 1.41 | -6.31 |
| 35 | MARUTI | Maruti Suzuki India Ltd. | AUTOMOBILES | 1510400300.00 | 78368.81 | 2.47 | 1.08 | 1.04 | 7.65 |
| 36 | NTPC | NTPC Ltd. | POWER | 82454644000.00 | 37364.32 | 1.18 | 0.84 | 0.99 | 2.06 |
| 37 | ONGC | Oil & Natural Gas Corporation Ltd. | OIL & GAS | 42777450600.00 | 51959.20 | 1.64 | 1.03 | 1.81 | 12.68 |
| 38 | POWERGRID | Power Grid Corporation of India Ltd. | POWER | 52315896480.00 | 38463.17 | 1.21 | 0.73 | 1.14 | -0.85 |
| 39 | RELIANCE | Reliance Industries Ltd. | OIL & GAS | 32429503780.00 | 173858.46 | 5.48 | 0.94 | 1.35 | -3.00 |
| 40 | SBIN | State Bank of India | BANKS | 7762777042.00 | 79987.65 | 2.52 | 1.67 | 1.28 | 2.53 |
| 41 | SUNPHARMA | Sun Pharmaceutical Industries Ltd. | PHARMACEUTICALS | 2406753959.00 | 81022.17 | 2.56 | 0.80 | 1.02 | 0.73 |
| 42 | TCS | Tata Consultancy Services Ltd. | COMPUTERS - SOFTWARE | 1970427941.00 | 127207.58 | 4.01 | 0.73 | 0.93 | -1.64 |
| 43 | TATAMTRDVR | Tata Motors Ltd DVR | AUTOMOBILES | 1016953408.00 | 17409.81 | 0.55 | 1.42 | 2.20 | 1.57 |
| 44 | TATAMOTORS | Tata Motors Ltd. | AUTOMOBILES | 5774407204.00 | 102901.81 | 3.25 | 1.73 | 1.97 | -0.54 |
| 45 | TATAPOWER | Tata Power Co. Ltd. | POWER | 2704629398.00 | 14152.51 | 0.45 | 1.01 | 1.70 | 3.58 |
| 46 | TATASTEEL | Tata Steel Ltd. | METALS & MINING | 9712154390.00 | 27120.51 | 0.86 | 1.56 | 1.98 | 8.14 |
| 47 | TECHM | Tech Mahindra Ltd. | COMPUTERS - SOFTWARE | 4858201210.00 | 27342.73 | 0.86 | 0.96 | 1.97 | 4.73 |
| 48 | ULTRACEMCO | UltraTech Cement Ltd. | CEMENT AND CEMENT PRODUCTS | 2744424080.00 | 41342.42 | 1.30 | 0.94 | 1.09 | 2.93 |
| 49 | WIPRO | Wipro Ltd. | COMPUTERS - SOFTWARE | 4941562572.00 | 29833.20 | 0.94 | 0.57 | 1.29 | -3.04 |
| 50 | YESBANK | Yes Bank Ltd. | BANKS | 4212165470.00 | 41605.79 | 1.31 | 1.35 | 1.31 | 0.93 |
| 51 | ZEEL | Zee Entertainment Enterprises Ltd. | MEDIA & ENTERTAINMENT | 960448720.00 | 28382.84 | 0.90 | 1.06 | 2.70 | -5.18 |

**Weekly and Bi-weekly Results**

**Table 7:** Summary of ATT Estimates and Covariate Effects for Share Turnover on Weekly Frequency

| **Outcome** | **Estimate** | **S.E.** | **CI Lower** | **CI Upper** | **p-value** |
|---|---|---|---|---|---|
| Share Turnover | -0.0311 | 0.1003 | -0.2277 | 0.1656 | 0.7569 |
| Covariate Effect (Policy Rate) | -0.1657 | 0.1488 | -0.4575 | 0.126 | 0.2655 |

**Table 8:** Period-by-Period ATT Estimates for Share Turnover on Weekly Frequency

| Period | ATT | S.E. | CI Lower | CI Upper | p-value |
|---|---|---|---|---|---|
| -9 | 0.0971 | 0.2006 | -0.2961 | 0.4903 | 0.6283 |
| -8 | 0.1073 | 0.2043 | -0.2932 | 0.5078 | 0.5995 |
| -7 | 0.0077 | 0.3068 | -0.5936 | 0.6090 | 0.9799 |
| -6 | -0.0826 | 0.2132 | -0.5005 | 0.3353 | 0.6985 |
| -5 | 0.1481 | 0.1463 | -0.1386 | 0.4348 | 0.3114 |
| -4 | 0.0113 | 0.1873 | -0.3557 | 0.3784 | 0.9518 |
| -3 | -0.1494 | 0.1811 | -0.5044 | 0.2055 | 0.4093 |
| -2 | 0.1020 | 0.1481 | -0.1882 | 0.3922 | 0.4909 |
| -1 | 0.1202 | 0.2518 | -0.3733 | 0.6137 | 0.6331 |
| 0 | -0.0398 | 0.2449 | -0.5197 | 0.4401 | 0.8710 |
| 1 | 0.0614 | 0.4040 | -0.7304 | 0.8532 | 0.8792 |
| 2 | 0.1163 | 0.2752 | -0.4230 | 0.6557 | 0.6725 |
| 3 | 0.0928 | 0.3625 | -0.6178 | 0.8033 | 0.7981 |
| 4 | -0.2342 | 0.3194 | -0.8603 | 0.3918 | 0.4634 |
| 5 | -0.3595 | 0.2959 | -0.9395 | 0.2204 | 0.2244 |
| 6 | -0.3346 | 0.3412 | -1.0033 | 0.3341 | 0.3267 |
| 7 | -0.3970 | 0.2422 | -0.8718 | 0.0778 | 0.1013 |
| 8 | -0.2911 | 0.5555 | -1.3798 | 0.7976 | 0.6002 |
| 9 | -0.3457 | 0.4861 | -1.2983 | 0.6070 | 0.4770 |
| 10 | -0.2079 | 0.3876 | -0.9676 | 0.5517 | 0.5916 |
| 11 | -0.1536 | 0.3464 | -0.8325 | 0.5254 | 0.6575 |
| 12 | 0.2793 | 0.2004 | -0.1134 | 0.6720 | 0.1634 |
| 13 | $0.6526^{**}$ | 0.2691 | 0.1253 | 1.1799 | 0.0153 |
| 14 | 0.0978 | 0.2340 | -0.3609 | 0.5566 | 0.6759 |
| 15 | -0.0123 | 0.2670 | -0.5355 | 0.5110 | 0.9634 |
| 16 | 0.1107 | 0.2296 | -0.3392 | 0.5606 | 0.6297 |
| 17 | 0.0637 | 0.2178 | -0.3631 | 0.4905 | 0.7699 |
| 18 | -0.0616 | 0.2044 | -0.4622 | 0.3390 | 0.7631 |

**Table 9:** Summary of ATT Estimates and Covariate Effects for Share Turnover on Bi-weekly Frequency

| Outcome | Estimate | S.E. | CI Lower | CI Upper | p-value |
|---|---|---|---|---|---|
| Share Turnover | -0.0081 | 0.1246 | -0.2523 | 0.2361 | 0.9482 |
| Covariate Effect (Policy Rate) | -0.1699 | 0.1256 | -0.4162 | 0.0763 | 0.1762 |

**Table 10:** Period-by-Period ATT Estimates for Share Turnover on Bi-weekly Frequency

| Period | ATT | S.E. | CI Lower | CI Upper | p-value |
|---|---|---|---|---|---|
| -11 | 0.1993 | 0.2168 | -0.2257 | 0.6242 | 0.3581 |
| -10 | -0.1936 | 0.2110 | -0.6072 | 0.2201 | 0.3590 |
| -9 | -0.2373 | 0.1590 | -0.5489 | 0.0744 | 0.1357 |
| -8 | -0.0935 | 0.1381 | -0.3643 | 0.1772 | 0.4984 |
| -7 | -0.0369 | 0.1246 | -0.2812 | 0.2074 | 0.7670 |
| -6 | 0.0543 | 0.2592 | -0.4537 | 0.5623 | 0.8341 |
| -5 | 0.0895 | 0.1529 | -0.2102 | 0.3892 | 0.5584 |
| -4 | 0.0716 | 0.1847 | -0.2904 | 0.4336 | 0.6983 |
| -3 | 0.0327 | 0.1864 | -0.3327 | 0.3981 | 0.8607 |
| -2 | -0.1320 | 0.1794 | -0.4837 | 0.2197 | 0.4619 |
| -1 | 0.0674 | 0.2068 | -0.3380 | 0.4729 | 0.7444 |
| 0 | -0.0240 | 0.2605 | -0.5346 | 0.4867 | 0.9267 |
| 1 | 0.1181 | 0.3074 | -0.4844 | 0.7207 | 0.7008 |
| 2 | -0.2764 | 0.3201 | -0.9037 | 0.3509 | 0.3878 |
| 3 | -0.3411 | 0.2601 | -0.8510 | 0.1688 | 0.1898 |
| 4 | -0.2309 | 0.4074 | -1.0293 | 0.5675 | 0.5709 |
| 5 | -0.2012 | 0.2496 | -0.6905 | 0.2881 | 0.4203 |
| 6 | $0.4267^{**}$ | 0.1993 | 0.0361 | 0.8173 | 0.0323 |
| 7 | 0.0875 | 0.2075 | -0.3192 | 0.4942 | 0.6733 |
| 8 | 0.0720 | 0.1772 | -0.2754 | 0.4193 | 0.6847 |
| 9 | 0.0048 | 0.2955 | -0.5744 | 0.5839 | 0.9871 |
| 10 | 0.1660 | 0.2271 | -0.2791 | 0.6111 | 0.4648 |
| 11 | -0.1798 | 0.2773 | -0.7233 | 0.3638 | 0.5168 |

# B. Estimation of Factor Loadings in GSCM

For CET, the model estimates four different factors by cross-validation as presented in Figure 11. Figure 12 gives the factor loadings of the estimated factors among the treated and control units. We observe a fairly positive correlation among the treated vs control units for Factors 1 and 3 and a weaker correlation for Factors 2 and 4.

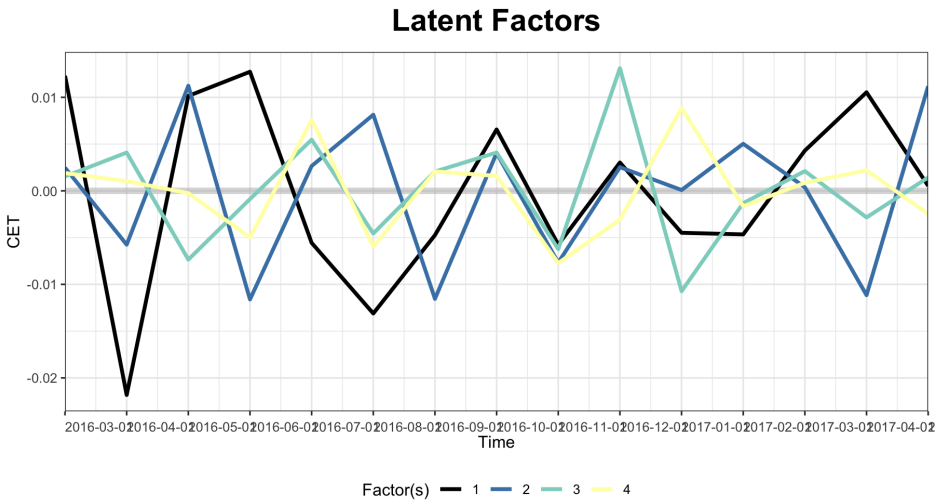


**Figure 11:** CET: Factors

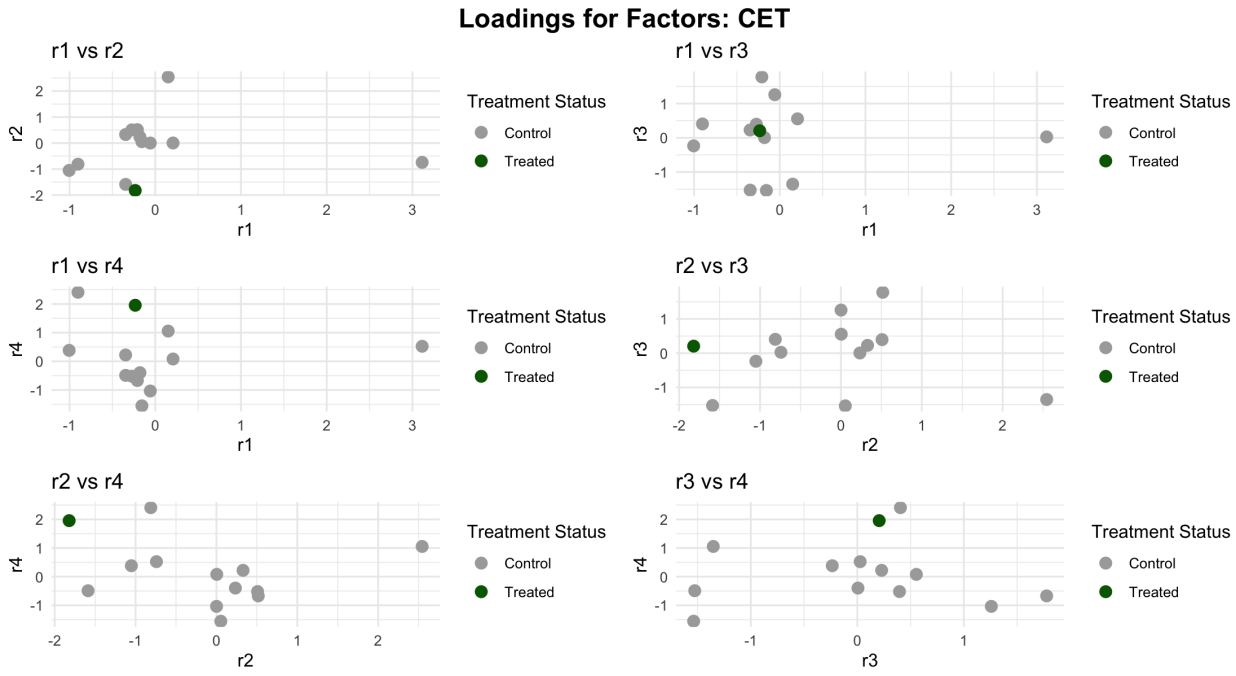


**Figure 12:** CET: Factor loadings

For share turnover, the model estimates only one factor as given in Figure 13. Figure 14 shows that the treated and control unit share similar values of the factor loading and a high degree of overlapping is seen.

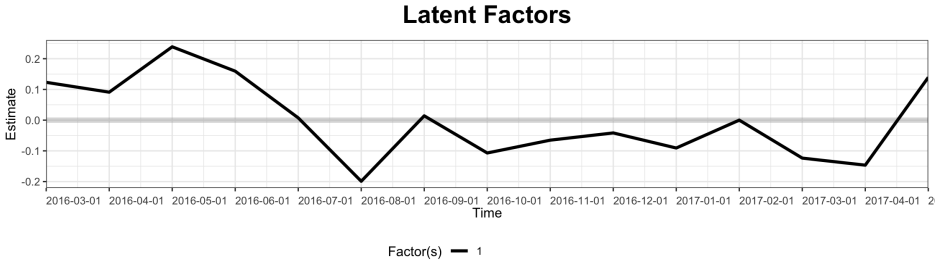


**Figure 13:** Share Turnover: Factors

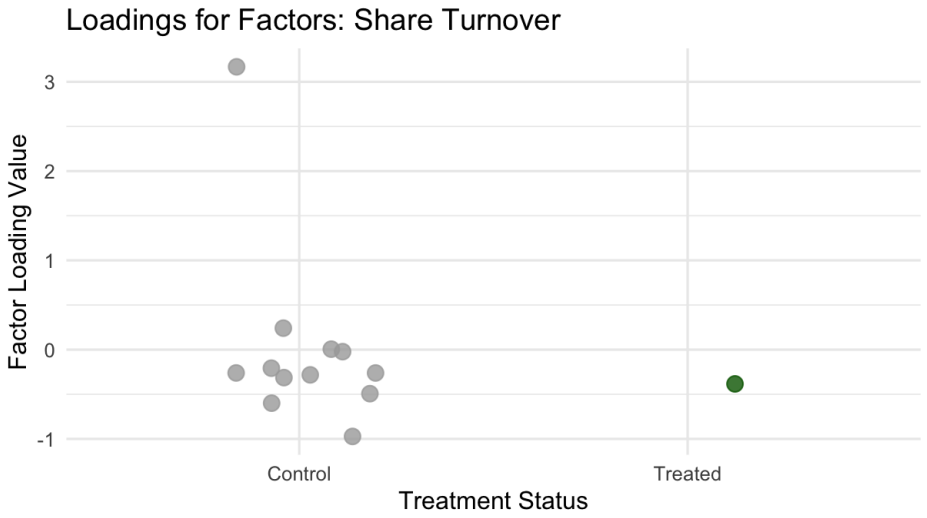


**Figure 14:** Share Turnover: Factor loadings

With Amihud illiquidity, the model estimates four factors as given in Figure 15. Figure 16 shows that the treated and control unit share similar values only for Factor 1 whereas little overlap is seen for the other three factors.

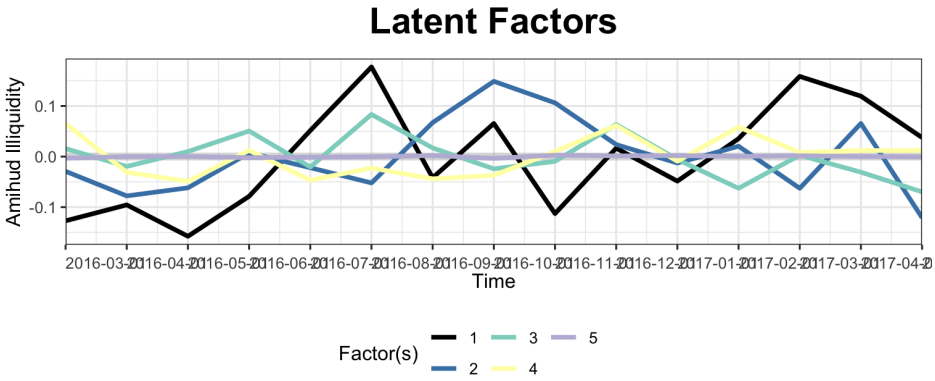


**Figure 15:** Amihud Illiquidity: Factors

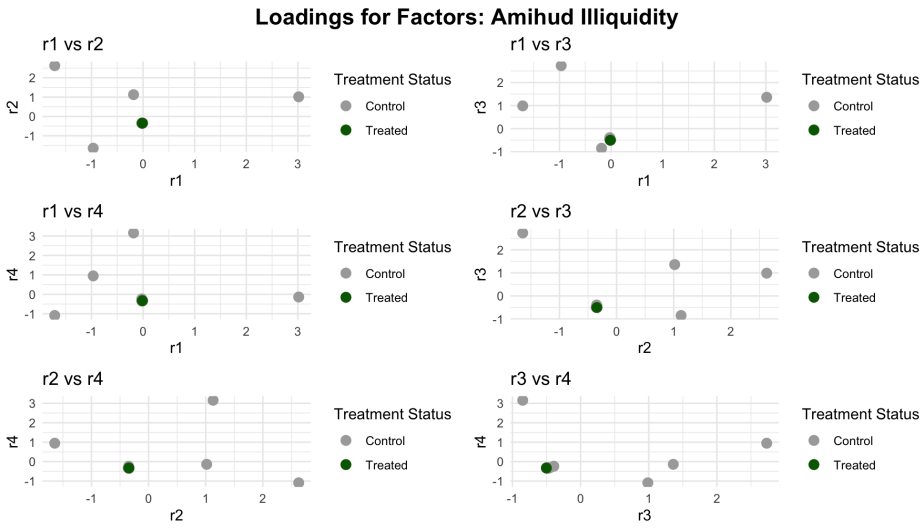


**Figure 16:** Amihud Illiquidity: Factor loadings